Received January 25, 2019, accepted February 8, 2019, date of publication February 13, 2019, date of current version March 8, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2899012

Centralized Fusion Based on Interacting Multiple Model and Adaptive Kalman Filter for Target Tracking in Underwater Acoustic Sensor Networks

JING QIU[1], ZIRUI XING[2], CHUNSHENG ZHU[3], KUNFENG LU[4], JIALUAN HE[2], YANBIN SUN[1], AND LIHUA YIN[1]

[1]Cyberspace Institute of Advanced Technology, Guangzhou University, Guangzhou 510006, China
[2]R&D and Application Center of Command Automation Technology, The 4th Institute of CASIC, Beijing 102308, China
[3]Department of Electrical and Computer Engineering, The University of British Columbia, Vancouver, BC V6T 1Z4, Canada
[4]Beijing Aerospace Automatic Control Institute, Beijing 100854, China

Corresponding authors: Yanbin Sun (sunyanbin@gzhu.edu.cn) and Lihua Yin (yinlh@gzhu.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 61871140, Grant 61872100, Grant U1636215, Grant 61572153, Grant 61572492, and Grant 61672020, in part by the National Key Research and Development Plan under Grant 2018YFB0803504, and in part by the Open Fund of the Beijing Key Laboratory of IOT Information Security Technology under Grant J6V0011104.

ABSTRACT Underwater acoustic sensor networks (UASNs) play an important role in the ocean's protection. They can realize real-time data collection, monitoring, exploration, and many other underwater applications by connecting and coordinating seafloor sensors and underwater vehicles. To achieve these application objectives, such as fishes tracking in biological monitoring field and submarines tracking in military field, target tracking is one of the key techniques. This paper presents a centralized fusion algorithm based on the interacting multiple models and the adaptive Kalman filter (IMMCFAKF) for target tracking in UASNs. Specifically, by introducing an adaptive forgetting factor into the optimal centralized fusion Kalman filter algorithm, the optimal centralized fusion adaptive Kalman filter (CFAKF) algorithm is obtained first. Then, combining the superiorities of both the optimal CFAKF algorithm and the conventional IMM algorithm, the optimal IMMCFAKF is achieved. The numerical simulations are provided to demonstrate the effectiveness of the proposed optimal IMMCFAKF algorithm.

INDEX TERMS Underwater acoustic sensor networks, target tracking, interacting multiple model, adaptive forgetting factor, optimal centralized fusion, Kalman filter.

I. INTRODUCTION

Marine resources are rich and valuable. Exploring the oceans is of great significance both in military and economic fields. However, the complex underwater environment has been restricting people's observation and utilization of the ocean. Nowadays, with the development of sensor technology, communication technology, computer technology and micro-electromechanical system technology, the application of Underwater Acoustic Sensor Networks (UASNs) to underwater data collection, tracking, monitoring and positioning has attracted great attention [1]–[6].

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

UASNs is a multi-hop self-organizing network system which consist of a variable number of sensors and vehicles that are deployed to perform collaborative monitoring tasks by underwater acoustic communication. UASNs was first developed for marine military defense. With the development of related technologies, such as Internet of things [7]–[12], wireless networks [13]–[22], and cooperation in scale-free networks [23], [24], its application scope is no longer limited to the military field. Now it is widely used in environmental monitoring, resource exploration, climate research and industrial automation [25]–[27]. It has very high research value and broad application prospects in economy and Commerce. In the research direction of UASNs, target tracking technology is a key part and the basis of most applications.

Whether in the military field for their own or enemy target tracking, or in the marine resources exploration and so on, underwater target tracking technology is needed as an assistant to achieve the objectives.

In the UASNs environment, target tracking task is achieved in multi-sensor system. In a multi-sensor tracking system, fusion can be used to combine sensory information to improve the tracking performance [28]. Multiple sensor fusion is widely used as a method of extracting useful information by observations obtained from multiple sensors. The information can then be applied to practical situations, such as target tracking in WSNs [29], [30].

As one of the most cost-effective approach for multiple model estimation and fusion multiple model tracking, the interacting multiple model (IMM) was firstly introduced in [31], it stems from a special input mixing step introduced at the beginning of each elemental filter in each cycle. It is this effective input mixing process that leads to an improvement in performance while without significantly increasing the computational requirement [32], [33]. After years of development, the IMM technique has been widely used in many systems [34]–[37]. Lang *et al.* [38] developed a distributed multirate IMM fusion algorithm, where out-of-sequence measurements were considered. Using IMM design, the novel $\alpha\beta$ and $\alpha\beta\gamma$ filters were proposed to track a single maneuver target [39]. An extended Kalman-based IMM smoother was proposed for mobile location estimation with the data fusion of the time of arrival (TOA) and the received signal strength (RSS) measurements in a rough wireless environment [40]. To improve the performance IMM Kalman filter in maneuvering target tracking, an Elman neural network is applied to learn and predict the estimation errors of IMM Kalman filter [41].

A standard IMM was carried out at each platform based on its own independent mode set [42]. The combined tracks at local platforms were transmitted to the fusion center and further fused there with a constructed global model [43]. There are basically two fusion architectures: centralized [44], [45] and distributed [46]–[48]. For the distributed fusion, which is also called as the state-vector or track fusion, a group of local Kalman filters are used in parallel to obtain individual sensor-based estimates and the distributed fusion formulae are then applied to yield an improved joint estimate. Hong [49] proposed an algorithm for multi-resolutional distributed filtering with the wavelet transform as a linking mechanism between different resolution sensor domains. Reference [50] addressed a distributed estimation fusion problem with nonlinear multiple dynamic models under asynchronous multi-rate multi-sensor conditions. The distributed fusion algorithm is then applied to multiple nonlinear models using an IMM approach. To carry out distributed fusion within the multiple model framework, novel equivalent platform and global models are constructed using the best fitting Gaussian approximation approach so that the developed distributed fusion formulae can be applied directly in the fusion center in [51].

The major advantages of the distributed fusion are reduced computational burden of central processing unit and lower communication loading along with parallel implementation. However, the distributed architecture is not theoretically optimal. Centralized fusion, which is also called measurement fusion in target tracking, uses all local raw measurements sent to a central processor. The processor categorizes all the available information and updates the estimates using these measurements. So, it can be widely used in many applications. Hu *et al.* [52] proposed a novel fusion algorithm that could be applied to general asynchronous multi-rate sensors. They derived a centralized fusion algorithm using an optimal batch asynchronous fusion algorithm [53] and extended it to a distributed fusion algorithm. The algorithms they developed do not require any constraints on the number, sampling rates, or initial sampling time instants of the sensors.

In this paper, a novel centralized fusion algorithm, named IMMCFAKF, which based on interacting multiple model and adaptive Kalman filter, is proposed for underwater target tracking. Firstly, the optimal centralized fusion adaptive Kalman filter (CFAKF) algorithm is obtained by introducing an adaptive forgetting factor into the optimal centralized fusion Kalman filter (CFKF). Then, optimal IMMCFAKF algorithm is proposed by combining the superiorities of both the optimal CFAKF algorithm and the conventional IMM algorithm. Finally, the numerical simulations are provided to demonstrate the effectiveness of the proposed optimal IMMCFAKF algorithm.

The remainder of this paper is organized as follows. Sections II presents the formulation of the problem. In Section III, the optimal IMMCFAKF algorithm is derived. The simulation and experiment results are presented in Section IV and concluding remarks are given in Section V.

II. MODEL AND PROBLEM STATEMENTS

A target is set to move in a two-dimensional plane. Its state $X(k)$ is composed of position, velocity, and acceleration, namely, $X(k) = [x(k), \dot{x}(k), \ddot{x}(k), y(k), \dot{y}(k), \ddot{y}(k)]^T$. Consider the following discrete-time linear motion model and observation model (assumed in the sampling time kT) with N sensors to observe the same object in the Cartesian coordinate system:

$$\begin{cases} X(k+1) = A(k)X(k) + B(k)w(k) \\ z_i(k) = C_i(k)X(k) + v_i(k) \quad i = 1, 2, \cdots, N \end{cases} \tag{1}$$

where $x_k \in \mathbb{R}^n$ is the state vector, T is the sampling period, $z_k^i \in \mathbb{R}^{m_i}$ $(i = 1, 2, \cdots, N)$ are measurement vectors, $A_k \in \mathbb{R}^{n\times n}$, $B_k \in \mathbb{R}^{n\times r}$ and $C_{i,k} \in \mathbb{R}^{m_i\times n}$ are known matrices. $w_k \in \mathbb{R}^r$ and $v_{i,k} \in \mathbb{R}^{m_i}$ $(i = 1, 2, \cdots, N)$ are correlated zero-mean Gaussian white noises, which satisfy

$$E\{[\, w(k) \;\, v_i(k)\,]^T [\, w(k) \;\, v_i(k)\,]\} = \delta_{kl} \begin{bmatrix} Q(k) & S_i(k) \\ S_i^T(k) & R_i(k) \end{bmatrix} \tag{2}$$

$$E\{w(k)v_i^T(l)\} = \delta_{kl} S_i(k) \tag{3}$$

where $Q_k \geq 0$ and $R_{i,k} > 0$ are process and measurement noise covariances, respectively, and δ_{kj} is the Kronecker function

$$\delta_{kl} = \begin{cases} 1 & \text{if } k = l, \\ 0 & \text{if } k \neq l. \end{cases}$$

Assumption 1: The initial state $x(0)$ is independent of w_k and $v_{i,k}$ $(i = 1, 2, \cdots, N)$, and

$$E\{x(0)\} = \hat{x}_0, \ E\{[x(0) - \hat{x}_0][x(0) - \hat{x}_0]^T\} = P_0.$$

The objective of this paper is to generate the optimal estimation of state $x(k)$ by an optimal IMMCFAKF algorithm based on the above description.

