IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received November 8, 2018, accepted November 24, 2018, date of publication December 11, 2018, date of current version January 7, 2019.

Digital Object Identifier 10.1109/ACCESS.2018.2885776

Decentralized Real-Time Estimation and Tracking for Unknown Ground Moving Target Using UAVs

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This work was supported in part by the National Natural Science Foundation of China under Grant 61773279, in part by the Research Foundation of Key Laboratory of System Control and Information Processing, Ministry of Education, under Grant Scip201608, and in part by the Open Project of Key Laboratory of Micro Opto-Electro Mechanical System Technology, Tianjin University, Ministry of Education, under Grant MOMST 2016-4.

ABSTRACT This paper presents a decentralized cooperative tracking strategy based on information filtering with consensus analysis and model predictive control (MPC) for multiple unmanned aerial vehicles (UAVs), tracking unknown ground moving target. For unknown target, squared-root cubature information filtering (SCIF) is designed to estimate the target states based on the measurement from the onboard sensor at each UAV. To eliminate the difference between estimations of UAVs, the consensus algorithm, hybrid consensus on measurement-consensus on information is applied for more accurate estimation of target. A fast MPC method is introduced to obtain the UAVs' path, where collision avoidance between UAVs and the change of communication topology among UAVs are taken into account. Finally, the simulation results demonstrate the effectiveness of the proposed method.

INDEX TERMS Information filtering, model predictive control, target tracking, UAVs.

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) have the advantages of low cost and strong maneuver etc., and play an important role in modern military and civilian applications [1], [2]. In the most of current research concerning path planning for UAV, the desired trajectory is generally given before carrying out missions. Nevertheless, the ground moving target is unknown in some cases, and therefore it is of significance to estimate the target information online and calculate the feasible path of UAV fast.

Target is generally divided into cooperative target and noncooperative target. For the former, either its trajectory is known to UAVs, or it can provide enough information to UAVs during implementing the mission. For the noncooperative target, UAVs have to estimate its states before path planning. Estimation accuracy and real-time performance have a strong impact on the control of UAVs. In the relevant study on target estimation, filtering and its modified versions are the most common technique. Ross *et al.* [3] implement Kalman filter to obtain smooth estimation of position and velocity of target. In [4], Kalman filter and unscented transformation are used to estimate the states of moving target based on onboard monocular vision sensor. Wang and Nguang [5] combine particle filter with extended Kalman filter (EKF) to improve the performance of tracking system. Kwon *et al.* [6] propose a robust method to estimate moving target based on out-of-order sigma point Kalman filter.

For multiple UAVs, the estimation fusion among UAVs needs to be taken into account for improvement of estimation accuracy. Fusion algorithm, commonly used in the field of wireless sensor network, is classified into state-vector fusion, measurement fusion, and gain fusion. For example, nonuniform estimation rates in wireless sensor network is considered in the measurement fusion process [7]. In [8], measurement fusion function is defined and improves the performance of target tracking problem. Chen *et al.* [9] design a networked multi-sensor fusion estimation system for observation delays, pocket dropouts and missing measurements caused by sensor failures. In the research on tracking control of UAVs, Kim *et al.* [10] fuse the measurements from two UAVs by means of EKF, and predict the positions of target in a fixed period to improve the tracking performance. Qunitero *et al.* [11], [12] add error covariance into performance index to fuse the data from two UAVs.

In [13]–[15], fusion algorithms are designed based on EKF for persistent tracking and standoff tracking. Although the fusion algorithms have made some achievement, most of them are centralized design. If something wrong or fault happens, data fusion will be unachievable. So the decentralized fusion algorithm receives more and more attentions. Since each UAV serves as a fusion center, difference will occur among different fusion centers inevitably. It is important and meaningful to solve the consensus problem in decentralized strategy. Consensus algorithm is currently applied to multi-agent, involving velocity consistency and state consistency among agents. Hong *et al.* [16] design a distributed feedback controller with a distributed state estimation rule to deal with the consensus of multiple autonomous agents. In [17] and [18], the influence of time-delays on consensus is analyzed for continuous-time agent and oscillator synchronization system respectively. For the target estimation in sensor network, consensus algorithm is similar to the application in multi-agent, though types of sensors are different.

Multiple UAV path planning is an important problem in tracking missions. Wu *et al.* [19] calculate cluster state prediction and collision probability to solve the problem of path conflicts for UAV clusters during flight. Sun *et al.* [20] utilize A^* algorithm to estimate the path of each UAV, and then the estimation serves as the input of the cluster method to generate the quasi-optimal task assignment. Finally, the flyable reference path is obtained by the cubic B-spline curve. Meng *et al.* [21] develop a systematic algorithm using geometric relations to generate an optimal path online for tracking target.

As an advanced process control method, model predictive control (MPC) has been widely applied to chemical process [22], industry manufacture [23], supply chain management [24], and revenue management [25]. Nowadays, MPC has a good perspective in UAVs application. The most important requirement in UAVs tracking control problem is real-time performance, and so a fast solving method is necessary for MPC. In 2002, Bemporad *et al.* [26] propose explicit MPC by introducing multi-parameter quadratic programming for linear time-invariant system. The system states are partitioned into convex polyhedral regions and the corresponding control law is obtained by solving the corresponding optimization problems. In addition, some researchers propose the approximation methods of explicit MPC to reduce the computational burden [27], [28]. Palomo *et al.* [29] utilize move-blocking strategy to restrict the number of optimization variables and extend the effective input horizon. Domahidi *et al.* [30] present effective interior point methods for online optimization with smaller size of code and less run time. Bleris *et al.* [31] take advantage of hardware platform such as FPGA to speed up calculation.

In this paper, for the unknown ground moving target, squared-root cubature information filtering (SCIF) is applied to estimate the target states based on the onboard sensor measurement at each UAV, by which predictive values and increments for information vector and information matrix are generated. By considering the communication topology, the consensus method hybrid consensus on measurement-consensus on information (HCMCI) is used to deal with estimation difference between UAVs. The appropriate weighting coefficients and iteration number are chosen to obtain more accurate estimation of moving target. Based on the target estimation, fast model predictive control (FMPC) is designed to generate UAVs' trajectory online to satisfy the real-time requirement of UAV control system. Each UAV model and constraints are linearized, and the objective function is reconfigured. The first-order KKT optimality condition and Newton method are used to update optimal variables during solution. Collision avoidance constraints are addressed for the UAVs flying at the same altitude. Besides, the change of topology among UAVs is also considered in the simulations.

