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CHANNEL MODELS FOR UNDERWATER ACOUSTIC COMMUNICATIONS

by

Abolfazl Falahati

A Doctoral Thesis submitted in partial fulfilment of the requirements for the award of Doctor of Philosophy of the Loughborough University of Technology.

May 1992

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ABSTRACT

The successful transmission of high-speed digital data through any medium requires a knowledge of the degradations and distortions introduced into the received signal by the medium itself. This knowledge can then be used to design suitable detection schemes, usually based around adaptive equations, to take account of the distortion when detecting data from the received signal. In the case of an underwater communication channel, these degradations are mainly caused by multipath propagation of the transmitted signal energy, which for the realistic cases of turbulent sea conditions, nonhomogeneous media and acoustic scattering will be time-varying in nature. It follows that the received signal can suffer severe and rapid amplitude fluctuations (fades) across the bandwidth of the signal.

The thesis is concerned with the simulation of such channels at 2400 symbols/second on the performance of digital communication links operating with 4-level QPSK (Quadrature Phase Shift Keying) scheme (i.e., achieving data transmission rate of 4800 bits/second). Two computer baseband channel models have been derived. The first model, called system A, is based on full-raised cosine channel modelling and is thought to be most suitable for vertical and short-range underwater communication channels, while the second model, called system B, is based on partial response channel modelling and is thought to be particularly useful in long-range distances.

In system A, the received signal consists of a direct steady component and a random, or diffused, component. The direct component may appear random in turbulent conditions and the random component could be the result of scattering from the boundaries. However, for system B, the received signal will be the superposition of a number of time-delayed random components arriving over different signal paths. Both models represent the time-varying characteristics of channels observed in practice and are used in full system simulations to predict the error performances of various detection techniques based around adaptive equations.
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# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABSTRACT</td>
<td>i</td>
</tr>
<tr>
<td>ACKNOWLEDGEMENTS</td>
<td>ii</td>
</tr>
<tr>
<td>TABLE OF CONTENTS</td>
<td>iii</td>
</tr>
<tr>
<td>1: INTRODUCTION</td>
<td>1</td>
</tr>
<tr>
<td>1.1 BACKGROUND</td>
<td>1</td>
</tr>
<tr>
<td>1.2 SURVEY OF RELATED RESEARCH</td>
<td>7</td>
</tr>
<tr>
<td>1.3 OUTLINE OF THE INVESTIGATION</td>
<td>9</td>
</tr>
<tr>
<td>2: NATURE OF AN UNDERWATER ACOUSTIC CHANNEL</td>
<td>13</td>
</tr>
<tr>
<td>2.1 INTRODUCTION</td>
<td>13</td>
</tr>
<tr>
<td>2.2 VELOCITY OF SOUND IN THE SEA</td>
<td>13</td>
</tr>
<tr>
<td>2.3 SOUND VELOCITY PROFILE</td>
<td>14</td>
</tr>
<tr>
<td>2.4 ATTENUATION DUE TO ABSORPTION OF SOUND</td>
<td>15</td>
</tr>
<tr>
<td>2.5 THE NOISE BACKGROUND OF THE SEA</td>
<td>17</td>
</tr>
<tr>
<td>2.5.1 Radiated and self-noise</td>
<td>17</td>
</tr>
<tr>
<td>2.5.2 Ambient noise</td>
<td>17</td>
</tr>
<tr>
<td>2.5.3 Thermal noise</td>
<td>18</td>
</tr>
<tr>
<td>2.6 DEEP WATER SPECTRA</td>
<td>18</td>
</tr>
<tr>
<td>2.7 AIR BUBBLES IN WATER</td>
<td>19</td>
</tr>
<tr>
<td>2.8 UNDERWATER ACOUSTIC CHANNEL BANDWIDTH</td>
<td>20</td>
</tr>
<tr>
<td>2.9 CONCLUDING REMARKS</td>
<td>20</td>
</tr>
<tr>
<td>3: UNDERWATER MULTIPATH PROPAGATION MODELS</td>
<td>27</td>
</tr>
<tr>
<td>3.1 INTRODUCTION</td>
<td>27</td>
</tr>
<tr>
<td>3.2 UNDERWATER FLUCTUATION MODEL:</td>
<td>27</td>
</tr>
<tr>
<td>A GENERAL STATEMENT</td>
<td>27</td>
</tr>
<tr>
<td>3.3 MULTIPATH PROPAGATION CONTRIBUTORS IN WATER</td>
<td>28</td>
</tr>
<tr>
<td>3.3.1 The sea surface</td>
<td>28</td>
</tr>
<tr>
<td>3.3.2 The sea volume</td>
<td>29</td>
</tr>
<tr>
<td>3.3.3 The sea bed</td>
<td>31</td>
</tr>
<tr>
<td>3.4 SOUND TRAPPING</td>
<td>32</td>
</tr>
<tr>
<td>3.4.1 Shallow water ducts</td>
<td>32</td>
</tr>
<tr>
<td>3.4.2 The surface duct</td>
<td>32</td>
</tr>
<tr>
<td>3.4.3 The deep sound channel</td>
<td>33</td>
</tr>
</tbody>
</table>
APPENDIX B
B1. DISTRIBUTION OF SINUSOIDAL-WAVES PLUS NOISE (RICE) 202
B2. PSEUDORANDOM NUMBERS (SEED INTEGER GENERATION) 204

APPENDIX C
VARIABLE FIFTH ORDER LOW PASS BESSEL FILTER 206

APPENDIX D
BASEBAND DESCRIPTION OF PASSBAND SYSTEM 212

APPENDIX E
DIFFERENTIAL ENCODING AND DECODING 216

APPENDIX F
ADAPTIVE ADJUSTMENT OF LINEAR TRANSVERSAL FILTER 221

APPENDIX G1
SYSTEM A CHANNEL MODEL PROGRAM 228

APPENDIX G2
SYSTEM B CHANNEL MODEL PROGRAM 235

APPENDIX G3
SYSTEM A RECEIVER PROGRAM 246

APPENDIX G4
SYSTEM B RECEIVER PROGRAM 255

REFERENCES 269
CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Although over seventy percent of the Earth's surface is covered by water, man still finds it difficult to tackle the problem of communication through this defying medium. At the present, the channel phase stability, channel impulse response fluctuation rate and bandwidth availability are the main bounds for a reasonable performance of an underwater data transmission system.

The received signal characteristics must be obtained considering the environmental properties of the water medium itself upon the positions and the distance between the transmitter and the receiver. In the short range channel (System A), the transmitter and the receiver are considered to be situated in either horizontal or vertical (deep) positions but in the long range channel (System B) the communication link is established over a horizontal distance via DSC (Deep Sound Channel) channel.

The characteristics of the channel fluctuation are then used to design equalizers and synchronization systems. For a given signalling method, the bandwidth limitation constrains the data rate, and phase stability is of great concern especially at long-ranges. With the recent advancement of Very Large Scaled Integrated circuits (VLSI) for digital signal processing, it is now possible to implement highly sophisticated techniques for modulation, demodulation, coding, decoding, and detection of digital signals for underwater communication applications.

A digital data communication system can be represented by the model shown in Fig. 1.1. The transmitter and receiver sections are typical of most communication system models when appropriately modified, but the transmission path is quite different for the underwater channel.

The transmitter comprises an encoder, a low pass filter and a modulator. The input to the encoder is a stream of binary digits representing the information to be
transmitted. The successive pairs of bits are then sampled by the encoder, which generates a 4-level stream of symbols. Each level corresponds to a different bit combination, e.g. 00, 01, 10, 11.

The baseband modelling of the full communication system is achieved by the low-pass filter which is essentially a waveform shaper that produces a 4-level shaped baseband waveform; it is this waveform that modulates the carrier waveform for transmission through the water.

The modulation considered is quadrature phase shift keying (QPSK), so that each of the four levels in the baseband waveform produces a phase change of 0°, 90°, 180°, and 270°. These absolute phase changes can be generated by the modulator, but because of the phase changes that inevitably occur in the underwater channel it is preferable if it generates differential phase modulation. This means the receiver has only to detect a phase change between any particular symbol and the preceding one rather than the first one in a long stream [1-3].

The underwater communication is accomplished here by utilising acoustic waves. The transformation of electrical signals into acoustic waves is normally achieved by transducers. The transducers (omnidirectional or an array) are constructed from electrostrictive materials which give them quite a good impedance match to water. Their design requires specialised techniques (Appendix A).

The information rate of 4800 bits per second employing 4-level Quaternary Amplitude Modulation (QAM) is investigated over this medium. The symbols are generated at 2400 symbols per second (2400 baud), i.e. each sample carries 2 bits of information. At this wide bandwidth which can only be obtained by high centre frequencies (bearing in mind that high centre frequencies leads to higher Doppler spreads), the acoustic signal propagating between the transmitter and receiver can be seriously distorted by multipath interference. This term describes the condition which causes the signals from a given transmitter to be received via a number of paths, each involving a different transit time. Two major factors contribute to this multipath propagation. First, the turbulent and thermal microstructure of the sea produces small continuous variation in the acoustic refractive index. This in turn leads to multipath refraction of the sound waves (usually termed forward scattering) and the received signal is subject to random fluctuations in amplitude, phase and transit time. For instance, the propagation through a random microstructure may be
viewed conceptually as consisting of a steady, direct path component that decreases with range, together with scattered or diffracted components that increase with range and eventually dominate the received signal.

Multipath propagation is also produced by reflection from the boundaries of the medium. The signal then consists of a direct component plus a number of distorted, delayed replicas. In general, this factor has far more effect upon acoustic communication than forward scattering owing to the much larger transit time differentials that can occur, typically 4 to 50 ms.

Moreover, at any distance, the resultant is the sum of a steady and random component, with amplitude distribution that depends only on the fraction of the total average power in the received random component. Therefore, signals can experience fading, either independently or collectively, implying that multipath fades can vary from Rayleigh to various degrees of Rician [3-15]. This indicates that the transmitted data signal is subject to amplitude and phase distortions or spreading out in time and eventually results in intersymbol interference where adjacent data elements overlap in time.

The characteristics of the spectrum of ambient noise in deep water indicate the existence of the number of different causes of the noise in different portions of the spectrum. These include tides, waves and earth seismicity at the low end, distant shipping and rough sea surface at moderate frequencies, and molecular thermal motion of the sea at very high frequencies. Moreover, the ambient noise background of the sea, in the absence of wave crashes, ice cracking and biological noise has been found to have a Gaussian amplitude distribution. This can be observed by adding all individual noise sources from the sea surface or ships. Because noise makes it difficult to determine the presence or absence of desired signals or their characteristics, an understanding of the origins of the noise is vital. Indeed, much work has been done by many researchers to determine its sources and characteristics [4,15].

At the receiver, transducers (single omnidirectional) are employed to convert acoustic signals into electrical waveforms, these signals are then demodulated, detected and decoded [Fig. 1.1]. The output of the demodulator is a noisy and distorted 4-level baseband signal. In principle, it is a noisy version of the waveform that was applied to the modulator in the transmitting transducers.
Two computer simulation models have been constructed to demonstrate all the nonlinear properties observed in practical underwater baseband channels just described. The first channel model (system A) employs a full raised cosine filter as its shaping filters while the second model (system B) employs cosine partial response filters for the transmitter and receiver shaping filtering. Comparing the two systems, a useful reduction in signal bandwidth can be achieved employing system B by allowing considerable but well-defined levels of intersymbol interference between neighbouring signal-elements and by using suitable adaptive techniques to eliminate the effects of this interference. This system can be particularly advantageous for long-range underwater communication where the gradual increase in the number of eigenrays leads to a flat fading response.

The detectors available to overcome inter-symbol interference (ISI) resulting from a multipath effects and added noise considered in real-time computation can be classified into two separate categories. The first group of detectors employs equalizers and the receiver has a prior knowledge of the interfering components. The received signal is passed through an equalizer before arriving at the detector input and the detection process is now a simple threshold comparator. The detector makes a decision on the value of the received data symbol, by comparing the corresponding sample value with the appropriate level (or levels). Equalization techniques used are the linear equalizer and the non-linear equalizer (or the decision feedback equalizer) with their tap gains adaptively adjusted for the appropriate time varying channel. The goal of filter D in Fig. 1.2 is to provide an all-pass network which does not change any amplitude distortions in the received signal but affects only the phase distortion. This filter also performs an adaptive adjustment process (minimum phase), if necessary, on the sampled impulse response of the channel, and can have a first component of value unity. The filter introduces a delay of \( n \) sampling intervals, so that, strictly speaking, it is minimum phase for the given delay [1,100].

The second group of detectors use maximum likelihood detection or maximum likelihood sequence estimation (MLSE). In such a system, the detector, instead of removing the ISI, takes full account of it, thus using the entire transmitted signal energy in the detection process.
The Viterbi algorithm is used to implement MLSE, but not in its true form because of the enormous computer memory requirements and equipment complexity for the system to be implemented in hardware. Moreover, the Viterbi algorithm achieves the same tolerance to noise as that of MLSE. A Viterbi detector operates by storing a complete set of possible sequences (vectors) of transmitted data symbol values together with the 'costs' of the vector. The detected message is selected as the particular sequence, or vector, which has the minimum cost [1-3,100].

The amount of storage and computational complexity required increases exponentially in a Viterbi detector, as the number of components in the sampled impulse response of the channel increases. This becomes considerably more difficult, particularly for the long range underwater data communication system, since the number of sampled impulse response of the channel increases as the number of received paths is increased. This problem can be overcome by further modification of the detector and the all-pass network ahead of the detector; the presence of this all-pass filter is to remove the phase distortion introduced by the time varying channel as previously explained for first group of detectors. The detector now limits the number of vectors held in the receiver at any time instant to a small value, regardless of the number of components in the sampled impulse response of the channel, but without reducing unduly the tolerance of the detector to noise. This type of detector is now referred to as near-maximum likelihood (NML) detector [Fig. 1.3]. It has been shown that NML detectors are not significantly inferior to true Viterbi detectors in terms of their tolerances to additive white Gaussian noise [16-18].

Decision-feedback equalizers have a poor performance over time varying channels [17]. At low error bit rates, they are 2.5-3.8 dB inferior to the corresponding NML detectors depending on the severity of fading. The errors are caused predominantly by sudden and deep fades; in addition, the equalizers suffer from inherent error propagation tendencies (i.e. accumulation of incorrectly detected data) Thus, the most suitable detector for a time varying underwater communication channel is an NML detector and an adaptive filter provided with the correct channel estimate. Any error in the estimation of the sampled impulse response of the channel directly affects the performance of the detector. Furthermore, an incorrect channel estimate leads to an incorrect adjustment of the adaptive filter. It is therefore essential for good performance of the detector that the channel estimator is able to make an accurate estimate of the sampled impulse response of the channel.
It is evident that, with an underwater channel, the channel characteristics vary considerably with time and season of the year, geographical location, turbulence, etc. The received signal is continuously varying randomly due to fading and therefore the sampled impulse response of the channel must be estimated continuously at the receiver. A receiver employing a NML detector can therefore be considered to consist of a detector and an estimator connected back to back. The input to the channel estimator is the current detected data and the received sample; its output is an estimate/prediction of the channel sampled impulse response for input to the detector at the next sampling instant. The channel estimator acts as an echo canceller and is basically a tapped delay line, finite impulse response (FIR) filter with the filter tap coefficients forming a channel sampled impulse-response. The tap coefficients of the filter are adjusted adaptively, according to a particular algorithm, in order to track a time varying channel. The algorithm is simple and works adequately in a variety of applications. It suffers from the disadvantage of having a slow convergence rate, but this can be overcome by knowing the number of different paths (eigenrays) that could be present at the receiver [1, 16-27].

In the underwater case considered here, the received signal fades which occur within the sampling time intervals have nearly the same level of the background noise. This causes a very high error rate and also a longer convergence timing requirement of the adaptive filter ahead of the detector. Faster convergence can be accomplished if the information transmission takes place in a block by block form. Each block can then contain a sequence of known training symbols s, followed by the information sequence Sd. The training symbols can then be employed by the estimator to predict the variations in the sampled impulse response of the channel, thus the occurrences of deep fades. This knowledge is then passed on to the detector.

Since the near-maximum likelihood detector takes into account all components of the sampled impulse response of the baseband channel and the communication can take place in a block by block form, the subject of element timing synchronization is given least attention in this investigation. However, this subject can be fully recognized when the system is fully implemented in hardware form.
1.2 SURVEY OF RELATED RESEARCH

Throughout the literature on underwater communications, there is little evidence of success in producing a perfect model of the sea (especially in electronic hardware) for a communication link with a data rate higher than 2kb/s. High data rate information systems require wide bandwidth which is only achieved by high centre frequencies, thus leading to higher Doppler spreads. In the ocean environment, increase in transmission bandwidth increases further the absorption of high frequency energy. Time and frequency spreading of signals due to reverberant conditions further limits data transmission rates.

World War II brought about the necessity of underwater communication for defensive purposes. This defensive necessity resulted in the development of underwater telephones for voice communication with submerged submarines, using an upper single sideband-suppressed carrier (SSBSC) of 8.3 kHz. Similar systems appeared later, all operating with AM or SSB modulation at around the same frequency, and a considerable amount of transmitter power, typically 100 W, was employed over a range of a few kilometres [28].

In 1966, telemetry was achieved over an 1800 m path with data rate of 45 bits/second employing frequency shift keying (FSK) modulation with a 40 kHz carrier. This system was later improved to achieve a data rate of up to 100 bits/second utilising some form of coding techniques for the first time. The basic system is still available but in its most advanced digital form [29].

Experimental results revealed in 1972 the feasibility of high rate digital data telemetry over a short-range (<10km) underwater channel [30]. In this project, an experimental frequency-hopping signalling format of 2.5kHz bandwidth was chosen with simultaneous FSK and PSK modulation schemes. Several modes of digital data transmission rates from 130 to 1640 bits/second were tested at sea. The outcome of such results encouraged many researchers to try higher rates of transmission over underwater channels.

In 1975, underwater amplitude fluctuations were experimentally observed using high frequency carrier of 150kHz in a short-range shallow water channel [31]. In this experiment, 0.8ms duration pulses were transmitted over ranges of 150-650m
to a receiver at a depth 16m. Fading by as much as 35dB was evident, which was thought to be due to the effect of wind generated waves. In 1976, the same authors [32] employed Amplitude Shift-Keying (ASK) techniques with a transmitted power of only 50mW; they recorded a transmitted bit rate of 600 bits/second over a range of 650m, with a bit-error rate of $10^{-3}$.

Estimation and signal processing in the detection of high bit rate transmitted signals through underwater channels was first introduced by French researchers in 1977 [33]. Although their publication gives some novel adaptation techniques employing estimated received signals, there are no clear indications of operating ranges, bit rates or the carrier frequency.

A locally optimum detector was employed in 1980 [34] to correlate a data spectrogram with a reference spectrogram in order to detect (i) a known signal with unknown delay and Doppler parameters, (ii) a known signal with a known covariance function, and (iii) the output of a random, time varying channel with a known scattering function. In this paper, maximum likelihood detectors employing mean square estimators were first mentioned in an underwater environment but there is no evidence that a channel model was realised.

In 1981, coherent quadrature receivers were first employed in an underwater channel [35]. It was observed that if an attempt was made to detect a distributed highlight reflector employing a sinusoidal transmit signal, in a multipath environment, the various multipath returns overlap, producing a nonresolvable multipath situation and causing the amplitude and phase of the signal fluctuate randomly with time. This publication was based on theoretical assumptions but clearly shows the output signal-to-noise dependence on the correlation characteristics of the input signal.

During the last decade, more complex modulation technique due to the advent of VLSI have been introduced. In 1981, an MFSK system was demonstrated using a 15 kHz carrier with the signal bandwidth of 3 kHz [36]. This was capable of a low probability of error ($10^{-5}$) within a multipath environment but at a data rate of only 40 bits/second. Higher data rate systems employing microprocessors were also introduced for a selection of transmission frequencies in the range of 45 to 55 kHz and transmitting separate synchronization and Doppler compensation frequencies. At a few kilometres range the same error probability was observed [29]. The problem of element-timing synchronization was further tackled in 1982 [37] when a timing subsystem was described that consisted of an N-point finite impulse response (FIR)
digital differentiator followed by an M-step adaptive linear predictor. The method was implemented as part of a microprocessor based FSK underwater acoustic telemetry system, and is found to be computationally efficient as well as extremely accurate.

In 1983, block coding was first introduced into underwater data telemetry [38]. Although no experimental or simulated results were given, examples of how a microprocessor system can be employed for coding and decoding of the underwater data were presented.

It is evident that for higher rates of data communication suppression of multipath components is of prime importance. Increasing the bandwidth available should enable the data rate to be increased whilst maintaining a reasonable error rate performance.

1.3 OUTLINE OF THE INVESTIGATION

Primarily, the thesis is concerned with the development of computer simulation models that can describe the multipath propagation existing in time-varying underwater channels for high speed digital data transmission at 4800b/s. The computer simulation is a valid means of evaluating the performance of such a modem because the system can be considered as a digital signal processor performing computer-like operations on a set of numbers.

Chapters 2 and 3 describe a broad description of the structure of the sea, noise and absorption losses that cause attenuation of the received signal.

Chapter 4 explains the multipath propagation mechanisms in the sea and computer simulation models that can describe this phenomenon for underwater high speed digital data transmission systems.

Chapter 5 presents a model of a synchronous serial QAM digital data transmission system, and describes the equivalent baseband models of both shallow and open sea data transmission systems.

Chapter 6 investigates the equalization techniques and the adaptive adjustments of the receiver employing feedforward transversal filters, assuming a known sampled
impulse response of the underwater channels. This chapter then compares the errors bit performances employing a near-maximum likelihood detector with those obtained for a simple threshold detector.

Chapter 7 employs adaptive channel estimators in order to predict the channel's sampled impulse responses. This chapter then describes a combined estimator-detector with an adaptively adjusted receiver. It also gives indications of how a modified estimator can result in cancellations of unwanted echoes.

Chapter 8 summarises first all constraints imposed upon acoustic communication paths as well as computer simulation analysis and improvements. It then provides a broad discussions of how practical models with their appropriate detection schemes can be generated employing sophisticated digital signal processors.

At the end of each chapter the results of the computer simulation tests are presented and concluding remarks are made. The systems have been approximately optimized within the available computer time for best performances.
A. I. PASS

B. MODULATOR

C. ENCODER

D. TRANSMISSION PATH

E. DEMODULATOR

F. DETECTOR

G. DECODER

H. TRANSMISSION PATH

Noise

a) transmitted/detected digits

b) coded/decoded symbols

c) baseband waveform

d) QPSK modulated waveform

Fig. 1.1 Model of digital data transmission system
\( \mathbf{e}_i \)  

\( \mathbf{p}_i \)  

\( \mathbf{d}_i \)  

\( \mathbf{s}_i \)  

\( \mathbf{s}'_i \)  

\( \mathbf{F}_i \)  

\( \mathbf{F}_m \)  

\( \mathbf{r}(t) \)  

\( t = iT \)  

\( \mathbf{r}'_i \)  

\( \mathbf{s}'_i \)  

\( \mathbf{NML detector} \)  

\( \mathbf{Delay} \)  

\( \mathbf{Channel estimator} \)  

**Fig. 1.2** Category one detector

**Fig. 1.3** Category two detector
CHAPTER 2

NATURE OF AN UNDERWATER ACOUSTIC CHANNEL

2.1 INTRODUCTION

The arrival pattern of an acoustical signal depends upon the sound speed between the source and the receiver. The sound speed is a strong function of temperature and to a lesser extent salinity. This chapter describes the acoustics of the sea, including the dependency of sound velocity on temperature, salinity and depth (i.e. the sound velocity profile), sound attenuation, the physical properties of the bottom material, the nature and spectra of environmental and man-made noise, limitations by cavitation and the underwater acoustic bandwidth.

2.2 VELOCITY OF SOUND IN THE SEA

The velocity of sound in sea water is determined by the temperature (T), salinity (S) or conductivity, and pressure (P) or depth.

The distribution of temperature with depth varies from one shallow-water area to the next and from one season to the next because of the flow of fresh water, currents, atmospheric variations and other causes. The resultant variations in sound velocity are generally greater and more variable in shallow water than over the same depth range in deep water but the layer-to-layer variation comes into effect in deep water.

The variation in salinity can be considered the least important and least variable factor, particularly in shallow water, except in areas where fresh water from a river mixes with sea water. In this case, a sharp salinity gradient with depth is often observed. In deep water the salinity causes an increase in the attenuation due to absorption.
The sound velocimeter is employed to determine the sound speed with a typical accuracy of 0.1m/s. The time requirements for a signal of the order of 1MHz are measured transversing a short distance of tens of centimetres.

Fig. 2.1 shows a common temperature, salinity, and density profile for shallow water. In contrast the deep water salinity variations are generally unimportant; and the pressure function is simply a constant gradient proportional to depth. So temperature is the principal variable especially at near surface.

The density is determined by the temperature and salinity. The most stable region, which is less subject to change, is the region of the steep density gradient. But the region above and below this is less stable and more subject to change through convective overturn or other mixing processes induced by external forces. These processes produce an admixture of water resulting in a constant distribution of temperature and salinity with depth, as shown in the upper 15 metres of Fig. 2.1. Such a situation also occurs in deep water.

The bottom properties pertinent to sound transmission in shallow water can also vary considerably from one area to the next. The sea bottom can be bounded by hard crystalline rock or rock covered by a thin veneer of sediment; gravel, sand, reef or reef debris; or sand and mud, or mud sediments. In several areas the sound velocity through the bottom has been measured but this is generally not sufficient to determine its acoustic properties for underwater sound transmission. Next chapter considers the bottom profile as an unpredictable process having statistical characteristics [4-9].

2.3 SOUND VELOCITY PROFILE

The sound velocity profile is the sound velocity variation with depth. Different characteristics and occurrences can be observed by dividing the profile into several layers as shown in Fig. 2.2.

Just below the sea surface is the surface or diurnal layer in which the velocity of sound is susceptible to daily variations due to local changes of heating, cooling and wind action. The surface layer may contain a mixed layer of isothermal water that is formed by the action of wind as it blows across the sea surface. This mixed layer tends to trap or channel the sound. It disappears under prolonged calm and sunny conditions and is replaced by water whose temperature decreases with depth.
Below the surface layer lies the seasonal thermocline, i.e. a layer that the temperature changes with depth. The seasonal thermocline is characterised by a negative thermal and velocity gradient (a decrease in temperature and velocity with depth) depending upon the season. During the warm (summer and autumn) season, the seasonal thermocline is strong and well defined but during the cold season (winter, spring and in the Arctic) it tends to merge with the surface layer.

Below the seasonal thermocline is the main thermocline, which is affected only slightly by seasonal changes. The major increase of temperature over that of the deep cold depths of the sea occurs in the main thermocline.

Below the thermocline and extending to the sea bottom is the deep isothermal layer, having a nearly constant temperature of around $5^\circ C$, in which the velocity of sound increases with depth due to the effect of pressure. Between the velocity gradient of the main thermocline and the deep isothermal layer, there is a velocity minimum towards which sound travelling at great depth tends to be bent or focussed by refraction. At most latitudes this minimum occurs at about 1 km depth and determines the centre of the so-called SOFAR channel [4].

With the source in the mixed layer, the intensity of sound tends to fall off with depth within the layer and to fall off faster with depth as the lower boundary of the mixed layer is crossed and as the shadow zone is entered, as shown in the ray diagram of Fig. 2.3.

In shallow waters, the velocity profile tends to be unpredictable and irregular. This irregular behaviour is caused by water currents, cooling, heating, and salinity changes [4-11, 38-39].

2.4 ATTENUATION DUE TO ABSORPTION OF SOUND

Any decrease in underwater acoustic signal strength with distance which does not depend on geometrical spreading is called attenuation. This decrease in the amplitude with distance depends upon the physical characteristics of the transmitting medium, including reflection, scattering, leakage in ducts and absorption. With one exception, these are all processes in which the energy radiated by a sound source is redistributed in the medium and can not be shown in the ray diagram. The exception is the absorption, which involves the conversion of the acoustic energy of a sound wave
into heat. The sea density variation determines the attenuation factor $\alpha(f)$; this is not a linear function of frequency, but a quadratic, i.e. the absorption is inversely proportional to the square of frequency.

For an homogeneous sea water medium, the attenuation of a radiated sound pressure wave is thus due mainly to spherical spreading and absorption. Spherical spreading is frequency independent and is given by;

$$20 \log_{10} \left( \frac{R}{R_0} \right) \ dB \quad \ldots 2.4.1$$

where $R$ is the range from the transmitter and $R_0$ a reference range, usually 1m.

Absorption loss, however, is frequency dependent. It is principally caused by the bulk viscosity of the water and can be approximated by considering three relaxation processes; in water, magnesium sulphate, and boric acid the relaxation times are, respectively, $t = 10^{-11}s$, $t = 10^{-3}s$, $t = 10^{-3}s$. The resultant absorption curves are shown in Fig. 2.4.

The total transmission loss can be closely approximated by the sum of the above losses:

$$TL = 20 \log_{10} \left( \frac{R}{R_0} \right) + \alpha(R - R_0) \quad \ldots 2.4.2$$

where $\alpha$ is the absorption coefficient in Fig. 2.4 which shows how the losses become very large at frequencies above 100kHz.

Eqn. 2.4.2 shows the difference in range dependence between the logarithmic transmission loss due to spreading and linear transmission loss due to absorption. Inserting a few numbers into Eqn. 2.4.2 makes it clear that the spreading loss is dominant near the source, whereas the absorption loss is the major term for longer ranges [4-10,40,41].
2.5 THE NOISE BACKGROUND OF THE SEA

2.5.1 Radiated and self-noise

Self-noise depends greatly upon the directivity of the hydrophone [Appendix A], its mounting and its location. On surface ships, the transducer is located in a streamlined dome projecting below the keel of the ship. Noise from the machinery, propeller and hydrodynamics of the ship are the three sources which result in self-noise as well as radiated noise which reaches the hydrophone through a variety of different acoustic paths.

The receiver noise, i.e. the noise at the output when there is no input, comes from filters and amplifiers. Careful design and choice of components can reduce this noise.

The irregular flow of water through which the vessel is moving generates hydrodynamic noise that could be considered as radiated noise or flow noise.

It is also evident that the noise from the ship's propeller creates a form of hybrid noise that contributes to machinery and hydrodynamic noise. It is convenient to consider propeller noise separately because of its importance of as a source of cavitation [4-10,44-46].

2.5.2 Ambient Noise

The ambient noise i.e. the noise of the body of the sea itself, is considered in the absence of other individual noise sources. Thus, the ambient noise is a residual noise background in the absence of individual identifiable sources that may be considered the natural noise environment of the hydrophone. Other types of noise contributing to ambient noise are the noise made by marine animals or the noise made by cracks forming in the ice-sheet over a hydrophone. A composite of ambient noise spectra, summarising results and conclusions concerning spectrum shape and level and probable sources and mechanisms of the ambient noise in various parts of the spectrum between 1 Hz and 100 kHz is shown in Fig. 2.5.
The ambient noise has different characteristics at different frequencies, with a level and slope that varies with conditions such as wind speed in different parts of the spectrum; this is the subject of the next section [4-9, 44-52].

2.5.3 Thermal noise

This type of noise is due to molecular motion of the sea causing agitation of the water molecules bombarding the transducers. Its effect is defined in terms of an equivalent noise spectrum level that could be seen by an omnidirectional transducer of 100% efficiency. This noise in water increases with increasing frequency. Thus, for a given transmitter output power and a signal-to-noise ratio to be achieved, the range that could be covered is reduced due to this noise [4-8, 53, 54].

2.6 DEEP WATER SPECTRA

The spectra of the ambient noise at one deep sea location can be shown as Fig. 2.5.

BAND A: The spectrum in this portion of the band is largely unknown at the present time. The noise is likely to be of hydrostatic origin (tides and waves), or originates in the earth as seismic unrest.

BAND B: In this band the most probable source of noise in deep water appears to be oceanic turbulence with only a slight wind speed dependence in deep water. This band is characterised by the slope of -8 to -10 dB/octave (about -30 dB/decade).

BAND C: Here nearly everyone measurements has shown the ambient noise spectrum flattens out into a "plateau". The noise in this band appears to be dominated by distant ship traffic.

BAND D: This band has a slope of -5 to -6 dB/octave (about -17 dB/decade) introducing the Knudsen Spectra in which the noise originates at the sea surface at points not very far from the point of measurement.

BAND E: Thermal noise originating in the molecular motion of the sea occupies this band and is uniquely characterised by a positive (rising) spectrum having a slope of +6 dB/octave.
Contrasting the ambient noise in deep water with that existing in shallow water, the sources of ambient noise in shallow water are highly variable, both from time to time and from place to place. The presence of high wind can degrade acoustic signals in shallow water up to 40dB, after which they can not be easily detected.

At a given frequency in shallow water the noise background of the sea is a mixture of three types of noise; shipping and industrial noise, wind noise and biological noise. The mixture of these sources of noise will determine the noise level at a particular time and place, and because the mixture is variable with time, the existing noise levels will exhibit considerable variability from time to time and from place to place [4-9,43,55].

2.7 AIR BUBBLES IN WATER

Gas bubbles normally occur immediately below the surface of the sea, although in many forms; they are mainly produced by the breaking of waves by the wakes of the ships, by certain biological organisms such as the swim bladders of fish, and also due to transducer cavitation. Naturally, the air has a markedly different density and compressibility from that of water, and because of the resonant characteristics of bubbles the suspended air content of water has a profound effect upon underwater sound.

The existence of air bubbles causes, to some extent, the compression and rarefaction of the incident sound waves thus making the phase speed of sound to be a function of frequency, i.e. producing a dispersive medium. At certain frequencies, depending upon the size of the bubbles, resonance occurs which causes the bubbles to pulsate with a maximum oscillation. This results in the extraction of a portion of the sound energy into heat, the remainder being scattered in all directions.

The resonant frequency of a free air bubble of radius \( a \) is given by:

\[
    f = \frac{1}{2\pi a} \left( \frac{3\gamma P_A}{\rho} \right)
\]  

...2.7.1

where \( \gamma \) is the ratio of specific heats for gas bubbles (1.4 for air), \( P_A \) is the ambient pressure at the bubble’s depth and \( \rho \) is the density of water.
Thus, the nonlinearity produced by air bubbles depends upon the frequency of oscillation, the size of the bubbles, and the physical and hydrodynamic properties of the two media involved. Fig. 2.6 describes the theoretical damping of air bubbles in water [4-9,55-58].

2.8 UNDERWATER ACOUSTIC CHANNEL BANDWIDTH

The transmission of acoustic energy through water is strongly frequency dependent and is subject to absorption, which is explained in details in the next chapter. This frequency dependence is the dominant factor determining the usable bandwidth of an acoustic channel for any particular ranges in the ocean.

Fig. 2.7 illustrates all forms of energy propagations in the sea. For the purpose of comparison a considerable liberty has been taken in order to simplify assumptions for systems transmitting information between two points in the ocean. The vertical positions at which the various forms of communication have been indicated in the figure correspond to the approximate bandwidth requirements range from the order of 10 Hz for control sensors and coded communication links to 100kHz for slow-scan television systems. Notice that the slow-scan television system requires the maximum capability of acoustic links over any appreciable distance [4-9,59-61].

2.9 CONCLUDING REMARKS

Investigation of the structure of the underwater medium suggests that for a shallow (vertical or horizontal) and deep (horizontal) regions the maximum velocity of sound is up to 1550m/s. In the SOFAR channel (depth of about 1km) the velocity of sound is at its minimum (1450m/s) and the occurrence of "sound trapping" in this region can provide a good communication link for long distance (10km) data transmission.

The most dominant factor that prohibits sound travelling in the sea is the absorption loss for any particular frequency. This factor determines the usable bandwidth and depends solely upon the distance between the transmitter and receiver. Transmission frequencies in the range 10-100kHz can provide the lowest attenuation.
Attenuation caused by surface randomness is due to near-resonant bubbles as well as multi-layer effects such as refraction and saturation that are thought to be controlled by surface decoupling. In the next chapter, statistical models are implemented to recognize each contributing element that could be added up to produce a randomly fluctuating received signal.

When all individual noise sources are added, the distribution of the total noise is at its lowest for frequencies in the range 20-150kHz. Resonant air bubbles, introduced primarily by rain or breaking waves, constitute the dominant noise generating mechanism and occupies the 10-20kHz band underwater acoustic communication spectrum. The total added random noise can be statistically modelled as having a normal Gaussian-type distribution with the noise components occurring within 95% of the central limit of the distribution.
Fig. 2.1 Variation of Density (in parts per thousands above 1g/cm³), Salinity (in parts per thousand) and Temperature with the depth [7].
Fig. 2.2 Typical deep sea velocity profile divided into layers [4].
Fig. 2.3 Typical ray paths propagation.

Fig. 2.4 Attenuation rate due to seawater and freshwater. Dashed lines indicate contributing attenuation rates due to relaxation processes [8]
Fig. 2.5 Various ambient noise existing in sea and deep sea noise frequency bands [50].
Fig. 2.6 Theoretical damping of resonant air bubbles in water [56].

Fig. 2.7 Bandwidth limitations and requirements of information channels in the ocean [59].
CHAPTER 3

UNDERWATER MULTIPATH PROPAGATION MODELS

3.1 INTRODUCTION

This chapter describes the time and frequency distortions introduced by multipath propagated underwater channels. The models are based on studies of the nature of multipath propagation initiated by the physical properties of the sea surface, volume and bottom scatterers that are the traditional domain of the physical oceanographer and geophysicist. In studies of multipath propagation, particularly in shallow environments, the transmission conditions are considered to be constantly changing, i.e. the received signals are affected by changes in the transmission medium. In order to simulate such channels, major processes in the structure of the sea and their effects on acoustic propagation must be well understood. The chapter also introduces the theory of probability distributions and stochastic processes in the context of channel models that could evaluate digital underwater acoustic information.

3.2 UNDERWATER FLUCTUATION MODEL: A GENERAL STATEMENT

One could state that the fluctuations of the signal from a steady distant source in the sea are caused by multipath propagation in an inhomogeneous moving medium. The reflection and scattering by the sea surface, the paths from the scatterers in the body or on the boundaries of the sea and the paths involving bottom-bounce propagation are the major contributors of multipath propagation.

The inhomogeneities are the result of the rough sea surface, the biological matter existing in the body of the sea and the temperature and salinity microstructures. These various inhomogeneities are always in motion relative to each other and to the source and the receiver or both, because of currents, turbulence and source or
receiver motion relative to each other. To simulate such channels, these non-linearities must be first understood in detail and represented by suitable mathematical expressions.

The investigation begins by considering the probability density function (PDF) of each individual reflection and scattering process which establishes a multipath propagation channel, and the effects of adding these to various other inhomogeneities. For each individual case of sea surface and bottom a general statistical model of reflections is first introduced within reasonable limits, this is used to explain scattering as a result of multi-layer reflections. In the case of the body of the sea, scattering is a predominant factor. This can be mathematically explained by assuming that the body of the sea is a combination of acoustically small, non-spherical bodies whose dimensions are less than a wavelength and that these can scatter in the same way as a sphere of the same volume and the same average physical characteristics could [3-10,13,14,19,62-64].

3.3 MULTIPATH PROPAGATION CONTRIBUTORS IN WATER

When an acoustic signal carries information over an underwater link, the signal is subjected to various types of time varying distortions and corrupted by various forms of noise. It is important to understand the parameters that characterize these types of distortions in order to appreciate the different classifications of such channels and consequently to develop channel models.

3.3.1 The sea surface

The acoustic waves are affected by the sea surface in many ways especially in the transmission of sound in shallow water. The surface causes reverberation produced by both back-scattering and forward scattering which is the dominant loss process in sound propagation in the mixed-layer; this surface scattering can reduce the power of the sound source situated a quarter wavelength or less below the surface [Fig. 3.1].

The sea surface produces interference effects with the direct path in the sound field from a shallow source and is a major contributor of ambient noise in the deep sea
up to 50 kHz. The surface also produces a Doppler shift in narrow band reflected and scattered sound, due to its wind-driven motion. A shadow zone can be produced in a negative gradient extending all the way up to the surface.

In the deep sea, the disturbance of acoustic signals by the sea surface may be given by:

$$\omega^2 = kg + \frac{Tk^3}{\rho}$$ ..................3.3.1

where \(\omega\) is the angular frequency, \(k = 2\pi/\lambda\) is the wave number, \(g\) is the acceleration due to gravity and \(T\) is the surface tension.

The frequency-wavelength relation of Eqn. 3.3.1 is known as the "Capillary-gravity" relation. It is the combination of gravity forces and surface tension. Capillary waves are the result of turbulent air-water environment in which the wavelength is less than about 2cm but gravity waves, are the result of oscillation in response to the restoring force of their own weight as they rise and fall relative to the average water level.

A reflection loss is produced when sound is incident upon the sea surface. This loss, though small, is a major contributor to the total loss for near-surface refracted paths in the deep sound channel at long ranges. This layer of the sea has the most bubbly layer of air just beneath it when it is rough, which often hides the surface itself [4-10,14,68-71].

3.3.2 The sea volume

Diffusion of the direct path signal is caused by the microstructure properties of the body of the sea. This can even cause the direct path signal to fluctuate in phase and amplitude. Scatterers in the body of the sea, such as fish, air bubbles and turbulent patches, are examples of such fluctuations in the received sound signal.

Generated within the ocean mass are the internal waves which are due to volume gravity. The maximum vertical displacement amplitude occurs at a plane where the density is changing most rapidly with depth or where water masses of different densities overlap. The effect of such phenomena on acoustic signals in some
circumstances could be much higher than that of the layer-to-layer temperature variation effects. Upon a long-crested wave in deep water, the depth dependence of the displacement amplitude $d$ due to material velocity may be given by:

$$d = d_0 e^{-z/\lambda} \quad \ldots 3.3.2$$

where $z$ is depth, $\lambda$ is the surface wavelength and $d_0$ is the orbital displacement amplitude at the surface. Eqn. 3.3.2 confirms that the particle velocity and the material displacement decrease exponentially with the increase in distance from the surface. This effect can be further amplified by increase in wind and turbulence at the surface.

The thermal waves are also a form of oceanic inhomogeneity that are believed to produce fluctuations of long range transmission where near surface refracted paths are involved in the transmission. The presence of inhomogeneities in the sea, together with motion of the sea and the motion of the source/or the receiver, are the underlying causes for the fluctuation of the signal from a distant, steady source of sound in the body of the sea. In deep ocean, the resulting ray path [Fig. 3.2] also depends on location, season and time of day.

Furthermore, the well known Rayleigh scattering function which was derived for a small non-resonant sphere can describe the change of scatter strength with sound frequency and the dependence of sound scatter on the size, compressibility and material density of marine bodies as,

$$P = \frac{(ka)^4}{\pi} \left[ \frac{\varepsilon - 1}{3\varepsilon} - \left( \frac{g - 1}{2g + 1} \right) \cos \theta \right]^2$$

for $ka \ll 1 \quad \ldots 3.3.3$

The two functions inside the squared bracket cause adding or cancelling of scattering depending upon the relative magnitudes of $\varepsilon$ and $g$, i.e. the ratios of elasticity and density of sphere to medium respectively. The term $(ka)^4$ is known as the Rayleigh scatter factor, where $a$ is the radius of the sphere and $k$ is the wave-number. This factor determines the degree of scattering and backscattering as it would be imposed on an acoustic signal; as it increases, an omnidirectional radiation pattern develops, supplemented by a growing forward scattering lobe upon the intensity pattern of transmitted acoustic energy [4-10,14,76-79].
3.3.3 The sea bed

The sea bottom has similar effects on sound propagation as does the sea surface. Bottom-bounce reflections are possible since it reflects and scatters sound, producing bottom reverberation. It produces a shadow in the positive gradient of the water overlaying it in deep water. But the received sound from the sea floor is considerably more complex than that from the sea surface.

The sea floor is formed by combining sedimentation theory and the process known as sea floor spreading, continental drift and global tectonics. The new sea floors keep on adding to the old ones as the Magma from the Earth’s interior rises to the surface of the midocean ridges and then solidifies. Thus the sea floor is often layered and may vary in composition from hard rock to a soft mud. Furthermore, in the trenches, the sea floor descends into the Earth’s interior that could result in spreading of up to 10 cm/year. There are also clay particles from land erosion which slowly fall to the sea floor as well as marine animal skeletons and plants.

To model such an environment, samples of horizontal layers must be considered (a sub-bottom profiler can provide the samples in practice as shown in Fig. 3.3). The transmitted signals, when received from the interface, are received at different times but can be separated provided the signal duration is short enough or the layers are thick enough. The overlap of multiple reflections occurs when the signal duration is longer than the travel times in the layers.