There are three kinds of motion models of a target in a two-dimensional plane described as follows:

1) CV Model: Approximate constant velocity model

The acceleration of the CV model is regarded as a stochastic perturbation (state noise). Then, the state transition matrix and the disturbance transition matrix and the measurement matrix are given as follows:

$$A(k) = \begin{bmatrix} 1 & T & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$$B(k) = \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \\ 0 & 0 \\ 0 & 0 \end{bmatrix},$$

$$C(k) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}.$$

2) CT Model: Constant turning model

Here, only consider the Constant acceleration (CA) model with known angular velocity. Then, the state transition matrix and the disturbance transition matrix and the measurement matrix are given as follows:

$$A(k) = \begin{bmatrix} 1 & \frac{sin(\omega T)}{\omega} & 0 & -\frac{1 - cos(\omega T)}{\omega} & 0 & 0 \\ 0 & cos(\omega T) & 0 & -sin(\omega T) & 0 & 0 \\ 0 & \frac{1 - cos(\omega T)}{\omega} & 1 & \frac{sin(\omega T)}{\omega} & 0 & 0 \\ 0 & sin(\omega T) & 0 & cos(\omega T) & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$$B(k) = \begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T \\ 0 & 0 \\ 0 & 0 \end{bmatrix},$$

$$C(k) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}.$$

3) CA Model: Constant acceleration model

The acceleration of the CA model is a constant value. Then, the state transition matrix and the disturbance transition matrix and the measurement matrix are given as follows:

$$A(k) = \begin{bmatrix} 1 & T & 0 & 0 & T^2/2 & 0 \\ 0 & 1 & 0 & 0 & T & 0 \\ 0 & 0 & 1 & T & 0 & T^2/2 \\ 0 & 0 & 0 & 1 & 0 & T \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

$$B(k) = \begin{bmatrix} T^2/4 & 0 \\ T/2 & 0 \\ 0 & T^2/4 \\ 0 & T/2 \\ 1 & 0 \\ 0 & 1 \end{bmatrix},$$

$$C(k) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix}.$$

Remark 1: In CV, CT and CA models, $C(k) = [C_1^T(k), \cdots, C_i^T(k), \cdots, C_N^T(k)]^T$. Here, $N = 2$.

III. OPTIMAL IMMCFAKF

In general, in the centralized fusion algorithm, let

$$z(k) = \left[z_1^T(k) \cdots z_i^T(k) \cdots z_N^T(k) \right]^T \quad (4)$$

$$C(k) = \left[C_1^T(k) \cdots C_i^T(k) \cdots C_N^T(k) \right]^T \quad (5)$$

$$v(k) = \left[v_1^T(k) \cdots v_i^T(k) \cdots v_N^T(k) \right]^T \quad (6)$$

Then, the pseudo measurement equation of the fusion center received all sensor measurements can be expressed as:

$$z(k) = C(k)X(k) + v(k) \quad (7)$$

According to (2) and (3), it follows that

$$R(k) = \begin{bmatrix} R_1(k) & \cdots & R_{1i}(k) & \cdots & R_{1N}(k) \\ \vdots & & \vdots & & \vdots \\ R_{i1}(k) & \cdots & R_i(k) & \cdots & R_{iN}(k) \\ \vdots & & \vdots & & \vdots \\ R_{N1}(k) & \cdots & R_{Ni}(k) & \cdots & R_N(k) \end{bmatrix} \quad (8)$$

$$S(k) = \left[S_1(k) \cdots S_i(k) \cdots S_N(k) \right] \quad (9)$$

A. OPTIMAL CFKF

Next, we first consider $\forall\ i = 1, 2, \cdots, N$, namely, when all the measurements are reliable, a recursive optimal centralized fusion algorithm is given. $z(k)$ can be written as

$$z(k) = C(k)X(k) + v(k) \quad (10)$$

For system (1), the optimal CFKF algorithm can be given by:

$$\hat{X}_c(k|k-1) = A(k-1)\hat{X}_c(k-1|k-1) + \hat{w}_b(k-1|k-1) \quad (11)$$

$$\begin{aligned}P_c(k|k-1) = {} & A(k)P_c(k-1|k-1)A^T(k) \\ & + A(k)P^c_{\tilde{x}\tilde{w}}(k-1|k-1) \\ & + P^c_{\tilde{w}\tilde{x}}(k-1|k-1)A^T(k)+P^c_{\tilde{w}}(k-1|k-1)\end{aligned} \tag{12}$$

$$\begin{aligned}K_c(k) = {} & P_c(k|k-1)C^T(k)[C(k)P_c(k|k-1)C^T(k) \\ & +R(k)]^{-1}\end{aligned} \tag{13}$$

$$K^c_w(k) = S(k)[C(k)P_c(k|k-1)C^T(k)+R(k)]^{-1} \tag{14}$$

$$\hat{w}_c(k|k) = K^c_w(k)[z(k)-C(k)\hat{X}_c(k|k-1)] \tag{15}$$

$$\begin{aligned}\hat{X}_c(k|k) = {} & \hat{X}_c(k|k-1)+K_c(k)[z(k) \\ & -C(k)\hat{X}_c(k|k-1)]\end{aligned} \tag{16}$$

$$P_c(k|k) = P_c(k|k-1)-K_c(k)C(k)P_c(k|k-1) \tag{17}$$

where the upper or lower index c represents the centralized fusion, $P^c_{\tilde{x}\tilde{w}}(k|k) = -K_c(k)S^T(k)$ is the filter error covariance matrix between the state and the process noise, and $P^c_{\tilde{w}}(k|k) = Q(k) - K^c_w(k)S^T(k)$ is the filter error covariance matrix between the process noises. $\hat{X}_c(k|k-1)$ and $P_c(k|k-1)$ are the one-step prediction state estimate and the one-step prediction error covariance of optimal CFKF algorithm, respectively. $K_c(k)$, and $K^c_w(k)$ are the Kalman gain and the process noise gain of optimal CFKF algorithm at time k, respectively. $\hat{w}_c(k|k)$, $\hat{X}_c(k|k)$ and $P_c(k|k)$ are the process noise estimate, the state estimate and the estimate error covariance of optimal CFKF algorithm at time k, respectively. The process derivation of optimal CFKF algorithm is presented in APPENDIX.

B. OPTIMAL CFAKF

In most cases, the model is mismatched from the true model in case of parameter uncertainty or great noises, which results in biased state estimations and generated large state estimation errors using optimal CFKF algorithm. For example, if the exact dynamic model is known, the innovation covariance is equal to $\Lambda(k) = C(k)P_c(k|k-1)C^T(k) + R(k)$. However, in the presence of uncertainties or great noises, the innovation covariance will be increased. The increased innovation covariance can be estimated as [54]

$$\Lambda'(k+1) = \begin{cases}\eta(1)\eta^T(1), & k=0 \\ \dfrac{\rho\cdot\Lambda'(k)+\eta(k+1)\eta^T(k+1)}{1+\rho}, & k\geq 1\end{cases} \tag{18}$$

where $\eta_k = z_k - \hat{z}_k$ is the innovation, and $0 \leq \rho \leq 1$ is a weighting factor which determines the weights given to a priori data or current data. $\Lambda'(k)$ is also called estimated innovation covariance. The relationship between $\Lambda'(k)$ and $\Lambda(k)$ can be expressed as $\Lambda'(k) = \tau_k\Lambda(k)$, where τ_k is a scalar variable which can be estimated by

$$\tau_k = max\left\{1, \frac{1}{m}tr(\Lambda'(k)\Lambda^{-1}(k))\right\} \tag{19}$$

or

$$\tau_k = max\left\{1, \frac{tr(\Lambda'(k))}{tr(\Lambda^{-1}(k))}\right\} \tag{20}$$

where tr denotes the trace operation of a matrix.

