Building the method for multi-target tracking based on the combination of PHD filter and JPDA filter using particle filter in 3D mixed coordinate system

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ABSTRACT

Changing the target number, non-linear measurement models and non-Gaussian noise faces a challenge to multi-target tracking problems which are factors affecting the accuracy, execution time and deciding the success of the method as well. In this paper, the authors present a method to solve these problems. Wherein, the motion of targets is represented in the mixed coordinate system 3D base on combining PHD (Probability Hypothesis Density) and JPDA (Joint Probability Data Association). This method can track multiple targets in the most general case, that is to change the target number, system model and measurement model which is non-linear as the noise is non-Gaussian. The result of this work can be applied to the real-time response system when the targets are moving in close distances with rapid maneuvering.

Keywords: Multi-target tracking; Mixed coordinates; PHD combined JPDA; Particle filter; Non-Gaussian; Constant velocity model**.**

1. INTRODUCTION

In multi-target tracking problem, there are two main issues to be solved, they are: The selection of data association methods suitable for assigning measurement signals to each target and choice of appropriate filter for state estimation based on the measurement, system and noise models of the target. The biggest challenge the methods of combining data face when the number of targets is changing. Currently, in the world, three methods of traditional data association often used [8] are: GNN (Global Nearest Neighbor), JPDA and MHT (Multiple Hypothesis Tracking).

However, some articles show that GNN method has low computational complexity, but only works well when the clutter between targets is low [9].

JPDA method has high reliability by combining all the measurement signals and could be able to distinguish targets highly and fast calculate speed, but only has good tracking results when the number of targets is known [10].

MHT method has high precision, but its installing algorithms are complex, computational complexity in terms of both time and space is large, the calculated results are delayed a period time, in addition, the precision depend on the prior information [11] could not meet the system requirements of fast computing speed and responsive real time.

In addition to the drawbacks mentioned above, three methods have further common drawbacks such that complexity increases rapidly when the number of targets increases.

To overcome these problems, recently, PHD method is proposed based on the theory of random finites set. The main advantage of PHD method is that computational complexity does not increase according to the number of targets, and its ability to identify the location and the number of the corresponding target change over time. However, PHD method is limited only to identifying the number and location of targets in the current time step without the ability to combine measurements of target signal in successive time steps [12-14].

After data association step, selection filter determines the accuracy and complexity of the tracking method. One of the challenges to target tracking problem is the nonlinear measurement model and non-Gaussian noise. In the target tracking, the motion of the target is the best performer in the Cartesian coordinate system, while the measurements are usually expressed in spherical coordinates. When tracking targets in mixed coordinates (the motion of target expressed in the Cartesian coordinate system, the measurement presented in spherical coordinates) a problem is the nonlinear measurement model because of the transformation from the Cartesian coordinate system to spherical coordinates [2].

When tracking targets in the Cartesian coordinate system, the system model and measurement system is linear, but another problem is encountered the measurement noise is no longer Gaussian distribution due to the transition from spherical system to coordinate system [2]. The typical filter used to solve nonlinear filter problem is Particle Filter [15].

In the world, there are some articles about surveying the combination of PHD method with a data association for tracking target, for example, PHD combined with MHT [8] or a combination of PHD with GNN algorithm (global nearest neighbor), but in these articles, the noise is assumed to be Gaussian and implementation on the two-dimensional coordinate system. In addition, the method in [8] makes it impossible for real-time applications due to delay a period time and the ability to distinguish targets of GNN algorithm is low when the targets operate closely.

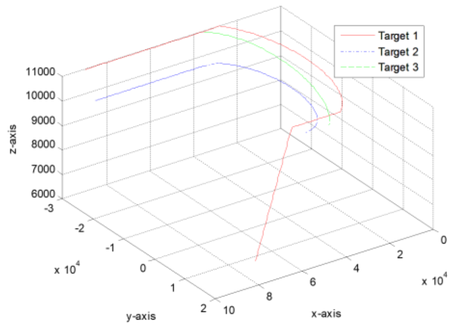
In Vietnam, there are some articles about MTT, in which [16] using MHT in combination with extended kalman filter, disadvantages of this method show in [8]. In [17] using HMM method (Hidden Markov Model) to determine the number of targets, there is no ability to tracking.

Based on the tracking capability of the target~~s~~ change over time of PHD method, the accuracy of JPDA method and the superior ability of particle filter in solving nonlinear filtering and non-Gaussian noise, in this article, author combines PHD, JPDA methods and particle filter to track multi-target change over time in mixed coordinates 3D.

