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Additional Information:

- This article was published in the Journal of Guidance, Control, and Dynamics [© American Institute of Aeronautics and Astronautics] and it was presented at the AIAA Guidance, Navigation, and Control Conference, Portland, Oregon, US, 8-11 Aug 2011. The definitive version is available at: http://dx.doi.org/10.2514/1.56254

Metadata Record: https://dspace.lboro.ac.uk/2134/17841

Version: Accepted for publication

Publisher: © American Institute of Aeronautics and Astronautics

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Nonlinear Model Predictive Coordinated Standoff Tracking of Moving Ground Vehicle*  

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This paper proposes a nonlinear model predictive control framework for coordinated standoff tracking by a pair of unmanned aerial vehicles. The benefit of this approach is to get optimal performance compared to using a decoupled controller structure: heading control for standoff-distance keeping and speed control for phase-keeping. The overall controller structure is fully decentralized in a fact that each unmanned aerial vehicle optimizes its controller based solely on the future propagation of the pair vehicle states and the target estimates received via communication. This paper uses an acceleration model for a sophisticated and realistic target dynamics, which can consider more reasonable system noise covariance matrix reflecting the target’s motion characteristics. To simplify optimization formulation and decrease computation burden, a new manipulation using inner product of position vectors of the unmanned aerial vehicles with respect to the target position is proposed for antipodal tracking instead of using the relative phase angle difference. To consider a more realistic situation, inequality constraints are considered for collision avoidance between unmanned aerial vehicles and control input saturations using penalty functions in the model predictive control scheme. Simulations with a pair of unmanned aerial vehicles are done using a realistic car trajectory data in a urban environment in the United Kingdom to verify the feasibility and benefit of the proposed approach with comparing to a Lyapunov vector field guidance.

*This paper was presented at AIAA Guidance, Navigation, and Control Conference, Portland, Oregon, US, 8-11 Aug 2011  
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I. Introduction

In the last decade, using a swarm of UAVs (Unmanned Airborne Vehicles) has received attention to accomplish synergy with manned systems in both military and civil applications. Searching and subsequent tracking of moving ground target of interest is one of the important capabilities of UAVs required to increase an overall knowledge of the target’s intent and to take proactive measures. In performing such missions, UAVs are to keep a certain distance from the moving target, known as a standoff distance, in order to track it without being noticed and at the same time to acquire the accurate target information. Lawrence\textsuperscript{1} firstly proposed the application of Lyapunov vector fields for standoff coordination of multiple UAVs, which was further investigated by Frew \textit{et. al.}\textsuperscript{2–4} to include phase-keeping as well as standoff tracking. They invented a decoupled control structure in which speed and rate of heading change are separately controlled for standoff distance and phase angle keeping, respectively. Quigley \textit{et. al.}\textsuperscript{5} firstly applied a concept of Hopf bifurcation\textsuperscript{6} to standoff tracking which has faster convergence to the standoff circle than the Lyapunov vector field approach. Chen \textit{et. al.}\textsuperscript{7} proposed the use of a tangent-plus-Lyapunov vector field which includes a simple switching logic between tangent and Lyapunov vector fields to make convergence to the standoff circle faster. Wise and Rysdyk\textsuperscript{8} well surveyed and compared the different methodologies for standoff tracking: Helmsman behavior, Lyapunov vector field, controlled collective motion, and model predictive control. Recently, Prevost \textit{et. al.}\textsuperscript{9} applied a receding horizon model-based predictive control for standoff tracking. Although the aforementioned two works tried to apply the model predictive control (also known as receding horizon control) to standoff tracking, Wise and Rysdyk\textsuperscript{8} used only a simple relative kinematics variation between UAV and target with still decoupling the speed and rate of heading change, and Prevost \textit{et. al.}\textsuperscript{9} focused on a single UAV applications for only the standoff distance keeping with a simple UAV/target trajectory prediction.

Unlike the aforementioned works, this study aims at developing a NMPCST (Nonlinear Model Predictive Coordinated Standoff Tracking) framework for both standoff distance and phase angle keeping by a pair UAVs. The Lyapunov vector field, the Hopf bifurcation and so on\textsuperscript{2,4,5,8} used the heading control for standoff distance keeping and the speed control for phase keeping, separately. Differently from these decoupled controller structure of the previous works, the most valuable benefit of this approach is that it can get an optimal performance in terms of tracking accuracy and fuel consumption. In this way, the proposed optimal control formulation adds value by providing a basis for gain selection or parameter tuning. The overall controller structure of UAV formation considered in this study is fully decentralized in a fact that each UAV optimizes its controller based on the future state predictions of the pair UAV to cooperate with and the target to be tracked. This decentralized optimization is performed after receiving only the control at the previous sampling, the current state, and the current target state/covariance estimation of the pair
UAV via communication. For target trajectory prediction, this paper uses an acceleration model for realistic
target dynamics, which can consider reasonable system noise covariance matrix reflecting the target’s motion
characteristics. For antipodal standoff tracking, the phase keeping term is included in a performance index
of optimization framework as well as standoff-distance keeping. To simplify optimization formulation and
decrease computation burden, a new manipulation using inner product of position vectors of the UAVs with
respect to the target position is proposed instead of using the relative phase angle difference which were used
in most of the existing works.2–4,8 To accomplish the safety under realistic situations, inequality constraints
are also considered for collision avoidance between UAV members and control input saturations in the model
predictive control scheme. Lastly, simulations with a pair of UAVs are done using realistic car trajectory
data in urban traffic in the UK to verify the feasibility and benefits of the proposed approach.

The overall structure of this paper is given as: Section II contains a definition of UAV dynamic model,
ground target model, and sensor model considered in this study. Section III discusses the tracking filter
design and the sensor fusion for target localization and prediction. As the main part of this paper, Section
IV proposes the decentralized structure, definition of performance index and constraints, and nonlinear model
predictive controller design for coordinated standoff tracking. Section V presents the simulation result using
ground driving vehicle trajectory data acquired from a traffic simulation program compared with Lyapunov
vector field guidance. Lastly, conclusions and future works are given in Section VI.