In case of uncertainties or biases in dynamic model, the predicted error covariance $P_c(k|k-1)$ will be increased. So we use a larger error covariance $P'_c(k|k-1)$ to compensate the effect of biased dynamic models, which can be expressed as

$$P'_c(k|k-1) = \lambda_k P_c(k|k-1) \tag{21}$$

Here $\lambda_k \geq 1$ is called an adaptive forgetting factor [55].

The relationship between $\Lambda'(k)$ and $P'_c(k|k-1)$ now is extended to optimal CFKF algorithm:

$$\Lambda'(k) = C(k)P'_c(k|k-1)C^T(k)+R(k) \tag{22}$$

Following is the development of optimal CFAKF algorithm. when λ_k is a scalar, it can be easily solved:

$$\lambda_k = max\left\{1, \frac{tr(\Lambda'(k)-R(k))}{tr(C(k)P_c(k|k-1)C^T(k))}\right\} \tag{23}$$

According to optimal CFKF algorithm described above and equations (18)-(23), optimal CFAKF algorithm can be implemented as follows:

Step 1: Compute the one-step prediction state estimate and the one-step prediction error covariance.

$$\begin{aligned}\hat{X}_c(k|k-1) = {} & A(k-1)\hat{X}_c(k-1|k-1) \\ & +\hat{w}_c(k-1|k-1)\end{aligned} \tag{24}$$

$$\begin{aligned}P_c(k|k-1) = {} & A(k)P_c(k-1|k-1)A^T(k) \\ & +A(k)P^c_{\tilde{x}\tilde{w}}(k-1|k-1) \\ & +P^c_{\tilde{w}\tilde{x}}(k-1|k-1)A^T(k) \\ & +P^c_{\tilde{w}}(k-1|k-1)\end{aligned} \tag{25}$$

Step 2: Compute the modified one-step prediction error covariance and the innovation covariance of optimal CFAKF algorithm.

$$P'_c(k|k-1) = \lambda_k P_c(k|k-1) \tag{26}$$

$$\begin{aligned}\Lambda'(k) &= \tau_k\Lambda(k) \\ &= \tau_k[C(k)P_c(k|k-1)C^T(k)+R(k)] \\ &= C(k)P'_c(k|k-1)C^T(k)+R(k)\end{aligned} \tag{27}$$

Step 3: Compute the Kalman gain and the process noise gain of optimal CFAKF algorithm.

$$\begin{aligned}K'_c(k) = {} & P'_c(k|k-1)C^T(k)[C(k)P'_c(k|k-1)C^T(k) \\ & +R(k)]^{-1}\end{aligned} \tag{28}$$

$$K'_{cw}(k) = S(k)[C(k)P'_c(k|k-1)C^T(k)+R(k)]^{-1} \tag{29}$$

Step 4: Compute the update values of the process noise, state and error covariance.

$$\hat{w}'_c(k|k) = K'_{cw}(k)[z(k)-C(k)\hat{X}_c(k|k-1)] \tag{30}$$

$$\begin{aligned}\hat{X}'_c(k|k) = {} & \hat{X}_c(k|k-1)+K'_c(k)[z(k) \\ & -C(k)\hat{X}_c(k|k-1)]\end{aligned} \tag{31}$$

$$P'_c(k|k) = P'_c(k|k-1)-K'_c(k)C(k)P'_c(k|k-1) \tag{32}$$

Remark 2: The proposed optimal CFAKF algorithm has similar operations with optimal CFKF algorithm. The only difference is that τ_k and λ_k are added. And the addition will slightly increase the computation costs. Therefore, the proposed optimal CFAKF algorithm can be used for complex dynamic systems with uncertainties or great noises without posing excessive computation load.

C. OPTIMAL IMMCFAKF ALGORITHM

First, suppose that there are r models:

$$X(k+1) = A_j(k)X(k) + w_j(k), \quad j = 1, \cdots, r \tag{33}$$

where $w_j(k)$ is zero-mean Gaussian white noise of the jth model, and $Q_j(k)$ is the process noise covariance of the jth model. A Markov chain is used to control the transition between these models, and the transition probability matrix of the Markov chain is given by:

$$P = \begin{bmatrix} p_{11} & \cdots & p_{1r} \\ \vdots & \ddots & \vdots \\ p_{r1} & \cdots & p_{rr} \end{bmatrix}$$

Then, the pseudo measurement equation for the jth model can be expressed as:

$$z(k) = C(k)X_j(k) + v(k), j = 1, \cdots, r \tag{34}$$

where $v(k)$ is zero-mean Gaussian white noise for the jth model, and $R(k)$ is the pseudo measurement noise covariance for the jth model.

According to general interacting multiple model (IMM) algorithm [32] and optimal CFAKF algorithm, the optimal IMMCFAKF algorithm is given as follows:

Step 1: Input interacting for model j.

The transition probability from model i to model j: p_{ij}.

The probability of model j at time $k-1$: $\mu_j(k-1)$.

The prediction probability of model j: $\bar{c}_j = \sum_{i=1}^{r} p_{ij}\mu_i(k-1)$.

The mixture probability from model i to model j: $\mu_{ij}(k-1|k-1) = \sum_{i=1}^{r} p_{ij}\mu_i(k-1)/\bar{c}_j$.

The hybrid state estimation of model j: $\hat{X}_{0j}(k-1|k-1) = \sum_{i=1}^{r} \hat{X}_i(k-1|k-1)\mu_{ij}(k-1|k-1)$.

The hybrid error covariance of model j: $P_{0j}(k-1|k-1) = \sum_{i=1}^{r} \mu_{ij}(k-1|k-1)\{P_i(k-1|k-1) + [\hat{X}_i(k-1|k-1) - \hat{X}_{0j}(k-1|k-1)][\hat{X}_i(k-1|k-1) - \hat{X}_{0j}(k-1|k-1)]^T\}$.

Step 2: Optimal centralized fusion adaptive Kalman filtering for model j with inputs $\hat{X}_{0j}(k-1/k-1)$, $P_{0j}(k-1/k-1)$ and $z(k)$.

Compute the one-step prediction state estimation and the one-step prediction error covariance.

$$\begin{aligned} \hat{X}_j^c(k|k-1) &= A_j(k-1)\hat{X}_{0j}(k-1|k-1) \\ &\quad + \hat{w}_j^c(k-1|k-1) \end{aligned} \tag{35}$$

$$\begin{aligned} P_j^c(k|k-1) &= A_j(k)P_{0j}(k-1|k-1)A_j^T(k) \\ &\quad + A_j(k)P_{j,\tilde{x}\tilde{w}}^c(k-1|k-1) \\ &\quad + P_{j,\tilde{w}\tilde{x}}^c(k-1|k-1)A_j^T(k) \\ &\quad + P_{j,\tilde{w}}^c(k-1|k-1) \end{aligned} \tag{36}$$

where $P_{j,\tilde{x}\tilde{w}}^c(k|k) = -K'_{j,c}(k)S^T(k)$ and $P_{j,\tilde{w}}^c(k|k) = Q_j(k) - K'_{j,cw}(k)S^T(k)$.

Compute the modified one-step prediction error covariance and the innovation covariance.

$$P'_{j,c}(k|k-1) = \lambda_{j,k}P_j^c(k|k-1) \tag{37}$$

$$\begin{aligned} \Lambda'_j(k) &= \tau_{j,k}\Lambda_j(k) \\ &= \tau_{j,k}[C(k)P_j^c(k|k-1)C^T(k) + R(k)] \\ &= C(k)P'_{j,c}(k|k-1)C^T(k) + R(k) \end{aligned} \tag{38}$$

where

$$\tau_{j,k} = max\left\{1, \frac{1}{m}tr(\Lambda'_j(k)\Lambda_j^{-1}(k))\right\} \quad or \quad max\left\{1, \frac{tr(\Lambda'_j(k))}{tr(\Lambda_j^{-1}(k))}\right\}$$

and

$$\lambda_{j,k} = max\left\{1, \frac{tr(\Lambda'_j(k) - R(k))}{tr(C(k)P_j^c(k|k-1)C^T(k))}\right\}$$

Compute the Kalman gain and the process noise gain.

$$\begin{aligned} K'_{j,c}(k) &= P'_{j,c}(k|k-1)C^T(k)[C(k)P'_{j,c}(k|k-1)C^T(k) \\ &\quad + R(k)]^{-1} \end{aligned} \tag{39}$$

$$K'_{j,cw}(k) = S(k)[C(k)P'_{j,c}(k|k-1)C^T(k) + R(k)]^{-1} \tag{40}$$

Compute the update values of the process noise, state and error covariance.

$$\hat{w}'_{j,c}(k|k) = K'_{j,cw}(k)[z(k) - C(k)\hat{X}_j^c(k|k-1)] \tag{41}$$

$$\begin{aligned} \hat{X}'_{j,c}(k|k) &= \hat{X}_j^c(k|k-1) + K'_{j,c}(k)[z(k) \\ &\quad - C(k)\hat{X}_j^c(k|k-1)] \end{aligned} \tag{42}$$

$$P'_{j,c}(k|k) = P'_{j,c}(k|k-1) - K'_{j,c}(k)C(k)P'_{j,c}(k|k-1) \tag{43}$$

Step 3: Model probability updation.

