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Article

An Improved UAV-PHD Filter-Based Trajectory Tracking Algorithm for Multi-UAVs in Future 5G IoT Scenarios

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Abstract: The 5G cellular network is expected to provide core service platform for the expanded Internet of Things (IoT) by supporting enhanced mobile broadband (eMBB), massive machine-type communication (mMTC), and ultra-reliable low latency communications (URLLC). Unmanned aerial vehicles (UAVs), also known as drones, provide civil, commercial, and government services in various fields. Particularly in a 5G IoT scenario, UAV-aided network communications will fulfill an increasingly important role and will require the tracking of multiple UAV targets. As UAVs move quickly, maintaining the stability of the communication connection in 5G will be a challenge. Therefore, it is necessary to track the trajectory of UAVs. At present, the GM-PHD filter has a problem that the new target intensity must be known, and it cannot obtain the moving target trajectory and the influence of the clutter is likely to cause false alarm. A UAV-PHD filter is proposed in this work to improve the traditional GM-PHD filter by applying machine learning to the emergency detection and trajectory tracking of UAV targets. An out-of-sight detection algorithm for multiple UAVs is then presented to improve tracking performance. The method is assessed by simulation using MATLAB, and OSPA distance is utilized as an evaluation indicator. The simulation results illustrate that the proposed method can be applied to the tracking of multiple UAV targets in future 5G-IoT scenarios, and the performance is superior to the traditional GM-PHD filter.

Keywords: 5G; IoT; UAV; multitarget tracking; GM-PHD filter; UAV-PHD filter; machine learning

1. Introduction

The communication industry has experienced massive growth over the past two decades. In the first generation (1G), only analog systems were used. However, in the fourth generation (4G), all-IP-based systems have been employed. It is conceivable that the fifth generation (5G) cellular network will achieve a qualitative breakthrough in various fields including equipment and technology [1–5]. The rapid evolution towards 5G is due to developments in digital modulation, the popularity of the Internet, and physical layer technologies such as WCDMA, OFDMA, MIMO, and HARQ. However, the development of 5G wireless systems remains challenging, and requires the inclusion of 5G wireless systems in new applications. A number of public and private sectors including urban management, healthcare, and transportation have already been improved due to 5G applications [6]. In the future, the 5G cellular network advantages of wide coverage, plug-and-play, and embedded security, will be utilized to support the expanded Internet of Things (IoT).

While IoT for smart devices was conceived as part of a common vision for the future of the Internet, technology available at the time could not facilitate its implementation [7]. Today, small computer devices have both sensing and communication capabilities, as well as universality, providing a path to realize the IoT vision [8]. The IoT is made up of multiple physical devices that have the ability to connect to remote computing. This also enables IoT to communicate between heterogeneous devices without human intervention [9–11]. As the IoT can create an environment conducive to daily life and business applications, as well as promote the development of the world economy, it has the capacity to transform lives in the near future.

Unmanned aerial vehicles (UAVs), also known as drones, are used in various civil, commercial, and government functions including environment monitoring, soil quality testing, and disaster relief. As UAVs can provide high-speed wireless communication, it is speculated that they will have an important role in implementing 5G [12,13]. The function of UAVs can be enhanced by additional technology. For example, when equipped with wireless access technology, drones can move to various locations to provide a network connection from the sky to a ground device in a desired area. Drones can also facilitate the potentials of 5G and are currently used to provide 5G connectivity for IoT devices. In addition, UAVs have the advantages of rapid deployment, high mobility, and low cost, which are not available in terrestrial communications [14]. However, as UAVs move quickly, maintaining the stability of the communication connection in 5G will be a challenge. Therefore, it is necessary to track the trajectory of UAVs. As multiple UAVs will be required for providing communication connections, multitarget tracking technology is the focus of this study.

Under multitarget tracking, the radar automatically determines the coordinates of multiple targets covering the airspace under computer control, and continuously provides target position data for determining the target and predicting target trajectory [15]. Numerous approaches exist for achieving multitarget tracking, including representative methods based on detected data associations and energy minimization. The method of detecting data association based on detection is most often used as it is more reliable for solving the data association of multiple frames together [16]. Most previous data association-based methods only consider the relationship between detections in the local finite time domain. As a result, such methods struggle to operate under long term occlusion or to distinguish spatially close targets with similar appearance in crowded scenes. Data association is one of the most difficult problems in multitarget tracking, and solutions can be broadly divided into the two categories of Bayesian and non-Bayesian. Another problem encountered in multitarget tracking is that the maximum tracking accuracy of the tracking algorithm is much lower than that of a single-target tracking algorithm and fails to meet operational requirements. Thus, multitarget tracking contains significant technical challenges that are not present in classical detection, estimation, and nonlinear filtering problems, mainly due to measurement source uncertainty.

