Active Sensing Based Cooperative Target Tracking using UAVs in an Urban Area

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Abstract—**To the problem of cooperative ground moving target tracking using UAVs in an urban area, a novel method is presented, which based on target state fusion estimation and prediction, as well as on-line trajectory planning. Firstly, based on active sensing, a solving framework was presented, the formal representation and system model of cooperative target tracking using a team UAVs was established; secondly, a filter, named unscented information filter, was suggested for fusion estimation and prediction of the target state; thirdly, with a predicted target state, an on-line trajectory planning algorithm was presented, which based on receding horizon control and genetic algorithm. Simulation results demonstrate that the performance of target tracking was improved with regard to the predicted target state.**

Keywords-UAV; ground moving target; cooperative tracking; active sensing; fusion estimation; on-line trajectory planning

I. INTRODUCTION

The problem of cooperative target tracking using UAVs has recently received considerable attention [1-3]. Literarily, there are two mainly challenges: 1) How to fusion the measurements from all UAVs to get more accurately estimation of the tracked target state (Fusion Estimation)? 2) How to drive those vehicles to get better measurements of the tracked object (trajectory planning)?

In fusion estimation, M. Ridley et al have implemented UAV systems with cameras using decentralized fusion (Information filtering) concepts[4]. Moreover, a distributed sigma point information filter have presented for nonlinear problems[5], and it has been used for cooperative tracking by Campbell and Whitacre[1], with some augmentations, including: 1) additional sensor measurements; 2) delayed communication transmissions; and 3) multiple model tracking. In[6], an improved Unscented Information Filter (UIF) is presented for distributed fusion estimation. In trajectory planning, several different methodologies for tracking a moving target with multiple UAVs in a free scenario are compared in [7]. Kim has presented an improved orbit coordination method for urban area. Further more, a centralized GA-based motion-planning algorithm that accounts for the UAVs' dynamic constraints, occlusions of LOS and airspace limitations, has been proposed [2].

In mostly of the research have been done, the fusion estimation and trajectory planning are considered independently. While many trajectory planning approaches are proposed, mostly of them assume that the tracked target state can be getting directly or by communication with friendly units, and only the current target state be taken into account. However, it is well-known that with consideration to the future target state in the trajectory planning algorithm, a better tracking result can be expected. Coincident, a kind of target state estimation based methods, named as active sensing, have been suggested to the problem of sensors network management, in which the estimation and prediction of the target state is employed to select the sensor nodes. Moreover, this idea has been used to provide mobility management in mobile sensors networks[8].

In this paper, inspired by [8-10], an active sensing based solving framework was presented for cooperative tracking of a ground target in an urban environment using UAVs, which integrate the unscented information filter based fusion estimation and prediction of target state with genetic algorithm based on-line trajectory planning.

The paper is organized as follows: Section Ⅱ formulates the problem of cooperative target tracking using UAVs in urban area. Section Ⅲ investigates an unscented information filter to get fusion estimation and prediction of the target state. We then propose a trajectory planning approach based on the predicted target state in section Ⅳ. Simulations and results are presented in section Ⅴ. Section Ⅵ is left for conclusions.

II. PROBLEM FORMULATION

The target tracking system is primarily composed of N pursuit UAVs $\boldsymbol{x}_i, i = 1:N$ and a target vehicle $\boldsymbol{x}_t$. The purpose of the UAVs is to track the target. UAVs are equipped with sensors s_i that return the measurements of the range and bearing to target objects with limited precision and reliability. The pursuit UAVs are coupled by a communication network over which needed information is exchanged. The environment is an urban area, in which the occlusions of the UAV's sensor LOS must to be considered.