II. Problem Definition

A. UAV Dynamic Model

Assuming each UAV has a low-level flight controller such as SAS(Stability Augmentation System) and
CAS(Controllability Augmentation System) for heading and velocity hold functions, this study aims to
design the model-predictive guidance inputs to this low-level controller for coordinated standoff tracking.
Consider a two-dimensional UAV kinematic model as:

\[
\begin{bmatrix}
\dot{x} \\
\dot{y} \\
\dot{\psi} \\
\dot{v} \\
\dot{\omega}
\end{bmatrix} = f(x, u) =
\begin{bmatrix}
v \cos \psi \\
v \sin \psi \\
\omega \\
-\frac{1}{\tau_v} v + \frac{1}{\tau_v} u_v \\
-\frac{1}{\tau_\omega} \omega + \frac{1}{\tau_\omega} u_\omega
\end{bmatrix}
\] (1)

where \( x = (x, y, \psi, v, \omega)^T \) are the inertial position, heading, speed and yaw rate of the UAV, respectively.
\( \tau_v \) and \( \tau_\omega \) are time constants for considering actuator delay. \( u = (u_v, u_\omega)^T \) are the commanded speed and
turning rate constrained by the following dynamic limits of UAV:

\[ |u_w - v_0| \leq v_{max} \]  
\[ |u_\omega| \leq \omega_{max} \]  

where \(v_0\) is a nominal speed of UAV. To design the nonlinear model predictive controller, the continuous UAV model in Eq. (1) can be discretized by Euler integration into:

\[ x_{k+1} = f_d(x_k, u_k) = x_k + T_s f(x_k, u_k) \]  

where \(x_k = (x_k, y_k, \psi_k, v_k, \omega_k)^T\), \(u_k = (u_v k, u_\omega k)^T\), and \(T_s\) is a sampling time.

**B. Ground Target Model**

General target tracking filters have traditionally been developed for monitoring aerial targets such as airplanes, missiles and so on. Although ground vehicles move with much lower speeds than aerial targets, they often and irregularly perform stop-and-go maneuvers with much smaller turn radius. A constant velocity model broadly used for radar target tracking seems thus unsuitable for tracking ground vehicles, and hence an acceleration or a jerk model can be a candidate instead. After analyzing the car trajectory data acquired by running a S-Paramics traffic simulation program\(^{10}\) and general driving behaviors, it is observed that the jerk is not negligible, but the acceleration is piecewise constant for a specific duration of time. This study, therefore, considers acceleration dynamics\(^{11}\) to apply it to tracking of the moving ground vehicle. This acceleration model regards the target acceleration as a process correlated and exponentially decreasing in time, which means if there is a certain acceleration rate at a time \(t\) then it is likely to be the same jerk also at a time instant \(t+\tau\). Then, discretized system equations for acceleration model are expressed as:

\[ x^t_{k+1} = F_k x^t_k + \eta_k, \]
where $x_k^T = (x_k, \dot{x}_k, \ddot{x}_k, y_k, \dot{y}_k, \ddot{y}_k)^T$, and $\eta_k$ is a process noise which represents the acceleration characteristics of the target. The state transition matrix $F_k$ can be represented as follows:

$$F_k = \begin{bmatrix}
1 & T_s & (e^{-\alpha T_s} + \alpha T_s - 1)/\alpha^2 & 0 & 0 & 0 \\
0 & 1 & (1 - e^{-\alpha T_s})/\alpha & 0 & 0 & 0 \\
0 & 0 & e^{-\alpha T_s} & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & T_s & (e^{-\alpha T_s} + \alpha T_s - 1)/\alpha^2 \\
0 & 0 & 0 & 0 & 1 & (1 - e^{-\alpha T_s})/\alpha \\
0 & 0 & 0 & 0 & 0 & e^{-\alpha T_s}
\end{bmatrix},$$

where $\alpha$ is a correlation parameter which allows for the modeling of the different classes of targets: small $\alpha$ for targets with relatively slow maneuvers and high $\alpha$ for targets with fast and evasive ones. The covariance matrix of the process noise $\eta_k$ can be modeled as follows:

$$Q_k = V[\eta_k] = \frac{\sigma_a^2}{\alpha^4} \begin{bmatrix}
q_{11} & q_{12} & q_{13} & 0 & 0 & 0 \\
q_{12} & q_{22} & q_{23} & 0 & 0 & 0 \\
q_{13} & q_{23} & q_{33} & 0 & 0 & 0 \\
0 & 0 & 0 & q_{11} & q_{12} & q_{13} \\
0 & 0 & 0 & q_{12} & q_{22} & q_{23} \\
0 & 0 & 0 & q_{13} & q_{23} & q_{33}
\end{bmatrix},$$

where $\sigma_a$ is the standard deviation related to target acceleration, and a definition of $q_{ij}$ is:

$$q_{11} = (1 - l + 2m + 2/3m^3 - 2m^2 - 4m \sqrt{l})$$
$$q_{12} = \alpha(l + 1/l - 2m + m^2)$$
$$q_{13} = \alpha^2(1 - l - 2m \sqrt{l})$$
$$q_{22} = \alpha^2(4\sqrt{l} - 3 - l + 2m)$$
$$q_{23} = \alpha^3(l + 1 - 2\sqrt{l})$$
$$q_{33} = \alpha^4(1 - l)$$

where $l = e^{-2\alpha T_s}$ and $m = \alpha T_s$. 