In the early 21st century, Ronald Mahler proposed the use of Finite Set Statistics (FISST) to achieve multitarget Bayesian estimation under multiple sensors. It was later discovered that RFS-based multitarget Bayesian filters contain multidimensional integrations that are difficult to implement. To solve this problem, Mahler proposed a PHD (Probability Hypothesis Density) filter [17], which uses first-order moment information to approximate multitarget states. This theory avoids the problem of data association between observed and state values in traditional multitarget tracking methods. However, its shortcoming is that there is a large number of integral operations based on functions of random finite set, which is difficult to apply in engineering. Ba-Ngu Vo et al. proposed the GM-PHD filter [18], which made linear, Gaussian assumptions on the target dynamics and birth process, using the linear Gaussian model to obtain the solution of the PHD recursive equation. The PHD filter is effectively improved and has the advantages of small calculation amount and simple target state extraction. Later, it was found that the PHD filter recursive process can transmit the target number information, but under certain conditions, its estimation of the target number is very unstable. In response to this problem, Mahler [19] further improved the PHD filter in 2006, and proposed a Cardinalized Probability Hypothesis Density (CPHD) filter that can simultaneously transmit the target posterior PHD and potential distribution (probability distribution of the target number). Mahler presupposes that the target appearance and disappearance process obey the multi-Bernoulli distribution [20]. Based on the independence of state between the targets, another approximation method of the optimal multiobjective Bayesian filter is given, which called Multitarget Multi-Bernoulli, MeMBer) filter.

Although GM-PHD filter is the most widely used, it still contains some limitations for practical engineering applications. On one hand, the intensity of the new target needs to be known, On the other hand, it has no trajectory correlation function. Gaussian mixture probability hypothesis density (GM-PHD) filters are widely used to track multiple targets [21,22]. The GM-PHD filter can propagate the posterior probability density function related to multiple targets, and avoids the data interconnection problem between the target and the measured value through recursion. This filter is combined with machine learning in this work, and a UAV-PHD filter is proposed to achieve multitarget tracking of UAVs.

The remainder of this paper is organized as follows. Section 2 introduces the UAV-IoT network as the application scenario of the proposed algorithm. Section 2 examines target tracking and traditional GM-PHD filter, and the proposed UAV-PHD filter is developed in Section 3. Section 4 presents the simulation results of the presented multitarget tracking method. Finally, Section 5 concludes the paper.

2. System Model

2.1. UAVs in a 5G-IoT Scenario

The IoT has expanded significantly in recent years, with UAVs playing a vital role in supplying wireless connectivity. Wireless communication provided by drones has provided an important contribution to expanding network coverage and supporting wireless connectivity [23]. As illustrated in Figure 1a, UAVs can be used as mobile flying base stations (MFBSs) and provide network connectivity to terrestrial devices when equipped with the relevant wireless access technologies. Such drones are quick and simple to deploy, and their configurations are more flexible, supplying a superior communication channel via short-range line of sight links [24]. Network performance can be improved further by precisely directing drones to specific targets, meaning UAVs will perform a significant role in 5G connectivity. These applications are particularly relevant for expanding network coverage to countryside zones or establishing temporary connectivity in areas where terrestrial networks could be unstable.

Drones also have the capacity to combine the benefits of 5G and IoT in a special mode. As demonstrated in Figure 1b, some IoT devices could be carried onboard UAVs. Drones equipped with remotely controlling IoT devices such as cameras and sensors possess the ability to provide IoT services during the initial tasks. Therefore, when UAVs reach a particular location, a designated time, or when a special event occurs, IoT devices can take measurements from the air as needed. As UAVs can easily fly to different locations, they can be redirected to a required zone specified by users [25]. This offer a possibility of quickly establishing IoT services in countryside zones or in areas without IoT, as well as offering IoT functions through the intelligent orchestration of drones and their airborne IoT devices. For example, drones could share tasks that measure the humidity and temperature of large forests in order to locate potential fires before they occur. As a communication network, 5G will assist in the integration of IoT platforms based on UAV and provide the desired services. The required quality of services will benefit from the high data speed of 5G, meaning it will be able to offer high-resolution videos captured by the UAVs, while ensuring the communication of information such as geographic location and remaining energy. In addition, as a large number of drones will be deployed in the era of 5G, they will have the ability to accommodate a large number of nodes. Thus, drones have an increasingly important role in IoT wireless connections and enable a variety of IoT services to be provided from the air.

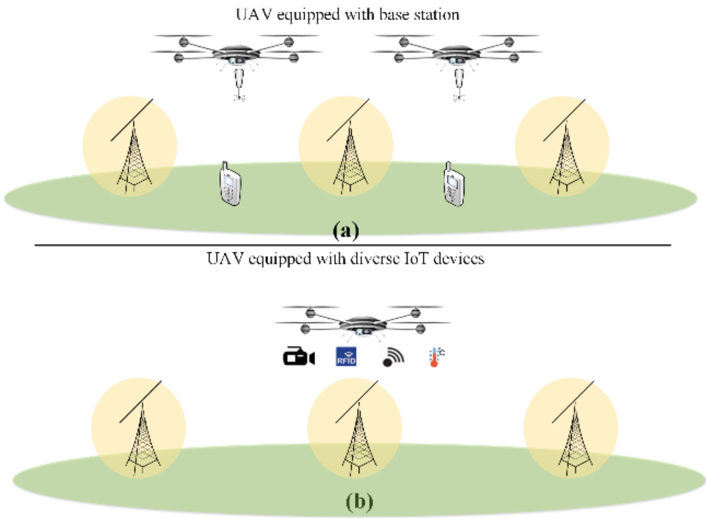

Figure 1. The role of UAVs (unmanned aerial vehicles) in a 5G-IoT (Internet of Things) scenario: (**a**) UAV equipped with base station; (**b**) UAV equipped with diverse IoT devices.

