IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received September 11, 2019, accepted October 6, 2019, date of publication October 15, 2019, date of current version October 30, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2947600

An Advanced Cubature Information Filtering for Indoor Multiple Wideband Source Tracking With a Distributed Noise Statistics Estimator

JIAHAO ZHANG[1], SHESHENG GAO[1], YONGMIN ZHONG[2], XIAOMIN QI[3], JUAN XIA[1], AND JIAHUI YANG[1]

[1]School of Automatics, Northwestern Polytechnical University, Xi′an 710064, China
[2]School of Engineering, RMIT University, Melbourne, VIC 3083, Australia
[3]Department of Electrical and Computer Engineering, COMSATS University Islamabad, Abbottabad Campus, Abbottabad 22060, Pakistan

Corresponding author: Jiahao Zhang (zjh_dr@126.com)

This work was supported in part by the National Natural Science Foundation of China under Grant 41704016, Grant 41804048, and Grant 41904028, in part by the Science, Technology and Innovation Commission of Shenzhen Municipality, China, under Grant JCYJ20180306171439979, and in part by the Shaanxi Province Key Research and Development Projects, China, under Grant 2018ZDXM-GY-024.

ABSTRACT Acoustic vector sensor (AVS) is an effective tool to tracking acoustic sources. However, for the problem of tracking multiple wideband sources using distributed AVS array (DAVS), there are still unsolved issues which include measurements-to-targets association and targets tracking under incorrect or unknown statistics of measurement noise. Joint probabilistic data association (JPDA) is an effective algorithm to solve data association between measurements and targets and JPDA based cubature information filter (MTCIF) is designed for nonlinear system. Meanwhile, noise statistics estimator (NSE) based on modified Sage-Husa maximum posterior (SHMP) is constructed to cope with incorrect or unknown statistics of measurement noise. Then, a two-step distributed information fusion based on weighted average consensus (WAC) is built for DAVS to improve the stability and accuracy of state estimator and NSE. Numerical simulations demonstrate the effectiveness of the proposed algorithms.

INDEX TERMS Acoustic vector sensor, cubature information filter, joint probabilistic data association, noise statistics estimator, weighted average consensus.

I. INTRODUCTION

Developed on the basis of acoustic pressure sensor, AVS is of low mass and small volume [1]. Since main components are one omni-directional pressure sensor and three orthogonal velocity sensors, AVS is capable of acquiring acoustic pressure and three-dimensional acoustic particle velocities [2]. Due to the above advantages, AVS is more attractive and applicable for positioning and tracking acoustic sources, comparing to the traditional sensor array [1]. DAVS belongs to the kind of distributed wireless sensor network, which adopts the cooperative adjacent nodes to replace the centralized computing node [3]. Therefore, DAVS possesses stronger stability and robustness as well as lower communication burden than centralized AVS array.

The associate editor coordinating the review of this manuscript and approving it for publication was Lin Zhang.

Research efforts have been dedicated on target tracking using DAVS [4]–[6]. A direct positioning method was studied for tracking multiple wideband sources [4], where the positions of acoustic sources were directly obtained through the measurements of DAVS. However, the dimension of the measurement vector is linearly increased with the increase of the AVS sampling rate, leading to the exponential growth of the computational load. A two-step or indirect positioning method was reported for a single wideband source [5], where direction of arrival (DOA) from the target to the AVS was estimated by capon beamforming, and then the algorithm of least squares was used to triangle the position of tracking target. However, this method is only suitable for positioning a single target, since capon beamforming can only extract the DOA of a single target and the least squares cannot be used to solve the problem of data association between targets and measurements. Zhong et al. proposed a two-step positioning method for multiple wideband sources [6], where an advanced capon beamforming was used to estimate the DOAs of multiple targets and then the random finite set (RFS) was adopted to locate multiple targets. The existing algorithms on multi-target tracking can be mainly classified into two categories [7]: RFS and data association. Although RFS based method avoids the problem of measurements-to-tracks association, the use of RFS causes a huge computation burden and lacks an exact solution for integral operations [7]. In addition, although the structure of DAVS is selected, the algorithm of information fusion in [4]–[6] is a centralized technology which transmits all the information of local nodes to the centralized computing node. Then a huge communication bandwidth of AVS array and the strong computing power of the computing node are needed in the process of centralized information fusion.

Distributed information fusion algorithms were investigated in [8]–[10] for multi-target tracking. Since only the information of adjacent nodes is accepted, the computing power for the local node and network bandwidth is much smaller in distributed information fusion algorithms, compared with the centralized fusion algorithm. A distributed multi-target tracking algorithm was proposed in [8] based on Kalman consensus filtering (KCF) and joint probabilistic data association (JPDA). JPDA-KCF is only suitable for linear system models, rather than nonlinear systems in practical applications. In order to solve the problem of nonlinearity in multi-target tracking, the distributed cubature information filtering based on JPDA and weighted consensus was proposed in [9] and [10] respectively. Cubature information filtering (CIF) is an algebraic equivalent form of cubature Kalman filtering (CKF) [11], which is designed to cope with state estimation for nonlinear systems. CIF can provide more stable and accurate state estimation than most of Gaussian filters [11], such as extended Kalman filtering (EKF) and unscented Kalman filtering (UKF) and their improved versions. Furthermore, compared with Kalman filtering, information filtering is more suitable for distributed information fusion [12]. However, two problems need to be solved for JPDA based algorithms. The first problem is that the prior knowledge of measurement noise is supposed already known, which is hardly satisfied in the real application. The second problem is that the selected algorithm for distributed information fusion belongs to consensus on measurements (CM), the stability of which can only be guaranteed by plentiful consensus steps [13].

State estimation for multi-target tracking is usually affected by the accuracy of measurements and the assumed system model. However, measurements are subject to the noise caused by metering instruments, and uncertainties like instrument failures, erroneous zero-injections, etc. are always classified into measurement noise which is usually unknown in practice [14]. Hence the statistics estimation of measurement noise is an essential problem for multi-target tracking. Noise statistics estimator (NSE) is an effective algorithm to take special care of incorrect or unknown statistics of measurement noise which belongs to the first problem in the previous paragraph. Sage et al. proposed a NSE based on SHMP to obtain the statistics of system noise including mean and error covariance [15]. However, stability of NSE based on SHMP cannot be guaranteed in high-order system on account of the nonpositive definite noise covariance [16]. To improve the stability of NSE, a new adaptive unscented Kalman filtering (AUKF) based on modified SHMP was designed in [17] at the expense of accuracy of NSE. Yu et al. proposed an adaptive CKF to cope with the time-varying system noise and given the expression of NSE based on SHMP [18]. Nevertheless, the stability of the designed NSE in adaptive CKF is not considered.

For the second problem, weighted average consensus (WAC) [19]–[21] is an effective solution to complete information fusion of distributed networks. WAC belongs to the algorithm of consensus on information (CI), which outperforms CM algorithm since the stability of CI can be guaranteed by any time of consensus steps (even a single one)[21]. Therefore, in terms of stability, CI is more suitable for information fusion of DAVS than the CM algorithm. Furthermore, each sensor node owns different estimations of statistics of measurement noise, which is made by the designed NSE. The difference in noise statistics of measurements indirectly affects the precision of the data fusion of information pairs. In other words, the precision of information pairs at each node depends on the accuracy of statistics of measurement noise. Hence, the distributed information fusion of statistics of measurement noise is considered in this paper.

In this work, we present an indirect localization method for multi-target tracking using DAVS. On the basis of acquired measurement DOAs, MTCIF with a NSE (MTCIF-NSE) is derived for state estimation of multiple targets under unknown or incorrect statistics of measurement noise. Then, a two-step information fusion, including information fusion of state estimation and information fusion of statistics of measurement noise, is designed based on WAC to improve the accuracy and stability of NSE and state estimator. Simulations in indoor multi-target tracking have comprehensively evaluate the performance of the proposed localization method. The main contributions of this work are as follows:

a) The specific expressions of MTCIF based on JPDA are deduced and given out.

b) In consideration of the stability of NSE, a modified SHMP based NSE is design for MTCIF to estimate unknown statistics of measurement noise.

c) A distributed NSE based on WAC is derived to improve the accuracy and stability of NSE. The improved precision of statistics of measurement noise indirectly enhances the accuracy of state estimation.

The structure of this paper is presented as follows. The method of DOA extraction is introduced in section 2. The system model is given in section 3. MTCIF with a statistics estimator of measurement noise is designed in section 4. Section 5 provides the process of two-step information fusion including information fusion of state estimation and information fusion of noise statistics. Results of different simulation scenarios is discussed in section 6 to verify the effectiveness of the proposed methods. The conclusion is drawn in section 7.

II. DOA MEASUREMENT ACQUISITION

This paper adopts the indirect positioning method for target tracking, which requires the acquisition of DOA measurement.

A. AVS ARRAY SIGNAL MODEL

Since this paper focuses on evaluating the effectiveness of AVS array in indoor environments, the target tracking in indoor environments is basically a problem of 2D positioning. Accordingly, a fixed elevation $\psi_0^n \in [-\pi/2, \pi/2]$, and a time-varying azimuth $\phi_k^{l,n} \in (-\pi, \pi]$ which denotes the angle from lth target to the nth sensor at time step k, are selected for modelling the AVS array signal. Let $\theta_k^{l,n} = \left[\phi_k^{l,n}, \psi_0^n\right]^T$ be the measurement DOA of the target l at node n. Then the unit vector $\mathbf{u}_k^{l,n}$ from sensor node n to target l is defined as

$$\mathbf{u}_k^{l,n} = \begin{bmatrix} \cos\psi_0^n \cos\phi_k^{l,n} \\ \cos\psi_0^n \sin\phi_k^{l,n} \\ \sin\psi_0^n \end{bmatrix} \tag{1}$$

According to [22], the signal model of AVS array is defined by

$$\tilde{\mathbf{y}}_k^n = \sum_{l=1}^{L} \begin{bmatrix} 1 \\ \mathbf{u}_k^{l,n} \end{bmatrix} s_k^l + \varepsilon_k^n \tag{2}$$

where $\tilde{\mathbf{y}}_k^n = \left[y_k^{n,p}, \mathbf{y}_k^{n,v}\right]^T \in \mathbf{C}^{4\times 1}$, $y_k^{n,p}$ and $\mathbf{y}_k^{n,v}$ represent outputs of the pressure sensor and velocity sensors respectively, and the particle velocity $\mathbf{y}_k^{n,v}$ is commonly normalized by multiplying with a constant $-\rho_0 c_0$ [6]. $s_k^l = p_k^l e^{j\varsigma_k^l}$ denotes the source signal with amplitude p_k^l and phase $\varsigma_k^l \in (0, 2\pi]$, which means s_k^l is the wideband signal. $\varepsilon_k^n \in \mathbf{C}^{4\times 1}$ is the complex Gaussian noise with distribution $cN(\mu, \Gamma)$, which denotes the mean μ and the covariance Γ.

For node n, we can select T_0 frames at each time step k to estimate the DOAs of targets and the value of T_0 is consistent with the sampling rate of AVS. Especially under a low signal-to-noise ratio (SNR), a larger T_0 compared with the normal circumstance is selected for better estimation effectiveness. When T_0 is small, the sources are supposed to be stationary at each sampling step. Then an extension form of (2) is defined by

$$\tilde{\mathbf{Y}}_k^n = \mathbf{A}\left(\theta_k^n\right)\mathbf{S}_k + \tilde{\varepsilon}_k^n \tag{3}$$

where $\tilde{\mathbf{Y}}_k^n \in \mathbf{C}^{4\times T_0}$ and $\tilde{\varepsilon}_k^n \in \mathbf{C}^{4\times T_0}$. $\theta_k^n = \left[\theta_k^{1,n}, \cdots, \theta_k^{L,n}\right] \in R^{2\times L}$ denotes the DOA measurement of all targets at node n. Let $\mathbf{a}\left(\theta_k^{l,n}\right) = \left[1, \left(\mathbf{u}_k^{l,n}\right)^T\right]^T$, then $\mathbf{A}\left(\theta_k^n\right) = \left[\mathbf{a}\left(\theta_k^{1,n}\right), \cdots, \mathbf{a}\left(\theta_k^{L,n}\right)\right] \in \mathbf{C}^{4\times L}$. $\mathbf{S}_k = \left[\mathbf{s}_k^1, \cdots, \mathbf{s}_k^L\right]^T \in \mathbf{C}^{L\times T_0}$.

B. CAPON BEAMFORMING

The traditional capon beamforming [23] acquires the DOA of a target by finding the maximum of the following equation

$$\hat{\theta}_k^n = \arg \max_{\theta\in(-\pi,\pi]\times[-\pi/2,\pi/2]} \left\| \left(\mathbf{A}^H(\theta)\left(\mathbf{R}_k^n\right)^{-1}\mathbf{A}(\theta)\right)^{-1} \right\| \tag{4}$$

where H denotes the conjugate transpose, $\|\cdot\|$ denotes the amplitude of a complex value, and $\mathbf{R}_k^n$ is the covariance matrix and defined by

$$\mathbf{R}_k^n = E\left\{\mathbf{Y}_k^n\left(\mathbf{Y}_k^n\right)^H\right\} \approx \frac{1}{N}\mathbf{Y}_k^n\left(\mathbf{Y}_k^n\right)^H \tag{5}$$

where $E\{\cdot\}$ denotes the expectation operation.