The remaining context of this paper is given as follows. Section 2 presents UAV model, target model and sensor measurement model. In section 3, target estimation algorithm based on the SCIF and HCMCI is proposed. The path planning algorithm for UAVs using FMPC is introduced in Section 4. Simulations are given in the Section 5. Finally, Conclusions are drawn in section 6.

II. PROBLEM FORMULATION

A. KINEMATIC MODEL OF UNMANNED AERIAL VEHICLES

In this paper, each UAV moves at a fixed altitude, and so the lift control is ignored. Consider the two-dimensional kinematic model for *jth* UAV

$$\begin{bmatrix} \dot{x}_j \\ \dot{y}_j \\ \dot{\theta}_j \end{bmatrix} = \begin{bmatrix} v_j \cos\theta_j \\ v_j \sin\theta_j \\ \omega_j \end{bmatrix}, \quad j = 1, 2, ..., N \tag{1}$$

where (x_j, y_j) is two-dimensional position of the UAV. θ_j is heading angle. v_j, ω_j are control inputs, representing linear velocity and heading angular velocity, respectively. N is the number of UAVs.

The control input constraints are

$$\begin{aligned} v_{\min} &\le v \le v_{\max} \\ \omega_{\min} &\le \omega \le \omega_{\max} \end{aligned} \tag{2}$$

The continuous UAV model in (1) is discretized into

$$\begin{bmatrix} x_j(k+1) \\ y_j(k+1) \\ \theta_j(k+1) \end{bmatrix} = \begin{bmatrix} x_j(k) \\ y_j(k) \\ \theta_j(k) \end{bmatrix} + \begin{bmatrix} \cos\theta_j(k) * T & 0 \\ \sin\theta_j(k) * T & 0 \\ 0 & T \end{bmatrix} * \begin{bmatrix} v_j(k) \\ \omega_j(k) \end{bmatrix} \tag{3}$$

where T is the sampling time. For simplicity, rewrite (3) as

$$X_j(k+1) = f_a(X_j(k), u_j(k)) \tag{4}$$

where $X_j(k) = \left[x_j(k)\ y_j(k)\ \theta_j(k)\right]^T$, $u_j(k) = \left[v_j(k)\ \omega_j(k)\right]^T$.

B. GROUND MOVING TARGET MODEL

Ground moving target has the characteristics of low velocity, irregular stop-and-go maneuver and small turning radius.

Considering target trajectory and moving behavior, a jerk model [32] is selected for target estimation and tracking.

$$\frac{d}{dt}\begin{bmatrix} x^t \\ \dot{x}^t \\ \ddot{x}^t \\ y^t \\ \dot{y}^t \\ \ddot{y}^t \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & -\alpha & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & -\alpha \end{bmatrix} \begin{bmatrix} x^t \\ \dot{x}^t \\ \ddot{x}^t \\ y^t \\ \dot{y}^t \\ \ddot{y}^t \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 1 \end{bmatrix} \delta(t) \tag{5}$$

where $x^t, \dot{x}^t, \ddot{x}^t, y^t, \dot{y}^t, \ddot{y}^t$ denote position, velocity and acceleration of the target in two dimensions. α is a model parameter. $\delta(t)$ is process noise with the covariance matrix

$$Q_\delta = diag(0, 0, \sigma_a^2, 0, 0, \sigma_a^2)$$

where σ_a is a standard deviation parameter related to target acceleration. The continuous model is discretized as

$$X_k^t = (I + TF_0)X_{k-1}^t + TB_0\delta_{k-1} \tag{6}$$

where $X_k^t = (x_k^t, \dot{x}_k^t, \ddot{x}_k^t, y_k^t, \dot{y}_k^t, \ddot{y}_k^t)$,

$$F_0 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & -\alpha & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & -\alpha \end{bmatrix}$$

$$B_0 = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 1 \end{bmatrix}^T.$$

C. SENSOR MEASUREMENT MODEL

Assuming each UAV has an onboard radar to measure the relative distance and angle between UAV and ground moving target in Fig. 1. The discrete sensor measurement model is

$$\begin{bmatrix} r_k \\ \phi_k \\ \varphi_k \end{bmatrix} = f_h(X_k^t) + \xi_k = \begin{bmatrix} \sqrt{(y_k^t - y_k)^2 + (x_k^t - x_k)^2 + h_k^2} \\ \tan^{-1}\frac{y_k^t - y_k}{x_k^t - x_k} \\ \tan^{-1}\frac{\sqrt{(y_k^t - y_k)^2 + (x_k^t - x_k)^2}}{h_k} \end{bmatrix} + \xi_k \tag{7}$$

where r_k, ϕ_k, φ_k represent the distance, azimuth angle and pitch angle between UAV and target at time k. x_k, y_k, h_k are horizontal position and height of UAV. ξ_k is measurement noise with covariance matrix

$$R_\xi = V[\xi_k] = \begin{bmatrix} \sigma_r^2 & 0 & 0 \\ 0 & \sigma_\phi^2 & 0 \\ 0 & 0 & \sigma_\varphi^2 \end{bmatrix}$$

where $\sigma_r^2, \sigma_\phi^2, \sigma_\varphi^2$ are noise parameters corresponding to distance, azimuth angle and pitch angle.

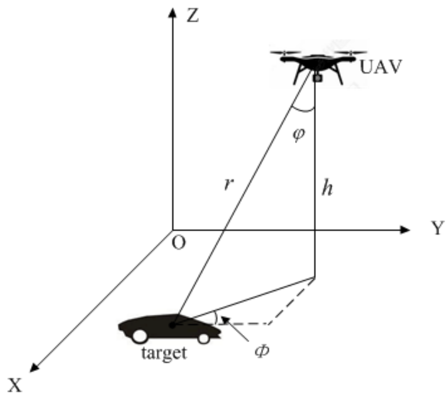

FIGURE 1. Geometry between the UAV and the ground target.