2. THE RADAR MULTI-TARGET TRACKING PROBLEM IN MIXED COORDINATE SYSTEM

2.1 The system model and measurement model

2.1.1. Physical Systems



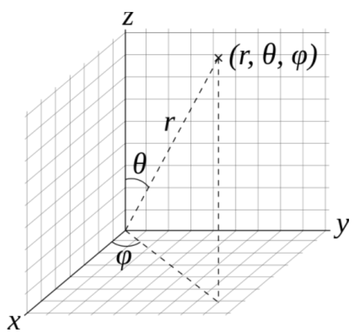


Figure 1. *Moving trajectories of the targets.* ***Figure 2****. Spherical coordinate system.*

The monitoring system of air targets, targets are fighters. The motion model of these targets is not stable and has rapid maneuvering, the targets move closer, the navigation is regular and the velocity doesn't change frequently. The motion of target in 3D space is a combination of four flying modes: increased height, reduced height, flying at a fixed height, and circled flight. In this article, the trajectories of targets are described as in figure 1. Measurement system uses a radar operation in spherical coordinates. Radar is placed at the origin. Information received from the radar covering a distance r, elevation θ and azimuth φ is described in figure 2.

2.1.2. Mathematical Model

Due to the characteristics of above target, the motion of target in 3D space is coupled across axes, so to study the characteristics of the methods, the motion of the target in XYZ space has to be considered. The dynamics model of the aircraft target is complex, but to simplify the process of calculating, the target in this paper is considered as a point in space [1]. The system model is chosen as the model constant velocity CV (Constant Velocity Model) [3], this is the control motion model, coupled across axes and velocity is considered to be constant in each sampling cycle.

2.1.2.1. The system model in the Cartesian coordinate system [2]

The target state vector is defined as follows:

$$\mathbf{x} = [p_x, v_x, p_y, v_y, p_z, v_z]^T \tag{1}$$

Where, $\{p_x, p_y, p_z\}$ is position component, $\{v_x, v_y, v_z\}$ is velocity component.

Continuous-time dynamic model of the target:

$$\mathbf{x}(t) = \begin{bmatrix} p_x \\ v_x \\ p_y \\ v_y \\ p_z \\ v_z \end{bmatrix}; \dot{\mathbf{x}}(t) = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \mathbf{x}(t) + \begin{bmatrix} 0 \\ w_x(t) \\ 0 \\ w_y(t) \\ 0 \\ w_z(t) \end{bmatrix} \tag{2}$$

where $w_x(t), w_y(t), w_z(t)$ is the acceleration noise, Gaussian distribution with zero mean value and independent distribution.

Discrete-time dynamic model of the target:

$$\mathbf{x}_{k+1} = \mathbf{F}\mathbf{x}_k + \mathbf{w}_k \tag{3}$$

$$\mathbf{F} = \begin{bmatrix} 1 & T & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4}$$

Where $T = t_{k+1} - t_k$.

2.1.2.2. The measurement model in the spherical coordinate system

$$\mathbf{z}_\mathrm{k} = \mathbf{h}(\mathbf{x}_\mathrm{k}) + \mathbf{n}_\mathrm{k} \tag{5}$$

$$\mathbf{z}_\mathrm{k} = \begin{bmatrix} r_k \\ \theta_k \\ \varphi_k \end{bmatrix} = \begin{bmatrix} \sqrt{x_k{}^2 + y_k{}^2 + z_k^2} \\ \arccos\left(\dfrac{z_k}{r_k}\right) \\ \arctan\left(\dfrac{y_k}{x_k}\right) \end{bmatrix} + \begin{bmatrix} n_{rk} \\ n_{\theta k} \\ n_{\varphi k} \end{bmatrix} \tag{6}$$

Observation noise $\mathbf{n}_k$ is considered to be Gaussian, the mean value is zero, independent, $n_{rk}, n_{\theta k}, n_{\varphi k}$ is measurement noise component, Gaussian distribution, impacting on the distance r, elevation θ and azimuth φ.

According to equations (3) and (6), it is to see that the model CV expressed in the mixed coordinates system model is linear but the measurement model is nonlinear.

