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Coordinated Standoff Tracking of Moving Target Groups Using Multiple UAVs

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This paper presents a methodology for coordinated standoff tracking of moving target groups using multiple unmanned aerial vehicles (UAVs). The vector field guidance approach for a single UAV is first applied to track a group of targets by defining a variable standoff orbit to be followed, which can keep all targets within the field-of-view of the UAV. A new feedback term is included in the guidance command considering variable standoff distance, and the convergence of the vector field to the standoff orbit is analyzed and enhanced by adjusting radial velocity using two active measures associated with vector field generation. Moreover, for multiple group tracking by multiple UAVs, a two-phase approach is proposed as a suboptimal solution for a Non-deterministic Polynomial-time hard (NP-hard) problem, consisting of target clustering/assignment and cooperative standoff group tracking with online local replanning. Lastly, localization sensitivity to the group of targets is investigated for different angular separations between UAVs and sensing configurations. Numerical simulations are performed using randomly moving ground vehicles with multiple UAVs to verify the feasibility and benefit of the proposed approach.

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cooperative standoff LOS tracking subject to uncertain dynamic environments and UAV sensing capability. In particular, the existing works in [27] and [28] focus on a mission planning side (more specifically, visiting order determination and optimal path planning) with perfectly known target positions and without much consideration on sensing constraints. Meanwhile, this paper introduces an online guidance and estimation algorithm to guarantee tracking of all targets within the field-of-view (FOV) of the sensor at all times for persistent tracking and surveillance purposes. As multiple UAVs are always overseeing targets within a sensor range, they can easily and quickly cope with environment/situation changes with continuous guidance commands. Although similar work was done by Deghat et al. [29] for simultaneous localization and circular tracking of multiple targets, their approach was only for a single UAV tracking a fixed number of targets without any autonomous decision-making process.

Therefore, this paper proposes a methodology for coordinated standoff tracking of moving target groups using multiple UAVs. In order to track a group of targets using the sensor with a limited FOV, the vehicle should be positioned as close as possible to multiple targets to obtain better estimation accuracy and far enough to keep the group of targets within its FOV. For this, amongst many standoff tracking guidance algorithms, the vector field guidance approach is selected since it produces stable convergence to a circling limit cycle [7, 30]. The objective of this study is to develop an active sensing/guidance algorithm to maximize information or estimation accuracy of targets as well as persistently keep all of them (or as many as possible) within the view of multiple UAVs while considering physical (turning radius and speed) and sensing (FOV and range) constraints.

The main contributions of this paper are fourfold. First, this paper proposes a new coordinated group target tracking method in the context of standoff tracking by defining a variable standoff orbit to be followed. This proposed tracking method can keep all targets within the FOV of the UAV even under uncertainty of estimated target information. Second, a new feedforward term is computed in the guidance command considering variable standoff distance compared to a single target tracking case having constant standoff distance. Moreover, convergence of the vector field to the variable standoff orbit is analyzed and enhanced by adjusting radial velocity using two active measures associated with vector field generation. Third, for multiple group target surveillance by multiple UAVs, a two-phase approach is proposed as a suboptimal solution for a Non-deterministic Polynomial-time hard (NP-hard) problem: 1) Multiple targets are clustered using K-means clustering algorithm, and UAVs are assigned to the appropriate target group in a way that maximizes information defined by the Fisher information matrix (FIM), and then 2) cooperative standoff group tracking is performed with online local replanning, including target handoff and discard from the group according to sensing capability and vector field convergence. Last, localization sensitivity to the group of targets is investigated for different angular separations between UAVs and sensing configurations as a basis for a future optimal separation scheme. Fig. 1 shows a flow chart of the overall algorithm for the proposed coordinated standoff tracking scheme for multiple UAVs.

The overall structure of this paper is given as follows. Section II contains problem formulation, including assumptions made in this study and tracking filter design with a UAV kinematic, ground target, and sensor model. Section III proposes the standoff tracking guidance algorithm for a group of moving targets using a single UAV, followed by tracking of several groups of targets using multiple cooperating UAVs in section IV. Section V presents numerical simulation results of a group target tracking scenario. Last, conclusions and future work are given in section VI.

II. PROBLEM FORMULATION

It is first assumed that the lateral and longitudinal dynamics of the UAV can be decoupled as in conventional fixed-wing aircraft. Therefore, a two-dimensional space is considered for the UAV flying at a constant altitude. In this study, it is also assumed that initial target information is given by other sources such as a search-and-monitoring UAV [23], and an onboard sensor can point at the group center using a gimbal system. Note that data association for multiple targets and communications between UAVs are not the scope of this study. UAV team members share a known global coordinate system such as the global positioning system (GPS) for their own and the targets’ position. The concept of the standoff tracking problem of moving target groups using multiple UAVs is illustrated in Fig. 2. The standoff orbit for each group followed by UAVs needs to be changed in terms of size and location according to the dispersion of the moving targets so that all targets can be inside the FOV of UAVs.