III. DECENTRALIZED ESTIMATION FILTER DESIGN FOR TARGET

A. SQUARED-ROOT CUBATURE INFORMATION FILTER

Considering the dimension of target states and nonlinear characteristic of sensor measurement model, SCIF method [33] is introduced and designed to estimate target states.

1) Time update:

Assume $(\hat{h}_{k-1|k-1}, S_{h,k-1|k-1})$ is known. $\hat{h}_{k-1|k-1}$ and $S_{h,k-1|k-1}$ represent the information state vector and the squared-root of the corresponding covariance matrix of the estimation error at time $k-1$, respectively. Squared-root covariance is written as

$$S_{x,k-1|k-1} = S_{h,k-1|k-1}^{-T} \tag{8}$$

Compute the state estimation of the target at time $k-1$:

$$\hat{X}_{k-1|k-1}^t = S_{x,k-1|k-1} S_{x,k-1|k-1}^T \hat{h}_{k-1|k-1} \tag{9}$$

The cubature points are obtained by:

$$X_{i,k-1|k-1}^t = S_{x,k-1|k-1}\xi_i + \hat{X}_{k-1|k-1}^t, \quad i = 1, \cdots, 2n$$
$$\xi_i = \begin{cases} \sqrt{n}e_i, & i = 1, 2 \ldots n \\ -\sqrt{n}e_{i-n}, & i = n+1, n+2 \ldots 2n \end{cases} \tag{10}$$

where n is the dimension of X_k^t. e_i represents the *ith* column componen of unit matrix.

Evaluate the propagated cubature points based on the target model:

$$X_{i,k|k-1}^{t,*} = FX_{i,k-1|k-1}^t \tag{11}$$

where $F = I + TF_0$.

Calculate the predictive state and squared-root error covariance

$$\hat{X}_{k|k-1}^t = \frac{1}{2n}\sum_{i=1}^{2n} X_{i,k|k-1}^{t,*}$$
$$S_{x,k|k-1} = qr[\ \chi_{k|k-1}^* \ \ S_Q\ ] \tag{12}$$

where

$$\chi_{k|k-1}^* = \frac{1}{\sqrt{2n}}[X_{1,k|k-1}^{t,*} - \hat{X}_{k|k-1}^t \quad \cdots \quad X_{2n,k|k-1}^{t,*} - \hat{X}_{k|k-1}^t],$$

S_Q is the squared-root of Q_{k-1}, $Q_{k-1} = T^2 Q_\delta$, qr denotes QR decomposition.

Estimate the square-root of the predictive information matrix and information vector

$$\begin{aligned} S_{h,k|k-1} &= S_{x,k|k-1}^{-T} \\ \hat{h}_{k|k-1} &= S_{h,k|k-1} S_{h,k|k-1}^T \hat{X}_{k|k-1}^t \end{aligned} \tag{13}$$

2) Measurement update:

Obtain the cubature points at time k by the same way as 1) time update

$$X_{i,k|k-1}^t = S_{x,k|k-1}\xi_i + \hat{X}_{k|k-1}^t \tag{14}$$

According to sensor measurement model, the propagated cubature points are obtained as

$$Z_{i,k|k-1} = f_h(X_{i,k|k-1}^t) \tag{15}$$

Estimate the predictive measurement and cross-covariance matrix:

$$\begin{aligned} \hat{z}_{k|k-1} &= \frac{1}{2n}\sum_{i=1}^{2n} Z_{i,k|k-1} \\ P_{xz} &= \chi_{k|k-1} Z_{k|k-1}^T \end{aligned} \tag{16}$$

where

$$\chi_{k|k-1} = \frac{1}{\sqrt{2n}}[X_{1,k|k-1}^t - \hat{X}_{k|k-1}^t \cdots X_{2n,k|k-1}^t - \hat{X}_{k|k-1}^t]$$

$$Z_{k|k-1} = \frac{1}{\sqrt{2n}}[Z_{1,k|k-1} - \hat{z}_{k|k-1} \cdots Z_{2n,k|k-1} - \hat{z}_{k|k-1}]$$

Information contribution vector and square-root of information contribution matrix are obtained as follows:

$$\begin{aligned} i_k &= S_{Ik} S_R^{-1}(z_k - \hat{z}_{k|k-1} + P_{xz}^T \hat{h}_{k|k-1}) \\ S_{Ik} &= S_{x,k|k-1}^{-T} S_{x,k|k-1}^{-1} P_{xz} S_R^{-T} \end{aligned} \tag{17}$$

where S_R is the square-root of R_ξ.

So the information vector and square-root of information matrix are updated:

$$\begin{aligned} \hat{h}_{k|k} &= \hat{h}_{k|k-1} + i_k \\ S_{h,k|k} &= qr([S_{h,k|k-1}, S_{Ik}]) \end{aligned} \tag{18}$$

B. SENSOR FUSION BASED ON HCMCI

Each UAV estimates the target states based on its sensor measurement. Then sensor fusion is performed between UAVs for more accurate estimation. Since each UAV is taken as a fusion center to handle the information from its neighbors, there will exist difference among fusion results. Thereby, a consensus algorithm is needed to eliminate or reduce this difference. In this paper, the consensus method HCMCI [34] in Table 1 is introduced. This algorithm combines consensus on measurement (CM) with consensus on information (CI), and has high precision and good convergence.

In Table 1, L is consensus step, a denotes the parameter related to communication topology of UAVs network. b is a proper scalar. The UAVs network can be described by the direct graph $\Phi = (E, \varepsilon)$. $E = \{1, 2, \ldots, N\}$ is the node set, where each UAV is regarded as a node. The edge ε denotes all the communication connection. The neighborhood nodes which UAV j can connect are presented as $E_j = \{m/(m, j) \in \varepsilon\}$, which has effect on precision and convergence, and needs to be chosen by tradeoff. The results in Table 1 are used as the initial values of predictive states of the target at each sampling.

TABLE 1. HCMCI algorithm.