5 of 26

American Institute of Aeronautics and Astronautics
C. Sensor Model of Moving Target Indicator Radar

This study assumes the UAVs are equipped with a MTIR (Moving Target Indicator Radar) to localize the position of target. Because the measurement of MTIR is composed of range and azimuth of the target with respect to the radar location, the actual measurements is the relative range and azimuth with respect to the position of the airborne UAV. The radar measurement \((r, \phi)^T\) can be defined as the following nonlinear relationship using the target position \((x^t_k, y^t_k)^T\) and the UAV position \((x_k, y_k)^T\) as:

\[
\begin{bmatrix}
  r_k \\
  \phi_k
\end{bmatrix}
= h(x^t_k) + \nu_k = \begin{bmatrix}
  \sqrt{(x^t_k - x_k)^2 + (y^t_k - y_k)^2} \\
  \tan^{-1}\left(\frac{y^t_k - y_k}{x^t_k - x_k}\right)
\end{bmatrix} + \nu_k
\]  

where \(\tan^{-1}\) is to be executed as the four quadrant inverse tangent in practice, \(\nu_k\) is a measurement noise vector, and its noise covariance matrix is defined as:

\[
V[\nu_k] = R = \begin{bmatrix}
  \sigma_r^2 & 0 \\
  0 & \sigma_\phi^2
\end{bmatrix}.
\]

III. Tracking Filter Design for Target Localization and Prediction

A. Extended Kalman Tracker

Considering \(h(x^t_k)\) in the measurement equation is nonlinear as shown in Eq. (14), the localization of target can be designed using an EKF(Extend Kalman Filter)\(^{13, 14}\) as:

Time update

\[
x^t_{k|k-1} = F_k x^t_{k-1|k-1}
\]

\[
P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k^T
\]

Measurement update

\[
K = P_{k|k-1} H^T \{H_k P_{k|k-1} H_k^T + R_k\}^{-1}
\]

\[
x^t_{k|k} = x^t_{k|k-1} + K (z_k - h(x^t_{k|k-1}))
\]

\[
P_{k|k} = (I - KH_k) P_{k|k-1}.
\]
where \( z_k \) is a measurement vector. The output matrix \( H_k \) is a Jacobian of Eq. (14) with respect to the time-update state \( \mathbf{x}^t_{k|k-1} \) as

\[
H_k = \frac{\partial h}{\partial \mathbf{x}^t_k} |_{\mathbf{x}^t_{k|k-1}}
\]

(21)

where

\[
\frac{\partial h}{\partial \mathbf{x}^t_k} = \begin{bmatrix}
\frac{y_k^t - y_k}{\sqrt{(x_k^t-x_k)^2 + (y_k^t-y_k)^2}} & 0 & 0 \\
0 & \frac{y_k^t - y_k}{\sqrt{(x_k^t-x_k)^2 + (y_k^t-y_k)^2}} & 0 \\
-\cos^2\{\tan^{-1}\left(\frac{y_k^t - y_k}{x_k^t-x_k}\right)\} & 0 & \cos^2\{\tan^{-1}\left(\frac{y_k^t - y_k}{x_k^t-x_k}\right)\} & 1 & 0 & 0
\end{bmatrix}
\]

(22)

B. State-vector fusion

Since this study assumes a pair of UAVs carry out the coordinated standoff tracking of a ground moving target, each UAV’s MTIR sensor can get its own measurement and execute the tracking filter algorithm separately. After each UAV receives the other’s estimation via communication link, it can run a decentralized sensor fusion to enhance the tracking accuracy. This study simply adopts the following state-vector fusion also known as a track-to-track fusion\(^{15}\) under the assumption that the communication bandwidth is wide enough to transmit the state (6-by-1) and covariance matrix (6-by-6) in both directions between a pair of UAVs.

\[
\hat{\mathbf{x}}^t_k = \mathbf{x}^t_{k|k} + P_k^{|k}(P_k^{p|k} + P_k^{p|k})^{-1}(\mathbf{x}^{tp|k} - \mathbf{x}^t_{k|k})
\]

(23)

\[
P_k = P_k^{|k} + P_k^{p|k}(P_k^{p|k} + P_k^{p|k})^{-1}P_k^{T}
\]

(24)

where \( \mathbf{x}^{tp|k} \) and \( P_k^{p|k} \) represent the state and error covariance estimations of the pair UAV. Instead of the state-vector fusion, the fusion using information filter\(^{16}\) can be used for minimizing the communication load. Subsequently, \( \hat{\mathbf{x}}^t_k \) in Eq. (23) will be used as the initial value of the state for the model prediction of the target for nonlinear model predictive control at each sampling.

IV. Nonlinear Model Predictive coordinated Standoff Target Tracking

A. Definition of Performance Index and Constraints

The geometry between the UAV, the pair UAV, and the ground target considered in this study is shown in Fig. 1. The basic aim of coordinated standoff target tracking is to maintain a distance \(|\vec{r}|\) between the UAV and the target as well as a relative phase angle \(\Delta \theta\) between UAVs to a desired value concurrently. Then, coordinated standoff target tracking can be formulated as a nonlinear model predictive control problem to
find a control input sequence \( U_k = \{u_0, u_1, \ldots, u_{N-1}\} \) that minimizes the following performance index.

\[
J = \phi(\tilde{r}_N, \tilde{d}_N) + \sum_{k=0}^{N-1} L(\tilde{r}_k, \tilde{d}_k, u_k)
\]

where

\[
\phi(\tilde{r}_N, \tilde{d}_N) = \frac{1}{2}(p_r \tilde{r}_N^2 + p_d \tilde{d}_N^2)
\]

\[
L(\tilde{r}_k, \tilde{d}_k, u_k) = \frac{1}{2} \left( q_r \tilde{r}_k + q_d \tilde{d}_k + r_v \left( \frac{u_{v_k} - v_0}{v_{max}} \right)^2 + r_\omega \left( \frac{u_{\omega_k} - \omega_0}{\omega_{max}} \right)^2 \right)
\]

with \( \tilde{r}_k = Cx_k - C_t x^t_k \) and \( \tilde{r}_k^p = Cx^p_k - C_t x^t_k \) representing the relative vectors from the target position to the positions of the current UAV and its pair UAV, respectively. \( Cx_k, Cx^p_k \) and \( C_t \) represent the positions of the current UAV, the pair UAV, and the ground target which will be propagated according to time update equation of the Extended Kalman tracker in Eq. (16), respectively. \( C \in R^{2x5} \) and \( C_t \in R^{2x6} \) is simply represented by the definition of state variables: \( x_k = (x_k, y_k, \psi_k, v_k, \omega_k)^T \), \( x^p_k = (x^p_k, y^p_k, \psi^p_k, v^p_k, \omega^p_k)^T \), and
\( x_k^l = (x_k^l, \dot{x}_k^l, \ddot{x}_k^l, y_k^l, \dot{y}_k^l)^T \):

\[
C = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
\end{bmatrix},
\]

\( C_l = \begin{bmatrix}
1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
\end{bmatrix} \) .

