The use of arc sound & on-line ultrasonic signal processing on computer technology in welding

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The Use of Arc Sound and On-Line Ultrasonic Signal Processing as a Monitoring Medium for Welding

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SUMMARY

Monitoring the welding process on-line with ultrasound is problematic, but promises great rewards. A fast classifier is required to exploit the redundancy available in ultrasonic interrogation and ensure an adequate signal / noise ratio.

TARDIS is such a classifier, using logical neural network techniques and dedicated hardware. The classification performance of TARDIS alone is noisy, but exceptionally fast. This speed of operation can be used to offset the fuzziness of individual classifications, using higher order correlations.

The expert manual welder is capable of simultaneously monitoring visual and acoustic data and, coupled with a knowledge of the process and past experience, is able to attempt an optimum weld. Observations of skilled manual welders has shown a subconscious tendency to change the angle of the electrode and length of arc by listening to adverse fluctuations in the process noise in addition to visual assessment. This has resulted in much research into the analysis of airborne acoustic emissions (AEs) of welding processes. It is evident that to artificially copy these skills requires a fast, robust signal processing and pattern recognition technique similar the known architecture and operation of the brain.

The Department of Design, Brunel University, has been researching the possibilities of including the monitoring of airborne acoustic emissions as an additional correcting factor in automated weld process control. Salient relationships between acoustic emissions and process parameters using off-line statistical techniques has been established, however, real time application remains problematic due to the computational intensity of such methods.

Statistical approaches to the interpretation of arc sounds relies on the direct correlation observable between the acquired signal or its' various transforms and the monitored process parameters. The method is a time consuming and often mathematically gruelling. Artificial neural networks (ANNs) provide an alternative. By the construction of different architectures and the application of various learning algorithms ANNs can provide a noise tolerant adaptive knowledge acquisition system.

The work discussed in this paper illustrates the methods of signal preprocessing and utilisation of artificial neural networks to interpret arc sounds. Techniques are used to filter and compress high dimensional erratic data patterns to form classifiable representations of the process state. Real time scenarios are discussed together with commercially viable hardware solutions.
TARDIS: A NEURAL SIGNAL PROCESSOR FOR WELD ULTRASOUND MONITORING

On-line ultrasonic monitoring of welding

Commercial seam tracking seems dominated by optical systems. CCD camera and spot triangulation technologies have proven accurate, cheap, rugged and compact and offer the potential of making joint metrology or even weldpool qualitative measurements (2). Unfortunately, the bulk of this research endeavour is of no use in monitoring submerged-arc welding. The flux covering complicates seam tracking and precludes the measurement of weldpool features.

On-line ultrasonic interrogation of the weldpool area 'Figure 1' offers direct measurement of penetration, is a front face technique, circumvents weldpool obscuration and is a well understood, much implemented technology in the sister field of NDT.

Transit time is the A-scan feature that is ultimately required. From this, the distance to the reflecting solid/liquid interface (for penetration monitoring) or unwelded plate edge (for seam tracking) can be determined. Identifying the correct echo is necessary for extraction of the transit time, so the echo's amplitude and shape, or profile, must be considered.

The over-riding problem when processing weld ultrasound is contamination of this transient echoes with noise. Echo amplitudes perhaps suffer most. Echoes are attenuated by a combination of HAZ scattering, molten interface scattering and variations in coupling efficiency. All of these effects are dynamic and non-deterministic, with the added complication that attenuated energy often recurs as noise.

A variety of noise sources act upon received transit times, called delay noise. There is an offset due to high temperature velocity reduction and a possible non-deterministic delay occurs dependant upon the incident angle to a weldpool's dendritic interface.

The associated shapes of the echoes are similarly erratic. The elementary wavelets of differing phase that make up a pulse can be considered to each undergo attenuation and delay noise as described above. In fact, there exists no single "ideal" echo (7) because there exists no ideal reflecting surface. Robust characterisation of the correct echoes is the technique's greatest problem (4).

However, the high repeat rates of ultrasonic monitoring are an advantage. Each complete echo-return offers an independent measure, with typically thousands generated per second. Updating a welding rig at, say, 20 Hz presents a fiftyfold data redundancy between available measurements and required outputs. Reducing this redundancy with some form of rapid on-line signal averaging is essential for this processing problem (3). It allows the very randomness of the various noise sources to be exploited.