$S_{j,h,k\|k-1}(0) = S_{j,h,k\|k-1}, \hat{h}_{j,k\|k-1}(0) = \hat{h}_{j,k\|k-1},$
$S_{j,Ik}(0) = S_{j,Ik}, i_{j,k}(0) = i_{j,k},$
$For\ p = 1, ..., L-1$
$S_{j,h,k\|k-1}(p+1) = \sum_{m\in N^j} a_{jm}(p) S_{m,h,k\|k-1}(p)$
$\hat{h}_{j,k\|k-1}(p+1) = \sum_{m\in N^j} a_{jm}(p) \hat{h}_{m,k\|k-1}(p)$
$S_{j,Ik}(p+1) = \sum_{m\in N^j} a_{jm}(p) S_{m,Ik}(p+1)$
$i_{j,k}(p+1) = \sum_{m\in N^j} a_{jm}(p) i_{m,k}(p+1)$
end
$S_{j,h,k\|k}(L) = qr([S_{j,h,k\|k-1}(L), bS_{j,Ik}(L)])$
$\hat{h}_{j,k\|k} = \hat{h}_{j,k\|k-1}(L) + bi_{j,k}(L)$

It should be noted that UAVs can communicate with each other in terms of a preset way during tracking. In addition, because the UAVs are moving, the topology will be updated continually in light of the communication capacity. How to improve the cooperative ability, enhance controllability of UAVs and reduce computation, should be considered.

IV. DECENTRALIZED PATH PLANNING

A. DESCRIPTION OF DECENTRALIZED PATH PLANNING PROBLEM

The purpose of cooperative target tracking is to maintain close to the target as much as possible and avoid collision between UAVs. The target tracking problem can be solved by nonlinear MPC method to find a control input sequence $U_k = \{u_k, u_{k+1}, \cdots, u_{k+M-1}\}$, where the following performance index of jth UAV, $j = 1, \ldots, N$ is minimized

$$J_j = \sum_{\tau=k+1}^{k+M}\left[w_{j,x}\left(x_j(\tau|k) - x_j^t(\tau)\right)^2 + w_{j,y}\left(y_j(\tau|k) - y_j^t(\tau)\right)^2\right] + \sum_{\tau=k}^{k+M-1}\left(w_{j,v}v_j^2 + w_{j,o}\omega_j^2\right) \tag{19}$$

$$\text{s.t. } X_j(\tau+1|k) = f_a(X_j(\tau), u(\tau)), \forall\tau \tag{20}$$

$$0 \le v_{j,\min} \le v_j(\tau) \le v_{j,\max}, \forall\tau \tag{21}$$

$$\omega_{j,\min} \le \omega_j(\tau) \le \omega_{j,\max}, \forall\tau \tag{22}$$

$$\sqrt{\left(x_j(\tau|k) - x_i(\tau|k)\right)^2 + \left(y_j(\tau|k) - y_i(\tau|k)\right)^2} \ge D \quad i = 1, \ldots, N, j \ne i \tag{23}$$

where M is prediction horizon. $w_{j,v}, w_{j,o}, w_{j,x}, w_{j,y}$ are weighting coefficients. $x_j^t(\tau), y_j^t(\tau)$ are target estimation achieved by UAV j. $x(\tau|k)$ denotes the predictive state of

UAV j. D is the safe distance of collision avoidance between two UAVs. For the UAVs flying at the same altitude, the collision avoidance constraint in horizon should be considered. Equation (23) guarantees that each UAV can keep safe distance to any others.

The computation of optimization problem is dependent on many factors, such as predictive horizon, dimensions of states and control variables. It is difficult to use traditional method to solve the problem online for the real system. In this paper, a strategy similar to [35]–[37] is employed to realize fast computation.

B. RECONFIGURATION OF PATH PLANNING

Firstly, jth UAV model is linearized by Jacobian matrix at reference point (x_j^r, y_j^r) as:

$$\begin{bmatrix} \dot{\tilde{x}}_j \\ \dot{\tilde{y}}_j \\ \dot{\tilde{\theta}}_j \end{bmatrix} = \begin{bmatrix} 0 & 0 & -\sin\theta_j^r * v_j^r \\ 0 & 0 & \cos\theta_j^r * v_j^r \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \tilde{x}_j \\ \tilde{y}_j \\ \tilde{\theta}_j \end{bmatrix} + \begin{bmatrix} \cos\theta_j^r & 0 \\ \sin\theta_j^r & 0 \\ 0 & 0 \end{bmatrix} * \begin{bmatrix} \tilde{v}_j \\ \tilde{\omega}_j \end{bmatrix} \quad (24)$$

where $\tilde{x}_j, \tilde{y}_j, \tilde{\theta}_j, \tilde{v}_j, \tilde{\omega}_j$ are differences between $x_j, y_j, \theta_j, v_j, \omega_j$ and reference $x_j^r, y_j^r, \theta_j^r, v_j^r, \omega_j^r$, written as:

$$\begin{cases} \tilde{x}_j = x_j - x_j^r \\ \tilde{y}_j = y_j - y_j^r \\ \tilde{\theta}_j = \theta_j - \theta_j^r \\ \tilde{v}_j = v_j - v_j^r \\ \tilde{\omega}_j = \omega_j - \omega_j^r \end{cases}$$

Discreting (24) with sampling time T, we have:

$$\begin{aligned} \begin{bmatrix} x_j(k+1) \\ y_j(k+1) \\ \theta_j(k+1) \end{bmatrix} &= \begin{bmatrix} 1 & 0 & -\sin\theta_j^r * v_j^r * T \\ 0 & 1 & \cos\theta_j^r * v_j^r * T \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} x_j(k) \\ y_j(k) \\ \theta_j(k) \end{bmatrix} \\ &+ \begin{bmatrix} \cos\varphi_j^r * T & 0 \\ \sin\varphi_j^r * T & 0 \\ 0 & T \end{bmatrix} * \begin{bmatrix} v_j(k) \\ \omega_j(k) \end{bmatrix} + \begin{bmatrix} x_j^r(k+1) \\ y_j^r(k+1) \\ \theta_j^r(k+1) \end{bmatrix} \\ &- \begin{bmatrix} 1 & 0 & -\sin\theta_j^r * v_j^r * T \\ 0 & 1 & \cos\theta_j^r * v_j^r * T \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} x_j^r(k) \\ y_j^r(k) \\ \theta_j^r(k) \end{bmatrix} \\ &- \begin{bmatrix} \cos\varphi_j^r * T & 0 \\ \sin\varphi_j^r * T & 0 \\ 0 & T \end{bmatrix} * \begin{bmatrix} v_j^r(k) \\ \omega_j^r(k) \end{bmatrix} \end{aligned}$$