A. Solving Framework

In the described target tracking system, the target state can not be measured directly or accurately. During the implementing of the tracking system, some statistic methods must be included to estimate the target state accurately, even to predict the target state during a horizon of future. Inspired by the idea of active sensing, a solving framework based on the fusion estimation and prediction of target state has been

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depicted as fig 1. This framework consists of four sections: the local filter of measurements, the target state fusion estimation, the target state prediction, and the on-line motion planning. The local filters are used to modify the measurements to get updating information of the target state; the fusion estimation to get the estimated target state after a synchronous measurement by each UAV, the target state prediction to predict the target state during a horizon of future by the estimated target state; then, an improved on-line trajectory planning is needed to control the vehicles to keep desired distance to the target, while maintain a sensor coverage. The first section will be located in each UAV, while the last three sections will be located in a leader UAV or the ground control station. Those sections implement circularly during the proceeding of target tracking. The details of those sections will be depicted during the Section Ⅲ and Ⅳ. More details of the models of using in the framework will be presented in the next of this section.

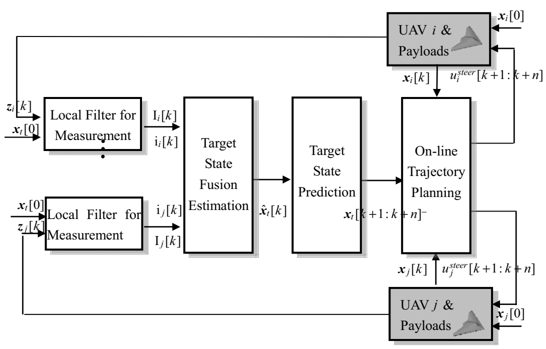


Figure 1. Solving Framework for Cooperative Target Tracking Based on Target State Fusion Estimation and Prediction

B. UAV model

This work assumes UAVs system model is a kinodynamic model[9] (assuming constant altitude):

$$\dot{\boldsymbol{x}}_i = \left[\dot{x}_i, \dot{y}_i, \dot{z}_i, \dot{\varphi}_i, \dot{v}_i\right]^T = \left[v_i \cdot \cos\varphi_i, v_i \cdot \sin\varphi_i, 0, u_i^{str}, u_i^{acc}\right]^T \quad (1)$$

where x_i, y_i and z_i are the Cartesian coordinates of the UAV, $\varphi_i \in [0, 2\pi)$ is its heading, v_i is its speed restricted to $0 < v_{\min} < v_i < v_{\max}$, u_i^{str} is its steering control limited by $|u_i^{str}| \le \mu_{\max}$, and u_i^{acc} is its speed control limited by $|u_i^{acc}| \le \eta_{\max}$, respectively. And, $\dot{z}_i = 0$ means that the altitude of the vehicle is a constant. Let $\boldsymbol{p}_i = [x_i, y_i, z_i]^T \in \mathbb{R}^3$ be the three-dimensional inertial position of the *ith* UAV.

C. Target model

The track target has been moving in two dimensional spaces. The state of target at time step k consists of the position in two dimensional Cartesian coordinates and the velocity toward those coordinates axes, denoted as $\boldsymbol{x}_t[k] = [x_t, y_t, \dot{x}_t, \dot{y}_t]^T$. The target's motion can be modeled as a linear discretized wiener velocity model[11]:

$$\boldsymbol{x}_t[k+1] = A \cdot \boldsymbol{x}_t[k] + G \cdot q[k] \quad (2)$$

where $q[k]$ is Gaussian process noise with zero mean and covariance $Q = E\left[q[k] \cdot q^T[k]\right]$.

D. Observation Model

Given a target located at $\boldsymbol{p}_t = [x_t, y_t, z_t]^T \in \mathbb{R}^3$, the measurement obtained by the *ith* UAV at $\boldsymbol{p}_v$ is[12]:

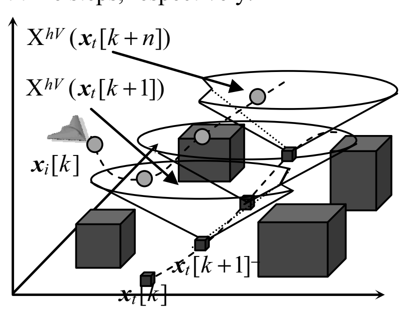
$$z_i[k] = \left[\rho_i[k], \varphi_i[k], \theta_i[k]\right]^T = \mathrm{H}_i(\boldsymbol{p}_{i.t.r}) + v_i[k] \quad (3)$$

where $\rho_i[k]$, $\varphi_i[k]$ and $\theta_i[k]$ are the observed range, azimuth, and elevation angles, $v_i[k] = [\sigma_{i.\rho}[k], \sigma_{i.\varphi}[k], \sigma_{i.\theta}[k]]^T$ is zero mean measurement errors with a covariance V, and $\boldsymbol{p}_{i.t.r} = \boldsymbol{p}_i - \boldsymbol{p}_t$ is the state vector of the *ith* UAV relative to the target. Additionally, we assume that the presence of a gimbaled camera system will guarantee availability of detections when the UAVs are meeting the limitations of target tracking in urban area.