Unfortunately, the pulsewidths and fundamental frequencies of NDT ultrasound demand very fast digitisation, causing an avalanche of data. Straightforward superposition of consecutive echo returns is problematic. Digital hardware to perform the task would be enormous, most general purpose computers too slow and analogue techniques using CCD or SAW devices too extravagant (8).
The usual approach towards large and unwieldy raw data sets is feature extraction, which implies some form of classification. The solution to the weld ultrasound problem thus becomes some very fast, on-line classification technology. TARDIS is such a classifier.

**TARDIS**

The time / amplitude rapid discriminator, or TARDIS, is a digital pattern correlator designed specifically for the rapid on-line classification required by ultrasound weld monitoring. It is based on n-tuple classification techniques (1) realised in fast bit-slice type dedicated hardware. The architecture is shown in Figure 2.

The TARDIS preprocessor's operation is, briefly, as follows.

1. The ADC generates a new sample. The ADC is on-line, and constantly inspects the ultrasound pressure with zero lag, every 100 ns.

2. Every stored sample value in the array of window registers is shifted to the right by one register. The rightmost, eldest sample is lost and the leftmost register loads the new sample from the ADC.

3. Each register presents its stored sample to its associated logical node. These are bipolar PROM devices, preprogrammed with templates of the sequence to be recognised ‘Figure 3’. The 8-bit binary code that represents the sample value is used to address a single location in the PROM.

4. The PROM outputs the data, a "1" or a "0", that it has stored at the selected address. A "1" signifies that this sample value, in this particular position in the window, could be part of the waveform sequence to be recognised. These data values are stored intermediately in pipeline registers, for speed of operation.

5. Three further nodes, that are also fast PROMs, one of which is combined with the state machine, form a summation pyramid, to total the number of affirmative logical node outputs. This total is known as the response level for the logical neural network (which is what the system amounts to). The response is a measure of the similarity of a particular waveform to the preprogrammed waveforms.

6. The state machine and window counter extract the highest response and its timebase position from a string of samples. Thus a most likely timebase position for an echo is extracted from hundreds of samples of raw data. The compression ratio is around 500 to 1. Remember, this data has been classified on-line and could be used to facilitate closed loop control.

**TARDIS performance**

Figure 4 shows the classification behaviour of the TARDIS system (solid line) as it encounters a plate edge echo (shaded line). The response characteristic is not particularly sharp. This is not unusual for n-tuple schemes, which tend to find themselves applied as
quite "rough-and-ready" but very fast classifiers (6).

If one considers the TARDIS pattern space, the independence of each pattern dimension leads to the formation of cruciform clusters 'Figure 5a'. This is more flexible than linear discriminant methods (Bayesian, FIR matched filter, cross-correlator) 'Figure 5b' but is less so than a minimum-distance (MD), K-nearest neighbour (K-NN) or backpropagation neural network 'Figure 5c'.

In fact, an inspection of the system's performance over complete echo-returns Figure 6' reveals how "rough" the classification performance is. The bogus classification peaks, incidentally, may be stray reflections from the seam, interface noise or occasionally the default result of the total loss of any recognisable signal.

Over many echo returns, of the many varying signal / noise qualities characteristic of tracking a hot weldplate with a moving probe, the classification performance of TARDIS is visibly fragile 'Figure 7'. A single plate edge position reading taken in isolation may well be wildly inaccurate.

In previous work (5), using a similar logical neural network emulated on a general purpose computer, these inaccurate echo returns had to be caught and rejected. This proved to be a huge burden on computing resources and partly responsible for the low eventual classification rate of 4 Hz. The corollary of such a low classification rate is that many potentially useful echo-returns are lost, even as a poor one is being processed.

Using, TARDIS, however, the feature extraction compresses the data and makes it easier to manipulate, for averaging or other further processing. Figure 8 shows the PDF of 80 classification results. Ignoring zeroes (no classification), a modal average easily pinpoints the correct seam position.

The four stage pipelining and bipolar technology allows the network to classify at 10 MHz. Every new window arrangement can be classified in the time it takes a new one to be generated by the ADC. The network throughput is 1.28 Gbits/s. This classification rate is close to supercomputer performance. Figure 9 provides performance measures for some other classification techniques on various computing platforms. The values are for a single classification on an input window of 16 8-bit integer values, assuming digitisation at 10 MHz and an echo duration of around 1.5 us. None approach the raw classification speed of TARDIS.

A current drawback is the primitiveness of the feature extraction state machine. This is necessarily a simple device 'Figure 10', due to the speed at which it must operate. It merely stores a highest response, comparing it with every input summed response and keeping the higher value. These limited and inflexible computing abilities cause many drawbacks.

