AN APPROACH TO SOLVE THE PROBLEM OF DATA FUSION FOR MULTI-TARGET TRACKING USING FUZZY LOGIC

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Abstract: *This paper presents a multitarget data fusion (identification) algorithm called the Fuzzy data fusion algorithm (FDFA) for radar target tracking. This approach is formulated using the Kalman filter and FDF, the algorithm is accomplished by using fuzzy logic. Simulation results for cluttered conditions show that the proposed algorithm's performance is better than the probability data fusion (PDF) and the joint probability data fusion (JPDF) filters, which were presented in [2-4, 6].*

Keywords: Data fusion (data association); Multi-target tracking; Fuzzy logic.

1. INTRODUCTION

Most of the multitarget tracking (MTT) algorithms have been developed for the applications of the transportation and air traffic control. However, the maneuvering conditions of object, the clutters within surveillance radar areas make tracking problem quite difficult [2]. The filtering, tracking to the trajectories of objects and the data fusion can be considered two sides of a problem. In fact, the design of an MTT algorithm in such a surveillance environment poses a challenging problem. One difficulty in MTT is data fusion (DF) [2÷4], especially in maneuvering targets tracking in the clutter environment. The probabilistic data fusion (PDF) [4, 6, 11] and joint probabilistic data fusion (JPDF) [6, 11] are conventionally used along with Kalman filters. However, in either dense target or cluttered environment, radar observations are degraded and this degrades target tracking performance.

In this paper the Kalman filter and the fuzzy data fusion (FDF) are proposed to improve the tracking performance. The algorithm uses the fuzzy "$IF-THEN$" rules for multitarget data fusion under a high cluttered environment [10, 14].

2. ABOUT TWO PROBABILISTIC DATA FUSION ALGORITHMS

2.1. Probabilistic data fusion

The probabilistic data fusion (PDF) is suboptimal Bayesian algorithm which assumes that there is only one target of interest whose track has been initialized [2÷4, 6, 9, 11, 12]. Given J observations – "return", $\{z_j(k), j=1\div J\}$ within the validation gate of the track t at the $k-th$ updated period (at the processing center), the PDA forms $J+1$ hypothesis Θ_j. The first hypothesis, H_0, is the case in which none of the J observations is originated from the track t, and $\Theta_j, (j>0)$ denotes the hypothesis that $j-th$ "return" is originated from the track t. The target tracking algorithm can be used by the Kalman filter that updates its state vector formed by position and velocity as:

$$\hat{x}_t(k|k) = \hat{x}_t[k|(k-1)] + K_t(k)\times v_t(k) \tag{1}$$

And the state updating in the PDF uses the combined innovation covarriance defined as:

$$v_t(k) = \sum_{j}^{J} \gamma_{jt}(k) \times v_{jt}(k) \tag{2}$$

Where: $\gamma_{jt}(k) = [b_{jt}(k)] \times [b_{j0} + \sum_{j}^{J} b_{jt}(k)]^{-1}$ - is the probability that the $j-th$ "return" is originated from the $t-th$ track;

$b_{j0}(k) = (2\pi)^{M/2} \sqrt{|S_t(k)|}.\{[1 - D(k).F(k)] / D(k)\}$;

$b_{jt}(k) = \exp\{(-0.5).[v_{jt}(k)]^T S_t^{-1}(k).v_{jt}(k)\}$

$D(k)$ - is the probability of target detection at the $k-th$ updated period; $D(k)$ - is the probability of a target return falling within the validation gate; $S_t(k)$ - is the innovation covariance and M is the dimension of the measurement vector.

The estimated error covariance matrix, associated with maneuvering state $\hat{x}_t(k|k)$, is given by the estimation of filter covariance:

$$\hat{P}_t(k|k) = \gamma_{0t}(k) \times \hat{P}_t[k|(k-1)] + [1 - \gamma_{0t}(k)] \times P_t^c(k|k) + \tilde{P}_t(k) \tag{3}$$

Where:

1. $P_t^c(k|k) = [I - K_t(k) \times H_t(k)] \times \hat{P}_t[k|(k)]$ (4)

2. $\tilde{P}_t(k) = K_t(k) \times \{\sum_{j}^{J} \gamma_{jt}(k) \times v_{jt}(k) \times [v_{jt}(k)]^T - v_t(k) \times [v_t(k)]^T\} \times [K_t(k)]^T$ (5)