The plane wave reflection coefficient $R$, and the sound incident angle $\theta$, are normally employed for bottom bounce computations which can give rise to a good approximation as long as $\theta$ does not reach the critical angle. Near this angle, part of sound energy is lost as it travels along the interface into the lower medium. Since sound can readily enter a sedimentary bottom and be reflected back into the sea by sub-bottom layers, or be refracted back by the steep velocity gradient in sediments, there exists a PDF that can describe a reasonably rough sea bed in terms of multilayer reflection and scattering. The latter could be the result of a further increase in randomness and prolonged transmission. Therefore, the loss of intensity by the sea floor is an unpredictable process.

Considering Fig 3.3, if the PDF of a rough surface is given by $p_\alpha(\alpha)$ then the probability of occurrence of an elevation between $\alpha$ and $\alpha + \delta\alpha$ is $p_\alpha(\alpha)\delta\alpha$. The effect of $\alpha$ on the signal is to alter the phase by $-2k\alpha\cos\theta$, where the phase change
of the signal relative to $\alpha = 0$ is $2k\alpha \cos \theta$. It is natural to assume a PDF as having Gaussian characteristics describing a random reflection sea bed with $\sigma$ as the rms roughness given by:

$$w_{G}(\alpha) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{\alpha^2}{2\sigma^2}}.$$  \[3.3.4\]

$w_{G}(\alpha)$ can show other forms of PDF distributions such as Rayleigh that could describe further roughness effects at over-populated multilayerd reflections, i.e. scattering and further to describe multipath propagation and fading [4-10,14,80,81].

3.4 SOUND TRAPPING

Ray trapping and waveguide phenomena are realised in deep waters when the reflection coefficients at the upper and lower boundaries have a value of unity, i.e. completely trapped waves.

3.4.1 Shallow water ducts

The acoustic definition indicates that shallow water exists whenever the propagation is characterised by numerous encounters with both surface and bottom.

It has long been known that the transmission loss in shallow water tends to be higher in summer than in winter. In winter, isothermal water is well-mixed by the wind, while in summer a negative gradient, caused by solar heating, forces sound downward to the bottom where it is normally lost, and thus poorer transmission result. A complication exists because of sea state, which tends to be higher in winter than in summer, and can reverse matters at high frequencies [4-10,14].

3.4.2 The surface duct

The surface duct occurs just below the sea surface and is due to wind and convection caused by surface cooling and evaporation produced by the layers of quasi-isothermal water. Within this layer, called the mixed-layer by oceanographers and the surface duct by acousticians, sound is trapped, sometimes poorly because
of losses at the boundaries. This layer is the characteristic feature of temperate, windy regions of the world's oceans. The thickness of the layer varies with the season and has a small negative gradient.

The rough sea surface and the presence of the air bubbles just under the surface affects the propagation of sound as well as the occurrence of internal waves at the base of the layer. All therefore act to scatter, absorb and diffract sound so as to destroy the effectiveness of the duct as an acoustic trap [4-10,14,82,83].

3.4.3 The deep sound channel

The deep sound channel (DSC) or the SOFAR channel is the best natural non-radio channel for long distance communication. Transmission in the DSC causes severe multipath effects. Yet the sound from a half kilogram explosive charge can be heard easily above the background noise at distances of thousands of kilometres [Fig. 3.4].

The DSC is created because the deep sea is warm on top and cold below. The surface warming effect is limited to the upper part of the water column where it forms the main thermocline. Below this region, the sea is nearly isothermal and therefore has a positive velocity gradient. Accordingly, a depth of minimum velocity exists, called the "axis" of the DSC, towards which sound rays are continuously bent by refraction [Figs. 3.4 and 3.5].

In the DSC, the ray-paths propagation is arcly and convexive; this is the result of a reversal of the velocity gradient at the axis. The upper and lower limits of the DSC are determined by the velocity profile and the water depth [Fig. 3.5]. Usually the near-surface region of the profile has the highest velocity. If the water depth is great enough, there is a depth below the axis where the velocity is the same as that at the surface. This depth is sometimes called the critical depth and forms the lower limit of the DSC. It is "critical" in that a receiver below it will not receive low-loss refracted sound from a distant shallow source, but instead only weak sound travelling via bottom reflected or near-surface refracted paths. When the water depth is less than critical, a near-surface source similarly lies outside the DSC and cannot transmit to long ranges via low-loss ducted paths [4-10,14].
3.4.4 Caustics and convergence zones

Caustic is defined as "the envelope of rays emanating from a point and reflected or refracted by a curved surface". In ocean the "curved surface" is the reverse bending of rays occurring in the DSC. A focus can occur when a caustic degenerates to a point or to a small region in space or in our case a three-dimensional ocean [Fig. 3.6].

Due to multipath properties of the sea the distribution of sound in the DSC is by no means uniform. The information about the presence and extent of the dark zones from the velocity profile and the location of surface, bottom and source relative to the profile can be used to determine the characteristics of a complex series of the existing shadow and convergence zones. In fact, the signals travelling over reflected paths never allow a completely "dark" region to occur. Some convergence zones, bounded by caustics, can provide regions of high intensity. These regions have a great practical importance for naval applications [4-10,14].

3.5 DISTORTION INTRODUCED BY THE UNDERWATER CHANNEL

3.5.1 Time dispersion

It was explained earlier that an acoustic wave may reach a remote receiver via several routes. All these routes will have different path lengths and hence the acoustic waves will take different times to transverse them especially in the long range transmission environment. Time dispersion is due to multipath propagation, as illustrated in Fig. 3.5. Different modes of propagation have different group delays and it is this difference that results in time dispersion.

Time dispersion gives rise to intersymbol interference, when the data transmission rate becomes comparable to the relative multipath delay. Multipath, and hence time dispersion is a function of frequency, path length, local time, season and also geographical location. Fig. 3.3, 3.5 and 3.6 can reveal the maximum expected time delay in the case of multipath propagation, as a function of an acoustic ray path length. Even with a single mode of propagation, there is time dispersion because of
the roughness of water layers and the finite transducer beamwidth. Judicious choice
of the operating frequency is one way of combating this time dispersion [1,4-10,12,14,19].

3.5.2 Frequency dispersion

Frequency dispersion arises in a single propagation path due to the Doppler effect
e.g by relative movement of a moving transducer carried by a diver or a submersible
vehicle with respect to a fixed transducer. The effect is negligible at low speeds
(divers) but has a drastic effect for high speed (submersible). Thus, the path covered
by a particular acoustic wave decreases or increases and the transmission frequency
appears to increase by an amount $+\delta f$ or decrease by $-\delta f$ depending upon the sea
environment [1,23].

3.6 CHARACTERIZATION OF FADING

Random variations of the signal strength at the receiver is referred to as fading.
Fading phenomena can be classified under the following heading [1,14,19,23].

3.6.1 Interference or selective fading

Acoustic signals arriving at same remote receiver are composed of a large number
of different rays, each having travelled via a different path. Due to varying physical
conditions, the path lengths are constantly changing. Hence their phase and field
strength are not only unequal but also vary with time. The total field strength of the
received signal is the phasor sum of all rays arriving at the receiver [Fig. 3.8].

Owing to random variations in the phase and amplitude of the individual waves,
they add up in a random manner. The acoustic waves are scattered and the individual
rays encounter different propagation conditions. Thus, a modulated carrier has,
within its bandwidth, large number of frequency components that are exposed to
randomly varying multipath propagation conditions. This can result in selective
blackouts or fading of a small section of the bandwidth. This effect is called selective
fading, causing interferences due to the superposition of random paths [1,4-10,19].
3.6.2 Multiplicative or flat fading

The variation of the amplitude of the received signal, whether constructive or destructive, is generally known as flat fading. This term flat fading, or multiplicative fading, arises due to the fact that all frequency components in the received signal are affected in a similar manner. Moreover, the envelope of the faded signal is said to follow a Rayleigh distribution with the phase being uniformly distributed [Fig. 3.7] giving rise to the term "Rayleigh Fading". This term is more clear in the long range models because of the lens-like convergence properties of the eigenrays arriving at the receiver, together with their delayed replicas [1,9,23].

3.6.3 Absorption fading

Absorption fading occurs due to the variation in the absorption characteristics of the sea with time. The attenuation characteristic of a layer slowly changes due to physical and environmental conditions. The depth of fading can be a few dB below the mean value [4-10].

3.7 UNDERWATER ENVIRONMENT SPECTRUM ANALYSIS

So far the thesis has introduced almost all nonlinear processes as well as their associated parameters invoking underwater acoustic transmissions at below and above 500Hz. Depending upon the frequency of the transmitting projector or hydrophone one can estimate the spectrum of the total attenuated signal. At a given particular frequency of transmission the associated processes with their parameters created by physical properties of the sea must be accounted for ignoring effects from other sources of distortions occurring outside the chosen frequency band. For instance, at frequencies less than 500Hz, the absorption and scattering of sound due to bubbles can be ignored. But at 1KHz or more, the effect of bubbles on sound energy in the SBL(surface bubble layer) becomes one of major contributor of channel distortion.
The best approach could be to separate the water medium into three sections, nominally as surface, volume and bottom and then estimate their associated PDF’s (probability distribution function) for a specified range.

Considering a 20-85kHz carrier, the PDF describing the sea surface effects is determined predominantly by sea surface scattering (namely Rayleigh) and primarily by SBL effects and biological objects. The latter is given the least priority since their occasional occupancies could introduce further error accumulation in a prolonged period of transmission. However, if the unlikely specular reflection occurs then the associated PDF (namely Rice) is implemented.

Unlike the surface effects, the predominant part of the PDF describing the volume backscattering (namely Rayleigh) is due to biological objects (or microstructural effects), depending upon their size. To a lesser extent further widening of PDF can be assumed due to interference in the spectrum at which the biological marine mammals communicate.

The PDF associated with the bottom section of the sea is determined from the literature on the geoacoustic profile that allows the sediment to be treated as part of the propagation medium, with ray paths reflected from the sediment surface and penetrating into the sediment. The kind of PDF that can describe the seafloor process depends upon the amount of time spread produced by the sediments with different characteristics and different places. An approximately rough seafloor described in the previous section, where the presence of multilayer reflections affect the PDF, is considered to behave rather like a sea surface (namely Rayleigh for very rough and Gaussian for moderate seafloors). But if perfect reflection occurs then the PDF of specular reflection (namely Rice) can be simulated [Fig. 3.8 and 3.9].

Furthermore, when all individual noise sources are added, the distribution of the total noise is at its lowest for frequencies in the range 20-140kHz. The signal-to-noise ratio which is an ultimate measure of reliability trade off as well as data rate in a data transmission system can be influenced by ambient noise of the sea fortunately at lower than 20kHz which is not acquired here. However, the total added random noise is statistically modelled as having a Gaussian PDF [14,80-96].
3.8 SIGNAL FLUCTUATION STATISTICS

In this section a general statistical model is presented to describe the distribution in amplitude and phase of the envelope of the signal from a distant, steady narrow-band source. The model is based on the assurance that fluctuations are the result of multipath degradation of the transmitted steady signal. The validity of the model will be verified by an examination of the fluctuations as they have been obtained by analysis or as reported in the literature under a variety of experimental and propagation conditions. At this stage, it should be emphasized that the model applies only to fluctuations that are stochastic, rather than deterministic, in origin.

Rice derived a distribution function of the envelope of a sine wave plus narrow-band Gaussian random noise. This is the same as the distribution of the sum of a constant vector and a random vector whose x and y coordinates are Gaussian time-function \[15\]. This so-called Rician distribution can be described as follows in terms of Fig. 3.8.

Consider \( q \) represent the magnitude of the constant vector with arbitrary phase angle \( \theta \), to which is added a number of vectors each having random phase and random amplitude that could be added constructively or destructively. \( X \) and \( Y \) are given as functions of time by

\[
X(t) = q \cos \theta + x(t) \quad \ldots 3.7.1
\]

\[
Y(t) = q \sin \theta + y(t) \quad \ldots 3.7.2
\]

with the resultant

\[
r = \sqrt{X^2 + Y^2} \quad \ldots 3.7.3
\]

The two Gaussian time variables \( x(t) \) and \( y(t) \) have zero mean and variances of \( \sigma_x^2 \) and \( \sigma_y^2 \) respectively. Their sum has a Rayleigh amplitude distribution. This can be visualised as a group of random vectors surrounding the tip of the constant vector; these represent the multipath or scattered contributions to the steady component \( q \).

The whole degree of random fluctuations is described by Rice as the imperial probability density function [Appendix B1, Fig. 3.9]. The easiest way to understand this distribution is to take \( \sigma_x^2 \) and \( \sigma_y^2 \) as unity. Then the Rice function on its own can describe the specular reflection \( p_R(r, q) \) as:
\[ p_R(r, q) = r \cdot e^{-\frac{(r^2 + q^2)}{2}} \cdot J_0(qr) \quad r \geq 0 \quad \ldots 3.7.4 \]

\( J_0(qr) \) is the modified Bessel function of argument \( qr \) and when the constant component \( q \) is totally destroyed by domination of the random components, then \( J_0(0) = 1 \), resulting

\[ p_R(r) = r \cdot e^{-\frac{r^2}{2}} \quad r \geq 0 \quad \ldots 3.7.5 \]

Eqn 3.7.5 signifies a Rayleigh distribution for the magnitude of the resultant of a large number of vectors of random phase and amplitude.

Now consider when the product \( qr \gg 1 \), then \( J_0(qr) \) can be expanded asymptotically [86] as;

\[ J_0(qr) = e^{-\pi \cdot (2\pi qr)^{\frac{1}{2}}} \left( 1 + \frac{1}{8qr} + \ldots \right) \quad \ldots 3.7.6 \]

This implies that the probability density function \( p_R(r, q) \) approaches a Gaussian distribution for a unity standard deviation.

\[ p_R(r, q) = \left( \frac{r}{2\pi q} \right)^{\frac{1}{2}} \cdot e^{-\frac{r^2 + q^2}{2}} \quad \ldots 3.7.7 \]

This well known Gaussian distribution applies when either the magnitude of the constant vector \( q \) is large, or when \( r \) is far out on the probability density curve, or both (Fig. 3.9).

The expressions above give rise to the most interesting cumulative distribution function

\[ f(\leq r_a) = \int_0^{r_a} p_R(r, q)dr \quad \ldots 3.7.8 \]

where \( f(\leq r_a) \) is the probability that \( r \) is less than or equal to some arbitrary value \( r_a \).

The cumulative distribution curves thus could indicate the percentage of a large number of fading occurrences in which the resultant \( r \) is equal to or less than the median value taken as the arbitrary value.
It is also interesting to introduce the parameter $\rho$ as the randomacity factor in order to evaluate the severity and rapidity of the signal fluctuations. This term is the ratio of the Rayleigh Power to the Total Power and is related to the direct steady path as:

$$\rho = \frac{\sigma_x^2 + \sigma_y^2}{q^2 + \sigma_x^2 + \sigma_y^2}$$

...3.7.9

The parameter $\rho$ can vary from zero for a completely constant signal, i.e. $q \to \infty$, to unity for a completely random signal, i.e. when $q \to 0$.

According to this model, no signal can have a greater fluctuation than that given by Rayleigh distribution [1,13,14,19,23,80-97].

3.9 CONCLUDING REMARKS

The main sources contributing to multipath propagation can be considered as scattering components due to the sea surface, main body and sea bed. The occurrence of these components can vary from time to time as well as being affected by the positions of the sound source or the receiver. Due to attenuation loss in the sediments, the reflected energy continues to reduce beyond the critical angle i.e. a gradual fading process.

The signal distortion severity that results in fading can vary from selective to flat fading depending upon the total number of multipath propagated components added. These components continue to increase as the source or the receiver, becomes mobile. This unpredictable property implies that only statistical models can describe such fluctuations in time.
Fig. 3.1 A typical surface ray scattering.

Fig. 3.2 Ray diagram for a typical Atlantic Ocean sound channel. The angles are the grazing angles at the axis of the sound channel [39]
Fig. 3.3 Sub-bottom profiling and transit time differentials mechanisms
Fig. 3.4 Ray propagation paths with the source at different layers in the deep sea.
Fig. 3.5 Different ray paths propagations. Figs. A and F show time differences in the reception of the eigenrays.

Fig. 3.6 Caustics or ray paths for a source above the axis. A similar pattern could indeed exist for the source below the axis.
a) single and multiple specular reflections

b) source and receiver ray paths picture

c) reverberation due to multiple reflections

Fig. 3.7 Typical scattering and reflected paths
Fig. 3.8 Vector representation of the random and the constant components

Fig. 3.9 Family of Rician distributions.
CHAPTER 4

TIME-VARYING UNDERWATER CHANNEL MODELS

4.1 INTRODUCTION

The two previous chapters presented all the degrading problems that can prevent a reasonably good communication link being established in underwater channels. They showed that knowledge of the mean value of the received signal is not sufficient to design an underwater digital communication system. The variation of phase and amplitude with time, collectively described as fading, also have to be taken into consideration.

This chapter presents the developments of channel simulators (in software and hardware), approximating the same multipath channel characteristics as observed throughout the published literature on underwater media.

4.2 DIGITAL CHARACTERISATION OF MULTIPATH FADING

Consider the transmission of an ideal impulse or, practically, an extremely short pulse over a time-varying multipath channel. The time spread introduced by the channel means that the received signal appears as a train of pulses and that the nature of signal varies with time. This characteristic has been observed in underwater channels by many researchers for many years. Thus, if an experiment is repeated over and over, one would observe that the received pulse train includes changes in;

i)-the size of the individual pulses;

ii)-the number of pulses in the received pulse trains;

iii)-the relative delays among the received pulse trains.

Therefore, it is reasonable to consider the time-variant multipath channel statistically, since the time variation causes the received signal to appear in an unpredictable manner [1,17,24].
4.3. STATISTICAL DISTRIBUTION OF THE RECEIVED SIGNAL

Consider a general form of a transmitted signal with a modulated carrier of centre frequency $f_c$, travelling through a multipath medium. 

$$s(t) = \Re[m(t)e^{j2\pi f_c t}]$$ 

where $\Re[.]$ is the real part of the complex-valued quantity in brackets and $m(t)$ represents the amplitude and phase variations due to modulation and is expressed in the form

$$m(t) = a(t)e^{j\theta(t)}$$

$a(t)$ and $\theta(t)$ represent the amplitude (envelope) and the phase variations in $s(t)$ respectively.

Due to multipath propagation the received bandpass signal is of the form

$$r(t) = \sum_n \alpha_n(t)s(t - \tau_n(t))$$

where $\alpha_n(t)$ is the amplitude of the signal received via the $n^{th}$ path at time $t$ and $\tau_n(t)$ is the propagation delay for the $n^{th}$ path. If the received signal is considered as consisting of a continuum of multipath components, then the summation in Eqn. 4.3.3 can be replaced by the integral;

$$r(t) = \int \alpha(\tau; t)s(t - \tau)d\tau$$

where $\alpha(\tau; t)d\tau$ is the resultant attenuated amplitude of all rays arriving with a relative time delay in the range $(\tau, \tau + d\tau)$ at time instant $t$. Combining Eqns. 4.3.1 and 4.3.4

$$r(t) = \Re\left\{\int_{-\infty}^{\infty} \alpha(\tau; t)m(t - \tau)e^{j2\pi f_c (t - \tau)}d\tau\right\}$$

or

$$r(t) = \Re\left\{\int_{-\infty}^{\infty} \alpha(\tau; t)e^{-j2\pi f_c \tau}m(t - \tau)d\tau e^{j2\pi f_c t}\right\}$$
Considering the low-pass relation

\[ h(\tau; t) = \alpha(t; t)e^{-j2\pi f_e \tau} \]  

...4.3.7

then the integral in Eqn. 4.3.6 represents the convolution of \( m(t) \) with an equivalent low pass time variant impulse-response \( h(\tau; t) \). This represents the response of the channel at time \( t \) due to an impulse applied at time \( (t - \tau) \).

Furthermore, the discrete multipath components channel can be described as an equivalent low pass channel having the time variant impulse-response given by

\[ h(\tau; t) = \sum_n \alpha_n(t)e^{-j2\pi f_e \tau_n(t)} \delta[\tau - \tau_n(t)] \]  

...4.3.8

Thus when an unmodulated carrier of frequency \( f_e \) is transmitted, then the equivalent low pass received signal is

\[ r(t) = \sum_n \alpha_n(t)e^{-j2\pi f_e \tau(t)} \]  

...4.3.9

where \( \theta_n(t) = 2\pi f_e \tau_n(t) \).

Thus the received signal, at any given instant \( t \), is the sum of a number of time variant vectors (phasors) having amplitudes \( \alpha_n(t) \) and phases \( \theta_n(t) \). \( \theta_n(t) \) changes by \( 2\pi \) radians whenever \( \tau_n(t) \) changes by \( (1/f_e) \) and since \( (1/f_e) \) is a small quantity, only a small change in the value of \( \tau_n(t) \) is needed to change \( \theta_n(t) \) by \( 2\pi \) radians. Owing to irregularity of the multipath media, the variation in \( \tau_n(t) \) is random and therefore variation in \( \theta_n(t) \) is also random. The multipath propagation model for the channel, in Eqn. 4.3.9, results in fading of the received signal. The fading is caused primarily by variation in the relative phases of the individual \( \{\theta_n(t)\} \). It is this factor that determines whether the fading introduced is destructive or constructive.

When there are a sufficiently large number of components, i.e. for large value of \( n \), of roughly equal size and their phases change randomly and independently of each other, then by central limit theorem, the two quadrant components of the resultant signal will each tend to be distributed as a zero-mean Gaussian variable, with equal variance and independent fluctuations.

The mean values considered in the two Gaussian distributions determine the type and strength of the scattering paths to be modelled. For instance, if there are fully reflected paths or fixed scatterers in the medium as well as randomly moving scatterers, then the fading is said to be Rician and can be described by the Rice
expression described in Sec. 3.9. But if the randomly moving scatterers which are considered here dominate the received signal the fading is said to be Rayleigh [Fig. 3.7].

In the case considered here the received waveform has all the characteristics of a very narrow band complex-valued Gaussian random process, characterised by a power spectral density of non-zero width, having an envelope that is Rayleigh distributed and a phase uniformly distributed between 0 and $2\pi$ radians [Fig. 4.1]. The Fourier transform of $h(t;\tau)$ gives the time variant transfer function $H(f;\tau)$, where $f$ is the frequency variable.

$$H(f;\tau) = \int_{-\infty}^{\infty} h(\tau;\tau) e^{-j2\pi f \tau} d\tau$$ \hspace{2cm} \ldots 4.3.10$$

$H(f;\tau)$ has the same statistics as $h(\tau;\tau)$ which is a complex valued zero mean Gaussian random process in the time domain.

The Rayleigh model described as a continuous random variable introduced by Eqn. 3.7.4 for unity variance, can be obtained from two independent Gaussian random variables, each having zero mean $(m)$ with the same variance $(\sigma^2)$ as

$$p_r(r) = \begin{cases} \frac{r}{\sigma^2} e^{-\frac{r^2}{2\sigma^2}} & \text{for } 0 \leq r \leq \infty \\ 0 & \text{for } r < 0 \end{cases}$$ \hspace{2cm} \ldots 4.3.11$$

this represents the probability density function of $r$ where

$$m_x = m_y = 0$$ \hspace{2cm} \ldots 4.3.12$$

and both uncorrelated with

$$\sigma_x^2 = \sigma_y^2 = \sigma^2$$ \hspace{2cm} \ldots 4.3.13$$

Since the resultant of the amplitude of the two Gaussian distributions cannot be negative, by definition the Rayleigh distribution must have a non-zero mean value, even though the two Gaussians have zero means.

The Cumulative distribution function (CDF), Eqn 3.7.8, of the Rayleigh distribution is now given by
At the point where CDF of \( f(r) \) in Eqn. 4.3.14 is 0.5, the median value occurs, i.e at \( r = r_m \) this is obtained as;

\[
r_m = \sigma(\sqrt{2 \ln 2}) \quad \ldots 4.3.15
\]

where \( \sigma \) is the standard deviation of the Gaussian random variables used in the derivation of the Rayleigh fading channel. The parameter \( r_m \) allows the determination of the number of faded elements in the received signal [1,15-17,19-22,94-96].

### 4.4 HARDWARE CHANNEL SIMULATION MODELS

The use of a channel simulator for evaluating the performance of a digital communication system offers several advantages. They are accurate and a large range of channel conditions can be simulated. It is also possible to compare the performances of several systems under same conditions and tests can be repeated any number of times with consistent results. Furthermore, it is possible to control any type of distortion in a channel simulator and the effect of the distortion on the system can be studied with greater accuracy.

The channel simulators can be referred to as either software, hardware or a combination of both. The software simulator can be represented by Eqn. 4.3.8 with predetermined parameters. In the hardware simulator investigated in this thesis, the input signal is fed to an adjustable tapped delay line.

This hardware model is based on the assumption that the channel operates under sufficiently short transmission times (<10mins) and is narrowband (<10kHz). Both conditions can not in anyway invalidate the models introduced in this thesis since the channels investigated are bandlimited and are well below 10kHz, and the transmission times are of the order of tens of seconds rather than minutes. At this point...
stage, it should be noted that the research carried out to develop the models are based on experimental results observed in the literature since World War II [4]. The assumptions are reasonable and valid for the research being carried out.

From knowledge of the underwater media, one can assume that the sea surface and bottom can have nearly the same characteristics. If such surfaces are specular reflectors (i.e. calm surface or smooth bottom) then the received signal only includes Doppler shift with no spectral spreading. This shift could be either constructive or destructive depending upon the relative speed of the source and receiver and the transmission frequency. Then, whether in a shallow channel or in a deep long range channel, the model for any path [Fig. 3.7] can be shown as in Fig. 4.2.

Spectral spreading starts to appear for the more realistic cases where the environmental properties of the two sections (sea surface and sea bed) are taken into account (i.e. rough surfaces). This will provide a random modulating signal as well as the Doppler shift [Fig. 4.3]. Further increases in roughness will introduce further frequency spreading which eventually dominates the multipath propagated scenario. The frequency spread can be determined either by the speed of that portion of the medium or by the speed of the source or receiver. Calculation of frequency spread introduced by the speed of the vessel can provide the best estimate of the width of the power spectral density associated with each section of the sea (surface, volume and bottom).

A single propagation path [17,19], whether in a shallow channel (a diffused component) or in a deep long range channel (an eigenray), is modelled as in Fig. 4.4. If a continuous signal $x(t)$ is fed to the input of this model, then its output is of the form

$$z(t) = v_1(t)x(t) + v_2(t)x(t)$$  \[4.4.1\]

where $v_1(t)$ and $v_2(t)$ are two random processes. The actual input signal (Eqn. 4.4.1) in digital system will be a binary stream of data. In the hardware simulation the random processes $v_1(t)$ and $v_2(t)$ are Gaussian with zero mean and the same variance. They are statistically independent and the shape of their power spectrum must be Gaussian having the same root mean square (rms) frequency, $f_{\text{rms}}$. This will then confirms Gaussian distributions [Fig. 4.4 and 4.5] to provide the Rayleigh statistics with complex envelope. Thus the power spectrum of $v_1(t)$ and $v_2(t)$ can be considered as
\[ |V_1(f)|^2 = |V_2(f)|^2 = \exp\left(\frac{f^2}{2f_{\text{rms}}^2}\right) \] ...4.4.2

where \( f_{\text{rms}} \) is related to the frequency spread (Doppler shift) \( f_{\text{sp}} \) introduced by moving transducers and can be large. The Doppler shift \( f_{\text{sp}} \) is calculated as

\[ f_{\text{sp}} = f_c \left(\frac{u}{c}\right) \] ...4.4.3

where \( f_c \) is the carrier frequency, \( u \) is the maximum source (transducer) relative velocity and \( c \) is the sound velocity.

The frequency (Doppler) spread, \( f_{\text{sp}} \), introduced by \( v_1(t) \) and \( v_2(t) \) into an unmodulated carrier is defined as the width of the power spectrum [Fig. 4.3] and is given by

\[ f_{\text{sp}} = 2f_{\text{rms}} \] ...4.4.4

The rms frequency is related to the fading rate \( f_s \), which is defined (for a single carrier) as the average number of downward crossings per unit time of the envelope through the median value that can be determined from the Cumulative Distribution Function, according to the equation

\[ f_{\text{rms}} = \frac{f_s}{1.475} \] ...4.4.5

Combining Eqns. 4.4.4 and 4.4.5 gives

\[ f_{\text{sp}} = 1.356f_s \] ...4.4.6

Eqn. 4.4.6 indicates that for a 1Hz frequency spread, there are theoretically 44.23 symbols in fade for every minute of transmission, i.e. on average 0.73 of a symbol (say 1 symbol) can be totally lost in every second.

The hardware simulator for a single multipath channel of Fig. 4.4 consists of two white Gaussian noise generators, two variable lowpass filters and two balanced modulators. Each low-pass filter should have a Gaussian frequency response matching the power spectra of the Gaussian variable \( v_1(t) \). The theoretical power spectrum of \( V_1(f) \) and \( V_2(f) \) given in Eqn. 4.4.2 is plotted in Fig. 4.5. The frequency response of the filter is given by
and the 3dB cut-off frequency of the filter is

\[ f_{co} = 1.17741 f_{rms} \]  \hspace{1cm} \text{...4.4.8}  

Thus from Eqn. 4.4.4 and 4.4.8

\[ f_{co} = 0.588705 f_{sp} \]  \hspace{1cm} \text{...4.4.9}  

It has been found that the impulse-response and the magnitude-response of a Bessel filter tends towards Gaussian as the order of the filter is increased [96,99] [Appendix C]. A Bessel filter has therefore, been used to obtain the necessary requirements in the design of the variable low-pass filters in the hardware simulation of multipath faded channels. This digital filter is implemented as shown in Fig. 4.6. It is a combination of two 2-pole sections and a 1-pole section. The 1-pole section has a real pole whereas the 2-pole sections have complex conjugate poles.

The values of the Bessel filter coefficients \( C_1 \) to \( C_5 \) for a frequency spread of 1Hz is given in Table C1 (Appendix C). The value of \( K_{dc} \), the gain of the filter in Eqn. C24, is chosen such that the \( \{v_i(t)\} \)s have a variance corresponding to \( \frac{1}{2\pi} \), where \( n_x \) represents the number of diffused components or eigenrays. This ensures that the mean length of the sampled impulse response vector is unity. The value of \( K_{dc} \) can be theoretically determined by the energy in the waveform \( H(f) \) in Eqn. 4.3.10 as

\[ E_A = \int |H(f)|^2 df \]  \hspace{1cm} \text{...4.4.10}  

The energy \( E_A \) in the waveform is normalised by the scalar \( K_{dc} \) [Fig. 4.6].

Each of the white Gaussian distributions are generated by a pseudo-random number (Appendix B2), that is, shuffling the random generators ensures no random sequence is recalled. Moreover, the random generators can result in different fading rates (i.e. fading depths) by employing different seed integer values [1,96-100].
4.5 COMPUTER SIMULATION TESTS AND RESULTS

The following two sections present details of the underwater communication channel models that will be employed by the two baseband systems (Chapter 5) under investigation. They discuss the way in which the multipath effects are taken into account in both baseband models.

The carrier frequency is assumed to be 20 kHz and the speed of sound in water is considered as 1500 ms⁻¹.

4.5.1 System A

The aim of this system is to produce a channel model for different speeds of the source when the receiver is assumed to receive only one diffused multipath propagated component. The proposed speeds of the source are assumed to be from approximately stationary to up to 1 knot (0.488 m/s). In total, there are four models considered individually for this system, namely, a direct path model and one for paths where the speed of the source is 0.035 m/s (very slow moving), 0.2 m/s (moderate) and 0.488 m/s (fast). The frequency (Doppler) spread [Eqn. 4.4.3] is found to be 0.466 Hz for slow-moving, 2.66 Hz for moderate and 6.51 Hz for the fast moving source/receiver (worse case condition).

For digital implementation of the channel model it is neither possible nor is necessary to represent the random fading sequence vᵢ(t) as a continuous signal. These must be represented as discrete samples in time. From the Nyquist sampling theorem, for faithful reproduction of the continuous signal, it is necessary that the sampling rate should be equal to or greater than twice the highest frequency present in the continuous signal. However, vᵢ(t) have Gaussian spectra, and hence theoretically they contain all the frequency components.

For testing a 4800 b/s QAM digital data modem on these channels, it is necessary to use sampling rate of 2400 samples/second. This means that the vᵢ(t) must also be sampled at 2400 Hz. This gross over sampling has an adverse effect on the digital filters having the required narrow band Gaussian shape. In order to be consistent with the sampling frequency the roots of the digital filter must be obtained at this sampling frequency and at the same time it is necessary to see that these roots are
not close to the unit circle in the $z$-plane. Unfortunately, at this high sampling frequency the pole locations of such filters in the $z$-plane are pushed so close to the unit circle that very high accuracy must be used to define the very large tap values required in order to achieve the required shaping, otherwise instability of the filter can occur. This problem can be overcome by employing a reduced sampling frequency in the digital filters and then employing interpolation between samples to compensate. Bearing this in mind the coefficients of the fifth order Bessel filters employed in the generation of the one diffused component model were sampled at 50 Hz for slow-moving, 200 Hz for moderate, and 300 Hz for the fast moving source or receiver. Furthermore, these sampling frequencies were chosen as a compromise between the requirements for the Nyquist sampling criterion, the need to limit the degree of interpolation used and the pole locations in the $z$-plane to be adequately away from the unit circle \[1,21-22\].

The interpolation considered here is of linear form when the two adjacent points of $v_i(t)$, (such as $v_{i,k}$ and $v_{i,k-1}$) are joined by a straight line; this line is then sampled to provide the sequence of the required $v_i$, such that

$$v_i = v_{i,k-1} + i \delta_{i,k} \quad \ldots 4.5.1$$

if $l$ represent the interpolation integer, then

$$\delta_{i,k} = \frac{(v_{i,k-1} - v_{i,k})}{l} \quad \ldots 4.5.2$$

Thus when 50 Hz is employed as the sampling frequency for the filter then by interpolating 48 points (i.e., $l = 48$) between samples the required sampling rate of 2400 samples/second can be met for slow moving source and similarly $l_m = 12$ and $l_r = 8$ for the moderate and fast moving source respectively.

Practical measurements of the vertical or the short range channel with multipath structure have shown [Fig. 3.7] a diffused path that has a convergence like propagation properties. The total random sequence $\widetilde{P}_T$ depends upon the transmitting device situation.

The output $z_A(t)$ from Fig. 4.4 is;

$$z_A(t) = v_1(t)x(t) + v_2(t)\tilde{x}(t) \quad \ldots 4.5.3$$

where $\tilde{x}(t)$ represents the Hilbert Transform of $x(t)$. This transformation is described in Chapter 5.
In the simulated channel model of system A there is thus one diffused random component which requires two random processes \( v_i(t) \) for \( i=1 \) and 2. Each of the random processes is similarly generated. The variance of both variables \( v_1(t) \) and \( v_2(t) \) is equal to 0.5 [Fig. 4.4]. This value of variance of each individual process ensures that the total variance of the system A channel is unity. Each value of \( v_i(t) \) is generated from independent sources so that both variables \( v_1(t) \) and \( v_2(t) \) are uncorrelated. The values of \( K_{dc} \) in Fig. 4.6 are given in Table 4.1. For each individual case (speed) \( K_{dc} \) is chosen such that \( v_i(t) \) has the required value of variance (0.5) for the one diffused component channel model [Appendix C][3-14,30].

The results of the tests carried out on the simulated channel are summarized in Figs. 4.7 - 4.13 and Tables 4.1-4.2 for the source travelling at moderate speed (0.2 m/s).

Figs. 4.7 and 4.8 show the 5th order Bessel filter impulse response and frequency response respectively for 1Hz frequency spread at sampling rate of 50Hz.

Figs. 4.9 and 4.10 show the polar diagrams for the small and large number of fade cycles respectively, indicating 99% of the samples stayed within the central limit theorem.

Table 4.1 gives the 5-pole Bessel filter coefficients for all four frequency spreads at the chosen sampling frequencies, while Table 4.2 indicates the fading rates per minute obtained for different seed integer values.

Fig. 4.11 presents the cumulative distribution function (CDF) of the single diffused component channel tested over a sequence of 50,000 elements for various Randomicity parameter \( \rho \).

Figs. 4.12 and 4.13 show the amplitude and phase variations of the channel simulator for the highest fading rate occurring for a seed integer of 57 (moderate channel).

4.5.2 System B

In this particular system which can be most suitable for the long range underwater channel modeling, the channel multipath structure present could be a superposition of a number of multipath components, the transmitter/receiver [30] both situated in the Deep Sound Channel [Chapter 3, Figs. 3.3, 3.5 and 3.6]. In this context, the receiver might be sited on a submersible vehicle. The components are called eigenrays here because of their gradual divergence or convergence to travel on an
individual rays. The number of eigenrays n considered for tests are 1, 2, 3, 5 and 8. The delay associated with the reception of the first ray is considered as zero for convenience, but the delays in receiving the second, third, fifth and eighth paths are assumed up to 3 ms relative to the first path, this is discussed in the next chapter. Thus the total random sequence $P_T$ is

$$P_T = P_0 + P_1 + \ldots + P_n$$  \hspace{1cm} \text{...4.5.4}

Fig. 4.14 summarises the complete model of long-range underwater channel for up to n eigenray components. The output $z_B(t)$ from the model is

$$z_B(t) = \{v_1(t)x(t) + v_2(t)x(t)\} + \{v_3(t)x(t - \tau) + v_4(t)x(t - \tau)\} +$$

$$\ldots + \{v_{2n-1}(t)x(t - \tau_{n-1}) + v_{2n}(t)x(t - \tau_{n})\}$$  \hspace{1cm} \text{...4.5.5}

where $x(t)$ represents the Hilbert Transform of $x(t)$.

The direct steady path is assumed to be dominated by over-populated random paths [3-14,30].

In the simulated channel model of this system the required number of random processes $v_i(t)$ for $i = 1, 2, \ldots, 16$ is given in the Table 4.3. Each of the random processes is similarly generated. The variances of all the $2n$ variables $v_i(t)$ to $v_{2n}(t)$ are equal [Fig. 4.14]. This value of variance of each individual process ensures that the total variance of the desired n-eigenray channel is unity. Each value of $v_i(t)$ is generated from independent sources so that all the $2n$ variables are uncorrelated. A seed integer (Appendix B2) of 191 [Table 4.4] has been used in the tests for the worst case channel conditions.

The value of $K_a$ in Fig. 4.6 is chosen such that $v_i(t)$ has the required value of variance according to the number of eigenrays in the channel, as can be observed in Table 4.3.

At this point, it must be noted that if a model of the form of Fig. 4.14 implemented for any number of eigenrays it can operate for fewer.

The proposed speed of the source is assumed to be at maximum of 0.388 m/s (0.8 knot). The frequency (Doppler) spread [Eqn. 4.4.3] is found to be 5.17 Hz for a moving source/receiver (worse case condition).
The model of this system too is implemented employing the Nyquist sampling theorem, as described in the previous section, for faithful reproduction of the continuous signal. For a fading signal with a frequency spread of 5.12 Hz, it was found adequate to sample the signal at 300 Hz, without aliasing. This indicates that when 300 Hz is employed as the sampling frequency then by interpolating 8 (i.e., $l = 8$) points between samples the required sampling rate of 2400 samples/second can be met.

Table 4.3 give the 5-pole Bessel filter coefficients for a frequency spread of 5.12 Hz at sampling frequency of 300 samples/second, while Table 4.4 indicates the fading rates per minute obtained for different seed integer values.

Figs. 4.15 and 4.16 show the amplitude and phase variations of the channel simulator for a single path using a seed integer of 191 to produce the highest fading rate. As can be seen from the Table 4.4, different seed integers produce different fading rates, thus, different amplitude and the phase variations.

4.6 CONCLUDING REMARKS

The results presented in this chapter indicate that both systems represent underwater channel models that have random amplitude fluctuation and phase characteristics that are distributed uniformly between 0 and $2\pi$. It was also realised that the models are capable of producing different number of fades by setting different seed integers into the random noise generator. Fading depths of up to 40 dB or more can be observed during a 10 second transmission (i.e. 24,000 symbols). It was also established that if a model of system B can be constructed for any number of eigenrays, it could well operate for fewer.
Fig. 4.1 Effect of signal transmission over a Rayleigh fading channel.
Fig. 4.2 Model of a specular path.

Fig. 4.3 Model of a specular path with added random path i.e. a spectral spreading model.
Fig. 4.4 One diffused or one eigenray multipath fading channel simulator (Rayleigh).

Fig. 4.5 Power spectrum of $v_1(t)$ and $v_2(t)$. 
Fig. 4.6 Digital fifth order Bessel filter.
<table>
<thead>
<tr>
<th>Speed of source</th>
<th>Frequency spread, $f_p$</th>
<th>Sampling frequency</th>
<th>Value of $K_{dc}$</th>
<th>Bessel filter coefficients $C_1$, $C_2$, $C_3$, $C_4$, $C_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Slow-moving(stationary)</td>
<td>0.035 m/s</td>
<td>0.466 Hz</td>
<td>50 Hz</td>
<td>$4.653 \times 10^4$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$C_1$: -1.94939691, $C_2$: 0.95020416, $C_3$: -1.96416084, $C_4$: 0.96519594, $C_5$: -0.97259734</td>
</tr>
<tr>
<td>Moderate speed</td>
<td>0.2 m/s</td>
<td>2.667 Hz</td>
<td>200 Hz</td>
<td>$11.940 \times 10^3$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$C_1$: -1.74094609, $C_2$: 0.76153577, $C_3$: -1.80059496, $C_4$: 0.82784548, $C_5$: -0.86226964</td>
</tr>
<tr>
<td>Fast-moving</td>
<td>0.488 m/s</td>
<td>6.506 Hz</td>
<td>300 Hz</td>
<td>$7.656 \times 10^3$</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$C_1$: -1.78692062, $C_2$: 0.80093507, $C_3$: -1.83890018, $C_4$: 0.85731877, $C_5$: -0.88625734</td>
</tr>
</tbody>
</table>

*Table 4.1 Characteristics of the fifth order Bessel filter for system A.*
<table>
<thead>
<tr>
<th>Seed integer</th>
<th>Fading rate</th>
<th>Seed integer</th>
<th>Fading rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>33</td>
<td>117.57</td>
<td>167</td>
<td>113.64</td>
</tr>
<tr>
<td>45</td>
<td>117.04</td>
<td>191</td>
<td>115.19</td>
</tr>
<tr>
<td>57</td>
<td>119.43</td>
<td>267</td>
<td>118.90</td>
</tr>
<tr>
<td>71</td>
<td>111.18</td>
<td>291</td>
<td>118.06</td>
</tr>
<tr>
<td>99</td>
<td>119.16</td>
<td>330</td>
<td>114.38</td>
</tr>
<tr>
<td>121</td>
<td>119.09</td>
<td>372</td>
<td>111.06</td>
</tr>
<tr>
<td>139</td>
<td>115.55</td>
<td>450</td>
<td>112.67</td>
</tr>
</tbody>
</table>

Table 4.2 System A channel fading rate/minute.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed of source/receiver</td>
<td>0.388 m/s (0.8 knot)</td>
</tr>
<tr>
<td>Frequency spread, $f_p$ (Hz)</td>
<td>5.17 Hz</td>
</tr>
<tr>
<td>Sampling frequency, $f_s$ (Hz)</td>
<td>300 Hz</td>
</tr>
<tr>
<td>Value of $K_{sc}$ for one eigenray</td>
<td>23727.114</td>
</tr>
<tr>
<td>Variance of $v_i(t)$ for $i=1,2$</td>
<td>0.5</td>
</tr>
<tr>
<td>Value of $K_{sc}$ for two eigenrays</td>
<td>34328.14</td>
</tr>
<tr>
<td>Variance of $v_i(t)$ for $i=1,2,...,4$</td>
<td>0.25</td>
</tr>
<tr>
<td>Value of $K_{sc}$ for three eigenrays</td>
<td>41939.81</td>
</tr>
<tr>
<td>Variance of $v_i(t)$ for $i=1,2,...,6$</td>
<td>0.1666</td>
</tr>
<tr>
<td>Value of $K_{sc}$ for five eigenrays</td>
<td>54226.417</td>
</tr>
<tr>
<td>Variance of $v_i(t)$ for $i=1,2,...,10$</td>
<td>0.1</td>
</tr>
<tr>
<td>Value of $K_{sc}$ for eight eigenrays</td>
<td>68530.46</td>
</tr>
<tr>
<td>Variance of $v_i(t)$ for $i=1,2,...,16$</td>
<td>0.0625</td>
</tr>
<tr>
<td>Bessel filter coefficients $C_1$</td>
<td>-1.83498584</td>
</tr>
<tr>
<td>$C_2, C_3$</td>
<td>0.84344436,-1.87758916</td>
</tr>
<tr>
<td>$C_4, C_5$</td>
<td>0.88862450,-0.911542526</td>
</tr>
</tbody>
</table>

Table 4.3 Characteristics of the fifth order Bessel filter for system B.
<table>
<thead>
<tr>
<th>Seed integer</th>
<th>Fading rate</th>
<th>Seed integer</th>
<th>Fading rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>33</td>
<td>292.03</td>
<td>167</td>
<td>292.11</td>
</tr>
<tr>
<td>45</td>
<td>294.88</td>
<td>191</td>
<td>307.44</td>
</tr>
<tr>
<td>57</td>
<td>301.19</td>
<td>267</td>
<td>300.08</td>
</tr>
<tr>
<td>71</td>
<td>291.31</td>
<td>291</td>
<td>288.54</td>
</tr>
<tr>
<td>99</td>
<td>294.95</td>
<td>330</td>
<td>294.37</td>
</tr>
<tr>
<td>121</td>
<td>301.72</td>
<td>372</td>
<td>296.48</td>
</tr>
<tr>
<td>139</td>
<td>287.77</td>
<td>450</td>
<td>302.66</td>
</tr>
</tbody>
</table>

Table 4.4 System B channel fading rates/minute.
Fig. 4.7 5th order Bessel filter impulse response.