For one, it is highly susceptible to glitches caused by noise (which are not uncommon in such a large, fast and power hungry system), with no available error checking. Also, the situation of multiple highest responses could be dealt with in a more satisfactory fashion. At present, only the earliest highest response is recorded. Embedding a fast microcontroller in the place of the state machine would solve both of these problems, also simplifying the communication to a host weld control system.
CHARACTERISATION OF ARC SOUNDS

Manual welders

It has been established that skilled manual welders are able to monitor arc sound and alter electrode position in response to changes in audible process noise. The Design Department at Brunel University has been researching the possibilities of including this as an additional correcting factor in automated weld process control. Salient relationships between acoustic emissions and process current using off-line statistical techniques has been established, however, real time application remains problematic due to the computational intensity of such methods.

Investigations of acoustics in MIG using various flux cored wires has proved that by numerically integrating the sound data and plotting a spectrum of the result, close similarities occur with the voltage and current data with a 1 ms delay (9). Further manipulation with moving averages, has highlighted the pulse or dip modes of the process, however, limited success has been found in assessing the spray current mode. This research concludes with a suggested correlation between arc current and integrated acoustic signals and substantiates the use of acoustics for quality assessment of the welding process. However, a faster and more robust method is recommended to utilise this parameter for on-line analysis and control.

In GTA welding Kaskinen et al (10) have provided relationships in acoustic emissions and voltage / current parameters in pulse mode. In this mode, the pulsed power input to the weld creates a corresponding volume change to the arc plasma which, in turn, generates an alternating sound pressure level which is audible. The sound intensity proved to be proportional to the power input to the process, from which voltage and current values were derived. The voltage level provides information concerning the arc length and the research concludes with feasible arc length controller utilising acoustic information.

Fast Fourier Transforms were applied, with limited success, to CO₂ laser welding (11). Acoustic data was acquired via a microphone suitably amplified and processed in real time with a PC hosted digital signal processing (DSP) card to generate an FFT between 4 Hz and 100 kHz. Further processing reduced the frequency range to isolate salient bandwidths. The acoustic emission energy was derived from integrating the FFT spectrum over all frequencies and reproducible correlations found with laser power, welding speed and lens focal position.

The evidence for research into the use of acoustic emission analysis in submerged arc welding is limited. This can be attributed to three main reasons. The lack of visual information on which to validate the results. For example, expensive and often complex apparatus such as X-Ray and infra-red thermography is required to examine weld pool dynamics. Secondly, sound pressures are suppressed by the shielding flux which, at the same time, is responsible for creating sporadic transients as gases escape from the layer of molten slag. Furthermore, material transfer mechanisms which are known to be partly responsible for changes in audible noise in welding processes (12) are limited to mainly slag protected transfer.

The effort evident in the area of acoustic emission analysis for welding processes,
focuses on the correlations with the fundamental process parameters. The use of acoustics as a valid aid to weld monitoring is debatable in some instances as the methods used to interpret them have revealed already known or more easily acquired metrics. However, the general conclusions call for more robust methods of signal processing and interpretation to yield more consistent and reliable measures of the process variables.

Consequently, the analysis of acoustic weld emissions using artificial neural network techniques, including Kohonen Self-organising feature map and Back Propagation methods, has been pursued.

**Experimentation**

Preliminary experimental investigations resulted in an optimised set up where an omni-directional electret condenser microphone (ECM) was mounted 300mm from the welding head in close proximity to suitably shielded pre-amplification. Typical time/amplitude sound pressure levels at varying voltage settings are illustrated in Figure 11.

The signals were then subjected to an active bandpass filter within the audible range and data manipulation achieved with the TMS320C30 system board hosting Hypersignal Workstation software. The transient capture sampling frequency was set to 20kHz and an on-line 128 point Radix 2 FFT instigated 'Figure 12'. Initially weld runs were carried out with optimum parameter settings which were qualified by post weld inspection. The acquired time variant FFT frames were considered as 64 component input vectors for the ANN model. The data from the ideal weld was used as training data for a self organising neural network utilising a Kohonen learning algorithm (13) as illustrated by Figure 13.

This two layered network of fully connected neurons self organised a topological map, from a random starting point, a display of the natural relationships of the patterns used in the training data sets. This is achieved by the competitive activation of an output neuron dictated by the learning algorithm. The output neurons are arranged in a matrix so that each has theoretical neighbours. The activation threshold of neighbouring neurons are adjusted proportionally to the distance in vector space from the winning neuron. In this way each neuron is inhibited or encouraged to activate when presented with the next training set. The training continues until a state of equilibrium occurs or an acceptable level of accuracy is reached.