3. $\hat{P}_t[k|(k-1)] = F_t(k-1) \times \hat{P}_t[(k-1)|(k-1)] \times [F_t(k-1)]^T + Q_t(k)$ (6)

4. $K_t(k) = \hat{P}_t[k|(k-1)] \times [H_t(k)]^T \times S_t^{-1}(k)$ (7)

$\gamma_{0t}(k)$ - is the a priori probability that all measurements in the validation gate of $t-th$ track are false; $F_t(k)$ - is the transition matrix in the state equation; $H_t(k)$ - is the linearization measurement matrix for $t-th$ target; $K_t(k)$ - is the Kalman filter gain; $Q_t(k)$ - is the the process noise covariance matrix.

Note that, in the calculation of $\gamma_{jt}(k)$, the PDFA assumes that all the tracks are isolated and does not take into account the possibility that some observations in the gate may come from other targets [9].

2.2. Joint probabilistic data fusion

According to [11], for the JPDF, the probability of $t-th$ track being associated with $j-th$ observation - "point", is the sum of the probabilities of all joint events, $\Theta(k)$, in which $t-th$ track is associated with $j-th$ observation - "point", which can be expressed as:

$$\gamma_{jt}(k) = \sum_{\Theta(k)} \mathrm{P}[\Theta(k)|Z^K] \times \omega_{jt}[\Theta(k)] \tag{8}$$

Where, $\omega_{jt}[\Theta(k)]$ is a binary variable indicating whether $t-th$ track is associated with $j-th$ fusion in the event $\Theta(k)$. The probability of the event $\Theta(k)$ given Z^K, the set of all the observations received up to the current scan k, is given by [3] (that to mean: $Z(k)=\{z_1(k),\cdots,z_j(k)\}$ - set of measurement points up to the time k, and $Z^K=\{Z(1),\cdots,Z(k)\}$.

$$\mathrm{P}[\Theta(k)\,|\,Z(k)]=\frac{1}{C}\times\frac{n!}{[V(k)]^n}\prod_{j=1}^{J}\{N[\pi_{jt}(k)]\}^{\tau_j}\prod_{m=1}^{M_t}[D_t(k)]^{\delta_t}[1-D_t(k)]^{(1-\delta_t)} \quad (9)$$

Where, C - is a normalization constant; $V(k)$ - is the gate volume, n - is the number of observations determined to be clutter in $\Theta(k)$ and $N[\pi_{jt}(k)]$ - is the normal probability density function with zero-mean and a covariance matrix equaling to $\pi_{jt}(k)$. Define two quantities, τ_j and δ_t, such that τ_j is equal to one if the $j-th$ observation is assigned to a track in the event $\Theta(k)$ and zero otherwise, and δ_t is equal to one if the $t-th$ track has been assigned an observation and zero otherwise. Assuming a Poission density function for clutter points, the probability of the event $\Theta(k)$ has to take into account the history of observations up until updated period $k[Z(k)]$. The Kalman filter is updated using the same set of equations as in the PDFA.

2.3. Discussion

1. The JPDFA approach provides an optimal data fusion solution in the Bayesian framework. However, the number of possible hypothesis associating different returns to targets in the JPDF increases rapidly with the number of targets and the presence of clutter. Consequently, this approach requires a large amount for processor time calculating the joint probabilities even for a small number of targets in the high level of the clutter [5, 7, 8].

2. To solve this problem, an alternative method of JPDA should be investigated. Possible approaches might be based on neural network and fuzzy logic.

3. SOLVING THE PROBLEM OF DATA FUSION FOR MULTI-TARGET TRACKING USING FUZZY LOGIC

Fundamentally, the conventional tracking techniques are too restrictive to deal with the complexity of tracking problem. There is a very sharp demarcation line between target and non-target at the intersecting gates [7, 8, 10]. This type of target classification clearly does not reflect well. By incorporating human-like reasoning into the tracking problem, results comparable to the JPDA can be achieved. The structural schematic of the fuzzy tracking system is showed in fig.1. It consists of the following function blocks.

+ KF: the standard suboptimal Kalman filter that gives values of state estimates and their covariances. Inputs are the state estimate vector $\hat{x}(k)$, its covariance matrix $\hat{P}(k)$, and the measurements vector z.