Drones can be utilized to establish an innovative aerial UAV-based IoT platform, which will minimize the capital and operating costs of creating a new communications ecosystem on land. On the IoT platform, UAVs can collect data onboard using remotely controlled IoT devices which can be triggered or shut down at the appropriate time, location, or particular event. Depending on the energy required, the collected data can be computed on a local airborne drone or offloaded to a cloud server on the ground [26]. In order to establish an efficient drone-based IoT platform, a platform coordinator is required to sense various contextual information such as drone flight routes, IoT devices, and battery status. Figure 2 shows the proposed architecture of the UAV-based IoT platform. The figure shows an extensive network of flying drones, each of which is assigned to a specific mission, with some flying and others prepared to fly when required.

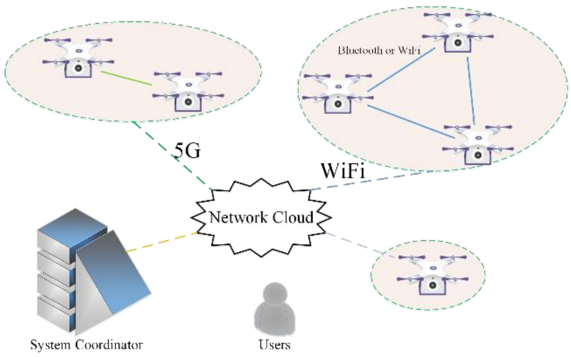

Figure 2. The UAV-based IoT platform we studied.

Drone data transmission is carried out by any wireless technology suitable for the required UAV application, including WIFI and 4G or 5G cellular networks. A variety of factors influence the choice of wireless technology including requested security, reliability, and system responsiveness. Apart from drone-to-ground communications, UAVs can also form clusters via the flying-self-organizing-network (FSONET), benefiting from short-range wireless communication technologies like Bluetooth and WIFI, and sharing the network's computing resources, data transfer links, and airborne IoT devices. A cluster head must be elected from the suitable UAVs, which will transmit the IoT data collected from all drones to the ground station [27]. This clustering method can be practical when the drones do not possess adequate capabilities or computing resources or they require other complementary IoT devices to perform an IoT task. As shown in Figure 2, the system coordinator (SC) is responsible for orchestrating the operations of drones and their onboard IoT devices, as well as dealing with user requests for IoT services. In order to provide satisfactory IoT services, the SC initially selects the most appropriate UAV depending on a number of principles such as the current route of the drone, onboard IoT device, remaining energy level, and the priority of the current task. The flying paths of drones are also coordinated by the SC, which ensures that no collision will occur during travel. To ensure the security of communications between drones and terrestrial stations, the SC determines which access technology should be employed on the UAV, when it must occur, and where the data should be transmitted (e.g., edge or cloud server).

In short, in 5G-IoT scenarios, UAVs promise to play a significant role. UAVs could be used as mobile flying base stations (MFBSs) and provide network connectivity to terrestrial devices when equipped with the relevant wireless access technologies. Furthermore, they could be equipped with onboard remotely controlling IoT devices to provide IoT services in countryside zones or in areas without IoT. Drones can also be utilized to establish an innovative aerial UAV-based IoT platform, which could compute the collected data and make real-time decisions from the air. However, maintaining the 5G communication connection when tracking UAVs could be a problem, since UAVs move rapidly in the sky.

2.2. Target Tracking

2.2.1. Target Tracking Background

Recursion plays a pivotal role in multitarget tracking. The trajectory of each object is determined at the beginning of radar scanning; then, measurement information from the sensors is used to update the initially established target track. When measurement data (echo) from the sensor enters the target's tracking gate, the echo is called a valid measurement (or valid back) wave [28–31]. Even with only one target, there may be multiple valid measurements due to clutter interference. To estimate the true motion trajectory of each object, the target tracking process includes three stages: target recognition, adaptive filtering, and prediction. In the tracking space, the data association input is a valid measurement, and measurements or echoes unrelated to the established target trajectory may come from potential new targets or clutter. The tracking start method first identifies if tracking can be performed and a new target track is set accordingly. If the target is fleeing or corrupted in the tracking space, the tracking termination method can eliminate tracking and reduce unnecessary computational overhead. Finally, the appropriate tracking gate center and size at the next moment can be selected based on the target prediction value and the received echo probability value. Data association is a vital technology for target tracking, especially for multitarget tracking. The accuracy of the data association will directly affect the performance of the tracking system as the associated results determine the observed echo of the updated target tracking.

2.2.2. Traditional GM-PHD filter

(a) Assumptions

The high computational complexity of the PHD filter and multidimensional integration problems with indefinite dimensions can create difficulties in practical engineering applications. Vo et al. proposed a GM-PHD filter based on a linear Gaussian system to address this issue [32–34]. The filter is based on certain assumptions that are summarized below.

It is assumed that the dynamical model and observation model for each object are both linear Gaussian.

$$f_{k|k-1}(x_k \middle| x_{k-1}) = N(x_k; F_{k-1}x_{k-1}, Q_{k-1}), \tag{1}$$

$$g_{k|k-1}(z_k|x_k) = N(z_k; H_{k-1}x_{k-1}, R_{k-1}), \tag{2}$$

where F_{k-1} is the state transition matrix, Q_{k-1} is the noise driven matrix, H_k is the measurement matrix, R_k is the measurement noise matrix, and $N(x; m, P)$ is a Gaussian distribution with mean m and covariance p.