2.2. Combining PHD and JPDA in multi-target tracking problem

2.2.1. Multi-target model

In the multi-target tracking problem, targets appear and disappear at random. The target may appear to be generated by the new or separated from the target that existed previously. A number of targets is born at a time to follow the distribution Poisson with average value λ_b. Each target at the moment k cannot exist until the next time and is lost. The target of this loss is modeled with probability $1-e_{k|k-1}(x_{k-1})$, where $1-e_{k|k-1}(x_{k-1})$ perform the probability that a target at time k-1 will survive to time k. The probability of target detection in existing time is $p_D(x_k)$.

At time k, called the number of appeared target is N_k with the state $x_{k,1},\ldots,x_{k,N_k}$ and the number of the received measurement signal is M_k

Denote $\mathbf{X}_k = \{\mathbf{x}_{k,1},\ldots,\mathbf{x}_{k,N_k}\} \subset E_s$, $\mathbf{Z}_k = \{\mathbf{z}_{k,1},\ldots,\mathbf{z}_{k,M_k}\} \subset E_0$ are a set of targets and measurement signal received at time k. E_s, E_0 represent state space and measurement space, in which there exists the target and measurement signal. Some observers signal can be due to clutter. The number of clutter is assumed to be distributed according to the portion law with average value λ_c.

2.2.2. Multi-target filtering with the PHD filter [12-14]

In multi-target filtering problems, the set of targets and measurement signal are modeled by a random finite set (RFS) Ξ, in the problem of multi-target tracking (MTT), $|\Xi|$ shows the number of targets and status of the respective targets.

PHD D_Ξ is the first moment of RFS Ξ and is defined as follows:

$$D_\Xi(x) = \mathbf{E}\left[\delta_\Xi(x)\right] = \int \delta_X(x) P_\Xi(dX) \tag{7}$$

Where $\delta_\Xi(x) = \sum_{x\in\Xi} \delta x$; $\delta_\Xi(x)$: Random density of Ξ ; P_Ξ : Probability distribution of RFS Ξ Integrals over regions S of the state space $S \in E_s$; $\int_S D_\Xi(x)\lambda(dx)$ show the target number of Ξ existing in the area S and PHD's highest peak N of Ξ show the target status of Ξ.

2.2.3. JPDA Filter [4-7]

In JPDA method, assuming that the number of targets is τ with index $t = \{1,\ldots,\tau\}$. The measurement value at time step k is denoted $\mathbf{z}_k = \{\mathbf{z}_k^j\}_{j=0}^{m_k}$, where z_0 denotes the error measurement signal or disturbance signal, number of measurement is m_k. Probability combined measurement values and targets simultaneously diagonal spread between the targets. Let θ denote the simultaneously combined event and θ_t^j be the events that assigned measurement signal j and target t.

$$\theta = \bigcap_{j=1}^{m_k} \theta_t^j \tag{8}$$

2.2.4. Combining PHD and JPDA in multi-target tracking problem

In this method, PHD filter serves to filter out false measurement signals, unreasonable, without altering the measurement signal as well as the randomness of the signal. The purpose of the block "filtering fault measurements" is to eliminate false measurement signals by the turbulence, thereby reducing the calculation load and errors of JPDA filter. Operation of the method is described in figure 3.

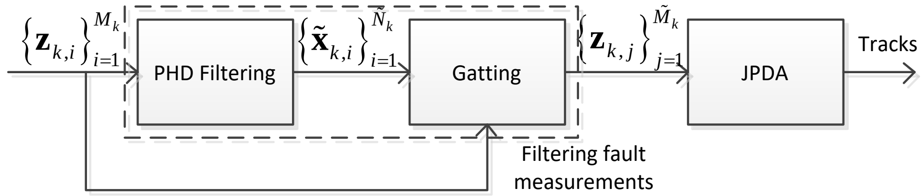


Figure 3. *Multi-target tracking with PHD combined JPDA Filter.*

2.3. Method Installation used particle filter

Called L_k is the number of particles proposed in the time step k.

Called J_k is the number of particles proposed for detecting new born targets at time step k.

Step 1: Initialize PHD $D_{k|k}$ at k=0 with a set of L_k particles $\left\{\omega_k^{(i)},\mathbf{x}_k^{(i)}\right\}_{i=1}^{L_k}$;

Step 2: When k ≥ 1, it yields $\left\{\omega_k^{(i)},\mathbf{x}_k^{(i)}\right\}_{i=1}^{L_k}$ by approximating $D_{k|k}$ recursively;

Step 3: Estimating the number of targets and state of targets;

Step 4: Create a valid gate and eliminate global false measurement signals, Obtain $\tilde{\mathbf{Z}}_k$ from $\mathbf{Z}_k$;

Step 5: When obtained $\left\{\tilde{\mathbf{z}}_{k,j}\right\}_{j=1}^{\tilde{M}_k}$ using JPDA to perform data association to determine the appropriate measurement signal to each target (number of targets is $\tilde{N}_k$).