A. UAV Dynamic Model

Assuming each UAV has a low-level flight controller such as a stability augmentation system (SAS) and controllability augmentation system (CAS) for heading
Fig. 2. Illustration of standoff tracking of moving target groups using multiple UAVs considering sensing constraints.

and velocity hold functions, this study aims to design guidance inputs to this low-level controller for standoff target tracking. Consider a two-dimensional UAV kinematic model \[18\] as:

\[
\begin{align*}
\dot{x} &= v \cos \psi \\
\dot{y} &= v \sin \psi \\
\dot{\psi} &= \omega \\
\dot{v} &= -\frac{1}{\tau_v} v + \frac{1}{\tau_v} u_v \\
\dot{\omega} &= -\frac{1}{\tau_\omega} \omega + \frac{1}{\tau_\omega} u_\omega
\end{align*}
\]  

(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; and \(u = (u_v, u_\omega)^T\) are the commanded speed and turning rate constrained by the following dynamic limits of fixed-wing UAVs:

\[
|u_v - v_0| \leq \Delta v_{max}
\]  

(2)

\[
|u_\omega| \leq \omega_{max}
\]  

(3)

where \(v_0\) is the nominal speed of the UAV. The continuous UAV model in (1) can be discretized by Euler integration into:

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

(4)

where \(x_k = (x_k, y_k, \psi_k, v_k, \omega_k)^T\), \(u_k = (u_{vk}, u_{w\omega})^T\), and \(T_s\) is a sampling time.

B. Ground Target and Sensor 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 perform irregular stop-and-go maneuvers with a much smaller turn radius. A constant-velocity model usually used for radar target tracking is thus unsuitable for tracking ground vehicles, and hence an acceleration or jerk model is a more suitable model. After analyzing the car trajectory data acquired by running the S-Paramics traffic simulation software \[31\] (Fig. 3a) and considering general driving behavior, it is observed that the jerk is not negligible, with the acceleration best modeled using a piecewise constant profile over a specific duration of time, as shown in Fig. 3b. Hence, a good model to apply to the tracking of ground targets considers acceleration dynamics \[32\]. This acceleration model defines the target acceleration as a correlated process with a decaying exponential autocorrelation function, which means if there is a certain acceleration rate at a time \(t\), then it is likely to be correlated via the exponential at a time instant \(t + \tau\). A discretized system equation for the acceleration model for a ground vehicle is thus expressed in the form:

\[
x_{k+1} = F_k x_k + \eta_k
\]  

(5)

where the state vector is \(x_k = (x_k, y_k, \psi_k, v_k, \omega_k)^T\), \(u_k = (u_{vk}, u_{w\omega})^T\), and \(\eta_k\) is a process noise that represents the acceleration characteristics of the target. The state transition matrix \(F_k\) is given by \[32\]:

\[
F_k = \begin{bmatrix}
F_{1k} & 0 \\
0 & F_{11k}
\end{bmatrix}
\]  

(6)

where \(F_{1k} = \begin{bmatrix}
1 & T_s (e^{-\alpha T_s} + \alpha T_s - 1)/\alpha^2 \\
0 & 1
\end{bmatrix}, \quad F_{11k} = \begin{bmatrix}
1 & (1 - e^{-\alpha T_s})/\alpha \\
0 & e^{-\alpha T_s}
\end{bmatrix}\), and \(\alpha\) is a correlation parameter that models different classes of targets: a small \(\alpha\) for targets with relatively slow maneuvers and a high \(\alpha\) for targets with fast and evasive
maneuvers. The details of acceleration dynamics can be found in [18].

In addition, this study assumes that UAVs are equipped with a ground moving target indicator (GMTI) sensor to localize the position of target. To produce appropriate surveillance data for multiple targets, a GMTI is a well-suited sensor due to its wide coverage and real-time capabilities [33]. Since the measurement of a GMTI is composed of range and azimuth of the target with respect to the radar location, the actual measurements are the relative range and azimuth with respect to the position of the UAV. The radar measurement \( z_k = (r_k, \theta_k)^T \) can be defined as the following nonlinear relation using the target position \((x^*_k, y^*_k)^T \) and the UAV position \((x_k, y_k)^T \) as:

\[
\begin{bmatrix}
    r_k \\
    \theta_k
\end{bmatrix} = h(x^*_k) + v_k = \begin{bmatrix}
    \sqrt{(x^*_k - x_k)^2 + (y^*_k - y_k)^2} \\
    \tan^{-1}\frac{y^*_k - y_k}{x^*_k - x_k}
\end{bmatrix} + v_k
\]

(7)

where \( v_k \) is a measurement noise vector, and its noise covariance matrix is defined as: \( V_n[v_k] = R_k = \text{diag}(\sigma_r^2, \sigma_\theta^2) \).

C. Ground Target Tracking Filter

Considering the nonlinear measurement equation as in (7) and the advantage of using information from multisensor systems, target localization is performed by using the extended information filter (EIF) [34] as:

Prediction

\[
y_{k|k-1} = Y_{k|k-1} F_k Y_{k-1|k-1}^{-1}
\]

(8)

Update

\[
y_{k|k} = y_{k|k-1} + H_k^T (R_k)^{-1}
\]

\[
\cdot [z_k - h(x^*_k)] + H_k x^*_k]
\]

\[
Y_{k|k} = Y_{k|k-1} + H_k^T (R_k)^{-1} H_k
\]

(10)

(11)

where \( Y_k = (P_k)^{-1} \) and \( y^*_k = Y_k x^*_k \) represent the information matrix and information state vector, respectively. The output matrix \( H_k \) is a Jacobian of (7) with respect to the time-update state \( x^*_k \). Given that multiple UAVs carry out the coordinated standoff tracking of groups of targets, each UAV’s GMTI sensor obtains its own measurement and executes the tracking filter algorithm separately. After each UAV receives the other’s estimation via communications, a decentralized EIF is applied to enhance the tracking accuracy [34, 35]. It is worthwhile noting that the estimation performance can be further improved by converting range and bearing measurement to inertial measurements before they are incorporated into the Kalman filter as shown in [36]. Depending on the noise characteristics of the measurements, the linear Kalman filter (when the bearing measurement is known to be accurate), the extended Kalman filter (EKF), or the unscented Kalman filter could be used with corresponding conversion techniques [37, 38].