However, the traditional capon beamforming is not applicable to acquire DOAs of multiple targets. Moreover, under low SNR, the acquired DOAs may be incorrect, especially in the situation of impulsive noise. A modified capon beamforming is presented in [6]. DOA estimations are provided by finding several local maximums of (4)

$$\left\{\hat{\theta}_{k,j}^n\right\}_{j=1}^{m_0} = \arg p_k^n(\theta) > \alpha p_{k,\max}^n, \quad \theta \in (-\pi, \pi] \times [-\pi/2, \pi/2] \tag{6}$$

where $p_{k,\max}^n = \max_{\theta\in(-\pi,\pi]\times[-\pi/2,\pi/2]} \left\| \left(\mathbf{A}^H(\theta)\left(\mathbf{R}_k^n\right)^{-1}\mathbf{A}(\theta)\right)^{-1} \right\|$ is the global maxima at time step k, $0 < \alpha < 1$ is the preset threshold value, and $p_k^n(\theta) = \left\| \left(\mathbf{A}^H(\theta)\left(\mathbf{R}_k^n\right)^{-1}\mathbf{A}(\theta)\right)^{-1} \right\|$ is the local maxima which is larger than $\alpha p_{k,\max}^n$.

Furthermore, a fixed elevation $\psi_0^n \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$ is selected in this paper for positioning in indoor environments. Therefore, (6) can be simplified by

$$\left\{\hat{\theta}_{k,j}^n\right\}_{j=1}^{m_0} = \arg p_k^n(\theta) > \alpha p_{k,\max}^n, \quad \phi_k^n \in (-\pi, \pi] \tag{7}$$

where $\hat{\theta}_{k,j}^n = \left[\phi_{k,j}^n, \psi_0^n\right]^T$, and ϕ_k^n is the azimuth of node n. Let

$$\hat{\mathbf{Z}}_k^n = \left\{\hat{\mathbf{Z}}_{k,j}^n\right\}_{j=1}^{m_0} \tag{8}$$

where $\hat{\mathbf{Z}}_{k,j}^n = \hat{\theta}_{k,j}^n$ is the DOA estimation and $\hat{\mathbf{Z}}_k^n$ is the DOA measurement set of node n.

III. SYSTEM MODEL

A nonlinear discrete-time system is selected to model DAVS. The process equation and the measurement equation of the nonlinear system are represented as

$$\begin{cases} \mathbf{X}_k^l = f\left(\mathbf{X}_{k-1}^l\right) + \omega_{k-1}, & l = 1, \cdots, L \\ \mathbf{Z}_k^n = h^n(\mathbf{X}_k^l) + \upsilon_k^n, & n = 1, \cdots, N \end{cases} \tag{9}$$

where $L \geq 1$ denotes the number of the tracking targets. $\mathbf{X}_k^l = \left[p_{k,x}^l, p_{k,y}^l, \dot{p}_{k,x}^l, \dot{p}_{k,y}^l\right]^T \in \mathbf{R}^{4\times 1}$ is the state vector of target l at time step k, $p_{k,x}^l$ and $p_{k,y}^l$ denote the position of target l, $\dot{p}_{k,x}^l$ and $\dot{p}_{k,y}^l$ denote the speed of target l. $N \geq 2$ is the number of sensor nodes, $\left(p_x^n,\ p_y^n\right)$ is the position of sensor node n, $\mathbf{Z}_k^n \in \mathbf{R}^J$ is the measurement vector of sensor node n at time step k. $f(\cdot)$ denotes the nonlinear state transition function. $h^n(\cdot) = arc\tan\left(\frac{p_{k,y}^l - p_y^n}{p_{k,x}^l - p_x^n}\right)$ denotes the nonlinear measurement function of sensor node n. $\omega_k \in \mathbf{R}^m$ and $\upsilon_k^n \in \mathbf{R}^J$ denote the process noise and measurement noise, and both are assumed as uncorrelated Gaussian noises. Statistics of ω_k and υ_k^n are defined by

$$\begin{cases} E[\omega_k] = \mathbf{q}_k \quad E\left[(\omega_k - \mathbf{q}_k)(\omega_j - \mathbf{q}_j)^T\right] = \mathbf{Q}_k\delta_{kj} \\ E\left[\upsilon_k^n\right] = \mathbf{r}_k \quad E\left[\left(\upsilon_k^n - \mathbf{r}_k\right)\left(\upsilon_j^n - \mathbf{r}_j\right)^T\right] = \mathbf{R}_k^n\delta_{kj} \\ E\left[(\omega_k - \mathbf{q}_k)\left(\upsilon_k^n - \mathbf{r}_k\right)^T\right] = 0 \end{cases} \tag{10}$$

where δ_{kj} denotes the Kronecker-δ function, $\mathbf{q}_k$ and $\mathbf{Q}_k$ denote the mean and the covariance matrix of the process noise, and $\mathbf{r}_k$ and $\mathbf{R}_k^n$ represent the mean and covariance of measurement noise.

The DAVS adopts the cooperative mechanism of adjacent nodes. Therefore, the network topology of DAVS is presented as $\Xi(\mathbf{N}, \varepsilon)$, where $N = \{1, \cdots, \mathbf{N}\}$ denotes the node set. If node j accepts the data transmitted from node n, then $(n, j) \in \varepsilon$. $\mathbf{N}_n = \{n | (n, j) \in \varepsilon\}$ denotes the adjacent nodes set of node n. If there is no adjacent node for node n, then $\mathbf{N}_n = \emptyset$.

IV. MULTI-TARGET DATA ASSOCIATION

Based on the DOA measurement set $\hat{\mathbf{Z}}_k^n = \left\{\hat{\mathbf{Z}}_{k,j}^n\right\}_{j=1}^{m_0}$, JPDA is introduced for data association, which means assigning the measurements to the targets. However, the traditional JPDA filtering is only suitable for linear system. Although JPDA based CIF was already designed in [9], [10] for nonlinear system, only partial expressions of information filtering were given and information state vector was not involved. A modified MTCIF is designed for nonlinear system model and employed in local node for multi-target tracking in this section. Further, since the prior information of measurement noise is unknown or inaccurate, the modified SHMP [20] based noise estimator is designed for MTCIF to improve the precision of state estimation in consideration of the stability of NSE.

A. JOINT PROBABILISTIC DATA ASSOCIATION BASED CIF

For the local node n, the general form of MTCIF is summarized as follows. Details for the derivation of MTCIF are presented in Appendix.

1) TIME UPDATE

For node n, the state estimation $\hat{\mathbf{X}}_{k-1}^{l,n}$ and the information matrix $\mathbf{Y}_{k-1}^{l,n}$ of target l are supposed already known at time step $k-1$. According to the spherical cubature integration rule, sigma points are generated by

$$\chi_{k-1}^{n,i} = \hat{\mathbf{X}}_{k-1}^{l,n} + \sqrt{\left(\mathbf{Y}_{k-1}^{l,n}\right)^{-1}}\xi^i, \quad i = 1, \cdots, 2m \tag{11}$$

where m is the dimension of the state vector, $\sqrt{\left(\mathbf{Y}_{k-1}^{l,n}\right)^{-1}}$ is the square root of $\left(\mathbf{Y}_{k-1}^{l,n}\right)^{-1}$, which equals to $\left(\mathbf{Y}_{k-1}^{l,n}\right)^{-1} = \sqrt{\left(\mathbf{Y}_{k-1}^{l,n}\right)^{-1}}\left(\sqrt{\left(\mathbf{Y}_{k-1}^{l,n}\right)^{-1}}\right)^T$, and $\xi^i = \begin{cases} \sqrt{m}\mathbf{e}_i, & i = 1, \cdots, m \\ -\sqrt{m}\mathbf{e}_i, & i = m+1, \cdots, 2m \end{cases}$, where $\mathbf{e}_i$ denotes the m-dimensional unit vector with the ith element being 1.

Then, transfer $\chi_{k-1}^{n,i}$ by the nonlinear state transition function

$$\chi_{k|k-1}^{n,i} = f\left(\chi_{k-1}^{n,i}\right), \quad i = 1, \cdots, 2m \tag{12}$$

Estimate the predicted state and the predicted covariance matrix

$$\hat{\mathbf{X}}_{k|k-1}^{l,n} = \frac{1}{2m}\sum_{i=1}^{2m}\chi_{k|k-1}^{n,i} + \mathbf{q}_k \tag{13}$$

$$\mathbf{P}_{k|k-1}^{l,n} = \frac{1}{2m}\sum_{i=1}^{2m}(\chi_{k|k-1}^{n,i} - \hat{\mathbf{X}}_{k|k-1}^{l,n})(\chi_{k|k-1}^{n,i} - \hat{\mathbf{X}}_{k|k-1}^{l,n})^T + \mathbf{Q}_{k-1} \tag{14}$$

Calculate the predicted information matrix and the predicted information state vector

$$\mathbf{Y}_{k|k-1}^{l,n} = \left[\mathbf{P}_{k|k-1}^{l,n}\right]^{-1} \tag{15}$$

$$\hat{\mathbf{y}}_{k|k-1}^{l,n} = \mathbf{Y}_{k|k-1}^{l,n}\hat{\mathbf{X}}_{k|k-1}^{l,n} \tag{16}$$

2) MEASUREMENT UPDATE

Based on (13) and (14), generate a new set of sigma points

$$\bar{\chi}_{k|k-1}^{n,i} = \hat{\mathbf{X}}_{k|k-1}^{l,n} + \sqrt{\mathbf{P}_{k|k-1}^{l,n}}\xi^i, \quad i = 1, \cdots, 2m \tag{17}$$

Propagate $\bar{\chi}_{k|k-1}^{n,i}$ through the nonlinear measurement function to generate the predicted measurement sigma points

$$\zeta_{k|k-1}^{n,i} = h(\bar{\chi}_{k|k-1}^{n,i}), \quad i = 1, \cdots, 2m \tag{18}$$

Calculate the mean of the predicted measurement

$$\hat{\mathbf{Z}}_{k|k-1}^{l,n} = \frac{1}{2m}\sum_{i=1}^{2m}\zeta_{k|k-1}^{n,i} + \mathbf{r}_k \tag{19}$$

Calculate the cross-covariance matrix

$$\mathbf{P}_{xz,k|k-1}^{l,n} = \frac{1}{2m}\sum_{i=1}^{2m}\left(\chi_{k|k-1}^{n,i} - \hat{\mathbf{X}}_{k|k-1}^{l,n}\right)\left(\zeta_{k|k-1}^{n,i} - \hat{\mathbf{Z}}_{k|k-1}^{l,n}\right)^T \tag{20}$$

Compute the information gain $\mathbf{K}_k^{l,n}$ via

$$\mathbf{K}_k^{l,n} = \left(\mathbf{Y}_{k|k-1}^{l,n} + \mathbf{Y}_{k|k-1}^{l,n}\mathbf{P}_{xz,k|k-1}^{l,n}(\mathbf{R}_k^n)^{-1}\left(\mathbf{P}_{xz,k|k-1}^{l,n}\right)^T \cdot \mathbf{Y}_{k|k-1}^{l,n}\right)^{-1}\mathbf{Y}_{k|k-1}^{l,n}\mathbf{P}_{xz,k|k-1}^{l,n}(\mathbf{R}_k^n)^{-1} \tag{21}$$

Update the information state contribution $\tilde{\mathbf{i}}_k^{l,n}$ and its associated information matrix $\mathbf{G}_k^{l,n}$ via

$$\tilde{\mathbf{i}}_k^{l,n} = \mathbf{Y}_{k|k-1}^{l,n}\mathbf{P}_{xz,k|k-1}^{l,n}(\mathbf{R}_k^n)^{-1} \cdot \left(\mathbf{Z}_k^{l,n} - \left(1-\beta_{n0}^l\right)\hat{\mathbf{Z}}_{k|k-1}^{l,n} + \left(\mathbf{P}_{xz,k|k-1}^{l,n}\right)^T\mathbf{Y}_{k|k-1}^{l,n}\hat{\mathbf{X}}_{k|k-1}^{l,n}\right) \tag{22}$$

$$\mathbf{G}_k^{l,n} = \mathbf{Y}_{k|k-1}^{l,n}\mathbf{K}_k^{l,n}\left[\left(\mathbf{M}_k^{l,n}\right)^{-1} - \left(\mathbf{K}_k^{l,n}\right)^T\mathbf{Y}_{k|k-1}^{l,n}\mathbf{K}_k^{l,n}\right]^{-1} \cdot \left(\mathbf{K}_k^{l,n}\right)^T\mathbf{Y}_{k|k-1}^{l,n} \tag{23}$$

where β_{n0}^l denotes the probability that no measurement is associated with target l for node n and $\beta_{n0}^l = 1 - \sum_{j=1}^{m_0}\beta_{nj}^l$. $\beta_{nj}^l = P\left[\chi_{nj}^l|\hat{\mathbf{Z}}_k^n\right]$ and χ_{nj}^l denotes that the measurement j on node n originated from target l. See [24] for details of β_{n0}^l and β_{nj}^l. $\mathbf{Z}_k^{l,n} = \sum_{j=1}^{m_0}\beta_{nj}^l\hat{\mathbf{Z}}_{k,j}^n$. See Appendix for the detail of $\mathbf{M}_k^{l,n}$.