3. SIMULATION RESULTS

3.1. Scenario of target tracking

In the simulation scenario of the article, the target moves during the observation area 90 km - 50 km - 12 km with the number of targets changing over time.

Simulations are performed 40 times and then the average value to ensure reliability is taken.

The lifetime(s) of targets: Target 1 (0÷340); Target 2 (0÷250); Target 3 (150÷240).

Initialization parameters of the targets as follows

Target 1: Position: $\left(x_0,y_0,z_0\right)=\left(90km,-30km,8k\,\mathrm{m}\right)$;

Velocity: $\left(v_{x0},v_{y0},v_{z0}\right)=(100\,\mathrm{m/s},0\,\mathrm{m/s},0m/s)$

Target 2: Position: $\left(x_0,y_0,z_0\right)=\left(90km,-27km,10km\right)$;

Velocity: $\left(v_{x0},v_{y0},v_{z0}\right)=(100\,\mathrm{m/s},\ 0\,\mathrm{m/s},\ 0m/s)$

Target 3: Position: $\left(x_0,y_0,z_0\right)=\left(30km,-30km,12km\right)$;

Velocity: $\left(v_{x0},v_{y0},v_{z0}\right)=(200\,\mathrm{m/s},\ 200\,\mathrm{m/s},\ 0m/s)$

The measurement system uses one radar located at position (0km, 0km, 0km). Measurement noises are as follows:

- System noise of target 1 and 3:

+) Acceleration noise w_x is Gaussian, zero mean value and the variance $0{,}1\, m/s^2$: $w_x \sim \mathrm{N}(0, 0.1)$

+) Acceleration noise w_y, w_z depend on w_x and moving trajectory in figure 1.

- System noise of target 2:

+) Acceleration noise w_x is Gaussian, zero mean value and the variance $0.2\, m/s^2$: $w_x \sim \mathrm{N}(0, 0.2)$.

+) Acceleration noise w_y, w_z depend on w_x and moving trajectory in figure 1.

- Measurement noise:

+) Gaussian measurement noise impact on the distance r (m): $v_r \sim \mathrm{N}(0, 80)$;

+) Gaussian measurement noise impact on the elevation angle θ (degree): $v_\theta \sim \mathrm{N}(0, 2)$;

+) Gaussian measurement noise impact on the azimuth angle φ (degree): $v_\varphi \sim \mathrm{N}(0, 2)$.

- Distribution of measurement signal:

Measurement signal $\mathbf{Z_k}$ is assumed to be Poisson distribution: *Z_k~Poi(6).*

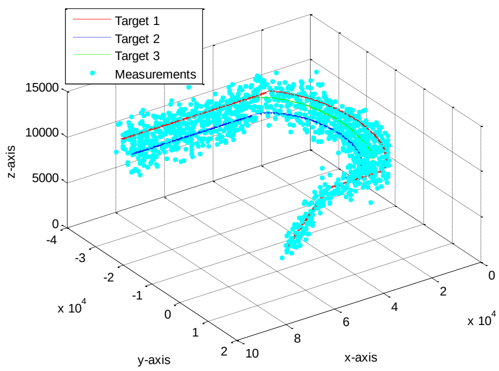


***Figure 4**. Measurement signals.*

3.2. Some criteria for evaluating the method

- The ability to estimate the number of targets.

- The ability to distinguish targets.

- The ability to recognize when to appear more targets and loss targets.

- Execution time.

- The accuracy of the method.

+ PRMSE (Position root-mean square error)

$$PRMSE_k = \left(\frac{1}{M} \sum_{i=1}^{M} (p_{xk}^{\,i} - \hat{p}_{xk}^{i})^2 + (\hat{p}_{yk}^{\,i} - \hat{p}_{yk}^{i})^2 + (p_{zk}^{i} - \hat{p}_{zk}^{i})^2 \right)^{1/2} \quad (9)$$

+ VRMSE (Velocity root-mean square error)

$$VRMSE_k = \left(\frac{1}{M} \sum_{i=1}^{M} (v_{xk}^{\,i} - \hat{v}_{xk}^{i})^2 + (v_{yk}^{\,i} - \hat{v}_{yk}^{i})^2 + (v_{zk}^{i} - \hat{v}_{zk}^{i})^2 \right)^{1/2} \quad (10)$$

Where: p_x, p_y, p_z: True position of the target; $\hat{p}_x, \hat{p}_y, \hat{p}_z$: Estimation position ; v_x, v_y, v_z: True velocity of the target; $\hat{v}_x, \hat{v}_y, \hat{v}_z$: Estimation velocity.