+ Fuzzy data fusion (FDF) was used to evaluate the association degree between the return and the actual of interest (not clutter or other targets). Inputs are the measurement innovation, which is based on the availability of objective and/or heuristic. Here, we will use the FDA approach instead of the JPDAF approach. Namely, the state estimate is then adjusted according to $\gamma_{jt}^{fus.}(k) = FDF(\Theta, A, \Psi)$ (10)

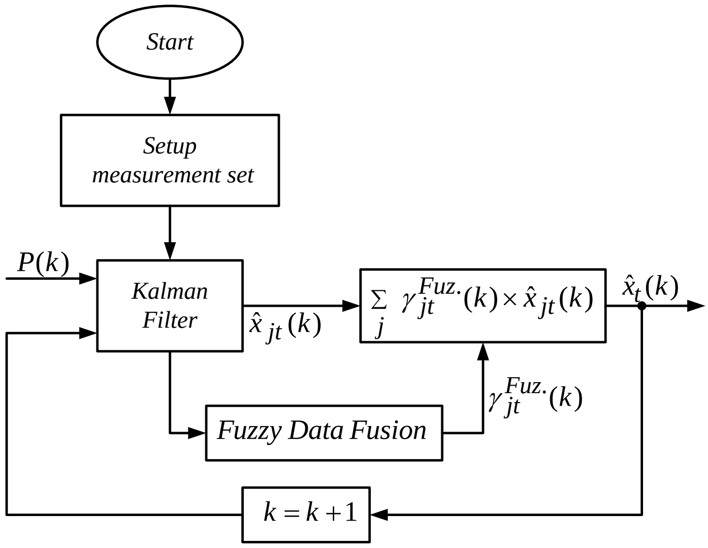

Figure 1. *The structure schematic of the fuzzy tracking system.*

The $FDF(*)$ - is fuzzy function, which is used to evaluate the association degree $\gamma_{jt}^{fus.}(k)$ at the $k-th$ updated period based on the set of membership functions A and the set of some proposition Ψ [10, 14]. Thus, the FDA keep the main idea of the JPDA, but can incorporate additional information or some of heuristic rules. Using fuzzy logic methodology, the rules in the FDF rule base are evaluated. The FDA rules to determine the degree of fusion are the form in:

$$\begin{cases} R_1: & If \quad \tilde{Z}_R \text{ is } NL \text{ and } \tilde{Z}_R \text{ is } NL \quad Then \quad \gamma_{jt}^{fus.}(k) = VL \\ R_2: & If \quad \tilde{Z}_R \text{ is } NL \text{ and } \tilde{Z}_R \text{ is } NM \quad Then \quad \gamma_{jt}^{fus.}(k) = VL \\ R_3: & If \quad \tilde{Z}_R \text{ is } NL \text{ and } \tilde{Z}_R \text{ is } NS \quad Then \quad \gamma_{jt}^{fus.}(k) = ML \\ .. & If \quad .. \quad Then \quad .. \end{cases} \tag{11}$$

For example, in the case of using the distance attribute (angle and distance), then the fuzzy variable, FDF, has 49 "$IF - THEN$" rules provided in table 1.

Table 1. *FDF Rule Base.*

Fusion Degree		**Range Error**						
		NL	*NM*	*NS*	*Z*	*PS*	*PM*	*PL*
Azimuth Error	*NL*	*VL*	*VL*	*ML*	*M*	*ML*	*VL*	*VL*
	NM	*VL*	*ML*	*ML*	*M*	*ML*	*ML*	*VL*
	NS	*ML*	*ML*	*M*	*MH*	*M*	*ML*	*ML*
	Z	*M*	*M*	*MH*	*VH*	*MH*	*M*	*M*

	PS	*ML*	*ML*	*M*	*MH*	*M*	*ML*	*ML*
	PM	*VL*	*ML*	*ML*	*M*	*ML*	*ML*	*VL*
	PL	*VL*	*VL*	*ML*	*M*	*ML*	*VL*	*VL*

In this table, the fuzzy terminology of *Input* variables are given by (12). And the fuzzy term set of output *Output* variables were given by (13):

$$\begin{cases} NL & denote & Negative\ Large \\ NM & denote & Negative\ Medium \\ NS & denote & Negative\ Small \\ Z & denote & Zero \\ PS & denote & Positive\ Small \\ PM & denote & Positive\ Medium \\ PL & denote & Positive\ Large \end{cases} \quad (12) \qquad \begin{cases} VL & denote & Very\ Low \\ ML & denote & Medium\ Low \\ M & denote & Medium \\ MH & denote & Medium\ High \\ VH & denote & Very\ High \end{cases} \quad (13)$$

4. SIMULATION RESULTS

In this section, we will present the simulation results of applying fuzzy data fusion for multi-target tracking. The initialization process of measurement set and data is presented in [1, 5]. The radar sensors provide range and azimuth measurements to the tracking algorithm, which estimates the position and velocity of the target in the horizontal plane. The setup data of measurement sets for simulation is presented in [5]. The simulation with minimum separation distance flight scenario is chosen from the benchmark problem for maneuvering targets. The measurement noise is zero-mean Gaussian with a standard deviation of 120m for range and 15 milidegree for azimuth and elevation angles.