Having estimated all available targets’ information, the information on the center of a target group is also estimated using the same target model as in section IIB, position measurements of the geometric centroid for targets in the group, and a linear Kalman filter providing \( \dot{x}^c_k, \dot{y}^c_k \) (hereafter, the subscript \( k \) will be omitted for simple notation). Estimated position and velocity of the center of a target group is used for standoff tracking guidance, which will be explained in the following section.

III. MULTITARGET TRACKING BY A UAV

A. LVFG with Variable Standoff Distance

This study applied a Lyapunov vector field guidance (LVFG) for standoff group tracking, which was initially proposed by Lawrence [39] and further developed by Frew et al. [7, 40]. The LVFG uses the vector field function:

\[
V_f(x, y) = (r^2 - r_d^2)^2
\]

(12)

and the following desired velocity \([\dot{x}_d, \dot{y}_d]^T\):

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

(13)

or, in polar coordinates:

\[
\begin{bmatrix}
    \dot{r} \\
    \dot{\theta}
\end{bmatrix} = \frac{v_d}{r^2 + r_d^2} \begin{bmatrix}
    -(r^2 - r_d^2) \\
    2rr_d
\end{bmatrix}
\]

(14)

where \( \delta x = x - x^c, \delta y = y - y^c \), and \( r = \sqrt{x^2 + y^2} \) is the distance of the UAV from the group center. Herein \((x^c, y^c)\) is the center position of a target group estimated from the tracking filter as shown in Fig. 4, and \( v_d \) is the desired UAV speed. Note that the vector field is not defined at \( r = 0 \); \( r_d \) is a desired standoff distance from the UAV to the center of a target group, which can be computed
considering the FOV $\alpha_f$ of the UAV as:
\[
    r_d = \frac{d_{\text{max}} + d_m}{\sin\left(\frac{\alpha_f - \alpha_m}{2}\right)} \tag{15}
\]

where $d_{\text{max}}$ is the distance between the group center and the target furthest from the center in the group, $d_m > 0$ is a distance margin for $d_{\text{max}}$, and $\alpha_m > 0$ is an angle margin for the FOV of the UAV. Compared to the single target tracking, where the target is located in the center of sensor view, the effect of uncertainty or estimation error of target information becomes more crucial to keep all the targets in view of UAVs for the group tracking. Thus, this study exploits the Mahalanobis distance concept [41, 42] to account for estimation error with relative uncertainties of the group center as:
\[
    d_m = \left[\hat{x}^c - \tilde{z}^c\right]^T \left[P_{\text{pos}}^{-1}\right] \left[\hat{x}^c - \tilde{z}^c\right] \tag{16}
\]

where $\tilde{z}^c = Hx^c$ is the predicted target center position, and $P_{\text{pos}}^{-1}$ is the position submatrix of the prediction covariance $P_{\text{pos}}$. By using the aforementioned standoff distance $r_d$, the UAV can keep all the targets in the group within its FOV as shown in Fig. 4. Note that a data association problem assigning which sensor measurement is from which target is not considered in this paper. However, since the proposed tracking guidance algorithm relies on the Kalman filter for tracking each target separately, it could be sensitive to false association. When multiple targets are densely positioned within a small area, the desired standoff distance can be determined more conservatively with a larger value to compensate for the error from false association and make sure all targets are within the FOV. This aspect remains as future work.

B. Convergence of the Vector Field to the Standoff Orbit

Since standoff distance $r_d$ varies according to the movement of the individual target in the group, the convergence of the vector field to the variable loiter circle (i.e., standoff orbit) is given as the following lemma.

**Lemma 3.1** If the threshold $\xi_{th} = (\hat{r} - r_d \hat{r}_d)\text{sgn}(r_d - r) \geq 0$, then the vector field as well as the UAV position is globally stable to the loiter circle of distance $r_d$ and its rate $\hat{r}_d$.

**Proof** The proof will be represented with two cases depending on the radial distance of the vehicle.

**Case 1** $r < r_d$ (the UAV is inside the standoff orbit).

In this case, $\text{sgn}(r_d - r) > 0$ and $\hat{r} > 0$ from (14), where the $\text{sgn}(x)$ represents:
\[
    \text{sgn}(x) = \begin{cases} 
    1, & \text{if } x > 0 \\
    0, & \text{if } x = 0 \\
    -1, & \text{if } x < 0 
\end{cases} \tag{17}
\]

Let us consider the vector field function
\[
    \dot{V}_t(x, y) = (r^2 - r_d^2) \left(\hat{r} - r_d \hat{r}_d\right) 
\]
\[
    = -\frac{4v_d (r^2 - r_d^2)}{k_l (r^2 + r_d^2)} - 4r_d \left(r^2 - r_d^2\right) \hat{r}_d \tag{18}
\]