The likelihood function of model j: $\Omega_j(k) = \frac{1}{(2\pi)^{n/2}|\Lambda'_j(k)|^{1/2}exp\{-\frac{1}{2}\nu_j^T[\Lambda'_j(k)]^{-1}\nu_j\}}$, where $\nu_j = z(k) - C(k)\hat{X}_j^c(k|k-1)$ and $\Lambda'_j(k) = C(k)P'_{j,c}(k|k-1)C^T(k)+R(k)$.

The probability of model j at time k: $\mu_j(k) = \Omega_j(k)\bar{c}_j/c$, where c is a normalization constant, and $c = \sum_{j=1}^{r} \Omega_j(k)\bar{c}_j$.

Step 4: Output interacting.

The total state estimation: $\hat{X}_{0j}(k-1|k-1) = \sum_{i=1}^{r} \hat{X}_i(k-1|k-1)\mu_{ij}(k-1|k-1)$.

The total estimation error covariance: $P_{0j}(k-1|k-1) = \sum_{i=1}^{r} \mu_{ij}(k-1|k-1)\{P_i(k-1|k-1) + [\hat{X}_i(k-1|k-1) - \hat{X}_{0j}(k-1|k-1)][\hat{X}_i(k-1|k-1) - \hat{X}_{0j}(k-1|k-1)]^T\}$.

IV. NUMERICAL SIMULATION AND EXPERIMENT

In this section, we use a numerical simulation and an experiment to demonstrate the performance and effectiveness of our proposed algorithm.

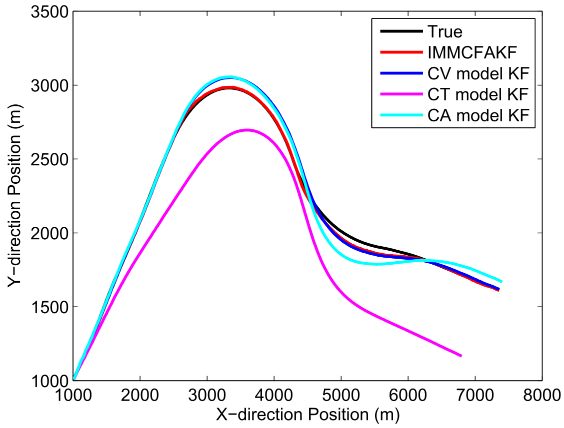


FIGURE 1. The true trajectory and the results of the optimal IMMCFAKF and three kind of model KFs.

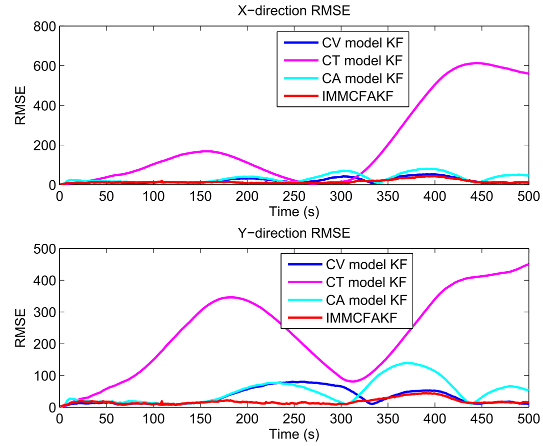


FIGURE 2. RMSEs of positions in X-direction and Y-direction of the optimal IMMCFAKF and three kind of model KFs.

A. NUMERICAL SIMULATION

For the simulation purpose, the target initial position coordinate $(x(0), y(0))$ is set as $(1000m, 1000m)$. The initial velocity $(\dot{x}(0), \dot{y}(0))$ is set as $(10m/s, 10m/s)$. The sample period is $T = 1s$. The angular velocity of CT model is $\omega = -\frac{\pi}{270} rad/s$, namely, it is a clockwise constant turning motion. The $(\ddot{x}(k), \ddot{y}(k))$ of CA model is $(5m/s^2, 5m/s^2)$, namely, it is a constant acceleration motion. x and y are independently observed. Their standard deviations both are 50m. The target motion model is CV model in $1s - 150s$. The target motion model is CT model in $151s - 300s$. The target motion model is CA model in $301s - 400s$. The target motion model is CV model in $401s - 500s$.

In our proposed optimal IMMCFAKF algorithm, we use a model sets, including CV, CT and CA models. The transition probability matrix of the Markov chain is given by:

$$P_1 = \begin{bmatrix} 0.98 & 0.01 & 0.01 \\ 0.01 & 0.98 & 0.01 \\ 0.01 & 0.01 & 0.98 \end{bmatrix}.$$

The number of Monte Carlo simulation is 100. The true trajectory of the target motion is shown in Fig. 1. And Fig. 1 depicts the results of the optimal IMMCFAKF and CV, CT, CA model Kalman filters (KFs). From Fig. 1, it can be seen that 1) the result of CT model KF and the real value has a large deviation, 2) the results of CV and VA model KFs and the real value has a certain degree of deviation in turning a corner, and 3) the result of the optimal IMMCFAKF algorithm can better track the target. It is the best in the tracking effect of four kinds of filters.

The root mean square errors (RMSEs) of positions in X-direction and Y-direction of the optimal IMMCFAKF and three kind of model KFs are depicted in Fig. 2. Meanwhile, the model probability of three kind of model KFs are shown in Fig. 3.

From Fig. 2, we can see that RMSEs of positions in X-direction and Y-direction of the optimal IMMCFAKF is smaller than that of other three kind of model KFs as a whole. Meanwhile, it can be seen from Fig. 3 that the model

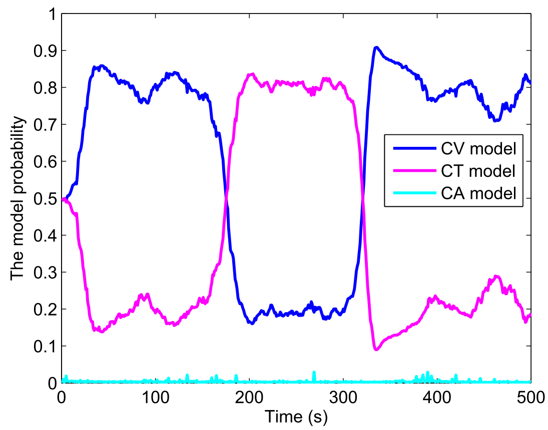


FIGURE 3. The model probability of three kind of model KFs when the Markov transition probability matrix is P_1.

probability of CA model tends to zero, and the model probability of CT model is greater than that of CV model in the stage of CT motion. At this stage the optimal IMMCFAKF depends on CT model. However, CV model play a major role at other stage, which is consistent with our experience. The optimal IMMCFAKF algorithm is used to complete maneuvering target tracking by automatically adjusting the model probability of each model. Compared with the single model KF, the optimal IMMCFAKF algorithm has a better tracking accuracy.

Next, the influence of different Markov transition probability matrix on the tracking results are discussed.

(1) The transition probability matrix of the Markov chain is given by:

$$P_2 = \begin{bmatrix} 0.32 & 0.33 & 0.35 \\ 0.33 & 0.35 & 0.32 \\ 0.35 & 0.32 & 0.33 \end{bmatrix}$$

It can be observed from Fig. 4 that all the model probability change trend is not big, but the model probability of CV and CT models have very slight differences and are greater

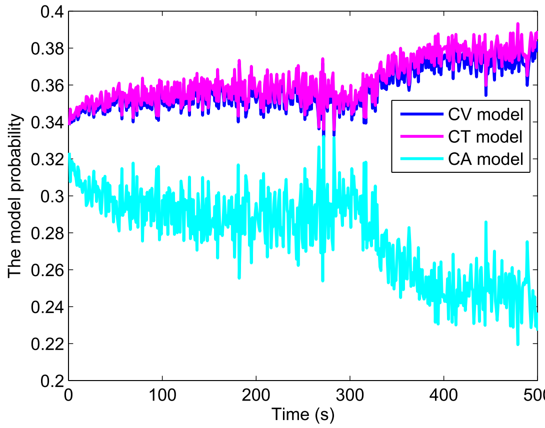


FIGURE 4. The model probability of three kind of model KFs when the Markov transition probability matrix is P_2.