It is assumed that the probability of survival and the probability of monitoring the target are independent of each other.

$$p_{S,k}(x) = p_{S,k}, \tag{3}$$

$$p_{D,k}(x) = p_{D,k}, \tag{4}$$

The intensities function of the new targets can be expressed in the form of Gaussian mixture and there are no spawn targets.

$$\gamma_k(\boldsymbol{x}) = \sum_{i=1}^{J_{\gamma,k}} \omega_{\gamma,k}^{(i)} N\left(\boldsymbol{x}; \boldsymbol{m}_{\gamma,k}^{(i)}, \boldsymbol{P}_{\gamma,k}^{(i)}\right), \tag{5}$$

(b) Filtering steps

The GM-PHD filter implements filtering by a prediction stage and an update stage.

Suppose that posterior intensity of multiple targets at time $k-1$ is a Gaussian mixture of the form:

$$v_{k-1}(\boldsymbol{x}) = \sum_{i=1}^{J_{k-1}} \omega_{k-1}^{(i)} N\left(\boldsymbol{x}; \boldsymbol{m}_{k-1}^{(i)}, \boldsymbol{P}_{k-1}^{(i)}\right), \tag{6}$$

Thus, the predicted intensity at time k, which is also a Gaussian mixture, is calculated by:

$$v_{k|k-1}(\boldsymbol{x}) = v_{S,k|k-1}(\boldsymbol{x}) + \gamma_k(\boldsymbol{x}), \tag{7}$$

where $\gamma_k(\boldsymbol{x})$ is the intensity function of the new object.

$$v_{S,k|k-1}(\boldsymbol{x}) = p_{S,k} \sum_{j=1}^{J_{k-1}} \omega_{k-1}^{(j)} N\left(\boldsymbol{x}; \boldsymbol{m}_{S,k|k-1}^{(j)}, \boldsymbol{P}_{S,k|k-1}^{(j)}\right), \tag{8}$$

$$\boldsymbol{m}_{S,k|k-1}^{(j)} = \boldsymbol{F}_{k-1} \boldsymbol{m}_{k-1}^{(j)}, \tag{9}$$

$$\boldsymbol{P}_{S,k|k-1}^{(j)} = \boldsymbol{Q}_{k-1} + \boldsymbol{F}_{k-1} \boldsymbol{P}_{k-1}^{(j)} \boldsymbol{F}_{k-1}^{T}, \tag{10}$$

Update: Suppose that posterior intensity at time k is a Gaussian mixture of the form:

$$v_{k|k-1}(\boldsymbol{x}) = \sum_{i=1}^{J_{k|k-1}} \omega_{k|k-1}^{(i)} N\left(\boldsymbol{x}; \boldsymbol{m}_{k|k-1}^{(i)}, \boldsymbol{P}_{k|k-1}^{(i)}\right), \tag{11}$$

Thus, the posterior intensity of time k which is also Gaussian mixture is calculated by:

$$v_k(\boldsymbol{x}) = \left(1 - p_{D,k}\right) v_{k|k-1}(\boldsymbol{x}) + \sum_{z \in Z_k} (\boldsymbol{x}; \boldsymbol{z}), \tag{12}$$

where,

$$v_{D,k}(x|z) = \sum_{j=1}^{k|k-1} \omega_k^{(j)}(z) N\left(x; m_k^{(j)}(z_0), P_{k|k}^{(j)}\right), \tag{13}$$

(c) Problems of GM-PHD filter in radar trajectory tracking

Although the GM-PHD filter has a simple structure and low computational complexity, it still contains some problems for practical engineering applications. First, the standard GM-PHD filter requires a known clutter priori-intensity. However, the probability distribution of clutter changes with time in the actual environment. Secondly, in the target initialization phase, the intensity of the new target is known; however, in the proposed scenario, the location and time that the UAV appears is unknown and random. Finally, although the GM-PHD filter can predict the number and status of targets within the monitored range, it has no trajectory correlation function, so the target trajectory cannot be extracted. These problems will affect the initialization and trajectory extraction of multitarget. The improved UAV-PHD filter effectively solves these problems, providing a solution for multi-UAV trajectory tracking in 5G IoT scenarios, and creating a basis for subsequent processing, including UAV identification and behavior discrimination prediction and so on.

3. Multitarget Tracking Algorithm for UAVs Based on Improved GM-PHD Filter

3.1. Proposed UAV-PHD Filter

The introduction of the GM-PHD filter in the previous section illustrates the difficulties in multitarget trajectory tracking. In this section, the proposed UAV-PHD filter is introduced. The development of artificial intelligence technology has facilitated increased use of machine learning in a variety of industries, providing new methods to solve problems efficiently. In this work, the classical algorithm k-nearest-neighbor (kNN) and k-means clustering in machine learning is applied to the traditional GM-PHD filter to improve its performance. The kNN algorithm is applied to the emergence detection of UAV targets, and a new target strength estimation algorithm is proposed based on observation information. In addition, the concept of clustering algorithm is applied to the output of the filter, and "tag technology" is used to achieve the "data association" between the current state information and the target historical state information, thereby extracting the motion trajectory of multiple UAV targets. In addition, an out-of-sight detection algorithm is proposed for use when the UAV target is far away from the monitoring range. The algorithm flow is illustrated in Figure 3.