Also, \( r_d \) is a desired standoff distance from the UAVs to the ground target position, \( N \) is the length of receding horizon, \( v_0 \) is a nominal speed of UAVs, and \( \omega_d \) is a nominal angular velocity. \( p_r, p_d, q_r, q_d, r_v, \) and \( r_\omega \) are constant weighting scalars.

In Eq. (29), \( \tilde{d}_k \) is derived from the inner product of \( \hat{r}_k \) and \( \hat{r}_p^p \) as:

\[
< \hat{r}_k, \hat{r}_p^p > = \hat{r}_k^T \hat{r}_p^p = |\hat{r}_k||\hat{r}_p^p| \cos \Delta \theta_k
\]

where \( \Delta \theta_k = |\theta_k^p - \theta_k| \) with the phase angles of UAV positions with respect to the current target location, \( \theta_k = \cos^{-1}<\hat{r}_k, i> |\hat{r}_k| \) and \( \theta_k^p = \cos^{-1}<\hat{r}_k, i> |\hat{r}_k| \) (i is a x-direction unit vector.). If the phase difference \( \Delta \theta_k \) is ideally maintained as \( \pi \) radian for antipodal tracking of a pair of UAVs, the above equation is rearranged since \( \cos \pi = -1 \) as:

\[
\hat{r}_k^T \hat{r}_p^p + |\hat{r}_k||\hat{r}_p^p| = 0.
\]

Therefore, the left-hand side of the above equation can be set as \( \tilde{d}_k \) in the performance index to be minimized for maintaining the phase angle between a pair of UAVs. The merit of using this inner product concept rather than \( \tilde{\theta}_k = \Delta \theta_k - \pi \) is two fold: the first is that practically it can minimize angular manipulations which might bring about unnecessary switching and laborious logic development at the boundary of angle range \((-\pi, \pi)\). The other is the unit of the phase-keeping term becomes the same as the first term in Eqs. (26)-(27) contributing to maintaining a standoff distance from the target. This is important for accomplishing the fast convergence of the optimization algorithm and also for avoiding unnecessary tuning of weighting parameters.

The dynamics of the UAVs in Eq. (4) is expressed as an equality constraint as:

\[
f_d(\mathbf{x}_k, \mathbf{u}_k) - \mathbf{x}_{k+1} = 0.
\]

The collision avoidance requirement between the UAV members is adopted as an inequality constraints as
well as admissible control input ranges described in Eq. (2)-(3).

\( S_v(u_k) = \frac{|u_{1k} - v_0| - v_{max}}{v_{max}} \leq 0 \) \hspace{1cm} (35)

\( S_\omega(u_k) = \frac{|u_{2k} - \omega_{max}}{\omega_{max}} \leq 0 \) \hspace{1cm} (36)

\( S_c(x_k) = \frac{r_c - |C(x_k - x^p_k)|}{r_c} \leq 0 \) \hspace{1cm} (37)

where \( r_c \) is a safe distance between the UAVs to prevent collision.

**B. Nonlinear Model Predictive Standoff Tracking Algorithm**

The augmented performance index is defined with incorporating the equality and inequality constraints discussed in the previous section as:

\[
J_a = \phi(\hat{r}_N, \hat{d}_N) + \sum_{k=0}^{N-1} [L(\hat{r}_k, \hat{d}_k, u_k) + \lambda_{k+1}^T \{ f_d(x_k, u_k) - x_{k+1} \} + \frac{1}{2} \mu_v l_{vk} S^2_v(u_k) + \frac{1}{2} \mu_\omega l_{\omega k} S^2_\omega(u_k) + \frac{1}{2} \mu_c l_{ck} S^2_c(x_k)]
\]

(38)

where \( \lambda_k \) is a Lagrange multiplier, and \( \mu_v, \mu_\omega, \) and \( \mu_c \) are penalty function parameters. \( l_{vk}, l_{\omega k}, \) and \( l_{ck} \) are defined to avoid unnecessary computation for satisfying inequality constraints as:\textsuperscript{17, 18}

\[
l_{sk} = \begin{cases} 
0, & S_s \leq 0 \\
1, & S_s > 0 
\end{cases} \hspace{1cm} (39)
\]

To facilitate the derivation of optimal control law, let us define a Hamiltonian as:

\[
M_k \equiv L(\hat{r}_k, \hat{d}_k, u_k) + \lambda_{k+1}^T f_d(x_k, u_k) + \frac{1}{2} \mu_v l_{vk} S^2_v(u_k) + \frac{1}{2} \mu_\omega l_{\omega k} S^2_\omega(u_k) + \frac{1}{2} \mu_c l_{ck} S^2_c(x_k).
\]

(40)

The variation of the augmented performance index is represented as:

\[
dJ_a = (\frac{\partial \phi(\hat{r}_N, \hat{d}_N)}{\partial x_N} - \lambda_N^T) dx_N + \sum_{k=1}^{N-1} [\frac{\partial M_k}{\partial x_k} dx_k + \frac{\partial M_k}{\partial u_k} du_k] + \frac{\partial M_0}{\partial x_0} dx_0 + \frac{\partial M_0}{\partial u_0} du_0.
\]

(41)