E. Limitations of target tracking in Urban Area

Two main limitations are considered, including the occlusion of LOS and the restricted region.

To reduce the computational burden, visibility polygons of target are calculated rather than to verify an occlusion for LOS exists for every candidate UAV position. The visibility polygon is calculated once for each target location and does not depend on the number of UAVs in the team. Let $\mathrm{X}^V(\boldsymbol{x}_t)$ be the visibility polygon of $\boldsymbol{x}_t$, $\mathrm{X}^{hV}(\boldsymbol{x}_t)$ be the visibility area of $\boldsymbol{x}_t$ in the altitude h. For given target location, urban terrain occlusion map, and UAV/sensor altitude, the $\mathrm{X}^{hV}(\boldsymbol{x}_t)$ can be calculated by a sweep algorithm[2]. Figure 2 presents a schematic example of the visibility regions of a ground moving vehicle in an urban area. The irregularly cones and circles are the visibility polygons of $\boldsymbol{x}_t$ and the visibility areas of $\boldsymbol{x}_t$ in altitude h at different time steps, respectively.



Another limitation is restricted regions. Let $L = \{1, 2, \ldots, N_l\}$ to be the set of airspace limitations imposed on the UAVs. Each element $l \in L$ is represented by a polyhedron's body R^l, then, all the airspace limitations imposed on the UAVs can be depicted as:

$$R = \bigcup_{l=1}^{N_l} R^l \quad (4)$$

By confining the *ith* UAV to the altitude h_i we obtain R^{h_i}, which is the UAV's restricted region in the given altitude.

III. Fusion Estimation and Prediction of the Target State

To the fusion estimation problem of cooperative tracking in this paper, assumed that N UAVs have measurements of the tracked object $\boldsymbol{x}$ synchronously, the system model can be presented as:

$$\begin{array}{c}\boldsymbol{x}[k]=\boldsymbol{f}(\boldsymbol{x}[k-1])+\boldsymbol{q}[k-1]\\ z_i[k]=\boldsymbol{h}_i(\boldsymbol{x}[\boldsymbol{k}])+\boldsymbol{r}_i[k]\end{array},\quad i=1,\cdots,N \tag{5}$$

For this system, the fusion architecture as fig.1 can be employed. Regarding that both $\boldsymbol{f}(\cdot)$ and $\boldsymbol{h}_i(\cdot)$ can be nonlinear, an unscented information filter[6] is suggested.

A. Unscented Information Filter for Target State Fusion Estimation

The information form of the Kalman filter is obtained by rewriting the state estimate and covariance in terms of two new variables: information state vector $\hat{\boldsymbol{y}}$ and Fisher information matrix $\boldsymbol{Y}$ as follow:

$$\boldsymbol{Y}[i\mid j]\triangleq\boldsymbol{P}^{-1}[i\mid j];\ \hat{\boldsymbol{y}}[i\mid j]\triangleq\boldsymbol{P}^{-1}[i\mid j]\hat{\boldsymbol{x}}[i\mid j] \tag{6}$$

For nonlinear estimation problem, an unscented information filter can be employed[6]. Firstly, the information prediction equations are derived by implementing the unscented transformation:

$$\boldsymbol{Y}[k]^-=(\boldsymbol{P}[k]^-)^{-1};\ \hat{\boldsymbol{y}}[k]^-=\boldsymbol{Y}[k]^-\sum_{i=0}^{2n}W_m^i\chi^i[k]^- \tag{7}$$

where the details of $\boldsymbol{P}[k]^-$ 、 $\chi^i[k]^-$ 、 W_m^i can see in [11].