3.3. Results

The execution time of the method implemented on a computer running OS Windows 7, 3.2 GHz Core i5 processor, 4 GB of RAM is 350 seconds. According to the simulation results shown in figure 5 and figure 6, it is seen that the PHD filter is capable to estimate the target number exactly, including the appearance time and disappearance time of the targets. The output of the filter is a set of target states, but this set of states is not for each target and its inability to distinguish, while it also demonstrates the advantage of the PHD filter that the ability to limit and reduce the measurement signal is not appropriate. Thereby it reduces implementation time and the complexity of multi-target tracking method, especially when the number of targets and the measurement signal is large.

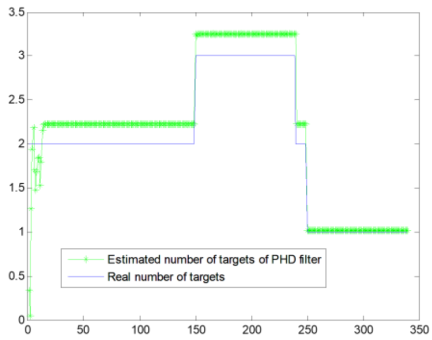


Figure 5. *Number of estimated targets of PHD filter.*

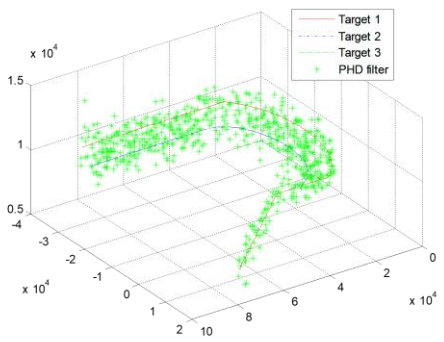


Figure 6. *State of the targets after PHD filtering.*

According to the simulation results shown in figure 7, it could be seen that the block "filtering fault measurements" function correctly, removing the majority of the measured signal is wrong (outside of the valid gate).

According to the simulation results shown in figure 8, figure 9, figure 10 it is seen that the combined method of combining PHD filter and data association JPDA performs with better results, the ability to distinguish high targets and not to be confused. However, uncertainty attached to new targets and suddenly disappearing targets during tracking (target 3 in figure 10) is greater, especially in the time of appearance (t = 150 s) and the time of disappearance (t = 240 s). Tracking results to the target exists from the beginning to the end of the tracking more stable, smaller errors. From the simulation results shown in figures 11 and 12 it derives that the position error and velocity error on the target tends to decrease, but the tracking error of new targets is greater and decreases slower.