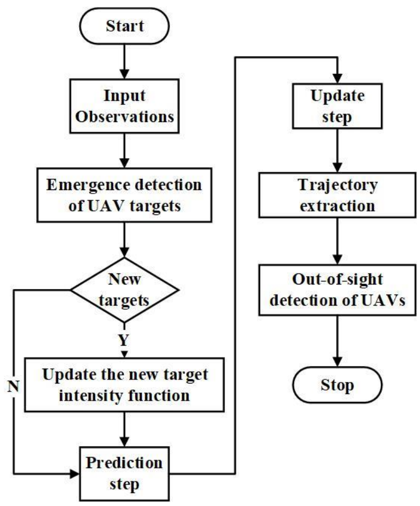

Figure 3. Flow chart of proposed multitarget tracking algorithm.

3.2. Steps for Trajectory Tracking of Multiple UAV Targets

3.2.1. Emergence Detection of UAV Targets

The kNN algorithm is a supervised learning algorithm composed of a data training set and a data test set. Each sample includes feature data and tags, so that the tags to which each training sample belongs can be determined. In the training process, by calculating the distance between each sample, they are divided into different spaces, and the output of the space is determined according to the voting method or the averaging method of the samples in the space. During the test, the test samples used are unlabeled, the distance between each feature of the new sample and each feature in the training sample is calculated, and the partition space most similar to the test sample is located. The obtained output of this space is the output of the test sample.

In kNN, the three elements of distance metric, selection of k value, and classification decision are considered respectively. Once the three rules are determined, a kNN algorithm can be uniquely determined. In the existing research on PHD filters, the intensity of the new target is often necessary as priori information. However, in the scenario studied in this paper, the moments and positions of the appearance of UAVs are random, so the intensities of new targets cannot be predicted in advance. In this article, we apply the idea of kNN of machine learning. The newly generated UAV target is determined by operating the observation values of the system at three adjacent moments to obtain the position information and the speed information. In this work, the three data frames utilized by kNN are used to monitor the new UAV target. If the new target is detected, the target intensity function is updated, and the UAV-PHD filter is used for subsequent processing for multiple UAVs. Real-time tracking is the first step of multitarget tracking, and the algorithm flow is as follows.

1. It is assumed that the observation sets at times k, $k-1$, and $k-2$ are M_k, M_{k-1}, and M_{k-2}, respectively, and $r_{k,i}(i = 1, 2, \ldots, N)$ represent the i-th observation generated at time k, with N observations at this time. In the two-dimensional scene, the observed value r = (x, y) represents the two-dimensional coordinates of a certain position.
2. The nearest point pairs are located if the following conditions are met:

$$\begin{cases} v_{\min} < \left| \frac{r_{(k,i)} - r_{(k-1,j)}}{T} \right| < v_{\max} \\ v_{\min} < \left| \frac{r_{(k-2,p)} - r_{(k-1,j)}}{T} \right| < v_{\max} \\ \left| \frac{r_{(k-2,p)} - r_{(k-1,j)}}{T} - \frac{r_{(k-1,j)} - r_{(k,i)}}{T} \right| < a_{\max} T \end{cases}, \tag{14}$$

In this work, $\left(r^*_{k-2,p}, r^*_{k-1,j}, r^*_{k,i}\right)$ is considered as a set of candidate occurrence and $r^*_{k,i}$ is taken as the location of the target. Subscript T is the radar scan period and $v_{\min}, v_{\max}, a_{\max}$ are the minimum speed, maximum speed, and maximum acceleration of the UAV targets, respectively, which can be obtained from prior knowledge.
3. The new target intensity function is calculated and updated.

3.2.2. Trajectory Extraction of UAV Targets

Group target tracking is a kind of complex multitarget tracking problem. The existing PHD filter tracking algorithm only models all target sets and cannot directly obtain the motion trajectories of multiple UAV targets. In the UAV target trajectory extraction process, two problems must be solved. Firstly, the output of the filter is a set, and the correlation information between the outputs at different times cannot be obtained by the filter. This means that the trajectories of multiple UAVs cannot be obtained and the historical information of the trajectory cannot be effectively utilized, affecting the tracking performance of the filter. Secondly, the filter cannot judge the demise of the UAV, which will increase the adverse effects caused by the clutter, and is not conducive to subsequent use of the filtering results. In this paper, the k-means algorithm is applied to the trajectory tracking of multi-UAV targets, clustering each filtering result of the UAV-PHD filter and extracting the motion trajectories of the UAVs.

The *k*-means algorithm is one of the clustering algorithms used to classify data by learning unlabeled training data. It is based on the observation that the centroid of the cluster should be the best position of the perfect center. Given a set of any k centers Z, for each center, let *V(z)* denote its neighborhood, where z is the nearest neighbor's set of data points. Each stage of the method moves each center point z to the centroid of *V(z)*, and then updates *V(z)* by recalculating the distance from each point to its nearest center. These steps are executed until a number of convergence conditions are met. For points in the general position, the algorithm eventually converges to the local minimum of the distortion. In the scenario studied in this paper, the process is as follows.