Fig. 4.8 5th order Bessel filter frequency response.
Fig. 4.9 Polar diagram for a small number of fading cycles.

Fig. 4.10 Polar diagram for a large number of fading cycles.
Fig. 4.11 Cumulative distribution for different randomness factor.
Fig. 4.12 Typical amplitude variation in system A.

Fig. 4.13 Typical phase variation in system A.
Fig. 4.14 n-eigenray channel model of system B.
Fig. 4.15 Typical amplitude fluctuation in system B.

Fig. 4.16 Typical phase variation in system B.
CHAPTER 5
MODEL OF DIGITAL DATA TRANSMISSION SYSTEM

5.1 INTRODUCTION

The aim of this chapter is to provide an introduction to the general requirements and potential of digital data communication system operating over underwater channels. A simplified system block diagram is first presented to illustrate various components of the system, including their implementation in a complex communication channel. The relationships of various system parameters with information and signalling rates, signal alphabet and bandwidth are then introduced. The causes of additive noise and signal distortion are discussed along with how these impairments force the use of a quite sophisticated receiver and detector structures.

Finally, the feasibility of transmitting data at 4800 bits per second is investigated for both predetermined channel conditions with particular reference to theoretical limits that a system designer is forced to make between the performance in the presence of noise and signal distortion, signal element rate and timing with a given system bandwidth.

5.2 DIGITAL DATA TRANSMISSION SYSTEMS

A digital data transmission system at any rate can be modelled over bandlimited channels by an equivalent baseband system. It can be shown that the baseband model reduces to a discrete time model which simplifies the mathematical description of the system and also aids in translating the basic model into a suitable program code to simulate the operation of what is, in reality, a bandpass analogue system [Appendix D]. The characteristics of all bandpass components within the system must be referred to baseband channel.

There are two types of data transmission systems, namely:-
(a) Serial data transmission system; and (b) Parallel data transmission system.

In a serial data transmission system, the signal elements are transmitted as a sequential stream whose frequency spectrum occupies the entire available bandwidth. In a parallel data transmission system two or more sequential streams of signal elements are sent simultaneously, and the spectrum of an individual data stream occupies only a part of the available bandwidth. A serial transmission system is considerably less complex than a parallel transmission system as the latter needs several identical receivers to separate out the different frequency channels. Data transmission systems can be further classified into synchronous systems and asynchronous systems and also by the type of modulation used. A synchronous system is one in which the transmitter and the receiver are operating continuously in synchronism with the same number of signal elements per second. In an asynchronous system, individual data elements are transmitted with arbitrary time intervals between adjacent elements; the time interval may vary considerably from one pair of adjacent elements to another. For an asynchronous system a separate timing signal may be transmitted shortly before each data element to prepare the receiver for the detection of the elements. In a synchronous serial system, the instantaneous frequency of the reference carrier is held constant at the average instantaneous frequency of the received signal carrier.

Furthermore, in a serial system the signal elements are transmitted at a steady rate, i.e. a given number of elements per second (bauds). The receiver recovers the synchronization information from the received signal and is, therefore, held in time synchronization. In applications where a relatively high transmission rate is required over a given channel, a synchronous serial system is the most commonly used system.

Over the years, a number of modulation methods have been introduced for digital data transmission systems, namely ASK (Amplitude-Shift Keying), PSK (Phase-Shift Keying) and FSK (Frequency-Shift Keying). Considering the targeted transmitting information rate, each method must be devised as effectively as possible to introduce a minimum amount of distortion to the data signal. The main factors involved are signal power, bandwidth and noise power. Thus, it is the ratio of signal power to noise power or output signal/noise ratio (S/N) specified for the system which determines its performance.
In multi-level digital signalling at a given element rate, an increase in the number of levels in FSK signalling (tones) results in only a small reduction in tolerance to noise even at high signal/noise ratios. This means that unlike ASK and PSK, the information rate for FSK multi-level signalling can be significantly increased but the system's complexity and BW also increases, and no noticeable reduction in tolerance to noise can be achieved. It is also accomplished that [2]; at high signal-to-noise ratios, when coherent detection is replaced by incoherent one, a reduction in tolerance to noise (additive white Gaussian) is around 1dB for ASK, FSK and binary PSK signals, 2.3dB for quaternary PSK signals and 3dB for higher level PSK signals.

Therefore, a synchronous (coherent) serial data transmission system employing 4-level QPSK modulation is considered in this thesis to study the performance of the detectors and estimators for the cancellation of possible echoes. Fig. 5.1 shows the general model of a data transmission system. The bandpass channel together with the linear modulator at the transmitter and the linear demodulator at the receiver, appears as a linear baseband channel with the same fading characteristics as those of the original baseband channel. The resultant system can now be analysed as a simple linear baseband system with the nominal bandwidth of the bandpass channel being 2400 Hz for any type of data.

The stream of binary signal \( \{ \alpha_i \} \) is first passed into an encoder [Appendix E] to deliver the signal \( s(t) \) at the input of the transmitter filter [Fig. 5.1]. Now \( s(t) \) is a sequence of regularly spaced impulses at an interval of \( T \) seconds.

\[
s(t) = \sum_i s_i \delta(t - iT) \quad \text{...5.2.1}
\]

where \( \delta(t - iT) \) is a unit impulse at time \( t=iT \) second. The \( \{ s_i \} \) are statistically independent and equally likely to have any of \( m \) possible values (\( m=4 \) here). When \( \{ s_i \} \) are not statistically independent, the transmitted sequence of data symbols is scrambled to ensure statistical independence at the transmitter. At the receiver it is appropriately descrambled. The sampled impulse response of the transmitter filter is \( a(t) \) and is such that it shapes the spectrum of the signal fed to the transmission path to match its available bandwidth. This maximises the signal to noise ratio at the receiver input for a given transmitted signal power. The transmission path could be a lowpass or a bandpass channel with an impulse response \( h(t) \).
The receiver filter with impulse response $b(t)$, band limits the noise component outside the signal frequency band but without excessively bandlimiting the signal itself. The receiver filter is such that the sample value of the noise component at its output remains almost statistically independent with zero mean and fixed variance. It is shown in [2] that for maximising the signal-to-noise power ratio at the detector input, the amplitude response $|B(f)|$ of the receiver filter must be in a constant ratio $p$ to the amplitude response $|A(f)|$ of the transmitter filter, over all values of the frequency $f$. This condition assumes that the transmission path introduces no attenuation, delay or distortion.

The transmitter filter, the transmission path and the receiver filter in cascade are assumed here to form a linear baseband channel with the impulse response $y(t)$. For an underwater acoustic link, $y(t)$ may vary significantly with time. However, in order not to complicate the model of the data transmission system, it is assumed that the sampled impulse response of the channel is time invariant at least over the period of the sampling interval. The impulse response of the baseband channel, in Fig. 5.1, $y(t)$ is assumed to be finite duration. When the transmission path is time invariant, $y(t)$ is given by

$$y(t) = a(t) * h(t) * b(t) \quad \ldots 5.2.2$$

where $*$ represents the convolution operation. However, when the transmission path is time variant then $y(t)$ will vary with time and the relationship between $y(t)$ and $a(t)$, $h(t)$ and $b(t)$ will depend on the nature of variation in $h(t)$.

The received signal at the output of the receiver filter is

$$r(t) = \sum_i s_i y(t - iT) + w(t) \quad \ldots 5.2.3$$

where $w(t)$ is the noise component (white Gaussian) in $r(t)$, it is real-valued and has a two sided power spectral density of $\frac{1}{2} N_0$ which is given by

$$w(t) = n(t) * b(t) \quad \ldots 5.2.4$$

As described in Chapter 3, the main source of additive noise $w(t)$ in an underwater link is the ambient-noise caused by adding all individual sea-noise sources. This has the same properties similar to those of additive white Gaussian noise. Other sources of noise, such as biological noise, noise from ice-cracking and wave crashes can be considered, as added to $w(t)$ but have been neglected here.
The tolerance of a modem to additive white Gaussian noise is not necessarily a good measure of its actual tolerance to any particular type of additive noise. However, the relative tolerance of different modems to white Gaussian noise is a reasonably good measure of their overall tolerance to the additive noise likely to be experienced in practice [2].

The received signal \( r(t) \) is sampled once per signal element at the time instant \( iT \), where \( i \) takes on all positive integer values. It is assumed that the delay in transmission is neglected here and only the one involved in the time dispersion of the transmitted signal is present,

hence for a channel of \( h \)-component sampled impulse response

\[
y(t) = 0 \quad \text{for} \quad h < 0 \quad \& \quad h > g \quad \& \quad 5.2.5
\]

for \( h = 0, 1, 2, \ldots, g \)

And the sampled values of the received signal at the output of the baseband channel at time \( t=iT \) is

\[
r_i = \sum_{h=0}^{g} s_{i-h}y_{i,h} + w_i \quad \& \quad 5.2.6
\]

where

\[
y_{i,h} = y(hT) \quad \& \quad 5.2.7
\]

The samples \( y_{i,h} \) form the \( (g+1) \)-component row vector given by

\[
Y = y_{i,0}, y_{i,1}, y_{i,2}, \ldots, y_{i,g} \quad \& \quad 5.2.8
\]

The vector \( Y \) is called the sampled impulse response of the baseband channel and \( \{w_i\} \) are samples of \( w(t) \) at time instants of \( iT \).

The detector operates on the adaptively adjusted received samples \( \{r_i\} \) to produce the sequence of detected data symbols \( \{s_i\} \). With correct detection, the \( \{s_i\} \) are identical to the transmitted data symbols \( \{s_i\} \). In practice, the detector detects data sequence in such a way that it has the least probability of error. Supposing in Eqn. 5.2.6, \( y_{i,h} = 0 \) for \( h=1, \ldots, g \), then the received sample \( r_i \) is given by

\[
r_i = s_{i}y_{i,0} + w_i \quad \& \quad 5.2.9
\]
and in the absence of noise, the detector detects \( s_i = r_i/y_{i,0} \) as the correct data. In the presence of noise, \( s_i' \), the detected data is taken as the nearest value to \( r_i/y_{i,0} \) and as long as \( |w_i/y_{i,0}| < 1 \) a correct decision is made. However, when \( y_{i,h} \) has a non-zero value for \( h=1,2,...,g \), then the received sample is given by

\[
r_i = s_i y_{i,0} + \sum_{h=1}^{g} s_{i-h} y_{i,h} + w_i \quad \ldots \text{5.2.10}
\]

The term \( \sum_{h=1}^{g} s_{i-h} y_{i,h} \) represents inter-symbol interference, and unless the inequality

\[
\left| \sum_{h=1}^{g} s_{i-h} y_{i,h} + w_i \right| < |y_{i,0}| \quad \ldots \text{5.2.11}
\]

is satisfied, the correct decision will not be obtained. Intersymbol interference is treated as noise by the detector and \( s_i \) is detected as its nearest possible value to \( r_i/y_{i,0} \). The decoder [Appendix E] then translates back the detected \( s_i' \) into \( \alpha_i' \) that should represent the original binary input signal [2,16-22,100-106].

### 5.3 TIME INVARIANT LINEAR BASEBAND CHANNEL

So far, the thesis has provided a clear understanding that, the transmission path in the model of underwater digital data transmission system has nonlinear characteristics, i.e. it is a fading multipath medium. In order to detect correct data symbols at the output of such a channel, no impairments must be introduced by any other components of the baseband channel. Moreover, the equipment filters (transmitter and receiver filters), modulator and demodulator must introduce minimum errors into the baseband channel, thus maximizing the signal to noise power ratio at the input of the detector [Fig. 5.1]. This can be achieved by first considering the transmission path to have a completely non-fading characteristics [2,104], i.e. it could introduce no delay, attenuation or distortion.

#### 5.3.1 Non-fading linear baseband channel

Consider Fig. 5.2 with the transmission path that has a non-fading characteristic. The transfer functions \( A(f) \) and \( B(f) \) of the transmitter and receiver filters determines the maximum signal-to-noise power ratio at the input to the detector.
The transmitter filter, transmission path and receiver filter in Fig. 5.2, together form a baseband channel with transfer function

\[ H(f) = p A(f) B(f) \]  

...5.3.1

where \( p \) is a constant multiplier. If the transmission path introduces no attenuation, delay or distortion, then

\[ \int |H(f)|\,df = 1 \]  

...5.3.2

This does not in any way restrict the possible combinations of transmitter and receiver filters, other than by adjusting the response of one of these by a constant multiplier, which may be taken to have a positive real value (i.e. \( p=1 \)) without affecting the signal-to-noise power ratio. Under these conditions, the maximum signal-to-noise power ratio at the detector input is determined when

\[ |B(f)| = |A(f)| \]  

...5.3.3

In fact, it can be stated that

\[ B(f) = \pm A(f) \]  

...5.3.4

indicating the necessity of designing the simplest combination of transmitter and receiver filters [2,90] that satisfy Eqn. 5.3.3. Eqns. 5.3.1-5.3.4 imply that

\[ \int A(f)^2\,df = \int B(f)^2\,df = \int |H(f)|\,df = 1 \]  

...5.3.5

In principle, the simplest design of the transmitter and receiver filters is that giving a rectangular spectrum [Fig. 5.3] for an individual received signal element at the output of the receiver filter. This arrangement has a disadvantage in the sense that a small error in the phase of the sampling instants at the detector input can introduce considerable intersymbol interference. This degradation can be readily improved by rounding off or smoothing the abrupt change in \( H(f) \) at \( f = \pm \frac{\pi}{2T} \). Generally, the more smooth or gradual the variation of \( H(f) \) with \( f \) for a given bandwidth over the total range of values of \( f \) for which \( H(f) \neq 0 \), the shorter becomes the effective duration of \( h(t) \). When \( f = \frac{1}{T} \), the spectrum has the shape of one cycle of a cosine wave between adjacent negative peaks (i.e. raised to zero, or raised cosine spectrum). The two following sections investigate two types of such signal spectra in detail.
5.3.2 Raised cosine spectrum

Amplifying the statements given in the previous section, the raised cosine filtering is chosen for the implementation of equipment filters employed in the construction of System A channel. It contains all the signal energy within a duration of two signal periods (±T) and it gives a good approximation to a more practical filter. Its transfer function is given by

\[ H(f) = \begin{cases} \frac{T}{2} (1 + \cos \pi f T) & -\frac{1}{T} < f < \frac{1}{T} \\ 0 & \text{elsewhere} \end{cases} \]  

with T=1/2400 seconds

The transfer function of both the transmitter filter A(£) and the receiver filter B(£) is \( H^{1/2}(f) \). The impulse response of the baseband channel is given by

\[ h(t) = \int_{-\infty}^{\infty} H(f)e^{i2\pi ft} df \]  

Combining Eqn. 5.3.6 and 5.3.7, \( h(t) \) is

\[ h(t) = \frac{T}{2} \int_{-1/T}^{1/T} (1 + \cos \pi f T)e^{i2\pi ft} df \]  

Hence, \( a(t) \) and \( b(t) \) are

\[ a(t) = b(t) = \int_{-1/T}^{1/T} H^{1/2}(f)e^{i2\pi ft} df \]  

Substituting \( H(f) \) from Eqn. 5.3.6 into Eqn. 5.3.9, gives

\[ a(t) = b(t) = \sqrt{\frac{T}{2} \int_{-1/T}^{1/T} \sqrt{(1 + \cos \pi f T)} e^{i2\pi ft} df} \]  

Simplify and replace the trigonometric function with its hyperbolic equivalent, then the impulse response of the transmitter and receiver filters [Fig. 5.4] is
This indicates that for no significant intersymbol interference and without the need for extreme precision in the timing of the sampling instants, the bandwidth of the baseband channel must be greater than its minimum possible value of \( f = \frac{1}{2T} \) Hz (for positive frequencies). Thus the data signal at the output of the baseband channel of Fig. 5.2 should ideally have a raised-cosine spectrum and bandwidth of \( \frac{T}{2} \) Hz (i.e. twice the bandwidth of the corresponding signal with a rectangular spectrum). However, a more efficient use of bandwidth can be achieved by the use of quaternary signalling with a raised cosine spectrum, where for a given information rate and transmitted signal power, up to 4 dB reduction in noise can be achieved over the binary polar signals. On the other hand, the signal bandwidth can be kept the same, while allowing the channel to respond partially as explained in the next section.

### 5.3.3 Partial-response spectrum

In this particular spectrum, a useful reduction in bandwidth can be achieved by allowing considerable but well-defined levels of intersymbol interference between neighbouring signal-elements [System B]. The degradations produced here can then be cancelled by employing suitable detection techniques.

Consider that the baseband channel of Fig. 5.2 is constructed to employ the partial response spectrum [Fig. 5.5] given by

\[
H(f) = \begin{cases} 
\frac{1}{2} \pi T \cos \pi fT & -\frac{1}{2T} < f < \frac{1}{2T} \\
0 & \text{elsewhere}
\end{cases}
\]

with \( T = 1/2400 \) seconds

The impulse response \( h(t) \) of the baseband channel can be obtained by replacing Eqn. 5.3.12 into Eqn. 5.3.7 as
After simplifying and replacing the trigonometric function with its hyperbolic equivalent, the impulse response of the baseband channel is

\[ h(t) = \frac{1}{2} \pi T \int_{-\pi T}^{\pi T} \cos \pi f T e^{j2\pi f t} \, df \]  \hspace{1cm} \text{...5.3.13}

It can be observed that, unlike raised cosine spectrum case, the impulse response of the individual transmitter and receiver filters cannot be derived separately, but the spectrum of \( H(f) \) can be separated in time as shown in Fig. 5.6. Before Fourier transformation can take place, the square root of each sample with adequately enforced zeros must be taken to obtain the required sampled impulse responses.

The baseband channel employing partial response filters has a disadvantage because the incorrect detection of an element prevents the cancellation of intersymbol interference of the elements in the sampled value used for the detection of the following elements, i.e. causing errors throughout. But, with multi-level signals (e.g. \( m=4 \)) which are statistically independent and equally likely to have any of their \( m \) possible values, this effect can no longer have a serious effect [2,107-109].

5.3.4 Windowing

In order to control the convergence of the Fourier series a weighting function is used to modify the Fourier coefficients. This time-limited weighting function is called a window. Since the multiplication of Fourier coefficients by a window corresponds to convolving the original frequency response with the Fourier transform of the window, a design criterion for windows is to find a finite window whose Fourier transform has relatively small sidelobes.

From three following windows tested [Fig. 5.7], the Hamming window was chosen since it is commonly employed to meet the required criterion; they are given by
Hamming: \[ w_n = 0.54 - 0.46 \cos \left( \frac{2\pi n}{N-1} \right) \quad 0 \leq n \leq N-1 \]

Hanning: \[ w_n = \frac{1}{2} \left[ 1 - \cos \left( \frac{2\pi n}{N-1} \right) \right] \quad 0 \leq n \leq N-1 \]

Blackman: \[ w_n = 0.42 - 0.5 \cos \left( \frac{2\pi n}{N-1} \right) + 0.08 \cos \left( \frac{4\pi n}{N-1} \right) \quad 0 \leq n \leq N-1 \]

This most commonly used window has 99.96 percent of its energy in the main lobe with the peak amplitude of the sidelobes down more than 20 dB from the peak \[108,109]\.

5.3.5 Model of QAM system

Quaternary amplitude modulation (QAM) is a multilevel, digital modulation method used to modulate information bearing data signals over practical bandpass channels. The method utilizes two double sideband suppressed AM carrier signals, one being in phase and the other in quadrature with the same carrier frequency; they have the same AM spectra and are transmitted simultaneously. The upper and lower sidebands are centred around the carrier frequency.

The QAM scheme provides many advantages; it is a linear and highly bandwidth efficient method and it can be implemented by \( m \) levels where \( m \geq 4 \). The transmission rate is increased by increasing the number of levels \( m \) over a given channel bandwidth but at the expense of the increase in intersymbol interference, timing and phase jitter problems.

The block diagram of Fig. 5.8 shows a model of a data transmission system that performs a QAM modulation scheme with two streams of data symbols \( \{s_{0,i}\} \) and \( \{s_{1,i}\} \) which are statistically independent and each have equally likely to have any one of \( \log_2 m \) possible values and assumed to be transmitted in the form of impulses every \( iT \) seconds as shown in Fig. 5.10.

The two separately generated data symbol impulses are initially passed through two low pass filters \( A_1 \) and \( A_2 \) having the same impulse response \( a(t) \) which is a real
value. The filters are signal spectrum shaping filters and their purpose is to limit the bandwidth of the resultant QAM signal to that available on the transmission path \([16-22,100]\). Their implementation will be explained in detail in the next section.

The two signals \(\{s_{0,i}\}\) and \(\{s_{1,i}\}\) at the output of \(A_1\) and \(A_2\) are modulated by two carriers with a frequency of \(f_c\). They are in phase quadrature and \(f_c\) is chosen such that the spectra of the baseband signals are shifted into the passband of the transmission path \([\text{Fig. 5.9}]\). These two carrier signals, when added \([\text{Fig. 5.8}]\), form the resultant QAM signal \(x(t)\), whose amplitude spectrum is \(|X(f)|\) and is shown in \(\text{Fig. 5.9}\) and may be expressed as

\[
x(t) = \sqrt{2} \sum_i s_{0,i} a(t - iT) \cos 2\pi f_c t - \\
\sum_i s_{1,i} a(t - iT) \sin 2\pi f_c t
\]

Replacing trigonometric functions with their hyperbolic equivalents results in

\[
x(t) = \frac{1}{\sqrt{2}} \sum_i a(t - iT) \left[(s_{0,i} + j s_{1,i})e^{j2\pi f_c t} + \\
(s_{0,i} - j s_{1,i})e^{-j2\pi f_c t}\right]
\]

Since

\[
s_i = s_{0,i} + j s_{1,i}
\]

where \(s_i\) is a complex data value, Eqn. 5.3.17 may be written as

\[
x(t) = \frac{1}{\sqrt{2}} \sum_i a(t - iT) \left[s_i e^{j2\pi f_c t} + s_i^* e^{-j2\pi f_c t}\right]
\]

The signal \(x(t)\) is now a QAM signal, transmitted over a channel with a real valued impulse response \(h(t)\). It is assumed that the channel introduces stationary, white Gaussian noise, which is added at the output of the transmission path \([\text{Fig. 5.8}]\). As explained before, the noise function, \(n(t)\), is a Gaussian random process with zero mean and a two-sided power spectral density of \(N_0\) \([\text{Fig. 5.12}]\).

The noisy QAM signal is now passed through an ideal bandpass filter \(C\) at the receiving end. The function of this filter is to remove any noise components lying outside the signal frequency band. It has a bandlimited amplitude spectrum \(|C(f)|\), with unity value for \(f_c - \frac{1}{2} \leq |f| \leq f_c + \frac{1}{2}\) and zero elsewhere, as shown in \(\text{Fig. 5.11}\), and a real valued impulse response \(c(t)\).
The signal $z(t)$ at the output of the receiver filter is then coherently demodulated by two reference carriers $f_e$ in phase quadrature, with reference phase of $\theta$ which is assumed to be constant at this stage. Thus $z(t)$ is

$$z(t) = x(t) * h(t) * c(t) + n(t) * c(t) \quad \ldots 5.3.20$$

where $*$ signifies the convolution process.

The signal $z(t)$ is passed through two coherent demodulators, as shown in Fig. 5.8. The output is then passed through two lowpass filters $B_1$ and $B_2$. These two filters remove the high frequency components which result as a consequence of the demodulation process. They both have a real valued impulse response $b(t)$ and with Fourier Transform $B(f)$ which bandlimit the signals at their inputs from $-1/T$ to $1/T$ Hz. The output $r(t)$ is the resultant of the addition of $r_1(t)$ and $r_2(t)$ at the output of these two filters, with $r_2(t)$ having imaginary value. The $r(t)$ is then sampled once per signal element at the time instants $t=iT$ to give samples $\{r_i\}$ which are then fed to the detector. The mathematical notations are as follows

$$r_1(t) = [\sqrt{2} z(t) \cos(2\pi f_c t + \theta)] * b(t) \quad \ldots 5.3.21$$

$$r_2(t) = [\sqrt{2} z(t) \sin(2\pi f_c t + \theta)] * b(t) \quad \ldots 5.3.22$$

where $\theta$ is the phase of the reference carrier relative to that of the signal carrier. Thus the received signal at the input to the sampler is the complex signal

$$r(t) = r_1(t) + jr_2(t) \quad \ldots 5.3.23$$

Substituting Eqns 5.3.21 and 5.3.22 into 5.3.23 we have

$$r(t) = [\sqrt{2} z(t) \{\cos(2\pi f_c t + \theta) - j \sin(2\pi f_c t + \theta)\}] * b(t)$$

$$= [\sqrt{2} z(t)e^{-j(2\pi f_c t + \theta)}] * b(t) \quad \ldots 5.3.24$$

Now substituting $z(t)$ from Eqn. 5.3.20 into Eqn. 5.3.24 gives

$$r(t) = \left\{ \sqrt{2} [x(t) * h(t) * c(t) + n(t) * c(t)] e^{-j(2\pi f_c t + \theta)} \right\} * b(t) \quad \ldots 5.3.25$$

Rearranging Eqn. 5.3.25 and substituting the value of $x(t)$ from Eqn. 5.3.19 gives

$$r(t) = \left\{ \left\{ \sum_i a_i (T - iT) \left[ s_i e^{j2\pi f_c t_i} + s_i^* e^{-j2\pi f_c t_i} \right] * h(t) * c(t) \right\} e^{-j(2\pi f_c t_i + \theta)} \right\} * b(t)$$

$$+ \sqrt{2} [n(t) * c(t)] e^{-j(2\pi f_c t + \theta)} \quad \ldots 5.3.26$$
Consider the convolution equality

\[ [u_1(t) * u_2(t)] e^{-j2\pi f_c t} = [u_1(t) e^{-j2\pi f_c t}] * [u_2(t) e^{-j2\pi f_c t}] \]  

...5.3.27

then Eqn. 5.3.26 becomes

\[ r(t) = \left\{ \left[ \sum_i s_i e^{j2\pi f_c t} + s_i^* e^{-j2\pi f_c t} \right] e^{-j2\pi f_c t} * \{h(t) * c(t)\} e^{-j2\pi f_c t} \right\} e^{-j\theta} \]

\[ + \sqrt{2} \{n(t) * c(t)\} e^{-j2\pi f_c t} * b(t) \]

...5.3.28

and when Eqn. 5.3.28 is simplified, \( r(t) \) is

\[ r(t) = \left\{ \sum_i s_i a(t - iT) * \{h(t) * c(t)\} e^{-j2\pi f_c t} \right\} e^{-j\theta} * b(t) \]

\[ + \left[ \sum_i s_i^* e^{-j2\pi f_c t} a(t - iT) * \{h(t) * c(t)\} e^{-j2\pi f_c t} \right] e^{-j\theta} * b(t) \]

\[ + \sqrt{2} \{n(t) * c(t)\} e^{-j2\pi f_c t} * b(t) \]

...5.3.29

The second term in the Eqn. 5.3.29 reduces to zero since the spectrum of \( e^{-j4\pi f_c t} a(t) \) lies outside the passband of the two lowpass filters \( B_1 \) and \( B_2 \), i.e

\[ r(t) = \sum_i s_i a(t - iT) * \{h(t) * c(t)\} e^{-j2\pi f_c t} e^{-j\theta} * b(t) \]

\[ + \sqrt{2} \{n(t) * c(t)\} e^{-j2\pi f_c t} * b(t) \]

...5.3.30

Now if \( y(t) \) represents the overall system impulse response which is a complex valued with

\[ y(t) = \left[ a(t) * \{h(t) * c(t)\} e^{-j2\pi f_c t} \right] e^{-j\theta} * b(t) \]

...5.3.31

and \( w(t) \) represents the resultant complex valued noise component as

\[ w(t) = \left[ \sqrt{2} \{n(t) * c(t)\} e^{-j2\pi f_c t} \right] * b(t) \]

...5.3.32

then the received signal is

\[ r(t) = \sum_i s_i y(t - iT) + w(t) \]

...5.3.33

The component \( e^{-j2\pi f_c t} \) makes \( y(t) \) appear not to be baseband waveform. But \( h(t) * c(t) \) has a bandpass waveform whose spectrum is centred at \( f_c \) Hz, and when \( h(t) * c(t) \) is multiplied by the factor \( e^{-j2\pi f_c t} \) it shifts in frequency by \( -f_c \) Hz to \( h(t) * c(t) e^{-j2\pi f_c t} \).
which has a lowpass response. This, together with the bandlimiting applied by \(A(f)\) and \(B(f)\), results in \(y(t)\) having a baseband response. Therefore, the channel model based on Eqn. 5.3.31 can represent the baseband equivalent of a bandpass QAM system as shown in Fig. 5.8. The values of \(\theta\), \(a(t)\), \(h(t)\), \(c(t)\) and \(b(t)\) are, however, either known or can be easily determined from their corresponding frequency characteristics [100, 103-106].

The noise component \(w(t)\) described earlier is a complex valued Gaussian noise waveform [Fig. 5.12]. In this model, it can be shown that since the amplitude spectrum \(|C(f)|\) of the receiver bandpass filter is symmetrical about the carrier frequency \(f_c\), any samples of real and imaginary parts of \(w(t)\) are statistically independent Gaussian random variables with zero mean and a fixed variance.

From Eqn. 5.3.27 and 5.3.32, the function \(w(t)\) can be expressed as;

\[
w(t) = \sqrt{2}n(t)e^{-j2\pi f_c t}c(t)e^{-j2\pi f_c \delta}e^{-j\theta}b(t)
\]

Since the multiplication of \(n(t)\) with \(e^{-j2\pi f_c t}\) shifts the spectrum of \(n(t)\) by \(-f_c\) without affecting its power density, and since the two-sided power density of \(n(t)\) is \(N_0/2\), it can be concluded that the power spectral density of \(n(t)e^{-j2\pi f_c t}\) is \(N_0/2\). This implies that

\[
|W(f)|^2 = 2N_0|C(f + f_c)|^2B(f)^2
\]

with \(|W(f)|^2\) representing the power spectral density of \(w(t)\).

The autocorrelation function \(R_w(t)\) of \(w(t)\) is the inverse discrete Fourier transform of the power spectral density and can be given by

\[
R_w(t) = N_0 \int_{-\infty}^{\infty} |C(f + f_c)|^2 B(f)^2 e^{j2\pi ft} df
\]

In the general model described here, the filters \(C, B_1\) and \(B_2\) have unity spectrum in the range of \(-1/T\) to \(1/T\), thus implying
\[ R_w(\tau) = N_0 \int_{-\frac{1}{T}}^{\frac{1}{T}} e^{i2\pi ft} df \]
\[ = \frac{2N_0 \sin(2\pi fT)}{T} \frac{1}{2\pi fT} \] \[ ...5.3.37 \]

The autocorrelation function of a random process at zero lag can give the variance of \( w(t) \) here which from Eqn. 5.3.37 is obtained as

\[ \sigma_w^2 = R_w(0) \]
\[ = \frac{2N_0}{T} \] \[ ...5.3.38 \]

It is also possible to show that the autocorrelation function of each of the real and imaginary parts of \( w(t) \) can be obtained by half the real part of autocorrelation function of \( w(t) \). The autocorrelation function here is purely real, since \( |C(f)| \) is symmetrical about \( f_c \) and thus for each real and imaginary part of \( w(t) \) the autocorrelation function \( R_w(\tau) \) is

\[ R_w(\tau) = \frac{1}{2} N_0 \int_{-\infty}^{\infty} |C(f + f_c)| \hat{P}_B(f) \hat{P}_C(f) e^{i2\pi ft} df \] \[ ...5.3.39 \]

thus leading to the variance \( (\sigma_w')^2 \) for real and imaginary parts \([110]\) as

\[ (\sigma_w')^2 = \frac{N_0}{T} \] \[ ...5.3.40 \]

The two important quantities which are used to evaluate the performance of the system, are the transmitter and the receiver signal energies especially for the calculation of the signal-to-noise ratios. If the average transmitted energy per symbol is

\[ E_u = E \left[ |s_i|^2 \int |a^2(t)| dt \right] \] \[ ...5.3.41 \]

where \([\cdot] \) represents the expected value. Since the \( |s_i| \) components are statistically independent and have zero mean, then
\[ E_u = \overline{s_i^2} \int a^2(t) dt \quad \cdots 5.3.42 \]

where \( \overline{s_i^2} \) is the expected value of \( |s_i|^2 \). Utilizing Parseval's theorem Eqn. 5.3.42 above becomes

\[ E_u = \overline{s_i^2} \int_{-\nu_T}^{\nu_T} |A(f)|^2 df \quad \cdots 5.3.43 \]

Now if the average transmitted energy per bit is \( E_\delta \), then

\[ E_\delta = \frac{\overline{s_i^2}}{\log_2 m} \int_{-\nu_T}^{\nu_T} |A(f)|^2 df \quad \cdots 5.3.44 \]

where \( m \) represents the level of the QAM signal and is 4 for the case considered here, i.e.

\[ E_\delta = \frac{\overline{s_i^2}}{2} \int_{-\nu_T}^{\nu_T} |A(f)|^2 df \quad \cdots 5.3.45 \]

But the average received energy per signal element is

\[ E_r = E \left[ |s_i|^2 \int y^2(t) dt \right] \quad \cdots 5.3.46 \]

Making use of the fact that, \( \{s_i\} \) are statistically independent and have zero mean, then by Parseval theorem, Eqn. 5.3.46 can be given as

\[ E_r = \overline{s_i^2} \int |Y(f)|^2 df \quad \cdots 5.3.47 \]

where \( Y(f) \) is the transfer function of \( y(t) \) [Eqn. 5.3.31], and is given by

\[ |Y(f)|^2 = |A(f)|^2 |H(f + f_c)|^2 |C(f + f_c)|^2 |B(f)|^2 \quad \cdots 5.3.48 \]

Substituting Eqn. 5.3.48 into 5.3.47 gives

\[ E_r = \overline{s_i^2} \int |A(f)|^2 |H(f + f_c)|^2 |C(f + f_c)|^2 |B(f)|^2 df \quad \cdots 5.3.49 \]
Assuming the filters \( C, B, \) and \( B_2 \) as before, then in this model Eqn. 5.3.49 can be written as

\[
E_r = \frac{1}{2} \int_{-\nu T}^{\nu T} |A(f)|^2 |H(f + f_c)|^2 df \quad \ldots 5.3.50
\]

The average received signal energy per bit is now

\[
E_r = \frac{1}{2} \int_{-\nu T}^{\nu T} |A(f)|^2 |H(f + f_c)|^2 df \quad \ldots 5.3.51
\]

Note that the QAM system explained in this section is for the general case of System A (raised-cosine channel), while for applications where System B (partial response channel) is concerned the value of \( T \) is replaced by \( 2T \) [2,100,110].

5.4 IMPLEMENTATION OF QAM SYSTEM OVER TIME-VARYING UNDERWATER CHANNELS

The previous section described all the components in the model of QAM data transmission system except that of transmission path. In this section, it is intended to broaden this investigation by incorporating the time-varying underwater models [Chapter 4] into the QAM transmission system model. Appropriate theoretical analysis for treating time-varying channels is presented first, followed by individual treatments of both System A and B.

At this stage, it should be emphasised that it is necessary to implement the transmitter and receiver filters with the frequency spread observed in any particular kind of transmission. For instance, if the channel is implemented for voice communications then the frequency spread available must be included in the equipment filters. Consider Fig. 5.13, the \([s_i] \) are a sequence of complex data symbol values or impulses with an element rate of \( \frac{1}{T} \) bauds, subjected to a fading medium, as would be the case in a practical time-varying underwater channel.

The signals at the output of the two low pass filters in the transmitter of Fig. 5.13 are \( \sum_i s_0, a(t - iT) \) \& \( \sum_i s_1, a(t - iT) \) where \( a(t-iT) \) is the overall transmitter filter response. The signal \( x(t) \) at the output of the adder in Fig. 5.13 is a real valued waveform and is given by
\[ x(t) = \sqrt{2} \sum_i s_{0,i} a(t-iT) \cos(2\pi f_i t) - \sqrt{2} \sum_i s_{1,i} a(t-iT) \sin(2\pi f_i t) \] 

...5.4.1

The factor \( \sqrt{2} \) in Eqn. 5.4.1 ensures that the mean square value or the average power level is unity for each of the two signals, \( \sqrt{2} \cos 2\pi f_i t \) and \( -\sqrt{2} \sin 2\pi f_i t \), when transmitted over an infinite period.

Replacing the trigonometric functions with their hyperbolic equivalence, Eqn. 5.4.1 can be written as

\[ x(t) = \sqrt{2} \sum_i s_{0,i} a(t-iT) \frac{1}{2} \left[ e^{j2\pi f_i t} + e^{-j2\pi f_i t} \right] - \sqrt{2} \sum_i s_{1,i} a(t-iT) \frac{1}{2j} \left[ e^{j2\pi f_i t} + e^{-j2\pi f_i t} \right] \]

or

\[ x(t) = \frac{1}{\sqrt{2}} \sum_i (s_{0,i} + j s_{1,i}) a(t-iT) e^{j2\pi f_i t} + \frac{1}{\sqrt{2}} \sum_i (s_{0,i} - j s_{1,i}) a(t-iT) e^{-j2\pi f_i t} \]

or

\[ x(t) = \frac{1}{\sqrt{2}} \sum_i s_i a(t-iT) e^{j2\pi f_i t} + \frac{1}{\sqrt{2}} \sum_i s_i^* a(t-iT) e^{-j2\pi f_i t} \] 

...5.4.2

Here \( s_i^* \) is the complex conjugate of \( s_i \). \( x(t) \) is real-valued and the second term in Eqn. 5.4.2 is the complex conjugate of the first term, bearing in mind that \( a(t-iT) \) is real-valued, indicating

\[ x(t) = \frac{1}{\sqrt{2}} \sum_i s_i a(t-iT) e^{j2\pi f_i t} + \frac{1}{\sqrt{2}} \sum_i s_i^* a(t-iT) e^{-j2\pi f_i t} \] 

...5.4.3
Eqn. 5.4.3 represents the overall filtering at the transmitter end, which includes the lowpass filter and the acoustic transducer's transmitter equipment filter in a bandpass form.

Fig. 5.13 shows the model of QAM system over a single multipath propagated fading channel [System A]. When $x(t)$ [Eqn. 5.4.3] is fed into this fading channel, the output would be

$$z(t) = x(t)v_1(t) + \hat{x}(t)v_2(t)$$

... 5.4.4

where $\{v_i(t)\}$ (here $i = 2$) are statistically independent Gaussian random processes that generate the fading sequences; they are characterized by lowpass Gaussian spectral shaping, with a very narrow bandwidth. $\hat{x}(t)$ represents the Hilbert transform of $x(t)$. The Hilbert transformer [100,103-106] is an all-pass filter which introduces a $-90^\circ/90^\circ$ phase shift to all positive and negative frequencies of its input signal, and is characterized by the impulse response $p(t)$ as

$$p(t) = \frac{1}{\pi t}$$

... 5.4.5

and by the transfer function as

$$P(f) = \begin{cases} 
  j & f < 0 \\
  0 & f = 0 \\
  -j & f > 0
\end{cases}$$

... 5.4.6

Thus

$$\hat{x}(t) = x(t) * p(t)$$

... 5.4.7

Substituting Eqn. 5.4.3 in Eqn. 5.4.7 we have

$$\hat{x}(t) = \frac{1}{\sqrt{2}} \left\{ \sum_i s_i a(t - iT)e^{j2\pi fi} + \sum_i s_i^* (a(t - iT))^* e^{-j2\pi fi} \right\} * p(t)$$

... 5.4.8

Now using the convolution definition of Eqn. 5.3.27, Eqn. 5.4.8 when rearranged can be written as
\[
\hat{x}(t) = \frac{1}{\sqrt{2}} \left[ \sum_i s_i a(t - iT)^* p(t) e^{-j2\pi f_c t} \right] e^{j2\pi f_c t} + \left[ \sum_i s_i^* (a(t - iT))^* p(t) e^{j2\pi f_c t} \right] e^{-j2\pi f_c t} \]

...5.4.9

The Fourier transform of \( p(t) \) is \( P(f) \), whereas the Fourier transform of \( p(t) e^{-j2\pi f_c t} \) is \( P(f + f_c) \) and from Eqn. 5.4.6 this has a value of \(-j\) over the frequency band \(-f_c\) to \(+f_c\). On the other hand, the Fourier transform of \( p(t) e^{j2\pi f_c t} \) is \( P(f - f_c) \), which has a value of \(+j\) in the frequency band \(-f_c\) to \(+f_c\). Moreover \( a(t) \) is bandlimited in a practical system. Therefore, after taking the Fourier transform of Eqn. 5.4.9, substituting the values for \( P(f + f_c) \) and \( P(f - f_c) \) from Eqn. 5.4.6 and then taking the inverse Fourier transform of the resultant relation, Eqn. 5.4.9 reduces to

\[
\hat{x}(t) = \frac{1}{\sqrt{2}} \left\{ \sum_i -js_i a(t - iT) e^{j2\pi f_c t} + \sum_i js_i^* (a(t - iT))^* e^{-j2\pi f_c t} \right\} \]

...5.4.10

where \( s_i^* \) and \( (a(t))^* \) are the complex conjugate of \( s_i \) and \( a(t) \) respectively.

Now consider \( x(t) \) and its imaginary counterpart \( \hat{x}(t) \) are transmitted over the system A and B channel models. \( z_A(t) \) At the input to the receiver filter in the system A model (one diffused component) [Fig. 5.13] is given by Eqn. 5.4.4 now as

\[
z_A(t) = x(t) v_1(t) + \hat{x}(t) v_2(t) \]

...5.4.11

But in the system B model (n-eigenray) [Fig. 5.14], the same equation can be written as

\[
z_B(t) = [x(t) v_1(t) + \hat{x}(t) v_2(t)] + [x(t - \tau_1) v_3(t) + \hat{x}(t - \tau_1) v_4(t)] + [x(t - \tau_2) v_5(t) + \hat{x}(t - \tau_2) v_6(t)] + \cdots + [x(t - \tau_n) v_{2n-1}(t) + \hat{x}(t - \tau_n) v_{2n}(t)] \]

...5.4.12
where $\tau_1, \tau_2, \ldots, \tau_n$ are the relative delays in the incoming second, third, \ldots and $n^{th}$ eigenrays with respect to the first one. The associated delay in the reception of the first eigenray or diffused path is considered non-existent for convenience.

Substituting the value of $x(t)$ and $\dot{x}(t)$ from Eqns. 5.4.3 and 5.4.10, into Eqns. 5.4.11 and 5.4.12 respectively for the system A model we have

$$z_A(t) = \frac{1}{\sqrt{2}} \{ \sum_{i} s_i^*(a(t-iT))^* [v_1(t) + jv_2(t)] e^{-j2\pi f_1 t} +$$

$$s, a(t-iT) [v_1(t) - jv_2(t)] e^{j2\pi f_1 t} \}$$

...5.4.13

and for the general [system B] model, we have

$$z_B(t) = \frac{1}{\sqrt{2}} \{ \sum_{i} s_i^*(a(t-iT))^* [v_1(t) + jv_2(t)] e^{-j2\pi f_1 t} +$$

$$s, a(t-iT) [v_1(t) - jv_2(t)] e^{j2\pi f_1 t} +$$

$$s_i^* (a(t-\tau - iT))^* [v_2(t) + jv_4(t)] e^{-j2\pi f_1 (t-\tau)} +$$

$$s, a(t-\tau - iT) [v_2(t) - jv_4(t)] e^{j2\pi f_1 (t-\tau)} +$$

$$\ldots +$$

$$s_i^* (a(t-\tau_n - iT))^* [v_2n-1(t) + jv_2n(t)] e^{-j2\pi f_1 (t-\tau_n)} +$$

$$s, a(t-\tau_n - iT) [v_2n-1(t) - jv_2n(t)] e^{j2\pi f_1 (t-\tau_n)} \}$$

...5.4.14

Now in the case of system A let

$$h(t-iT) = a(t-iT) [v_1(t) - jv_2(t)]$$

...5.4.15

Then

$$z_A(t) = \frac{1}{\sqrt{2}} \{ \sum_i (s_i h_i(t-iT)) e^{j2\pi f_1 t} +$$

$$s_i^* (h_i(t-iT))^* e^{-j2\pi f_1 t}) \}$$

...5.4.16

In the case of system B Eqns. 5.4.15 and 5.4.16 are similarly re-written as
\[ h_i(t - iT) = a(t - iT) [v_i(t) - jv_2(t)] + \]
\[ a(t - \tau - iT) [v_3(t) - jv_4(t)] e^{-j2\pi \frac{\tau}{T}} + \]
\[ , \ldots , + \]
\[ a(t - \tau_n - iT) [v_{2n-1}(t) - jv_{2n}(t)] e^{-j2\pi \frac{\tau_n}{T}} \]
\[ \ldots 5.4.17 \]

and
\[ z_b(t) = \frac{1}{\sqrt{2}} \left\{ \sum_i s_i h_i(t - iT)e^{j2\pi \frac{t}{T}} \right\} \]
\[ \ldots 5.4.18 \]

The relative delays \( \tau \) in the system B case are assumed constant. Therefore \( e^{-j2\pi \frac{\tau}{T}} \) is a fixed complex valued scalar quantity with an absolute value of 1. Since \( e^{-j2\pi \frac{\tau}{T}} \) is a fixed scalar constant, it would not affect the statistical properties of \([v_3(t) - jv_4(t)] e^{-j2\pi \frac{T}{T}}, \ldots, \), bearing in mind that \( v_i(t) \)’s are statistically independent Gaussian random processes with zero mean values.