By selecting the Lagrange multiplier as:

\[
\lambda_N^T = \frac{\partial \phi(\hat{r}_N, \hat{d}_N)}{\partial x_N} \hspace{1cm} (42)
\]

\[
\lambda_k^T = \frac{\partial M_k}{\partial x_k} \quad \text{for} \ k = N - 1, \ldots, 0, \hspace{1cm} (43)
\]
the variation of $J_a$ is changed to:

$$dJ_a = \sum_{k=0}^{N-1} \frac{\partial M_k}{\partial u_k} du_k + \lambda_0^T dx_0. \quad (44)$$

The right-hand side of Eq. (42) is derived from Eq. (26) as:

$$\frac{\partial \phi(\tilde{r}_N, \tilde{d}_N)}{\partial x_N} = p_r \tilde{r}_N \frac{\partial \tilde{r}_N}{\partial x_N} + p_d \tilde{d}_N \frac{\partial \tilde{d}_N}{\partial x_N}. \quad (45)$$

The right-hand side of Eq. (43) is derived from Eq. (40) as:

$$\frac{\partial M_k}{\partial x_k} = q_r \tilde{r}_k \frac{\partial \tilde{r}_k}{\partial x_k} + q_d \tilde{d}_k \frac{\partial \tilde{d}_k}{\partial x_k} + \lambda_{k+1}^T \frac{\partial f_d(x_k, u_k)}{\partial x_k} + \mu_c f_{ck}(x_k) \frac{\partial S_c(x_k)}{\partial x_k}. \quad (46)$$

Jacobians in Eqs. (45)-(46) are derived from the definitions discussed in the previous section.

$$\frac{\partial \tilde{r}_k}{\partial x_k} = \frac{1}{r^2} \begin{bmatrix} 1 & 0 & -2(x_k - x_p) & -2(y_k - y_p) & 0 & 0 \\ 0 & 1 & T_s v_k \sin \psi_k & T_s \cos \psi_k & 0 & 0 \\ 0 & 0 & 1 & 0 & T_s \\ 0 & 0 & 0 & 1 - \frac{1}{r_c} T_s & 0 \\ 0 & 0 & 0 & 0 & 1 - \frac{1}{r_c} T_s \\ \end{bmatrix} \quad (47)$$

$$\frac{\partial \tilde{d}_k}{\partial x_k} = \frac{1}{r^2} \begin{bmatrix} x_p - x_k & |r_k - r_p| \sin \psi_k & -(y_p - y_k) & 0 & 0 \\ y_p - y_k & |r_k - r_p| \cos \psi_k & 0 & 0 & 0 \\ \end{bmatrix} \quad (48)$$

$$\frac{\partial f_d(x_k, u_k)}{\partial x_k} = \begin{bmatrix} 1 & 0 & -T_s v_k T_s \sin \psi_k & T_s \cos \psi_k & 0 \\ 0 & 1 & T_s v_k \cos \psi_k & T_s \sin \psi_k & 0 \\ 0 & 0 & 1 & 0 & T_s \\ 0 & 0 & 0 & 1 - \frac{1}{r_c} T_s & 0 \\ \end{bmatrix} \quad (49)$$

$$\frac{\partial S_c(x_k)}{\partial x_k} = \frac{1}{r_c} \begin{bmatrix} -x_k - x_p & |r_k - r_p| - y_k - y_p & 0 & 0 \\ \end{bmatrix} \quad (50)$$

Now substituting $du_k$ into Eq. (44) with the following equation which is basically a gradient method to minimize $M_k$

$$du_k = -\Delta_k \frac{\partial M_k^T}{\partial u_k} \quad (51)$$

gives the following decreasing variation of $J_a$.

$$dJ_a = -\sum_{k=0}^{N-1} \Delta_k \frac{\partial M_k}{\partial u_k} \frac{\partial M_k^T}{\partial u_k} + \lambda_0^T dx_0. \quad (52)$$

Therefore, the control input can be updated using Eq. (51) as:

$$u_k^{i+1} = u_k^i - \Delta_k \frac{\partial M_k^T}{\partial u_k} \quad \text{for } k = 0, \ldots, N - 1 \quad (53)$$
where \( i \) is the index of iteration, and \( \Delta_k \) is a step size. \( \frac{\partial M_k}{\partial u_k} \) is defined as:

\[
\left( \frac{\partial M_k}{\partial u_k} \right)^T = \begin{bmatrix}
\frac{\tau_r}{v_{max}} (u_{vk} - v_0) \\
\frac{\tau_r}{\omega_{max}} (u_{\omega k} - \nu_0) \\
\frac{\tau_r}{v_{max}} (u_{vk} - \nu_0) \\
\frac{\tau_r}{\omega_{max}} (u_{\omega k} - \nu_0)
\end{bmatrix} + \lambda_{k+1} \frac{\partial f_d(x_k, u_k)}{\partial u_k} + \begin{bmatrix}
\frac{\nu_r}{v_{max}} l_{v k} S_v(u_k) sgn(u_{vk} - v_0) \\
\frac{\nu_r}{\omega_{max}} l_{\omega k} S_\omega(u_k) sgn(u_{\omega k} - \nu_0)
\end{bmatrix}
\]

(54)

where

\[
\frac{\partial f_d(x_k, u_k)}{\partial u_k} = \begin{bmatrix}
1 & 0 \\
0 & 1 \\
0 & 0 \\
\frac{1}{\tau_r} T_s & 0 \\
0 & \frac{1}{\tau_\omega} T_s
\end{bmatrix},
\]

(55)

and \( sgn(*) \) is a sign function satisfying

\[
sgn(a) = \begin{cases}
1 & \text{if } a \geq 0 \\
-1 & \text{if } a < 0
\end{cases}
\]

(56)

C. Online Optimization via Decentralized Structure

The online optimization is run under the decentralized structure at each sampling \( T_s \) as shown in Fig. 2. When the MTIR measurement on the target composed of the relative range and azimuth with respect to each UAV position comes in, each UAV performs the localization of the target by the Extended Kalman tracker. Then, control \((U_{k-1})/state (x_k)\) of the UAVs and those state \((x_{k|k})/covariance (P_{k|k})\) estimation information of the target are shared via communication between the UAVs. This study assumes all the required information can be shared between the UAVs via communications within a single sampling. If communications delay happens or optimizations are performed at slightly different instances between in a real world, the performance of the proposed approach might be degraded. However, our decentralized structure is advantageous in the sense that each UAV performs its own optimization individually using as best information as possible with a reduced computation burden compared to a centralized approach. Also, the proposed decentralized strategy can improve the probability of mission completion because the remaining pair UAV can continue the standoff tracking mission in spite of a failure of one UAV.