1. Input the existing trajectory set E_{k-1} at time *k-1* and the *k* time filter result set X_k, where $E_{k-1} = \left\{e_{1,k-1}, e_{2,k-1}, \ldots, e_{n,k-1}\right\}$, $X_k = \{x_1, x_2, \ldots, x_m\}$.
2. Cluster centers $U = \{\mu_1, \mu_2, \ldots, \mu_n\}$ are set and the k time track set $C = zeros(1, n)$ is initialized.
3. The Euclidean distance of the filtered values $X_{k,j}$ and u_i, are determined respectively, and recorded as d_{ji}. The nearest value of the distance $X_{k,j}$ is obtained and recorded as i^*.
4. The sample $X_{k,j}$ is divided into the corresponding cluster: $Ci^* = X_{k,j}$.
5. The above steps are repeated until all the values in $X_{k,j}$ have been iterated.
6. Steps 2–5 are repeated until the algorithm results converge.
7. If $C_i = 0$, the current target has no observations, and the algorithm calculates the estimated value based on the first two frames of data.
8. If $X \neq \varnothing$, the unclassified value is used as the starting point for the new track.
9. Output: The updated tracks set $C = \{C_1, C_2, \ldots, C_n\}$

3.2.3. Out-of-Sight Detection of UAV

In our studied scenario, if we cannot judge the disappearance of the UAV target, the existing filter will continually focus on the target and false alarms are easily generated. In the proposed 5G-IoT scenario, the radar has a certain monitoring range. If the UAV disappears, the PHD filter will likely misinterpret the clutter as the target and affect the accuracy of trajectory tracking. Targets that have died out will no longer produce observations. Although some targets being tracked may also have missed detection in a certain test, combined with the existing set of tracks, the time of successive missed detections of a UAV target can be recorded. If the time of successive missed detections of a UAV target is greater than three, the target is determined to have disappeared. The specific out-of-sight detection algorithm of UAVs is as follows.

1. Using the algorithm proposed in the previous section, the track set $C = \left\{e_{k,i}\right\}, (i = 1, 2, 3, \ldots n)$ is input at time k, and the matrix $S_{1\times N}$ is used to represent the state of N targets. The initial state of S is entirely 0 matrix.
2. If $C_i = 0$, the estimated value is calculated based on the first two frames of data: $C_i = e_{k-1,i} + (e_{k-1,i} - e_{k-2,i})$, and $S[i] += 1$ is set to record the disappearance of the target at this time frame.
3. The above steps are repeated to iterate through all the data.
4. If $S[i] \geq 3$, it indicates that the i-th target has been missed three times in a row, and the target can be judged as out of sight.
5. Set $E = E - \{e_{k,i}\}$. The targets in the trajectory that are far away from the radar monitoring range are thus eliminated, and the updated trajectory set E is output.

4. Simulation Results

4.1. Model and Parameter Settings

4.1.1. Proposed UAV Dynamic System Model

The experiments in this paper simulate the scenario of tracking multi-UAVs in future 5G IoT networks and are performed in MATLAB software. After the radar monitoring range is converted into a two-dimensional plane, the monitoring range of the x–y axis of the two-dimensional plane is assumed to be $[-1000, 1000]$, the radar scanning period is $T = 1$, the radar monitoring duration is 100, and the location, speed, and time at which UAV targets appear are random. The vector $\left[x, v_x, y, v_y\right]^T$ is used to represent the state of the UAV target, where x and y represent the position information of the two axes, and v_x and v_y are the velocity information of the two axes directions. According to the theory of GM-PHD filter, assuming that UAVs have a uniform linear motion, the following state space model is used to describe the proposed multi-UAV dynamic system.

$$X_k = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 11 \end{bmatrix} X_{k-1} + \begin{bmatrix} \frac{T^2}{2} & 0 \\ T & 0 \\ 0 & \frac{T^2}{2} \\ 0 & T \end{bmatrix} V_k, \tag{15}$$

$$Y_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} X_k + W_k, \tag{16}$$

The above two equations are the state equation and the observation equation, respectively, where V_k and W_k are uncorrelated Gaussian white noise. V_k is the process noise, which is the acceleration during UAV motion, while W_k is the observed noise with the variance $\sigma_w^2 = 10^2$. The clutter is evenly distributed over the entire monitoring range. The number of clutter follows a Poisson distribution whose density is λ, and the target survival probability is $p_s = 0.99$ when the target detecting probability is $p_D = 0.98$. The combination threshold is $U = 4$, Gaussian term pruning threshold is $\tau = 10^{-5}$, and maximum Gaussian component is $J_{\max} = 100$. The simulation assumes that the maximum flight speed and minimum flight speed of the UAVs are $V_{\max} = 30m/s$ and $V_{\min} = 0m/s$, respectively.

4.1.2. Tracking Performance Evaluation Indicators

An evaluation of the quality of the proposed multi-UAV tracking algorithm must gauge the error between the target state and the true value in the random finite set, as well as the potential of the set, that is, the error between the number of targets and the true value. Therefore, traditional evaluation methods such as mean error and mean square error are no longer applicable in the multi-UAV scenario. In order to consider these two differences at the same time, the main evaluation schemes are Hausdorff Distance, Wasserstein Distance and OSPA Distance. Hausdorff Distance is not sensitive to the difference between the cardinalities, and the treatment of outliers is too serious. The Wasserstein Distance has made improvements and is sensitive to the cardinality error of the set, but there are still some limitations. In the case of an empty set, there is no reasonable physical meaning. After comprehensive considerations, the optimal subpattern assignment (OSPA) distance is thus used to evaluate the performance of the proposed UAV-PHD filter.