The above equation can be rewritten as

$$X_j(k+1) = A_j X_j(k) + B_j u_j(k) + R_{es,j}(k) \quad (25)$$

where

$$\begin{aligned} X_j(k) &= [\, x_j(k) \quad y_j(k) \quad \theta_j(k)]^T, \\ u_j &= [\, v_j(k) \quad \omega_j(k)\,]^T, \\ R_{es,j}(k) &= X_j^r(k+1) - A_j X_j^r(k) - B_j u_j^r(k) \\ A_j &= \begin{bmatrix} 1 & 0 & -\sin\theta_j^r * v_j^r * T \\ 0 & 1 & \cos\theta_j^r * v_j^r * T \\ 0 & 0 & 1 \end{bmatrix}, \\ B_j &= \begin{bmatrix} \cos\varphi_j^r * T & 0 \\ \sin\varphi_j^r * T & 0 \\ 0 & T \end{bmatrix}. \end{aligned}$$

Then, the collision avoidance constraint (23) is rewritten as follows.

$$\sqrt{\frac{\left(x_j(\tau|k) - x_i(\tau|k)\right)^2 + \left(y_j(\tau|k) - y_i(\tau|k)\right)^2}{2}} \geq \frac{D}{\sqrt{2}} \quad (26)$$

Considering inequality $\sqrt{\frac{a^2+b^2}{2}} \geq \frac{a+b}{2}$, the following equation can be achieved

$$\sqrt{\frac{\left(x_j(\tau) - x_i(\tau)\right)^2 + \left(y_j(\tau) - y_i(\tau)\right)^2}{2}} \geq \frac{x_j(\tau) - x_i(\tau) + y_j(\tau) - y_i(\tau)}{2} \quad (27)$$

Further, there is

$$\frac{x_j(\tau) - x_i(\tau) + y_j(\tau) - y_i(\tau)}{2} \geq \frac{D}{\sqrt{2}} \quad (28)$$

The collision avoidance constraint is replaced by the following inequality

$$-\left(x_j(\tau) + y_j(\tau)\right) \leq -\left(\sqrt{2}D + x_i(\tau) + y_i(\tau)\right) \quad (29)$$

Therefore, the path optimization problem (19)-(23) is reformulated as:

$$\min \left[\frac{1}{2}(z_j - z_j^t)^T H_j (z_j - z_j^t)\right] \quad (30)$$

$$P_j^* z_j \leq m_j^* \quad (31)$$

$$C_j z_j = b_j \quad (32)$$

where $z_j = [u_j(k), x_j(k+1), \cdots, x_j(k+M-1), u_j(k+M-1), x_j(k+M)]^T$, $P_j \in R^{(2M\times n_u, M(n_x+n_u))}$, $m_j \in R^{2M\times n_u}$, $C_j \in R^{(Mn_x, M(n_x+n_u))}$, $b_j \in R^{Mn_x}$.

Equation (32) contains all the equality constraint (20), while (31) contains all the inequality constraints (21),(22) and (29). C_j, b_j are defined as

$$C_j = \begin{bmatrix} -B_j & I & 0 & 0 & \cdots & 0 & 0 \\ 0 & -A_j & -B_j & I & \cdots & 0 & 0 \\ 0 & 0 & 0 & -A_j & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & -A_j & -B_j & I \end{bmatrix}$$

$$b_j = [A_j x_j(k) + R_{es,j}(k)\; R_{es,j}(k+1) \cdots R_{es,j}(k+M)]^T$$

C. FAST MODEL PREDICTIVE CONTROL

In order to realize real-time optimization and ensure optimality of solution, the optimization strategy [37] is implemented, where KKT condition is used to avoid heavy iterative computation of traditional nonlinear programming [38]. The Lagrangian function of optimization problem (30)-(32) is built as:

$$\Gamma_j(z_j,\lambda_j,v_j)=\frac{1}{2}(z_j-z_t^j)^T H_j(z_j-z_t^j)+\lambda_j(C_j z_j-b_j) + \gamma_j(P_j z_j+s_j-m_j) \quad (33)$$

where λ_j, γ_j are Lagrange multipliers. s_j is slack variable.

If the optimal solution to problem (30)-(32) exists, the following first-order KKT condition holds.

$$F_j(\gamma_j,\lambda_j,v_j)=\begin{bmatrix} H_j(z_j-z_t^j)+C_j^T\lambda_j+P_j^T\gamma_j \\ C_j z_j-b_j \\ P_j z_j+s_j-m_j \\ \Upsilon_j S_j I\end{bmatrix}=0 \quad (34)$$

where Υ_j, S_j are diagonal matrixes dependent on γ_j, s_j. The last term in (34) is the complementary slackness condition. In order to speed up convergence, the Newton method is implemented to solve (34). Update $\Delta z_j, \Delta\lambda_j, \Delta\gamma_j, \Delta s_j$ by following equation.

$$J_j(z_j,\lambda_j,\gamma_j,s_j)\begin{bmatrix}\Delta z_j\\ \Delta\lambda_j\\ \Delta\gamma_j\\ \Delta s_j\end{bmatrix}=-F_j(z_j,\lambda_j,\gamma_j,s_j) \quad (35)$$

where J_j is the Jacobian matrix of F_j at point $(z_j,\lambda_j,\gamma_j,s_j)$.