Instigating subsequent weld runs with various weld process parameter settings and analysing the activation levels of neurons in the output layer, differing patterns emerged indicative of the process state. Figure 13 show resultant three dimensional contour mappings of the network output layer highlighting the responses to changes in the process parameters of voltage, current and travel speed.

In this way the very erratic time variant FFT frames are compressed into an interpretable three dimensional representation of the process state. The generalising capabilities of the network enable further sets of FFT frames to be analysed in a more robust way. The number of output nodes of the self organising map relates to the resolution of the activation map as well as the robustness of the compression technique as each node represents a generalised version of an FFT frame. Too few nodes creates an overgeneralised representation whilst too many results in a slower response time. The optimum number has yet to be established, however, it is evident that the number necessary is dependent upon the welding process and configuration
being instigated.

The resultant three dimensional representations can be classified by use of further neural network models. In this instance both Kohonen Feature Maps and Backpropagation (14) methods were used. In the case of the back propagation model, a network was constructed to monitor the voltage. The activation map was used as the input with the corresponding voltage level as the desired output, the approach is shown in figure 14. The results of this model 'Figure 16' show a definite trend towards the actual monitored voltage with increased accuracy gained by lengthening the training times and extending the training set.

Figure 15 shows the approach for the feature map classifier. The activation maps were presented to the unsupervised learning model which grouped similar maps into regions on the output layer. These regions were then labelled by presenting known classified activation maps to the network. Recall was tested with unknown activation maps with encouraging results, however, more data is required to train a usable network in comparison to the backpropagation method. Furthermore, this network possessed a slower recall time.

**Hardware Considerations**

The application of neural networks entails a substantial amount of signal preprocessing to ensure network compatibility. The computational time for network recall is small in comparison to the necessary on-line DSP. Figure 17 shows the system setup. Data was initially collected on a PC hosted TMS320C30 DSP board. The off line training of the networks was carried out on a 486/66 PC and tested on this platform with prerecorded data. The final trained networks were embedded on a TMS320C32 50MHz DSP board hosted by a PC. The TMS series CPUs are tailored towards signal processing applications which rely on floating point and Multiply Accumulate Cycle (MAC) computation (15). Executing a neural network in recall is usually very calculation intensive. In the case of backpropagation methods each node requires the repetitive calculation of an inner product term to establish the nodal value or weight (16). The TMS320C32 is capable of a MAC rate of 20MHz which enables very fast real time recall for this application.

**Conclusions**

The research presented in this paper suggest a method to interpret the erratic signals obtained from airborne acoustics from the submerged arc welding process. The use of neural networks for audible sound analysis in SAW is possible at real time rates although the information so far gained relates only to already known metrics. Future work will entail the use of these techniques to assess the stability of transfer mechanisms within the process.

**REFERENCES**


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FIGURE 1. ON-LINE ULTRASONIC MONITORING

FIGURE 2. TARDIS HARDWARE ARCHITECTURE

FIGURE 3. PLATE EDGE RAM-NODE TEMPLATES
FIGURE 4. PLATE EDGE CLASSIFICATION

FIGURE 5. PATTERN SPACES
(a) TARDIS (b) LDF (c) PIECEWISE

FIGURE 6. TARDIS CLASSIFICATION OVER COMPLETE ECHO RETURNS

FIGURE 7. CLASSIFIED PLATE-EDGE ECHO LOCATION OVER SUCCESSIVE RUNS
FIGURE 8. PDF OF PLATE EDGE ECHO POSITION

FIGURE 9. PERFORMANCE OF MAC CLASSIFIERS ON GENERAL PURPOSE PLATFORMS

FIGURE 10. HIGH RESPONSE EXTRACTION STATE MACHINE
Figure 11. Typical Time/Amplitude Signals, Sound Pressure Level

Figure 12. 6th Order Time Variant FFT

Figure 13. Feature Map Training and Recall Activations
187 Input Nodes
25 Hidden Nodes
1 Output Node
(Voltage Full Scale Range)

Figure 14. Backpropagation Activation Map Classifier

Figure 15. Labelled Feature Map Classifier
Figure 16. Response from Backpropagation Model to Monitored Voltage (Accuracy improvement gained with increased training set)

Figure 17. System Setup and Hardware Requirements