The UKF update equation, however, is not an explicit function of the linearized measurement matrix H_k, thus the UKF can not be embedded into the information update equations. However, as in [6], the nonlinear measurement model can be rewriting approximately as follow:

$$\boldsymbol{z}[k]=\boldsymbol{h}(\boldsymbol{x}[\boldsymbol{k}])\approx\mathrm{H^p}[k]\boldsymbol{x}[k]+\tilde{\boldsymbol{u}}[k] \tag{8}$$

where $\tilde{\boldsymbol{u}}[k]=\mathrm{h}(\hat{\boldsymbol{x}}[k]^-)-\mathrm{H^p}[k]\hat{\boldsymbol{x}}[k]^-$, is a measurement residual term, and the details of $\mathrm{H^p}[k]$ can be see in [6]. Based on (8), the information associated with an observation $\boldsymbol{z}[k]$ can be derived:

$$\mathrm{I}[k]\triangleq(\mathrm{H^p}[k])^T\boldsymbol{R}^{-1}[k]\mathrm{H^p}[k];\ \mathrm{i}[k]\triangleq(\mathrm{H^p}[k])^T\boldsymbol{R}^{-1}[k]\boldsymbol{z}[k] \tag{9}$$

And then, the Update step of UIF can be derived:

$$\begin{array}{l}\boldsymbol{Y}[k]=\boldsymbol{Y}[k]^-+\underbrace{(\mathrm{H^p}[k])^T\boldsymbol{R}^{-1}[k]\mathrm{H^p}[k]}_{\mathrm{I}[k]}\\ \hat{\boldsymbol{y}}[k]=\hat{\boldsymbol{y}}[k]^-+\underbrace{(\mathrm{H^p}[k])^T\boldsymbol{R}^{-1}[k]\boldsymbol{z}[k]}_{\mathrm{i}[k]}\end{array} \tag{10}$$

For FC based fusion estimation, new measurements from each sensor are fused into the central information state estimate additively as:

$$\boldsymbol{Y}[k]=\boldsymbol{Y}[k]^-+\sum_{j=1}^{N}\mathrm{I}_j[k];\ \hat{\boldsymbol{y}}[k]=\hat{\boldsymbol{y}}[k]^-+\sum_{j=1}^{N}\mathrm{i}_j[k] \tag{11}$$

Then, the target state fusion estimation can be derived:

$$\hat{\boldsymbol{x}}[k]=\boldsymbol{Y}^{-1}[k]\hat{\boldsymbol{y}}[k] \tag{12}$$

B. Prediction of Target state and expected information returns

Once the estimated object's states $\hat{\boldsymbol{x}}_t[k]$ have been calculated, its future states and trajectory can be predicted. Respectively, the Expected Information Returns (EIR) associated with coordinated control sequence $u_i^{steer}[k+1:k+n]$ can be derived.

The states of the object over a future time horizon n, denoted as $\boldsymbol{X}_t^{pred}[k+n\mid k]$, can be calculated by two steps. At first, by a predict step of UIF, we can obtain:

$$\boldsymbol{x}_t^{pred}[k+1\mid k]=\boldsymbol{x}_t[k+1]^-=\sum_{i=0}^{2n}W_m^i\chi^i[k+1]^- \tag{13}$$

Moreover, based on $\boldsymbol{f}(\cdot)$, we can obtain:

$$\boldsymbol{X}_t^{pred}[k+N\mid k]=\begin{bmatrix}\boldsymbol{x}_t^{pred}[k+1\mid k]\\ \boldsymbol{x}_t^{pred}[k+2\mid k]\\ \cdots\\ \boldsymbol{x}_t^{pred}[k+N\mid k]\end{bmatrix}=\begin{bmatrix}\boldsymbol{x}_t[k+1]^-\\ f(\boldsymbol{x}_t[k+1]^-)\\ \cdots\\ f^n(\boldsymbol{x}_t[k+1]^-)\end{bmatrix} \tag{14}$$