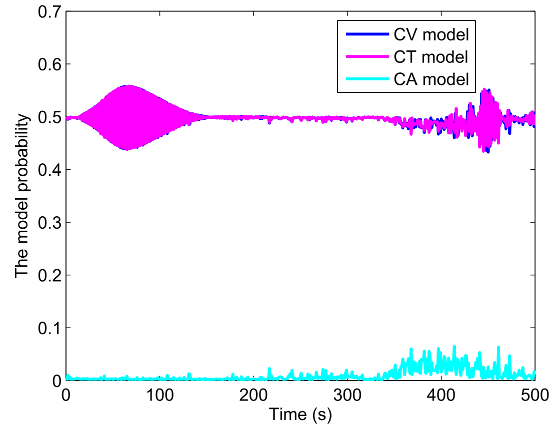


FIGURE 6. The model probability of three kind of model KFs when the Markov transition probability matrix is P_3.

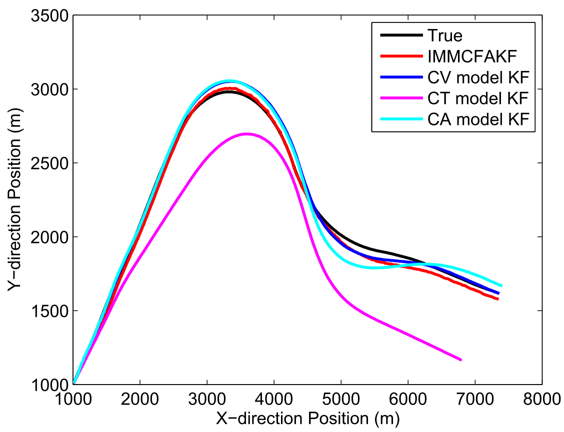


FIGURE 5. Positions in X-direction and Y-direction of the optimal IMMCFAKF and three kind of model KFs when the Markov transition probability matrix is P_2.

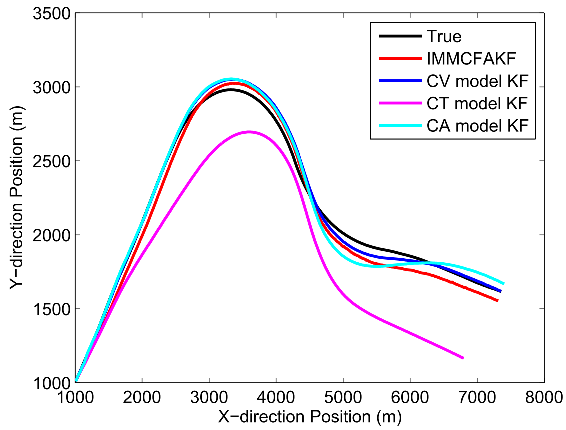


FIGURE 7. Positions in X-direction and Y-direction of the optimal IMMCFAKF and three kind of model KFs when the Markov transition probability matrix is P_3.

than that of CA model. Compared with the single model KF in Fig. 5, the optimal IMMCFAKF algorithm has a better tracking accuracy in the part about $x \leq 5300m$ of the whole stage. However, its tracking accuracy is lower than that of CV model KF in the rest of the whole stage, and lower than that of the optimal IMMCFAKF when the Markov transition probability matrix is P_1.

(2) The transition probability matrix of the Markov chain is given by:

$$P_3 = \begin{bmatrix} 0.01 & 0.98 & 0.01 \\ 0.98 & 0.01 & 0.01 \\ 0.01 & 0.01 & 0.98 \end{bmatrix}$$

Fig. 6 shows that the model probability of CV and CT models are almost coincident, and the model probability of CA model tends to zero. From Fig. 7, we can see that the tracking accuracy of the optimal IMMCFAKF algorithm is lower than that of CV model KF in the bulk of the whole stage, and lower than that of the optimal IMMCFAKF when the Markov transition probability matrix is P_1 or P_2.

(3) The transition probability matrix of the Markov chain is given by:

$$P_4 = \begin{bmatrix} 0.01 & 0.01 & 0.98 \\ 0.01 & 0.98 & 0.01 \\ 0.98 & 0.01 & 0.01 \end{bmatrix}$$

It can be seen from Fig. 8 that the model probability of CV and CA models are completely coincident, and the model probability of CA model tends to zero. The model probability of CT model is greater than that of CV and CA models in the stage of CT motion. At this stage the optimal IMMCFAKF depends on CT model. However, CV and CA models play a major role at other stage. Fig. 9 shows that the tracking accuracy of the optimal IMMCFAKF algorithm is better than that of CV, CT, CA model KFs, and roughly equivalent to that of the optimal IMMCFAKF when the Markov transition probability matrix is P_1.

In summary, the greater the sum of the diagonal or anti diagonal elements of the Markov transition probability matrix, the higher the tracking accuracy of the optimal IMMCFAKF. On the contrary, the lower the tracking accuracy of that.

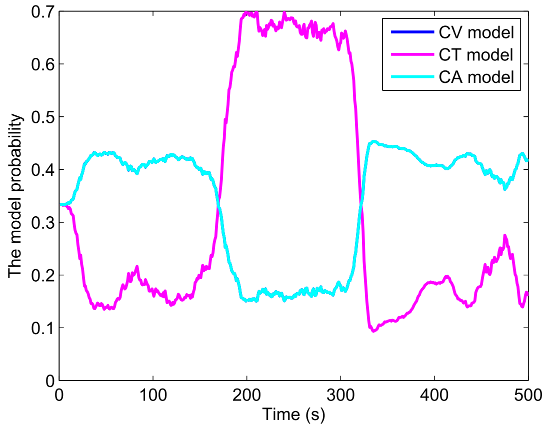


FIGURE 8. The model probability of three kind of model KFs when the Markov transition probability matrix is P_4.

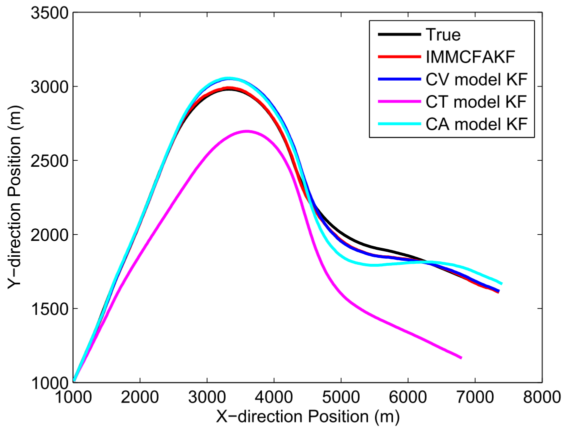


FIGURE 9. Positions in X-direction and Y-direction of the optimal IMMCFAKF and three kind of model KFs when the Markov transition probability matrix is P_4.

V. CONCLUSIONS

In this paper, an optimal IMMCFAKF algorithm has been proposed for tracking the moving targets in UASNs. Firstly, the optimal CFAKF algorithm is presented, which introduce an adaptive forgetting factor into the optimal CFKF algorithm. Secondly, the optimal IMMCFAKF algorithm is proposed based on the optimal CFAKF algorithm. The proposed optimal IMMCFAKF algorithm possesses the advantages of both the optimal CFAKF algorithm and the conventional IMM algorithm. Finally, simulation results and experiment results have been summarized as follows: 1) the tracking accuracy of the optimal IMMCFAKF is the best in the tracking effect of four kind of filters, and the relationship of different Markov transition probability matrix and the tracking accuracy of the optimal IMMCFAKF is verified and given. The proposed algorithm can be used in many ocean monitoring and exploration applications. In future work, we will focus on noise correlation and distributed fusion in IMM algorithm for target tracking in UASNs.