If $\xi_{th} = (\hat{r} - r_d \hat{r}_d)\text{sgn}(r_d - r) \geq 0$, then the sign of $(\hat{r} - r_d \hat{r}_d)\text{sgn}(r_d - r)$ is equal or greater than zero (or equivalently, $\hat{r} \geq \frac{\alpha_r}{\alpha_d} r_d$) makes $\hat{V}_t \leq 0$. Thus, $r$ converges to the largest invariant set $r = r_d$, satisfying $\hat{V}_t = 0$ by LaSalle’s invariance principle [43], except $r = 0$, which makes the vector field globally stable to the loiter circle. Since the UAV speed is set to track the constant vector field speed, the vehicle speed converges to the vector field. Moreover, since the vector field is globally stable to the standoff orbit, so is the UAV position.

**Case 2** $r \geq r_d$ (the UAV is outside the standoff orbit).

In this case, $\text{sgn}(r_d - r) \leq 0$ and $\hat{r} \leq 0$ from (14). Using the same vector field function as above, it can be easily shown that if $\xi_{th} \geq 0$ (or equivalently, $\hat{r} \leq \frac{\alpha_r}{\alpha_d} r_d$), then $\hat{V}_t \leq 0$. Thus, $r$ converges to the largest invariant set $r = r_d$ from the outside the loiter circle.

**Remark 3.1** The proof of Lemma 3.1 implies that if the sign of $\hat{r}_d$ is different from that of $\hat{r}$, satisfying $\xi_{th} \geq 0$ in both cases, then the vector field always converges to the loiter circle.

For $\xi_{th} < 0$, since the vector field is not guaranteed to converge to the loiter circle from Lemma 3.1, and the following holds:
\[
    0 < \hat{r} < \frac{r_d}{r} \hat{r}_d, \quad \text{if } r < r_d \\
    0 \geq \hat{r} \geq \frac{r_d}{r} \hat{r}_d, \quad \text{otherwise} \tag{19}
\]

this study proposes two active measures in order to guarantee the convergence (or at least to improve the current convergence speed) of the vector field to the loiter circle by increasing $|\hat{r}|$ such that $|\hat{r}| \geq \frac{\alpha_r}{\alpha_d} \hat{r}_d$. The first one is done by introducing $k_l$ in the radial equation in (14) to adjust the convergence of the vector field as:
\[
    \hat{r}_{\text{new}} = \frac{v_d r^2 - r_d^2}{k_l r^2 + r_d^2} \tag{20}
\]

where $0 < k_l \leq 1$ is a positive constant. By doing this, a rate of change of $V_t$ in (18) also becomes faster as:
\[
    \dot{V}_t(x, y) = -\frac{4v_d (r^2 - r_d^2)}{k_l (r^2 + r_d^2)} - 4r_d \left(r^2 - r_d^2\right) \hat{r}_d \tag{21}
\]

The second measure is to use a virtual standoff distance $r_{d, \text{vir}}$ in proportion to $\hat{r}_d$ as:
\[
    r_{d, \text{vir}} = r_d + k_{r_d} \hat{r}_d \tag{22}
\]
where \( k_{r_d} \) is a positive control gain. The basic idea of this is to exploit the approximated future standoff distance using the current change rate of \( r_d \), rather than chasing the loiter circle behind it. It can be easily shown that substituting \( r_d \) from (22) into \( r_d \) of (20) increases \(|r|\) for the UAV inside as well as outside the loiter circle. However, note that these two strategies do not guarantee the convergence of the vector field all the time, especially when \( r_d \) or \( \dot{r}_d \) is big due to dispersion of the targets or a high-speed vehicle in the target group. This leads to a condition for discarding a target from the group, which will be discussed in section IVB.

C. Vector Field Guidance Command

The desired heading can be decided using the desired velocity components in (13) as:

\[
\psi_d = \tan^{-1} \frac{\dot{y}_d}{\dot{x}_d} \tag{23}
\]

where \( \tan^{-1} \) is to be executed as a four-quadrant inverse tangent in practice. The guidance command \( u_w \) for turn rate is selected as the sum of proportional feedback and feedforward terms by differentiating (23) as:

\[
u_w = -k_{\omega} (\psi - \psi_d) + \dot{\psi}_d \tag{24}\]

where

\[
\dot{\psi}_d = 4v_d \frac{r_d r^2}{(r^2 + r_d^2)^2} - 2r_d \frac{r \dot{r}_d}{r^2 + r_d^2} \tag{25}\]

\( \dot{\psi}_d \) can be obtained by differentiating (23). As \( r \) approaches \( r_d \), the left term of (25) increases monotonically, and magnitude of the right term also increases. Then, the guidance vector field will be feasible as long as the loiter circle pattern itself is feasible considering variable \( r_d \), which satisfies the following when \( r = r_d \):

\[
\dot{\psi}_d = \frac{v_d}{r_d} - \frac{\dot{r}_d}{r_d} < \omega_{\text{max}} \tag{26}\]

Using (26), the feasible standoff distance can be determined as:

\[
r_d \geq \frac{v_d}{\omega_{\text{max}}} - \frac{\dot{r}_d}{\omega_{\text{max}}} = r_{d,\text{min}} \tag{27}\]

Therefore, \( r_{d,\text{min}} \) can be determined by both the maximum speed of a ground vehicle, which determines \( \dot{r}_d \), and the UAV kinematic constraints \( \omega_{\text{max}} \). Note that for the guidance command to be feasible (i.e., within \( \omega_{\text{max}} \)), the gain \( k_{\omega} \) and standoff distance \( r_d \) need to be carefully determined.