Obtain the updated information state vector $\hat{\mathbf{y}}_k^{l,n}$ and the updated information matrix $\mathbf{Y}_k^{l,n}$ via

$$\begin{cases}\hat{\mathbf{y}}_k^{l,n} = \hat{\mathbf{y}}_{k|k-1}^{l,n} + \tilde{\mathbf{i}}_k^{l,n}\\ \mathbf{Y}_k^{l,n} = \mathbf{Y}_{k|k-1}^{l,n} + \mathbf{G}_k^{l,n}\end{cases} \tag{24}$$

Finally, the state estimation $\hat{\mathbf{X}}_k^{l,n}$ is obtained by

$$\hat{\mathbf{X}}_k^{l,n} = \left(\mathbf{Y}_k^{l,n}\right)^{-1}\hat{\mathbf{y}}_k^{l,n} \tag{25}$$

B. NOISE STATISTIC ESTIMATOR

If the statistics character of system noise is kept unknown or inaccurate, the accuracy of state estimation and the divergence of filtering algorithms are usually affected. In this paper, the prior information of DOA measurement noise is unknown. Hence, a measurement noise estimator is desirable to enhance the accuracy of multi-target state estimation. Similar to NSE proposed in [17], [25], a SHMP based measurement noise estimator for MTCIF is derived and displayed as follows.

1) Compute mean of measurement noise

$$\hat{\mathbf{r}}_k^{l,n} = (1-d_k)\,\hat{\mathbf{r}}_{k-1}^n + d_k\left[\mathbf{Z}_k^{l,n} - \frac{1}{2m}\sum_{i=1}^{2m}\zeta_{k|k-1}^{n,i}\right] \tag{26}$$

TABLE 1. MTCIF-NSE on node *n*.

Given $\hat{\mathbf{X}}_{k-1}^{l,n}$, $\mathbf{Y}_{k-1}^{l,n}$, $\hat{\mathbf{r}}_{k-1}^{l,n}$ and $\hat{\mathbf{R}}_{k-1}^{l,n}$ of target l
Step 1 : Complete the procedure (11)-(16) of MTCIF for time update to obtain the predicted information matrix $\mathbf{Y}_{k\|k-1}^{l,n}$ and the predicted information state vector $\hat{\mathbf{y}}_{k\|k-1}^{l,n}$.
Step 2 : Complete the procedure (17)-(24) of MTCIF for measurement update to obtain the updated information state vector $\hat{\mathbf{y}}_k^{l,n}$ and the updated information matrix $\mathbf{Y}_k^{l,n}$. Then, the state estimation is $\hat{\mathbf{X}}_k^{l,n} = \left(\mathbf{Y}_k^{l,n}\right)^{-1}\hat{\mathbf{y}}_k^{l,n}$
Step 3 : Update noise statistics of measurements $\left(\hat{\mathbf{r}}_k^{l,n}, \hat{\mathbf{R}}_k^{l,n}\right)$ via $\begin{cases}\hat{\mathbf{r}}_k^{l,n} = (1-d_k)\,\hat{\mathbf{r}}_{k-1}^n + d_k\left[\mathbf{Z}_k^{l,n} - \frac{1}{2m}\sum_{i=1}^{2m}\zeta_{k\|k-1}^{n,i}\right]\\ \hat{\mathbf{R}}_k^{l,n} = (1-d_k)\,\hat{\mathbf{R}}_{k-1}^n + d_k\mathbf{e}_{k,j}^{l,n}\left(\mathbf{e}_{k,j}^{l,n}\right)^T\end{cases}$
Step 4 : Repeat step 1, step 2 and step 3 until results of all targets are obtained.

where d_k is defined by

$$d_k = \frac{1-b}{1-b^k} \tag{27}$$

where b is the forgetting factor and regularly selected by 0.95.

2) Compute covariance matrix of measurement noise

$$\hat{\mathbf{R}}_k^{l,n} = (1-d_k)\,\hat{\mathbf{R}}_{k-1}^n + d_k\left[\mathbf{e}_{k,j}^{l,n}\left(\mathbf{e}_{k,j}^{l,n}\right)^T - \frac{1}{2m}\sum_{i=1}^{2m}\left(\zeta_{k|k-1}^{n,i} - \hat{\mathbf{Z}}_{k|k-1}^{l,n}\right)\left(\zeta_{k|k-1}^{n,i} - \hat{\mathbf{Z}}_{k|k-1}^{l,n}\right)^T\right] \tag{28}$$

where $\mathbf{e}_{k,j}^{l,n}$ is the innovation vector and given by

$$\mathbf{e}_{k,j}^{l,n} = \mathbf{Z}_k^{l,n} - \hat{\mathbf{Z}}_{k|k-1}^{l,n} \tag{29}$$

where $\mathbf{Z}_k^{l,n} = \sum_{j=1}^{n_0}\beta_{nj}^l\hat{\mathbf{Z}}_{k,j}^n$ and $\hat{\mathbf{Z}}_{k,j}^n$ is the jth DOA estimation. However, the stability and accuracy of Sage-Husa noise estimator are sensitive to its complicated calculation and the convergence of the measurement noise′s covariance [26]. To improve the stability of designed noise estimator, the related item of the predicted error covariance in equation (28) is abandoned at the expense of accuracy for NSE based on the modified SHMP [17]. Then, the estimated covariance matrix of measurement noise is defined by

$$\hat{\mathbf{R}}_k^{l,n} = (1-d_k)\,\hat{\mathbf{R}}_{k-1}^n + d_k\mathbf{e}_{k,j}^{l,n}\left(\mathbf{e}_{k,j}^{l,n}\right)^T \tag{30}$$

Finally, steps of MTCIF-NSE are outlined in Table 1.

V. DISTRIBUTED INFORMATION FUSION

This section mainly focuses on information fusion of DAVS. To improve the precision and stability of state estimator and NSE, WAC based algorithms are designed for distributed information fusion. MTCIF-NSE is employed in the local node for multi-target state estimation. Next, two different parts are contained in the distributed information fusion.

The first one is the data fusion of information pairs, which is conducted to make an agreement on the information pairs among all the sensor nodes. The second one is the information fusion of statistics of measurement noise. In order to improve the precision of NSE in the local node, a distributed noise statistic estimator (DNSE) is derived to make an agreement on the noise statistics of measurements among all the sensor nodes. Furthermore, to verify the effectiveness of DNSE, two different algorithms are designed for distributed multi-target tracking. The one is the distributed multi-target CIF with noise statistic estimator (DMTCIF-NSE), which only incorporates the first part of distributed information fusion. The other one is the distributed multi-target CIF with distributed noise statistic estimator (DMTCIF-DNSE), which includes both parts of distributed information fusion. The general form of DMTCIF-NSE and DMTCIF-DNSE are displayed as follows.

A. DATA FUSION OF INFORMATION PAIRS

Let t be the consensus time. For node n, information pairs $\left(\hat{\mathbf{y}}_k^{l,n}, \mathbf{Y}_k^{l,n}\right)$ of target l are supposed already known at time step k. The consensus weight is defined by $\pi^{n,j}$, where $j \in \mathbf{N}_n$, $\pi^{n,j} \geq 0$, $\sum_{j\in N_n} \pi^{n,j} = 1$. The information pair in different sensor node has the same behavior

$$\left(\hat{\mathbf{y}}_k^{*}, \mathbf{Y}_k^{*}\right) = \lim_{t\to\infty} \left(\hat{\mathbf{y}}_{k,t}^{l,n}, \mathbf{Y}_{k,t}^{l,n}\right) \tag{31}$$

The WAC update of information pairs is defined by

$$\begin{cases} \hat{\mathbf{y}}_{k,t+1}^{l,n} = \sum_{j\in N_n} \pi^{n,j}\hat{\mathbf{y}}_{k,t}^{l,j} \\ \mathbf{Y}_{k,t+1}^{l,n} = \sum_{j\in N_n} \pi^{n,j}\mathbf{Y}_{k,t}^{l,j} \end{cases} \tag{32}$$

Let $\bar{T}$ be the number of WAC iterations, where $t \in [0, \bar{T}-1]$. For node n, initial information pairs are given as $\begin{cases} \hat{\mathbf{y}}_{k,0}^{l,n} = \hat{\mathbf{y}}_k^{l,n} \\ \mathbf{Y}_{k,0}^{l,n} = \mathbf{Y}_k^{l,n} \end{cases}$. Updated information pairs are $\left(\hat{\mathbf{y}}_{k,\bar{T}}^{l,n}, \mathbf{Y}_{k,\bar{T}}^{l,n}\right)$ after $\bar{T}$ iterations. Next, the updated state estimation $\hat{\mathbf{X}}_k^{l,n}$ at time step k after the information fusion are presented by

$$\hat{\mathbf{X}}_k^{l,n} = \left(\mathbf{Y}_{k,\bar{T}}^{l,n}\right)^{-1}\hat{\mathbf{y}}_{k,\bar{T}}^{l,n} \tag{33}$$

Then, the general form of DMTCIF-NSE is presented in Table 2.

B. DISTRIBUTED NOISE STATISTIC ESTIMATOR

The information fusion of statistics of measurements noise must be considered to improve the stability and accuracy of noise estimator and the filtering. The DNSE is founded on the assumption that sensor nodes own the same statistics of measurement noise. Performing the similar fusion procedure as the data fusion of information pairs. The WAC update of

TABLE 2. DMTCIF with noise statistic estimator.

Step 1 : For target $l = 1, \cdots, L$, perform MTCIF-NSE to obtain information pairs $\left(\hat{\mathbf{y}}_{k,0}^{l,n}, \mathbf{Y}_{k,0}^{l,n}\right)$ and the updated noise statistics of measurements $\left(\hat{\mathbf{r}}_k^{l,n}, \hat{\mathbf{R}}_k^{l,n}\right)$ at each node n.
Step 2 : For $t = 0, 1, \cdots \bar{T}-1$, execute the following consensus steps.
a) Broadcast the information pairs $\left(\hat{\mathbf{y}}_{k,t}^{l,n}, \mathbf{Y}_{k,t}^{l,n}\right)$ to its neighbors $j \in \mathbf{N}_n$.
b) Receive the information pairs $\left(\hat{\mathbf{y}}_{k,t}^{l,j}, \mathbf{Y}_{k,t}^{l,j}\right)$ from its neighbors $j \in \mathbf{N}_n$.
c) Complete the data fusion of information pairs via $\begin{cases} \hat{\mathbf{y}}_{k,t+1}^{l,n} = \sum_{j\in N_n} \pi^{n,j}\hat{\mathbf{y}}_{k,t}^{l,j} \\ \mathbf{Y}_{k,t+1}^{l,n} = \sum_{j\in N_n} \pi^{n,j}\mathbf{Y}_{k,t}^{l,j} \end{cases}$
Step 3 : The updated state estimation $\hat{\mathbf{X}}_k^{l,n}$ at time step k are obtained by $\hat{\mathbf{X}}_k^{l,n} = \left(\mathbf{Y}_{k,\bar{T}}^{l,n}\right)^{-1}\hat{\mathbf{y}}_{k,\bar{T}}^{l,n}$

TABLE 3. DMTCIF with distributed noise statistic estimator.

Step 1 : For target $l = 1, \cdots, L$, perform MTCIF-NSE to obtain information pairs $\left(\hat{\mathbf{y}}_{k,0}^{l,n}, \mathbf{Y}_{k,0}^{l,n}\right)$ and the updated noise statistics of measurements $\left(\hat{\mathbf{r}}_k^{l,n}, \hat{\mathbf{R}}_k^{l,n}\right)$ at each node n.
Step 2 : For $t = 0, 1, \cdots \bar{T}-1$, execute the following consensus steps.
a) Broadcast the information pairs $\left(\hat{\mathbf{y}}_{k,t}^{l,n}, \mathbf{Y}_{k,t}^{l,n}\right)$ and the noise statistics of measurements $\left(\hat{\mathbf{r}}_k^{l,n}, \hat{\mathbf{R}}_k^{l,n}\right)$ to its neighbors $j \in \mathbf{N}_n$.
b) Receive the information pairs $\left(\hat{\mathbf{y}}_{k,t}^{l,j}, \mathbf{Y}_{k,t}^{l,j}\right)$ and the noise statistics of measurements $\left(\hat{\mathbf{r}}_k^{l,j}, \hat{\mathbf{R}}_k^{l,j}\right)$ from its neighbors $j \in \mathbf{N}_n$.
c) Complete the data fusion of information pairs and the information fusion of statistics of measurement noise via $\begin{cases} \hat{\mathbf{y}}_{k,t+1}^{l,n} = \sum_{j\in N_n} \pi^{n,j}\hat{\mathbf{y}}_{k,t}^{l,j} \\ \mathbf{Y}_{k,t+1}^{l,n} = \sum_{j\in N_n} \pi^{n,j}\mathbf{Y}_{k,t}^{l,j} \end{cases}$ and $\begin{cases} \hat{\mathbf{r}}_{k,t+1}^{l,n} = \sum_{j\in N_n} \pi^{n,j}\hat{\mathbf{r}}_{k,t}^{l,n} \\ \hat{\mathbf{R}}_{k,t+1}^{l,n} = \sum_{j\in N_n} \pi^{n,j}\hat{\mathbf{R}}_{k,t}^{l,n} \end{cases}$, respectively.
Step 3 : The updated state estimation $\hat{\mathbf{X}}_k^{l,n}$ at time step k are obtained by $\hat{\mathbf{X}}_k^{l,n} = \left(\mathbf{Y}_{k,\bar{T}}^{l,n}\right)^{-1}\hat{\mathbf{y}}_{k,\bar{T}}^{l,n}$. And the fused noise statistics of measurements is $\left(\hat{\mathbf{r}}_{k,\bar{T}}^{l,n}, \hat{\mathbf{R}}_{k,\bar{T}}^{l,n}\right)$.

statistics of measurement noise is defined by

$$\begin{cases} \hat{\mathbf{r}}_{k,t+1}^{l,n} = \sum_{j\in N_n} \pi^{n,j}\hat{\mathbf{r}}_{k,t}^{l,n} \\ \hat{\mathbf{R}}_{k,t+1}^{l,n} = \sum_{j\in N_n} \pi^{n,j}\hat{\mathbf{R}}_{k,t}^{l,n} \end{cases} \tag{34}$$

Then, when $\bar{T}$ times WAC iterations are finished, updated noise statistics of measurements $\hat{\mathbf{r}}_k^{l,n}$ and $\hat{\mathbf{R}}_k^{l,n}$ are defined by $\left(\hat{\mathbf{r}}_{k,\bar{T}}^{l,n}, \hat{\mathbf{R}}_{k,\bar{T}}^{l,n}\right)$. Finally, the procedure of DMTCIF-DNSE is summarized in Table 3.