Assuming that current point is strictly feasible, there will be

$$\begin{bmatrix} H_j & C_j^T & P_j^T & 0\\ C_j & 0 & 0 & 0\\ P_j & 0 & 0 & I\\ 0 & 0 & S_j & \Upsilon_j\end{bmatrix}\begin{bmatrix}\Delta z_j\\ \Delta\lambda_j\\ \Delta\gamma_j\\ \Delta s_j\end{bmatrix}=-F_j((z_j,\lambda_j,\gamma_j,s_j)) = -\begin{bmatrix} r_{z_j}\\ r_{\lambda_j}\\ r_{\gamma_j}\\ r_{s_j}\end{bmatrix} \quad (36)$$

where $r_{z_j}, r_{\lambda_j}, r_{\gamma_j}, r_{s_j}$ are obtained by (35). Further, (36) is simplified to

$$\begin{aligned} C_j L_j^{-1} L_j^{-T} C_j^T \Delta\lambda_j &= -C_j L_j^{-1} L_j^{-T}\left(r_{z_j}+P_j^T W_j^{-2}(r_{\gamma_j}-\Upsilon_j^{-1} r_{s_j})\right)+r_{\lambda_j}\\ L_j L_j^T \Delta z_j &= -r_{z_j}-P_j^T W_j^{-2}(r_{\gamma_j}-\Upsilon_j^{-1} r_{s_j})-C_j^T\Delta\lambda_j \end{aligned} \quad (37)$$

where $\Upsilon_j^{-1} S_j = W_j^T W_j$. In fact, since W_j is a diagonal matrix, $W_j = W_j^T$, $\Upsilon_j^{-1} S_j = W_j^2$, and $L_j L_j^T = H_j + P_j^T (W_j)^{-2} P_j$.

If $H_j + P_j^T (W_j)^{-2} P_j$ is singular, (37) can be changed into

$$\begin{aligned} C_j L_j^{-1} L_j^{-T} C_j^T \Delta\lambda_j &= -C_j L_j^{-1} L_j^{-T}(r_{z_j}+P_j^T W_j^{-2}(r_{\gamma_j} -\Upsilon_j^{-1} r_{s_j})+C_j^T r_{\lambda_j})+r_{\lambda_j}\\ L_j L_j^T \Delta z_j &= -r_{z_j}-P_j^T W_j^{-2}(r_{\gamma_j}-\Upsilon_j^{-1} r_{s_j})-C_j^T r_{\lambda_j} - C_j^T\Delta\lambda_j \end{aligned} \quad (38)$$

$\Delta s_j, \Delta\gamma_j$ are obtained by the following equation

$$\begin{cases}\Delta s_j = -P_j\Delta z_j - r_{\gamma_j}\\ \Delta\gamma_j = S_j^{-1}(-r_{s_j}-\Upsilon_j\Delta s_j)\end{cases} \quad (39)$$

To guarantee that the Lagrange multipliers and slack variables are nonnegative, the step size $a_j(q)$ is selected as follows.

$$a_j(q)=\min\begin{bmatrix} -(s_j(q)/\Delta s_j(q)) : \Delta s_j(q)<0\\ -(\lambda_j(q)/\Delta\lambda_j(q)) : \Delta\lambda_j(q)<0\\ -(\gamma_j(q)/\Delta\gamma_j(q)) : \Delta\gamma_j(q)<0\end{bmatrix} \quad (40)$$

where q is iterative number. Optimization variables are updated by (41) at each iteration.

$$\begin{bmatrix} z_j(q+1)\\ \lambda_j(q+1)\\ \gamma_j(q+1)\\ s_j(q+1)\end{bmatrix}=\begin{bmatrix} z_j(q)\\ \lambda_j(q)\\ \gamma_j(q)\\ s_j(q)\end{bmatrix}+a_j(q)\begin{bmatrix}\Delta z_j(q)\\ \Delta\lambda_j(q)\\ \Delta\gamma_j(q)\\ \Delta s_j(q)\end{bmatrix} \quad (41)$$

In order to realize less iteration, a fixed $q < q^{\max}$ is considered to be chosen. Although it may only find a suboptimal solution, it is effective in most cases to maintain good performance by less calculation.

Algorithm steps of decentralized estimation and tracking are presented in detail as follows.

Step 1: Initialize parameters of SCIF, HCMCI and FMPC.

Step 2: Estimate the target states based on measurement of each UAV by SCIF, and obtain the square-root of the predictive information matrix and information vector, square-root of information contribution matrix, and information contribution vector.

Step 3: Calculate consensus for the information obtained in Step 2 using HCMCI, and obtain the predictive values of target states accurately.

Step 4: Solve path optimization problem of each UAV by FMPC. Update directions and step size in Newton method.

Step 5: Update optimization variables as (41) and $q = q + 1$. If $q < q_{\max}$, return to step 4. Otherwise turn to step 6.

Step 6: Apply u(k) to UAVs. Update k and return to step 2 until tracking mission finishes.

V. SIMULATIONS

In the simulations, we choose quadrotor UAVs to track ground target. The number of UAVs is four. Two UAVs fly at a fixed height, and the other two fly at another fixed height. The collision avoidance constraint between two UAVs at the same height has to be considered. The communication topology is constructed among four UAVs. The evaluation criterion is defined as follows.

The position estimation error is:

$$e_{pj}=\sqrt{(x_j^t-x^t)^2+(y_j^t-y^t)^2}$$

The consensus error is:

$$e_{cj}=\sqrt{(x_j^t-\bar{x}^t)^2+(y_j^t-\bar{y}^t)^2}$$

where x^t, y^t are the accurate position of the target. x_j^t, y_j^t are the estimation by *jth* UAV. $\bar{x}^t, \bar{y}^t$ are the average of four UAVs' estimation. The real trajectory of target is shown in Fig. 2.