D. Taking Target Group Velocity into Account

Since the velocity of the center of each group can be estimated as explained in section IIC, the guidance vector can be adjusted in order to take 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 target group center \([\dot{x}^{\text{tc}}, \dot{y}^{\text{tc}}]\) using a scale factor \( \alpha \), and the desired \( x \) and \( y \) velocity components derived in (13) [7].

\[
\begin{bmatrix}
\dot{x}_{dn} \\
\dot{y}_{dn}
\end{bmatrix}
= \begin{bmatrix}
\dot{x}^{\text{tc}} + \alpha_x \dot{x}_d \\
\dot{y}^{\text{tc}} + \alpha_y \dot{y}_d
\end{bmatrix} \tag{28}
\]

The condition such that the UAV flies with the desired speed \( v_d \) can be expressed by taking the norm of (28) as:

\[
|\dot{x}^{\text{tc}} + \alpha_x \dot{x}_d|^2 + |\dot{y}^{\text{tc}} + \alpha_y \dot{y}_d|^2 - v_d^2 = 0 \tag{29}
\]

This equation has one positive real solution for \( \alpha \), only if the desired speed of the UAV is larger than the target speed. Substituting this solution into (28) yields the modified desired guidance vector of the UAV.

IV. COORDINATED MULTITARGET TRACKING BY MULTIPLE UAVS

This section proposes a multitarget group surveillance strategy by cooperating multiple UAVs with benefits such as better estimation accuracy with sensor/data fusion and more robust tracking performance. Since multitarget tracking using multiple UAVs is typically NP-hard both in the number of sensing agents and targets [27], this study uses a two-step approach: 1) target clustering/resource allocation; and 2) cooperative standoff group tracking with local replanning.

A. Target Clustering and Resource Allocation

Since this study uses a standoff tracking concept in which UAVs are continuously orbiting around moving targets, one of the suboptimal approaches to partition the targets would be treating geographically close targets as the same target group. This is done by a \( K \)-means clustering algorithm to group objects based on attributes into a predefined \( K \) number of groups [44]. The grouping is done by minimizing the sum of squares of distances between data and the corresponding cluster centroid as Algorithm 1, where the optimization objective \( J \) is in the form:

\[
J = \sum_{i=1}^{K} \sum_{x_{\text{pos}} \in \text{cluster } k} (x_{\text{pos}} - \mu_k)^2
\]

The algorithm is given as follows:

**Algorithm 1** \( K \)-means algorithm to cluster multiple targets.

Input \( K \) (number of clusters) and target position data \( \{x_{\text{pos}}^1, \ldots, x_{\text{pos}}^m\} \)
1: Randomly initialize \( K \) cluster centroids \( \mu_1, \mu_2, \ldots, \mu_K \in \mathbb{R}^2 \)
2: while \( \Delta J > \epsilon \) (\( J := \text{optimization objective (30)} \)) do
3: for \( i = 1 \) to \( m \) do
4: Compute \( e_i^{(k)} := \text{index (from 1 to } K \) of cluster centroid closest to \( x_{\text{pos}}^i \)
5: end for
6: for \( k = 1 \) to \( K \) do
7: Compute \( \mu_k := \text{average (mean) of target positions assigned to cluster } k \)
8: end for
9: end while
form:

$$J \left( e^{(1)}, \ldots, e^{(m)}, \mu_1, \mu_2, \ldots, \mu_K \right) = \frac{1}{m} \sum_{i=1}^{m} \left\| x^{\text{pos}}_i - \mu_{e^{(i)}} \right\|$$

(30)

where $e$ is the index of clusters closest to the target point $x^{\text{pos}}_i$, and $\mu_{e^{(i)}}$ is the centroid position of cluster $e^{(i)}$, equivalently, the mean of target positions assigned to that cluster. This study considers the situation where either one or two UA Vs are engaging the same target group; thus the number of clusters is determined by the number of UAVs, $N_u$ as $N_{tg} = \text{round} \left( \frac{N_u}{2} \right)$, where $\text{round}()$ represents rounding the inside element to the nearest integer.

After clustering, UA Vs need to be assigned to the corresponding target group. The optimal assignment approach is used as the one that gathers the most information about targets using a Fisher information matrix (FIM). The FIM describes the amount of information a set of measurements contains about the state variable in terms of sensitivity of the estimation process [21]. Thus, maximizing the FIM is more likely to improve the estimation performance and to reduce uncertainty as variable in terms of sensitivity of the estimation process [21].

$$
\text{det}(FIM) = \sum_{i=1}^{N_u} H_i^T R_i^{-1} H_i
$$

(31)

where $\theta_i$ represents the bearing angle of $i$th UAV to the target. The determinant $\eta_D = \det(FIM)$ is used to measure the size of the FIM. Then, the assignment solution to maximize the FIM can be obtained by solving the following formulation:

$$
\max J = \det \left( \sum_{i=1}^{N_u} \sum_{j=1}^{N_{tg}} I_{ij}^{FIM} x_{ij} \right)
$$

(32)

$$\sum_{j=1}^{N_{tg}} x_{ij} \leq 1, x_{ij} \in \{0, 1\}, \quad \text{for } i = 1, \ldots, N_s
$$

(33)

where $N_s = 2N_{tg} - 1$ is the number of possible combinations of $N_{tg}$ UAVs to observe the target group, and $I_{ij}^{FIM}$ represents the FIM of $i$th UAV combination assigned to $j$th target group. Equation (33) represents that one target group is assigned to one UAV combination at most. Note that this optimization process is performed only once at the initial stage.