At the receiving end, the overall receiver filter \( b(t) \) [Figs. 5.13 and 5.14] like the overall transmitter filter \( a(t) \), could be the resultant of cascaded filters depending upon the type of data transmission and transducers employed. Here it is assumed that at the output of the linear demodulator in Figs. 5.13 and 5.14, the received signal \( r(t) \) is
\[ r(t) = \sqrt{2} \left[ |z(t)*c(t)| e^{-j2\pi \frac{t}{T}} * b(t) + \right. \]
\[ \left. \sqrt{2} \left[ |n(t)*c(t)| e^{-j2\pi \frac{t}{T}} * b(t) \right] \right] \]
\[ \ldots 5.4.19 \]

where \( n(t) \) is complex valued additive white Gaussian noise with a two sided power spectral density \( \frac{1}{2} N_0 \) for each of the real and imaginary parts. Now let
\[ w(t) = \sqrt{2} \left[ |n(t)*c(t)| e^{-j2\pi \frac{t}{T}} * b(t) \right] \]
\[ \ldots 5.4.20 \]

where \( w(t) \) represents band-limited Gaussian noise. It may be mentioned at this point that the sampled values of \( n(t) \) represent uncorrelated noise. However, band-limiting \( n(t) \) to \( w(t) \) introduces a small amount of correlation in the noise samples due to filtering. Thus in both cases
\[ r(t) = \sqrt{2} \left[ z(t) e^{-j2\pi \frac{t}{T}} \right] * b(t) + w(t) \]
\[ \ldots 5.4.21 \]
Replacing the value of $z(t)$ from Eqn. 5.4.16 or 5.4.18 into Eqn. 5.4.21, the general expression for $r(t)$ becomes

$$r(t) = \sum_i [s_i h_i(t-iT) + s_i^*(h_i(t-iT)) e^{-j\phi_i t}] * b(t) + w(t)$$

...5.4.22

It is also assumed that the receiver is operating in synchronism with the transmitter and any constant phase difference between the reference carrier and the received signal is neglected.

Hence $h_i(t-iT)$ consists of the time invariant impulse response $a(t)$ and the random components $v_i(t)$, $i=1, \ldots, n$, for a general n-eigenray channel may be considered to be strictly bandlimited.

$$|H(f)| = 0 \quad |f| > f_c$$

...5.4.23

This indicates that the second term in Eqn. 5.4.22 $[s_i^*(h_i(t-iT)) e^{-j\phi_i t}]$ is outside the pass band of the low pass filter, with an impulse response $b(t)$. Hence it is filtered out. Thus

$$r(t) = \sum_i s_i h_i(t-iT)*b(t) + w(t)$$

...5.4.24

Now let

$$Y_i(t-iT) = h_i(t-iT)*b(t)$$

...5.4.25

Then

$$r(t) = \sum_i s_i Y_i(t-iT) + w(t)$$

...5.4.26

Substituting Eqn. 5.4.15 into Eqn. 5.4.25, $Y_i(t-iT)$ for the system A model can be written as

$$Y_i(t-iT) = [a(t-iT)] [v_i(t) - jv_2(t)] * b(t)$$

...5.4.27

and similarly for a general n-eigenray channel, when combining Eqn. 5.4.17 into Eqn. 5.4.25, we have
\[ Y_i(t - iT) = \{ a(t - iT)[v_1(t) - jv_2(t)] + \\
+ a(t - \tau_1 - iT)[v_3(t) - jv_4(t)] + \\
+ a(t - \tau_2 - iT)[v_5(t) - jv_6(t)] + \\
+ \ldots + \\
+ a(t - \tau_n - iT)[v_{2n-1}(t) - jv_{2n}(t)] \} \star b(t) \] ...5.4.28

The average transmitted energy per symbol at the output of the transmitter filter [Eqn. 5.3.41] in Figs. 5.13 and 5.14 for both cases is now given by

\[ E_u = E \left[ \int_{-\infty}^{\infty} |s_i a(t - iT)|^2 dt \right] \] ...5.4.29

Where \( E[.] \) represents the expected value of \([.].\)

But the average transmitted energy per bit at the output of transmitter filter when Parseval's theorem [Eqn. 5.3.43] is employed is

\[ E_{ib} = \frac{s_i^2}{\log_2 m} \int_{-\pi}^{\pi} |A(f)|^2 df \] ...5.4.30

For the case of 4-level QAM signal \((m=4)\) considered here, where

\[ s_i = s_{0,i} + s_{1,i} = \pm 1 \pm j \] ...5.4.31

The mean-square value of the complex-valued \( s_i \) is

\[ E_s = s_i^2 = 2 \] ...5.4.32

For all integer values of \([i],\) and since the symbols are statistically independent and have zero mean, thus making them statistically orthogonal, i.e

\[ E[s_i, s_j] = 0 \quad i \neq j \] ...5.4.33

But, when considering system \( A \)

\[ \int_{-\pi}^{\pi} |A(f)|^2 df = \int_{-\pi}^{\pi} \frac{T}{2} (1 + \cos \pi fT) df = 1 \] ...5.5.34

And for system \( B \)
\[
\int_{-\pi T}^{\pi T} |A(f)|^2 \, df = \int_{-\pi T}^{\pi T} \frac{\pi T}{2} \cos \pi f T \, df = 1 \quad \cdots \text{5.4.35}
\]

Now replacing the value of Eqns. 5.4.34 and 5.4.35 into 5.4.30 for \(m=4\), we have
\[
E_{sb} = \frac{s_i^2}{2} = 1 \quad \cdots \text{5.4.36}
\]

Thus, the lowpass filtering introduces no change in signal level in both systems.

The average energy per signal element at the input of the receiver filter in Fig. 5.13 is therefore given by
\[
E_{rs} = E \left[ \int_{-\pi T}^{\pi T} |s_i(a(t-iT) [v_1(t) - jv_2(t)])|^2 \, dt \right] \quad \cdots \text{5.4.37}
\]
or
\[
E_{rs} = \overline{s_i^2} \overline{[v_1^2(t) + v_2^2(t)]} \int_{-\pi T}^{\pi T} |A(f)|^2 \, df \quad \cdots \text{5.4.38}
\]

and the corresponding energy per bit is
\[
E_{rb} = \frac{s_i^2}{\log_2 m} \overline{[v_1^2(t) + v_2^2(t)]} \int_{-\pi T}^{\pi T} |A(f)|^2 \, df \quad \cdots \text{5.4.39}
\]

since the respective functions \(v_1(t)\) and \(v_2(t)\) represents their mean square values (which are also their variances) and all have zero mean. Substituting Eqn. 5.4.30 into Eqn. 5.4.39 we get
\[
E_{rb} = [\overline{v_1^2(t)} + \overline{v_2^2(t)}] E_{sb} \quad \cdots \text{5.4.40}
\]

and similarly for the system B model we have
\[
E_{rb} = [\overline{v_1^2(t)} + \overline{v_2^2(t)} + \overline{v_3^2(t)} + \overline{v_4^2(t)} + \ldots + \overline{v_{2n}^2(t)}] E_{sb} \quad \cdots \text{5.4.41}
\]

Therefore, as the sum of the variances of \(v_1(t)\) is equal to unity when generated for both cases, the average energy per symbol at the output of the transmitter filter and at the input to the receiver filter in Figs. 5.13 and 5.14 are equal.

The signal-to-noise power ratio is defined as
\[ \psi = \frac{\text{Transmitted energy per bit}}{\text{Average noise power}} \quad \ldots 5.4.42 \]

or

\[ \psi = 10.0 \log_{10} \left( \frac{E_{ib}}{\frac{1}{2}N_0} \right) \quad \ldots 5.4.43 \]

Replacing the value of \( E_{ib} \) from Eqn. 5.4.36 into Eqn. 5.4.43 for each real and imaginary noise component, we get

\[ \frac{E_{ib}}{\frac{1}{2}N_0} = \frac{1}{\sigma^2} \quad \ldots 5.4.44 \]

where \( \sigma^2 \) is the variance of each real and imaginary parts of the additive Gaussian noise, i.e.

\[ \psi = 10.0 \log_{10} \left( \frac{1}{\sigma^2} \right) \quad \ldots 5.4.45 \]

5.5 COMPUTER SIMULATION TESTS AND RESULTS

The computer simulation carried out is mainly concerned with the overall convolution \( a(t) * y(t) * c(t) * b(t) \) at the rate of 2400 samples per second.

5.5.1 System A

As indicated in Chapter 4, the sampling rate at which the Bessel filters generate \( v_i(t) \) were sampled at different sampling frequencies and then interpolations were applied to satisfy the transmission rate of 2400 samples/second.

In order to achieve the Nyquist sampling criterion the transfer function of the equipment filters \( A(f) \) and \( B(f) \) are sampled at a rate of \( 10 \times 2400 \) for this system. There are 101 components in the DFT (Discrete Fourier Transform) of \( A(f) \) and \( B(f) \), which leads to \( a(t) \) and \( b(t) \) having 10 components (i.e. choosing every 10th).
It is appropriate to note that the first few samples (the components less than 0.01% of the peak value) of \( a(t) \) are discarded since they are significantly small and could result in a large discrepancy in the overall convolution process in the practical system.

Fig. 5.15 shows the sampled impulse response of \( a(t) \) and \( b(t) \). Theoretically \( a(t) \) and \( b(t) \) are of finite durations, so in practice it is limited to \( d \) seconds duration. This impulse response must then be delayed in time by \( \frac{d}{2} \) seconds to make it physically realisable (causal), thus changing the frequency response from zero phase to linear phase [Fig. 5.16], without affecting the amplitude response. Fig. 5.16 also gives the plot of the Hamming window sampled impulse response of \( a(t) \) and \( b(t) \).

Fig. 5.17 presents the IDFT (Inverse Discrete Fourier Transform) of \( a(t) \) and \( b(t) \) and compares this with the IDFT of the windowed version. Although the windowed time function seems to overlap the original one, a clear reduction in sidelobes can be observed in the frequency response (up to 20 dB).

First, convolution (i.e. transmitter filter with the channel) takes place by applying the first two laws of convolution (Folding and Displacement) on \( a(t) \) since it is a symmetrical function [Figs. 5.15-5.16]. The sum of the product of this function with \( y(t) \) is then the first convolution. Similar procedure is performed to obtain the overall convolution (the convolution of the first convolution with \( b(t) \) i.e. \( Y_1(t) \) given in Eqns. 5.4.26 and 5.4.27) with the two laws of convolution applied on symmetrical function of \( b(t) \). Thus, when overall convolution is performed the vector \( Y_1 \) is obtained by sampling \( Y_1(t) \) at a rate of 2400 samples per second. This vector then has a \( h \)-complex sequence (with \( h = 0, 1, 2, \ldots, g \)) given by

\[
Y_i = Y_{i,0} \quad Y_{i,1} \quad Y_{i,2} \cdots Y_{i,2g-1}
\]

where \( g \) is the number of overall sampled impulse response of the channel and is given by \( N+Q-1 \), where \( N \) and \( Q \) are the components of \( a(t) \) and \( b(t) \) respectively.

Figs. 5.18 and 5.19 show and compare the amplitude and phase variations obtained before and after overall convolution. These figures confirm that the equipment filters (\( a(t) \) and \( b(t) \)) only introduce about 0.25 dB amplitude distortion into the received signal amplitude but no phase distortion.

Fig. 5.20 presents the three-dimensional plot of the overall baseband channel sampled impulse responses [SIR] for 55 sampling instants, i.e. it presents the characteristics of the overall constructed baseband channel for the first 55 of the 2400 samples per second baud rate transmission. It means that at any time instant \( t = i/2400 \), the
channel delivers g discrete components to the detector. The variation of the energy (or SIRs) contained within each components [Eqn. 5.5.1] at the given time instants i are then employed by the detector in order to accomplish means by which the correct data can be smeared out.

5.5.2 System B

In the computer simulation tests carried out for system B the vector $Y_i$ as suggested for system A is obtained by sampling $Y_i(t-iT)$ given by Eqn. 5.4.28 at a rate of 2400 samples per second. For the general case of n-eigenray channel, any aliasing that can occur because of the rapid changes in any of $v_i(t)$ [Fig. 4.14], the overall convolution (Eqn. 5.4.28) is performed at a sampling rate of 4800 samples.

The corresponding sequences of $v_i(t)$ for up to n-eigenray are given by

$$V_{i,1} = v_{i,1} \quad v_{2,1} \quad v_{3,1} \ldots v_{2i,1}$$

$$V_{i,2} = v_{i,2} \quad v_{2,2} \quad v_{3,2} \ldots v_{2i,2}$$

$$V_{i,3} = v_{i,3} \quad v_{2,3} \quad v_{3,3} \ldots v_{2i,3}$$

$$\ldots \ldots \ldots \ldots$$

$$V_{i,n} = v_{i,n} \quad v_{2,n} \quad v_{3,n} \ldots v_{2i,n}$$

Now assume that the sequences of $A_1, A_2, A_3, \ldots, A_n$ and $B_1$ represent the impulse responses of the $a(t), a(t-\tau_1), a(t-\tau_2), \ldots, a(t-\tau_n)$ and $b(t)$ respectively sampled at 4800 samples per second. i.e.

$$A_1 = a_{1,0} \quad a_{1,1} \quad a_{1,2} \ldots a_{1,q}$$

$$A_2 = a_{2,0} \quad a_{2,1} \quad a_{2,2} \ldots a_{2,q}$$

$$\ldots \ldots \ldots$$

$$A_n = a_{n,0} \quad a_{n,1} \quad a_{n,2} \ldots a_{n,q}$$

and
\[ B_1 = b_0 \ b_1 \ \ldots \ b_q \quad \ldots 5.5.4 \]

where \( q \) is an integer representing the number of the filter's impulse responses, its value will become clear in due course later.

But

\[ a_{1,k} = a\left( \frac{kT}{2} \right) \]

\[ a_{2,k} = a\left( \frac{kT}{2} - \tau_1 \right) \]

\[ \ldots \ldots \ldots \]

\[ a_{n,k} = a\left( \frac{kT}{2} - \tau_n \right) \quad \ldots 5.5.5 \]

and

\[ b_k = b\left( \frac{kT}{2} \right) \quad \ldots 5.5.6 \]

In the practical system [Fig. 5.21], the two filters [100] have a limit given by

\[ a(t) = b(t) = 0 \quad \text{for} \quad t < 0 \quad \& \quad t > (q - q') \frac{T}{2} \quad \ldots 5.5.7 \]

and integer \( q' \) [Fig. 5.21] is given by

\[ \tau = q' \frac{T}{2} + \tau' \quad \ldots 5.5.8 \]

and \( \tau' < \frac{T}{2} \). This with the aid of Fig. 5.21 indicates that

\[ a_{1,k} = b_k = 0 \quad \text{for} \quad k < 0 \quad \& \quad k > q - q' \]

\[ a_{2,k} = 0 \quad \text{for} \quad k < q' \quad \& \quad k > q \quad \ldots 5.5.9 \]

In Fig. 5.21 if

\[ (q - q') \frac{T}{2} = q' \frac{T}{2} \quad \ldots 5.5.10 \]
where \( q_f \) is a constant.

Now from Eqns. 5.4.28 and 5.5.2-5.5.10 the overall n-eigenray baseband convolution \( y_i(t-iT) \) at time \( t = iT \) is given by

\[
y_{i,h} = \left( \frac{T}{2} \right)^{2h} \sum_{k=0}^{2h} \left( a_{1,h}(v_{2(i-h)+k,1} - jv_{2(i-h)+k,2}) + a_{2,h}(v_{2(i-h)+k,3} - jv_{2(i-h)+k,4}) + \cdots + a_{1,h}(v_{2(i-h)+k,2n-1} - jv_{2(i-h)+k,2n}) \right) b_{2h-k}
\]

...5.5.11

for \( h = 0, 1, 2, 3, \ldots, g \)

where \( g \) is the number of the sampled impulse response of the overall channel convolution in this system [90] and is calculated by Eqn. 5.5.9 as

\[
g = \frac{2q_f - q' + 1}{2}
\]

...5.5.12

Eqn. 5.5.12 implies that \( g \) is a function of \( q' \) and hence a function of \( \tau \) [Eqn. 5.5.8].

As suggested earlier this particular channel is sampled at 4800 s/s (i.e 16 points interpolation) and every other sample is observed at the receiver, since the model assumes that the signal elements are within the neighbouring signal components (i.e. a partial response channel).

In order to achieve Nyquist sampling and to obtain different sampling phases (i.e. the insertion of delays \( \tau \)) [Eqn. 5.5.5], the transfer function of \( A(f) \) and \( B(f) \) has been oversampled at 18 times the original sampling rate of 4800 Hz, i.e at a sampling rate of 86,400 samples per second. This is done by injecting 288 zero-valued components into \( A(f) \) [Fig. 5.6] from 19 to 307. The inverse DFT of this expanded sequence gives the impulse response of \( a(t) \) sampled at 86,400 samples/second, thus resulting in \( a(t) \) with 325 components. The transmitter filter impulse response \( \{a_{2h}\} \) [Eqn. 5.5.3] corresponding to \( a(t-iT) \) is obtained by taking every 18th sample of \( \{a_k\} \).

In this model the \( \{a_{2h}\} \) is considered to be delayed by 0.5 ms with respect to first eigenray. Expressing this delay as a fraction of the number of samples, \( \beta \), gives

\[
\beta = \frac{0.5 \times 10^{-3}}{\frac{1}{4800}} = 2.40
\]
In other words the first samples of \( \{a_{2,k}\} \) is delayed by 2.40 samples with respect to the first chosen samples of \( \{a_{1,k}\} \). It is however necessary to obtain the samples of the delayed filters at the sampling instants of the non-delayed filter. This delay can be expressed as a whole number of samples and a fractional part (i.e. 2+0.40). The first component of \( \{a_{2,k}\} \) is thus added to the (2+1) third component of \( \{a_{1,k}\} \). This leaves a discrepancy of (3-2.40) i.e 0.60 sampling intervals. This discrepancy is taken care of by choosing (from the oversampled version) the sample that is \((0.60*86400)/4800=10.8\) 10 samples ahead of the first component of \( \{a_{1,k}\} \). The remaining sample of \( \{a_{2,k}\} \) is, of course, chosen at every 18th sample from the oversampled version. This process is similarly employed for up to eight eigenrays with a delay of 0.85ms for third, 1.50ms for fourth, 1.85ms for fifth, 2.15ms for sixth, 2.45ms for seventh and 3ms for the eighth relative to the first eigenray to obtain the values of \( \tau \)'s for \( \{a_{n,k}\} \), for \( n=1 \) to 8.

Fig. 5.22 shows the impulse response of oversampled filters \( a(t) \) and \( b(t) \). Like that of system A \( a(t) \) and \( b(t) \) are of finite durations, so their impulse response is then delayed in time by \( d \) seconds to make it physically realisable (causal). Thus changing the frequency response from zero phase to linear phase [Fig. 5.23], without effecting the amplitude response. Fig. 5.23 also gives the plot of the hamming windowed sample impulse response of \( a(t) \) and \( b(t) \) for system B.

Fig. 5.24 presents the IDFT (Inverse Discrete Fourier Transform) of \( a(t) \) and \( b(t) \) and compares this with the IDFT of the windowed version of \( a(t) \) and \( b(t) \). Like system A, the windowed time function seems to overlap the original one, but a clear reduction in sidelobes can be observed in the frequency response (up to 20 dB).

Fig. 5.25 presents and compares the amplitude variations obtained before and after overall convolution [Eqn. 5.11] of the transmitter and the receiver filters \( a(t) \) and \( b(t) \) with the multipath propagated 1-eigenray channel. The equipment filters have introduced only about 0.2 dB distortion into the received signal amplitude but no phase distortions.

Figs. 5.26 to 5.33 show the amplitude and phase fluctuations of the system B models [Eqn. 5.5.11] for 2,3,5,8 eigenrays respectively. Figures clearly indicate that as the number of eigenrays are increased the fading depths in the given eigenray channel is reduced.
Figs. 5.34 to 5.38 present the three dimensional plot of the overall baseband channel sampled impulse responses [SIR] for a number of sampling instants in 1, 2, 3, 5, 8 eigenrays channels. They show the variation of the energy contained within each samples at the given time instant. Notice that, as the number of eigenrays are increased, the number of the sampled impulse responses of the channels too increases and the peaks are no longer concentrated around $y_{\text{avg}}$.

5.6 CONCLUDING REMARKS

In this chapter, it was observed that in the construction of the two baseband channel models, the equipment filters (shaping filters) only introduced between 0.2-0.3 dB amplitude distortion into the received signal but no phase distortion. It was also observed that, in construction of the system B model, the depth of the signals in fades was reduced as the number of eigenrays were increased. This will result in lower data error rates for a given signal-to-noise ratio at the receiving end. It should be noted from Figs. 5.34-5.38 that as the number of eigenrays detected by the receiver is increased, the number of the sampled impulse responses is also increased. This will of course require further memory capacity as well as processing time for the signal processors at the receiver to combat the intersymbol interference introduced into the received signal elements.
Fig. 5.1 Model of digital data transmission system.
Fig. 5.2 Assumed model of the data transmission system.

Fig. 5.3 Non-fading channel transfer function having a rectangular signal spectrum.
Fig. 5.4 Non-fading channel transfer function having a full raised-cosine signal spectrum.

Fig. 5.5 Non-fading channel transfer function having a partial response cosine signal spectrum.
Fig. 5.6 Partial response spectrum separated in time.

Fig. 5.7 Three tested window functions.
Fig. 5.8 QAM model of data transmission system.
Fig. 5.9 Spectra of signals for quadrature amplitude modulation (QAM).
Fig. 5.10 A 4-level QAM signal constellation.

Fig. 5.11 Receiver lowpass filter $C(f)$ amplitude response.
Power spectral density

- **a) White Gaussian noise**

- **b) Bandpass white noise**

- **c) Quadrature noise components**

Fig. 5.12 The noise power spectral densities.
Fig. 5.13 QAM model with one multipath propagated channel.
Fig. 5.14 QAM model with n-eigenray multipath propagated channel.
Fig. 5.15 Oversampled impulse response of ideal root raised-cosine lowpass filter.

Fig. 5.16 Impulse response (causal) of practical root raised-cosine lowpass filter with and without window.
Fig. 5.17 Frequency response (causal) of practical root raised cosine lowpass filter.

Fig. 5.18 Expanded amplitude fluctuation before and after convolution with transmitter and receiver filters for system A channel.
Fig. 5.19 Expanded phase fluctuation before and after convolution with transmitter and receiver filters for system A channel model.
Fig. 5.20 Three dimensional plot of sampled impulse responses for system A channel.
Fig. 5.21 The transmitter filter impulse response timing relationship with delays.
Fig. 5.22 Impulse response of oversampled root partial response lowpass filter.

Fig. 5.23 Impulse response of practical (causal) oversampled root partial response lowpass filter with and without window.
Fig. 5.24 Frequency response of practical (causal) oversampled root partial response lowpass filter with and without window.

Fig. 5.25 Expanded amplitude fluctuation before and after convolution with transmitter and receiver filters for system B channel.
Fig. 5.26 Amplitude fluctuation after convolution with transmitter and receiver filters for two eigenray system B channel.

Fig. 5.27 A phase fluctuation after convolution with transmitter and receiver filters for two eigenray system B channel.
Fig. 5.28 Amplitude fluctuation after convolution with transmitter and receiver filters for three eigenray system B channel.

Fig. 5.29 A phase fluctuation after convolution with transmitter and receiver filters for three eigenray system B channel.
Fig. 5.30 Amplitude fluctuation after convolution with transmitter and receiver filters for five eigenray system B channel.

Fig. 5.31 Phase fluctuation after convolution with transmitter and receiver filters for five eigenray system B channel.
Fig. 5.32 Amplitude fluctuation after convolution with transmitter and receiver filters for eight eigenray system B channel.

Fig. 5.33 Phase fluctuation after convolution with transmitter and receiver filters for eight eigenray system B channel.
Fig. 5.34 Three dimensional plot of sampled impulse responses for one eigenray system B channel.
Fig. 5.35 Three dimensional plot of sampled impulse responses for two eigenray system B channel.
Fig. 5.36 Three dimensional plot of sampled impulse responses for three eigenray system B channel.
Fig. 5.37 Three dimensional plot of sampled impulse responses for five eigenray system B channel.
Fig. 5.38 Three dimensional plot of sampled impulse responses for eight eigenray system B channel.
CHAPTER 6

EQUALISATION AND DETECTION TECHNIQUES

6.1 INTRODUCTION

The simulated channel models presented so far described the frequency selective nature of the practical underwater communication link with multipath fading characteristics. At the receiver, the system driver contains waveforms highly distorted in phase and amplitude. This signal is now sampled at regular intervals, once per data symbol. Polynomials of a non-linear nature characterizing the sampled impulse response of such channels are then studied to establish a minimum phase response. At every sampling instant time $iT$ the effect of intersymbol interference on correct detection is discussed. Equalizers are then employed to act as the inverse of the channel by assuming that the sampled impulse response is known to the receiver i.e. all of their polynomials are converged within specified roots. The intersymbol interference caused by phase distortion can be removed by means of a pre-filter ahead of the detector with tap gains given by the roots of the polynomial (sampled impulse response of the channels) with no reduction in tolerance to noise. The remaining intersymbol interference, caused by amplitude distortion, can be eliminated by a decision feedback equalizer. The amplitude distortion tends to reduce tolerance to noise of even the most optimum detector performing the maximum likelihood process.

6.2 REALIZATION OF CHANNEL DISTORTIONS

The complex valued continuous signal at the output of the baseband channel, given in Fig. 5.1, was stated in Eq. 5.4.26 for both systems under investigation as

$$r(t) = \sum_i s_i y(t - iT) + w(t)$$

...6.2.1
where \( w(t) \) represents added Gaussian noise at the output of the transmission path. 
\( r(t) \) is now sampled at instants \( \{iT\} \) to deliver received samples \( \{r_i\} \). The linear baseband channel is now described by the sampled impulse response with \((g+1)\) component row vector as

\[
Y_i = [y_{i,0} y_{i,1} y_{i,2} \ldots y_{i,g}]
\]

having a z-transform

\[
Y_i(z) = y_{i,0} + y_{i,1}z^{-1} + y_{i,2}z^{-2} + \ldots + y_{i,g}z^{-g}
\]

which is a polynomial in \( z^{-1} \) of order \( g \).

\( y_i = y(iT) \) and \( \{y_i\} \) are components which are all complex valued. The delay in transmission is neglected here and for practical purposes, \( y_i = 0 \) for \( i < 0 \) and \( i > g \). This implies the sampled received signal to be considered is

\[
r_i = \sum_{h=-g}^{g} s_{i-h}y_{i,h} + w_i
\]

so that \( r_i = r(iT) \) and \( w_i = w(iT) \). These samples now contains all the useful information in the received noisy data signal; the real and imaginary parts of the noise component \( \{w_i\} \) are statistically independent Gaussian random variables with zero mean and fixed variance of \( \sigma^2 \).

It is now desired to realise the amplitude and phase distortions within the received sampled impulse response of the baseband channels that cause the appearance of intersymbol interference in the detection of correct data-symbols.

In order to realise the two distortions, the z-transform of the channel sampled impulse response (Eq. 6.2.3) can be written in a general form as

\[
Y(z) = y_0(1 - y_1z^{-1})(1 - y_2z^{-1}) \ldots (1 - y_gz^{-1})
\]

The distortions are then recognized by setting this empirical expression to zero so that the values of \( z \) define the roots(zeros) of \( Y(z) \).

In order for the polynomials to achieve full convergence the roots must be accurate to at least 8 decimal points. This goal can only be achieved by the availability of extensive processing time as well as a large computer memory. Numerical Algorithm software Group (NAG) can achieve this with an error of less than \( 1*10^{-8} \) for up to 99 sample elements.
Consider $z = e^{iT}$, where $T$ is the time interval between the adjacent samples and $s = \sigma + j\omega$. (Note that $s$ and $\sigma$ are Laplace operator and a constant value respectively and should not be confused with the definition given to them throughout the thesis).

Now replacing value of $s$ into $z$ leads to

$$z = e^{(\sigma + j\omega)T} = e^{\sigma T} e^{j\omega T} \quad \ldots 6.2.6$$

This indicates that for those values of $\gamma$ in Eqn. 6.2.5 in which $|\gamma_i| > 1$ where here $i = 1, 2, 3, \ldots, g$, the corresponding positions of $\gamma_i$ in the $s$-plane can be obtained from

$$e^{\sigma T} |e^{j\omega T}| > 1 \quad \ldots 6.2.7$$

hence

$$\sigma > 0 \quad \ldots 6.2.8$$

Thus the roots implying Eq. 6.2.8 must lie within the right-hand section of the $s$-plane, indicating the violation of the definition of a minimum phase process. In $z$-plane, this means that any sequence which has roots of its $z$-transform with absolute values greater than unity is not a minimum phase sequence.

Those sequences of $Y(z)$ which do not lie within the unit circle can be forced to be minimum phased by including poles at the locations $z = \gamma_i$, where $|\gamma_i| > 1$ can cancel the effect of these zeros, and by adding new zeros at values of $z$ given by the complex conjugates of their reciprocals of $\gamma_i$. This describes a phase transformation process on the sequences of $Y_i$.

The most effective method of ensuring such a phase transformation could be the employment of a linear pre-filter or an adaptive phase equaliser ahead of the detector, so that the channel and the linear filter together have a response that is a minimum phase. This phenomenon can be accomplished by separating $Y(z)$ into two polynomials, one including those roots that are situated inside the unit circle plus the constant multiplication factor (amplitude distortion), and the other including those roots which are situated outside the unit circle plus the delay (phase distortion). It is assumed that no roots of $Y(z)$ lie exactly on the unit circle in the $z$-plane.

$$Y(z) = Y_1(z)Y_2(z) \quad \ldots 6.2.9$$

where
\[ Y_1(z) = \mu (1 + \alpha_1 z^{-1})(1 + \alpha_2 z^{-1}) \ldots (1 + \alpha_{-m} z^{-1}) \ldots \text{6.2.10} \]

and

\[ Y_2(z) = z^{-m} (1 + \beta_1 z) (1 + \beta_2 z) \ldots (1 + \beta_n z) \ldots \text{6.2.11} \]

where \( \alpha_i \) is the negative of a root of \( Y(z) \) and \( \beta_i \) is the negative of the reciprocal of a root of \( Y(z) \), so that

\[ |\alpha_i| < 1 \quad \& \quad |\beta_i| < 1 \ldots \text{6.2.12} \]

\( \mu \) represents the appropriate complex value needed to satisfy Eqs. 6.2.10-6.2.11, and |\( \alpha_i \)| and |\( \beta_i \)| are the absolute values of \( \alpha_i \) and \( \beta_i \), respectively.

Now the sampled impulse response of the pre-filter can be approximately written as

\[ D(z) = z^{-n} Y_2^{-1}(z) Y_3(z) \ldots \text{6.2.13} \]

where

\[ Y_3(z) = (1 + \beta_1^* z^{-1})(1 + \beta_2^* z^{-1}) \ldots (1 + \beta_m^* z^{-1}) \ldots \text{6.2.14} \]

and \( \beta_i^* \) is the complex conjugate of \( \beta_i \). Thus the z-transform of the channel and linear filter is approximately

\[ F(z) = Y(z) D(z) \]

\[ = z^{-n} Y_1(z) Y_3(z) \ldots \text{6.2.15} \]

The accuracy of the system given by Eqs. 6.2.13-6.2.15 can only be satisfied when \( n \to \infty \). Such a large unacceptable value for \( n \) indicates that an \( n \) tap filter can be reduced to a realizable value by taking good approximation procedures.

It is now evident that all the roots of \( F(z) \) lie inside the unit circle in the z-plane, thus satisfying the condition that the baseband channel together with a linear pre-filter have a minimum phase response.

Furthermore, the roots of \( Y_3(z) \) are the complex conjugates of the reciprocals of the roots of \( Y_2(z) \), so that the linear filter replaces all roots of \( Y(z) \) that lie outside the unit circle(those of \( Y_2(z) \)) by the complex conjugates of their reciprocals, leaving
the remaining roots (those of $Y_i(z)$) unchanged. The linear filter achieves linear transformation on the received sequences of $\{r_i\}$ while keeping the level of data signal as well as the channel noise statistics unchanged [17, 19, 100].

In this chapter, Numerical Algorithm Group (NAG library software routines) are employed as a conventional method of root finding in order to perform a perfect adjustment of the pre-filter. The NAG routine employed here (c02adf) attempts to find all the roots of the $(n-1)^{th}$ order complex polynomial equation and is based on the use of Newton's method. The method performs the root finding task by long divisions until the 'convergence point' is achieved. This process assumes that the receiver has prior knowledge of the sampled impulse response of the channel. The results are then compared with those obtained in the next chapter where a novel technique for determining the roots of $Y(z)$ is introduced by performing this task in hardware implementation [111, 114].

6.3 EQUALISATION AND DETECTION SCHEMES

6.3.1 Channel distortions

The previous section identified both amplitude (Eq. 6.2.10) and phase (Eq. 6.2.11) distortions present in the sampled impulse response of the baseband channel. It was well established that the severe phase distortion existing in an underwater channel causes the first few components of the received sampled impulse response of this channel to be too small. An adaptive filter was then introduced so that the resultant sampled impulse response has a first component of relatively large magnitude (i.e. a minimum phase response).

After employing this algorithm a feedforward transversal filter can be utilized to boost the signal level for the receiver to have a good tolerance to additive noise.

In the case of amplitude distortion a non-linear equalizer can result in the most cost effective detection process. This is because the channel transfer function may have a zero value when the channel is subjected to a deep fade, which is most likely to occur with a mobile underwater communication system.
The conventional nonlinear (decision-feedback) equalizer is the least effective detection process. It minimizes the mean-square error in the equalized signal, with the condition that, the equalizer achieves accurate equalization of the linear baseband channel.

The detection process can be reached even without a minimum phasing system, thus operating on a noisy data signal. This optimum detection process, which is widely known as Viterbi-algorithm detection, can perform the maximum-likelihood process. This class of detector selects the detected data message as the possible sequence of transmitted data symbols for which there is minimum mean-square difference between the samples of the corresponding received data signal. Such an optimum detector requires an excessive amount of storage as well as operations per received data symbol. This problem magnifies as the number of sampled impulse responses of the channel increases. A sub-optimum detection process, known as near maximum-likelihood detection can achieve the same process with no loss in tolerance to additive white Gaussian noise. But the detector considers the magnitude of the first component of the sampled impulse response to have no small value, thus needing the inclusion of the pre-filter described in the previous section.

6.3.2 Feedforward transversal filter

The feedforward transversal filter studied here is a linear equalizer. Such a system is employed widely where the linear processing of the signal prior to detection is desired in an optimum linear receiver. The signals here, at the input to the equalizer shown in Fig. 6.1, are all real valued and the linear transversal filter has m+1 taps.

The equalizer performs its tasks on sample values (or numbers) which may be in analogue or digital form, in this case digital. As indicated throughout the thesis, the sampling at the receiver is at time instant \( t = iT \). Each square marked T shown in Fig. 6.1 introduces a delay of T seconds. This holds the corresponding signal’s sample value \( \{ r_i \} \), thus acting as storage element which is triggered at time instants \( \{ iT \} \), for all positive integers \( \{ i \} \). Each time the transversal filter is triggered, the stored signals \( \{ r_i \} \) are shifted one place to the right for each new received sample. The output of each store is multiplied by the tap value \( d_i \) and then summed to give the equalized sample \( e_i \) as
The sampled impulse response of the equalizer is thus given by

\[ D = [d_0 \ d_1 \ d_2 \ d_3 \ldots \ d_m] \]  \hspace{1cm} (6.3.2)

which has a z-transform

\[ D(z) = d_0 + d_1 z^{-1} + d_2 z^{-2} + \ldots + d_m z^{-m} \]  \hspace{1cm} (6.3.3)

In general, \( \{d_m\} \) are complex valued samples. Now having the z-transform of the sampled impulse response of the channel in Eq 6.2.3 the sampled impulse response of the channel and the equalizer will be the \((g+m+1)\)-component row vector

\[ E = [e_0 \ e_1 \ e_2 \ e_3 \ldots \ e_{g+m}] \]  \hspace{1cm} (6.3.4)

and having a z-transform

\[ E(z) = e_0 + e_1 z^{-1} + e_2 z^{-2} + \ldots + e_{g+m} z^{-(g+m)} \]  \hspace{1cm} (6.3.5)

Clearly, \( E(z) \) is given by

\[ E(z) = D(z)Y(z) \]  \hspace{1cm} (6.3.6)

If the equalizer achieves the exact equalization of the channel, then Eqn. 6.3.4 can be written as

\[ E = [0 \ 0 \ 0 \ldots 0 \ 1 \ 0 \ 0 \ 0 \ldots 0] \]  \hspace{1cm} (6.3.7)

The number of zeros before the 1 in the above equation is in the range 0 to \( m+g \) and if denoted as \( h \) then it indicates that the equalizer and the channel together introduce a delay of \( h \) sampling intervals. This would result \( E(z) \) to be written as

\[ E(z) = z^{-h} \]  \hspace{1cm} (6.3.8)

and from Eqn. 6.3.6

\[ D(z) = z^{-h}Y^{-1}(z) \]  \hspace{1cm} (6.3.9)

Eqn. 6.3.9 is a polynomial in \( z^{-1} \) with an infinite number of co-efficients, which is the condition for the exact equalization. This equation assumes that no roots(zeros) of \( Y(z) \) lies outside or on the unit circle in the z-plane.
Considering the exact equalization of the channel, then the equalized sample at the input to the detector (Fig. 6.1) at time \((i+h)T\), is given by

\[ e_{i+h} = s_i + u'_{i+h} \] \hspace{1cm} ...6.3.10

\( u'_{i+h} \) is the noise component in \( e_{i+h} \), and is given by

\[ u'_{i+h} = \sum_{l=0}^{m} d_l u_{i+h-l} \] \hspace{1cm} ...6.3.11

Since the noise samples \( \{u_i\} \) are statistically independent Gaussian random variables with zero mean and variance \( \sigma^2 \), then \( \{u'_{i+h}\} \) are Gaussian random variables with zero mean and variance \( \eta^2 \), and if \( |D| \) is the length of the vector D then

\[ \eta^2 = \sigma^2 \sum_{l=0}^{m} |d_l|^2 = \sigma^2 |D|^2 \] \hspace{1cm} ...6.3.12

Amplitude distortion is introduced to the channel when \( |D| > 1 \) and thus \( \eta^2 > \sigma^2 \).

The number of taps in a practical linear feedforward transversal equaliser could vary from 8 to 64 taps, and is often implemented in a rather different form from that suggested in Fig. 6.1. For a channel with sampled impulse responses varying in time, such as in the cases considered in this thesis, the information needed for the optimum setting of the tap gains is derived from the received samples \( \{y_i\} \) or in this case \( \{e_i\} \). The equalizer in this case is known as an adaptive linear equalizer. The adaptation techniques of the tap gains are based on the determination of the error in the equalized signal which will be explained in Sec. 6.4.

### 6.3.3 Decision feedback equaliser

The decision feedback equalizer or a pure nonlinear equaliser has a structure shown in Fig. 6.2. It is implemented as a linear feedforward transversal filter fed from the output of the detector. The term nonlinear is given to this system because the detector is a nonlinear device which is included in the feedback path of the equalizer. The signals given here are those at time instant \( t=iT \) as before, and unlike a linear equalizer, this class of equalizer uses the detected data symbols \( s_i' \) to form an estimate of the intersymbol interference components in the received samples.
At the input to the detector the received samples are divided by the first component to result in a unity value as a first component for all h, where h=0,1,2,3,....,n and n=m+g+1. This equalizer assumes the signal at its input has already passed through the minimum phasing network with n components or taps. The output signal from transversal filter in Figs. 6.1 and 6.2 is then an estimate of the intersymbol interference at the output of the multiplier. The subtraction from this signal results in the equalised signal x_i at the detector input (Fig. 1.2). The equalizer therefore operates by decision-feedback correction, removing the intersymbol interference from the detector input signal, as will now be explained in more detail.

The nonlinear equalizer shown in Fig. 6.2 first assumes that the signal at its input is passed through a linear pre-filter D with (g+m+1)-components, i.e. has a minimum phase response given by Eqn. 6.3.4 and its z-transform obtained as Eqn 6.3.5. Thus the signal at the input to the multiplier at time t=iT is now

\[ p_i = \sum_{h=0}^{n} s_{i-h}e_{i,h} + w_i \]  

Eqn. 6.3.13 is expanded in order to obtain the wanted signal \( s_i \) as

\[ p_i = s_i e_{i,0} + \sum_{h=1}^{n} s_{i-h}e_{i,h} + w_i \]  

Just prior to the input of the detector, the corresponding signal is then

\[ \frac{p_i}{e_{i,0}} = s_i + \sum_{h=1}^{n} s_{i-h} \frac{e_{i,h}}{e_{i,0}} + \frac{w_i}{e_{i,0}} \]

\[ = s_i + \sum_{h=1}^{n} s_{i-h}q_{i,h} + \frac{w_i}{e_{i,0}} \]

\[ = s_i + d_{i,0} + u_i \]  

where

\[ q_{i,h} = \frac{e_{i,h}}{e_{i,0}} \]

and

\[ d_{i,0} = \sum_{h=1}^{n} s_{i-h}q_{i,h} \]
In Eqn. 6.3.15 $s_i$ is now the wanted signal, $d_{i,0}$ is the intersymbol interference and the component $u_i$ is the noise.

The detector shown in Fig. 6.2 is a simple threshold detector which makes its decision of the data symbol $s_i$ upon the two known possible values $\pm k$.

The detected data-symbols ($s'_i$) are then fed back to the linear transversal filter, thus producing at its output the signal

$$d'_{i,0} = \sum_{h=1}^{n} s'_{i-h} q_{i,h}$$ ...6.3.16

The detector now consider the signal

$$x'_{i,0} = \frac{p_i}{e_{i,0}} - d'_{i,0}$$

$$= s_i + d_{i,0} + u_i - d'_{i,0}$$ ...6.3.17

with the correct detection of each $s_{i,h}$ such that

$$d'_{i,h} = d_{i,0}$$ ...6.3.18

i.e

$$s'_{i-h} = s_{i-h}$$ ...6.3.19

for $h = 1, 2, 3, \ldots, n$ the data symbol is detected as

$$x'_{i,0} = s_i + u_i$$ ...6.3.20

From Eqns. 6.3.15 and 6.3.20 it can be observed that both $p_i/e_{i,0}$ and $x_{i,0}$ have the same wanted-signal component $s_i$ and noise component $u_i$ so that the nonlinear equalizer removes the intersymbol interference without changing the signal/noise ratio.

Conceptually, in such a system (conventional decision feedback equalizer), the data symbol $s_i$ is now as its value $s'_i$ for which $|x_{i,0} - s'_i e_{i,0}|$ is minimum, with the condition that the $e_{i,0}$ (the first component of E) is the largest component in E, i.e. it has a minimum phase response.

Now consider that $s_i$ is correctly detected from $x_i$ such that $s'_i = s_i$, and given the correct detection of $s_{i+1}, s_{i+2}, s_{i+3}, \ldots, s_{i+n}$. At the next sampling instant $t=(i+1)T$ the received signal is $p_{i+1}$ and the signal at the input to the pure nonlinear equalizer is then
\[ \frac{P_{t+1}}{e_{i,0}} = s_{t+1} + d_{t,1} + u_{t+1} \] ...6.3.21

In order to obtain the equalized signal \( x_{i,1} \) at the detector input, the procedure is the same as that described for the time \( t = iT \), so that

\[ x_{i,1} = s_{i+1} + u_{t+1} \] ...6.3.22

At this time, now conceptually, the conventional decision feedback equalizer makes its decision upon \( |x_{i,1} - s_{i+1}e_{i,0}| \) to be minimum for the given conditions.