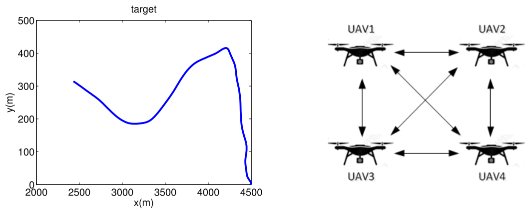

FIGURE 2. **Target trajectory and communication topology.**

The parameters in target model are set as $T = 0.5, \alpha = 0.6, \sigma_\alpha = 0.67$. The covariance matrixes are

$$R1 = diag(1, 0.5 * d2r, 0.5 * d2r)$$
$$R2 = diag(2.5, 0.3 * d2r, 0.6 * d2r)$$
$$R3 = diag(1.5, 0.1 * d2r, 0.5 * d2r)$$
$$R4 = diag(1, 0.1 * d2r, 0.5 * d2r)$$

where $d2r = \pi/180$. The parameters for SCIF are

$$S_1 = S_2 = S_3 = S_4 = diag(0.1, 0.1, 0.1, 0.1, 0.1, 0.1)$$
$$h_1 = h_2 = h_3 = h_4 = diag(0, 0, 0, 0, 0, 0)$$

At the initial time, UAV1 and UAV2 are hovering at the height of 100m, while UAV3 and UAV4 are hovering at the height of 110m, and their states are

$$\begin{cases} X_1 = \begin{bmatrix} 4510 & -8 & 2 \end{bmatrix}; \\ X_2 = \begin{bmatrix} 4490 & -8 & 2 \end{bmatrix}; \\ X_3 = \begin{bmatrix} 4509 & -8 & 2 \end{bmatrix}; \\ X_4 = \begin{bmatrix} 4491 & -8 & 2 \end{bmatrix}; \end{cases}$$

Predictive horizon $M = 10$. The safe distance of collision avoidance is 10m. The constraints of control inputs are $0 \leq v_j \leq 40, -5 \leq \omega_j \leq 5$. The whole tracking time is $400 \times T = 200s$, where 400 is the sampling number.

A. CASE 1: FIXED COMMUNICATION TOPOLOGY

Without considering UAVs' position and communication range etc., it is assumed that UAVs can communicate with each other under the topology in Fig. 2. Connected lines indicate that two UAVs can transmit messages bidirectionally. The parameters of objective function (19) are given as

$$\begin{cases} w_v^1 = 5, w_o^1 = 180, w_x^1 = 0.5, w_y^1 = 0.5; \\ w_v^1 = 4, w_o^1 = 180, w_x^1 = 0.4, w_y^1 = 0.5; \\ w_v^1 = 5, w_o^1 = 180, w_x^1 = 0.5, w_y^1 = 0.5; \\ w_v^1 = 4, w_o^1 = 180, w_x^1 = 0.4, w_y^1 = 0.5; \end{cases}$$

Simulation results are shown in Fig. 3 to Fig. 6. The estimations of target position using four UAVs are given in Fig. 3

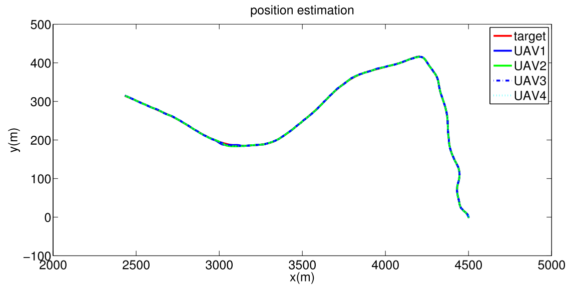

FIGURE 3. **Position estimation of Case 1.**

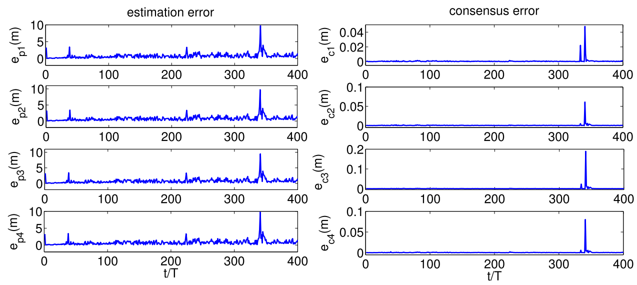

FIGURE 4. **Estimation error and consensus error of Case 1.**

and Fig. 4. The position errors are lower than 10m. The largest error appears at the moment when the target is at the turn. The consensus errors are lower than 0.05m.

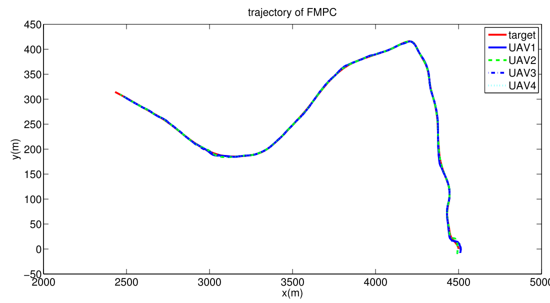

FIGURE 5. **Tracking trajectory of Case 1.**

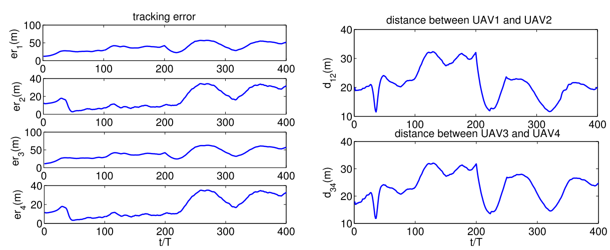

FIGURE 6. **Tracking error and distance of UAVs of Case 1.**

Fig. 5 and Fig. 6 show tracking trajectory, tracking errors, and distance between two UAVs at the same height. The collision avoidance distance is much larger than 10m. By the similar initialization and control parameters, the distance between UAV1 and UAV2 has the same trend with that between UAV3 and UAV4. The UAVs not only fly close to target as much as possible, but also keep the safe distance to other UAVs. The tracking errors are not too small, which is relevant to the velocity of target. The faster the target moves, the larger tracking error may be.

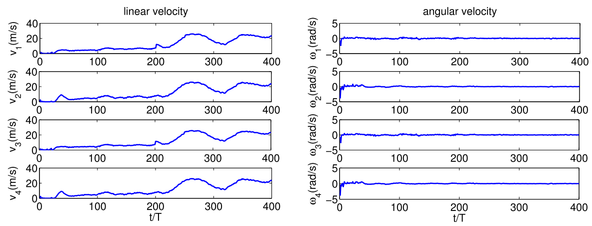

FIGURE 7. **Linear velocity and angular velocity of Case 1.**

The curves in Fig. 7 are the linear velocities and angular velocities. It can be seen that the control inputs satisfy the constraints strictly. However, they are not so smooth on account of linearization. In view of linear and angular velocities being controlled simultaneously, UAVs have the similar control behaviors. Their drastic changes also arise at the moment when the target is at the turn.