VI. PERFORMANCE EVALUATION AND DISCUSSIONS

The indoor scenario has been designed for multi-target tracking using the DAVS. Simulations are conducted to evaluate the effectiveness of the proposed methodology for target tracking in the presence of incorrect statistics of measurement noise. Centralized fusion technology based multi-target square-root cubature Kalman filtering (CMTSCKF) [7] and weighted consensus based multi-target square-root

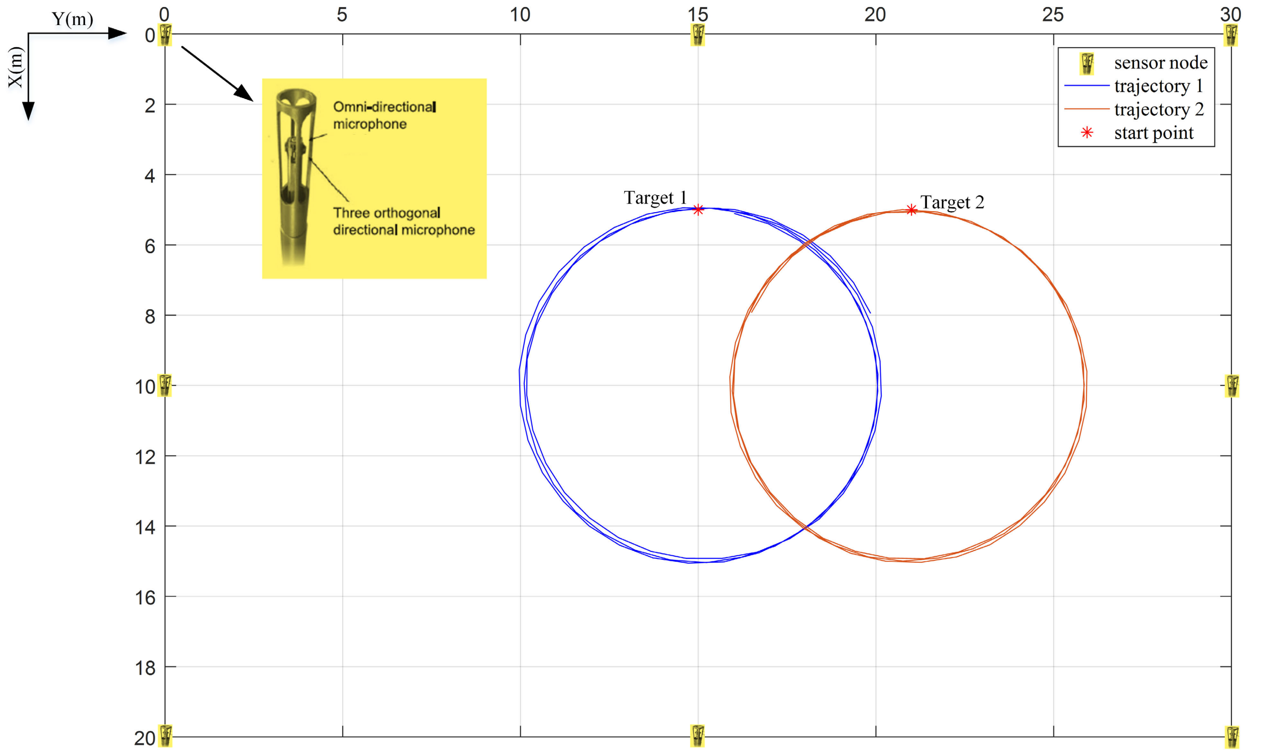


FIGURE 1. **The preset simulation scene.**

CIF (DMTSCIF) [12] are selected for comparison analysis. The coordinated turn (CT) model is chosen for targets tracking in DAVS and a fixed angular speed γ of turning is employed for the maneuvering target in X/Y plane. The process equation is defined by

$$\mathbf{X}_k = \begin{bmatrix} 1 & 0 & \frac{\sin(\gamma T)}{\gamma} & \frac{-(1-\cos(\gamma T))}{\gamma} \\ 0 & 1 & \frac{1-\cos(\gamma T)}{\gamma} & \frac{\sin(\gamma T)}{\gamma} \\ 0 & 0 & \cos(\gamma T) & -\sin(\gamma T) \\ 0 & 0 & \sin(\gamma T) & \cos(\gamma T) \end{bmatrix} \mathbf{X}_{k-1} + \begin{bmatrix} \frac{T^2}{2} & 0 \\ 0 & \frac{T^2}{2} \\ T & 0 \\ 0 & T \end{bmatrix} \omega_{k-1} \quad (35)$$

where $\mathbf{X}_k = \left[p_{k,x}, p_{k,y}, \dot{p}_{k,x}, \dot{p}_{k,y}\right]^T$ is the state vector at time step k. $p_{k,x}$ and $p_{k,y}$ denote the target position. $\dot{p}_{k,x}$ and $\dot{p}_{k,y}$ denote the target speed. $\omega_k \sim N(\mathbf{q}_k, \mathbf{Q}_k)$ denotes the process noise with mean $\mathbf{q}_k$ and covariance matrix $\mathbf{Q}_k$. T is the sampling period of the system.

A. SIMULATION SETUP

For the simulation setup, a preset simulation scene is displayed in Fig. 1. The size of simulated room is chosen as $(20m \times 30m \times 4m)$. The preset height and elevation of AVSs are $0.5m$ and $60°$, respectively. The azimuth of AVSs is varied from $-90°$ to $90°$. In terms of X/Y plane, AVSs are employed at the position of (0, 0), (0, 15), (0, 30), (10, 0), (10, 30), (20, 0), (20, 15) and (20, 30), respectively. Interactive trajectories which are generated by two different acoustic sources are displayed in Fig. 1. The first target starts at the point (5, 15) and moves at a constant angular speed $\gamma = -0.2rad/s$. And the initial point of the second target is (5, 21) and its angular speed is $\gamma = 0.2rad/s$. The simulation period is $T = 100s$.

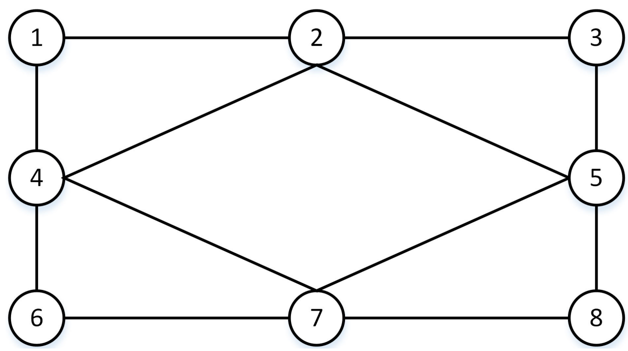


FIGURE 2. **The topology map of DAVS.**

The topology map of DAVS is presented in Fig. 2. According to [19]–[21], the weight matrix is defined through

Metropolis weight rule.

$$\pi^{n,j} = \begin{cases} 1/\left(1+\max\left\{d_n, d_j\right\}\right), & if\ (n,j) \in \varepsilon \\ 1 - \sum\limits_{(n,j)\in\varepsilon} \pi^{n,j}, & if\ n = j \\ 0, & otherwise \end{cases} \tag{36}$$

Sensor nodes are equivalent to each other. Hence node 1, 2, 4, 7 are selected and 50 independent Mentos Carlo is chosen for the following simulation with the same initial conditions. Then root mean square error (RMSE) is adopted to verify the effectiveness of the proposed algorithms. Position RMSE at node n is defined by

$$RMSE^{n}_{p,k} = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\left(\left(p^{i}_{k,x} - \hat{p}^{i}_{k,x}\right)^2 + \left(p^{i}_{k,y} - \hat{p}^{i}_{k,y}\right)^2\right)} \tag{37}$$

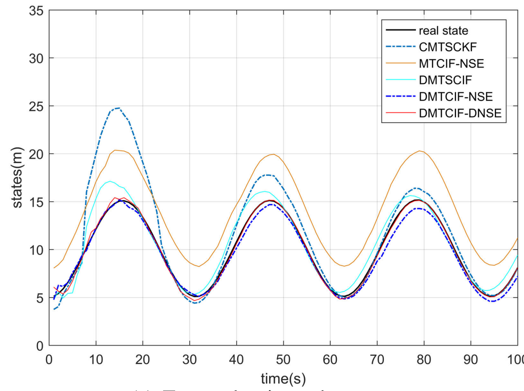
where the variable M denotes the number of Monte Carlo runs. $\left[p_{k,x}, p_{k,y}\right]$ and $\left[\hat{p}_{k,x}, \hat{p}_{k,y}\right]$ stand for the real position and estimated position of targets respectively at time step k. DOAs from the target to the sensor node are supposed unchanged in one second. According to [6], the SNR of signals achieved by AVS is set as $4dB$, the sampling frequency of AVS is $64Hz$ and the preset threshold for DOA extraction is set as $\alpha = 1/20$. Then a set of measurement for proposed information filtering is acquired by the Capon Spectra Estimator, which is used for measurement update. The initial parameters for filtering algorithms are given as follows. The number of clutter λ is an adjust parameter which is changed with the SNR of signals achieved by AVS and $\lambda = 2$ is selected in this paper. The gate probability is $P_G = 0.99$ and the probability of detecting a target is $P_D = 0.9$. The number of consensus steps is $\bar{T} = 5$ for WAC based consensus algorithms and the weighted consensus based algorithm. The mean and the covariance matrix of process noise are $\mathbf{q}_k = [0.001,\ 0.001,\ 0.001,\ 0.001]^T$ and $\mathbf{Q}_k = 10^{-4} * diag\,[1,\ 1,\ 1,\ 1]$, respectively. The mean and the covariance matrix of measurement noise are $\mathbf{r}_k = 0.02$ and $\mathbf{R}_k = 16 * 10^{-4}$, respectively. The frequency of measurement update for filtering algorithms is $1Hz$. Initial state vectors of target 1 and target 2 are $\mathbf{X}^1_k = [5, 15, 0, 1]^T$ and $\mathbf{X}^2_k = [5, 21, 0, -1]^T$, respectively. And the related error covariance matrix of state vectors is $\mathbf{P}_k = diag\,[25, 16, 0.25, 0.25]$. To quantitatively analyze the performance of proposed algorithms, two different scenarios of unmatched or incorrect statistics of measurement noise are constructed and defined as follows.

Scenario 1 : The real prior information of measurement noise is greater than the initial noise statistics of measurements. Then, statistics of real measurement noise are defined by

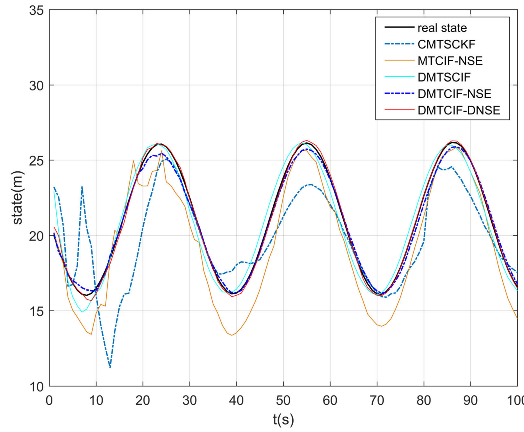
$$\begin{cases} \tilde{\mathbf{r}}_k = 2 * \mathbf{r}_k = 0.04 \\ \tilde{\mathbf{R}}_k = 10 * \mathbf{R}_k = 1.6 * 10^{-2} \end{cases}$$

Scenario 2 : The real prior information of measurement noise is less than the initial noise statistics of measurements. Then, statistics of real measurement noise are defined by

$$\begin{cases} \tilde{\mathbf{r}}_k = 0.1 * \mathbf{r}_k = 0.002 \\ \tilde{\mathbf{R}}_k = 0.5 * \mathbf{R}_k = 8 * 10^{-4} \end{cases}$$



(a) True and estimated state $p_{k,x}$



(b) True and estimated state $p_{k,y}$

FIGURE 3. Single target tracking under scenario 1.

B. SIMULATION RESULTS AND DISCUSSION

1) SINGLE TARGET TRACKING

Target 2 is chosen as the tracking object, the trajectory of which is shown in Fig. 1. Because of centralized fusion technology adopted in CMTSCKF, sensor node 1 is selected as the central computing node. In other word, measurements of node 2, node 4 and node 7 are transmitted to node 1 for measurement update and sequential approach is adopted in this process. The proposed MTCIF-NSE is designed for the target tracking of a single node. DMTSCIF, DMTCIF-NSE and DMTCIF-DNSE are used for distributed target tracking. The method for information fusion in DMTSCIF is weighted consensus based method which belongs to CM. The method for information in DMTCIF-NSE and DMTCIF-DNSE is WAC based method which belongs to CI. For better comparison analysis, estimated values of node 1 are presented in Fig. 3.