Furthermore, the nonlinear equalizer thus removes intersymbol interference from the equalized signal as long as the data-symbols \( \{s_i\} \) are correctly detected. It should be noted that to start the process of nonlinear equalization, a known sequence of more than \( n \) data-symbols \( \{s_i\} \) is transmitted, and the intersymbol interference introduced by these data symbols is removed automatically in the nonlinear equalizer without requiring the detection of the corresponding \( \{s_i\} \). When the channel is correctly equalized the received data-symbols are detected [100-107].

6.4 MODIFIED EQUALIZER (NEAR-MAXIMUM LIKELIHOOD ESTIMATION)

In the conventional decision feedback equalizer described in Sec. 6.3.3, at every instant of time \( t = iT \) the detector makes its decision upon the information contained within the first component derived from the linear pre-filter prior to the nonlinear equalizer. The remaining components are recognized as intersymbol interference which are therefore removed without unduly affecting the removal of noise components. In the system to be explained here, it is desired to take into account the removed intersymbol interference components since they too contain useful information about the transmitted data symbols. This detector is software controlled but can be implemented by VLSI (Very Large Scaled Integrated System) technology.

Such a system can be arranged by modifying Fig. 1.2, where the threshold detector and transversal filter \( F \) are replaced by the more complex system to be described here. Filter \( D \) has the properties explained in Sec. 6.2.

First assume the receiver has formed the equalized signal \( x_{i,0} \) as described in Sec. 6.3.3 given by Eqn 6.3.20, as
\[ x_{i,0} = s_i + u_i \] ...6.4.1

Now consider the detection of the signal \( s_i \) through a delay of one sampling interval \( T \) (i.e. \( t = (i+1)T \)), until the receipt of the signal

\[ p_{i+1} = \sum_{h=0}^{n} s_{i+1-h} e_{i+h} + u_{i+1} \] ...6.4.2

At the output of the filter D, the receiver signal at time \( t = (i+1)T \) is

\[ d'_{i,1} = \sum_{h=1}^{n-1} s'_{i-h} e_{i+h+1} \] ...6.4.3

which is subtracted from \( p_{i+1} \), to result in the signal

\[ x_{i,1} = p_{i+1} - d'_{i,1} \] ...6.4.4

which implies

\[ x_{i,1} = s_{i+1} e_{i,0} + s_i e_{i,1} + u_{i+1} \] ...6.4.5

assuming the correct detection of \( s_i \).

Eqn. 6.4.5 now contains not only the signal at \( t = (i+1)T \) but that of time \( t = iT \), so that both \( x_{i,0} \) and \( x_{i,1} \) are available for the detection of \( s_i \).

Thus, for given possible values \( s'_i \) and \( s'_{i+1} \) of the data-symbols \( s_i \) and \( s_{i+1} \), Eqns. 6.4.1-6.4.5 indicate that with the correct detection of \( s_{i+1}, s_{i+2}, s_{i+3}, \ldots, s_{k+1} \) \( s'_i e_{i,0} \) and \( s'_{i+1} e_{i,0} + s'_i e_{i,1} \) are the corresponding values of \( x_{i,0} \) and \( x_{i,1} \), respectively, in the absence of noise, so that \( s'_i e_{i,0} \) and \( s'_{i+1} e_{i,0} + s'_i e_{i,1} \) are the estimate of \( x_{i,0} \) and \( x_{i,1} \). It should be stated now that the smaller the Euclidean distance between the two-component vectors \([x_{i,0} \ x_{i,1}]\) and \([s'_i e_{i,0} \ (s'_{i+1} e_{i,0} + s'_i e_{i,1})]\) the better is the estimate of \([s_i \ s_{i+1}]\) given by \([s'_i \ s'_{i+1}]\).

Now the square of the Euclidean distance between the vectors \([x_{i,0} \ x_{i,1}]\) and \([s'_i e_{i,0} \ (s'_{i+1} e_{i,0} + s'_i e_{i,1})]\) is given by

\[(x_{i,0} - s'_i e_{i,0})^2 + (x_{i,1} - s'_{i+1} e_{i,0} - s'_i e_{i,1})^2 \] ...6.4.6

The data-symbol \( s_i \) is now detected as its possible value \( s'_i \), for which the Eqn. 6.4.6 is minimum over all combinations of possible values of \( s'_i \) and \( s'_{i+1} \).
It should be emphasized that the detected value of $s'_{i+1}$ is determined here for the data-symbol $s_{i+1}$, but discarded since now the detected value of $s_{i+1}$ is found from $x_{i+1,0}$ and $x_{i+1,1}$ at time $t = (i+2)T$ by delaying $s_i$ for two sampling intervals. With the correct detection of $s_{i+1}, s_{i+2}, \ldots, s_{i+n}$, the partially equalized signal at the detector input, at time $t=(i+2)T$, is

$$x_{i,2} = s_{i+2}e_{i,0} + s_{i+1}e_{i,1} + s_i e_{i,2} + u_{i+2}$$ \quad \ldots \quad 6.4.7$$

Now the three signals $x_{i,0}, x_{i,1}$ and $x_{i,2}$ are available in the detection of $s_i$ such that its detected value $s'_i$ is taken as its possible value for which the square of the Euclidean distance between the three component vectors $[x_{i,0} \ x_{i,1} \ x_{i,2}]$ and $[s'_ie_{i,0} \ (s'_{i+1}e_{i,0} + s'_{i+1}e_{i,1}) \ (s'_{i+2}e_{i,0} + s'_{i+2}e_{i,1} + s'_ie_{i,2})]$ given by

$$
\begin{align*}
(x_{i,0} - s'_ie_{i,0})^2 + (x_{i,1} - s'_{i+1}e_{i,1})^2 + (x_{i,2} - s'_{i+2}e_{i,2})^2
+ (x_{i,0} - s'_ie_{i,0} - s'_{i+1}e_{i,1} - s'_ie_{i,2})^2
\end{align*}
$$

\ldots \quad 6.4.8

is minimum over all combinations of possible values of $s'_{i}, s'_{i+1}$, and $s'_{i+2}$.

With the correct detection of $s_{i+1}, s_{i+2}, \ldots, s_{i+n}$, the detection process just described is the maximum likelihood detection of the vector $[s_i \ s_{i+1} \ s_{i+2}]$ from the vector $[x_{i,0} \ x_{i,1} \ x_{i,2}]$ (and hence from the vector $[p_i \ p_{i+1} \ p_{i+2}]$).

This process can proceed in this way for all $h$ sampling intervals, such that $s_i$ is detected at time $t=(i+h)T$ from the $h+1$ signals $x_{i,0}, x_{i,1}, x_{i,2}, \ldots, x_{i,h}$ through $n$ delay intervals of $T$. This is the general form of the modified equalizer. With a sufficiently large number of $h$ (say $h > 12$) the process come close to achieving the best available tolerance to additive white Gaussian noise, for the given delay in detection. Taking all sample components into account for this kind of detection scheme involves either an excessive number of sequential operations per received data-symbol or else becomes unduly complex. Various techniques for simplifying this kind of detection process have been developed and these can often achieve a tolerance to noise as an optimum available, without the use of complex equipment [100, 116]. The weakness of these techniques is that they still require quite a large number of sequential operations per received data-symbol.

In practice, it is very difficult to achieve this single optimum detection process for large value of $h$ which is inevitable in the long range underwater communication models. However, essentially the same performance can be achieved by means of appropriate detectors that determine the detected data-symbols successively (in
sequence) rather than simultaneously, and, for our purposes, the most important of these is the Viterbi-algorithm detector [115]. This type of detector becomes unduly complex for large values of \( h \) and multilevel signals, but a performance almost as good can often be obtained by means of the simplified detector to be described below [100].

6.5 REDUCED STATE VITERBI-ALGORITHM DETECTOR

The data transmission system is as suggested in Sec. 6.4, shown in Fig. 1.1, with the threshold detector and transversal filter \( F \) [Fig. 1.2] being replaced by a more complex system now to be illustrated here.

The signal at the output of the filter \( D \), at time \( t = nT \), is

\[
P_i = \sum_{k=0}^{K} s_{i-k+1} e_{i,k} + u_i
\]

... 6.5.1

Transmission takes place by the \( m \) level data-symbols \( \{ s_i \} \). The detector having a large storage capacity so that it can hold in store \( k \) \((k=mn^k)\) \( n \)-component vectors (sequences) \( \{ Q_{1k} \} \) before the reception of the signal \( P_i \) from the transversal filter \( D \), where

\[
Q_{i-1} = [x_{i-n} x_{i-n+1} \ldots x_{i-1}]
\]

... 6.5.2

\( x_{i-k} \) are taken on as a possible value for \( s_{i-k} \) for \( h=1,2, \ldots, n \), the \( k \)-vectors \( \{ Q_{1k} \} \) being all different, indicating that all possible sequence of values that could be given by the data-symbols \( s_{i-n} s_{i-n+1} \ldots s_{i-1} \) is represented by the vector \( Q_{1k} \).

Further to the reception of the signal \( P_i \), at the output of the filter \( D \) at time \( t=nT \), each stored vector \( Q_{1k} \) is expanded into \( m \) \((n+1)\)-component vectors \( \{ P_i \} \), where

\[
P_i = [x_{i-n} x_{i-n+1} \ldots x_i]
\]

... 6.5.3

In each group of \( m \) vectors \( \{ P_i \} \), derived from any one vector \( Q_{1k} \), the first \( n \)-components are as in the original \( Q_{1k} \) and the last component \( x_i \) takes on its \( m \) different possible values. Now introducing a parameter \( c \) (vector cost) that is calculated for each of the resulting \( m \) vectors \( \{ P_i \} \) as

\[
c_i = c_{i-1} + |f_i - \sum_{k=0}^{K} x_{i-k} e_{i,k}|^2
\]

... 6.5.4
The smaller the value of $c_i$, the more likely is the corresponding data sequence correct. The appropriate stored value $c_{i+1}$ is given by

$$c_{i-1} = \sum_{j=0}^{i-1} |P_j - \sum_{k=0}^{i} x_{j-k} e_{i,k}|^2$$ 

...6.5.5

where $x_i = 0$ for $i < 0$ and $i > n$.

The detected value $s'_{i-a}$ of the data-symbol $s_{i-a}$ is now taken as the value of $x_{i-a}$ in the vector $P_i$ with the smallest cost. The detector then discards any vector $P_i$ whose first component $x_{i-a}$ differs from $s'_{i-a}$ and selects $k$ vectors having the smallest costs $\{c_i\}$ from the remaining vectors $\{P_i\}$ (including that from which $s_{i-a}$ was detected). The first component of each of the $k$ selected vectors $\{P_i\}$ is now dropped (without changing its cost) to give the corresponding vectors $\{Q_i\}$, which are then stored, together with the associated costs $\{c_i\}$, ready for the next detection process. Such a discarding method employed here to the vectors $\{P_i\}$ ensures that the $k$ stored vectors $\{Q_i\}$ are always different, provided only that they were different at the first detection process, which can easily be arranged [115-116].

The performance of such a detector depends solely on severity of the amplitude distortion in the received signal as well as the number of stored vectors $k$. The main weakness of this detection process is the number of operation involved for $k$ searches through $km$ costs particularly when $h$ is large (say 16 or more). This excessive number of operations that could rise exponentially with increase in $h$ can be reduced employing pseudobinary and pseudoquaternary systems [100,114].

In these systems only two or four of the expanded vectors $\{P_i\}$ are considered by the detector, originating from any one $Q_{i-a}$, that have the smallest costs; the resulting vectors are left unused. This is achieved by means of a simple threshold-level comparison technique that does not itself involve the evaluation of any costs, thus achieving a reduction in the complexity of the detection process. Further reduction in the number of operations can be derived by employing the following system

### 6.6 SIMPLE NEAR-MAXIMUM LIKELIHOOD DETECTOR

The detector illustrated here considers the same data transmission system given in Secs. 6.4-6.5 and is derived from reduced-state Viterbi-algorithm detector.
In the pseudobinary version of the system, described in Sec. 6.5 just prior to the receipt of the signal \( p_n \), the detector stores \( k \) vectors \( \{ Q_{i-1} \} \) together with their costs \( \{ c_{i-1} \} \), as before. The vectors \( \{ Q_{i-1} \} \) are arranged in pairs, where the two vectors \( \{ Q_{i-1} \} \) in any one pair differ only in the values of the last component \( x_i \), with \( k \) taking only even values. For the given values of \( x_{i-1}, x_{i-2}, \ldots, x_{i-2} \) in a pair of vectors \( \{ Q_{i-1} \} \), the value of \( x_i \) in the second of the pair is one of its possible values giving the second smallest cost. On receipt of \( p_n \), each vector \( Q_{i-1} \) is expanded into the corresponding vector \( P_i \) having the smallest cost. A simple threshold-level comparison can achieve the \( P_i \) without involving the comparison of any costs.

Next the costs \( \{ c_i \} \) of the \( k \) vectors \( \{ P_i \} \) are calculated. The vector with the smallest cost is considered as the detected value of \( s_{i-1} \), i.e. the first component \( x_{i-1} \) of the data-symbol \( s_{i-1} \). All vectors \( \{ P_i \} \) for which \( x_{i-1} \) not equal to \( s_{i-1} \) are now discarded, and then the first components of all remaining vectors \( \{ P_i \} \) are omitted without changing their costs to obtain the corresponding \( n \)-component vectors \( \{ Q_i \} \). Now having selected and stored the vector \( Q_i \) with the smallest cost, the detector selects from the remaining vectors \( \{ Q_i \} \) the \( \frac{1}{2}k - 1 \) vectors with the smallest costs, to give a total of \( \frac{1}{2}k \) selected vectors \( \{ Q_i \} \). An additional vector \( Q_i \) is then added to each of these vectors, whose first \( n-1 \) components are as in the original vector \( Q_i \) and whose last component \( x_i \) takes on its value for which the cost of \( Q_i \) has its second smallest value. The value of \( x_i \) giving the smallest cost is, of course, that in original vector \( Q_i \). The simple algorithm previously mentioned in Sec. 6.5 is employed, so that no actual costs need be evaluated. The detector now holds in store \( k \) vectors \( \{ Q_i \} \) in the form of \( \frac{1}{2}k \) pairs of vectors, the two vectors of any pair having, of course, the same values of \( x_{i-1}, x_{i-2}, \ldots, x_{i-2} \). The costs \( \{ c_i \} \) of the \( \frac{1}{2}k \) vectors \( \{ Q_i \} \) not yet determined are next evaluated, and associated with each vector \( Q_i \) the corresponding cost is then too stored.

The pseudoquaternary type of system is quite similar to the pseudobinary version just described. Here again just prior to the receipt of \( p_n \), the detector holds in store \( k \) vectors \( \{ Q_{i-1} \} \) together with their costs \( \{ c_{i-1} \} \). \( k \) is now a multiple of 4; thus the detector arranges \( \{ Q_{i-1} \} \) in groups of four, where the four in one group have the same values of \( x_{i-1}, x_{i-2}, \ldots, x_{i-2} \) and four different values of \( x_{i-1} \). The four different values of \( x_{i-1} \) are determined by simple threshold-level system explained above without requiring the evaluation of any costs [100].
The detection process proceeds exactly as described for the pseudobinary version on the receipt of the signal \( p_n \), until the detector has \( k \) vectors \( \{ Q_i \} \) together with the associated costs \( \{ c_{ij} \} \). The same procedure for every vector \( \{ Q_i \} \) having been derived from the corresponding vector \( P_i \) by omitting the first component is carried out again in the same manner as pseudobinary type of the simple near-maximum likelihood detector. In this case in addition to the vector \( Q_i \) with the smallest cost, which has already been selected, the detector now selects from the remaining vectors \( \{ Q_i \} \) the \( \frac{1}{2}k - 1 \) vectors with the smallest costs, to give a total of \( \frac{1}{2}k \) selected vectors \( \{ Q_i \} \).

Each of these vectors is then expanded into four vectors \( \{ Q_i \} \), through the addition of three vectors to the original. The four vectors in any one group have the same values of \( x_{i+1}, x_{i+2}, \ldots, x_i \) as the original \( Q_i \) and the four different values of \( x_i \). The latter four values are determined in the same way as the four values of \( x_{i+1} \), in any one group of four vectors \( \{ Q_i \} \) at the start of the detection process, using simple threshold-level comparisons and not requiring the evaluation of any costs [90,104].

The costs \( \{ c_{ij} \} \) of the \( \frac{1}{2}k \) vectors \( \{ Q_i \} \) not yet determined are now evaluated, and the detector then stores the \( k \) vectors \( \{ Q_i \} \) together with the associated costs, ready for the next detection process.

Now employing the above pseudoquaternary and the pseudobinary detectors of this type, a less complex type of near-maximum-likelihood detection can be obtained. This can be best realised by the following example.

Consider the detector holds first \( j = 8 \) vectors given by \( \{ Q_{c=1} \} \), each are then expanded into \( P_{i=1} \) together with their smallest costs. The detection of \( s_{c=1} \) is done as exactly as explained in the above case for the pseudobinary and pseudoquaternary case to obtain the corresponding \( 8 \) vectors \( \{ P_{i=1} \} \). The detector then selects the smallest cost vector from these \( 8 \) vectors and add them to the \( 3 \) vectors giving the next smallest costs, i.e there are now a total of \( 4 \) selected vectors. The detector then selects the second smallest vector from the original \( 8 \) vectors \( P_{i=1} \) and add to it another vector, the same as the case of pseudobinary system. Thus, now the detector has \( 6 \) (4 from first set and 2 from the second set) selections, it carries on selecting one from the third and fourth smallest costs until there are a total of \( 8 \) vectors plus their costs. This process is done for every instant of time \( t = iT \). This system takes into account all the intersymbol interference available within the received signal to make its decision for the correct detection of data-symbols.
6.7 COMPUTER SIMULATION TESTS AND RESULTS

This section compares the computer simulation results obtained for the two different detection schemes namely decision feedback equaliser and the near maximum likelihood detector for the two systems (A and B) under investigation.

Throughout this work differential encoding and decoding is employed. This is for the reason that when the transmitted signal is in deep fade, the carrier experiences large and rapid phase changes. These changes are noticeable in the equivalent, complex-valued, time varying baseband channel models as rotations of multiples of radians in each of the received samples. This, of course would result in the detected data symbol values, and the occurrence of these errors would continue until the end of the transmitted message, even in the absence of noise. The differential coding prevents these prolonged error bursts by coding the difference in phase between two consecutive symbol values; here, the transmitted signal would now represent a phase rotation [117].

From the plots of Fig. 6.3, it can be observed that when differential encoding and decoding is introduced, the tolerance to white Gaussian noise is reduced by about 3dB over that of bit error rate but slightly better performance is obtained than that of the symbol error rate. It should be also noted that throughout this chapter and Chapter 7, the channel's noise components are passed through the receiver filter indicating that slightly correlated noise samples are accompanying the received signal.

6.7.1 System A

It was observed in the three dimensional plot of Fig. 5.20 that no components of the sampled impulse response of this system was outside the unit circle of the z-plane, thus the signals at the input to the receiver are only severely distorted in amplitude. The process of decision feedback cancellation of intersymbol interference (non-linear equalizer) was first employed here for the mobile transmitting source producing different frequency spreads of up to 6.51 Hz (from almost stationary to 0.5 m/s) [Fig. 6.4J. Notice that as the speed of the source is increased the number of bits in error too increases.
Fig. 6.5 shows the differential bit error plot when the near maximum likelihood detector with \( j = 8 \) is employed at the receiver. Comparing this plot with that obtained when the non-linear equalizer was employed indicates that the near maximum likelihood detector provides an advantage of about 2-3 dB better tolerance to noise than that of non-linear equalizer.

### 6.7.2 System B

As described earlier, in this chapter the process of minimum phasing over the channel of System B takes place by the employment of a perfect available NAG library routine (c02adf) based around zero finding algorithms. The results are plotted in Figs. 6.6-6.10 in three dimensions for 1, 2, 3, 5 and 8 eigenray channels respectively. They clearly indicate that the energy of the sampled impulse responses of the channels are now situated around the first components considering 50 samples (\( i = 50 \)).

Fig. 6.11 shows the differential bit error plots of all five channels of this system when non-linear equalizer is employed at the receiver on the minimum phased channel sampled impulse responses. In this system too, the error plots [Fig. 6.12] show a superiority of the near maximum likelihood detector (\( j = 8 \)) of about 2-3 dB over the non-linear equalizer.

### 6.8 CONCLUDING REMARKS

This chapter concludes with the remarks that whenever there is significant amplitude distortion, a useful improvement in performance, over that of a decision-feedback equalizer can be achieved by appropriately modifying the equalizer or maximum-likelihood detector. The resulting system achieves a significantly better tolerance to noise than a conventional equaliser but without an undue increase in equipment complexity.

In these particular channel models, system A and B, perfect estimation of the channels was assumed, and phase jumps that occur are known to the receiver, making differential coding seem rather superfluous. Nevertheless, in any practical modem operating over a fading channel, differential coding is an essential constituent part,
hence its inclusion here. However, Chapter 7 will deal with these problems by introducing channel estimators that can track the variations in the sampled impulse response of the channel models and also recognise and cancel echoes.
**Fig. 6.1** Feedforward Transversal Filter.

**Fig. 6.2** Decision Feedback Cancellation of Intersymbol Interference (Non-Linear Equalizer).
Fig 6.3 Symbol, bit and Differential coding comparison plot for system A at 2 Hz frequency spread.
Fig. 6.4 Non-linear Equalizer operating over System A at different speed of submersible.
Fig. 6.5 Near-Maximum likelihood detector operating over System A at different speed of submersible.
Fig. 6.6 Minimum phased sampled impulse of one eigenray channel of System B.
Fig. 6.7 Minimum phased sampled impulse of two eigenray channel of System B.
Fig. 6.8 Minimum phased sampled impulse of three eigenray channel of System B.
Fig. 6.9 Minimum phased sampled impulse of five eigenray channel of System B.
Fig. 6.10 Minimum phased sampled impulse of eight eigenray channel of System B.
Fig. 6.11 Non-linear Equalizer operating over System B for different number of eigenrays.
Fig. 6.12 Near-Maximum likelihood detector operating over System B at different number of eigenrays.
CHAPTER 7

ECHO CANCELLATION AND COMBINED ESTIMATOR DETECTOR

7.1 INTRODUCTION

In the previous chapter, it was stated that the receiver has a driver containing a highly distorted signal in phase and amplitude. The detection processes employed at the receiver suggested that a useful advantage in tolerance to Gaussian noise was achieved by employing a near-maximum likelihood detection process in place of a conventional non-linear equalizer to cancel the effect of amplitude distortion. Both methods required the setting of tap gains associated with the linear pre-filter ahead of the detector. The roots(zeros) employed by the pre-filter were obtained at the expense of extensive computer processing time (NAG routine) so that the error in convergence of the polynomials became negligible.

In this chapter, a novel technique is studied which ensures the polynomial's convergence with the aid of an adaptive estimator for a practical adaptive adjustment technique. The objective of the estimator is to estimate the errors obtained in the determination of the roots(zeros) but with a limited processing time. The bit error performance of this system, when combined with a near-maximum likelihood detector at the receiver shown in Fig 1.3 is then compared with that obtained in the previous chapter where an accurate knowledge of the sampled impulse response of the channels was assumed.

Further, the receiver could be trained prior to the transmission of valid data to enable it to derive the required estimator settings. It must also track or predict any variations such as echoes in the channel sampled impulse response during the transmission period. Intuitively, the training period, which usually consists of the transmission of a data sequence known to the receiver, should be as short as possible but consistent with the adjustment time required by the receiver.
7.2 CHANNEL ESTIMATION AND ECHO CANCELLATION TECHNIQUES

In Chapter 6, the receiver was assumed to have "know" the variation in the sampled impulse response of the channels under investigation, i.e. the channels were perfectly estimated. In this chapter the data detection takes place by employing a more sophisticated receiver that smears out the correct data by estimating (if necessary, predicting) the variation in the sampled impulse response of the channels. These sampled impulse responses could now include echoes present in the channels and can be identified by the channel estimator for removal by the detector, which regards them as intersymbol interference [118].

Fig. 7.1 shows the arrangement of the receiver employing a near maximum likelihood detector and channel estimator. The delay of n-1 symbols duration clearly indicates that the channel estimator, on receipt of $r_n$, forms an estimate $Y'_{i,e}$ of the sampled impulse response of the channel with $s_{i,e}$ and the early detected data symbols. In a time invariant channel, a good estimate of $Y_i$ can be achieved since the sampled impulse response does not vary in time. But for time varying channels such as those considered here, the estimate of $Y_i$ (called $Y'_{i,e}$) is quite different from $Y_i$. The best way to discuss channel estimators, and particularly those which employ some form of prediction, is to consider the nature of the amplitude variations in the sampled impulse responses of the channel models.

The amplitude variation of the real or imaginary parts of the complex sampled impulse response of the channels (system A or B) under investigation could be given as shown in Fig. 7.2. For the purpose of discussing the nature of the amplitude variations, only a single component is considered since all the components in the sampled impulse responses are tracked independently from one another. The result of the estimator then holds for all the impulse responses in the channel under test. The amplitude variations of the interpolated samples shown in Fig. 7.2 can be observed as very slow, which could result in highly predictable changes. To ease the understanding of channel estimators, a simple feedforward estimator is first explained and then the algorithms for predicting the variations in the amplitude of the sampled impulse response of the channels are discussed [1,100].
7.2.1 Channel estimation using least mean-square-error method

Consider the channel estimator shown in Fig. 7.3. The system is essentially a linear feedforward transversal filter. Each square $T$ is a storing device holding the corresponding detected data symbol $s'_{i,n}$. On receipt of $r_i$, each time the stores are triggered, the stored values are shifted one place to the right. The detected data symbols $s'_1, s'_{1+1}, s'_{1+2}, \ldots, s'_{1+g}$ are then held in store following the detection of $s_i$. Each data symbol $s'_{i,n}$ is multiplied by the corresponding component $y'_{i-1,n}$ of the estimate $Y'_{i-1}$ of the vector $Y_{i-1}$. Then their products are summed to produce the estimate $r'_i$ of the received sample $r_i$ as

$$r'_i = \sum_{h=0}^{g} s'_{i-h} y'_{i-1,h}$$  \ldots 7.2.1

The error signal $e_i$ is then obtained by subtracting Eqn. 7.2.1 from the received signal $r_i$ which is already held in store, i.e.

$$e_i = r_i - r'_i$$  \ldots 7.2.2

The error signal $e_i$ is then multiplied by a small positive real quantity $b$ to give $b e_i$, which multiplies the complex conjugate $(s'_{i,n})^*$ of each detected data symbol $s'_{i,n}$. This product is then added to the corresponding components of $Y'_{i-1}$ to produce the new stored estimate $Y'_{i}$ as shown in Fig. 7.3. This implies the $(h+1)^{th}$ component of $Y'_{i}$ given as

$$y'_{i,n} = y'_{i-1,n} + b e_i (s'_{i-n})^*$$  \ldots 7.2.3

for $h = 0, 1, 2, 3, \ldots, g$.

The smaller the value of the parameter $b$, the smaller becomes the effect of additive noise on $Y'_{i}$ but the slower the rate of response of $Y'_{i}$ to changes in $Y_i$.

In the detection of $s_i$ with a delay of $n-1$ sampling intervals (i.e. $s_i$ is detected after the reception of $r_{i-n+1}$) the estimate of $Y_i$ is only accessible on receipt of $r_{i+n}$ for the detection of $s_{i+1}$, so that the delay in estimation is $n$ sampling interval. Obviously, for the generation of error signals $e_i, e_{i+1}, e_{i+2}, \ldots, e_{i+n-1}$, the received samples $r_i, r_{i+1}, \ldots, r_{i+n-1}$ must be stored in a shift register. The error in using $Y'_{i}$ becomes excessive if the delay $n$ or the number of the sampled impulse responses is large.
The prediction $Y'_{\text{err},i}$ of $Y_{\text{err}}$ from the estimates of $Y'_{i}, Y'_{i-1}, \ldots$ then becomes necessary and the accuracy of the prediction is determined by the square of the error in $Y'_{\text{err},i}$ as

$$|Y_{i+n} - Y'_{i+n,i}|^2 = \frac{1}{k} \sum_{h=0}^{k} |y_{i+n,h} - y'_{i+n,i,h}|^2 \quad \ldots 7.2.4$$

The mean square error in $Y'_{\text{err},i}$ is thus the average value of the squared error given in Eqn. 7.2.4 over $k$ transmitted symbols which is

$$\xi = 10 \log_{10} \left( \frac{1}{k} \sum_{j=1}^{k} (Y_{i+n,j} - Y'_{i+n,j})^2 \right) \quad \ldots 7.2.5$$

The process just described (zero degree prediction) is probably the least complex form of estimation and involves relatively few operations per iteration. However, a more complex system based on prediction algorithms is described in the following section [1,100,118-120].

### 7.2.2 Estimation with least-mean-square fading predictions

The first degree least-mean-square fading memory prediction operates the same way as described in section 7.2.1 except that the updating equation $Y_{i-1,i} = Y'_{i-1,i}$, for a channel amplitude that is slowly varying in time (or time invariant), is now replaced by the three following equations.

$$\phi_{i} = Y_{i} - Y'_{i,i-1} \quad \ldots 7.2.6$$

$$Y_{i+1,i}'' = Y_{i+1,i-1}'' + (1-\Theta)^2 \phi_{i} \quad \ldots 7.2.7$$

$$Y_{i+1,i}' = Y_{i+1,i-1}' + Y_{i+1,i-1}' + (1-\Theta^2) \phi_{i} \quad \ldots 7.2.8$$

where $Y'_{i-1,i}$ is the one step prediction given by

$$Y'_{i-1,i} = [y'_{i-1,0}, y'_{i-1,1}, \ldots, y'_{i-1,x}] \quad \ldots 7.2.9$$

to form the updated estimate of $Y'_{i}$ which is the estimate of $Y_{i}$ described in Sec. 7.2.1 and is given by

$$Y'_{i} = [y'_{i,0}, y'_{i,1}, \ldots, y'_{i,x}] \quad \ldots 7.2.10$$
and $Y'_i$ is a $(g+1)$-component row vector. The vector $Y'_{i+1}$ is the first degree least-mean-square fading memory prediction of $Y_i$, and $Y''_{i+1}$ is the prediction of the rate of change with $i$ of $Y'_{i+1}$. The parameter '$\theta$' is a real-valued constant in the range 0 to 1, usually close to 1. At the start of estimation process, $Y''_{0,1} = 0$ and $Y'_{0,1} = Y'_1$, where $Y'_1$ is determined from setting this vector to the actual received sampled impulse responses or an appropriate training signal preceding transmission of data.

The estimation employing degree-2 prediction is given in a similar way except that the two Eqns. 7.2.7-7.2.8 are replaced by the three following equations

$$Y''_{i+1} = Y''_{i-1} + \frac{1}{2} (1 - \theta)^3 \Phi_i \quad \ldots 7.2.11$$

$$Y'_{i+1} = Y''_{i-1} + 2Y''_{i+1,1} + \frac{1}{2} (1 - \theta)^3 (1 + \theta) \Phi_i \quad \ldots 7.2.12$$

$$Y'_{i+1} = Y''_{i-1} + Y''_{i+1,1} - Y''_{i+1,1} + (1 - \theta)^3 \Phi_i \quad \ldots 7.2.13$$

with $\Phi$ given by Eqn. 7.2.6.

It has been observed by many researchers [1,100,118] that the specific degree of the polynomial that results in the least mean square error may not produce the same mean square error on a different channel employing the same degree of prediction [100,118-121].

7.3 STRUCTURE OF THE RECEIVER MODEM

The aim of this section is to present a receiver structure that can be implemented in a practical communication system operating over the multipath channel models of systems A and B upon the estimate (and predictions) of the sampled impulse response of the channels rather than the sampled impulse responses themselves.

The signal fed from the hydrophone has extra noise components outside the frequency of the received signal. These are first band-pass filtered, then an analogue-to-digital conversion is performed at a sampling rate much higher than the data rate.
The in-phase and quadrature components of the demodulator multiply the received data signal by the reference carrier, which is in phase quadrature. This has the same frequency and is identical to the average instantaneous power of the receiver signal carrier. This pair of signals is then passed through two identical low-pass filters, detailed in Chap. 5, and the resultant $r(t)$ is sampled at 2400 samples/second to provide $r_i$.

The real and imaginary parts of the complex-valued noise components $\{w_i\}$ have the properties explained in chapters 5 and 6. If ideal low-pass filters are employed as the equipment filters, then the real and imaginary parts of $\{w_i\}$ are uncorrelated, but slightly correlated if the actual equipment filters are implemented.

### 7.3.1 Computer simulation of system A receiver

Fig. 7.4 shows the structure of the receiver employed for the detection of data signals with the system A underwater channel models. This is the combined detector and estimator which performs coherent detection at the receiver.

Table 7.1 presents the computer simulated values of the parameters 'b' and 'θ' for the given signal to noise ratios. These values of 'b' and 'θ' were noted when the mean square error $\xi^2$ for each channel of system A reached its minimum for all three degrees of prediction. Notice that, in the channels of system A, $\xi^2$ is at its minimum when degree-2 prediction is employed ($k=24000$). It should be also noted that although the value of 'θ' stays approximately the same for every individual channel, the value of 'b' changes drastically at a given signal power applied at the receiver.

Figs. 7.5-7.7 show the plots of one computer simulation test (moderate channel) for the evaluation of the most optimum values of the parameters 'b' and 'θ' that would result in the best mean square error values when different degrees of prediction are employed. Plot of Fig. 7.7 confirms that in this particular channel the degree two prediction could result in the most optimum adjustment of the estimator to track the variations produced in the sampled impulse response of this particular channel for the mobile source travelling at a "moderate" speed of 0.2 m/s. It should be emphasized that the assumptions noted in section 7.2 are employed here and the results plotted in Fig. 7.5-7.7 assume correct detection of the received data signal.
Table 7.2 shows the differential bit error rates when the near maximum likelihood detector for \( j=8 \) (described in chapter 6) is employed after the insertion of the values of the parameters 'b' and '\( \theta \)' for the specific signal powers employed at the receiver for the source travelling at different speeds with estimator of degree-2 prediction.

Computer simulation tests clearly emphasized that differential coding must be employed with this combined estimator detector. This is because a deep fade often seemed to cause a phase change of ±90° or 180° to be introduced into the prediction of the channel. The following stream of detected data symbols is now all rotated in phase by the appropriate multiple of 90° as described in Appendix E.

The tolerance to noise of the combined estimator detector was found to be approximately the same when the detected data symbols were fed back to the estimator as when the actual data symbols were employed. Furthermore, without employing any retraining sequences for the source travelling at moderately low speed, the combined detector and estimator seemed to be working at a stable manner with differential coding. This implies that, the deep fades occurring in the channel only causes short bursts of errors of several symbols duration.

### 7.3.2 Computer simulation of system B receiver

Fig. 7.8 shows the structure of the receiver employed for the detection of data signals with system B channel models. This is a combined estimator/detector employing a pre-detection filter ahead of the detector where the receiver performs coherent detection of the data symbols.

Tables 7.3a-7.3b present the computer simulated values of the parameters 'b' and '\( \theta \)' for the given signal-to-noise ratios. These values of 'b' and '\( \theta \)' were noted when the mean square error '\( \xi \)' for each channel of system B (considering different number of eigenrays) reached its minimum for all three degrees of prediction. In system B unlike system A, '\( \xi \)' is at its minimum when degree-1 prediction is employed (\( k=24000 \)). It should be also noted that although the value of '\( \theta \)' stays approximately the same for every individual channel, but the value of 'b' changes drastically at a given signal power applied at the receiver.

Fig. 7.9-7.11 show the plots of one computer simulation test considering two eigenray channel for the evaluation of the most optimum values of 'b' and '\( \theta \)' that would result in the best mean square error values '\( \xi \)' for different degrees of
prediction. Plot of Fig. 7.11 confirms that in this particular channel the degree one prediction could result in the most optimum adjustment of the estimator to track the amplitude variations produced in the sampled impulse response of this particular channel for the mobile source considering the reception of two eigenrays. The assumptions noted in section 7.2 are also employed here and the results plotted in Figs. 7.9-7.11 assume correct detection of the received data.

The adaptive linear feedforward transversal filter shown in Fig. 7.8 is included in this system since the sampled impulse response here, unlike for system A does not have minimum phase response. This problem has already been explained in detail in chapter 6 and was dealt with by NAG library routines. It is now desired to further analyse this problem for a more realistic practical system. Appendix F describes the root finding algorithms employed here. Now consider this filter has a response given by

\[ D_i = [d_{i,0} d_{i,1} d_{i,2} \ldots d_{i,n}] \]  \hspace{1cm} ...7.3.1

where \( n \) is the number of tap gains of the filter. The filter output \( r'_i \) upon the reception of \( r_{i+n} \) is then

\[ r'_i = \sum_{k=0}^{n} r_{i+n-k} d_{i,k} \]  \hspace{1cm} ...7.3.2

This is now further processed by the detector which operates on the estimated sampled impulse response of the cascaded channel and the filter given by

\[ F_i = [f_{i,0} f_{i,1} f_{i,2} \ldots \ldots f_{i,n}] \]  \hspace{1cm} ...7.3.3

Determination of \( F_i \) takes place by the adaptive filter prior to the receipt of \( r_{i+n} \). The adjustment of the tap gains of \( D_i \) are obtained straight from the one-step prediction of the channel's sampled impulse response given by \( \{ Y'_{i+1,1} \} \).

The root-finding algorithm fully explained in Appendix F is employed by the filter which functions in an iterative process to obtain the zeros of \( \{ Y'_{i+1,1} \} \) in sequence. These roots are then used by the filter to assess the new tap gains of the adaptive filter \( D_{i+1} \) as well as forming the new resultant sampled impulse response of the channel and the filter \( F_{i+1} \). The prior knowledge of the channel becomes available to the root-finding system since it processes on the previously determined roots.

Employing Appendix F, the root-finding procedure is briefly explained below for the simulation purposes now that the estimated sampled impulse response of the channel is obtained.
The root-finding algorithm first sets $F_i$ to the latest one-step predicted sampled impulse responses $Y'_{i-1,1}$ as well as setting the transform function of $D$ to $z^{-a}$. Then the corresponding values of the already determined roots in the previous iteration is set for $\lambda_0$ [Fig. 7.12] after which the initial start-up values (Appendix F) are considered. The evaluation of each $\lambda_0$ value is as indicated below;

\( j_{\text{conv}} = 0 \)

REPEAT THE LOOP FOR CONVERGENCE

\[ e_{\text{conv}, h} = f_h - \lambda_{j_{\text{conv}}} e_{\text{conv}, h+1} \quad \text{for} \quad h = g, g-1, \ldots, 1, 0 \]

\[ & \quad & \quad \text{&} \quad e_{\text{conv}, g+1} = 0 \]

\[ e_{\text{conv}} = \sum_{h=1}^{g} e_{\text{conv}, h} \lambda_{j_{\text{conv}}}^{h-1} \]

\[ \lambda_{j_{\text{conv}}+1} = \lambda_{j_{\text{conv}}} + \frac{e_{\text{conv}, 0}}{e_{\text{conv}}} \]

\[ j_{\text{conv}} = j_{\text{conv}} + 1 \]

\[ \text{IF} \quad |e_{\text{conv}, g} e_{\text{conv}}|^2 < d \]

\[ \text{ELSEIF} \quad j_{\text{conv}} > 40 \quad \& \quad |\lambda_{j_{\text{conv}}}| > 1 \quad \& \quad e_{j_{\text{conv}}} \rightarrow 0 \]

TERMINATE (provided the condition for convergence is fulfilled)

THEN precede to the next value of $\lambda_0$

IF a root is located THEN store $\lambda_4$ for the next iteration

Then determine $F$ and $D$ components

\[ f_h = e_{k,h+1} + \lambda_{k}^* e_{k,h} \quad \text{for} \quad h = -1, 0, 1, \ldots, g \]

\[ e_h = d_h - \lambda_4 e_{h+1} \quad \text{for} \quad h = n, n-1, n-2, \ldots, 1, 0 \quad (e_{n+1} = 0) \]

\[ d_h = d_{h+1} + \lambda_{4}^* e_{h} \quad \text{for} \quad h = -1, 0, 1, \ldots, n \quad (e_{-1} = 0) \]

where \[ d_{-1} = e_0 = 0 \]

where \[ e_{k,-1} = 0 \]
and

\[ f_{-1} = e_{k_0} = 0 \]

with the one and two tap filters described in Fig. 7.12.

Using the updated values of F and D, the procedure is repeated with a new value of \( \lambda_0 \).

ENDIF all the previous located roots have been assigned and all the nine start-up values of \( \lambda_0 \) have been tried out and no roots have been located. The resultant F and D values are now considered to be the updated values of \( F_i \) and \( D_i \).

The root-finding algorithm can be obtained "off-line" since it could be considered as fully independent on other systems in the receiver box. For a slowly time-varying channel, where transmitter and receiver transducers are considered to be almost stationary, this procedure can be carried out once for every four or six samples or so. As the system starts to move, fewer samples are taken, at the expense of higher computational storage and processing time.

The detector shown in Fig. 7.8 is the near maximum likelihood detector already explained in chapter 6 and was also used in the previous section for the system A model with \( j = 8 \).

The tolerance to noise of the combined estimator detector employing the adaptive pre-filter was found to be approximately 1-2dB inferior [Table 7.4a and 7.4b] to that when adaptive adjustment of the receiver was performed with NAG routines considering different numbers of eigenray channels. An estimation of the sampled impulse responses is used here instead of the actual ones.

Further, without employing any retraining sequences for the source travelling at "moderate" speed (0.8 knots), the combined detector and estimator seemed to be working in a stable manner with differential coding [100,121-128].

7.4 CONCLUDING REMARKS

System A, employing an estimator of degree-2 prediction, combined with the near-maximum likelihood detector, gave approximately the same results as those obtained when the sampled impulse responses of the channel was known to the receiver (see chapter 6). In this type of detector, where the channel estimator plays an important part, the values of 'b' and 'θ' must be obtained from a look-up estimator
table for full estimator stability. The instability of the estimators was only observed for high speed of the source/receiver (over 0.2 m/s) even with the employment of differential coding. This is because of the rapid phase changes due to Doppler spread. Unlike system A, the estimator employing degree-1 prediction was found to be superior to the channel estimator of degree-2 prediction in testing the channel estimators of system B channels. The results of the computer simulation for system B employing adaptive pre-filter ahead of the detector shows a more gradual decrease in the differential bit error rates for a given signal power at the receiver instead of the sharp decreases observed when the NAG routines were employed for the given number of eigenrays.
Fig. 7.1 Combined data detector and channel estimator.