The consistency distance metric OSPA takes into account differences in the state of elements between sets and the number of elements between sets. Its components are divided into two parts, the distance error and the associated error, with p used for the distance sensitivity parameter and c for the associated sensitivity parameter. Define two nonempty sets $X = \{x_1, x_2, x_3, \ldots, x_m\}$ and $Y = \{y_1, y_2, y_3, \ldots, y_n\}$, which have the following definitions

$$D_{p,c}(X,Y) = \left[\frac{1}{n}\left(\min\sum_{i=1}^{m}\left(d_c(x_i, y_{\pi(i)})\right)^p + (n-m)\cdot c^p\right)\right]^{\frac{1}{p}}, \tag{17}$$

The value of p represents the weight of the distance deviation in the position estimation error, and the value of c represents the weight of the correlation error between the real element set and the estimated element set. The difference between p and c will affect the weight of the two error types in the position estimation error. To summarize, using the OSPA distance to measure the similarity between data sets can better reflect the local features and dynamic characteristics of the situational information, and the operation process is relatively simple. In this paper the parameters are set as $c = 1, p = 100$.

4.2. Experiment Results

4.2.1. UAV-PHD Filter Simulation

The simulation scenario is shown in Figure 4. It is assumed that there are 10 UAV targets, and the x-axis and y-axis define the monitoring range of the two-dimensional scene. In order to simulate the motion of multiple UAV targets in a real 5G IoT situation, the location, speed, and time of each target are random, and each target survives for no less than 20 monitoring periods. Figure 4 shows the real trajectories of 10 UAV targets in the simulation experiment, in which the start and end points of the trajectory are marked with different symbols in the results.

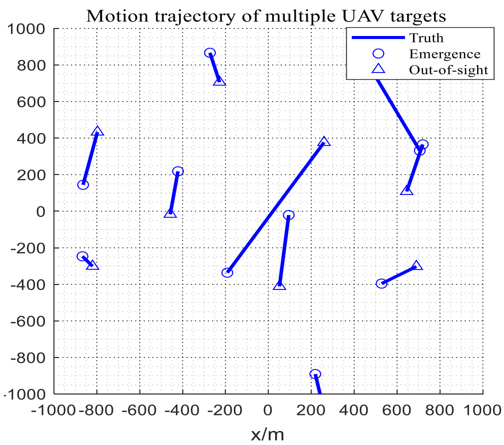

Figure 4. Real motion trajectories of UAV targets.

In the experiment, all parameters are controlled to be consistent, the same set of measured values are sent to the traditional GM-PHD filter and the new UAV-PHD filter for processing, and the new target intensity of the UAV is used as the prior information of the UAV-PHD filter.

Figures 5 and 6 show the trajectory filtering results of the traditional GM-PHD filter and the proposed UAV-PHD algorithm, respectively. As shown in the simulation figures, in the high-clutter UAV target tracking scene, the GM-PHD filter generates more clutter. The performance of the traditional algorithm is compromised because in the IoT scenario, the number of UAVs in the monitoring range changes very fast, and GM-PHD filter cannot utilize the UAV trajectory history information or judge UAV disappearance. Conversely, the proposed UAV-PHD filter effectively reduces false alarms, improves tracking accuracy, and accomplishes the task of multi-UAV target tracking.

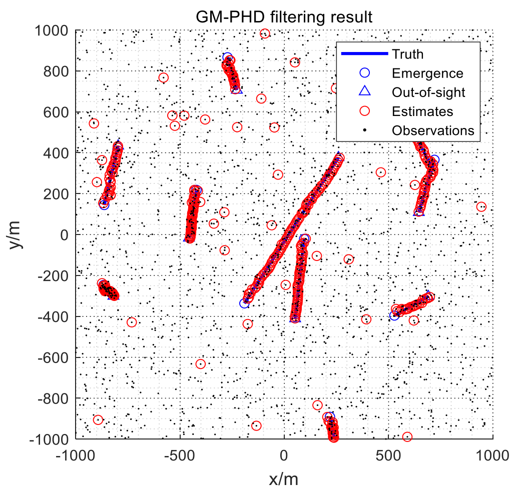

Figure 5. Filter results of GM-PHD filter.

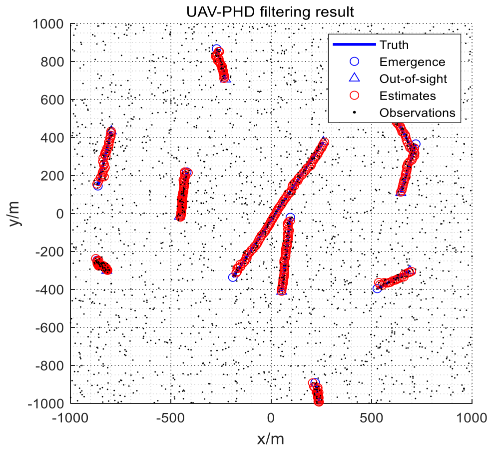

Figure 6. Filter results of UAV-PHD filter.

4.2.2. Performance Evaluation

The prediction of the number of targets for the two different filters is shown in Figure 7. It can be seen that the GM-PHD filter has a large number of false alarms throughout the observation time. For example, at 12 to 20 and 50 to 80, the estimated number of targets of the GM-PHD filter is generally higher than the real situation while UAV-PHD is more in line with the real situation. This is because the GM-PHD filtering results are independent of each other at different times, and the trajectory information is not utilized, which is greatly affected by the clutter. It can be seen that when the number of targets changes drastically, the proposed UAV-PHD filter estimates are more accurate and display better target tracking performance than traditional GM-PHD filter.