Then, each UAV carries out the state-vector fusion using its own estimation and the information from its pair UAV as shown in Eq. (23) in order to enhance the tracking accuracy against the moving target, which is then used as the initial value for propagating the target’s state using the time update equation of
the Extended Kalman tracker in Eq. (16). Following this, the state of the pair UAV is propagated using Eq. (4) with the received pair-UAV information: the current state information and the optimal control over the receding horizon computed at the previous sampling. Now all the external information is ready for the online optimization of nonlinear model predictive control.

The detailed online optimization has the following procedures: the initialization of control input over a receding horizon, state propagation (equality constraint), the computation of an augmented performance index, the finding of a Lagrange multiplier by backward integration, the computation of a Jacobian matrix of Hamiltonian $M_k$ with respect to the control input, and the update of control inputs. As a practical and efficient way, the initial guess of control inputs over the receding horizon at the first sampling $k = 0$ can use a desired nominal speed of UAV and a provisional desired angular velocity as:

$$U^0_0 = \{u_0, u_0, \ldots, u_0\} \in \mathbb{R}^{2 \times N}$$ \hspace{1cm} (57)

where $u_0 = (u_{v0}, u_{\omega 0})^T$, $u_{v0} = v_d$, and $u_{\omega 0} = \frac{\omega_d}{T}$. Then, if $k > 0$, the initialization can be done by shifting the optimized control history from the previous sampling $U_{k-1} = \{u_0, u_1, \ldots, u_{N-2}, u_{N-1}\}$ as:

$$U^0_k = \{u_1, u_2, \ldots, u_{N-1}, u_{N-1}\}.$$ \hspace{1cm} (58)

The detailed optimization routine of the proposed approach is shown in Fig. 2.
Figure 2. Decentralized Structure of Nonlinear Model Predictive coordinated Standoff Tracking

<table>
<thead>
<tr>
<th>current UAV</th>
<th>Communications</th>
<th>Pair UAV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Start $k$-th sampling time</td>
<td>MTIR measurement acquisition</td>
<td>MTIR measurement acquisition</td>
</tr>
<tr>
<td>MIR measurement acquisition</td>
<td>EKF Target localization [Eqs.(16)-(20)]</td>
<td>Target localization by EKF</td>
</tr>
<tr>
<td>EKF Target localization [Eqs.(16)-(20)]</td>
<td>$\hat{x}_{tp_k</td>
<td>k}, \hat{p}_{tp_k</td>
</tr>
<tr>
<td>State-vector fusion [Eq.(23)]</td>
<td>$\hat{x}_{tp_k</td>
<td>k}, \hat{p}_{tp_k</td>
</tr>
<tr>
<td>Target state propagation [Eq.(16)]</td>
<td>$\hat{x}_{tp_k</td>
<td>k}, \hat{p}_{tp_k</td>
</tr>
<tr>
<td>$i = 1$</td>
<td>$i = 1$</td>
<td>$i = 1$</td>
</tr>
<tr>
<td>while $dJ_a &gt; \epsilon$</td>
<td>while $dJ_a &gt; \epsilon$</td>
<td>while $dJ_a &gt; \epsilon$</td>
</tr>
<tr>
<td>If $i == 1$,</td>
<td>If $i == 1$,</td>
<td>If $i == 1$,</td>
</tr>
<tr>
<td>$U^0_k$ Initialization [Eqs.(57)-(58)]</td>
<td>$U^0_k$ Initialization</td>
<td>$U^0_k$ Initialization</td>
</tr>
<tr>
<td>end</td>
<td>end</td>
<td>end</td>
</tr>
<tr>
<td>Self state propagation [Eq.(4)]</td>
<td>Self state propagation</td>
<td>Self state propagation</td>
</tr>
<tr>
<td>$J_a$ computation [Eq.(38)]</td>
<td>$J_a$ computation [Eq.(38)]</td>
<td>$J_a$ computation [Eq.(38)]</td>
</tr>
<tr>
<td>$\lambda_k$ computation [Eqs.(42)-(43)]</td>
<td>$\lambda_k$ computation [Eqs.(42)-(43)]</td>
<td>$\lambda_k$ computation [Eqs.(42)-(43)]</td>
</tr>
<tr>
<td>Computation of $\frac{\partial M_k}{\partial u_k}$ [Eq.(54)]</td>
<td>Computation of $\frac{\partial M_k}{\partial u_k}$ [Eq.(54)]</td>
<td>Computation of $\frac{\partial M_k}{\partial u_k}$ [Eq.(54)]</td>
</tr>
<tr>
<td>If $dJ_a &lt; 0$: $U_k^i \leftarrow U_k^{i-1} - \Delta_k \frac{\partial M_k}{\partial u_k}$</td>
<td>If $dJ_a &lt; 0$: $U_k^i \leftarrow U_k^{i-1} - \Delta_k \frac{\partial M_k}{\partial u_k}$</td>
<td>If $dJ_a &lt; 0$: $U_k^i \leftarrow U_k^{i-1} - \Delta_k \frac{\partial M_k}{\partial u_k}$</td>
</tr>
<tr>
<td>else: reduce step size $\Delta_k$</td>
<td>end</td>
<td>else: reduce step size $\Delta_k$</td>
</tr>
<tr>
<td>end</td>
<td>$i = i + 1$</td>
<td>end</td>
</tr>
<tr>
<td>$i = i + 1$</td>
<td>$i = i + 1$</td>
<td>$i = i + 1$</td>
</tr>
<tr>
<td>end</td>
<td>end</td>
<td>end</td>
</tr>
</tbody>
</table>