4.1. Configuration problem

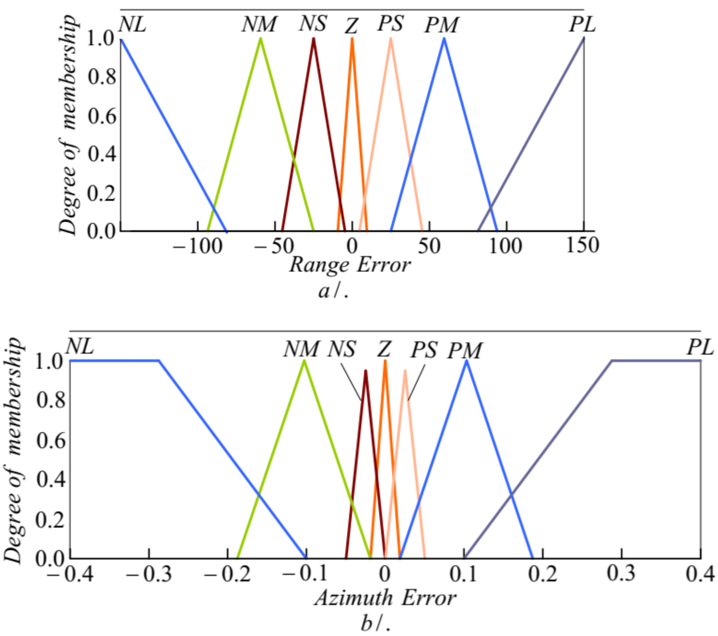

Figure 2. *FDF input membership functions.*

The fuzzy data fusion is presented to demonstrate the feasibility of using fuzzy logic for maneuver detection and data association in cluttered environment.

For the FDF configurations, the sets of membership functions which fuzzify these crisp inputs, defined over appropriate universe of discourse are shown in fig.2 (*a*, *b*). fig. 3 shows the output of the FDF membership functions which are used to evaluate the crisp outputs through the application of fuzzy inference and center of gravity defuzzification [10, 14].