For scenario 1, tracking results of node 1 are presented in Fig. 3. Although poor tracking performance acquired by CMTSCKF, the estimated error decreases with the increased

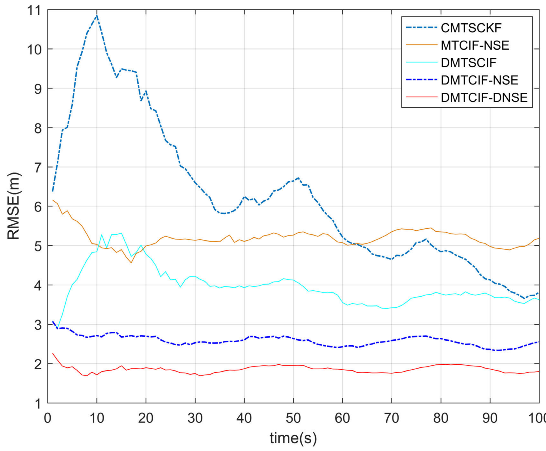
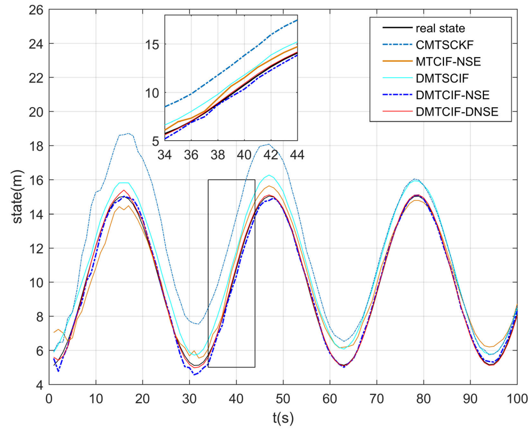


FIGURE 4. **Position RMSE for single target tracking under scenario 1.**

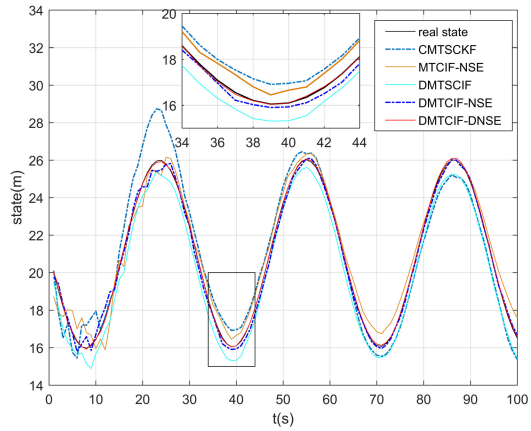
time step. Hence we can get that centralized technology based information fusion algorithms can reduce the impact of mismatched noise statistics on state estimation in some aspects. Since the stability of designed NSE is improved at the expense of accuracy and there is no information fusion for state estimation, large errors still exist in the estimated results of MTCIF-NSE. For the reason that NSE is not contained, the tracking performance of DMTSCIF cannot hold a candle to DMTCIF-NSE, but outperforms MTCIF-NSE. Hence one point is obvious that the algorithm of distributed information fusion also can reduce the impact of mismatched noise statistics on state estimation. In terms of stability and accuracy, DMTCIF-DNSE outperforms other algorithms since the designed DNSE can acquire more accurate statistics of measurement noise and WAC based fusion algorithms can get more precise information pairs after distributed data fusion.

The comparison of position RMSE for different algorithms is displayed in Fig. 4. CMTSCKF and DMTSCIF obtain worse divergence speed than MTCIF-NSE. But after 10s, the RMSE of CMTSCKF decreases quickly and is better than MTCIF-NSE after 62s. Meanwhile, the RMSE of DMTSCIF is better than MTCIF-NSE after 20s. Then the inference in the previous paragraph is confirmed again that centralized technology and distributed information fusion can reduce the impact of mismatched noise statistics on state estimation. Since the distributed information fusion of statistics of measurement noise is contained, DMTCIF-DNSE acquires better RMSEs than DMTCIF-NSE. Hence DMTCIF-DNSE is more suitable for distributed target tracking compared with the reference algorithms under scenario 1.

For scenario 2, tracking results of node 1 are presented in Fig. 5. Estimated values of MTCIF-NSE are relatively stable, but large errors still exist because of lacking distributed information fusion of state estimation and the affection of accuracy of the designed NSE. The estimated error of CMTSCKF decreases with the increased time instants due to the centralized fusion algorithm, and the estimated value of DMTSCIF is relatively stable because of weighted consensus based distributed information fusion. DMTCIF-DNSE



(a) True and estimated state $p_{k,x}$



(b) True and estimated state $p_{k,y}$

FIGURE 5. **Single target tracking under scenario 2.**

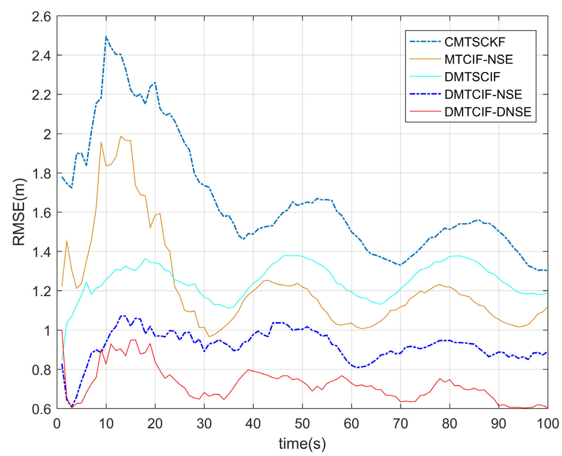
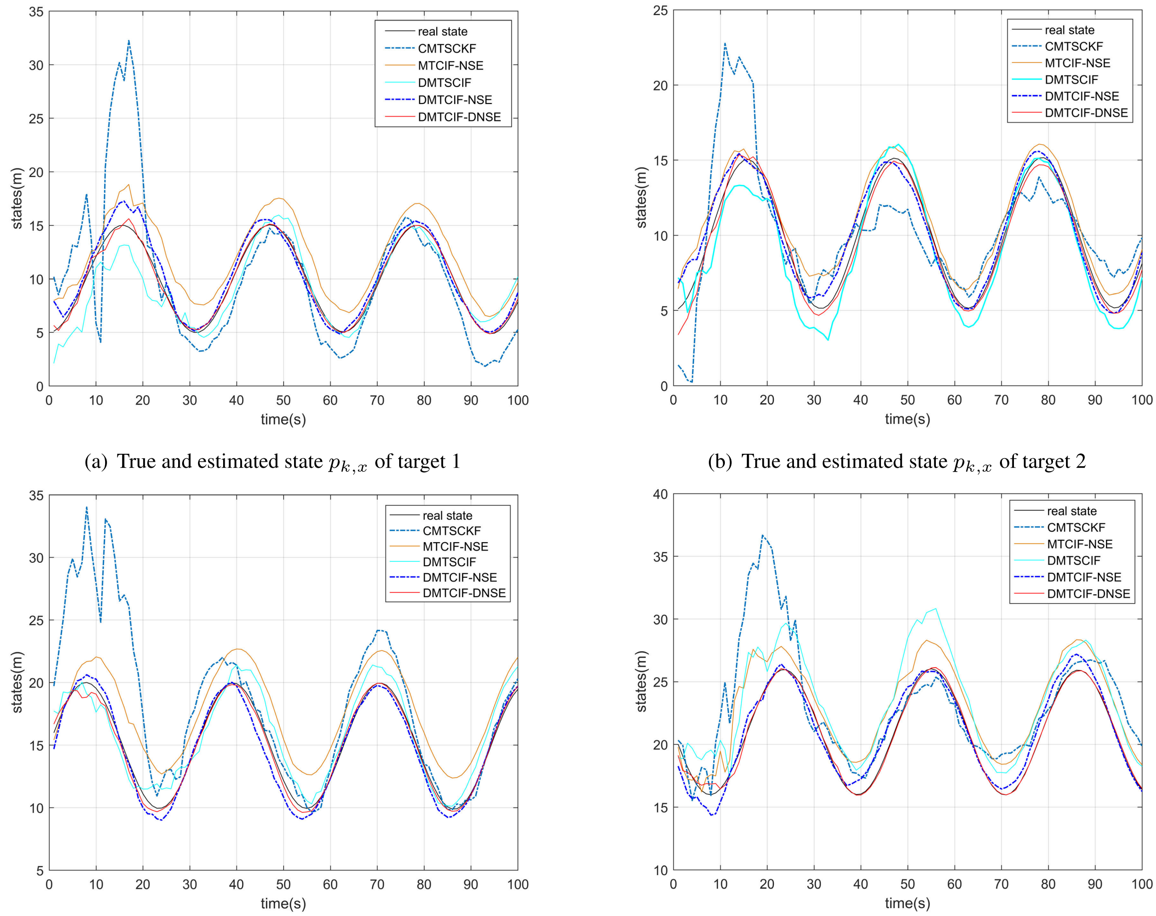


FIGURE 6. **Position RMSE for single target tracking under scenario 2.**

achieves the best result of target tracking on account of WAC based two-step information fusion and the accurate estimation of statistics of measurement noise.

Position RMSEs of different algorithms are presented in Fig. 6. Although noise statistics of measurement are mismatched, CMTSCIF and DMTSCIF obtain the approximate



(a) True and estimated state $p_{k,x}$ of target 1

(b) True and estimated state $p_{k,x}$ of target 2

(c) True and estimated state $p_{k,y}$ of target 1

(d) True and estimated state $p_{k,y}$ of target 2

FIGURE 7. Multiple-target tracking under scenario 1.

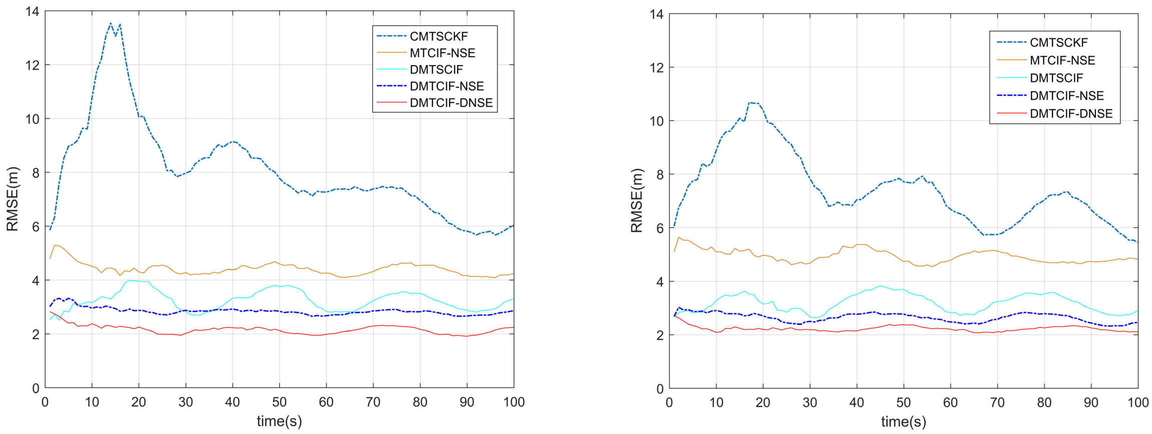
RMSE compared with MTCIF-NSE when the state estimation is stable. But after 24s, the RMSE of MTCIF-NSE is smaller than DMTSCIF because of precise noise statistics obtained by NSE. Then, weighted consensus based distributed information fusion and centralized technology can depress the effect of mismatched statistics of measurement noise on state estimation in some aspects under scenario 2. Although the distribution information fusion is included in both algorithms, DMTCIF-NSE achieves much better RMSEs than DMTSCIF due to the contained NSE. Besides, since more precise noise statistics of measurements are acquired by DNSE, the RMSE of DMTCIF-DNSE is much lower than DMTCIF-NSE.

2) MULTI-TARGET TRACKING

Target 1 and target 2 in Fig. 1 are selected as the tracking sources. Sensor 1 is also selected as the central computing node for CMTSCKF. Both targets start moving at the same time and tracking results of node 1 are presented as follows for better comparison.

For scenario 1, multi-target tracking results are given in Fig. 7 and position RMSEs of both targets are displayed in Fig. 8. From Fig. 7, DMTCIF-DNSE obtains the best tracking result than the other algorithms on account of the contained two-step information fusion which is designed for DAVS. DMTCIF-NSE acquires better tracking results than DMTSCIF because of more precise measurement noise statistics obtained by the designed NSE. Although estimated values of MTCIF-NSE are relatively stable, there is still deviation in its tracking results which are worse than the estimation of DMTSCIF. Hence we can get that the distributed information fusion of state estimation can reduce the affection of mismatch statistics of measurement noise. The CMTSCKF obtains the worst tracking result due to the mismatch noise statistics of measurements, but the estimation error is decreased with the increased time steps. Similarly, the centralized technology also can improve the quality of tracking results under mismatched noise statistics of measurements.