APPENDIX

The Process Derivation of optimal CFKF Algorithm: If all the measurements are reliable, by using the projection theory [56], the innovation sequence $\tilde{z}(k|k-1)$ is defined as follows

$$\tilde{z}(k|k-1) = z(k) - \hat{z}(k|k-1) \tag{44}$$

where

$$\hat{z}(k|k-1) = C(k)\hat{X}_c(k|k-1) \tag{45}$$

Then, substituting (45) to (44) yields

$$\tilde{z}(k|k-1) = z(k) - C(k)\hat{X}_c(k|k-1) \tag{46}$$

According to the projection theory [56], we have the following fusion filter estimation

$$\hat{X}_c(k|k) = \hat{X}_c(k|k-1) + K_c(k)\tilde{z}(k|k-1) \tag{47}$$

Next, based on the projection theory [56], we have the following fusion filter error and one-step prediction error for the state

$$\begin{aligned}\tilde{X}_c(k|k) &= X(k) - \hat{X}_c(k|k)\\ &= \tilde{X}_c(k|k-1) - K_c(k)\tilde{z}(k|k-1)\end{aligned} \tag{48}$$

$$\begin{aligned}\tilde{X}_c(k|k-1) &= x(k) - \hat{X}_c(k|k-1)\\ &= A(k-1)\tilde{x}_c(k-1|k-1) + \tilde{w}_c(k-1|k-1)\end{aligned} \tag{49}$$

Then, another form of the innovation sequence as follows

$$\tilde{z}(k|k-1) = C(k)\tilde{X}_c(k|k-1) + v(k) \tag{50}$$

From the projection theory [56], we have the following white noise filter and the noise filter error

$$\begin{aligned}\hat{w}_c(k|k) &= \hat{w}_c(k|k-1) + K_w^c(k)\tilde{z}(k|k-1)\\ &= K_w^c(k)\tilde{z}(k|k-1)\end{aligned} \tag{51}$$

$$\begin{aligned}\tilde{w}_c(k|k) &= w(k) - \hat{w}_c(k|k)\\ &= w(k) - K_w^c(k)\tilde{z}(k|k-1)\end{aligned} \tag{52}$$

We have the covariance matrix of $\tilde{z}(k|k-1)$

$$\begin{aligned}P_{\tilde{z}}(k) &= E\{\tilde{z}(k|k-1)\tilde{z}^T(k|k-1)\}\\ &= E\{(C(k)\tilde{X}_c(k|k-1) + v(k))\\ &\quad \times(C(k)\tilde{X}_c(k|k-1) + v(k))^T\}\\ &= C(k)P_c(k|k-1)C^T(k) + R(k)\end{aligned} \tag{53}$$

The gain for the white noise is computed by

$$\begin{aligned}K_w^c(k) &= E\{w(k)\tilde{z}^T(k|k-1)\}P_{\tilde{z}}^{-1}(k)\\ &= E\{w(k)(C(k)\tilde{X}_c(k|k-1) + v(k))^T\}P_{\tilde{z}}^{-1}(k)\\ &= E\{w(k)v^T(k)\}P_{\tilde{z}}^{-1}(k) = S(k)P_{\tilde{z}}^{-1}(k)\end{aligned} \tag{54}$$

Similarly, we define the fusion filter gain for the state as follows

$$K_c(k) = E\{X(k)\tilde{z}^T(k|k-1)\}P_{\tilde{z}}^{-1}(k) \tag{55}$$

where,

$$\begin{aligned}E\{X(k)\tilde{z}^T(k|k-1)\} &= E\{X(k)[C(k)\tilde{X}_c(k|k-1)+v(k)]^T\}\\ &= E\{X(k)\tilde{X}_c^T(k|k-1)C^T(k)\}\\ &\quad +E\{X(k)v^T(k)\}\\ &= P_c(k|k-1)C^T(k) \end{aligned}\tag{56}$$

Then, we have

$$K_c(k) = P_c(k|k-1)C^T(k)P_{\tilde{z}}^{-1}(k)\tag{57}$$

Substituting (48) into $P_c(k|k)$, where $P_c(k|k) = E\{\tilde{X}_c(k|k)\tilde{X}_c^T(k|k)\}$, we have the error covariance matrix for the state

$$\begin{aligned}P_c(k|k) &= P_c(k|k-1) - E\{\tilde{X}_c(k|k-1)\tilde{z}^T(k|k-1)\}K_c^T(k)\\ &\quad - K_c(k)E\{\tilde{z}(k|\,k-1)\tilde{X}_c^T(k|\,k-1)\}\\ &\quad + K_c(k)P_{\tilde{z}}(k)K_c^T(k)\\ &= P_c(k|k-1) - K_c(k)E\{\tilde{z}(k|k-1)\tilde{X}_c^T(k|k-1)\}\\ &= P_c(k|k-1) - K_c(k)C(k)P_c(k|k-1)\\ &= P_c(k|k-1) - K_c(k)P_{\tilde{z}}(k)K_c^T(k)\end{aligned}\tag{58}$$

Then, substituting (49) into $P_c(k|k-1)$, where $P_c(k|k-1) = E\{\tilde{X}_c(k|k-1)\tilde{X}_c^T(k|k-1)\}$, we have the prediction error covariance matrix

$$\begin{aligned}&P_c(k|\,k-1)\\ &\quad = E\{\tilde{X}_c(k|k-1)\tilde{X}_c^T(k|k-1)\}\\ &\quad = A(k)P_c(k-1|k-1)A^T(k)\\ &\qquad + A(k)E\{\tilde{X}_c(k-1|\,k-1)\tilde{w}_c^T(k-1|\,k-1)\}\\ &\qquad + E\{\tilde{w}_c(k-1|\,k-1)\tilde{X}_c^T(k-1|\,k-1)\}A^T(k)\\ &\qquad + E\{\tilde{w}_c(k-1|\,k-1)\tilde{w}_c^T(k-1|\,k-1)\}\\ &\quad = A(k)P_c(k-1|k-1)A^T(k)\\ &\qquad + A(k)P_{\tilde{x}\tilde{w}}^c(k-1|k-1)\\ &\qquad + P_{\tilde{w}\tilde{x}}^c(k-1|\,k-1)A^T(k)\\ &\qquad + P_{\tilde{w}}^c(k-1|\,k-1)\end{aligned}\tag{59}$$

where

$$\begin{aligned}P_{\tilde{x}\tilde{w}}^c(k|k) &= E\{\tilde{X}_c(k|k)\tilde{w}_c^T(k|k)\}\\ &= E\{[\tilde{X}_c(k|k-1) - K_c(k)\tilde{z}(k|k-1)]\\ &\qquad \times [w(k) - K_w^c(k)\tilde{z}(k|k-1)]^T\}\\ &= -E\{\tilde{X}_c(k|k-1)\tilde{z}^T(k|k-1)\}K_w^{c,T}(k)\\ &\quad - K_c(k)E\{\tilde{z}(k|k-1)w^T(k)\}\\ &\quad + K_c(k)E\{\tilde{z}(k|k-1)\tilde{z}^T(k|k-1)\}K_w^{c,T}(k)\\ &= -K_c(k)P_{\tilde{z}}(k)K_w^{c,T}(k) = -K_c(k)S^T(k)\end{aligned}\tag{60}$$

and

$$\begin{aligned}P_{\tilde{w}}^c(k|k) &= E\{\tilde{w}_c(k|k)\tilde{w}_c^T(k|k)\}\\ &= E\{[w(k) - K_w^c(k)\tilde{z}(k|k-1)]\\ &\qquad \times[w(k) - K_w^c(k)\tilde{z}(k|k-1)]^T\}\\ &= Q(k) - K_w^c(k)P_{\tilde{z}}(k)K_w^{c,T}(k)\\ &\quad - K_w^c(k)P_{\tilde{z}}(k)K_w^{c,T}(k) + K_w^c(k)P_{\tilde{z}}(k)K_w^{c,T}(k)\\ &= Q(k) - K_w^c(k)P_{\tilde{z}}(k)K_w^{c,T}(k)\\ &= Q(k) - K_w^c(k)S^T(k)\end{aligned}\tag{61}$$

ACKNOWLEDGMENT

The authors would like to thank the Associate Editor and the anonymous reviewers for their constructive suggestions and comments, which are very valuable for improving the quality of the paper.

REFERENCES

[1] G. Han, S. Shen, H. Song, T. Yang, and W. Zhang, "A stratification-based data collection scheme in underwater acoustic sensor networks," *IEEE Trans. Veh. Technol.*, vol. 67, no. 11, pp. 10671–10682, Nov. 2018.

[2] G. Han, J. Jiang, L. Shu, and M. Guizani, "An attack-resistant trust model based on multidimensional trust metrics in underwater acoustic sensor network," *IEEE Trans. Mobile Comput.*, vol. 14, no. 12, pp. 2447–2459, Dec. 2015.

[3] J. Jiang, G. Han, C. Zhu, S. Chan, and J. J. P. C. Rodrigues, "A trust cloud model for underwater wireless sensor networks," *IEEE Commun. Mag.*, vol. 55, no. 3, pp. 110–116, Mar. 2017.