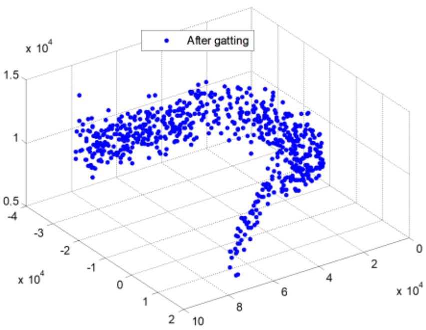


Figure 7. *Results after removing error measurement signals.*

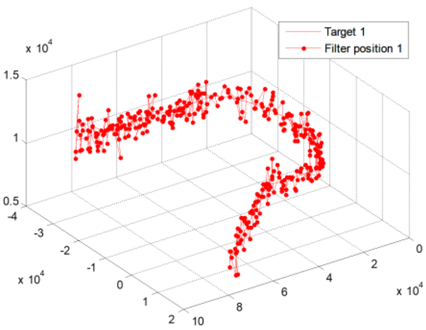


Figure 8. *PHD + JPDA filtered position of the target 1.*

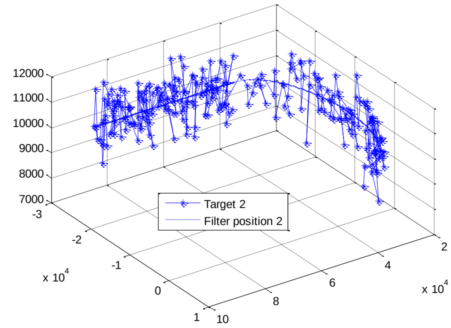


Figure 9. *PHD + JPDA filtered position of the target 2.*

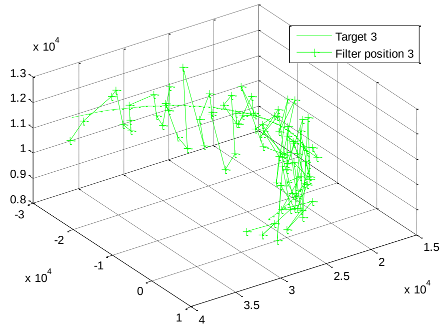


Figure 10. *PHD + JPDA filtered position of the target 3.*

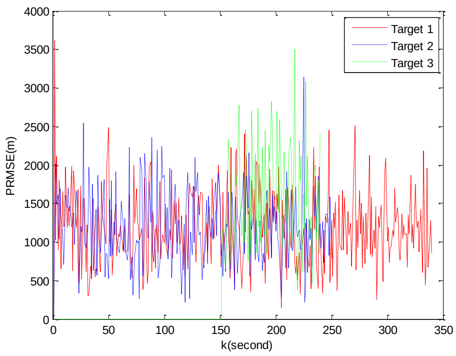


Figure 11. *PRMSE.*

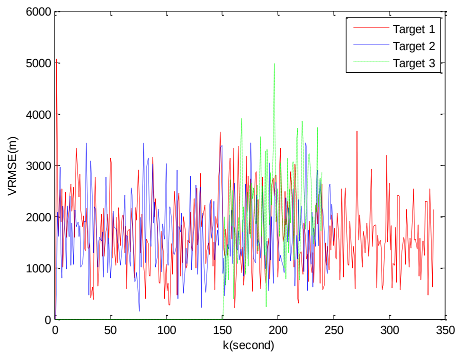


Figure 12. *VRMSE.*

4. CONCLUSIONS

Method for multi-target tracking on the basis of combining PHD filter and the data association JPDA using particle filter in the 3D mixed coordinate system above has following advantages:

The method can track multi-target change over time, to distinguish good targets, not being mistaken target even if the target has complex motion at close distance, the error of the method is low and tends to reduce. The method can solve the non-linear model and non-Gaussian noise. In short, multi-target tracking method mentioned above can track the target in the most complicated cases, the most general and feasible for real-time application system by minimizing processing time. However, some points of the method that need to be resolved are on its execution time, due to implementation by the particle filter for both JPDA and PHD filter, so the method increases the processing time. Thus, for the more complete algorithm, researching on more optimal algorithms are necessary and should continue to be studied.

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TÓM TẮT

Xây dựng phương pháp bám đa mục tiêu trên cơ sở kết hợp bộ lọc PHD và phương pháp kết hợp dữ liệu JPDA sử dụng bộ lọc phần tử trong hệ tọa độ hỗn hợp 3 chiều

Số mục tiêu thay đổi, mô hình đo lường phi tuyến và nhiễu phi Gaussian là những thử thách đối với bài toán bám đa mục tiêu; các yếu tố này ảnh hưởng đến độ chính xác, thời gian thực hiện và quyết định sự thành công của phương pháp. Trong bài báo này, tác giả trình bày một phương pháp để giải quyết các vấn đề trên. Trong phương pháp này chuyển động của mục tiêu được biểu diễn trong hệ tọa độ hỗn hợp 3 chiều trên cơ sở kết hợp bộ lọc PHD và phương pháp kết hợp dữ liệu JPDA. Phương pháp đề xuất có khả năng bám đa mục tiêu trong trường hợp tổng quát nhất, đó là: số mục tiêu thay đổi, mô hình hệ thống và mô hình đo lường là phi tuyến và nhiễu là phi Gaussian. Kết quả nghiên cứu của bài báo có thể áp dụng với những hệ thống đáp ứng theo thời gian thực, trong khi các mục tiêu chuyển động ở khoảng cách gần nhau và có tính cơ động cao.

Từ khóa: Bám đa mục tiêu; Hệ tọa độ hỗn hợp; PHD kết hợp JPDA; Lọc phần tử; nhiễu phi Gaussian; Mô hình động học vận tốc không đổi.