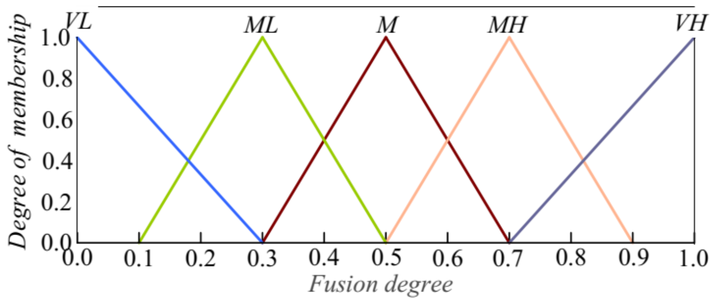

Figure 3. *FDF output membership functions.*

4.2. Simulation results and experiment

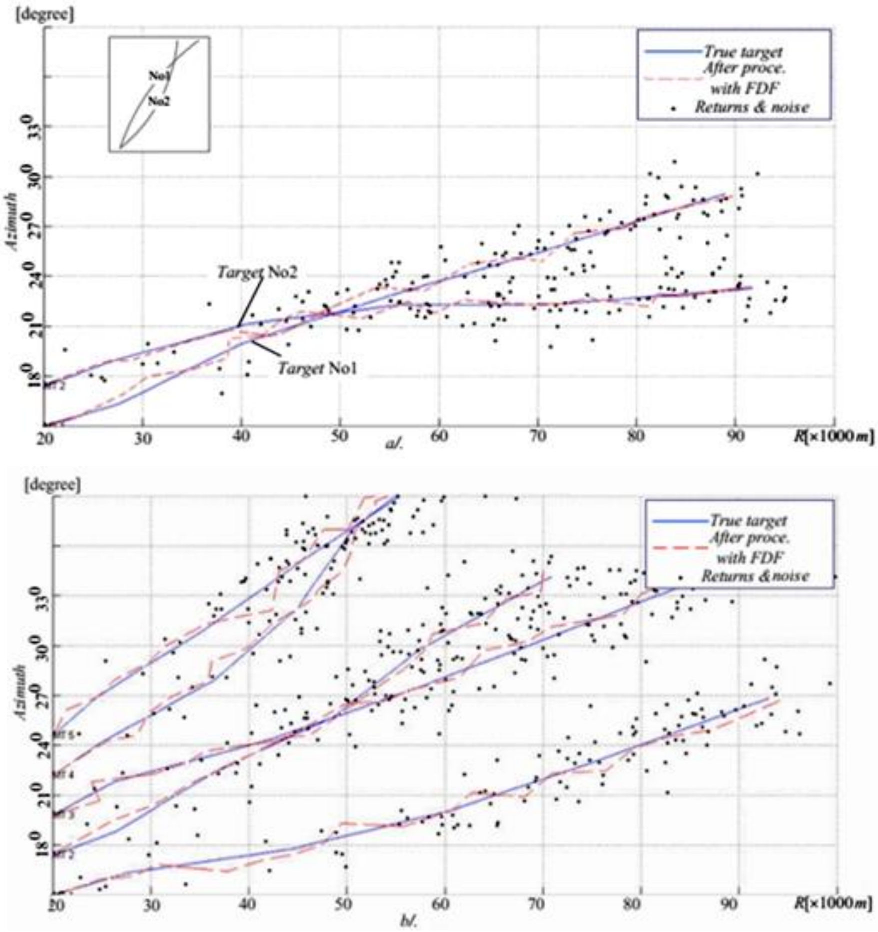

Figure 4. *The simulation results of tracking 2 (a) and 5 targets (b) using FDFA.*

Some of the simulation results were performed to demonstrate the ability of the FDF algorithm in solving problems multitarget tracking which is shown in fig 5. It can be shown that, when compared to the simulation results of target tracking using JPDF algorithm, presented in [5], the FDA improved not only the quality of filtration but also the ability to the trackability.

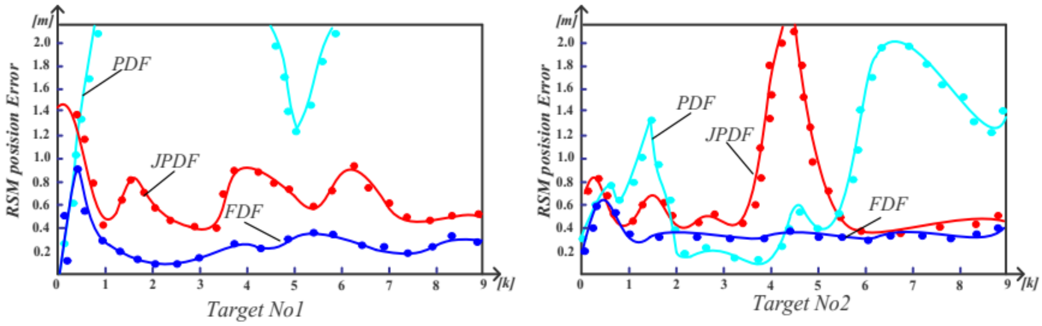

Figure 5. *RMSE of position estimates for different tracking algorithms (clutter density) for targets No1 and No2 in the figure 4 (a).*

The root mean square error (RMSE) is used to compare tracking performance. From figure 5, it can be shown that position errors can be considerably reduced by using FDF algorithm in solving multi-target tracking problem. The examination of these figures indicates that the fuzzy approach is not only can converge on the target tracks form light to heavy cluttered environment but also high tracking accuracy. Simulations have revealed that the FDA is much more robust and stable than PDF and JPDF.