[4] J. Jiang, G. Han, L. Shu, S. Chan, and K. Wang, "A trust model based on cloud theory in underwater acoustic sensor networks," *IEEE Trans. Ind. Informat.*, vol. 13, no. 1, pp. 342–350, Feb. 2017.

[5] A. A. Syed, W. Ye, and J. Heidemann, "T-Lohi: A new class of MAC protocols for underwater acoustic sensor networks," in *Proc. IEEE 27th Conf. Comput. Commun. (INFOCOM)*, Phoenix, AZ, USA, Apr. 2008, pp. 231–235.

[6] V. Kebkal, O. Kebkal, and K. Kebkal, "Network coding for underwater acoustic sensor networks," in *Proc. MTS/IEEE OCEANS*, Bergen, Norway, Jun. 2013, pp. 1–5. doi: 10.1109/OCEANS-Bergen.2013.6607957.

[7] M. Li, Y. Sun, Y. Jiang, and Z. Tian, "Answering the min-cost quality-aware query on multi-sources in sensor-cloud systems," *Sensors*, vol. 18, no. 12, p. 4486, 2019.

[8] C. Zhu, V. C. M. Leung, K. Wang, L. T. Yang, and Y. Zhang, "Multi-method data delivery for green sensor-cloud," *IEEE Commun. Mag.*, vol. 55, no. 5, pp. 176–182, May 2017.

[9] C. Zhu, L. Shu, V. C. M. Leung, S. Guo, Y. Zhang, and L. T. Yang, "Secure multimedia big data in trust-assisted sensor-cloud for smart city," *IEEE Commun. Mag.*, vol. 55, no. 12, pp. 24–30, Dec. 2017.

[10] Y. Wang, Z. Tian, H. Zhang, S. Su, and W. Shi, "A privacy preserving scheme for nearest neighbor query," *Sensors*, vol. 18, no. 8, p. 2440, 2018. doi: 10.3390/s18082440.

[11] C. Zhu, J. J. P. C. Rodrigues, V. C. M. Leung, L. Shu, and L. T. Yang, "Trust-based communication for the industrial Internet of Things," *IEEE Commun. Mag.*, vol. 56, no. 2, pp. 16–22, Feb. 2018.

[12] C. Zhu, V. C. M. Leung, J. J. P. C. Rodrigues, L. Shu, L. Wang, and H. Zhou, "Social sensor cloud: Framework, greenness, issues, and outlook," *IEEE Netw.*, vol. 32, no. 5, pp. 100–105, Sep./Oct. 2018.

[13] W. Han, Z. Tian, Z. Huang, S. Li, and Y. Jia, "Bidirectional self-adaptive resampling in Internet of Things big data learning," in *Multimedia Tools and Applications*. New York, NY, USA: Springer, 2018. doi: 10.1007/s11042-018-6938-9.

[14] Z. H. Wang, C. Liu, J. Qiu, Z. Tian, X. Cui, and S. Su, "Automatically traceback RDP-based targeted ransomware attacks," *Wireless Commun. Mobile Comput.*, vol. 2018, Dec. 2018, Art. no. 7943586. doi: 10.1155/2018/7943586.

[15] Z. Tian, S. Su, W. Shi, X. Du, M. Guizani, and X. Yu, "A data-driven method for future Internet route decision modeling," *Future Gener. Comput. Syst.*, vol. 95, pp. 212–220, Jun. 2018. doi: 10.1016/j.future.2018.12.054.

[16] J. Qiu, Y. Chai, Y. Liu, Z. Gu, S. Li, and Z. Tian, "Automatic non-taxonomic relation extraction from big data in smart city," *IEEE Access*, vol. 6, pp. 74854–74864, 2018. doi: 10.1109/ACCESS.2018.2881422.

[17] Y. B. Sun, M. H. Li, S. Su, Z. H. Tian, W. Shi, and M. Han, "Secure data sharing framework via hierarchical greedy embedding in darknets," in *Mobile Networks and Applications*. New York, NY, USA: Springer, to be published.

[18] X. Yu, Z. Tian, J. Qiu, and F. Jiang, "A data leakage prevention method based on the reduction of confidential and context terms for smart mobile devices," *Wireless Commun. Mobile Comput.*, vol. 2018, Oct. 2018, Art. no. 5823439. doi: 10.1155/2018/5823439.

[19] Z. Tian *et al.*, "A real-time correlation of host-level events in cyber range service for smart campus," *IEEE Access*, vol. 6, pp. 35355–35364, 2018. doi: 10.1109/ACCESS.2018.2846590.