B. Online Local Replanning

Once initial assignment of UA Vs to target groups is done, online local replanning is followed, either by handing over targets between groups or discarding a target out of the group according to sensing range or the convergence of the vector field while UA Vs are persistently following corresponding groups.

1) Target Handoff: By running a $K$-means clustering algorithm in a recursive manner, a target handoff event between groups can be done inherently, since clustering itself can regroup targets according to their proximity to the target group and UA Vs. To avoid frequent change of the group for a target on the boundary between two (passing/receiving) groups, as well as to make sure that the target passed to the receiving group is inside the FOV of UA Vs of that group, handoff occurs for a certain period of time $T_{hd}$:

$$T_{hd} \geq \left[ \frac{|r - r_d|}{|r_{new} - r_d|} \right]_{t=t_{hd}}$$

(34)

where $t_{hd}$ represents the time when the target is first requested for the handoff by the clustering algorithm. For $T_{hd}$, the handoff target will be included in both passing and receiving groups. Until UA Vs for the receiving group reach the desired standoff orbit, keeping the handoff target in their FOV, the UAV for the passing group sends the position of the handoff target to the receiving group.

2) Target Discard: If the standoff distance for the group tracking becomes larger than the sensing range (i.e., $r_d > r_{d,max}$), or the radial velocity difference between the vector field and desired standoff orbit is larger than a certain value (i.e., $\xi_d < -\xi_d$ from Lemma 3.1), the target furthest from the center in the group is removed from the group.

C. Sensitivity Analysis to Orbit Coordination

In case that a pair of UA Vs are involved for the same target group, the angular separation between UA Vs is additionally performed by controlling the speed of UA Vs in order to obtain more accurate target information and to avoid collision between them as explained in [7]:

$$u_v = \pm k_v (\gamma - \theta_d) r_d + v_d$$

(35)

where $k_v$ is a control gain, $\theta_i$ is the azimuth angle of the $i$th UAV relative to the group center, $\gamma = \theta_2 - \theta_1$ is the angular phase separation of UA Vs, and $\theta_d$ is a desired phase difference between the UA Vs. Different approaches to this angular separation can be applied, such as controlling the orbit radius instead of the speed [15, 19] and using a decentralized approach for more than two UA Vs [20, 35]. During the target handoff process, physical collision between UA Vs in different groups could be avoided by operating them in different altitudes for each target group or using a local collision avoidance algorithm [51]. The desired phase difference $\theta_d$ can be determined differently depending on the objective of the mission, such as estimation accuracy or visibility of an adversarial target. This study adopts the strategy that maximizes
Fig. 5. Geometric relation between UAVs and ground target.

information (or equivalently, provides the best estimation accuracy) in the current measurements without considering previous information using the FIM as used in the previous section. The determinant of the FIM from two UAVs for the same single target can be given using (31) and trigonometric identities as:

\[
\eta_{D,pair} = \det \left( \sum_{i=1}^{2} H_i^T R_i^{-1} H_i \right) \\
= \frac{1}{\sigma_r^2 \sigma_q^2} \left( \frac{1}{r_1^2} + \frac{1}{r_2^2} \right) + \frac{\sin^2 \gamma}{\sigma_r^4} \frac{\sin^2 \gamma}{\sigma_q^4} \frac{1}{r_1^4 r_2^4}
\]

(36)

For single target tracking, the optimal value of \( \gamma \) that maximizes \( \eta_D \) can be analytically obtained from (36). It can be easily shown that the value is \( \pi/2 \) when two UAVs have the same distance to the target (i.e., \( r_1 = r_2 = r_d \) on the same standoff orbit) to maximize the information UAVs can obtain from the target. However, in this study, since the targets are dispersed around the group center, it is difficult for a pair of UAVs loitering around the same target group to determine one specific optimal \( \gamma \). To check a tendency of \( \eta_D \) depending on target position specified with the range \( 0 \leq d_r \leq 180 \) m and angle \( 0 \leq \theta_i < 360^\circ \) from the group center, numerical analysis is performed for different angular separations \( \gamma_{sep} \) with fixed \( r_d = 400 \) m as illustrated in Fig. 7. For the analysis, the standard deviation of measurement noise is generalized with \( \sigma_{scale} = \frac{\sigma_{scale}}{3} \), such that the small scale represents sensor characteristics close to bearing-only, and the large value represents pure ranging.