Based on $\boldsymbol{X}_t^{pred}[k+n\mid k]$, the EIR $\mathrm{I}_i[k+1:k+n]^-$ can be derived. Firstly, *ith* UAV's predicted state $\boldsymbol{x}_i[k+1:k+n]^-$ associated with $u_i^{steer}[k+1:k+n]^-$ can be predicted by the UAV model. According to [6], the $\mathrm{H^p}[k]$ is determined by $\boldsymbol{x}_t[k]^-$ and $\boldsymbol{x}_i[k]^-$, denoted as $\mathrm{H^p}[k]^-$. Based on $\boldsymbol{x}_i[k+1:k+n]^-$, $\boldsymbol{X}_t^{pred}[k+n\mid k]$, we can obtain:

$$\begin{array}{l}\mathrm{I}_i[k+1]^-=(\mathrm{H^p}[k+1]^-)^T\boldsymbol{R}^{-1}[k]\mathrm{H^p}[k+1]^-\\ \mathrm{I}_i[k+2]^-=(\mathrm{H^p}[k+2]^-)^T\boldsymbol{R}^{-1}[k]\mathrm{H^p}[k+2]^-\\ \cdots\\ \mathrm{I}_i[k+n]^-=(\mathrm{H^p}[k+n]^-)^T\boldsymbol{R}^{-1}[k]\mathrm{H^p}[k+n]^-\end{array} \tag{15}$$

IV. On-line Trajectory Planning Based on Receding Horizon Ccontrol

During the on-line trajectory planning of UAVs, because of the uncertainty of environment or target state, a type of methods, named as Receding Horizon Control (RHC), have always been employed[3],[13]. In this paper, an optimum formulation of on-line trajectory planning for cooperative target tracking will be presented, which integrates the RHC with the target state fusion estimation and prediction. A genetic algorithm is employed to solve this formulation.

A. Receding Horizon Control Formulation of on-line trajectory planning

Let $\boldsymbol{u}[k:k+T]$ be candidate control sequence from time step k to $k+T$. Let $J_{rhc}(\boldsymbol{x}[k],\boldsymbol{u}[k:k+T])$ be the cost function. The main steps of RHC as fellows:

(1)Calculating the optimal control sequence during a planning time horizon T_h:

$$\boldsymbol{u}^*[k:k+T_h]=\arg\min J_{rhc}(\boldsymbol{x}[k],\boldsymbol{u}[k:k+T_h]) \tag{16}$$

(2)Implementing the front of the optimal control sequence $\boldsymbol{u}^*[k:k+T_c]$ control time horizon T_c $(1<T_c<T_h)$.

(3) Replaying step (1) and (2) at time step $k=k+T_c$.

In this paper, the UAVs are controlled to minimize the uncertainty by better measurements, namely to maximize the EIR. Additionally, control cost and safety cost are taken into account. In a short, the objective of RHC is:

$$J_{rhc}(\boldsymbol{x}[k],\boldsymbol{u}[k:k+T_h]) = a_1\cdot J_{in} + a_2\cdot J_u + a_3\cdot J_{safe} \quad (17)$$

where a_1, a_2, a_2 are positive weighted factors.

According to equation (9) and (15), EIR cost function J_{in} can be derived as fellows:

$$J_{in}(\boldsymbol{x}_t[k],\boldsymbol{u}[k:k+T_h]) = \sum_{j=k+1}^{k+T_h}\sum_{i=1}^{N}\left(EIR_i(j)\right)^{-1} \quad (18)$$

where:

$$EIR_i(j) = \begin{cases} \mathrm{I}_i[j]^-, & \mathrm{D}\boldsymbol{x}_i[j]\in \mathrm{X}^{hV}(\boldsymbol{x}_t[j]) \\ W_{vis}, & \mathrm{D}\boldsymbol{x}_i[j]\notin \mathrm{X}^{hV}(\boldsymbol{x}_t[j]) \end{cases} \quad (19)$$

By choosing $W_{vis}\to 0$, we can impose a solution that UAVS are within the visibility area in all time steps.

The details of the control cost function J_u and safety cost function J_{safe} can see in [2].

B. Genetic Algorithm for RHC Formulation

For the optimization problem depicted in equation(16), a Genetic Algorithm (GA) is employed. Details of the main parts of genetic algorithm will be present, including coding and Candidate Solutions Evaluation.