[20] Q. Tan, Y. Gao, J. Shi, X. Wang, B. Fang, and Z. Tian, "Towards a comprehensive insight into the eclipse attacks of Tor hidden services," *IEEE Internet Things J.*, to be published. doi: 10.1109/JIOT.2018.2846624.
[21] J. Chen, Z. Tian, X. Cui, L. Yin, and X. Wang, "Trust architecture and reputation evaluation for Internet of Things," in *Journal of Ambient Intelligence and Humanized Computing*, vol. 2. Berlin, Germany: Springer, 2018, pp. 1–9.
[22] C. Zhu, H. Zhou, V. C. M. Leung, K. Wang, Y. Zhang, and L. T. Yang, "Toward big data in green city," *IEEE Commun. Mag.*, vol. 55, no. 11, pp. 14–18, Nov. 2017.
[23] X. Xu, Z. Rong, Z.-X. Wu, T. Zhou, and C. K. Tse, "Extortion provides alternative routes to the evolution of cooperation in structured populations," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 95, nos. 1–5, 2017, Art. no. 052302.
[24] Y. Mao, X. Xu, Z. Rong, and Z.-X. Wu, "The emergence of cooperation-extortion alliance on scale-free networks with normalized payoff," *EPL (Europhys. Lett.)*, vol. 122, no. 5, p. 50005, 2018.
[25] I. F. Akyildiz, D. Pompili, and T. Melodia, "Challenges for efficient communication in underwater acoustic sensor networks," *ACM SIGBED Rev.*, vol. 1, no. 2, pp. 3–8, Jul. 2004. doi: 10.1145/1121776.1121779.
[26] I. F. Akyildiz, D. Pompili, and T. Melodia, "Underwater acoustic sensor networks: Research challenges," *Ad Hoc Netw.*, vol. 3, no. 3, pp. 257–279, Mar. 2005. doi: 10.1016/j.adhoc.2005.01.004.
[27] M. Sharif-Yazd, M. R. Khosravi, and M. K. Moghimi, "A survey on underwater acoustic sensor networks: Perspectives on protocol design for signaling, MAC and routing," *J. Comput. Commun.*, vol. 5, no. 5, pp. 12–23, 2017. doi: 10.4236/jcc.2017.55002.
[28] C. Wu, C. Zhao, and H. Gong, "Energy-efficient target tracking algorithm for WSNs," *3D Res.*, vol. 10, p. 1, Mar. 2019. doi: 10.1007/s13319-018-0210-y.
[29] Y. Xia, J. Shang, J. Chen, and G.-P. Liu, "Networked data fusion with packet losses and variable delays," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 39, no. 5, pp. 1107–1120, Oct. 2009.
[30] X. Yang, W.-A. Zhang, M. Z. Q. Chen, and L. Yu, "Hybrid sequential fusion estimation for asynchronous sensor network-based target tracking," *IEEE Trans. Control Syst. Technol.*, vol. 25, no. 2, pp. 669–676, Mar. 2017.
[31] H. A. P. Blom, "An efficient filter for abruptly changing systems," in *Proc. 23rd IEEE Conf. Decis. Control*, Las Vegas, NV, USA, Dec. 1984, pp. 656–658.
[32] L. Hong and Z. Ding, "A distributed multirate IMM algorithm for multiplatform tracking," in *Proc. Amer. Control Conf.*, Albuquerque, NM, USA, Jun. 1997, pp. 1458–1462.
[33] H. Song, V. Shin, and M. Jeon, "Mobile node localization using fusion prediction-based interacting multiple model in cricket sensor network," *IEEE Trans. Ind. Electron.*, vol. 59, no. 11, pp. 4349–4359, Nov. 2012.
[34] Z. Ding and L. Hong, "A distributed IMM fusion algorithm for multiplatform tracking," *Signal Process.*, vol. 64, no. 2, pp. 167–176, Jan. 1998.
[35] W. Li and Y. Jia, "An information theoretic approach to interacting multiple model estimation," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 51, no. 3, pp. 1811–1825, Jul. 2015.
[36] X. Fu, Y. Shang, and H. Yuan, "Improved diagonal interacting multiple model algorithm for manoeuvering target tracking based on H_∞ filter," *IET Control Theory Appl.*, vol. 9, no. 12, pp. 1887–1892, Aug. 2015.
[37] I. Hwang, C. E. Seah, and S. Lee, "A study on stability of the interacting multiple model algorithm," *IEEE Trans. Autom. Control*, vol. 62, no. 2, pp. 901–906, Feb. 2017.
[38] L. Hong, S. Cong, and D. Wicker, "Distributed multirate interacting multiple model fusion (DMRIMMF) with application to out-of-sequence GMTI data," *IEEE Trans. Autom. Control*, vol. 49, no. 1, pp. 102–107, Jan. 2004.
[39] D. Mohammed, K. Mokhtar, O. Abdelaziz, and M. Abdelkrim, "A new IMM algorithm using fixed coefficients filters (fastIMM)," *AEU-Int. J. Electron. Commun.*, vol. 64, no. 12, pp. 1123–1127, Dec. 2010.
[40] Y. Hu, X. He, L. Zhang, and C. Sun, "IMM fusion estimation with multiple asynchronous sensors," *Signal Process.*, vol. 102, pp. 46–57, Sep. 2014.
[41] M. Sun, Z. Ma, and Y. Li, "Maneuvering target tracking using IMM Kalman filter aided by Elman neural network," in *Proc. 7th Int. Conf. Intell. Hum.-Mach. Syst. Cybern.*, Hangzhou, China, Aug. 2015, pp. 144–148.
[42] B. S. Chen, C. Y. Yang, F. K. Liao, and J. F. Liao, "Mobile location estimator in a rough wireless environment using extended Kalman-based IMM and data fusion," *IEEE Trans. Veh. Technol.*, vol. 58, no. 3, pp. 1157–1169, Mar. 2009.
[43] Y. Gao, X. R. Li, and Z. Duan, "Estimation fusion for Markovian jump linear system via data transformation," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 50, no. 1, pp. 240–253, Jan. 2014.
[44] Z. Xing and Y. Xia, "Comparison of centralised scaled unscented Kalman filter and extended Kalman filter for multisensor data fusion architectures," *IET Signal Process.*, vol. 10, no. 4, pp. 359–365, 2016.
[45] C. Zhu, Y. Xia, L. Yan, and M. Fu, "Centralised fusion over unreliable networks," *Int. J. Control*, vol. 85, no. 4, pp. 409–418, Apr. 2012.
[46] W. Li, Y. Jia, J. Du, and J. Zhang, "Distributed multiple-model estimation for simultaneous localization and tracking with NLOS mitigation," *IEEE Trans. Veh. Technol.*, vol. 62, no. 6, pp. 2824–2830, Jul. 2013.
[47] Z. Xing, Y. Xia, L. Yan, K. Lu, and Q. Gong, "Multisensor distributed weighted Kalman filter fusion with network delays, stochastic uncertainties, autocorrelated, and cross-correlated noises," *IEEE Trans. Syst., Man, Cybern. B, Cybern.*, vol. 48, no. 5, pp. 716–726, May 2018. doi: 10.1109/TSMC.2016.2633283.
[48] Z. Xing and Y. Xia, "Distributed federated Kalman filter fusion over multi-sensor unreliable networked systems," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 63, no. 10, pp. 1714–1725, Oct. 2016.
[49] L. Hong, "Multiresolutional filtering using wavelet transform," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 29, no. 4, pp. 1244–1251, Oct. 1993.
[50] D. Jeon and Y. Eun, "Distributed asynchronous multiple sensor fusion with nonlinear multiple models," *Aerosp. Sci. Technol.*, vol. 39, no. 12, pp. 692–704, Dec. 2014.
[51] W. Li and Y. Jia, "Distributed interacting multiple model H_∞ filtering fusion for multiplatform maneuvering target tracking in clutter," *Signal Process.*, vol. 90, no. 5, pp. 1655–1668, May 2010.
[52] Y. Hu, Z. Duan, and D. Zhou, "Estimation fusion with general asynchronous multi-rate sensors," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 46, no. 4, pp. 2090–2102, Oct. 2010.
[53] Y. Hu, Z. Duan, and C. Han, "Optimal batch asynchronous fusion algorithm," in *Proc. IEEE Int. Conf. Veh. Electron. Saf.*, Shaan'xi, China, Oct. 2005, pp. 237–240.
[54] Y. Liang, D. X. An, D. H. Zhou, and Q. Pan, "A finite-horizon adaptive Kalman filter for linear systems with unknown disturbances," *Signal Process.*, vol. 84, no. 11, pp. 2175–2194, Nov. 2004.
[55] K. H. Kim, J. G. Lee, and C. G. Park, "Adaptive two-stage extended Kalman filter for a fault-tolerant INS-GPS loosely coupled system," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 45, no. 1, pp. 125–137, Jan. 2009.
[56] B. D. O. Anderson and J. B. Moore, *Optimal Filtering*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1979.

JING QIU received the Ph.D. degree in computer applications technology from the Beijing Institute of Technology. She was a Visiting Scholar with the University of Southern California, Los Angeles, CA, USA, under the supervision of Prof. C. A. Knoblock. Her current research interests include information extraction, network representation, and big data analysis.

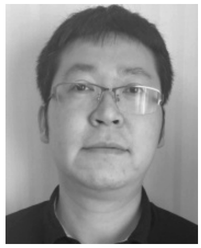
ZIRUI XING received the B.S. and M.S. degrees from the Hebei University of Science and Technology, Shijiazhuang, China, in 2010 and 2013, respectively, and the Ph.D. degree from the School of Automation, Beijing Institute of Technology, Beijing, China, in 2017.

He is currently an Engineer with the R&D and Application Center of Command Automation Technology, The 4th Institute of CASIC. His main research interests include multi-sensor information fusion, fault diagnosis, nonlinear filters, and signal processing.

CHUNSHENG ZHU received the Ph.D. degree in electrical and computer engineering from The University of British Columbia, Canada, where he is currently a Postdoctoral Research Fellow with the Department of Electrical and Computer Engineering. He has authored more than 100 publications published by refereed international journals (e.g., the IEEE Transactions on Industrial Electronics, the IEEE Transactions on Computers, the IEEE Transactions on Information Forensics and Security, the IEEE Transactions on Industrial Informatics, the IEEE Transactions on Vehicular Technology, the IEEE Transactions on Emerging Topics in Computing, the IEEE Transactions on Cloud Computing, the *ACM Transactions on Embedded Computing Systems*, and the *ACM Transactions on Cyber-Physical Systems*), magazines (e.g., the *IEEE Communications Magazine*, the *IEEE Wireless Communications Magazine*, and the *IEEE Network Magazine*), and conferences (e.g., IEEE INFOCOM, IEEE IECON, IEEE SECON, IEEE DCOSS, IEEE ICC, and IEEE GLOBECOM). His research interests mainly include the Internet of Things, wireless sensor networks, cloud computing, big data, social networks, and security.

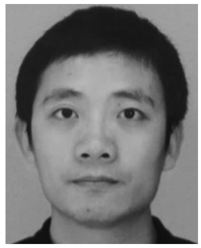
KUNFENG LU received the B.S. degree in information and computer science and the M.S. degree in applied mathematics from the Hebei University of Science and Technology, Shijiazhuang, China, in 2007 and 2010, respectively, and the Ph.D. degree from the School of Automation, Beijing Institute of Technology, Beijing, China, in 2014.

He is currently a Senior Engineer with the Beijing Aerospace Automatic Control Institute and the National Key Laboratory of Science and Technology on Aerospace Intelligent Control. His main research interests include guidance and control for vehicle, finite-time control, active disturbance rejection control, and sliding mode control.

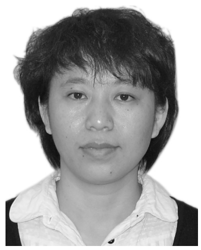


JIALUAN HE received the B.E. degree in measurement and control techniques and instruments and the M.E. degree in test metrology techniques and instruments from the Harbin Institute of Technology, Harbin, China, in 2006 and 2009, respectively. He is currently pursuing the Ph.D. degree with the School of Mechanical Electronic and Information Engineering, China University of Mining and Technology, Beijing, China.

He is also a Senior Engineer with the R&D and Application Center of Command Automation Technology, The 4th Institute of CASIC. His main research interests include overall design of wireless communication, automatic control, and network and command information systems.



YANBIN SUN received the B.S., M.S., and Ph.D. degrees in computer science from the Harbin Institute of Technology, Harbin, China. He is currently an Assistant Professor with Guangzhou University, China. His research interests include network security, future networking, and scalable routing.



LIHUA YIN was born in 1973. She received the Ph.D. degree from Guangzhou University, where she is currently a Professor and the Ph.D. Supervisor. Her current research interests include computer networks and network security. He is a member of the China Computer Federation.