First, Fig. 5 shows the example of \( \eta_{D,norm} \) (scaled by \( \eta_{D,0} \) with \( d_r = 0, \theta_i = 0^\circ \), and \( \gamma_{sep} = 90^\circ \)) for specific angular separations (\( \gamma_{sep} = 0^\circ, 90^\circ, 180^\circ \)) for \( \sigma_{scale} = 1 \). This shows that \( \eta_D \), the determinant of the FIM, is substantially subject to the distance of the target from UAVs, which is determined by \( d_r \) and \( \theta_i \). For instance, in Fig. 5a, when UAVs and the target are closest (or, in turn, \( \theta_i \) is zero and \( d_r \) is the maximum), \( \eta_{D,norm} \) has the highest value, and it decreases as the target gets further away from UAVs until reaching \( \theta_i = 180^\circ \), which shows the lowest value. After this point, as the target gets closer to UAVs again, \( \eta_{D,norm} \) tends to increase, resulting in a symmetrical evolution with respect to \( \theta_i = 180^\circ \). Depending on the location of UAVs (or separation angle \( \gamma_{sep} \)), \( \eta_{D,norm} \) shows a different but similar periodic evolution as shown in Figs. 5b and 5c. Fig. 6 shows \( \eta_{D,norm} \) (averaged for all \( \theta_i \)) for different \( \sigma_{scale} \) with respect to the target distance \( d_r \) and angular separation \( \gamma_{sep} \). For \( \sigma_{scale} = 0.01 \) in Fig. 6a, both the optimality criterion and the optimal value of \( \gamma_{sep} \) change as a function of the range \( d_r \), since this configuration is close to a bearing-only measurement as explained above. For \( \sigma_{scale} = 100 \) (or, pure ranging), the optimality criterion changes as \( \gamma_{sep} \) changes, and the optimal value remains around \( \pi/2 \) independent of \( d_r \). Last, in case of a sensor with \( \sigma_{scale} = 1 \) (i.e., range and bearing sensor such as a GMTI), \( \eta_{D,norm} \) is only a function of range for small \( d_r \), (\( < 100 \) m); however, angular separation has some effect on it as \( d_r \) gets larger. The implication with which Fig. 6 shows that the optimal separation angle \( \gamma \) between UAVs varies depending on the distance \( (d_r) \) of the target from the group center and sensor characteristics; however, the optimal angle still stays around \( 90^\circ \), which is similar to the single target tracking case. Thus, \( 90^\circ \) is used as the separation angle between UAVs on the same standoff orbit in the following numerical simulation section. In addition, although an online algorithm to determine the optimal \( \gamma_{sep} \) could be developed for better group tracking performance based on this analysis, it remains as future work.

V. NUMERICAL SIMULATIONS

This section carries out numerical simulations using the proposed standoff group tracking algorithm for moving ground targets using multiple UAVs to show the feasibility and benefits of the proposed approach. The true target trajectories (randomly moving by target model as in section IIB) are used to generate GMTI measurements at 2 Hz mixing with white Gaussian noise. The parameters used for the simulation are shown in Table I.

First, the localization and tracking guidance performance for a single group of four randomly moving targets using either a single or two UAVs are shown in Table II. For this, Monte Carlo simulations with 200 independent runs (for which the sample run is shown in Fig. 8) are performed, and then the results are averaged. Localization error in position and velocity of targets using multiple UAVs is less than that of a single UAV case with the help of sensor fusion using the decentralized EIF. The MVSD-LVFG (modified LVFG algorithm with a variable standoff distance [VSD] and two active measures as explained in section IIB) shows much better performance than that of the VSD-LVFG in terms of standoff distance tracking and phase angle keeping. In line with this, the mean value of the maximum LOS angle from the UAV to the targets is the lowest when using the MVSD-LVFG as a
Fig. 6. Nondimensional \( \eta_D \) with respect to (w.r.t) target distance from group center \( (d_r) \) and specific angular separations \( (\gamma_{\text{sep}} = 0^\circ, 90^\circ, 180^\circ) \) for \( \sigma_{\text{scale}} = 1 \).

Fig. 7. Nondimensional \( \eta_D \) (average for \( 0 \leq \theta_t < 360^\circ \)) w.r.t. target distance from group center \( (d_r) \) and angular separation \( (\gamma_{\text{sep}}) \) for different values of scaled noise standard deviation.

TABLE I
Simulation Parameters

<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>s</td>
</tr>
<tr>
<td>( \alpha )</td>
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<tr>
<td>( (\alpha_f, \alpha_m) )</td>
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<td>deg</td>
</tr>
<tr>
<td>( (\sigma_f, \sigma_m) )</td>
<td>(10,3)</td>
<td>(m, deg)</td>
</tr>
<tr>
<td>( \theta_d )</td>
<td>90</td>
<td>deg</td>
</tr>
<tr>
<td>( v_0 )</td>
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<td>m/s</td>
</tr>
<tr>
<td>( (\sigma_{\text{min}}, \sigma_{\text{max}}) )</td>
<td>(250,700)</td>
<td>m</td>
</tr>
<tr>
<td>( \Delta v_{\text{max}} )</td>
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<td>m/s</td>
</tr>
<tr>
<td>( \omega_{\text{max}} )</td>
<td>0.3</td>
<td>rad/s</td>
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<tr>
<td>( \tau_{\text{v}}, \tau_{\alpha} )</td>
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<td>s</td>
</tr>
<tr>
<td>( (k_v, k_{\alpha}, k_i, k_{\dot{i}}) )</td>
<td>(0.5,2,0.2,3)</td>
<td>N/A</td>
</tr>
</tbody>
</table>