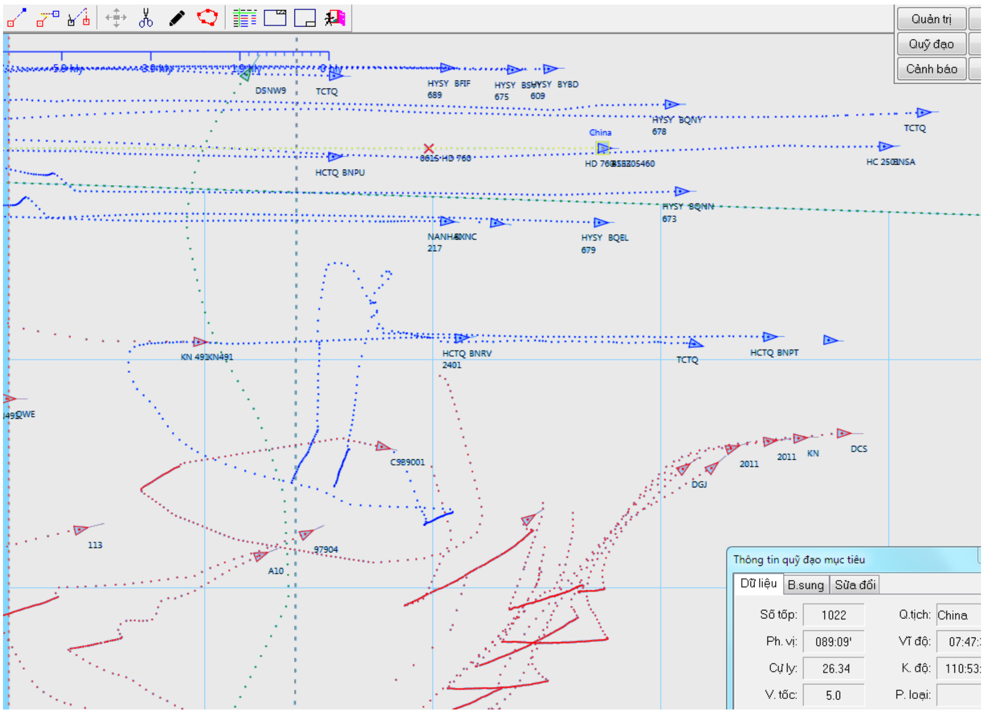

Figure 6. *Experimental results of tracking multiple targets at sea when using FDFA.*

The FDA has been partially experimented in the Integration and Management System of Coastal Surveillance in the Navy Headquarter, in order to improve the performance of multiple-radar target data processing and ensuring the near real-time of the observation. It was proven to be effective in reducing computing load and simplify the computation structure. The novel method gives an explicit indication of the possibility to incorporate useful knowledge into tracking problem. A mid-range workstation, on which the FDF algorithm has been performed, can fully handle the correlation processing hundreds of multi-sensor target data in the same region, which transmitted from 4 to 5 medium range coastal surveillance radar stations. On the command and control stations located in the headquarter, the combined sea target data was displayed on top of the digital map layers for the operator (fig 6).

5. CONCLUSION

In this paper, we have presented a set of fuzzy-based methods that can be applied in combination with the conventional Kalman filter for multi-target tracking in a cluttered environment. The given simulation examples show that the proposed approach effectively reduces the tracking error due to maneuvering and cluttered effects. The FDF approach was based on 49 heuristics hypotheses. These heuristics hypotheses are implemented to estimate the degree of association to which each measurement within the gate of tracking filter belongs to the true measurement fuzzy set. This algorithm has been partially experimented. Is was shown to be effective in reducing computing capacity and had a simple structure.

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TÓM TẮT

MỘT CÁCH TIẾP CẬN GIẢI QUYẾT VẤN ĐỀ HỢP NHẤT DỮ LIỆU TRONG BÁM SÁT ĐA MỤC TIÊU SỬ DỤNG LÔ GÍC MỜ

Bài báo trình bày về một thuật toán hợp nhất (liên kết) dữ liệu đa mục tiêu được gọi là thuật toán hợp nhất dữ liệu mờ (Fuzzy Data Fusion Algorithm - FDFA) dùng để lọc,bám sát quỹ đạo đa mục tiêu ra đa. Cách tiếp cận này được xây dựng dựa trên cơ sở sử dụng công cụ lọc Kalman và hợp nhất dữ liệu mờ (Fuzzy Data Fusion - FDF. Các kết quả mô phỏng cho các điều kiện nhiễu cho thấy hiệu suất của thuật toán được đề xuất tốt hơn so hai thuật toán hợp nhất dữ liệu theo xác xuất (Probabilistic Data Fusion - PDF) và hợp nhất dữ liệu theo xác xuất liên kết (Joint Probabilistic Data Fusion - JPDF), như đã được trình bày trong [2-4, 6].

Từ khóa: Hợp nhất dữ liệu (liên kết dữ liệu); Bám sát đa mục tiêu; Lô-gích mờ.

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