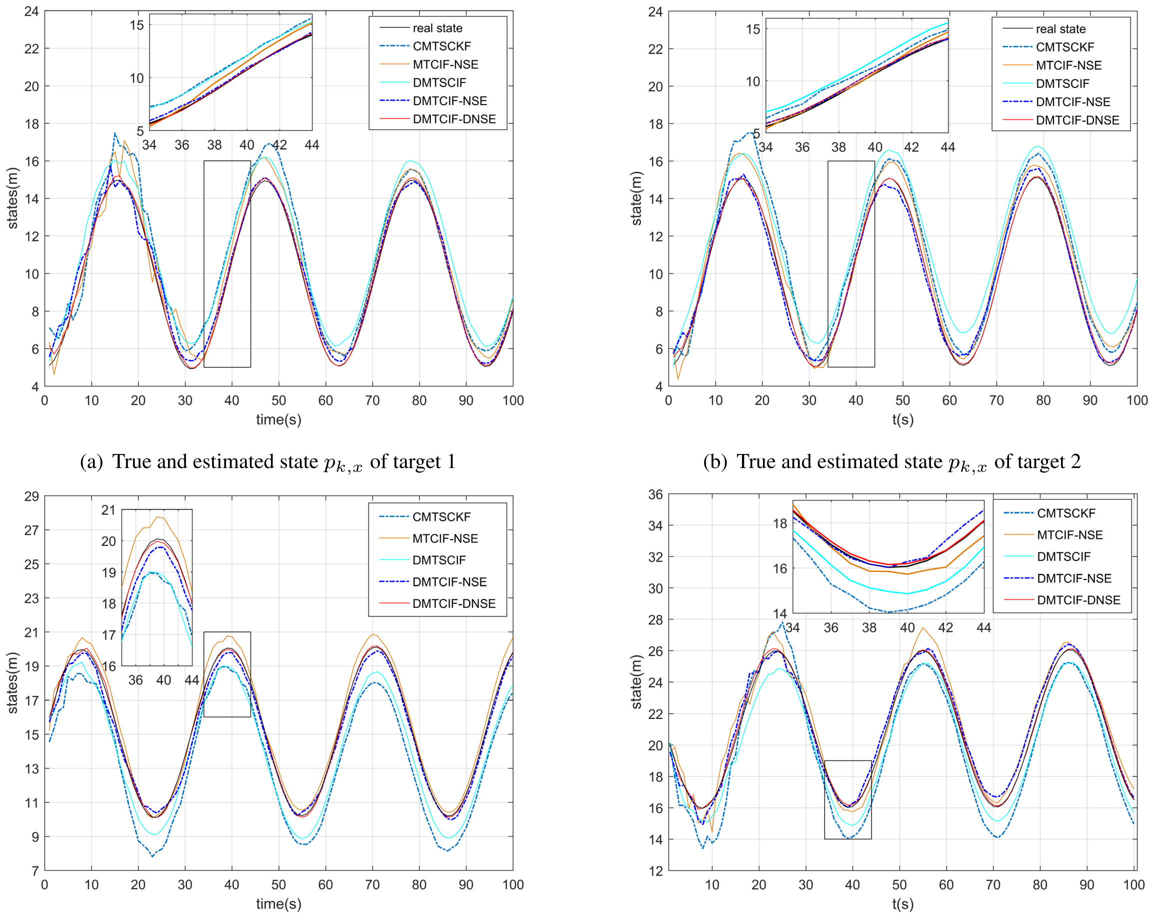
In Fig. 8, (a) and (b) stand for the position RMSE of target 1 and target 2, respectively. As far as the rate of convergence is concerned, MTCIF-NSE, DMTCIF-NSE and DMTCIF-DNSE obtain better results than CMTSCKF and DMTSCIF since more accurate statistics of measurement noise are acquired by the designed NSE and DNSE.



(a) Position RMSE of target 1

(b) Position RMSE of target 2

FIGURE 8. **Position RMSE for multi-target tracking under scenario 1.**



(a) True and estimated state $p_{k,x}$ of target 1

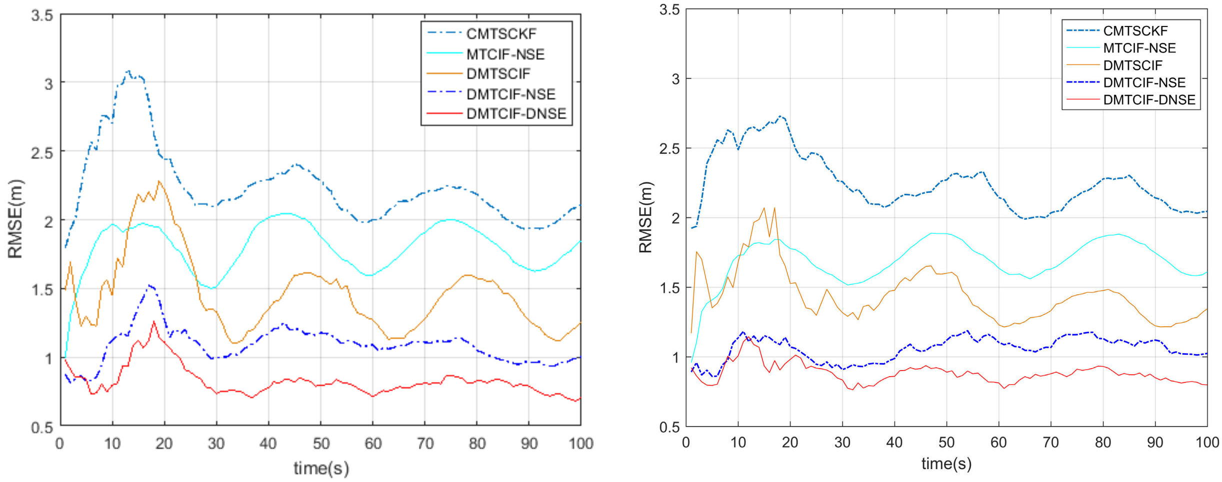
(b) True and estimated state $p_{k,x}$ of target 2

(c) True and estimated state $p_{k,y}$ of target 1

(d) True and estimated state $p_{k,y}$ of target 2

FIGURE 9. **Multiple-target tracking under scenario 2.**

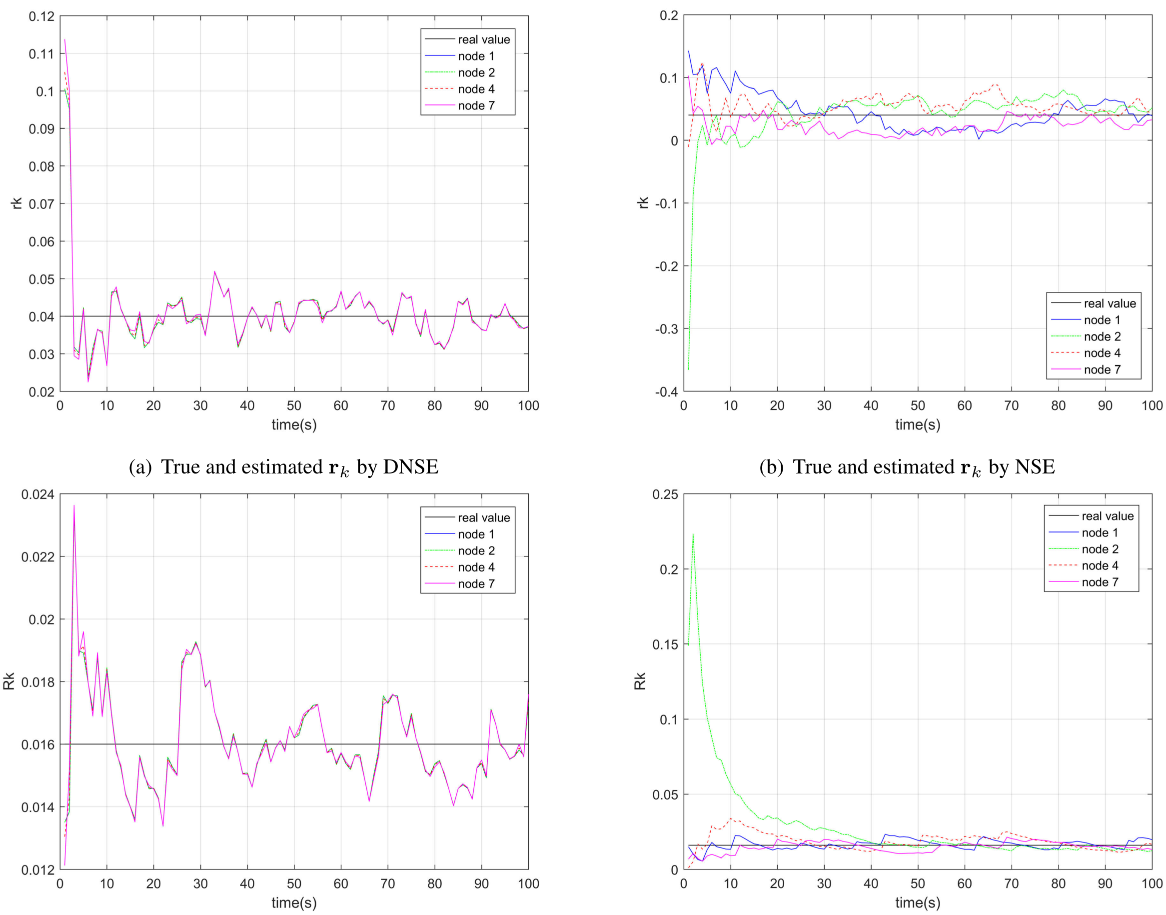
Benefited from the distributed information fusion of state estimation, the RMSE of DMTSCIF is lower than MTCIF-NSE, but the stability of which is better. DMTCIF-DNSE obtains the best RMSE while the RMSE of CMTSCKF is the worst, but after 17s, the RMSE of CMTSCKF decreases quickly which benefits from the affection of centralized fusion technology on state estimation under mismatched noise statistics of measurements. In terms



(a) Position RMSE of target 1

(b) Position RMSE of target 2

FIGURE 10. Position RMSE for multi-target tracking under scenario 2.



(a) True and estimated $\mathbf{r}_k$ by DNSE

(b) True and estimated $\mathbf{r}_k$ by NSE

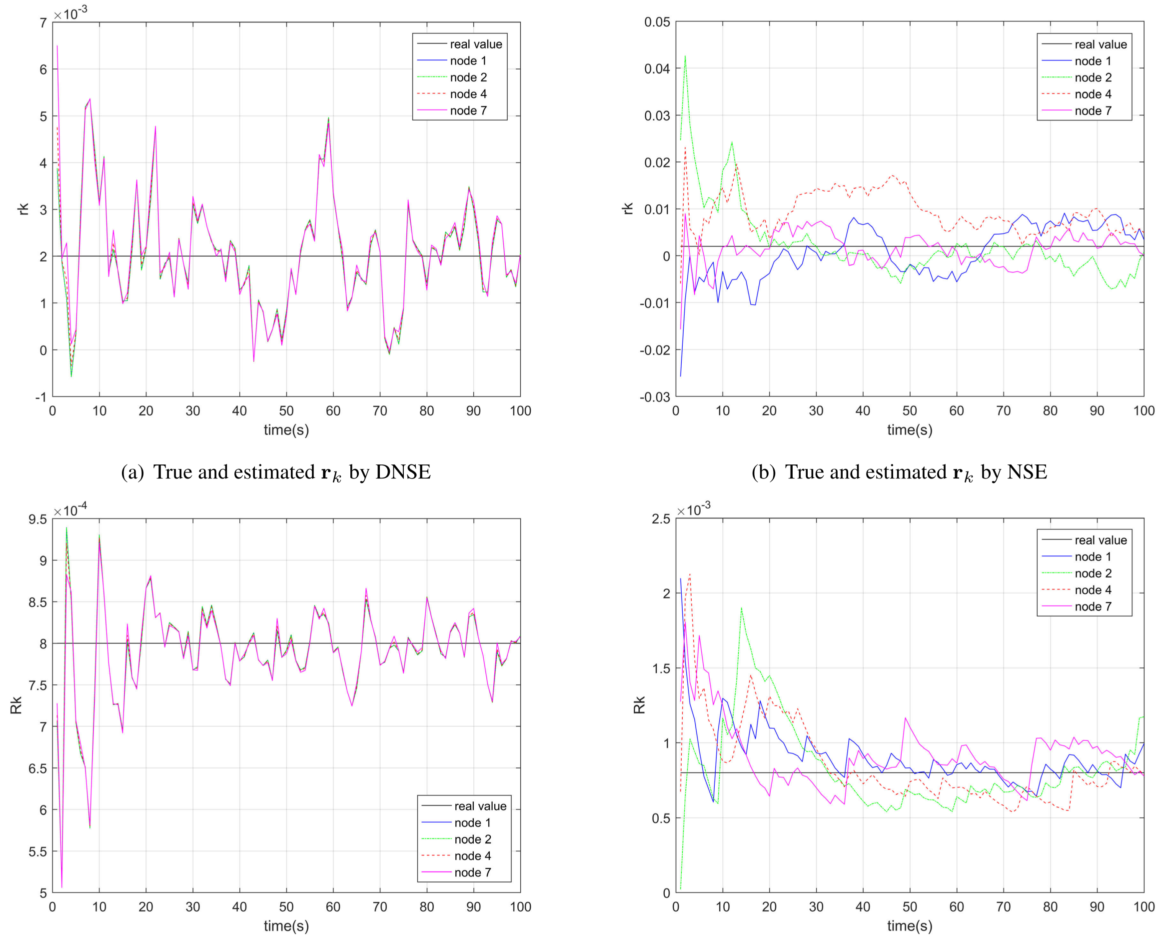
(c) True and estimated $\mathbf{R}_k$ by DNSE

(d) True and estimated $\mathbf{R}_k$ by NSE

FIGURE 11. Comparison of estimation values obtained by DNSE and NSE under scenario 1.

of accuracy and convergence, DMTCIF-DNSE outperforms the other algorithms on account of the two-step information fusion including the information fusion of state estimation and the information fusion of statistics of measurement noise. Hence compared with the other algorithms, DMTCIF-DNSE is more suitable for multi-target tracking under scenario 1.