Start $k + 1$-th sampling time

::
V. Simulation result

A. Comparison to the Lyapunov vector field guidance method

The guidance law to be compared is a LVFG (Lyapunov Vector Field Guidance) which was initially proposed by Lawrence\(^1\) and further developed by Frew \textit{et al.}\(^2, 4\) The LVFG uses the following desired velocity \([\dot{x}_d, \dot{y}_d]^T\) (Hereafter the subscript \(k\) will be omitted for simple notation.):

\[
\begin{bmatrix}
\dot{x}_d \\
\dot{y}_d
\end{bmatrix} = -v_d \begin{bmatrix}
\frac{\delta x(r^2 - r_d^2) + \delta y(2rr_d)}{r(r^2 + r_d^2)} \\
\frac{\delta y(r^2 - r_d^2) - \delta x(2rr_d)}{r(r^2 + r_d^2)}
\end{bmatrix}
\]  
(59)

where \(r = \sqrt{\delta x^2 + \delta y^2} = \sqrt{(x - x_t)^2 + (y - y_t)^2}\) is the distance of the UAV from the ground vehicle. Herein \((x_t, y_t)\) is the position of the ground vehicle which can be estimated from the tracking filter, and \(r_d\) is a desired standoff distance from the UAV to the ground vehicle. \(v_d\) is a desired UAV speed. The desired heading can be decided using the desired two dimensional velocity components in Eq. (59) as:

\[
\psi_d = \tan^{-1} \frac{\dot{y}_d}{\dot{x}_d}
\]  
(60)

where \(\tan^{-1}\) is to be executed as the four quadrant inverse tangent in practice. The guidance command \(u_\omega\) for turn rate is selected as the sum of proportional feedback and feedforward terms as:

\[
u_\omega = -k_\omega(\psi - \psi_d) + \dot{\psi}_d.
\]  
(61)

where

\[
\dot{\psi}_d = 4v_d\frac{r_d^2}{(r^2 + r_d^2)^2}.
\]  
(62)

If the velocity of a ground target vehicle could be estimated, the guidance vector needs to be adjusted in order to take a target velocity into account. Let us define the following relation between the new desired velocity of the UAV \([\dot{x}_{dn}, \dot{y}_{dn}]^T\) and the velocity of the ground vehicle \([\dot{x}_t, \dot{y}_t]\) using a scale factor \(\alpha_s\) and the desired \(x\) and \(y\) velocity components derived in Eq. (59).\(^2, 4\)

\[
\begin{bmatrix}
\dot{x}_{dn} \\
\dot{y}_{dn}
\end{bmatrix} = \begin{bmatrix}
\dot{x}_t + \alpha_s \dot{x}_d \\
\dot{y}_t + \alpha_s \dot{y}_d
\end{bmatrix}
\]  
(63)
The condition so that the UAV flies with the desired speed $V_d$ can be expressed by taking the norm of Eq. (63) as:

$$
(\dot{x}_d^2 + \dot{y}_d^2)\alpha_s^2 + 2(\dot{x}_d\dot{x}_t + \dot{y}_d\dot{y}_t)\alpha_s + (\dot{x}_t^2 + \dot{y}_t^2 - v_d^2) = 0
$$

Eq. (64) has one positive real solution for $\alpha_s$ only if the desired speed of the UAV is larger than the target speed. Substituting this solution into Eq. (63) yields the modified desired guidance vector of the UAV. Then the final modified desired heading can also be obtained using the relation $\psi_d = \tan^{-1}(\dot{y}_dn/\dot{x}_dn)$.

The phase-angle keeping is separately accomplished by controlling the speed of UAVs as:

$$
u_v = k_v(\Delta \theta - \theta_d)r_d + v_d \quad (65)$$

$$u_v^p = -k_v(\Delta \theta - \theta_d)r_d + v_d \quad (66)$$

where $\theta$ is the azimuth angle of the UAVs relative to the target position, and $\theta_d = \pi$ is a desired phase difference between the UAVs.

**B. Assumptions and conditions**

The vehicle trajectory data acquired at 2Hz in a S-Paramics traffic model of Devizes, Wiltshire, United Kingdom, are used to generate the MTIR measurements composed of relative range and azimuth angle with respect to a position of UAV as shown in Figure 3. The ground vehicle departs at the western side of Devizes.
and traverses a part of the town center and then turns back until the journey ends at the northwestern side of
Devizes. As shown in Figs. 3-4, the ground vehicle moves complicatedly with frequently changing direction
of driving, and the most challenge is its speed is irregularly changing. These true MTIR measurements of a
pair of UAVs were mixed with the white noise having the following standard deviations.

\[
\text{UAV1: } (\sigma_r, \sigma_\phi) = (5.0\, \text{m}, 3.5\, \text{deg}) \quad (67)
\]
\[
\text{UAV2: } (\sigma_r, \sigma_\phi) = (7.5\, \text{m}, 2.0\, \text{deg}) \quad (68)
\]