1) Coding

An important part of solving such a problem using a GA is to select the appropriate chromosome encoding. The candidate Solution of problem (16) is a $N\times T_h$ matrix g, which is a string of discrete commands $u_i[k]$. Because of the need to account for the dynamic constraints of the UAVs, $u_i[k]$ are referred to:

$$u_i[k]\in[-\eta_{MAX},\eta_{MAX}],\ i=1,\cdots,N; k=1,\cdots,T_h \quad (20)$$

Each solution can be seeing as a chromosome of GA. Initially, the initial set $G_{init}=\{g_1,\cdots,g_M\}$ is composed of M chromosomes, which can be generated randomly under the limitation of (20).

2) Candidate Solutions Evaluation.

The fitness $f(g)$ of each of the solutions, coded in the chromosomes can be calculated as (21).

$$f(g_m) = \underbrace{1/J_{rhc}}_{f_1} + \underbrace{f_{dis}(\boldsymbol{x}_t^-,\boldsymbol{x}_i^-)}_{f_2} \quad (21)$$

where f_1 is the fitness of cost function, it is the inverse of the cost function of candidate solution. f_2 is the fitness of solution space, when the EIR is zero, it will be worked to control UAVs to circle about the target. And:

$$f_{dis}(\boldsymbol{x}_t^-,\boldsymbol{x}_i^-) = \begin{cases} \left(\sum_{j=k+1}^{k+T_h}\sum_{i=1}^{N}\left| dis(\boldsymbol{x}_t[j]^-,\boldsymbol{x}_i[j]^-)-d_r\right|\right)^{-1}, & J_{in}=0 \\ 0, & J_{in}\neq 0 \end{cases} \quad (22)$$

where $dis(\boldsymbol{x}_t[j]^-,\boldsymbol{x}_i[j]^-)$ is the distance between the predicted state of target and UAVs. f_2 assures that an appropriate distance between UAV and target is maintained, when the UAV's sensor LOS are occluded.

More details of genetic algorithms can see [14].

C. On-line trajectory planning algorithm

The active sensing based on-line trajectory algorithm (ASTP-Algorithm) is summarized as fellows:

Algorithm 1 On-line trajectory planning Algorithm based on Target State Fusion Estimation and Prediction(ASTP-Algorithm)

Step 1: Begin with initialized UAV and target state: $\boldsymbol{x}_i[0]$, $\boldsymbol{x}_t[0]$, $i=1,...,N$. Urban terrain map and restricted regions.

Step 2: Loop: At each control period $k:k+T_c$ of UAVs

Step 2.1: Local and FC UIF are used to calculate the fusion $\hat{\boldsymbol{x}}_t[k]$ by the measurements $\{\boldsymbol{z}_i[k]\}$ of all UAVs.

Step 2.2: (14) will be used to get $\boldsymbol{X}_t^{pred}[k+T_h\mid k]$ over T_h .and $\mathrm{X}^{hV}(\boldsymbol{X}_t^{pred}[k+T_h\mid k])$ will be calculated.

Step 2.3: Solving the optimal control sequence $\{{}^*u_i^{steer}[k+1:k+T_h+1]\}$ over time horizon T_h by GA.

Step 2.4: Implementing part of the optimal control sequence $\{{}^*u_i^{steer}[k+1:k+T_c+1]\}$ during T_c .

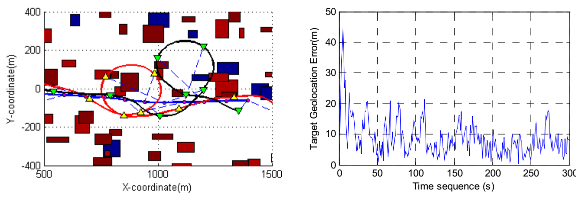
Step 3: End loop when the mission is completed.

Remark 1: the runtime of GA is controlled to assure that the runtime of ASTP-Algorithm is within T_c . Experiments show the whole runtime of GA is round about 1.0 seconds, when $N=5, T_h=5$.