Fig. 7.2 Examples of degree 0, 1, and 2 predictions.
Fig. 7.3 Complex linear feedforward estimator
<table>
<thead>
<tr>
<th>Slow-moving source/receiver (Stationary)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Degree-0 Prediction</strong></td>
<td><strong>Degree-1 Prediction</strong></td>
</tr>
<tr>
<td><strong>SNR dB</strong></td>
<td>$\xi$ dB</td>
</tr>
<tr>
<td>15</td>
<td>-18.3</td>
</tr>
<tr>
<td>30</td>
<td>-26.1</td>
</tr>
<tr>
<td>40</td>
<td>-32.3</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Moderate-moving source/receiver</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Degree-0 Prediction</strong></td>
<td><strong>Degree-1 Prediction</strong></td>
</tr>
<tr>
<td><strong>SNR dB</strong></td>
<td>$\xi$ dB</td>
</tr>
<tr>
<td>15</td>
<td>-17.2</td>
</tr>
<tr>
<td>30</td>
<td>-23.4</td>
</tr>
<tr>
<td>40</td>
<td>-26.6</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Fast-moving source/receiver</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Degree-0 Prediction</strong></td>
<td><strong>Degree-1 Prediction</strong></td>
</tr>
<tr>
<td><strong>SNR dB</strong></td>
<td>$\xi$ dB</td>
</tr>
<tr>
<td>15</td>
<td>-12.1</td>
</tr>
<tr>
<td>30</td>
<td>-14.5</td>
</tr>
<tr>
<td>40</td>
<td>-21.9</td>
</tr>
</tbody>
</table>

Table 7.1 System A simulation results of channel estimator employing degree 0, 1 and 2 predictions.
Fig. 7.4 System A combined estimator/detector arrangement.
Fig. 7.5 Variation of $\xi$ with 'b' in the estimator of system A channel with degree-2 prediction for moderate speed of the source/receiver.
Fig. 7.6 Variation of $\xi$ with $\theta$ in the estimator of system A channel with degree-2 prediction for moderate speed of the source/receiver.
Fig. 7.7 Variation of $\xi$ with different power applied at the receiver of system A channel with degree-2 prediction for moderate speed of the source/receiver.
<table>
<thead>
<tr>
<th>SNR  dB</th>
<th>$\xi$  dB</th>
<th>b</th>
<th>$\theta$</th>
<th>Diff. Bit error rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>-18.3</td>
<td>0.018</td>
<td>0.981</td>
<td>$3.02 \times 10^{-1}$</td>
</tr>
<tr>
<td>30</td>
<td>-29.7</td>
<td>0.020</td>
<td>0.967</td>
<td>$5.61 \times 10^{-4}$</td>
</tr>
<tr>
<td>40</td>
<td>-34.5</td>
<td>0.031</td>
<td>0.953</td>
<td>0.0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>SNR  dB</th>
<th>$\xi$  dB</th>
<th>b</th>
<th>$\theta$</th>
<th>Diff. Bit error rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>-17.11</td>
<td>0.110</td>
<td>0.962</td>
<td>$7.01 \times 10^{-1}$</td>
</tr>
<tr>
<td>30</td>
<td>-27.09</td>
<td>0.223</td>
<td>0.956</td>
<td>$8.09 \times 10^{-2}$</td>
</tr>
<tr>
<td>40</td>
<td>-31.70</td>
<td>0.451</td>
<td>0.943</td>
<td>$7.15 \times 10^{-3}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>SNR  dB</th>
<th>$\xi$  dB</th>
<th>b</th>
<th>$\theta$</th>
<th>Diff. Bit error rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>-12.20</td>
<td>0.131</td>
<td>0.961</td>
<td>$7.20 \times 10^{-1}$</td>
</tr>
<tr>
<td>30</td>
<td>-15.09</td>
<td>0.394</td>
<td>0.954</td>
<td>$8.17 \times 10^{-2}$</td>
</tr>
<tr>
<td>40</td>
<td>-26.10</td>
<td>0.651</td>
<td>0.941</td>
<td>$6.25 \times 10^{-3}$</td>
</tr>
</tbody>
</table>

Table 7.2 Performance of the combined estimator/detector employed at the receiver of system A channel with degree-2 prediction at different speed of the source/receiver.
### One eigenray channel

<table>
<thead>
<tr>
<th>SNR (dB)</th>
<th>$\xi$ (dB)</th>
<th>$b$</th>
<th>$\theta$</th>
<th>$\xi$ (dB)</th>
<th>$b$</th>
<th>$\theta$</th>
<th>$\xi$ (dB)</th>
<th>$b$</th>
<th>$\theta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>-9.17</td>
<td>0.045</td>
<td>0.983</td>
<td>-9.16</td>
<td>0.170</td>
<td>0.943</td>
<td>-9.15</td>
<td>0.181</td>
<td>0.943</td>
</tr>
<tr>
<td>30</td>
<td>-16.1</td>
<td>0.069</td>
<td>0.981</td>
<td>-16.2</td>
<td>0.232</td>
<td>0.931</td>
<td>-16.1</td>
<td>0.209</td>
<td>0.940</td>
</tr>
<tr>
<td>40</td>
<td>-20.0</td>
<td>0.122</td>
<td>0.976</td>
<td>-20.2</td>
<td>0.316</td>
<td>0.926</td>
<td>-19.9</td>
<td>0.287</td>
<td>0.938</td>
</tr>
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</table>

### Two eigenray channel

<table>
<thead>
<tr>
<th>SNR (dB)</th>
<th>$\xi$ (dB)</th>
<th>$b$</th>
<th>$\theta$</th>
<th>$\xi$ (dB)</th>
<th>$b$</th>
<th>$\theta$</th>
<th>$\xi$ (dB)</th>
<th>$b$</th>
<th>$\theta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>-11.0</td>
<td>0.036</td>
<td>0.984</td>
<td>-11.19</td>
<td>0.080</td>
<td>0.948</td>
<td>-11.1</td>
<td>0.092</td>
<td>0.951</td>
</tr>
<tr>
<td>30</td>
<td>-18.9</td>
<td>0.051</td>
<td>0.983</td>
<td>-23.24</td>
<td>0.193</td>
<td>0.939</td>
<td>-20.0</td>
<td>0.162</td>
<td>0.948</td>
</tr>
<tr>
<td>40</td>
<td>-19.5</td>
<td>0.051</td>
<td>0.980</td>
<td>-26.19</td>
<td>0.241</td>
<td>0.929</td>
<td>-22.3</td>
<td>0.215</td>
<td>0.931</td>
</tr>
</tbody>
</table>

### Three eigenray channel

<table>
<thead>
<tr>
<th>SNR (dB)</th>
<th>$\xi$ (dB)</th>
<th>$b$</th>
<th>$\theta$</th>
<th>$\xi$ (dB)</th>
<th>$b$</th>
<th>$\theta$</th>
<th>$\xi$ (dB)</th>
<th>$b$</th>
<th>$\theta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>-13.7</td>
<td>0.035</td>
<td>0.985</td>
<td>-13.66</td>
<td>0.069</td>
<td>0.948</td>
<td>-13.5</td>
<td>0.091</td>
<td>0.966</td>
</tr>
<tr>
<td>30</td>
<td>-19.8</td>
<td>0.049</td>
<td>0.985</td>
<td>-21.14</td>
<td>0.233</td>
<td>0.952</td>
<td>-20.1</td>
<td>0.121</td>
<td>0.963</td>
</tr>
<tr>
<td>40</td>
<td>-25.3</td>
<td>0.059</td>
<td>0.984</td>
<td>-27.07</td>
<td>0.333</td>
<td>0.934</td>
<td>-26.0</td>
<td>0.199</td>
<td>0.958</td>
</tr>
</tbody>
</table>

**Table 7.3a** System B simulation results of channel estimator employing degree 0, 1 and 2 predictions for 1, 2 and 3 eigenray channels.
### Five eigenray channel

<table>
<thead>
<tr>
<th>SNR dB</th>
<th>$\xi$ dB</th>
<th>$b$</th>
<th>$\theta$</th>
<th>$\xi$ dB</th>
<th>$b$</th>
<th>$\theta$</th>
<th>$\xi$ dB</th>
<th>$b$</th>
<th>$\theta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>-14.0</td>
<td>0.032</td>
<td>0.986</td>
<td>-14.33</td>
<td>0.052</td>
<td>0.952</td>
<td>-13.3</td>
<td>0.087</td>
<td>0.977</td>
</tr>
<tr>
<td>30</td>
<td>-20.1</td>
<td>0.143</td>
<td>0.985</td>
<td>-23.94</td>
<td>0.181</td>
<td>0.951</td>
<td>-22.0</td>
<td>0.097</td>
<td>0.975</td>
</tr>
<tr>
<td>40</td>
<td>-26.0</td>
<td>0.193</td>
<td>0.985</td>
<td>-31.36</td>
<td>0.321</td>
<td>0.949</td>
<td>-30.9</td>
<td>0.113</td>
<td>0.974</td>
</tr>
</tbody>
</table>

### Eight eigenray channel

<table>
<thead>
<tr>
<th>SNR dB</th>
<th>$\xi$ dB</th>
<th>$b$</th>
<th>$\theta$</th>
<th>$\xi$ dB</th>
<th>$b$</th>
<th>$\theta$</th>
<th>$\xi$ dB</th>
<th>$b$</th>
<th>$\theta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>15</td>
<td>-14.3</td>
<td>0.041</td>
<td>0.988</td>
<td>-14.21</td>
<td>0.040</td>
<td>0.957</td>
<td>-14.1</td>
<td>0.071</td>
<td>0.979</td>
</tr>
<tr>
<td>30</td>
<td>-23.7</td>
<td>0.210</td>
<td>0.987</td>
<td>-25.76</td>
<td>0.111</td>
<td>0.951</td>
<td>-24.8</td>
<td>0.111</td>
<td>0.977</td>
</tr>
<tr>
<td>40</td>
<td>-27.8</td>
<td>0.270</td>
<td>0.987</td>
<td>-33.06</td>
<td>0.201</td>
<td>0.947</td>
<td>-32.8</td>
<td>0.119</td>
<td>0.977</td>
</tr>
</tbody>
</table>

Table 7.3b System B simulation results of channel estimator employing degree 0, 1 and 2 predictions for 5 and 8 eigenray channels.
Fig. 7.8 Combined estimator/detector employing pre-detection filter of system B channel.
Fig. 7.9 Variation of $\xi$ with 'b' in the estimator of system B channel with degree-1 prediction for 2 eigenray channel.
Fig. 7.10 Variation of $\xi$ with $\theta$ in the estimator of system B channel with degree-1 prediction for 2 eigenray channel.
Fig. 7.11 Variation of $\xi$ with different power applied at the receiver of system B channel with degree-1 prediction for 2 eigenray channel.
I. 

a) One-tap feedback filter

b) Two-tap feedforward filter

Fig. 7.12 One and two tap filters employed by pre-detection filter.
<table>
<thead>
<tr>
<th>One eigenray channel</th>
<th></th>
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</thead>
<tbody>
<tr>
<td><strong>SNR dB</strong></td>
<td><strong>ξ dB</strong></td>
</tr>
<tr>
<td>15</td>
<td>-9.16</td>
</tr>
<tr>
<td>30</td>
<td>-16.2</td>
</tr>
<tr>
<td>40</td>
<td>-20.2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Two eigenray channel</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SNR dB</strong></td>
<td><strong>ξ dB</strong></td>
</tr>
<tr>
<td>15</td>
<td>-11.19</td>
</tr>
<tr>
<td>30</td>
<td>-23.34</td>
</tr>
<tr>
<td>40</td>
<td>-26.19</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Three eigenray channel</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SNR dB</strong></td>
<td><strong>ξ dB</strong></td>
</tr>
<tr>
<td>15</td>
<td>-13.66</td>
</tr>
<tr>
<td>30</td>
<td>-21.14</td>
</tr>
<tr>
<td>40</td>
<td>-27.07</td>
</tr>
</tbody>
</table>

Table 7.4a Performance of the combined estimator/detector employed at the receiver of system B channel with degree-1 prediction for 1, 2, 3 eigenray channels.
Table 7.4b Performance of the combined estimator/detector employed at the receiver of system B channel with degree-1 prediction for 5 and 8 eigenray channels.
CHAPTER 8

CONCLUSIONS AND FURTHER INVESTIGATIONS

8.1 CONCLUSIONS

The initial stages of this project were an investigation of the nonlinearities affecting the transmission of digital data through water at a rate of 4800b/s. These include the depth and configuration of the bottom, the physical properties of the bottom material, the sound velocity profile with depth, the distribution and character of sound scatterers within the water, and the nature of the sea surface in both shallow and deep water and over short and long ranges. This survey suggested that the main causes of signal distortion were due to acoustic scattering, causing multipath propagation of the transmitted signal energy. These degradations were further studied by developing channel simulators in two baseband computer models. Adaptive equalisers were then studied to tackle the problem of intersymbol interference caused by multipath fading.

In summary, it was established that:

1. As sound propagates through water it encounters changes in temperature, density and salinity, as well as free bubbles and objects. In the order of seconds, there could be significant changes due to the underwater effect of surface waves and turbulence. These can then be superimposed on changes due to internal waves that could have been produced from a longer period, of minutes to hours, or even from seasonal changes.

2. Looking at the competing theories on the main causes of attenuation at the sea surface, it appears that surface waves are the predominant cause and to a lesser extent the effect of bubbles in the 10-20kHz band and fish at even lower frequencies. The existence of different sediments in different parts of the sea is probably the main causes of attenuation at sea bed, irrespective of the transmission frequency. The reflection and the material density and elasticity coefficients usually determine the allowable transmission bandwidth. Furthermore, the body of the sea itself is subject
to temperature and density variations, causing further attenuation loss. Thus, it is natural to treat the acoustic propagation as an unpredictable process which is studied by developing statistical models.

3. The propagation of sound in the sea can be described by three methods; these are the wave, ray and a mixture of wave and ray solutions. Differential equations and Huygen's principle can be utilized to establish the basis for the wave equation and ray tracing methods. The mixture of the first and second method, i.e. the third method, that is adopted in this thesis involves the adaptations of simplified quantitative models to the real ocean.

4. The signal-to-noise ratio is an ultimate measure of reliability trade off, but data rate is influenced by ambient noise of the sea which along with other noise sources is dominant below 20kHz and localised. Employing a high frequency of transmission is inconsistent with path losses which are due to absorption and geometrical spreading.

5. The Rice probability distribution function that defines the unsaturated propagation was implemented for stable processes (specular reflection) and is independent of the number of paths, i.e. at short ranges and low frequencies. As the range or frequency increases, saturation processes are observed from the envelope and the phase of the total received signal. This means that the phase can be characterized as a random variable uniformly distributed between 0 and 2π and was considered to obey a Rayleigh probability distribution function, especially for fully saturated channels (eigenrays).

6. The sea surface, volume and floor are major contributors of sound scattering in the sea and their characteristics are considered to follow that of a Rayleigh distribution model. Their effects on acoustic signals depend solely upon environmental circumstances. This confirms the unlikeliness of no reflections occurring since a perfectly calm surface (smooth) or plane sea floor (i.e reflection index of two media of unity) can be visualized. However, at the sea surface, gas bubbles produce large omnidirectional scatterers due to elasticity. In the ka>>1 domain, resonance can take place even by highly compressible bodies.

7. In shallow water, acoustic transmission is highly dependent upon the presence of high winds which can degrade the transmitted signal by up to 40dB, after which complete fading can occur, i.e. transmission blackout. The models constructed provide such fluctuations as well as considering the possibility of a component of the scattering or absorption coming from shallow layers of entrained bubbles.
8. The relative motion between the transmitter and the receiver or water motion can introduce Doppler spreading. The former Doppler shift can be compensated for if the relative motion is very slow but for the latter case continuous spreading occurs by random motion due to physical properties of the water media itself.

9. Depending upon the frequency of the transmitting projector or the hydrophone, the spectrum of the attenuated signal can be estimated. At any desired frequency, as the distance between the source and receiver increases, the total spectrum associated with the physical properties of water media broadens, i.e. encountering further random processes.

10. The overall models (systems A and B) are capable of representing the underwater channels according to the frequency spread produced by the observed degradations of the received signal spectrum. The number of symbols in fade are independent of the rate of transmission. Fading depths of up to 70dB [13] can occur for extreme sea conditions, i.e. 10Hz frequency spread. Furthermore, the channel of system B when developed for a given number of paths, can well operate for fewer.

11. Transmitters and receivers here are assumed to consist of a single large transducer, hydrophone and array of smaller hydrophones (for adaptively aligning transmitter and receiver for continuous line of sight contact). The directivity index and power requirements are the main parameters that determine the design of the underwater modem, which can be implemented with a microprocessor system. The advancement of VLSI CMOS technology now allows very low-power implementations of the electronics and thus virtually all the power employed by the receiver/transmitter are required by the power amplifiers. Unfortunately, the low efficiencies of wideband low-Q transducers allow a lot of power to be consumed by these amplifiers.

12. For faithful reproduction of the transmitted signal at the receiver, there is a limit to the speed of the source or the receiver, even for high transmitted powers. The Doppler spread caused by movement of the source or receiver leads to severe and rapid amplitude fluctuations (fades) across the bandwidth of the transmitted signal, resulting in the collapse of even the most sophisticated detection scheme. The received signal also exhibits severe phase distortions. After a deep fade, differential coding is found essential to correct the phase ambiguities of ±90° that often occur in both systems.
13. For the construction of both system’s baseband channels, the transmitter and receiver filters developed here were first tested over a non-fading channels and later, when tested over the fading channel models, small increases in amplitude and phase fluctuations were observed, i.e. the equipment filters do not cause any further degradation of the transmitted signals.

14. In constructing the baseband channel of system A, an efficient use of bandwidth was achieved by employing the quaternary signalling with a raised cosine spectrum, where for a given information rate and transmitted signal power, up to 4dB reduction in noise was achieved over the binary polar signals. In the system B baseband model (long range channel), equipment filters with partial response spectrum were employed to allow lower power requirements i.e. further reduction in bandwidth. The degradations produced here were then cancelled by employing adaptive detectors.

15. In the receiver of system B, it was found that as the number of eigenrays reaching the receiver increased, the number of sampled impulse responses of the baseband channel also increased. This increase in the number of sampled impulse responses enforced the use of longer computer processing time. This increase also caused the operation of the receiver to be slower i.e. employment of further adaptive adjustment.

16. At the receiver, equalizers were employed to fulfil the process of channel inversion and adaptive adjustment. Tests with both channels indicated that a considerably better tolerance to noise can be achieved over that of a conventional equalizer by appropriately adjusting the received samples where the samples delivered to the detector have peaks that occur at precise locations, i.e. minimum phased. This process can further reduce the complexity of a simple near-maximum likelihood detector.

17. Further equalization (estimators with different degrees of prediction) were employed to track the variations in the received sampled impulses of both channels. With system A, further degrees of predictions resulted in better estimation of the channel’s sampled impulse response. The results of the tests indicated that system B performed best with the employment of only the first degree of prediction but the receiver here employed further adaptive adjustment.
8.2 SUGGESTIONS FOR FURTHER INVESTIGATION

8.2.1 HARDWARE IMPLEMENTATION

The signal processing involved throughout this work can be performed in block by block structured programming in software as presented in Appendix G. The digital modems for both baseband channels can be built in hardware with existing signal processors such as the TMS320 and INMOS transputers device families [129,130]. The powerful instructions such as MACD in the TMS320-C25 can be of great use in the operation of shift multiply-and-add employed throughout the algorithms.

Consider Fig. 8.1 DSP1 can generate and differentially encode the four level QPSK at 2400 symbols per second including 400 symbols for training (200 symbols for every half second) on a 20kHz carrier. The shaping filter (raised cosine for system A and cosine partial response for system B) and modulation is performed by DSP2. The digital modulated signal is then converted into analogue form and the low pass filter (Butterworth of four or six pole) then removes the spurious harmonics. The delay Doppler and Bessel filtering, Hilbert transform (feedforward transversal filter), Rayleigh fading with specular reflection and White Gaussian noise are then processed by DSP3, DSP4, DSP5 and DSP6 respectively. DSP7 then identifies and removes the phase changes in the carrier as shown in Fig. 8.2. The function of DSP8 will be then to demodulate the incoming signal at the given carrier with the same shaping filter employed in the modulator section. The real and complex channel impulse responses are now identified by the receiver to perform complex detection schemes. The detector/adaptive adjustment/estimation sections employs at least four further DSPs (Fig. 8.1) and a memory card. The capacity of the storage card depends on the number of vectors utilized by the near-maximum likelihood detector.

When frame by frame transmission is performed, the use of FIFO (First In First Out) buffers the receiver modem and can give rise to even better performance of the modem. Here the complete set of samples in any one frame is processed by the receiver while the modem is filling up the second buffer; as soon as the receiver sends out the complete frame to the detector/estimator section switches to operate on the second buffer. This is now completely filled up, with the first frame filling up the newly arrived samples; the process is continued in this way for all transmitted signal elements.
This buffer can provide delays required by the various sub-systems of the receiver, such as the adaptive filter ahead of the detector. This enables the channel estimator to perform its function by a delay of n samples relative to those fed to the filter. A further advantage of utilizing such a system is to use the full computing powers of a digital signal processor in the receiver.

Depending upon the actual symbol error rate, signal-to-noise ratio and levels of other signal impairments introduced by the proposed underwater channels, the use of concurrent programming may save a considerable number of operations in a practical system. It is unlikely that a single processor will be powerful enough (or fast enough) to perform both detection and estimation and so a separate processor operating in parallel to the detector would probably be necessary. However, as the parallel processor may well be able to perform other functions, such as the control of the carrier phase tracking loop, this implies that any operation saving techniques will be worth considering when attempting to implement a practical modem.

8.2.2 FURTHER SIMULATIONS

Further investigations must be concentrated on an advancement of estimation techniques in tracking the rapid amplitude variations observed in both system's channels. Research to find a better updating of the estimator’s algorithm is probably a good start. The tests carried out (Chapter 7) suggested that precisely predicted values of the parameters 'b' and 'θ' at a given receiver power were always necessary in establishing a good estimate of the sampled impulse responses of the channels. This problem forces the system user to have a look-up table for the two parameters for a viable estimator in the communication link.

It would also be worth exploring better coding schemes that can respond to changes in variations of amplitude of the sampled impulse response of the channels. Block coding schemes and the introduction of training sequences into the transmitted data signals should introduce significant changes into the detector’s performances while employing channel estimators working at a given receiver power. Employing the same power at the receiver, when transmitting frame by frame with training sequences, also allows much longer transmission time; this is a drawback because of limited computer processing time and storage capacity.
Since the systems under analysis utilized QPSK signalling with coherent demodulation and also operated at close to the Nyquist sampling rate, neither the timing (sampling) phase nor the phase of the reference carriers in the coherent demodulator should have a significant effect on the system performance. Hence, a great reduction in the complexity of the retraining process becomes possible and relatively simple algorithms can be employed for the frequency control of both carrier and timing phase when the hardware system is constructed.
Fig. 8.1 Structure of an underwater modem.
Fig. 8.2 Element timing synchronization diagram.
The transformation of electrical signal into sound waves suitable for underwater communication is done by electrostrictive transducers. These devices are made from materials which have a good impedance match to water. Such devices convert electrical energy into the mechanical energy, or vice versa, and are usually referred to as solid state generators (or detectors) of acoustic radiation. The transducer at the transmitting end that converts electrical energy into sound waves is known as a projector and the transducer at the receiving end which converts the sound waves into an electrical signal is called a hydrophone.

The electrostrictive transducers such as lead zirconate titanate and barium titanate are polycrystalline ceramics which are widely used nowadays. They produce stress when a voltage is applied across them and, conversely, they acquire a charge between their faces when subjected to pressure [4,11].

Permanent polarization of these materials can be obtained by cooling from above its Curie point in a strong electric field (up to 20 kV cm\(^{-1}\)). They possess the advantage of being easily cast into any shape and can be polarized with any given field configuration. The advent of titanate materials in composite form with steel can lead to a design of low Q (quality factor) transducers, thus providing high speed data transmission through underwater sound channels.

For the carrier frequency of 20 kHz considered in this thesis, it is assumed that $Q = 4$ (considering a well designed transducer) so that each cycle of the carrier has a duration of 50 $\mu$s, then a transmission of 5000 b/s can be achieved. This implies that a lower value of Q could lead to a higher transmission rate with the same carrier frequency.
APPENDIX B

B1 DISTRIBUTION OF SINUSOIDAL-WAVE PLUS NOISE (RICE)

Consider a steady sinusoidal source as a current described by

\[ I_p(t) = P \cos(\omega_p t - \phi_p) \]  \hspace{1cm} \ldots B1.1

The corresponding values of current can be noted at times \( t_1, t_2, \ldots \). Picking times at random in Eqn. B1.1 is the same, statistically, as holding \( t \) constant and picking the phase angles \( \phi_p \) at random over the range 0 to 2\( \pi \).

A noise component \( I_N \) represented by its in phase component \( I_c \) and quadrature component \( I_s \) as

\[ I_N = I_c + I_s \]  \hspace{1cm} \ldots B1.2

is now added to \( I_p \), to give

\[ I(t) = P \cos pt + I_N \]  \hspace{1cm} \ldots B1.3

where \( \omega_p \) is replaced by \( p \) and \( \phi_p = 0 \).

The components \( I_c \) and \( I_s \) of \( I_N \) can be conveniently described in series form so that

\[ I(t) = P \cos(\omega_p t - \phi_p) + \sum_{n=1}^{N} c_n \cos(\omega_n t - \phi_n) \]  \hspace{1cm} \ldots B1.4

where \( c_n^2 = 2\omega(f_n)\Delta f \) and \( \phi_p \) as well as \( \phi_1, \phi_2, \ldots, \phi_M \) are independent random angles.

Thus the envelope \( R \) can be now defined as

\[ R = (I_c + P)^2 + I_s^2 \]  \hspace{1cm} \ldots B1.5
This implies that the noise current flowing in the output of a relatively narrow bandpass filter has the character of a sine-wave of roughly the midband frequency whose amplitude is regular. The rapidity of fluctuation is of the order of the chosen bandwidth.

\[ I_N = I_c \cos pt - I_s \sin pt \]  ...B 1.6

and

\[ \overline{I_N^2} = \overline{I_c^2} = \overline{I_s^2} = \psi_0 \]  ...B 1.7

where \( \psi_0 \) is the average total power and is given by

\[ \psi_0 = \int \omega(f)df \]  ...B 1.8

Now since \( I_c \) and \( I_s \) are distributed normally about zero with variance \( \psi_0 \), the probability densities of the variables, \( x = p + I_c \) and \( y = I_s \), are

\[ (2\pi\psi_0)^{-\frac{1}{2}} e^{-\frac{x^2 - y^2}{2\psi_0}} \]  ...B 1.9

and

\[ (2\pi\psi_0)^{-\frac{1}{2}} e^{-\frac{y^2}{2\psi_0}} \]  ...B 1.10

Using these distributions it can be shown that the probability of a point (x,y) lying in the ring (envelope) \( R, R+dR \) is

\[ \frac{RdR}{2\pi\psi_0} \int_0^{2\pi} e^{-\frac{1}{2\psi_0}(R^2 + r^2 - 2RR\cos\theta)} d\theta \]

\[ = \frac{RdR}{\psi_0} e^{-\frac{1}{2\psi_0}\frac{r^2 + r^2}{2}} J_0\left(\frac{RP}{\psi_0}\right) \]  ...B 1.11

where \( J_0 \) is the zero order Bessel function with imaginary argument given by

\[ J_0(z) = \sum_{n=0}^{\infty} \frac{z^{2n}}{2^n n! n!} \]  ...B 1.12
assuming

\[ r = \frac{R}{\psi_0} \]

\[ dr = \frac{dR}{\psi_0} \]

and

\[ q = \frac{p}{\psi_0} \]

Instead of the random variable \( R \) we have now the random variable \( r \) whose probability density is;

\[ p(r) = re^{-\frac{r^2}{2}} \int_0^r f_0(rq) \]

Fig. 3.9 shows a family of distribution curves originally drawn by Rice. His curves indicated Rayleigh distribution for \( q=0 \) approaching a sensible Gaussian distribution for \( q=5 \), except for \( r \ll 1 \) [4,13-15].

**B2. PSEUDORANDOM NUMBERS (SEED INTEGERS GENERATION)**

The generation of pseudorandom numbers was first suggested by Lehmer in 1951 by a recurrence relation

\[ x_i = ax_{i-1} \mod (m - m) \]

The notation signifies that \( x_i \) is the remainder when \( ax_{i-1} \) is divided by \( m \). This can be subsequently generalised by

\[ x_i = ax_{i-1} + c \mod (m - m) \]

\[ x_{i+1} = ax_i + c \mod (m - m) \]

. . . .

. . . .
where \( m \) is a large integer determined by the actual design of the digital computer (usually a large power of 2 or 10) and \( a, c, x_i \) are integers between 0 and \( m-1 \).

The numbers \( \frac{x_i}{m} \) are then used as the pseudorandom sequence. The two sets of Eqns. B2.1 and B2.2 are called the congruential methods of generating pseudorandom numbers, in particular Eqn. B2.1 is a multiplicative congruential method.

Clearly, such a sequence will repeat itself after at most \( m \) steps and is periodic if for instance, \( m=16, a=3 \) and \( c=1 \); then with \( x_0 \) the sequence of \( x \) are generated as 2,7,6,3,10,15,... with a period of 8, meaning that a 1 is added to the remainder for the ones that are divisible, but for the undivisible ones a 1 is added before division. One must always ensure that the period is longer than the number of random numbers required in any single experiment. The value of \( m \) is usually long enough to permit this.

In order to understand the shuffling phenomenon used in our channel simulations to produce random generators \( v_x(t) \) and the data \( s_c(t) \) the above congruential method was used with \( x=2^{13}+1 \).

The routine uses the multiplicative congruential method with

\[
x_i = 13^{13} x_{i-1}, \text{modulo } 2^{59}
\]

This routine returns to a pseudorandom real number taken from a uniformly distributed value between 0 to 1 [101].
A single multipath propagated channel is modelled as in Fig. 4.2. Each low-pass filter should have a Gaussian frequency response matching the power spectra of the Gaussian variable \( V_i(t) \). The theoretical power spectra of \( V_1(f) \) and \( V_2(f) \) given in Eqn. 4.4.2 are plotted in Fig. 4.5. The frequency response of the filter is given by

\[
F(f) = \exp\left(-\frac{f^2}{4f_{nc}^2}\right)
\]

and the 3dB cut-off frequency of the filter is

\[
f_{nc} = 1.17741 \ f_{ns}
\]

Thus from Eqn. 4.4.4 and C2

\[
f_{nc} = 0.588705 \ f_{rs}
\]

It has been found that the impulse-response and the magnitude-response of a Bessel filter tends towards Gaussian as the order of the filter is increased [99]. A Bessel filter has therefore, been used to obtain the necessary requirements in the design of the variable low-pass filters in the hardware simulation of single multipath faded channels [Fig. 4.6].

If \( B_n(s) \) is the \( n^{th} \)-order Bessel Polynomial, then the Bessel filters have transfer function of the form

\[
H(s) = \frac{d_0}{B_n(s)}
\]

where \( d_0 \) is a normalising constant is given by

\[
d_0 = \frac{(2n)!}{2^n n!}
\]

and \( B_n(s) \) can be presented as
\[ B_n(s) = \sum_{k=0}^{n} d_k s^k \]  

where

\[ d_k = \frac{(2n-k)!}{2^{n-k} k! (n-k)!} \]  

for \( k=0,1,2,\ldots,n \)

When \( n=5 \), one observes a 5th order Bessel filter as a practical choice since the frequency response of this filter can be compared with that of the desired theoretical frequency response (Gaussian) shown in Fig. 4.5, at least in the range of interest.

Eqn. C4 now becomes of the form

\[ H(s) = \frac{945}{s^5 + 15s^4 + 105s^3 + 420s^2 + 945s + 945} \]  

Alternatively,

\[ H(s) = \frac{945}{\prod_{i=1}^{5} (s - P_i)} \]  

\( P_i \) are the poles [99] of \( H(s) \) in the s-plane and are given by

\[ P_1 = -3.64674 \]
\[ P_2, P_3 = -3.35196 \pm j1.74266 \]
\[ P_4, P_5 = -2.32467 \pm j3.57102 \]  

where \( s = j\Omega \) in Eqn. C9, the frequency response of the Bessel filter is

\[ H(j\Omega) = \frac{945}{\prod_{i=1}^{5} (j\Omega - P_i)} \]  

where \( j = \sqrt{-1} \) and \( \Omega \) is the angular frequency. \( \Omega = \Omega_{\infty} \text{ rad/sec} \) when the amplitude response of the fifth order Bessel filter drops by 3dB from its peak value and is given by

\[ \Omega_{\infty} = 2.4274 \text{ rad/sec} \]  

\[ \ldots \text{C12} \]
The frequency spread, $f_{sp}$, that was explained in section 4.4 is an important parameter in the characterization of the channel and it is desirable to express the cut-off frequency of the Bessel filter in terms of this parameter. Let

$$\omega = C_8 \Omega \quad \text{...C13}$$

where

$$C_8 = \frac{\omega_{co}}{\Omega_{co}} = \frac{2\pi f_{co}}{\Omega_{co}} \quad \text{...C14}$$

and $f_{co}$ is the cut-off frequency of the required filter. From Eqns. C12 and C14

$$C_8 = 2.58844 f_{co} \quad \text{...C15}$$

Substituting the value of $\omega$, from Eqn. C13 into C11 gives

$$H(j\Omega) = \frac{945}{\prod_{i=1}^{s-1} \left( j \Omega - P_i \right)} \quad \text{...C16}$$

Let

$$P'_i = C_8 P_i \quad \text{...C17}$$

then from Eqns. C16 and C17

$$H(j\Omega) = \frac{945 C_8^s}{\prod_{i=1}^{s-1} \left( j \Omega - P'_i \right)} \quad \text{...C18}$$

and from Eqns. C15 and C18

$$H(j\omega) = \frac{109805.518 f_{co}^5}{\prod_{i=1}^{s-1} (j \omega - P'_i)} = \frac{d'_0}{\prod_{i=1}^{s-1} (s - P'_i)} \quad \text{...C19}$$

where
\[ s = j\omega \]
\[ d_0' = 109805.0518 \cdot f_{\text{co}} \]  \( \ldots \text{C20} \)

and

\[ P_i' = 2.58844 \cdot f_{\text{co}} P_i \]  \( \ldots \text{C21} \)

for \( i = 1, 2, 3, \ldots, 5 \)

The transfer function represented by Eqn. C19 is the fifth order Bessel filter. This analog filter is digitized for use in computer-simulation. The method used for this is called the impulse-invariant transformation method [99]. The impulse-response of the resulting digital filter is a sampled version of the impulse-response of the analog filter. In this technique the poles \( \{ P_i \} \) in the \( s \)-plane of Eqn. C19 are transformed to the equivalent poles at \( \{ e^{P_i' T} \} \) in the \( z \)-plane, with \( T \) as the sampling interval.

Thus, using the impulse-invariant transformation method, Eqn. C19 can be written as

\[ H(z) = \frac{K}{\prod_{i=1}^{5} (1 - e^{P_i' T} z^{-1})} \]

\[ = \frac{K}{\prod_{i=1}^{5} (1 - \nu_i z^{-1})} \]  \( \ldots \text{C22} \)

\( K \) is the DC gain of the filter and \( \nu_i \) are the poles and are equal to

\[ \nu_i = e^{P_i' T} \]  \( \ldots \text{C23} \)

\( \nu_i(t) \) contain all the frequency components that are present in Gaussian spectra. However, for a small frequency spread, the 3dB bandwidth of the analog filter is also small. Therefore, frequency components above about 25Hz have negligibly small amplitude as can be seen from Eqn. 4.4.6. Therefore, an adequate sampling rate is necessary to obtain accurate measurements of \( \nu_i(t) \).

The digital filter was implemented as shown in the Fig. 4.6. It consists of a cascade of two 2-pole section and a single pole section. Each of the two-pole sections has complex conjugate poles and the single-pole section has a real pole. The transfer function of the filter of Fig. 4.6 is thus
\[ H(z) = \frac{K}{(1 - v_1 z^{-1})((1 - v_2 z^{-1})(1 - v_3 z^{-1}))((1 - v_4 z^{-1})(1 - v_5 z^{-1}))} \]

\[ = \frac{K}{(1 - v_1 z^{-1})(1 - (v_2 + v_3)z^{-1} + (v_2 v_3)z^{-2})(1 - (v_4 + v_5)z^{-1} + (v_4 v_5)z^{-2})} \]

...C24

Hence, from the Fig. 4.6 and Eqn. C24, the filter co-efficients \( \{c_i\} \) are given by,

\[ C_1 = -v_1 \]
\[ C_2 = -(v_2 + v_3) \]
\[ C_3 = v_2 v_3 \]
\[ C_4 = -(v_4 + v_5) \]
\[ C_5 = v_4 v_5 \]

...C25

Fig. 4.7 show the impulse response and Fig. 4.8 the power response of the Bessel filter.

The values of the Bessel filter coefficients \( C_1 \) to \( C_5 \) for a frequency spread of 1Hz at 50 samples/second is given in Table Cl. The value of K, the gain of the filter in Eqn. C24, is chosen such that the \( \{v_i(t)\} \) have a variance corresponding to \( \frac{1}{2\gamma} \), where \( \gamma \) represents the number of diffused components or eigenrays. This ensures that the mean length of the channel sampled impulse response vector is unity. The value of \( K \) can be determined by the energy in the waveform \( H(t) \) in Eqn. C19

\[ E_a = \int H(t)^2 \, dt \]

...C26

The energy \( E_a \) in the waveform is normalised by the scalar \( K \) [Table C1]. However, a simpler method is to pass a sequence of digital data whose first element is a 1 and the rest of the elements are zero through the 5 pole digital filter [Fig. C1 and C2]. For a sufficiently long sequence, the sum of the squares of the output of the digital filter, \( E_{sum} \), is very close to \( E_a \), particularly since the sampling frequency of the filter is considerably larger than the filter bandwidth.
<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
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<tbody>
<tr>
<td>Order of the filter, L</td>
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</tr>
<tr>
<td>Sampling frequency (Hz)</td>
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<tr>
<td>Frequency spread, $f_p$</td>
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<tr>
<td>Value of K</td>
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</tr>
<tr>
<td>Cutoff frequency, $f_c$</td>
<td>1.1774</td>
</tr>
<tr>
<td>Filter poles in the s-plane</td>
<td>$p_1' = -3.64674 + j0$</td>
</tr>
<tr>
<td></td>
<td>$p_2', p_3' = -3.35196 \pm j1.74266$</td>
</tr>
<tr>
<td></td>
<td>$p_4', p_5' = -2.32467 \pm j1.74266$</td>
</tr>
<tr>
<td>Unit circle roots</td>
<td></td>
</tr>
<tr>
<td>$P_0$</td>
<td>0.89481307 ± j0</td>
</tr>
<tr>
<td>$P_1, P_2$</td>
<td>0.90161486 ± j0.04793039</td>
</tr>
<tr>
<td>$P_3, P_4$</td>
<td>0.92609144 ± j0.10118887</td>
</tr>
<tr>
<td>Filter coefficients</td>
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<td>$C_1$</td>
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</tr>
<tr>
<td>$C_2, C_3$</td>
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</tr>
<tr>
<td>$C_4, C_5$</td>
<td>0.8678845, -0.8948130</td>
</tr>
</tbody>
</table>

**Table C1** Characteristics of fifth order Bessel filter.
Throughout this thesis, an equivalent baseband system has been employed to describe underwater channels that are in reality in the form of passband. A full description of baseband modelling was given in Chapter 5, and now the validity of such a system is explored in more detail. This objective is investigated here by first presenting a general form of a passband signal which is given as:

\[ M(t) = A(t) \cos(\omega_c t + \theta(t)) \]  \( \text{...D1} \)

where \( A(t) \) is the amplitude and \( \theta(t) \) the phase of the modulating waveform. If amplitude modulation is requested (as in the case considered in this thesis), \( \theta(t) \) is either zero or a constant value and the parameter \( \omega_c = 2\pi f_c \), where \( f_c \) is the frequency of the desired carrier around which the spectrum of \( M(t) \) can be centred. In order to determine the quadrature components of \( M(t) \) this function is expanded as:

\[ M(t) = A(t) \cos(\theta(t)) \cos(2\pi f_c t) - A(t) \sin(\theta(t)) \sin(2\pi f_c t) \]  \( \text{...D2} \)

and

\[ M(t) = x(t) \cos(2\pi f_c t) - y(t) \sin(2\pi f_c t) \]  \( \text{...D3} \)

where \( x(t) = A(t) \cos(\theta(t)) \) and \( y(t) = A(t) \sin(\theta(t)) \). This implies that \( x(t) \) and \( y(t) \) are the quadrature components of \( M(t) \) since both are related in phase and both represent the low frequency components of \( M(t) \).

Therefore, in the case of amplitude modulation \( x(t) = J A(t) \) and \( y(t) = K A(t) \) where \( J \) and \( K \) are both constants and the signal \( A(t) \) is the baseband signal that is carried by \( M(t) \).

To express this phenomenon in a baseband form given in Eqn. 5.1.1, \( M(t) \) is written in its exponential form and Fourier Analysis is performed to obtain its spectrum as follow:

\[ M(t) = \Re \left[ s(t)e^{2\pi if_c t} \right] \]  \( \text{...D4} \)

where
\[ s(t) = x(t) + jy(t) \]  ...

and its Fourier Transform is

\[ \mathcal{Q}(f) = \int M(t) e^{-2\pi j ft} \, dt \]  ...

Replacing Eqn. D4 into D6 leads to

\[ \mathcal{Q}(f) = \int \mathfrak{R}[s(t)e^{2\pi j ft}] e^{-2\pi j ft} \, dt \]  ...

But

\[ \mathfrak{R}[s(t)] = \frac{1}{2} [s(t) + s^*(t)] \]  ...

and

\[ \mathfrak{R}[s(t)e^{2\pi j ft}] = \frac{1}{2} [s(t)e^{2\pi j ft} + s^*(t)e^{-2\pi j ft}] \]  ...

then Eqn. D7 can be written as

\[ \mathcal{Q}(f) = \frac{1}{2} \left[ \int s(t)e^{2\pi j ft} e^{-2\pi j ft} \, dt \right. \]

\[ + \left. \int s^*(t)e^{-2\pi j ft} e^{-2\pi j ft} \, dt \right] \]  ...

i.e.,

\[ \mathcal{Q}(f) = \frac{1}{2} [S(f-f_s) + S^*(-f-f_s)] \]  ...

where \( S(f) \) here is the Fourier Transform of \( s(t) \) and its complex conjugate is expressed by * . The signal \( s(t) \) can be now called the baseband signal since its spectrum is at low frequency and is situated around \( f=0 \).

Now in order to represent a linear baseband channel having impulse response \( h(t) \) with its transfer function \( H(f) \), a function \( C(f-f_s) \) is defined as \( H(f) \) for \( f>0 \) and to be equal to zero for \( f<0 \) then its complex conjugate pair \( C^*(f-f_s) \) now defines \( H^*(-f) \) for \( f<0 \) and is equal to zero for \( f>0 \). Then for a real value impulse response we have
Thus, in the frequency domain
\[ H(f) = C(f - f_c) + C^*(-f - f_c) \] ...D13
and since
\[ h(t) = \int H(f)e^{2\pi if} df \]
\[ = c(t)e^{2\pi if} + c^*(t)e^{-2\pi if} \] ...D14
and so in the time domain
\[ h(t) = 2\Re[c(t)e^{2\pi if}] \] ...D15
Here, c(t) now represents the equivalent (complex) impulse response that can be referred to baseband.

Now that Fourier analysis lead to the representation of both bandpass signal and system by baseband, it is now required to show that the response of a bandpass signal can be determined from knowledge of the baseband input signal and thus the equivalent baseband impulse response. This is obtained as follows.

Assume that p(t) is the output of the bandpass system with the baseband equivalent given by r(t), so that
\[ p(t) = \Re[r(t)e^{2\pi if}] \] ...D16
But p(t) is also related to the input signal q(t) and that of the impulse response of the system, i.e. by h(t), by the convolution integral
\[ p(t) = \int q(\tau)h(t - \tau)d(\tau) \] ...D17
In frequency domain it is represented as
\[ P(f) = Q(f)H(f) \] ...D18
Now substituting for Q(f) from Eqn. D11, and for H(f) from Eqn. D13 into D18, then we get
\[ P(f) = \frac{1}{2} \left[ S(f - f_c) + S^*(-f - f_c) \right] \left[ C(f - f_c) + C^*(-f - f_c) \right] \]

...D19

Since all the signals and systems under investigation throughout the thesis have the baseband equivalent bandwidth of less than the carrier frequency, then \( S(f - f_c) = C(f - f_c) = 0 \), for \( f < 0 \). This simplifies Eqn. D19 as

\[ P(f) = \frac{1}{2} \left[ S(f - f_c) \cdot C(f - f_c) + S^*(-f - f_c) \cdot C^*(-f - f_c) \right] \]

\[ = \frac{1}{2} \left[ R(f - f_c) + R^*(-f - f_c) \right] \]

...D20

where \( R(f) = S(f) \cdot C(f) \) i.e,

\[ r(t) = \int s(\tau)c(t - \tau)d(\tau) \]

...D21

Therefore, the equivalent baseband output signal from the bandpass channel is represented by the convolution of the baseband input signal and the equivalent baseband impulse response of the bandpass channel [1,100,104].
APPENDIX E

DIFFERENTIAL ENCODING AND DECODING

As indicated in Fig. 5.1, the information to be transmitted is a sequence of binary digits \( \{\alpha_i\} \), they are statistically independent and equally likely to have either of the values

\[
\{\alpha_i\} = 0 \quad \& \quad 1
\]  \( \text{...E.1} \)

\( \{\alpha_i\} \) values are then fed to a differential encoder. The existence of the differential encoder and decoder in the system is for the following reason.

During the deep fade caused by the transmission path, large and rapid changes are experienced by the carrier. These changes could result in a subsequent phase shift of a multiple of 90° in each of the complex valued received signal samples, i.e. resulting in a string of errors in the detected data symbol values which would continue until the end of the transmitted message even in the absence of noise. The differential coding can prevent these prolonged and serious error extension effects by coding the difference in phase between two consecutive symbol values, where the transmitted signal now represents a phase rotation.

In the encoding process, the transmitted stream of binary digits \( \{\alpha_i\} \) is first divided successively into groups of two. The two binary digits in the \( i^{th} \) group are represented by \( \alpha_{0,i} \) and \( \alpha_{1,i} \) as shown in Fig. E1. These binary digits are next encoded into the two binary digits \( \beta_{0,i} \) and \( \beta_{1,i} \) then to \( \beta_{0,i-1} \) and \( \beta_{1,i-1} \) according to the Table E1. Then, \( \beta_{0,i} \) and \( \beta_{1,i} \) are recoded into the complex valued \( s_i \) according to Table E3 as illustrated in Fig. E2, where \( s_i \) is presented as \( s_{0,i} + js_{1,i} \).