In this case, the estimation and tracking performance can meet the demand of tracking mission. The control inputs also satisfy the constraints. In addition, the run time, is 61.918996s when using an Intel Pentium with 2.7GHz and 4 GB RAM. It indicates the algorithm proposed in this paper has high real-time performance, comparing to the whole tracking time.

B. CASE 2: CHANGE OF COMMUNICATION TOPOLOGY

So far, most filtering algorithm is based on fixed communication topology in wireless sensor network. However, sensors move with UAVs in the target tracking system, where communication topology will change according to circumstances, communication capacity or other factors. The change of communication topology in sensor network of UAVs can be considered as the network reconfiguration of UAVs. Most studies on this problem aim at communication performance, including routing protocol, route optimization, information safety, etc. However, we focus on the estimation and tracking of the target. In order to verify the performance of the algorithm proposed in this paper, assume that when $150\times T \leq t \leq 200 \times T$, UAV1 do not exchange information with UAV3 as Fig. 8(a), and when $300 \times T \leq t \leq 350 \times T$, the communication between UAV1 and UAV4 is broken as Fig. 8(b). During the remaining time, the communication topology is the same with previous simulation. The parameters are given as follows.

$$\begin{cases} w_v^2 = 5, w_o^2 = 180, w_x^2 = 0.2, w_y^2 = 0.2; \\ w_v^2 = 4, w_o^2 = 180, w_x^2 = 0.4, w_y^2 = 0.5; \\ w_v^2 = 5, w_o^2 = 180, w_x^2 = 0.2, w_y^2 = 0.2; \\ w_v^2 = 4, w_o^2 = 180, w_x^2 = 0.4, w_y^2 = 0.5; \end{cases}$$

The results are shown in Fig. 9 to Fig. 13 The estimation errors and consensus errors increase as the communication topology varies in Fig. 10. Nevertheless, it has little influence on the tracking performance, which can be seen from Fig. 11 and Fig. 12. Hence, the proposed algorithm is feasible even if the topology changes, which demonstrates its robustness.

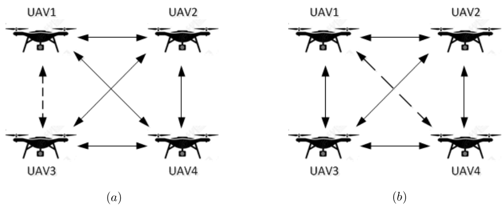

FIGURE 8. **Changes of communication topology.**

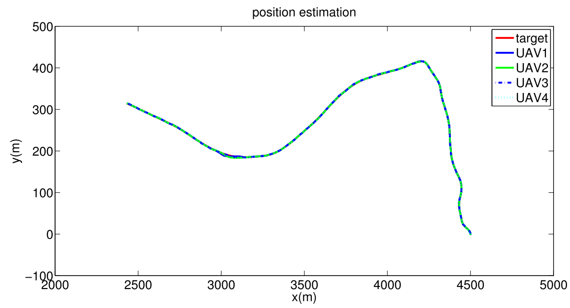

FIGURE 9. **Position estimation of Case 2.**

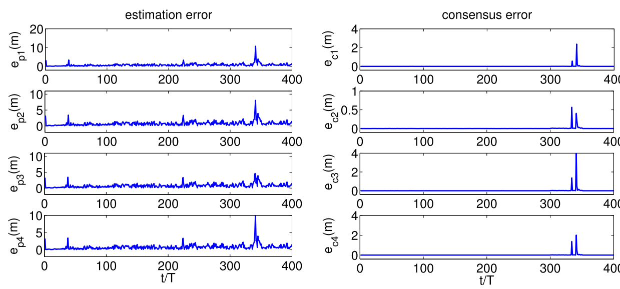

FIGURE 10. **Estiamtion error and consensus error of Case 2.**

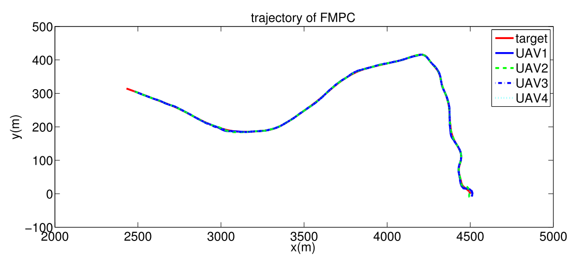

FIGURE 11. **Tracking trajectory of Case 2.**

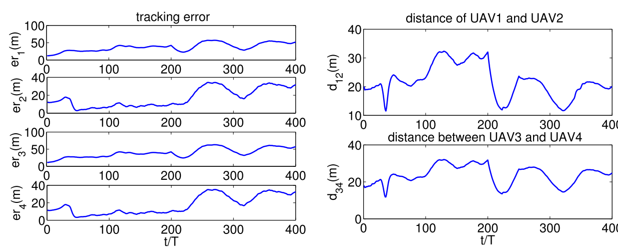

FIGURE 12. **Tracking error and distance of UAVs of Case 2.**

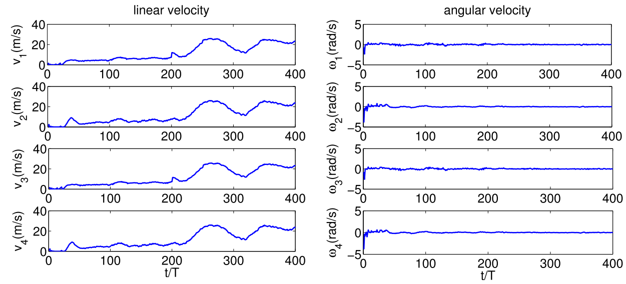

FIGURE 13. Linear velocity and angular velocity of Case 2.

VI. CONCLUSIONS

The decentralized estimation and tracking method is proposed for UAVs tracking ground moving target in this paper. The SCIF and HCMCI methods are applied to estimate the target states online. The FMPC algorithm is used to compute the UAVs' trajectories online according to the estimated target information. Simulations with different communication topologies show the accurate estimation ability for target, and high real-time and robust calculation ability of path planning.

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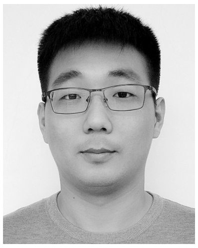

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