For scenario 2, results of multi-target tracking are presented in Fig. 9 and position RMSEs of targets are displayed



(a) True and estimated $\mathbf{r}_k$ by DNSE

(b) True and estimated $\mathbf{r}_k$ by NSE

(c) True and estimated $\mathbf{R}_k$ by DNSE

(d) True and estimated $\mathbf{R}_k$ by NSE

FIGURE 12. Comparison of estimation values obtained by DNSE and NSE under scenario 2.

in Fig. 10. From Fig. 9, estimated values of MTCIF-NSE are worse than DMTCIF-NSE because of lacking information fusion for state estimation, but are better than CMTSCKF and DMTSCIF while the state estimation is stable due to more accurate statistics of measurement noise acquired by the designed NSE. Tracking results of DMTCIF-DNSE are still the best among the tracking algorithms in this paper. Hence the proposed two-step information fusion is an effective tool to deal with state estimation under mismatched statistics of measurement noise. From Fig. 10, the RMSE of MTCIF-NSE is lower than DMTSCIF for both targets after 26*s*. Benefited from the distributed information fusion, RMSE curves of DMTCIF-NSE and DMTCIF-DNSE are lower and more flat than MTCIF-NSE when the algorithm is stable after 30*s*. DMTCIF-DNSE achieves the best RMSE under scenario 2. Above all, DMTCIF-DNSE is more suitable for distributed target tracking under mismatched noise statistics of measurements.

3) PERFORMANCE ANALYSIS OF DNSE

Target 1 is selected as the tracking source. The estimated values and its mean of statistics of measurement noise produced by DMTCIF-DNSE and DMTCIF-NSE are selected as the comparison items to verify the effectiveness of DNSE under mismatched noise statistics of measurements. For simplicity, NSE and DNSE are used to stand for DMTCIF-NSE and DMTCIF-DNSE, respectively. Estimated values produced by DNSE and NSE in node 1, node 2, node 4 and node 7 are presented in the following simulations.

For scenario 1, (a) and (c) in Fig. 11 respectively stand for the estimated mean $\mathbf{r}_k$ and covariance $\mathbf{R}_k$ of measurement noise produced by DNSE under scenario 1. (b) and (d) denote $\mathbf{r}_k$ and $\mathbf{R}_k$ obtained by NSE, respectively. Because of the randomness of NSE, the worst noise statistics of measurements is obtained by node 2 from (b) and (d). From (a) and (c), similar estimated values are obtained by the chosen sensor nodes due to the distributed information fusion of noise statistics. We can get that WAC based DNSE can improve the stability of NSE. The mean estimation of statistics of measurement noise is displayed in Table 4. Then one point is obvious, benefited from WAC based distributed information algorithms, DNSE can obtain more precise noise statistics of measurements, compared with NSE. Hence, the accuracy and stability of DNSE are better than NSE under scenario 1.

TABLE 4. Mean estimation of statistics of measurement noise under scenario 1.

	$\mathbf{r}_k$(DNSE)	$\mathbf{R}_k$(DNSE)	$\mathbf{r}_k$(NSE)	$\mathbf{R}_k$(NSE)
Node 1	0.0404	0.0161	0.0466	0.0164
Node 2	0.0404	0.0161	0.0414	0.0291
Node 4	0.0403	0.0161	0.0542	0.0185
Node 7	0.0402	0.0161	0.0236	0.0150

TABLE 5. Mean estimation of statistics of measurement noise under scenario 2.

	$\mathbf{r}_k$(DNSE)	$\mathbf{R}_k$(DNSE)	$\mathbf{r}_k$(NSE)	$\mathbf{R}_k$(NSE)
Node 1	0.0021	$7.884 * 10^{-4}$	0.0008	$9.035 * 10^{-4}$
Node 2	0.0021	$7.884 * 10^{-4}$	0.0025	$8.318 * 10^{-4}$
Node 4	0.0021	$7.885 * 10^{-4}$	0.0092	$8.574 * 10^{-4}$
Node 7	0.0021	$7.885 * 10^{-4}$	0.0015	$9.202 * 10^{-4}$

For scenario 2, estimated values of statistics of measurement noise obtained by DNSE and NSE are displayed in Fig. 12 and the mean of obtained noise statistics is presented in Table 5. From (b) and (d) in Fig. 12, large biases exist in the estimated values of node 4 which are worse than estimations of other nodes. And from a) and (c), similar estimations obtained by DNSE benefited from WAC based information fusion algorithm. Therefore, the stability of DNSE is stronger than the designed NSE. From table 2, DNSE obtains better estimations of statistics of measurement noise in all nodes, compared with NSE. Hence in terms of stability and precision, DNSE acquires better performance than NSE under scenario 2. Above all, benefited from WAC based distributed information fusion, the designed DNSE outperforms NSE under mismatched noise statistics of measurements and DNSE is more suitable for noise estimation in DAVS than NSE.

VII. CONCLUSION

The multi-target tracking algorithm presented in this paper is an indirect algorithm. Firstly, Measurement DOAs are acquired by capon spectra estimator through sampling points obtained by the AVS. Then, JPDA based MTCIF is used for multi-target tracking to solve the problem of measurements-to-targets association on the basis of acquired measurement DOAs. However, the prior knowledge of measurement noise is usually kept unknown in the real application and initial statistics of measurement noise are also incorrect, which always affects the precision of state estimation. Hence, in view of the stability of NSE, the modified SHMP based NSE is designed for MTCIF to obtain accurate statistics of measurement noise. To further improve the stability and accuracy of NSE and state estimator, a two-step information fusion is designed for MTCIF-NSE, including the information fusion of state estimation and the information fusion of statistics of measurement noise. The information fusion algorithm in this paper which belongs to distributed algorithms, owns better robustness and lower communication burden than the centralized information fusion technology. Meanwhile, the algorithm for distributed information fusion is founded based on WAC since the stability of WAC can be guaranteed by any number of consensus steps.

In addition, traditional Cramer-Rao lower bound (CRLB) is only suitable for the performance evaluation of state estimator on single sensor node with given noise statistics, but not applicable to the performance evaluation of distributed state estimator based on sensor networks under unknown or incorrect noise statistics. Hence, the further work of this paper will focus on stability analysis and construction of distributed CRLB for the proposed multi-target tracking algorithms, including MTCIF-NSE, DMTCIF-NSE and DMTCIF-DNSE. Meanwhile, performance verification of the proposed algorithms will be designed under various SNR. MTCIF-NSE is founded for targets tracking on single sensor node and DMTCIF-NSE and DMTCIF-DNSE are designed for targets tracking in distributed networks.

APPENDIX

Derivation of MTCIF

According to [8], the state estimation $\hat{\mathbf{X}}_k^{l,n}$ and its error covariance matrix $\mathbf{P}_k^{l,n}$ of JPDA filtering are defined by

$$\hat{\mathbf{X}}_k^{l,n} = \hat{\mathbf{X}}_{k|k-1}^{l,n} + \mathbf{K}_k^{l,n}\left(\mathbf{Z}_k^{l,n} - \left(1-\beta_{n0}^l\right)\mathbf{H}_k^n\hat{\mathbf{X}}_{k|k-1}^{l,n}\right) \quad (38)$$

$$\begin{aligned}\mathbf{P}_k^{l,n} &= \mathbf{P}_{k|k-1}^{l,n} - \left(1-\beta_{n0}^l\right)\mathbf{K}_k^{l,n}\mathbf{P}_{zz,k|k-1}^{l,n}\left(\mathbf{K}_k^{l,n}\right)^T \\ &\quad + \mathbf{K}_k^{l,n}\tilde{\mathbf{P}}_{zz,k|k-1}^{l,n}\left(\mathbf{K}_k^{l,n}\right)^T \end{aligned} \quad (39)$$

where β_{n0}^l denotes the probability that no measurement is associated with target l for node n and $\beta_{n0}^l = 1 - \sum_{j=1}^{m_0}\beta_{nj}^l$. $\beta_{nj}^l = P\left[\chi_{nj}^l|\hat{\mathbf{Z}}_k^n\right]$ and χ_{nj}^l denote that the measurement j on node n originated from target l. See [24] for details of β_{n0}^l and β_{nj}^l. $\mathbf{K}_k^{l,n}$ is the Kalman gain. $\mathbf{Z}_k^{l,n} = \sum_{j=1}^{m_0}\beta_{nj}^l\hat{\mathbf{Z}}_{k,j}^n$. $\tilde{\mathbf{P}}_{zz,k|k-1}^{l,n}$ is defined by

$$\begin{aligned}\tilde{\mathbf{P}}_{zz,k|k-1}^{l,n} &= \sum_{j=1}^{m_0}\beta_{nj}^l\left(\hat{\mathbf{Z}}_{k,j}^n - \mathbf{H}_k^n\hat{\mathbf{X}}_{k|k-1}^{l,n}\right)\left(\hat{\mathbf{Z}}_{k,j}^n - \mathbf{H}_k^n\hat{\mathbf{X}}_{k|k-1}^{l,n}\right)^T \\ &\quad - \left(\mathbf{Z}_k^{l,n} - \mathbf{H}_k^n\hat{\mathbf{X}}_{k|k-1}^{l,n}\right)\left(\mathbf{Z}_k^{l,n} - \mathbf{H}_k^n\hat{\mathbf{X}}_{k|k-1}^{l,n}\right)^T \end{aligned} \quad (40)$$

Transform state estimation $\hat{\mathbf{X}}_k^{l,n}$ and its error covariance matrix $\mathbf{P}_k^{l,n}$ into the form of information filtering for nonlinear system model. According to [27], the Kalman gain $\mathbf{K}_k^{l,n}$ and the predicted measurement covariance matrix $\mathbf{P}_{zz,k|k-1}^{l,n}$ is defined by

$$\mathbf{K}_k^{l,n} = \left(\mathbf{Y}_k^{l,n}\right)^{-1}\mathbf{Y}_{k|k-1}^{l,n}\mathbf{P}_{xz,k|k-1}^{l,n}\left(\mathbf{R}_k^n\right)^{-1} \quad (41)$$

$$\mathbf{P}_{zz,k|k-1}^{l,n} = \left(\mathbf{P}_{xz,k|k-1}^{l,n}\right)^T \mathbf{Y}_{k|k-1}^{l,n} \mathbf{P}_{xz,k|k-1}^{l,n} + \mathbf{R}_k^n \quad (42)$$

According to [11], the information matrix of CIF is defined by

$$\mathbf{Y}_k^{l,n} = \mathbf{Y}_{k|k-1}^{l,n} + \mathbf{Y}_{k|k-1}^{l,n} \mathbf{P}_{xz,k|k-1}^{l,n} (\mathbf{R}_k^n)^{-1} \cdot \left(\mathbf{P}_{xz,k|k-1}^{l,n}\right)^T \mathbf{Y}_{k|k-1}^{l,n} \quad (43)$$

Substitute (43) into (41), the information filtering form of Kalman gain $\mathbf{K}_k^{l,n}$ is given by

$$\mathbf{K}_k^{l,n} = \left(\mathbf{Y}_{k|k-1}^{l,n} + \mathbf{Y}_{k|k-1}^{l,n} \mathbf{P}_{xz,k|k-1}^{l,n} (\mathbf{R}_k^n)^{-1} \left(\mathbf{P}_{xz,k|k-1}^{l,n}\right)^T \cdot \mathbf{Y}_{k|k-1}^{l,n}\right)^{-1} \mathbf{Y}_{k|k-1}^{l,n} \mathbf{P}_{xz,k|k-1}^{l,n} (\mathbf{R}_k^n)^{-1} \quad (44)$$

Multiply $\mathbf{Y}_k^{l,n}$ to both sides of (38) to obtain information state vector

$$\hat{\mathbf{y}}_k^{l,n} = \mathbf{Y}_k^{l,n} \hat{\mathbf{X}}_{k|k-1}^{l,n} + \mathbf{Y}_k^{l,n} \mathbf{K}_k^{l,n} \left(\mathbf{Z}_k^{l,n} - \left(1 - \beta_{n0}^l\right) \hat{\mathbf{Z}}_{k|k-1}^{l,n}\right) \quad (45)$$

where $\hat{\mathbf{y}}_k^{l,n} = \mathbf{Y}_k^{l,n} \hat{\mathbf{X}}_k^{l,n}$.