TABLE II
Tracking Performance for a Group of Four Targets (Averaged over 200 Monte Carlo Simulations)

<table>
<thead>
<tr>
<th>Error Measure</th>
<th>Single UAV</th>
<th>Multiple UAVs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>VSD-LVFG(^a)</td>
<td>VSD-LVFG</td>
</tr>
<tr>
<td>Mean Error: Position (m)</td>
<td>9.5227</td>
<td>6.8615</td>
</tr>
<tr>
<td>Mean Error: Velocity (m/s)</td>
<td>1.6252</td>
<td>1.2887</td>
</tr>
<tr>
<td>Mean Error: Standoff distance (m)</td>
<td>31.5984</td>
<td>29.8649</td>
</tr>
<tr>
<td>Mean Error: Phase keeping (deg)</td>
<td>–</td>
<td>2.3173</td>
</tr>
<tr>
<td>Mean Error: Line-of-sight (deg)</td>
<td>15.6864</td>
<td>15.4000</td>
</tr>
</tbody>
</table>

\(^a\)LVFG with a variable standoff distance (VSD).

\(^b\)Modified VSD-LVFG.

result of precise standoff orbit tracking; this means all targets are more likely to be within the UAV sensor FOV.

Fig. 9 shows the absolute trajectories of seven ground target (six randomly moving and one maneuvering) with four UAVs using the proposed standoff tracking framework. First, targets are clustered into two groups, and UAVs are assigned to the appropriate group using the proposed assignment algorithm as shown in Fig. 9a. Note that data association regarding which measurement comes from which target is assumed to be solved as mentioned in section II in this study. However, since our approach to track multiple targets is to exploit the center of the group and furthest target information from the center only, even some false data association at the beginning in a cluttered situation as shown in Fig. 9a would not affect the guidance performance in terms of keeping all targets in the standoff orbit. At around 35 s since the target handoff event was triggered, the target (moving toward the northeast direction) is included in both target groups until UAVs of the receiving group (group 2) reach the desired standoff orbit for \( T_{hd} \) seconds as shown in Fig. 9b and Fig. 10a. Fig. 9c shows the situation after the target handoff (from group 1 to group 2) process is finished. As targets in the group get dispersed widely, the furthest target from the center is removed from the group depending on the sensing range or convergent limit as introduced in section IVB. The Mahalanobis distance in Fig. 10c is used to account for estimation error of the group center position.
when the group center changes abruptly due to target handoff or discard, and it shows the same tendency as center position estimation error (i.e., $|x_{\text{true}} - x_{\text{ht}}|$), as shown in Fig. 10d. Figures 9 and 10 show successful cooperative standoff group tracking results in terms of standoff distance error and desired angular separation while placing all targets of interest inside the FOV of the UAV at all times in a dynamic environment.

Fig. 11 represents the LOS angle history between UAVs and the furthest target from the target group center using the same scenario as above but with either 1) basic standoff tracking guidance or 2) the two active guidance measures explained in section III and the target handoff time $T_{\text{hd}}$. In this figure, when the LOS angle to the furthest target (or the maximum LOS) is less than half of the FOV, all the targets can be regarded to be inside the FOV of the UAV. In the basic guidance case shown in Fig. 11a, the maximum LOS angle is often higher or close to the FOV limit (represented as black dashed line) as a desired loiter circle expands/contracts rather quickly. In addition, due to the frequent group change of the target on the boundary between two groups during target handoff, the maximum LOS angle gets significantly higher than the FOV limit for around 35 to 40 s. On the other hand, in the latter case (Fig. 11b), the maximum LOS angle is always less than half of the FOV since the proposed active measures enhance the convergence property of the UAV to the loiter circle and $T_{\text{hd}}$ prevents the abrupt change of the target group while ensuring the handoff target can be inside the FOV of UAVs in the receiving group. Movie clips for standoff tracking guidance simulations, including the two cases presented here, can be downloaded at https://dl.dropboxusercontent.com/u/17047357/MultiTracking.zip.
VI. CONCLUSIONS AND FUTURE WORK

This paper has presented the coordinated standoff tracking of moving target groups using multiple UAVs. Based on the vector field guidance approach, an active sensing/guidance algorithm was developed to maximize information of the targets and keep all targets inside the view of multiple UAVs considering physical and sensing constraints. For multiple group target surveillance by multiple UAVs, a two-phase approach was proposed consisting of target clustering/assignment and cooperative standoff tracking with online local replanning, including target handoff and discard from the group. Localization sensitivity to the group of targets was also investigated for different angular separations between UAVs and sensing configurations as a basis of future optimal separation schemes. Numerical simulation showed successful standoff group tracking as well as local replanning while keeping all targets of interest within the FOV of the UAV at all times in a dynamic environment. Since this study is in the phase of the initial proof of concept, various implementation issues will be tackled as future work, such as the effect of imperfect communication between UAVs, and measurement data association in conjunction with group clustering and angular spacing strategies in consideration of LOS blockage by obstacles in an urban environment. Redesign of the proposed algorithm for
systems that can hover will be considered as well, because this could greatly improve the performance without constraints of fixed-wing UAVs such as the minimum speed and the maximum turn rate. In addition, inclusion of no-fly zones and other restrictions due to cross winds in an urban environment will be considered in the future work.

REFERENCES


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