The decoding process is performed in reverse to encoding in order to obtain the correct value of the \( \{\alpha_i\} \) by the decoder shown in Fig. 5.1. This process is illustrated in Fig. E2, the detected binary digits \( \beta_{0,i}^* \) and \( \beta_{1,i}^* \) are first determined from the detected data symbol values \( \{s_i\} \), according to the relationships given in Table E3 and Fig.
The difference is that the values used now are the corresponding detected values $\beta_{i,2}$ and $\beta_{i,1}$, which are used in the detector along with $\beta'_{0,i-1}$ and $\beta'_{1,i-1}$, to give the detected values of $\alpha_{o,i}$ and $\alpha_{i,i}$, namely $\alpha'_{o,i}$ and $\alpha'_{i,i}$ according to Table E2.

Table E1 and Fig. E2 indicate that the signal corresponding to the group of digits $\alpha_{o,i}$ and $\alpha_{i,i}$ represents the difference in phase between the two signals corresponding to the two groups of digits $\beta_{0,i}$ $\beta_{1,i}$ and $\beta_{0,i-1}$ $\beta_{1,i-1}$. Indeed, the phase of the signal corresponding to $\beta_{0,i}$ $\beta_{1,i}$ is equal to the sum of the two phases corresponding to $\alpha_{o,i}$ $\alpha_{i,i}$ and $\beta_{0,i-1}$ $\beta_{1,i-1}$. Therefore, when the two groups of digits $\alpha_{o,i}$ $\alpha_{i,i}$ and $\beta_{0,i-1}$ $\beta_{1,i-1}$ are given, the group of digits $\beta_{0,i}$ $\beta_{1,i}$ can readily be determined. Furthermore, the detected binary digits $\beta_{i}$ no longer contain any prolonged error burst of the received signal effected by multiple phase shifts of 90°, since the transmitted binary digits are now symbolised by the phase differences. It should be also noted here that, in addition to differential coding, the coding must be as near as possible to Gray coding, such that the adjacent values of $s_{i}$ would differ in only one digit [Fig. E3]. This reduces further the probability of error in the detected data symbols [104,107].
Differential Encoding (QAM)   Differential Decoding (QAM)

Table E1

<table>
<thead>
<tr>
<th>$\beta_{i-1}$</th>
<th>$\alpha_i$</th>
<th>$\beta_i$</th>
<th>$\beta_{i-1}'$</th>
<th>$\beta_i'$</th>
<th>$\alpha_i'$</th>
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<td>$\alpha_{1,i}$</td>
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</table>
Encoding relationship

Table E3

<table>
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<tr>
<th>$\beta_{0,i}$</th>
<th>$\beta_{1,i}$</th>
<th>$s_i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>1+j1</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>-1+j1</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1-j1</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>-1-j1</td>
</tr>
</tbody>
</table>

Divide into two groups.

Fig. E1 The process of differential encoding
Imaginary part

Real part

Fig. E2 Table E3 mapping relationships.

Fig. E3 The process of differential decoding.
APPENDIX F

ADAPTIVE ADJUSTMENT OF LINEAR TRANSVERSAL FILTER

The following standard algorithm determines the roots of the z-transform of the channel transfer function, and evaluates $D(z)$ and $F(z)$. The algorithm is first presented for time invariant channels and then modified for time varying underwater baseband channels. The pre-filter, is considered to operate on the actual sampled impulse response of the channels rather than the estimate (or prediction) of the channel's sampled impulse response.

In this technique the receiver first forms a filter with a z-transform

$$A_i(z) = (1 + \lambda_i z^{-1})$$

for $i=0,1,2,...,k$ in turn, using an iterative process to adjust $\lambda_i$ so that as $i$ increases, $\lambda_i$ tends towards $\beta_i$, i.e. $\lambda_i \to \beta_i$. $\beta_i$ is now taken as the negative reciprocal of the first root to be processed by the system and $|\beta_i| < 1$. Since the filter with the z-transform $A_i(z)$ does not operate on the received signal in real time (as will be explained here later), its z-transform is not limited to zero and negative powers of $z$. At the end of the iterative process, the z-transform of the filter is given by

$$A_k(z) \sim (1 + \beta_1 z^{-1})$$

The receiver then forms a filter with the z-transform

$$C_1(z) = (1 + \lambda_2 z^{-1}) (1 + \lambda_3 z^{-1})$$

$$\sim (1 + \beta_1 z^{-1}) (1 + \beta_2 z^{-1})$$

The operation is now fully carried out for $\beta_k$ ($h=1,2,3,...,m$) to obtain a total of $m$ filters with z-transforms $\{C_h(z)\}$. The $m$ filters are then connected in cascade with an added delay of $(n-m)$ sampling intervals. The $m$ filters and the associated delay are, in fact, implemented as a single filter whose z-transform now approximates to $D(z)$ in Eqn. 6.2.13 in Chap 6.
The following algorithm now aims to calculate $D(z)$ and $F(z)$ required in Section 6.2 given by Eqn. 6.2.13-6.2.15.

The sequence of $Y$ is first stored by the receiver with an estimate of $\lambda_i$ given the quantity $\beta_1$. The first estimate of $\beta_1$ at the start of the operation is one of a number of different starting points. The value of these starting points changes according to the types of channels involved, i.e. time invariant or otherwise.

Once the value of $\lambda_i$ has been determined the receiver appropriately adjusts the one-tap feedback transversal filter shown in Fig. 7.12a. The stored sequence of $Y$ is now reversed in order, so that it starts with the last component $y_G$, i.e. the sequence $Y$ is now taken to be moving backwards in time starting with the component $y_0$ at time $t=0$. The delay of one sampling interval, $T$, in the feedback filter, now becomes an advance of $T$ with $z$-transform $z$. This implies that the effective $z$-transform of the feedback filter becomes $A_i(z)$ with an output sequence $\{e_i\}$. The $(g+1)$ components $e_i, e_{i+1}, e_{i+2}, \ldots, e_{i+g}$ are then generated. This is used to improve the estimate of $\beta_1$ given by

$$\lambda_{i+1} = \lambda_i + \frac{ce_i}{e_i} \quad \ldots F4$$

where $c$ is a constant in the range of 0 to 1 and

$$e_i = e_{i,1} - e_{i,2} \lambda_i + e_{i,3} \lambda_i^2 - \ldots + e_{i,g} (-\lambda_i)^{(g-1)} \quad \ldots F5$$

Eqn. F5 now presents a new one-tap feedback transversal filter with $\lambda_i$ replaced by $\lambda_{i+1}$. The effective $z$-transform of this filter, now operating on the sequence $Y$ in reverse order, is

$$A_{i+1}(z) = (1 + \lambda_{i+1}z)^{-1} \quad \ldots F6$$

with $e_{i+1,k}$ as the coefficient of $z^{-k}$ in $Y(z)A_{i+1}(z)$.

This iterative process is continued until one of the following conditions are reached.

(a).  \[ |\frac{e_i}{e_i}| < d \quad \ldots F7 \]

where $d$ is an appropriate small, positive, real constant.

(b).  \[ i = 40 \quad \ldots F8 \]
(c). \(|\lambda_i| > 1\)  

When any of the above three given conditions satisfied, the process of iteration is terminated. When condition (a) is met, the iterative process is taken to have reached the point of convergence, but in cases (b) and (c), divergence occurs which will be dealt with later.

Let the value of \(i\) at convergence be \(k\), such that

\[ \lambda_k \sim \beta_i \]

Then a two tap feedforward transversal filter of Fig. 7.12b with a z-transform of

\[ B_k(z) = 1 + \lambda_i z^{-1} \]

is appropriately adjusted by the receiver.

The sequence \(\{e_{k,n}\}\) is fed through this two-tap feedforward transversal filter in the correct order, to obtain the (g+2) component output sequence,

\[ f_{i,-1} + f_{i,0} z^{-1} + f_{i,1} z^{-2} + \ldots + f_{i,\lambda} z^{-(\lambda+1)} \]

When \(f_{i,-1} \sim 0\) in Eqn. F12 now approximates to \(Y(z)A_k(z)B_k(z)\). The resulting effect of the sequence \(Y\) passing through the two filters in Figs. 7.12a and 7.12b is the same as that of the sequence \(Y\) passing through a single filter with the z-transform

\[ C_i(z) = A_k(z)B_k(z) \]

From Eqns. F6, F10, F11 and F13

\[ C_i(z) = (1 + \beta_i z^{-1}) (1 + \beta_i z^{-1}) \]

thus deriving the same expression given in Eqn. F3.

Finally, the output sequence, \(\{f_{i,n}\}\) is advanced by one sampling interval (multiplication by \(z\)), and the first component, \(f_{i,-1}\), is discarded to give the sequence \(F_i\), with the z-transform

\[ F_i(z) = f_{i,0} + f_{i,1} z^{-1} + f_{i,2} z^{-2} + \ldots + f_{i,\lambda} z^{-\lambda} \]

\( \sim z Y(z) C_i(z) \)
The linear factor \((1 + \beta_1 z^{-1})\) in Eqn. 6.2.11 is replaced in \(F_1(z)\) by the linear filter \((1 + \beta_1 z^{-1})\) for practical purposes. Therefore, the root \(-\frac{1}{\beta_1}\) of \(Y(z)\), is replaced by the root \(-\beta_1\)^*, i.e., one root of \(Y(z)\) which was situated outside the unit circle is replaced by the complex conjugate of its reciprocal, and hence now lies inside the unit circle. \(F_1(z)\) contains, in addition, an advance of one sampling interval. The iterative process is now repeated with \(Y\) replaced by \(F_1\), for the tracking of more roots.

The next aim is to explain the adjustment of the tap gains of the filter whose ideal z-transform was \(D(z)\) given in Eqn. 6.2.13. All the tap gains of this \((n+1)\) tap linear feedforward transversal filter are initially set to zero, except for the last tap whose gain is set to unity. Thus, the initial z-transform of the filter is

\[
D_0(z) = z^{-n}
\]  

and the initial z-transform of the channel and the filter \(z^{-n}Y(z)\), when convergence has been obtained in the iterative process previously described, such that \(\lambda_k \sim \beta_1\). The sequence \(D_0\) is fed through the two tap feedforward transversal filter with z-transform \(B_k(z)\) in Fig. 7.12b starting with the first component of \(D_0\). This gives an output sequence with \((n+2)\) components and z-transform \(D_0(z)B_k(z)\). This output sequence is now fed in reverse order starting with the last component through the one-tap feedback transversal filter shown in Fig. 7.12a. \(A_k(z)\) now is the effective z-transform of the one-tap feedforward transversal filter, and with the output z-transform sequence of

\[
D_0(z)A_k(z)B_k(z) = D_0(z)C_1(z)
\]  

The process is stopped when \((n+1)\) components of the output sequence are achieved. These \((n+1)\) components, in the order in which they are received, are the coefficients of \(z^{-(n+1)}, z^{-n}, \ldots, z^{-1}\), in \(D_0(z)C_1(z)\). The tap gain of the \(h^{th}\) tap of the adaptive filter is now set to the coefficient \(z^h\) (for \(h = 1, 2, 3, \ldots, n+1\)), to give the required tap gains. Thus the z-transform of the adaptive filter is approximately

\[
D_1(z) = zD_0(z)C_1(z)
\]  

The full processes of the root finding the tap adjustment just described is now repeated, although using \(F_1(z)\) in Eqn. F4 (in place of \(Y(z)\)), and \(D_1(z)\) in Eqn. F17.
(in place of \( D_0(z) \)). At the end of the root finding iteration, \( \lambda_4 = \beta_2 \), and as such, in order to process the value of \( \beta_3 \), the values of \( F_2(z), \lambda_4 \), and \( D_1(z) \). \( F_2(z) \) and \( D_2(z) \) are used in place of \( F_1(z) \) and \( D_1(z) \).

The whole process is continued in this manner until no roots outside the unit circle in \( F_b \) remain, starting from any possible value of \( \lambda_1 \). Thus one of the divergence conditions \( F_8 \) and \( F_9 \) are met, regardless of the starting point \( \lambda_1 \). Therefore, it can be now assumed that all the \( m \) roots of \( Y(z) \) that lie outside the unit circle have been replaced by the complex conjugate of their reciprocals, in the \( z \)-transform of the channel and the adaptive filter with the \( z \)-transform of

\[
D_m(z) = D(z)
\]

so that the \( z \)-transform of the channel and the adaptive filter

\[
Y(z)D_m(z) = a_0 + a_1z^{-1} + a_2z^{-2} +, \ldots, + a_{n+z}z^{-(n+z)}
\]

where \( a_n = 0 \) for \( h = 0, 1, 2, 3, \ldots, (n-1) \).

The estimate of the sampled impulse response of the channel and the adaptive filter employed by the detector is the sequence \( F_m \) with \( z \)-transform

\[
F_m(z) = f_{m,0} + f_{m,1}z^{-1} + f_{m,2}z^{-2} +, \ldots, + f_{m,n}z^{-n}
\]

\[\sim z^{n}F(z)\]

Now from Eqn. 6.2.15, the Eqn. F22 above can be written as

\[
F_m(z) = Y_1(z)Y_2(z)
\]

For convenience, the delay of \( n \) sampling intervals introduced by the adaptive filter is ignored here, but must be taken into account when \( Y(z)D_m(z) \) is compared with \( F_m(z) \).

As indicated earlier, the algorithm under investigation is for the estimation of the sampled impulse response of the channel and filter, and for the adjustment of the tap gain of the filter when the channel is considered to be time invariant. In the time varying underwater channels the following modifications must be met.

First of all, the given algorithm must be implemented at any sampling instant, so that at each time instant of \( t = iT \) \((i = 1, 2, 3, \ldots, k)\) both \( F_m \) and the tap gains are calculated. It may be sufficient to perform the adjustment of the filter tap gain once
every so often, say, once every four sampling instant if the channel is varying only very slowly with time (long range or sofar channel). The research in this thesis, however, is based on the adaptation of the filter at every sampling instant.

The second procedure is to take nine starting point [Table F1 or F2] for the adaptive filter, when operating over time varying channels. The algorithm always starts with \( \lambda_1 \) set to starting point number 1, and it uses all the nine possible starting points for tracking any new roots. This is done in this way to track, at the beginning, as many as of possible the number of the roots that exist outside the unit circle. When the algorithm diverges [Eqn. F8 and F9] for each of the nine starting points, it is assumed that all the \( m \)-roots which are then lie outside of the unit circle have been found. For subsequent runs, however, the \( m \) roots that were tracked in the previous run are then added to the nine starting points, to give a total of \((m+9)\) starting points. These \((m+9)\) starting points are arranged as shown in Table F1 or F2, and the algorithm now starts with \( \lambda_1 \) set to \( \beta_1 \), where \( \beta_1 \) here is the first root tracked in the previous run. Now as soon as a root is found or a new starting point is required due to divergence of the algorithm, the next of the \((m+9)\) starting points is used. This process is repeated until all \((m+9)\) starting points have been employed, and then terminated, with the assumption that there are no roots outside the unit circle. Thus, once a set of roots is found, it is added to the original nine starting points such that the starting points for any subsequent run are the roots tracked from the previous run, plus the nine original starting points.

The final possible modification for the operation of the adaptive filter considering time varying channels (especially in a very worse of situations) is to increase the value of \( i \) in Eqn. F8 to 100, so that a greater range is allowed in iteration process, before determining that the process is diverged.
Table F1. The nine starting points used in the adaptive filter when operating over channel of System B for 1, and 2 eigenrays.

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<th>Number of points</th>
<th>Real parts</th>
<th>Imaginary parts</th>
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<td>0.00000</td>
</tr>
<tr>
<td>2</td>
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<tr>
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Table F2. The nine starting points used in the adaptive filter when operating over channel of System B for 3, 5 and 8 eigenrays.

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<td>-0.53533</td>
<td>0.53533</td>
</tr>
<tr>
<td>9</td>
<td>-0.53533</td>
<td>-0.53533</td>
</tr>
</tbody>
</table>
APPENDIX G1

System A Channel Model

1. Computer simulate model of system A
2. Use system A model to construct the underwater baseband channel

Transmission rate 2400 samples/second

One diffused component path

carfr = carrier frequency

spdiv = speed of diver or sub.

bfc1-bfc5 = bessel filter coefficients

velofs = velocity of sound in sea

frsp = frequency spread

f = cut-off frequency of the bessel filter

sr = sampling rate in bessel filter

ksamp = no. of iteration run for each vi(t) after interpolation

nolp = no. of loops run for vi(t) before interpolation

tns = total no. of symbols generated i.e. transmission time

scalf = scaling factor --> val. of b

xmed = bessel median value

program systema
implicit double precision (a-h, o-z)
parameter (nosamp=5900, n=2, jntran=nosamp+30)
parameter (iseed=57, kp=10, nolp=2150, kts=25000)
double precision v(n, nosamp), g05bcf, g05df, stdvn
double precision vv(n), sfunc(n), transf(kp), recf(kp)
double precision vr(kp, kp), vi(kp, kp), yr(kp), yi(kp)
double precision y1r(kts, kp), y1i(kts, kp), y2r(kts, kp)
double precision y2i(kts, kp)

stdvn = sqrt(1.0)

spdiv = 0.2020

call bescof(spdiv, bfc1, bfc2, bfc3, bfc4, bfc5)
call dcgaink(bfc1, bfc2, bfc3, bfc4, bfc5, dcgain)
dcgain = 1.0/dcgain

initializations and open files for output channel sir

tdl1 = 0.0

tdl2 = 0.0

tdl3 = 0.0

tdl4 = 0.0

tdl5 = 0.0

jntran = jntran + 1

call g05cbf(iseed)

itrpol = 12

trpol = 1.0/itrpol

tcount = 0

bandw = 2400

scalf = 1.110d0

kp1 = kp - 1
kp2=kp+kl
kp3=kp2-1
open(15, file='sirsysa', form='unformatted')
c generate v1(t) and v2(t)
do 25 i=1,n
jh=1
c run gaussian random noise through the filter
do 24 j=1,jntran
c0=g05ddf(0.0d0, stdvn)
c1=c0-(td11*bfc1+td12*bfc2)
c2=c1-(td13*bfc3+td14*bfc4)
c3=c2-(td15*bfc5)
vdcg=c3*dgain
td15=c3
td14=td13
td13=c2
td12=td11
td11=c1
if (j .le. 51) goto 24
v(i,jh)=vdcg
jh=jh+1
24 continue
25 continue
call frcosf(bandw, transf, recf)
c construct baseband channel
c convolution process begins by entering the main loop
do 77 ksamp=1,nolp
do 39 i=1,n
sfunc(i)=(v(i,ksamp+1)-v(i,ksamp))*trpol
continue
do 66 jsec=1,itrpol
do 40 i=1,n
vv(i)=v(i,ksamp)+(jsec-1)*sfunc(i)
40 continue
vv(2)=-vv(2)
icount=icount+1
do 42 i=1,kp2
do 41 j=1,kp3
y1r(i,kp2+1-j)=y1r(i,kp2-j)
y1i(i,kp2+1-j)=y1i(i,kp2-j)
41 continue
42 continue
do 43 i=1,kp2
y1r(i,1)=0.0
y1i(i,1)=0.0
43 continue
do 44 i=1,kp
y1r(i,1)=vv(1)*transf(i)
y1i(i,1)=vv(2)*transf(i)
44 continue
if (icount .lt. 50) goto 77
iout=0
do 46 i=1,kp2


```fortran
        iout=iout+1
        y2r(iout)=0.0
        y2i(iout)=0.0
        do 45 j=1,i
           mconv=i-j+1
           y2r(iout)=y2r(iout)+y1r(j,mconv)*recf(mconv)
           y2i(iout)=y2i(iout)+y1i(j,mconv)*recf(mconv)
        continue
        y2r(iout)=y2r(iout)*scalf
        y2i(iout)=y2i(iout)*scalf
        continue
        write(15)(y2r(i),i=1,kp3)
        write(15)(y2i(i),i=1,kp3)
        c to graph the output call subroutine graphs
        call graphs(yr,yi,kp,icount,vv,sigamp,sigphase,ysir3d)
       45 continue
       77 continue
       stop
end

subroutine bescof(spdiv,bfc1,bfc2,bfc3,bfc4,bfc5)

finding the roots and the coefficient of the
fifth-order Bessel filter

carfr=20000.d0
velofs=1500.0d0
frsp=carfr*(spdiv/velofs)
f=0.588705*frsp
sr=200.0d0
t=1.0/sr

c the poles obtained at 1 Hz frequency spread
pl1=-9.4394
pl2r=-8.6764
pl2i=4.5108
pl3r=pl2r
pl3i=-pl2i
pl4r=-6.0173
pl4i=9.2434
pl5r=pl4r
pl5i=-pl4i

c calculation of the bessel filter roots
zb1=dexp(pl1*f*t)
zb2r=(dexp(pl2r*f*t)*dcos(pl2i*f*t))
zb2i=(dexp(pl2r*f*t)*dsin(pl2i*f*t))
zb3r=zb2r
zb3i=zb2i
zb4r=(dexp(pl4r*f*t)*dcos(pl4i*f*t))
zb4i=(dexp(pl4r*f*t)*dsin(pl4i*f*t))
zb5r=zb4r
zb5i=-zb4i

c calculate the modulus of the roots
zbb1=zb1
zbb2=((zb2r**2)+(zb2i**2))**0.5
zbb2=((zb4r**2)+(zb4i**2))**0.5
```

230
calculate the filter coefficients
bfcl=-2.0*zb2r
bfcl=(zb2r**2)+(zb2i**2)
bfc3=-2.0*zb4r
bfc4=(zb4r**2)+(zb4i**2)
bfc5=-1.0*zb1
write(O, l)bfc1
format ('co-efficients of filter',1x,e30.20)
write(O,2)bfc2,bfc3,bfc4,bfc5
return
end
subroutine dcgaink(bfc1,bfc2,bfc3,bfc4,bfc5,dcgain)
parameter (nosamp=59900,n=2,jntran=nosamp+30,iseed=57)
double precision p(n,nosamp),vardcg(n),g05ddf,stdvn
dcorig=1.0
stdvn=sqrt(1.0)
c initialize delays in the bessel filter
tdl1=0.0
tdl2=0.0
tdl3=0.0
tdl4=0.0
tdl5=0.0
jntran=jntran+1
call g05cbf(iseed)
c generate v1(t) and v2(t)
do 25 i=1,n
jh=1
c initialize for the mean and the variance
tfin=0.0
tvfin=0.0
tfindc=0.0
tvfindc=0.0
c run gaussian random noise
do 24 j=1,jntran
v0=g05ddf(0.0d0,stdvn)
v1=v0-(tdl1*bfc1+tdl2*bfc2)
v2=v1-(tdl3*bfc3+tdl4*bfc4)
v3=v2-(tdl5*bfc5)
vdcg=v3*dcorig
tdl5=v3
tdl4=tdl3
tdl3=v2
tdl2=tdl1
tdl1=v1
if (j .le. 51) goto 24
p(i,jh)=vdcg
jh=jh+1
tfin=tfin+v3
tvfin=tvfin+(v3**2)
tfindc=tfindc+vdcg
tvfindc=tvfindc+(vdcg**2)
25 continue
24 continue

continue
etfin=etfin/(nosamp+1)
vartfin=vartfin/(nosamp+1)
etfindc=etfindc/(nosamp+1)
vardcg(i)=etfindc/(nosamp+1)
write(0,3)etfin,vartfin
write(0,4)etfindc,vardcg(i)
format('fmean=',1x,e20.10,5x,'fvariance=',e20.10)
format('meanofdc=',1x,e20.10,5x,'totaldcg',e20.10)
dcg=dcg+vardcg(i)
continue
dcgain=sqrt(dcg)
return
define subroutine frcosf(bandw,transf,recf)
c find shaping filter impulse responses
parameter (irs1=100,irs2=300,mwz=250,mwzl=mwz/2)
parameter (mwz2=mwzl+1,ig=10)
double precision hf(-irs1:irs1),ahf(-irs2:irs2)
double precision chf(irs2),chr(irs2),chi(irs2)
double precision a(irs2),ahw(irs2),ahwf(irs2)
double precision transf(ig),cgahwf(irs2),cgahwfi(irs2)
double precision ahwf(irs2),cgchr(irs2),cgchi(irs2)
double precision hfinvr(irs2),hfinv(irs2),hfinmr(irs2)
double precision hfinwr(irs2),shfr(irs2),shfw(irs2),recf(ig)
fsamp=10.0*bandw
tsamp=1.0/fsamp
g=50
g1=2*g+1
piv=acos(-1.0)
open(11,file='sirati',form='formatted')
open(12,file='sirwti',form='formatted')
open(13,file='fraf',form='formatted')
open(14,file='frwf',form='formatted')
do 5 i=0,g
hf(i)=sqrt(bandw)*(sin(piv*(2.0d0*i*tsamp*bandw+0.50d0))
/(piv*(2.0d0*i*tsamp*bandw+0.50d0))
+sin(piv*(2.0d0*i*tsamp*bandw-0.50d0))
/(piv*(2.0d0*i*tsamp*bandw-0.50d0))
do 5 continue
do 6 i=-g,-1,1
hf(i)=hf(-i)
do 7 i=-g,g,1
ahf(0)=0.0
ahf(0)=ahf(0)+hf(i)**2
continue
do 8 i=-g,g,1
hf(i)=hf(i)/sqrt(ahf(0))
do 8 continue
c making samples casual
233
do 9 k=-g,g,1

chf(k+g)=hf(k)
9 continue

sumO=0.0
do 10 i=0,g1,1

chr(i+1)=chf(i)

sumO=sumO+chr(i+1)**2+chi(i+1)**2

write(11,93)i+1,chr(i+1)
10 continue

c apply hamming window

do 11 j=1,g1

st=(2*pi*v)/g1

ahw(j)=0.54-(0.46*a(j))

a(j)=cos(st*j)

11 continue

continue
do 12 j=5,g1,10

transf(j)=chr(j)*ahw(j)

recf(j)=chr(j)*ahw(j)

write(12,93)j,transf(j)

continue
do 13 i=1,g1

ahwfr(i)=chr(i)*ahw(i)

ahwfi(i)=chi(i)*ahw(i)

13 continue

continue
do 14 i=g1+1,mwz

chr(i)=0.0

chi(i)=0.0

ahwfr(i)=0.0

ahwfi(i)=0.0

14 continue

continue
do 15 i=1,mwz

cgchr(i)=chr(i)

cgchi(i)=chi(i)

cgahwfr(i)=ahwfr(i)

cgahwfi(i)=ahwfi(i)

15 continue

c obtain frequency response employing nag routines(dft)

ifail=0

call c06gcf(cgchi,mwz,ifail)
call c06ecf(cgchr,cgchi,mwz,ifail)
call c06gcf(cgchi,mwz,ifail)
call c06gcf(cgahwfr,mwz,ifail)
call c06ecf(cgahwfr,cgahwfi,mwz,ifail)
call c06gcf(cgahwfi,mwz,ifail)
do 16 i1=1,mwz

hfinvr(i1)=cgchr(i1)**2+cgchi(i1)**2

hfinvw(i1)=cgahwfr(i1)**2+cgahwfi(i1)**2

hfinmr(i1)=10.0*log10(hfinvr)

hfinwr(i1)=10.0*log10(hfinvw)

16 continue

continue
do 17 i2=mwz2,mwz

shfr(i2-mwz1)=hfinmr(i2)

shfw(i2-mwz1)=hfinwr(i2)
write(13,93)i2-mwzl,shfr(i2-mwzl)
write(14,93)i2-mwzl,shfw(i2-mwzl)
17 continue
do 18 i3=1,mwzl
shfr(i3+mwzl)=hfinmr(i3)
shfw(i3+mwzl)=hfinwr(i3)
write(13,93)i3+mwzl,shfr(i3+mwzl)
write(14,93)i3+mwzl,shfw(i3+mwzl)
18 continue
93 format (1x,i10,5x,e21.10)
return
end
subroutine graphs(yr,ti,kp,icount,vv,sigamp,sigphase,
y3ir3d)
  subroutine to calculate the phase, amplitude, ysir in 3d. before or after
  convolution
double precision yr(kp), yi(kp), y3d1(kp), ysir3d(kp)
open(16, file='amp', form='formatted)
open(17, file='phase', form='formatted)
open(18, file='y3denergy', form='formatted)
xmed=0.588705
pi=acos(-1.0)
jcount=jcount+1
count=real(jcount)
time=countl2400
sigamp1=sq(v(1)**2+vy(2)**2
sigamp=10.0*log10(sigamp/xmed)
sigphas1=atan(vy(2)/vy(1))
sigphase=sigphas1*(180.0/pi)
if(sigphase .lt. 0.0)then
  sigphase=sigphase+180.0
else
  sigphase=sigphase-180.0
endif
write(16,98)time,sigamp
write(17,98)time,sigphase
do 55 i=1,kp
y3d1(i)=yr(i)**2+yi(i)**2
ysir3d(i)=sqrt(y3d1(i))
55 continue
write(18,99)(ysir3d(i),i=1,kp)
99 format(5f10.6,1x))
98 format(1x,f21.17,10x,f21.17)
return
end
C APPENDIX G2

System B Channel Model

1. Computer simulate model of system B
2. Use system B model to construct the underwater baseband channel

Transmission rate 2400 samples/second

8-eigenray channel implementation

carfr = carrier frequency
spsub = speed of sub.
bfc1-bfc5 = bessel filter co-efficients
velos = velocity of sound in sea
frsp = frequency spread
frc = cut-off frequency of bessel filter
sr = sampling rate of bessel filters
ksamp = no. of iteration run for each vi(t) after interpolation
nolp = no. of loops run for vi(t) before interpolation
tns = total no. of symbols generated i.e. transmission time
xscal = scaling factor --> val. of b
xmed = bessel median value
dele1-delen = delays in the reception of eigenray
sampr = sampling rate to delay

program systemb

Implicit double precision (a-h-o-z)
parameter (nosamp=5900, n=16, jntran=nosamp+30)
parameter (iseed=191, kp=11, nolp=2150, ktns=25000)
parameter (kp1=25, kp2=kp1-1)
double precision v(n, nosamp), g05bca, g05ddf, stdvn
double precision vv(n), sfunc(n), transf1(kp), transf2(kp)
double precision transf3(kp), transf4(kp), transf5(kp)
double precision transf6(kp), transf7(kp), transf8(kp)
double precision recf(kp1), vr(kp1, kp1), vi(kp1, kp1), yor(kp1)
double precision yoi(kp1), ynar(kp2), ynagri(kp2)
double precision rezir(kp2), rezii(kp2), ymr(kp2), ymi(kp2)
double precision dmr(kp2), dmi(kp2), ytmr(kp2), ytmi(kp2)
integer ifail, nroot
common v
stdvn = sqrt(1.0)
spsub = 0.4802

call bescof(spsub, bfc1, bfc2, bfc3, bfc4, bfc5)
call dcgaink(bfc1, bfc2, bfc3, bfc4, bfc5, dcgain)
dcgain = 1.0 / dcgain

c initializations and open files for output channel sir

td11 = 0.0
td12 = 0.0
td13 = 0.0
td14 = 0.0
td15 = 0.0
dele1 = 0.50d0
dele2=0.850d0
dele3=1.50d0
dele4=1.850d0
dele5=2.150d0
dele6=2.450d0
dele7=3.0d0

idt1=int(samp*2*dele1)
idt2=int(samp*2*dele2)
idt3=int(samp*2*dele3)
idt4=int(samp*2*dele4)
idt5=int(samp*2*dele5)
idt6=int(samp*2*dele6)
idt7=int(samp*2*dele7)

kp1=kp+idt7
totebm=0.0
toteam=0.0

jntran=jntran+1

call g05cbf(iseed)
itrpol=16
trpol=1.0/itrpol
icount=0
alter=1.0
bandw=2400
ncscl=1.285d0

open(15, file='sirsysb', form='unformatted')
open(16, file='sirsysbm', form='unformatted')

c
generate v1(t) and vn(t)
doi=1,n
jh=1
c
run gaussian random noise through the filter
do j=1,jntran

c0=g05ddf(0.0d0,stdvn)
c1=c0-(td1*bf1+td2*bf2)
c2=c1-(td3*bf3+td4*bf4)
c3=c2-(td5*bf5)
vdcg=c3*dclgain

td5=c3
td4=td13
td3=c2
td2=td11
td1=ct1

if (j .le. 51) goto24
v(i,jh)=vdcg
jh=jh+1
24continue
25continue

call fprcosf(bandw,transf1,transf2,transf3,transf4,transf5,
transf6,transf7,transf8,recf)
doi=1=kpl
recf(i)=0.0
26continue

cconstruct baseband channel

cconvolution process begins by entering the main loop
do 27 i=1,kp2
rezir(i)=0.0
rezii(i)=0.0
continue
do 77 ksamp=1,nolp
do 39 i=1,n
sfunc(i)=-(v(i,ksamp+1)-v(i,ksamp))*trpol
continue
do 66 jsec=1,itrpol
do 40 i=1,n
vv(i)=v(i,ksamp)+((jsec-1)*sfunc(i))
continue
vv(2)=-vv(2)
vv(4)=-vv(4)
vv(6)=-vv(6)
vv(8)=-vv(8)
vv(10)=-vv(10)
vv(12)=-vv(12)
vv(14)=-vv(14)
vv(16)=-vv(16)
icount=icount+1
c first rule of convolution (shifting arrays)
do 41 i=1,kpl
do 41 j=1,kp2
j1=kpl-j
vr(i,j1+1)=vr(i,j1)
vi(i,j1+1)=vi(i,j1)
continue
do 42 i=1,kpl
vr(i,1)=0.0
vi(i,1)=0.0
continue
c 1st convolution (transmitter filter with the channel)
do 43 i=1,kp
vr(i,1)=transf1(i)*vv(1)
vi(i,1)=transf1(i)*vv(2)
continue
do 44 i=1,kp
vr(i+idt1,1)=vr(i+idt1,1)+transf2(i)*vv(3)
vi(i+idt1,1)=vi(i+idt1,1)+transf2(i)*vv(4)
continue
do 45 i=1,kp
vr(i+idt2,1)=vr(i+idt2,1)+transf3(i)*vv(5)
vi(i+idt2,1)=vi(i+idt2,1)+transf3(i)*vv(6)
continue
do 46 i=1,kp
vr(i+idt3,1)=vr(i+idt3,1)+transf4(i)*vv(7)
vi(i+idt3,1)=vi(i+idt3,1)+transf4(i)*vv(8)
continue
do 47 i=1,kp
vr(i+idt4,1)=vr(i+idt4,1)+transf5(i)*vv(9)
vi(i+idt4,1)=vi(i+idt4,1)+transf5(i)*vv(10)
continue
do 48 i=1,kp
vr(i+idt5,1) = vr(i+idt5,1) + transf6(i)*vv(11)
vi(i+idt5,1) = vi(i+idt5,1) + transf6(i)*vv(12)
48 continue
do 49 i=1,kp
vr(i+idt6,1) = vr(i+idt6,1) + transf7(i)*vv(13)
vi(i+idt6,1) = vi(i+idt6,1) + transf7(i)*vv(14)
49 continue
do 50 i=1,kp
vr(i+idt7,1) = vr(i+idt7,1) + transf8(i)*vv(15)
vi(i+idt7,1) = vi(i+idt7,1) + transf8(i)*vv(16)
50 continue

c 2nd convolution (1st convolution with the receiver filter)
alter=-alter
if (alter .lt. 0.0) go to 777
ig=0
lcount=lcount+1
do 52 i=1,kp1,2
ig=ig+1
yor(ig)=0.0
yoi(ig)=0.0
do 51 j=1,i
j2=i+1-j
yor(ig)=yor(ig)+vr(j,j2)*recf(j2)
yoi(ig)=yoi(ig)+vi(j,j2)*recf(j2)
51 continue
yor(ig)=yor(ig)*scalf
yoi(ig)=yoi(ig)*scalf
52 continue
do 54 i=1,kp2,2
ig=ig+1
yor(ig)=0.0
yoi(ig)=0.0
j3=i+1
j4=kpl+1+i
yor(ig)=yor(ig)+vr(j,j4-j)*recf(j4-j)
yoi(ig)=yoi(ig)+vi(j,j4-j)*recf(j4-j)
53 continue
yor(ig)=yor(ig)*scalf
yoi(ig)=yoi(ig)*scalf
54 continue
write(15)(yor(i),i=1,kp1)
write(15)(yoi(i),i=1,kp1)
c call nag routine to minimum phase the sirs of the channel
do 55 i=1,kp2
ynagrr(i)=yor(i)
ynagri(i)=yoi(i)
55 continue
ifail=0
ucir=1.05
nroot=kp2
tol=x022aaf(1.0)
call c02adf(ynagrr,ynagri,nroot,rezir,rezii,tol,ifail)
rp=1.0
do 56 i=1,kp2
   rsq=rezir(i)*rezir(i)+rezii(i)*rezii(i)
   rpmod=rsq**0.5
   if(rpmod .gt. ucir)then
      rp=rp*rpmod
      rezir(i)=rezir(i)/rsq
      rezii(i)=rezii(i)/rsq
   else
      goto 56
   endif
   continue
56 do 57 i=1,kp2
   rezir(i)=-rezir(i)
   rezii(i)=-rezii(i)
57 continue

C  channel adaptation algorithm

   do 58 i=1,kp2
      ymr(i)=0.0
      ymi(i)=0.0
58 continue
   ymr(1)=1.0
   do 61 i=1,kp2-1
      do 59 j=1,kp2-1
         dmr(j)=ymr(j)*rezir(i)-ymi(j)*rezii(i)
         dmi(j)=ymi(j)*rezir(i)+ymr(j)*rezii(i)
      59 continue
   do 60 j5=1,kp2-1
      j6=j5+1
      ymr(j6)=ymr(j6)+dmr(j5)
      ymi(j6)=ymi(j6)+dmi(j5)
60 continue
61 do 62 j=2,kp2,2
   ymr(j)=-ymr(j)
   ymi(j)=-ymi(j)
62 continue
   do 63 j=1,kp2
      ymr(j)=(ymr(j)*yor(1)-ymi(j)*yoi(1))*rp
      ymi(j)=(ymr(j)*yoi(1)+ymi(j)*yor(1))*rp
63 continue
   write(16)(ytmr(i),i=1,kp2)
   write(16)(ytmi(i),i=1,kp2)

C  to graph the output call subroutine graphs

   call graphs(yor,yoi,kp2,icount,sigamp,sigphase,ysir3d)

66 continue
77 continue
stop
end

subroutine bescof(spdiv,bfc1,bfc2,bfc3,bfc4,bfc5)
C  finding the roots and the coefficient of the
C  fifth-order Bessel filter
carfr=20000.d0
velofs=1500.0d0
frsp=carfr*(spdiv/velofs)
f=0.588705*frsp
sr=300.0d0
t=1.0/sr
c the poles obtained at 1 Hz frequency spread
pl1=-9.4394
pl2r=-8.6764
pl2i=4.5108
pl3r=pl2r
pl3i=-pl2i
pl4r=-6.0173
pl4i=9.2434
pl5r=pl4r
pl5i=-pl4i
c calculation of the bessel filter roots
zb1=dexp(pl1*f*t)
zb2r=(dexp(pl2r*f*t)*dcos(pl2i*f*t))
zb2i=(dexp(pl2r*f*t)*dsin(pl3i*f*t))
zb3r=zb2r
zb3i=-zb2i
zb4r=(dexp(pl4r*f*t)*dcos(pl4i*f*t))
zb4i=(dexp(pl4r*f*t)*dsin(pl5i*f*t))
zb5r=zb4r
zb5i=-zb4i
c calculate the modulus of the roots
zbb1=zb1
zbb2=((zb2r**2)+(zb2i**2))**0.5
zbb2=((zb4r**2)+(zb4i**2))**0.5
c calculate the filter coefficients
bfc1=-2.0*zb2r
bfc2=(zb2r**2)+(zb2i**2)
bfc3=-2.0*zb4r
bfc4=(zb4r**2)+(zb4i**2)
bfc5=1.0*zb1
write(0,1)bfc1
1 format ("co-efficients of filter",1x,e30.20)
write(0,2)bfc2,bfc3,bfc4,bfc5
2 format (24x,e30.20)
return
end
subroutine dcgaink(bfc1,bfc2,bfc3,bfc4,bfc5,dcgain)
parameter (nosamp=49900,n=16,jntran=nosamp+30,iseed=191)
double precision p(n,nosamp),vardcg(n),g05ddf,stdvn
dcorig=1.0
stdvn=sqrt(1.0)
c initialize delays in the bessel filter
tdl1=0.0
tdl2=0.0
tdl3=0.0
tdl4=0.0
tdl5=0.0
jntran=jntran+1
call g05cbf(iseed)
c generate v1(t) to vn(t)
do 25 i=I,n
jh=1
c initialize for the mean and the variance
tfin=0.0
tvfin=0.0
tfindc=0.0
tvfindc=0.0
c run gaussian random noise
do 24 j=I,jntran
v0=g05ddf(0.0d0, stdvn)
v1=v0-(tdl1*bfc1+tdl2*bfc2)
v2=v1-(tdl3*bfc3+tdl4*bfc4)
v3=v2-(tdl5*bfc5)
vdcg=v3*dcorig
tdl5=v3
tdl4=tdl3
tdl3=v2
tdl2=tdl1
tdl1=v1
if (j .le. 51) goto 24
p(i,jh)=vdcg
jh=jh+1
tfin=tfin+v3
tvfin=tvfin+(v3**2)
tfindc=tfindc+vdcg
tvfindc=tvfindc+(vdcg**2)
24 continue
etfin=tfin/(nosamp+1)
ervar=tvfin/(nosamp+1)
etfindc=tfindc/(nosamp+1)
ervar(i)=tvfindc/(nosamp+1)
write(0,3)etfin,ervar
write(0,4)etfindc,ervar(i)
3 format(’fmean=’,1x,e20.10,5x,’fvariance=’,e20.10)
4 format(’meanofdc=’,1x,e20.10,5x,’totaldcg’,e20.10)
dcg=dcg+ervar(i)
25 continue
dcgain=sqrt(dcg)
return
end
subroutine fprcosf(bandw,transf1,recf,transf2,transf3,
           transf4,transf5,transf6,transf7,transf8)
c find shaping filter impulse responses
parameter (irs1=500,irs2=800,mwz=685,mwz1=mwz/2)
parameter (mwz2=mwz1+1,ig=11)
double precision hf(-1:irs1),ahf(0:irs2)
double precision recf(ig),chr(irs2),chi(irs2),chp(irs1)
double precision a(irs1),ahw(irs2),ahwfr(irs2),chf1(irs1)
double precision chfr(irs2),chfi(irs2)
double precision transf1(ig),transf2(ig),transf3(ig)
double precision transf4(ig),transf5(ig),transf6(ig)
double precision transf7(ig),transf8(ig),chp(irs1)
double precision cgahwfr(irs2),cgahwfi(irs2),chf(irs1)
double precision ahwfi(irs2),cgchr(irs2),cgchi(irs2)
double precision hfinwr(irs2),hfinvw(irs2),hfinmr(irs2)
double precision hfinwr(irs2),shfr(irs2),shfw(irs2)
integer ifail
fsamp=18.0*bandw
bandw2=bandw/2.0
tsamp=1.0/fsamp
g=325
fsq=sqrt(g)
h=fsamp/g
piv=acos(-1.0)
q0=0.0
q1=bandw2
q2=fsamp-bandw2
q3=fsamp
piv=acos(-1.0)
t1=1.0/bandw
t2=(t1/2.0)*piv
hf(-1)=h
open(11,file='sirati',form='formatted')
open(12,file='sirwlti',form='formatted')
open(13,file='frac',form='formatted')
open(14,file='frwf',form='formatted')
do 5 i=0,g-1
hf(i)=h+hf(i-1)
if ((hf(i) .ge. q0) .and. (hf(i) .le. q1)) then
   alfa=piv*t1*hf(i)
et=cos(alfa)
elseif ((hf(i) .ge. q2) .and. (hf(i) .le. q3)) then
   alfa=piv*t1*hf(i)
et=cos(alfa)
else
   v=0.0
   ahf(i)=sqrt(v)
5 continue
l=0
do 6 i=0,g-1
l=l+1
chr(l)=ahf(i)
chi(l)=0.0
6 continue
n=g
ifail=0
c obtain the impulse response
    call c06gcf(chi,n,ifail)
call c06ecf(chr,chi,n,ifail)
call c06gcf(chi,n,ifail)
do 7 i=1,n
    chpr(i)=chr(i)/fsq
    chpi(i)=chi(i)/fsq
continue

c scale the components of sampled impulse responses
    fcomp=chpr(1)
do 8 i=1,n
    chf(i)=chpr(i)/fcomp
continue

c making samples casual
    n1=(n-1)/2
do 9 i=(n1+1),n
    chf1(i-n1)=chf(i)
continue
do 10 i=1,n1
    chf1(n1+1+i)=chf(i)
continue
    chfr(n-1)=chf1(1)
do 11 i=1,n
    chfr(i)=chf1(i)
write(11,93)i,chfr(i)
continue

c apply hamming window
    do 12 j=1,n
        st=(2*piv)/n
        a(j)=cos(st*j)
    12 continue
    do 13 j=1,n
        ahw(j)=0.54-(0.46*a(j))
write(12,93)j,ahw(j)
continue
do 14 i=73,n,18
    transf1(i)=ahwfr(i)
    recf(i)=ahwfr(i)
write(12,94)recf(i)
continue
do 15 i=83,n,18
    transf2(i)=ahwfr(i)
continue
do 16 i=92,n,18
    transf3(i)=ahwfr(i)
continue
do 17 i=87,n,18
    transf4(i)=ahwfr(i)
continue
do 18 i=75,n,18
    transf5(i)=ahwfr(i)
continue
do 19 i=85,n,18
transf6(i)=ahwfr(i)
19 continue

do 20 i=76,n,18
transf7(i)=ahwfr(i)
20 continue

do 21 i=84,n,18
transf8(i)=ahwfr(i)
21 continue

do 13 i=n,mwz
chfr(i)=0.0
chfi(i)=0.0
ahwfr(i)=0.0
ahwfi(i)=0.0
23 continue

do 24 i=1,mwz
cgchr(i)=chfr(i)
cgchfi(i)=chfi(i)
cgahwfr(i)=ahwfr(i)
cgahwfi(i)=ahwfi(i)
24 continue

c obtain frequency response employing nag routines(dft)
ifail=0

ifail=0

call c06gcf(cgchfi,mwz,ifail)
call c06ecf(cgcchr,cgchfi,mwz,ifail)
call c06gcf(cgcchfi,mwz,ifail)
call c06ecf(cgcgahwfi,cgahwfi,mwz,ifail)
call c06gcf(cgcgahwfi,mwz,ifail)
do 25 i1=1,mwz
hfinvri(i1)=cgchfr(i1)**2+cgchfi(i1)**2
hfinvw(i1)=cgahwfr(i1)**2+cgahwfi(i1)**2
hfinmr(i1)=10.0*log10(hfinvri)
hfinwr(i1)=10.0*log10(hfinvw)
25 continue

do 26 i2=mwz2,mwz
shfr(i2-mwz1)=hfinmr(i2)
shfw(i2-mwz1)=hfinwr(i2)
write(13,93)i2-mwz1,shfr(i2-mwz1)
write(14,93)i2-mwz1,shfw(i2-mwz1)
26 continue

do 27 i3=1,mwz1
shfr(i3+mwz1)=hfinmr(i3)
shfw(i3+mwz1)=hfinwr(i3)
write(13,93)i3+mwz1,shfr(i3+mwz1)
write(14,93)i3+mwz1,shfw(i3+mwz1)
27 continue

93 format (1x,i10,5x,e21.10)
94 format (1x,f21.10)
return
end

subroutine graphs(yr,ti,kp,icount,vv,sigamp,sigphase,
ysir3d)

subroutine to calculate the phase, amplitude, ysir in 3d. before or after convolution

double precision yr(kp), yi(kp), y3d1(kp), ysir3d(kp)
open(16, file='amp', form='formatted)
open(17, file='phase', form='formatted)
open(18, file='y3denergy', form='formatted)
xmed=0.588705
piv=acos(-1.0)
jcount=jcount+1
count=real(jcount)
time=count/2400

xmed=0.588705
piv=acos(-1.0)
jcount=jcount+1
count=real(jcount)
time=count/2400

sigamp1 = vv(1)**2 + vv(2)**2
sigamp = 10.0*log10(sigamp/xmed)
sigphas1 = atan(vv(2)/vv(1))
sigphase = sigphas1*(180.0/piv)
if(sigphase .lt. 0.0) then
  sigphase = sigphase + 180.0
else
  sigphase = sigphase - 180.0
endif
write(16,98) time, sigamp
write(17,98) time, sigphase

do 55 i=1,kp
y3d1(i) = yr(i)**2 + yi(i)**2
ysir3d(i) = sqrt(y3d1(i))
55 continue
write(18,99) (ysir3d(i), i=1,kp)
99 format(5(f10.6,1x))
98 format(1x,f21.17,10x,f21.17)
return
end
APPENDIX G3

Receiver of System A Channel Model

1. estimate system A
2. employ differential coding/decoding (look-up table).
3. use estimated (prediction-d2) of system A sirs.
4. employ first nonlinear equaliser and then compare with nml detector.