Substitute (43) and (41) into (45), the equivalent form of (45) is given by

$$\hat{\mathbf{y}}_k^{l,n} = \hat{\mathbf{y}}_{k|k-1}^{l,n} + \mathbf{Y}_{k|k-1}^{l,n} \mathbf{P}_{xz,k|k-1}^{l,n} (\mathbf{R}_k^n)^{-1} \cdot \left(\mathbf{Z}_k^{l,n} - \left(1 - \beta_{n0}^l\right) \hat{\mathbf{Z}}_{k|k-1}^{l,n} + \left(\mathbf{P}_{xz,k|k-1}^{l,n}\right)^T \mathbf{Y}_{k|k-1}^{l,n} \hat{\mathbf{X}}_{k|k-1}^{l,n}\right) \quad (46)$$

Denote

$$\tilde{\mathbf{i}}_k^{l,n} = \mathbf{Y}_{k|k-1}^{l,n} \mathbf{P}_{xz,k|k-1}^{l,n} (\mathbf{R}_k^n)^{-1} \cdot \left(\mathbf{Z}_k^{l,n} - \left(1 - \beta_{n0}^l\right) \hat{\mathbf{Z}}_{k|k-1}^{l,n} + \left(\mathbf{P}_{xz,k|k-1}^{l,n}\right)^T \mathbf{Y}_{k|k-1}^{l,n} \hat{\mathbf{X}}_{k|k-1}^{l,n}\right) \quad (47)$$

Then information state vector $\hat{\mathbf{y}}_k^{l,n}$ is defined by

$$\hat{\mathbf{y}}_k^{l,n} = \hat{\mathbf{y}}_{k|k-1}^{l,n} + \tilde{\mathbf{i}}_k^{l,n} \quad (48)$$

Next, readjust the error covariance matrix $\mathbf{P}_k^{l,n}$ of state estimation into the form of information filtering and substitute (42) into (39)

$$\begin{aligned}\mathbf{P}_k^{l,n} &= \mathbf{P}_{k|k-1}^{l,n} - \mathbf{K}_k^{l,n} \times \left(\left(1 - \beta_{n0}^l\right) \mathbf{P}_{zz,k|k-1}^{l,n} - \tilde{\mathbf{P}}_{zz,k|k-1}^{l,n}\right) \cdot \left(\mathbf{K}_k^{l,n}\right)^T \\ &= \mathbf{P}_{k|k-1}^{l,n} - \mathbf{K}_k^{l,n} \left(\left(1 - \beta_{n0}^l\right) \left(\left(\mathbf{P}_{xz,k|k-1}^{l,n}\right)^T \mathbf{Y}_{k|k-1}^{l,n} \cdot \mathbf{P}_{xz,k|k-1}^{l,n} + \mathbf{R}_k^n\right) - \tilde{\mathbf{P}}_{zz,k|k-1}^{l,n}\right) \left(\mathbf{K}_k^{l,n}\right)^T \end{aligned} \quad (49)$$

Transform $\tilde{\mathbf{P}}_{zz,k|k-1}^{l,n}$ into the form of nonlinear and substitute (19) into (40)

$$\tilde{\mathbf{P}}_{zz,k|k-1}^{l,n} = \sum_{j=1}^{m_0} \beta_{nj}^l \left(\hat{\mathbf{Z}}_{k,j}^n - \hat{\mathbf{Z}}_{k|k-1}^{l,n}\right)\left(\hat{\mathbf{Z}}_{k,j}^n - \hat{\mathbf{Z}}_{k|k-1}^{l,n}\right)^T - \left(\mathbf{Z}_k^{l,n} - \hat{\mathbf{Z}}_{k|k-1}^{l,n}\right)\left(\mathbf{Z}_k^{l,n} - \hat{\mathbf{Z}}_{k|k-1}^{l,n}\right)^T \quad (50)$$

Let

$$\mathbf{M}_k^{l,n} = \left(1 - \beta_{n0}^l\right)\left(\left(\mathbf{P}_{xz,k|k-1}^{l,n}\right)^T \mathbf{Y}_{k|k-1}^{l,n} \mathbf{P}_{xz,k|k-1}^{l,n} + \mathbf{R}_k^n\right) - \tilde{\mathbf{P}}_{zz,k|k-1}^{l,n} \quad (51)$$

According to the matrix inversion lemma, equation (49) is written as

$$\begin{aligned}\mathbf{Y}_k^{l,n} &= \left(\mathbf{P}_{k|k-1}^{l,n} - \mathbf{K}_k^{l,n} \mathbf{M}_k^{l,n} \left(\mathbf{K}_k^{l,n}\right)^T\right)^{-1} \\ &= \left(\mathbf{P}_{k|k-1}^{l,n}\right)^{-1} + \left(\mathbf{P}_{k|k-1}^{l,n}\right)^{-1} \mathbf{K}_k^{l,n} \left(\left(\mathbf{M}_k^{l,n}\right)^{-1} - \left(\mathbf{K}_k^{l,n}\right)^T \cdot \left(\mathbf{P}_{k|k-1}^{l,n}\right)^{-1} \mathbf{K}_k^{l,n}\right)^{-1} \left(\mathbf{K}_k^{l,n}\right)^T \left(\mathbf{P}_{k|k-1}^{l,n}\right)^{-1} \\ &= \mathbf{Y}_{k|k-1}^{l,n} + \mathbf{Y}_{k|k-1}^{l,n} \mathbf{K}_k^{l,n} \left(\left(\mathbf{M}_k^{l,n}\right)^{-1} - \left(\mathbf{K}_k^{l,n}\right)^T \mathbf{Y}_{k|k-1}^{l,n} \cdot \mathbf{K}_k^{l,n}\right)^{-1} \left(\mathbf{K}_k^{l,n}\right)^T \mathbf{Y}_{k|k-1}^{l,n} \end{aligned} \quad (52)$$

where $\mathbf{Y}_k^{l,n} = \left(\mathbf{P}_k^{l,n}\right)^{-1}$. Let

$$\mathbf{G}_k^{l,n} = \mathbf{Y}_{k|k-1}^{l,n} \mathbf{K}_k^{l,n} \left[\left(\mathbf{M}_k^{l,n}\right)^{-1} - \left(\mathbf{K}_k^{l,n}\right)^T \mathbf{Y}_{k|k-1}^{l,n} \mathbf{K}_k^{l,n}\right]^{-1} \cdot \left(\mathbf{K}_k^{l,n}\right)^T \mathbf{Y}_{k|k-1}^{l,n} \quad (53)$$

Then information matrix $\mathbf{Y}_k^{l,n}$ is defined by

$$\mathbf{Y}_k^{l,n} = \mathbf{Y}_{k|k-1}^{l,n} + \mathbf{G}_k^{l,n} \quad (54)$$

Finally, for target l, the state estimation $\hat{\mathbf{X}}_k^{l,n}$ at time step k is given by

$$\hat{\mathbf{X}}_k^{l,n} = \left(\mathbf{Y}_k^{l,n}\right)^{-1} \hat{\mathbf{y}}_k^{l,n} \quad (55)$$

REFERENCES

[1] J. Cao, J. Liu, J. Wang, and X. Lai, "Acoustic vector sensor: Reviews and future perspectives," *IET Signal Process.*, vol. 11, no. 1, pp. 1–9, Feb. 2017.

[2] M. J. Berliner, J. F. Lindberg, and O. B. Wilson, "Acoustic particle velocity sensors: Design, performance, and applications," *Acoust. Soc. Amer. J.*, vol. 100, no. 6, pp. 3478–3479, 1996.

[3] Y. Wang, J. Li, and Q. Sun, "Coordinated target tracking by distributed unscented information filter in sensor networks with measurement constraints," *Math. Problems Eng.*, vol. 2013, Sep. 2013, Art. no. 402732.

[4] X. Zhong, A. B. Premkumar, and H. Wang, "Multiple wideband acoustic source tracking in 3-D space using a distributed acoustic vector sensor array," *IEEE Sensors J.*, vol. 14, no. 8, pp. 2502–2513, Aug. 2014.

[5] M. Hawkes and A. Nehorai, "Wideband source localization using a distributed acoustic vector-sensor array," *IEEE Trans. Signal Process.*, vol. 51, no. 6, pp. 1479–1491, Jun. 2003.

[6] X. Zhong and A. B. Premkumar, "Multiple wideband source detection and tracking using a distributed acoustic vector sensor array: A random finite set approach," *Signal Process.*, vol. 94, pp. 583–594, Jan. 2014.

[7] Y. Liu, J. Liu, G. Li, L. Qi, Y. Li, and Y. He, "Centralized multi-sensor square root cubature joint probabilistic data association," *Sensors*, vol. 17, no. 11, p. 2546, Nov. 2017.

[8] N. F. Sandell and R. Olfati-Saber, "Distributed data association for multi-target tracking in sensor networks," in *Proc. 47th IEEE Conf. Decis. Control*, Dec. 2008, pp. 1085–1090.

[9] Y. Chen, Q. Zhao, and R. Liu, "A novel square-root cubature information weighted consensus filter algorithm for distributed camera networks," *Acta Electronica Sinica*, vol. 44, no. 10, pp. 2335–2343, 2016.

[10] Y. Chen, Q. Zhao, Z. An, P. Lv, and L. Zhao, "Distributed multi-target tracking based on the K-MTSCF algorithm in camera networks," *IEEE Sensors J.*, vol. 16, no. 13, pp. 5481–5490, Jul. 2016.

[11] K. Pakki, B. Chandra, D.-W. Gu, and I. Postlethwaite, "Cubature information filter and its applications," in *Proc. Amer. Control Conf.*, Jun./Jul. 2011, pp. 3609–3614.

[12] Y. Chen and Q. Zhao, "A novel square-root cubature information weighted consensus filter algorithm for multi-target tracking in distributed camera networks," *Sensors*, vol. 15, no. 5, pp. 10526–10546, 2015.

[13] G. Battistelli, L. Chisci, G. Mugnai, A. Farina, and A. Graziano, "Consensus-based linear and nonlinear filtering," *IEEE Trans. Autom. Control*, vol. 60, no. 5, pp. 1410–1415, May 2015.

[14] J. Zhao and L. Mili, "A framework for robust hybrid state estimation with unknown measurement noise statistics," *IEEE Trans. Ind. Informat.*, vol. 14, no. 5, pp. 1866–1875, May 2018.

[15] A. P. Sage and G. W. Husa, "Algorithms for sequential adaptive estimation of prior statistics," in *Proc. 8th Decis. Control IEEE Symp. Adapt. Processes*, Nov. 1969, p. 61.

[16] Q. Song and R. Liu, "Weighted adaptive filtering algorithm for carrier tracking of deep space signal," *Chin. J. Aeronaut.*, vol. 28, no. 4, pp. 1236–1244, 2015.

[17] S. Peng, C. Chen, H. Shi, and Z. Yao, "State of charge estimation of battery energy storage systems based on adaptive unscented Kalman filter with a noise statistics estimator," *IEEE Access*, vol. 5, pp. 13202–13212, Jul. 2017.

[18] H. Yu, X. Wei, S. Song, and M. Liu, "Relative motion estimation of non-cooperative spacecraft based on adaptive CKF," (in Chinese), *Acta Aeronautica et Astronautica Sinica*, vol. 35, no. 8, pp. 2251–2260, 2014.

[19] W. Li, G. Wei, F. Han, and Y. Liu, "Weighted average consensus-based unscented Kalman filtering," *IEEE Trans. Cybern.*, vol. 46, no. 2, pp. 558–567, Feb. 2016.

[20] Q. Tan, X. Dong, Q. Li, and Z. Ren, "Distributed event-triggered cubature information filtering based on weighted average consensus," *IET Control Theory Appl.*, vol. 12, no. 1, pp. 78–86, Jan. 2018.

[21] Q. Chen, W. Wang, C. Yin, X. Jin, and J. Zhou, "Distributed cubature information filtering based on weighted average consensus," *Neurocomputing*, vol. 243, pp. 115–124, Jun. 2017.

[22] A. Nehorai and E. Paldi, "Acoustic vector-sensor array processing," *IEEE Trans. Signal Process.*, vol. 42, no. 9, pp. 2481–2491, Sep. 1994.

[23] M. Hawkes and A. Nehorai, "Acoustic vector-sensor beamforming and capon direction estimation," *IEEE Trans. Signal Process.*, vol. 46, no. 9, pp. 2291–2304, Sep. 1998.

[24] Y. Bar-Shalom, F. Daum, and J. Huang, "The probabilistic data association filter," *IEEE Control Syst.*, vol. 29, no. 6, pp. 82–100, Dec. 2009.

[25] J. Sun, X. Xu, Y. Liu, T. Zhang, and Y. Li, "FOG random drift signal denoising based on the improved ar model and modified Sage-Husa adaptive Kalman filter," *Sensors*, vol. 16, no. 7, p. 1073, Jul. 2016.

[26] J. Meng, G. Luo, and F. Gao, "Lithium polymer battery state-of-charge estimation based on adaptive unscented Kalman filter and support vector machine," *IEEE Trans. Power Electron.*, vol. 31, no. 3, pp. 2226–2238, Mar. 2016.

[27] Y. S. Kim, J. H. Lee, H. M. Do, B. K. Kim, T. Tanikawa, K. Ohba, G. Lee, and S. H. Yun, "Unscented information filtering method for reducing multiple sensor registration error," in *Proc. IEEE Conf. Multisensor Fusion Integr. Intell. Syst. (MFI)*, vols. 1–2, Aug. 2008, pp. 326–331.

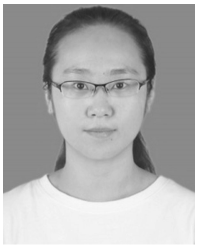
JIAHAO ZHANG is currently pursuing the Ph.D. degree with the School of Automatics, Northwestern Polytechnical University, China. His research interests include control theory and engineering, navigation, guidance, and control, target tracking, signal processing, and information fusion.

SHESHENG GAO is currently a Professor with the School of Automatics, Northwestern Polytechnical University, China. His research interests include control theory and engineering, navigation, guidance, and control, optimum estimation and control, integrated inertial navigation systems, and information fusion.

YONGMIN ZHONG is currently a Senior Lecturer with the School of Aerospace, Mechanical and Manufacturing Engineering, RMIT University, Australia. His research interests include virtual reality and haptics, soft tissue modeling and surgery simulation, robotics, mechatronics, optimum estimation and control, and integrated navigation systems.

XIAOMIN QI received the B.Sc. degree in electronic and information engineering from Henan Normal University, in 2010, and the M.Sc. degree in control theory and control engineering from the Zhongyuan University of Technology, in 2014. He is currently pursuing the Ph.D. degree in wireless communication with COMSATS University Islamabad.

JUAN XIA is currently pursuing the Ph.D. degree with the School of Automatics, Northwestern Polytechnical University, China. Her research interests include control theory and engineering, navigation, guidance, and control, optimum estimation and control, information fusion, target tracking, and integrated navigation.



JIAHUI YANG is currently pursuing the Ph.D. degree with the School of Automatics, Northwestern Polytechnical University, China. Her research interests include control theory and engineering, navigation, guidance, and control, and target tracking.