V. Simulations and Results

In order to demonstrate feasibility of our methods, Results from a number of simulations will be presented. In these simulations, two UAVs are employed to track a ground moving vehicles. The various models are given as follow: 1)the simulated urban area: 400 buildings within a 3km*3km area; 2)The initialized state of UAVs: $\boldsymbol{x}_1[0]=[0m,-1500m,200m,0rad,25m/s]^T$, $\boldsymbol{x}_2[0]=[500m,-1500m,200m,0rad,25m/s]^T$, and $\eta_{i.\max}=0.5m/s^2; \mu_{i.\max}=0.2rad/s; v_{i.v}\in[20m/s,30m/s]$, Measuring errors covariance $V_i=[10m,0.05rad,0.05rad]^T$. 3) The target motion is modeled as (2) with initial position $\boldsymbol{p}_t[0]=[0m,0m]^T$ and unknown initial speed, as well as $Q=[1.0m/s,1.0\text{m/s}]$, the altitude of target is 0m. 4) The simulating time of each simulation is 300s. $T_h=5s, T_c=1s$. 5) GA settings: the size of the chromosomes set is 100; the maximum iteration time is 500, the maximum runtime of genetic algorithm is 0.9seconds.

The tracking results have been showed in fig 3. The actual trajectories of UAVs and the measurements have been depicted in fig. 3(a), and the geolocation errors of the fusion estimated target state can be see in fig. 3(b), it can be see that a small error is maintained. More over, the time target had been measured are depicted in table 1, the time that the target have been measured by at least one of UAVs is 289. Aforementioned results show that ASTP-Algorithm can be employed to have a good cooperative tracking.



(a) Actual trajectories of UAVs and the target (k=50s-150s)

((b) Geolocation errors of fusion estimated target state

Figure 3. Tracking results of the ASTP-Algorithm

TABLE 1. The times that the target has been measured

	Total times	Measured by UAV1	Measured by UAV2	Measured by one UAV
Times	300	244	238	289

Moreover, the performance can be see clearly in fig 4, in which 10 times simulation results are compared with the tracking results by the root mean square error(RMSE) of measured, estimated, and fused target position errors. It can be see that the RMSE of fused target position errors are round about 6 m, while the RMSE of measured and estimated by one of UAVs solely are round about 10m and 18m respectively. Additionally, the times that the target has been measured by at least one of UAVs have been showed in fig.5, which are 290 times approximately.

Father more, to illustrate the efficacy of the proposed solving framework, The tracking result is compared with the tracking result without the active sensing based solving framework, in which the ASTP-Algorithm is used with the target position calculated by measurements directly and the assumed target speed initially without a prediction, denoted as $T_h = 0$ .It can be seeing in fig 5 that the times the target has been measured by the proposed solving framework is improved clearly. And that a more accurately estimation (a smaller RMSE) of the target state can be maintained by the proposed approach, which can be see in fig.6.

VI. Conclusions

An active sensing based solving framework for cooperative tracking with an “unfriendly” target in an urban area is presented, which integrate the target state estimation and prediction with on-line trajectory planning. The simulation results here demonstrate the availability of proposed approach, and show the improvement of performance in terms of the time that the target is measured and the accurate of the target position estimation.

One of the ongoing works is to integrate the altitude control of UAVs with ASTP-algorithm.

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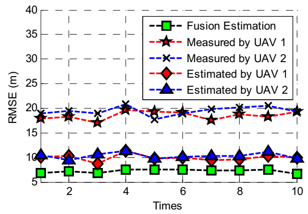

Figure 4. RMSE of measured, estimated, and fused target position errors

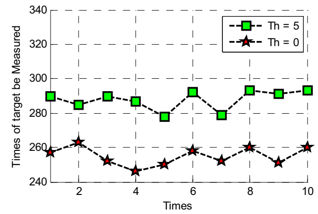

Figure 5．Comparison of times that the target has been measured by at least one UAV

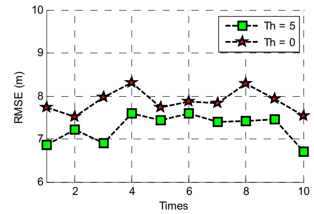

Figure 6．Comparison of RMSE of fusion estimated target position errors