Transmission rate 2400 samples/second.
or 4800 bits/second.
one diffused component channel.

Program detsysa
implicit double precision (a-h,o-z)
parameter (nosamp=24000,kp=10,ns=16,ndeco=32)
parameter (iseed=57,kvec=8,nd=2,ntot=1000,msec=1200)
parameter (mvec1=1,mvec2=1,mvec3=2)
parameter (mvec=mvect1+mvect2+mvect3)
double precision hnosr(kp),hnosi(kp),g05cbf,g05ddf,stdvn
double precision wlinr(kp),wlini(kp),recf(kp),yor(kp)
double precision yoi(kp),sigr(ndeco),sigi(ndeco)
double precision xsigr(kvec,ndeco),xsigi(kvec,ndeco)
double precision detr(kvec),deti(kvec),vdeitr(kvec)
double precision vdeiti(kvec),vderl(kvec),vdei1(kvec)
double precision cost(kvec),cost1(kvec),cost2(mvect)
double precision cost3(kvec),rect(kp),reci(kp)
double precision yperdr(kp),yperdi(kp),ygestr(kp)
double precision ydgestr(kp),ydgesti(kp),ugestr(kp)
double precision ugesti(kp),estr(kp),esti(kp),ygesti(kp)
integer ipers1(ndeco),ipers2(ndeco),ipers3(ndeco)
integer iperv1(ns,nd),iperv2(ns,nd),iperv3(ns,nd)
integer ibit1(ntot),ibit2(ndeco),idbit1(ndeco),idbit2(ndeco)
integer isigr(ndeco),isigi(ndeco),ixsigr(kvec,ndeco)
integer ixsigi(kvec,ndeco),ixtor(kvec,ndeco)
integer itotr(kvec,ndeco),ipbq(mvect)
stdvn=sqrt(1.0)

initializations
xx=0.0
icount=0
tperder=0.0
isymer=0
iber1=0
iber2=0
idber1=0
idber2=0
ipdber1=0
ipdber2=0
do 1 i=1,ntot
ibit1(i)=0.0
ibit2(i)=0.0
idbit1(i)=0.0
idbit2(i)=0.0
sigr(i)=0.0
sigi(i)=0.0
isigr(i)=0.0
isigi(i)=0.0
continue
1 do 2 i=1,kp
recre(i)=0.0
reci(i)=0.0
2 continue
continue
1 do 3 j=1,kp
hnosr(j)=0.0
hnosi(j)=0.0
3 continue

1 initialise the stored vectors and costs in the detector
2 do 5 i=1,kvec
 cost(i)=10000.0d0
3 do 4 j=1,ndeco
 xsigr(i,j)=1.0
 xsigi(i,j)=1.0
4 ixsigr(i,j)=1
5 ixsigi(i,j)=1
5 continue
4 continue
3 initializing the arrays where sir and data as well as the
4 arrays for the prediction are situated this ensures that
5 there are initially some values for sir before estimation
6 do 8 i=1,kp
 ypredr(i)=0.0
7 ypredi(i)=0.0
6 ygestr(i)=0.0
7 ygesti(i)=0.0
8 ydgestr(i)=0.0
9 ydgesti(i)=0.0
8 continue
7 continue
6 cost(1)=0.0
5 ndeco1=ndeco-1
4 kp1=kp-1
3 const1=(1.0-theta)**3
2 const2=((1.0-theta)**2)*(1.0+theta)
1 const3=1.0-(theta**3)
data ipers1 /0,0,0,0,1,0,1,1,1,0,1,1,0,0,1,0,1,0,0,0,
1 1,1,0,1,1,1,0,1,0,1,0,0/
data ipers2 /1,1,-1,1,1,1,-1,1,1,1,1,1,-1,1,1,1,-1,1,1,1,
1 1,-1,1,1,-1,-1,1,1,1,-1,1,1,1,1,1,1,1,1,1/
data ipers3 /0,0,0,1,1,0,1,1,1,0,0,0,1,1,0,1,0,1,1,1,
1 0,0,1,0,1,1,1,0,0,1,0,0/
kl=0
1 do 10 i=1,ns
2 do 9 j=1,nd
3 iperv1(i,j)=ipers1(kl+j)
4 iperv2(i,j)=ipers2(kl+j)
iperv3(i,j)=ipers3(kl+j)
9 continue
kl=kl+2
10 continue
c open files to receive sampled impulse responses of the system B channel
c and that of the receiver filter
open(15,file='sirsysa',form='unformatted')
open(12,file='sirwti',form='formatted')
call g05cbf(iseded)
stdvn=10.0**(-snr/20.0)
c now enter the actual receiver with shift registers
do 200 kmain=1,nosamp
icount=icount+1
count=real(icount)
do 11 i=1,ndecol
j1=i+1
ibit1(i)=ibit1(j1)
ibit2(i)=ibit2(j1)
idbit1(i)=idbit1(j1)
idbit2(i)=idbit2(j1)
isigr(i)=isigr(j1)
isigi(i)=isigi(j1)
11 continue
do 12 i=1,kp1
j2=i+1
recr(i)=recr(j2)
reci(i)=reci(j2)
12 continue
do 14 i=1,kvec
do 13 j=1,ndecol
j3=j+1
xsigr(i,j)=xsigr(i,j3)
xsigi(i,j)=xsigi(i,j3)
ixsigr(i,j)=ixsigr(i,j3)
ixsigi(i,j)=ixsigi(i,j3)
13 continue
14 continue
c insert sampled impulse responses from short range channel
read(15)(yor(i),i=1,kp)
read(15)(yoi(i),i=1,kp)
if (i, i).or. mod(i, kvec) .eq. 0) then
do 18 j=1,kp
yperdr(j)=yor(1,j)
yperdi(j)=yoi(1,j)
ygestr(j)=0.0
ygesti(j)=0.0
18 continue
do 20 i=1,kvec
do 19 j=1,ndecol
xsigr(i,j)=sigr(j)
xsigi(i,j)=sigi(j)
ixsigr(i,j)=isigr(j)
ixsigi(i,j)=isigi(j)
19 continue
cost(i)=10000.0
20 continue
cost(1)=0.0
endif
do 21 i=1,kp
yor(i)=yperdr(i)
yoi(i)=yperdi(i)
21 continue
c calculation of the intersymbol interference
do 25 i=1,kvec
detr(i)=0.0
det(i)=0.0
do 24 j=2,kp
j5=ndeco+1-j
detr(i)=detr(i)+xsigr(i,j5)*yperdr(j)-xsigi(i,j5)*yperdi(j)
det(i)=det(i)+xsigr(i,j5)*yperdi(j)+xsigi(i,j5)*yperdr(j)
24 continue
25 continue
c generation of signals in bits
xx=g05caf(xx)
if(xx-0.5)30,30,31
30 ibit1(ndeco)=0
goto 32
31 ibit1(ndeco)=1
32 xx=g05caf(xx)
if(xx-0.5)34,34,35
34 ibit2(ndeco)=0
goto 36
35 ibit2(ndeco)=1
36 continue
c differential encoding and qpsk signalling
jenc=idbit1(ndeco)*8+idbit2(ndeco)*4+ibit1(ndeco)*2+ibit2(ndeco)+1
idbit1(ndeco)=iperv1(jenc,1)
idbit2(ndeco)=iperv1(jenc,2)
isigr(ndeco)=iperv2(jenc,1)
isigi(ndeco)=iperv2(jenc,2)
sigr(ndeco)=real(isir(ndeco))
sigr(ndeco)=real(isii(ndeco))
c generate noise and passing it through the receiver filter
read(12,93)recf
12 format(16x,f21.10)
do 40 m=1,2
do 37 i=1,kp1
j6=i+1
hnosr(i)=hnosr(j6)
hnosi(i)=hnosi(j6)
37 continue
hnosr(kp)=g05ddf(0.0,stdvn)
hnosi(kp)=g05ddf(0.0,stdvn)
w=0.0
wi=0.0
do 38 i=1,kp
j7=kp-i+1
wr=wr+hnosr(j7)*recf(i)
wi=wi+hnosi(j7)*recf(i)
38 continue
40 continue
c calculate the received signal and then add the gauss noise
recr(kp)=0.0
reci(kp)=0.0
do 41 i=1,kp
j8=ndeco+1-i
recr(kp)=recr(kp)+sigr(j8)*yor(i)-sigi(j8)*yoi(i)
reci(kp)=reci(kp)+sigr(j8)*yoi(i)+sigi(j8)*yor(i)
41 continue
recr(kp)=recr(kp)+wr
reci(kp)=reci(kp)+wi
c start the detection process, this process begins with
c calculation of the lowest cost vector in the
c threshold detector
do 43 i=1,kvec
vs1=recr(kp)-detr(i)
vs2=reci(kp)-deti(i)
v detr(i)=vs1
v deti(i)=vs2
if (vs1 .ge. 0) then
xsigr(i,ndeco)=1.0
ixsigr(i,ndeco)=1
else
xsigr(i,ndeco)=-1.0
ixsigr(i,ndeco)=-1
endif
if (vs2 .ge. 0) then
xsigi(i,ndeco)=1.0
ixsigi(i,ndeco)=1
else
xsigi(i,ndeco)=-1.0
ixsigi(i,ndeco)=-1
endif
detr=vs1-xsigr(i,ndeco)
deti=vs2-xsigi(i,ndeco)
detr(i)=detr
deti(i)=deti
cost(i)=(i)=cost(i)+detr*detr+deti*deti*deti
43 continue
c vector selection in the first 1k vectors
c cost=1000000.0
do 45 i=1,kvec
if (cost1(i)-ccost)44,45,45
44 c cost=cost1(i)
kcl=i
45 continue
cost2(1)=ccost
ipbq(1)=kc1
cost1(kc1)=10000000.0

c now that the vectors obtained, find them in bit forms
jadn=ixsigr(kc1,1)+ixsigi(kc1,1)
if (jadn-0)46,48,47
46 idb1=1
idb2=1
goto 50
47 idb1=0
idb2=0
goto 50
48 if (ixsigi(kc1,1).eq.1)then
   idb1=1
   idb2=0
else
   idb1=0
   idb2=1
endif
50 continue
c do differential decoding and do the error count
jdec=ipdb1*8+ipdb2*4*idb1*2+idb2+1
isigb1=iperv3(jdec,1)
isigb2=iperv3(jdec,2)
if (icount.le.ntl)go to 55
if (isigr(1)-ixsigr(kc1,1)52,51,52
51 if (isigi(1)-ixsigi(kc1,1)52,53,52
52 iesym=iesym+1
53 if (idbit1(1).ne.idb1)ieb1=ieb1+1
if (idbit2(1).ne.idb2)ieb2=ieb2+1
if (ibit1(1).ne.isigb1)ideb1=ideb1+1
if (ibit2(1).ne.isigb2)ideb2=ideb2+1
55 continue
c discard the vectors which are far out
56 if (ixsigr(i,1)-ixsigr(kc1,1))57,56,57
57 cost1(i)=1000000.0
58 continue
c now select vectors for expansion
if (mvect.eq.1)goto 63
do 62 i=1,mvect-1
ccost=1000000.0
60 continue
ccost=cost1(l)
kc2=1
60 continue
cost2(i+1)=ccost
ipbq(i+1)=kc2
cost1(kc2)=10000000.0
62 continue
63 continue
c pseudo-quaternery expansion and selections
mc1=1
jd1=0
do 70 i=1,mvec1
kc3=ipbq(i)
cost3(mc1)=cost2(i)
do 65 i1=1,4
jd1=jd1+1
do 64 k=1,n deco
itotr(jd1,k)=ixsigr(kc3,k)
itoti(jd1,k)=ixsigi(kc3,k)
64 continue
65 continue
itotr(jd1,n deco)=ixsigr(kc3,n deco)
itoti(jd1,n deco)=ixsigi(kc3,n deco)
itotr(jd1-1,n deco)=ixsigr(kc3,n deco)
itotr(jd1-2,n deco)=ixsigr(kc3,n deco)
jd2=2
do 66 i2=2,4
jd3=jd1-jd2
ddetr=v detr(kc3)-real(itotr(jd3,n deco))
ddeti=v detr(kc3)-real(itoti(jd3,n deco))
cost3=cost1(kc3)+ddetr*ddetr+ddeti*ddeti
jd2=jd2-1
66 continue
mc1=mc1+4
70 continue
c pseudo-binary expansion and selections
if (mvec2.eq.0)goto 100
nd1=mvec1*4
do 95 i=1,mvec2
kc3=ipbq(mvec1+i)
cost3(mc1)=cost2(mvec1+i)
do 80 i1=1,2
nd1=nd1+1
do 75 j=1,n deco
itotr(nd1,j)=ixsigr(kc3,j)
itoti(nd1,j)=ixsigi(kc3,j)
75 continue
80 continue
txr=ixsigr(kc3,n deco)
txi=ixsigi(kc3,n deco)
vmr=sign(2.10d0,detr(kc3))
ivmr=int(vmr)
vmi=sign(2.10d0,detvi(kc3))
ivmi=int(vmi)
if (abs(detvi(kc3))-abs(detr(kc3))) 81,81,85
81 itotr(nd1,n deco)=txr+ivmr
if (abs(itotr(nd1,n deco))-2) 90,84,84
84 itotr(nd1,n deco)=txr
itoti(nd1,n deco)=txi+ivmi
if (abs(itoti(nd1,n deco))-2) 90,86,86
86 itoti(nd1,n deco)=txi-ivmi
goto 90
85 \[ \text{itoti}(\text{nd1,ndeco})=txi+ivmi \]
if (abs(itoti(\text{nd1,ndeco}))<2) 90,87,87
87 \[ \text{itotr}(\text{nd1,ndeco})=txr+ivmr \]
\[ \text{itoti}(\text{nd1,ndeco})=txi \]
if (abs(itotr(\text{nd1,ndeco}))<2) 90,88,88
88 \[ \text{itotr}(\text{nd1,ndeco})=txr-ivmr \]
90 continue

ddetr=detvr(kc3)-real(itotr(\text{nd1,ndeco}))
ddeti=detvi(kc3)-real(itoti(\text{nd1,ndeco}))
cost3(\text{nd1})=cost(kc3)+ddetr*ddetr+ddeti*ddeti
mcl=mcl+2
95 continue
100 continue
c the single vector selection
if (mvec3 .eq. 0) go to 110
105 do i=1,mvec3
kc3=ipbq(mvecl+mvec2+i)
do 103 j=1,ndeco
itotr(mcl,j)=ixsigr(kc3,j)
103 itoti(mcl,j)=ixsigi(kc3,j)
cost3(mcl)=cost2(mvec1+mvec2+i)
mcl=mcl+1
110 continue

120 continue
c now transfer the detected vectors to the original data
125 continue
130 continue
135 continue
140 continue
c the single vector selection
150 continue
160 continue
165 continue
170 continue
175 continue
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205 continue
210 continue
215 continue
220 continue
225 continue
230 continue
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1010 continue
1015 continue
1020 continue
1025 continue
1030 continue
1035 continue
1040 continue
1045 continue
1050 continue
1055 continue
1060 continue
1065 continue
1070 continue
1075 continue
1080 continue
1085 continue
1090 continue
1095 continue
1100 continue
1105 continue
1110 continue
1115 continue
1120 continue
1125 continue
1130 continue
1135 continue
1140 c use the detected data to estimate the sampled impulse responses
recr=0.0
recei=0.0
do 140 i=1,kp
140 j=ndeco-i+1
recr=recr+xsigr(1,j10)*yperdr(i)-xsigi(1,j10)*yperdi(i)
recei=recei+xsigr(1,j10)*yperdi(i)+xsigi(1,j10)*yperdr(i)
continue
erestr=recr(1)-recr
eresti=recei(1)-recei
do 150 i=1,kp
j11=ndeco-i+1
estr(i)=b*(erestr*xsigr(1,j11)+eresti*xsigr(i,j11))
esti(i)=b*(eresti*xsigr(1,j11)-erestr*xsigr(i,j11))
ugestr(i)=yperdr(i)+estr(i)
ugesti(i)=yperdi(i)+esti(i)
150 continue
c employ degree two prediction

do 160 i=1,kp
ydgestr(i)=ydgestr(i)+0.5*((const1*estr(i))
ydgesti(i)=ydgesti(i)+0.5*((const1*esti(i))
ygestr(i)=ygestr(i)+2.0*dgestr(i)+1.5*(const2*estr(i))
ygesti(i)=ygesti(i)+2.0*dgesti(i)+1.5*(const2*esti(i))
yperdr(i)=yperdr(i)+ygestr(i)-ydgesti(i)+(const3*estr(i))
yperdi(i)=yperdi(i)+ygesti(i)-ydgesti(i)+(const3*esti(i))
160 continue
200 continue
c calculate error logs and check the snr

snrcalc=10.0*log10(1.0/(stdvn*stdvn))
symerr=iesym/(count-ntr1)
biterr=(ieb1+ieb2)/(2.0*(count-ntr1))
dbiterr=(ideb1+ideb2)/(2.0*(count-ntr1))
print *, 'symbol error rate=', symerr
print *, 'bit error rate=', biterr
print *, 'diff. bit error rate=', dbiterr
stop
end
APPENDIX G4

Receiver of System B Channel Model

1. estimate system B
2. employ differential coding/decoding (look-up table).
3. use estimated (prediction) of system B sirs.
4. adaptively adjust the estimated sirs of the channel
5. employ first nonlinear equaliser and then compare with nml detector.

Transmission rate 2400 samples/second.
or 4800 bits/second.
max. eight eigenray channel.

program detsysb
implicit double precision (a-h,o-z)
parameter (nosamp=24000,ntot=81,kp=24,ns=16,ndeco=32)
parameter (isseed=191,linf=50,kvec=8,nd=2,ntr1=1000)
parameter (mvvec1=1,mvvec2=1,mvvec3=2)
parameter (mvect=mvvec1+mvvec2+mvvec3,msec=1200)
double precision hnosr(kp),hnosi(kp),g05cbf,g05ddf,stdvn
double precision wlinr(kp),wlini(kp),recf(kp),yor(kp)
double precision youi(kp),sigr(ntot),siog(ntot)
double precision xsigr(kvec,ndeco),xsigi(kvec,ndeco)
double precision detr(kvec),deti(kvec),vdeitr(kvec)
double precision vdei(kvec),deter(kvec),vdei(kvec)
double precision cost(kvec),cost1(kvec),cost2(mvect)
double precision cost3(kvec),yomr(kp),yomi(kp),symor(kp)
double precision yosr(linf,kp),yosi(linf,kp)
double precision syadf(r(linf),syadfl(linf),rec(r(linf)
double precision rec(r(linf),yperdr(kp),yperdr(kp)
double precision youg(r(kp),yegest(kp),ugest(kp)
double precision ugest(kp),estr(kp),est(kp)
integer ipers1(ndeco),ipers2(ndeco),ipers3(ndeco)
integer iperv1(ns,nd),iperv2(ns,nd),iperv3(ns,nd)
integer ibit1(ntot),ibit2(ntot),ibit1(ntot),ibit2(ntot)
integer isigr(ntot),isigi(ntot),ixsigr(kvec,ndeco)
integer ixsigi(kvec,ndeco),itotr(kvec,ndeco)
integer itoti(kvec,ndeco),ibpq(mvect)
stdvn=sqrt(1.0)

snr=30.0d0
b=0.110d0
theta=0.975
ntotl=ntot-1
linfl=linf-1
linf2=linf-2

initializations
xx=0.0
icount=0
iperder=0.0
isymer=0
ibrl=0
iber2=0
idber1=0
idber2=0
ipdber1=0
ipdber2=0
do 1 i=1,ntot
  ibit1(i)=0.0
  ibit2(i)=0.0
  idbit1(i)=0.0
  idbit2(i)=0.0
  sigr(i)=0.0
  sigi(i)=0.0
  isigr(i)=0.0
  isigi(i)=0.0
1 continue

do 2 i=1,linf
  recr(i)=0.0
  reci(i)=0.0
2 continue
do 3 j=1,kp
  hnosr(j)=0.0
  hnos(i)=0.0
3 continue

c initialise the stored vectors and costs in the detector
do 5 i=1,kvec
  cost(i)=10000.0d0
do 4 j=1,ndeco
  xsigr(i,j)=1.0
  xsigi(i,j)=1.0
  ixsigr(i,j)=1
  ixsigi(i,j)=1
4 continue
5 continue

c initializing the arrays where sirs and data as well as the
c arrays for the prediction are situated this ensures that
c there are initially some values for sir before estimation
c for the adaptive filter.
do 7 i=1,linf
  do 6 j=1,kp
    yosr(i,j)=0.0
    yosi(i,j)=0.0
  6 continue
  yosr(i,1)=1.0
  yosr(i,2)=-1.0
7 continue
do 8 i=1,kp
  ypredr(i)=0.0
  ypredi(i)=0.0
  yggest(i)=0.0
  yggest(i)=0.0
8 continue
  ypredr(1)=1.0
  ypredr(2)=-0.1
cost(1)=0.0
ndeco1=ndeco-1
const1=(1.0-theta)*(1.0-theta)
const2=1.0-(theta*theta)
data ipers1 /0,0,0,1,1,0,1,0,1,1,0,1,0,0,1,0,1,0,0,0,
1,1,0,1,1,1,0,1,0,1,0,0/
data ipers2 /1,1,-1,1,1,-1,-1,-1,1,1,-1,1,1,1,-1,
1,1,1,1,-1,-1,1,1,-1,1,1,1,1,1,1/
data ipers3 /0,0,0,1,1,0,1,1,0,0,0,1,1,0,1,0,1,0,1,1,1,
1,0,0,1,0,1,1,1,0,0,0,1,0,0,0/
k1=0
do 10 i=1,ns
do 9 j=1,nd
iperv1(i,j)=ipers1(k1+j)
iperv2(i,j)=ipers2(k1+j)
iperv3(i,j)=ipers3(k1+j)
9 continue
k1=k1+2
10 continue
c open files to receive sampled impulse response of the system
c B channel and that of the receiver filter
open(15,file='sirsysb',form='unformatted')
open(12,file='sirwlti',form='formatted')
call g05cbf(iseed)
stdvn=10.0**(-snr/20.0)
c now enter the actual receiver with shift registers
do 200 kmain=1,nosamp
icount=icount+1
count=real(icount)
do 11 i=1,ntot1
j1=i+1
ibit1(i)=ibit1(j1)
ibit2(i)=ibit2(j1)
idbit1(i)=idbit1(j1)
idbit2(i)=idbit2(j1)
isigr(i)=isigr(j1)
isigi(i)=isigi(j1)
11 continue
do 12 i=1,linfl
j2=i+1
recr(i)=recr(j2)
reci(i)=reci(j2)
12 continue
do 14 i=1,kvec
do 13 j=1,ndeco1
j3=j+1
xsigr(i,j)=xsigr(i,j3)
xsigi(i,j)=xsigi(i,j3)
ixsigr(i,j)=ixsigr(i,j3)
ixsigi(i,j)=ixsigi(i,j3)
13 continue
14 continue
do 17 i=1,linfl
do 16 j=1,kgp
j4=i+1
yosr(i,j)=yosr(j4,j)
yosi(i,j)=yosi(j4,j)
16 continue
17 continue

insert sampled impulse responses from long range 8-e channel
read(15)(yosr(linf,i),i=1,kp)
read(15)(yosi(linf,i),i=1,kp)
if (icount.eq. linf .or. mod(icount,msec).eq. 0) then
do 18 j=1,kp
yperdr(j)=yosr(1,j)
yperdi(j)=yosi(1,j)
ygestr(j)=0.0
ygesti(j)=0.0
18 continue
do 20 i=1,kvec
do 19 j=1,ndecol
xsigr(i,j)=sigr(j)
xsigi(i,j)=sigi(j)
ixsigr(i,j)=isigr(j)
ixsigi(i,j)=isigi(j)
19 continue
cost(i)=10000.0
20 continue
cost(1)=0.0
endif
do 21 i=1,kp
yor(i)=yperdr(i)
yoi(i)=yperdi(i)
21 continue

c at this point, the estimated samples are sent to the linear filter to first minimum phase and the produce the adaptively adjusted tap gains
call adapfil(yor,yoi,icount,yomr,yomi,yadfr,yadfi)
c scale the outputs of the filter
syq=yomr(1)**2+yomi(1)**2
do 22 i=1,kp
symor(j)=(ymor(1)*ymor(j)+ymoi(1)*ymoi(j))/syq
symoi(j)=(ymoi(1)*ymoi(j)-ymor(1)*ymor(j))/syq
22 continue
do 23 i=1,linf
syadfr(j)=(ymor(1)*yadfr(j)+ymoi(1)*yadfi(j))/syq
syadfi(j)=(ymoi(1)*yadfi(j)-ymor(1)*yadfr(j))/syq
23 continue
c calculation of the intersymbol interference
do 25 i=1,kvec
detri(i)=0.0
deti(i)=0.0
do 24 j=2,kp
j5=ndeco+1-j
detri(i)=detri(i)+xsigr(i,j5)*symor(j)-xsigi(i,j5)*symoi(j)
\texttt{deti(i)=deti(i)+xsigr(i,j)*symoi(j)+xsigi(i,j)*symor(j)}

\texttt{continue}
\texttt{continue}

\texttt{c generation of signals in bits}
\texttt{xx=g05caf(xx)}
\texttt{if(xx-0.5)30,30,31}
\texttt{ibit1(ntot)=0}
\texttt{goto 32}
\texttt{ibit1(ntot)=1}
\texttt{xx=g05caf(xx)}
\texttt{if(xx-0.5)34,34,35}
\texttt{ibit2(ntot)=0}
\texttt{goto 36}
\texttt{ibit2(ntot)=1}
\texttt{continue}

\texttt{c differential encoding and qpsk signalling}
\texttt{jenc=idbit1(ntot)*8+idbit2(ntot)*4+ibit1(ntot)*2+ibit2(ntot)+1}
\texttt{idbit1(ntot)=iperv1(jenc,1)}
\texttt{idbit2(ntot)=iperv1(jenc,2)}
\texttt{isigr(ntot)=iperv2(jenc,1)}
\texttt{isigi(ntot)=iperv2(jenc,2)}
\texttt{sigr(ntot)=real(isigr(ntot))}
\texttt{sigi(ntot)=real(isigi(ntot))}

\texttt{c generate noise and passing it through the receiver filter}
\texttt{read(12,93)recf}
\texttt{format(1x,t21.17)}
\texttt{do 40 m=1,2}
\texttt{do 37 i=1,kp-1}
\texttt{j6=i+1}
\texttt{hnosr(i)=hnosr(j6)}
\texttt{hnosi(i)=hnosi(j6)}
\texttt{continue}
\texttt{hnosr(kp)=g05ddf(0.0, stdvn)}
\texttt{hnosi(kp)=g05ddf(0.0, stdvn)}
\texttt{wr=0.0}
\texttt{wi=0.0}
\texttt{do 38 i=1,kp}
\texttt{j7=kp-i+1}
\texttt{wr=wr+hnosr(j7)*recf(i)}
\texttt{wi=wi+hnosi(j7)*recf(i)}
\texttt{continue}
\texttt{continue}

\texttt{c calculate the received signal and then add the gauss noise}
\texttt{recr(linf)=0.0}
\texttt{reci(linf)=0.0}
\texttt{do 41 i=1,kp}
\texttt{j8=ntot+1-i}
\texttt{recr(linf)=recr(linf)+sigr(j8)*yosr(linf,i)-sigi(j8)*yosi(linf,i)}
\texttt{reci(linf)=reci(linf)+sigr(j8)*yosr(linf,i)+sigi(j8)*yosi(linf,i)}
\texttt{continue}
\texttt{recr(linf)=recr(linf)+wr}
\texttt{reci(linf)=reci(linf)+wi}
pass this signal through the adaptive filter

c defr=0.0
c def1=0.0
do 42 i=1,linf
j9=linf-i+1
c defr=adfr+syadfr(i)*recr(j9)-syadfi(i)*reci(j9)
c def1=adfi+syadfr(i)*reci(j9)+syadfi(i)*recr(j9)
42 continue

c start the detection process, this process begins with
c calculation of the lowest cost vector in the
c threshold detector

do 43i=1,kvec
vs1=adfr-detr(i)
vs2=adfi-deti(i)
vs detr(i)=vs1
vs deti(i)=vs2
if (vs1.ge.0) then
xsigr(i,ndeco)=1.0
ixsigr(i,ndeco)=1
else
xsigr(i,ndeco)=-1.0
ixsigr(i,ndeco)=-1
endif
if (vs2.ge.0) then
xsigi(i,ndeco)=1.0
ixsig(i,ndeco)=1
else
xsigi(i,ndeco)=-1.0
ixsig(i,ndeco)=-1
endif
detr=vs1-xsigr(i,ndeco)
deti=vs2-xsigi(i,ndeco)
detr(i)=detr
deti(i)=deti
cost1(i)=cost(i)+detr*detr+deti*deti
43 continue

c vector selection in the first 1k vectors
ccost=1000000.0

do 45 i=1,kvec
if (cost1(i)-ccost)44,45,45
44 ccost=cost1(i)
kci=i
45 continue

c now that the vectors obtained, find them in bit forms
jadn=ixsigr(kc1,1)+ixsigi(kc1,1)
if (jadn-0)46,48,47
46 idb1=1
idb2=1
goto 50
47 idb1=0
idb2=0
goto 50
48 if (ixsigr(kcl,l) .eq. 1) then
  idb1=1
  idb2=0
else
  idb1=0
  idb2=1
endif
50 continue
do differential decoding and do the error count
  jdec=ipdb1*8+ipdb2*4+idb1*2+idb2+1
  isigb1=iperv3(jdec,1)
  isigb2=iperv3(jdec,2)
if (icount .le. ntr) go to 55
if (isigr(l)-ixsigr(kcl,l))52,51,52
  51 if (isigi(I)-ixsigr(kcl,l))52,53,52
  52 iesym=iesym+1
  53 if (idbit1(l).ne. idbl)iebl=iebl+1
  54 if (idbit2(l).ne. idb2)ieb2=ieb2+1
  55 continue
discard the vectors which are far out
do 58 i=1,kvec
  57 cost1(i)=100000.0
  58 continue
now select of vectors for expansion
if (mvect .eq. 1) goto 63
do 62 i=1,mvect-1
  ccost=1000000.0
  do 61 l=1,kvec
    if (cost1(l)-ccost)59,60,60
      59 ccost=cost1(l)
      kc2=l
      continue
    cost2(i+1)=ccost
    ipbq(i+1)=kc2
    cost1(kc2)=1000000.0
  60 continue
  62 continue
peusodo-quarternery expansion and selections
  mc1=1
  jd1=0
  do 70 j=1,mvec1
    kc3=ipbq(j)
    cost3(mc1)=cost2(i)
    do 65 il=1,4
      jm=il+1
      do 64 k=1,ndeco
        itotr(jd1,k)=ixsigr(kc3,k)
  65 continue
  64 continue
  70 continue
itoti(jd1,k)=ixsigi(kc3,k)

continue

continue

itotr(jd1,ndeco)=-ixsigr(kc3,ndeco)
itoti(jd1,ndeco)=-ixsigi(kc3,ndeco)
itoti(jd1-1,ndeco)=-ixsigi(kc3,ndeco)
itotr(jd1-2,ndeco)=-ixsigr(kc3,ndeco)
jd2=2
do 66 i2=2,4
jd3=jd1-jd2
ddetr=vdetr(kc3)-real(itotr(jd3,ndeco))
ddetti=vdetti(kc3)-real(itoti(jd3,ndeco))
cost3=cost1(kc3)+ddetr*ddetr+ddetti*ddetti
jd2=jd2-1

continue

mc1=mc1+4

continue

c pseudo-binary expansion and selections
if (mvec2 .eq. 0) goto 100
nd1=mvec1*4
do 95 i=1,mvec2
kc3=ipbq(mvec1+i)
cost3(mc1)=cost2(mvec1+i)
do 80 i1=1,2
nd1=nd1+1
do 75 j=1,ndeco
itotr(nd1,j)=ixsigr(kc3,j)
itoti(nd1,j)=ixsigi(kc3,j)

continue

80

81

84

86

85

87

88

90

continue

ddetr=vdetr(kc3)-real(itotr(nd1,ndeco))
ddetti=vdetti(kc3)-real(itoti(nd1,ndeco))
cost3(nd1)=cost(kc3)+ddetr*ddetr+ddetti*ddetti
mc1 = mc1 + 2
95 continue
100 continue

c the single vector selection
if (mvec3 .eq. 0) go to 110
do 105 i = 1, mvec3
   kc3 = ipbc(mvec1 + mvec2 + i)
   do 103 j = 1, ndeco
      itotr(mc1, j) = ixsigr(kc3, j)
      itoti(mc1, j) = ixsigi(kc3, j)
   103 continue
   cost3(mc1) = cost2(mvec1 + mvec2 + i)
105 continue
110 continue

c now transfer the detected vectors to the original data
sequences for the next iteration and do subtraction for
the lowest cost vectors going to zero
do 120 i = 1, kvec
   do 115 j = 1, ndeco
      ixsigr(i, j) = itotr(i, j)
xsigr(i, j) = real(ixsigr(i, j))
      ixsigi(i, j) = itoti(i, j)
xsigi(i, j) = real(ixsigi(i, j))
   115 continue
   cost(i) = cost3(i)
120 continue
130 continue
140 continue
130 continue
120 continue
115 continue
110 continue

use the detected data to estimate the sampled impulse responses
recer = 0.0
recei = 0.0
do 140 i = 1, kp
   j10 = ndeco - i + 1
   recret = recer + xsigr(1, j10) * yperdr(i) - xsigi(1, j10) * yperdi(i)
   recei = recei + xsigr(1, j10) * yperdi(i) + xsigi(1, j10) * yperdr(i)
140 continue

erestr = recer(1) - recer
esteti = receti(1) - recei
140 continue
150 continue

c employ degree one prediction
do 160 i=1,kp
  ygestr(i)=ygestr(i)+(const1*estr(i))
  ygesti(i)=ygesti(i)+(const1*esti(i))
  yyperdr(i)=yperdr(i)+ygestr(i)+(const2*estr(i))
  yperdi(i)=yperdi(i)+ygesti(i)+(const2*esti(i))
160 continue
200 continue
93 format(1x,f21.10)
c calculate error logs and check the snr
snrcalc=10.0*log10(1.0/(stdvn*stdvn))
symerr=iesym/(count-ntrl)
biterr=(iebl+ieb2)/(2.0*(count-ntrl))
dbiterr=(idebl+ideb2)/(2.0*(count-ntrl))
print *, 'symbol error rate=', symerr
print *, 'bit error rate=', biterr
print *, 'diff. bit error rate=', dbiterr
stop
end
c linear filter subroutine
subroutine adapfil(yor,yoi,icount,yomr,yomi,yadfr,yadfi)
  implicit double precision (a-h,o-z)
  parameter(nstp=9 ,kp=24,linf=50,linfl=linf+1,kpl=kpl+1)
  double precision yor(kp),yoi(kp),yomr(kp),yomi(kp)
  double precision err(kpl),eri(kpl),frr(kpl)
  double precision fri(kpl),rorl(kp),roim(kp),str(nstp)
  double precision sti(nstp),tstr(kp),sti(kp),yadfr(linfl)
  double precision yadfi(linfl),vdr(linfl),vdi(linfl)
  double precision pdfr(kp),pdfi(kp)
  c data str
  /0.00000,0.90909,0.00000,0.00000,-0.90909,
  0.64282,0.64282,-0.64282,-0.64282/  
c data sti
  /0.00000,0.00000,-0.90909,0.90909,0.00000,
  -0.64282,0.64282,0.64282,-0.64282/  
data str
  /0.00000,0.50000,0.00000,0.00000,-0.50000,
  0.53354,0.53354,-0.53354,-0.53354/  
data sti
  /0.00000,0.00000,-0.50000,0.50000,0.00000,
  -0.53354,0.53354,0.53354,-0.53354/  
  istr=int(str(nstp)*100.0)
  isti=int(sti(nstp)*100.0)
  jf=1
  c=1.0
d=10.0e-6
uncr=1.05
alt=1.0/uncr
nrt=0
kpp=kp-2
idivgc=40
if (icount .eq. 1) then
  do 210 i=1,nstp
    tstr(i)=str(i)
  210 continue
  do 220 i=nstp+1,kp
    tstr(i)=0.0
c

tsti(i)=0.0
continue
endif
do 230 i=1,kp
yomr(i)=yor(i)
yomi(i)=yoi(i)
continue
do 300 continue

one tap feedback filter

betr=tstr(jf)
beti=tsti(jf)
do 500 i=1,divgc
do 310 j=1,kpl
err(j)=0.0
eri(j)=0.0
continue

pcr=0.0
pci=0.0
do 320 j=1,kp
j12=kp+1-j
fotr=yomr(j12)-(betr*pcr-beti*pci)
foti=yomi(j12)-(betr*pci+beti*pcr)
pcr=fotr
pci=foti
er(j12)=fotr
eri(j12)=foti
continue

alfr=-betr
alfi=-beti
epsilr=err(kp)
epsili=eri(kp)
do 330 i=1,kpp
j13=kp-i
palfi=epsilr*alfr-epsili*alfi
palfi=epsilr*alfr+epsili*alfi
epsilr=palfi+err(j13)
epsili=palfi+eri(j13)
continue

epsilm=epsilr*epsilr+epsili*epsili
dvalr=(err(1)*epsilr+eri(1)*epsili)/epsilm
dvali=(eri(1)*epsilr-err(1)*epsili)/epsilm
dvalm=dvalr*dvalr+dvali*dvali
continue the iteration to obtain convergence if not allready
if (dvalm .lt. d)then
goto 700
else
dvalr=c*dvalr
dvali=c*dvali
betr=betr+dvalr
beti=beti+dvali
dval1=sqrt(betr*betr+beti*beti)
if(dval1 .gt. alt)then
goto 550
endif
endif
500 continue
550 continue

if divergence is occurred then obtain a new set of starting points

if (icount .eq. 1) then
if (jf .lt. nstp) then
jf=jf+1
goto 300
else
goto 600
endif
itstr=int(tstr(jf)*100.0)
itsti=int(tsti(jf)*100.0)
if (itstr .eq. istr .and. itsti .eq. isti) then
goto 600
else
jf=jf+1
goto 300
endif
endif
700 continue

pass now through the two tap filter (feedforward transversal)
nt=nt+1
rorl(nt)=betr
roim(nt)=beti
frr(1)=err(1)
fri(1)=eri(1)
do 710 i=2,kp1
j14=i-1
frr(i)=err(i)+err(j14)*betr+eri(j14)*beti
fri(i)=eri(i)+eri(j14)*betr-err(j14)*beti
yomr(j14)=frr(i)
yomi(j14)=fri(i)
710 continue

try again for new starting points
if (icount .eq. 1) then
if (jf .lt. nstp) then
jf=jf+1
goto 300
else
goto 600
endif
else
if (jf .lt. nt) then
jf=jf+1
goto 300
else
goto 600
endif
endif
600 continue

c set the starting points for the next time round when all
c roots are found
ntot=nt+nspl+1
npt=nt
do 730 i=1,nt
tstr(i)=rorl(i)
tsti(i)=roim(i)
730 continue
do 740 i=1,nspl
tstr(nt+i)=str(i)
tsti(nt+i)=sti(i)
740 continue
if(ntot lt kp) then
do 750 i=ntot,kp
tstr(i)=0.0 tsti(i)=0.0
750 continue
else
goto 800
endif
800 continue
do 850 j=1,nt
ctr=rorl(j)
ci=roim(j)
rx=ctr*ctr+cti*cti
pdfr(j)=(-1.0*ctr)/rx
pdfi(j)=cti/rx
850 continue
now Here the arrays of yomr and yomi contain the minimum
phase response of the sampled impulse response of the channels under investigations. The following determines the linear filter’s tap gains
do 860 i=1,linfl
yadfr(i)=0.0
yadfi(i)=0.0
860 continue
yadfr(linfl)=1.0
do 900 i3=1,nt
gamr=rorl(i3)
gami=roim(i3)
do 865 j=1,linfl
vdr(j)=0.0
vdi(j)=0.0
865 continue
vdr(1)=yadfr(1)
vdi(1)=yadfi(1)
do 870 j=1,linfl
j15=j+1
vdr(j15)=yadfr(j15)+(yadfr(j)*gamr+yadfr(j)*gami)
vdi(j15)=yadfi(j15)+(yadfi(j)*gami-yadfr(j)*gami)
870 continue
pass this through one tap filter and process the reverse order
qcr=0.0
qci=0.0
do 880 i=1,linf
    j16=linf-i+2
    qfr=vdr(j16)-(gamr*qcr-gami*qci)
    qfi=vdi(j16)-(gamr*qci+gami*qcr)
    qcr=qfr
    qci=qfi
    yadfr(j16-1)=qfr
    yadfi(j16-1)=qfi
  880 continue
return
end
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272


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