The other setting of parameters needed for the NMPCST (Nonlinear Model Predictive Coordinated Stand-
off Tracking) and LVFG can be found in Table 1.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>(T_s)</td>
<td>0.5</td>
<td>sec</td>
</tr>
<tr>
<td>(\alpha)</td>
<td>0.6</td>
<td>N/A</td>
</tr>
<tr>
<td>(\sigma_a)</td>
<td>0.66</td>
<td>(m/s^2)</td>
</tr>
<tr>
<td>(\theta_d)</td>
<td>(\pi)</td>
<td>rad</td>
</tr>
<tr>
<td>(v_0, v_d)</td>
<td>40</td>
<td>m/s</td>
</tr>
<tr>
<td>(r_d)</td>
<td>500</td>
<td>m</td>
</tr>
<tr>
<td>(r_c)</td>
<td>30</td>
<td>m</td>
</tr>
<tr>
<td>(v_{max})</td>
<td>10</td>
<td>m/s</td>
</tr>
<tr>
<td>(\omega_{max})</td>
<td>0.2</td>
<td>rad/s</td>
</tr>
<tr>
<td>(\tau_v, \tau_\omega)</td>
<td>1/3</td>
<td>sec</td>
</tr>
<tr>
<td>(N)</td>
<td>4 (equivalent to 2 secs)</td>
<td>N/A</td>
</tr>
<tr>
<td>((p_r, p_d, q_r, q_d, r_v, r_\omega))</td>
<td>((2e5, 5e6, 1e2, 5e1))</td>
<td>N/A</td>
</tr>
<tr>
<td>(\mu_v, \mu_\omega, \mu_c)</td>
<td>1e3</td>
<td>N/A</td>
</tr>
<tr>
<td>Initial value of (\Delta_k)</td>
<td>0.3</td>
<td>N/A</td>
</tr>
<tr>
<td>(\epsilon)</td>
<td>0.8</td>
<td>N/A</td>
</tr>
<tr>
<td>((k_v, k_\omega))</td>
<td>(0.12, 2)</td>
<td>N/A</td>
</tr>
</tbody>
</table>

C. Simulation results

To verify the feasibility and benefits of the proposed approach in this study, the same scenarios discussed
in the previous section were fairly tested for both the LVFG and NMPCST. Firstly, the target localization
by the extended Kalman filter and decentralized sensor fusion shows a reasonable accuracy even in x and
y coordinate velocities as shown in Fig. 4. Figure 5 displays the absolute trajectories of UAVs and ground
vehicle, and Figure 6 displays the relative trajectories of the UAVs with respect to the ground vehicle.

As can be seen in Figs. 6-7 and Table 2, the mean error of standoff-distance keeping by the NMPCST is
much more lower than that of LVFG (which was tuned at best by trial and error procedure) even though
its control consumption on rate of heading change is slightly higher than that of LVFG. This results from
the fact that the NMPCST optimizes its control input by taking account of the propagated histories of the
states of target and UAVs over the receding horizon. The control consumptions of $u_v$ and $u_\omega$ in Table 2 are
computed by integrating the time histories of $|u_v - v_0|$ and $|u_\omega|$, respectively.

Although the mean error of phase-angle keeping by the LVFG could be improved by increasing the
gain $k_v$, its value is set as 0.12 so that the LVFG has a similar level of control input consumption for fair
comparison. As can be seen in Table 2, the NMPCST has a slightly lower mean error for phase-angle keeping
than the LVFG with a similar level of speed consumption. This is beneficial to fixed-wing UAVs since they
generally consume higher fuel when controlling their forward speed. Intuitively, this merit results from the
fact that part of heading rate control as well as speed change by the NMPCST contributes on keeping a
phase difference to meet the inner product relation of position vectors as in Eq. (33) during optimization.
Figures 9-10 shows the control input histories of speed and heading-rate change of both the approaches.

The comparison performed in this simulation does not assert that the NMPCST can always get more
optimal performance than the LVFG in terms of mission performance or fuel efficiency because the LVFG does
not aim only precision in tracking. However, this simulation results implies that the proposed nonlinear model
predictive approach can add a beneficial value to the coordinated standoff tracking problem by providing a
basis for gain selection or parameter tuning. The mean computation time of each UAV’s NMPCST routine
at every sampling is approximately 0.1 second when using Intel Xeon CPU E5440 2.83GHz and 3GB RAM.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>LVFG</th>
<th>NMPCST</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean standoff distance error (m)</td>
<td>25.73</td>
<td>7.87</td>
</tr>
<tr>
<td>mean phase keeping error (deg)</td>
<td>7.61</td>
<td>7.28</td>
</tr>
<tr>
<td>$u_v$ control consumption (m/s)</td>
<td>18.79e2</td>
<td>17.33e2</td>
</tr>
<tr>
<td>$u_\omega$ control consumption (rad/s)</td>
<td>28.61</td>
<td>29.30</td>
</tr>
</tbody>
</table>

VI. Conclusions

This paper proposed a novel nonlinear model predictive control framework for coordinated standoff
tracking by a pair of unmanned aerial vehicles. The benefits of this approach are to add value to the
coordinated standoff tracking problem by providing a guideline for gain selection or the trade-off of standoff
tracking requirements. This can contribute towards acquiring optimal performance in terms of standoff
tracking performance and fuel consumption compared to using the existing decoupled guidance structure.
Also, this paper proposed the use of inner product manipulation for phase angle keeping, which helped
Figure 4. Ground target trajectory and velocity estimation using state-vector fusion based on the EKF.
minimize angular manipulation and weight tuning. Comparative simulations with a pair of unmanned aerial vehicles using a realistic car trajectory data in an urban environment were performed to show the properties and performance of the proposed nonlinear model predictive coordinated standoff tracking. One of the future works is to analyze the effect of changing the receding horizon size and to test different optimization solvers for standoff tracking problems. Then, systematic formulation of an automatic weight tuning will be another future work for avoiding the slow convergence when the UAVs locate far from the target initially. An additional important future work is to integrate the energy efficiency of UAVs into the performance index for optimization after mathematically formulating the relation between maneuver and fuel consumption of their engine or battery. The last promising future work is to integrate a map-based tracking filter with this model predictive scheme since it can provide more accurate target trajectory prediction. Since the proposed nonlinear model predictive coordinated standoff tracking is inherently decentralized, it can be easily extended to an unmanned system formation having more than two members for ground convoy and covert tracking.

References


3Lawrence, D., Frew, E., and Pisano, W., “Lyapunov Vector Fields for Autonomous UAV Flight Control,” Journal of
Figure 6. Relative trajectories of UAVs with respect to ground vehicle
Figure 7. Standoff distance from UAVs to ground vehicle

(a) LVFG

(b) NMPCST
Figure 8. Phase angle difference of UAVs with respect to ground vehicle
Figure 9. Control input of UAVs: $u_\alpha$
Figure 10. Control input of UAVs: $u_\omega$