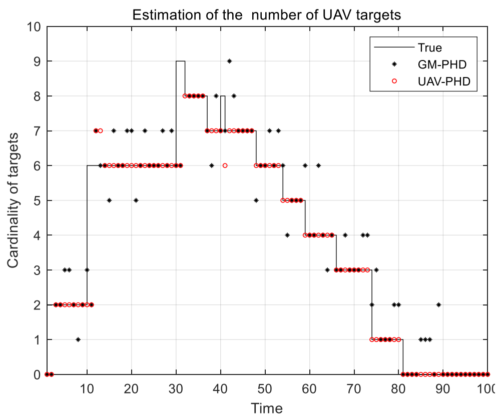

Figure 7. Estimation of the number of UAV targets.

Figure 8 shows the OSPA error between the filter's results and the real results, where OSPA Dist represents the combined error in the target state and target number estimates, OSPA Loc represents the error in the target state estimate, and OSPA Card represents the target number estimated error. It can be seen that the OSPA parameters of the traditional filter generally have higher values in the observation interval of 100 moments. The GM-PHD filter has a number of as high as 40 fluctuations at the OSPA Loc value from 60 to 70 moments. At 10 to 90, the total OSPA Dist and the OSPA Card generally have large fluctuations. On the contrary, the proposed scheme only has a high OSPA value at 0, 10, 30, 40 moments. It can be seen that the tracking performance of the UAV-PHD algorithm is greatly improved compared to the traditional GM-PHD filter.

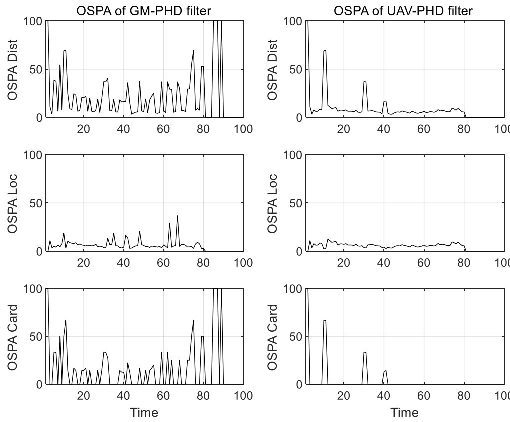

Figure 8. Comparison of OSPA (optimal subpattern assignment) performance of different methods.

In Figure 9, we compare the performance of the proposed UAV-PHD filter and the conventional GM-PHD filter in the case of different clutter density λ. We randomly generated 10 UAV targets and set the clutter density variation range as $[0, 50]$. We can see that when the clutter density λ is less than 15, the performance of two schemes are similar. However, with the clutter density increases, it is clear that the average OSPA distance of the GM-PHD filter increases sharply. On the contrary, the proposed UAV-PHD filter tends to be stable.

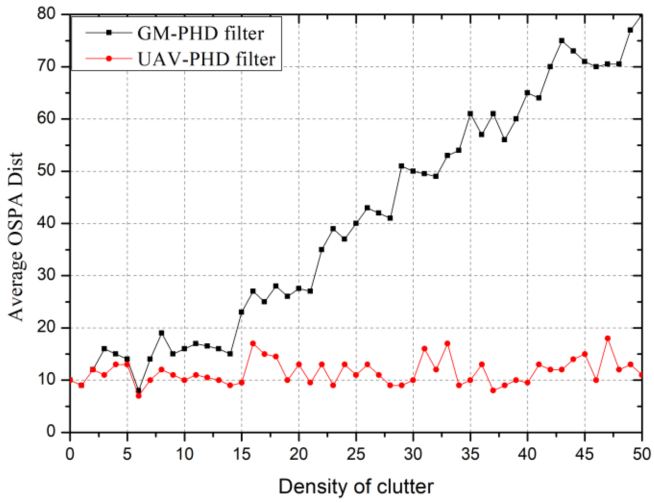

Figure 9. Average OSPA distance at different clutter densities.

In the scene where the clutter is dense, the traditional GM-PHD filter will generate more false alarm information, resulting in larger errors. By contrast, the proposed method utilizes the historical trajectory information of the UAV targets, and clusters the filtering results, which can eliminate false alarms caused by short-time clutter.

5. Conclusions

This paper explored the vital role of UAVs in future 5G-IoT networks. A UAV-PHD filter was then proposed to track the trajectories of multiple UAVs for subsequent processing including target behavior recognition and so on. The new approach works to improve the traditional GM-PHD filter by applying kNN and k-means algorithms in machine learning to the emergence detection and trajectory tracking of UAV targets. An out-of-sight detection algorithm for multiple UAVs was also presented to judge the demise of a target. Finally, the proposed algorithm was implemented in MATLAB, and OSPA distance was used to evaluate the performance of the UAV-PHD filter. From the simulation results, we can see that the proposed UAV-PHD filter effectively reduces false alarms and improves tracking accuracy. The combined error in the target state and target number estimates has been improved when compared with the traditional GM-PHD filter. The simulation results illustrate that the proposed improved UAV-PHD algorithm can be applied to the tracking of multiple UAV targets in future 5G-IoT scenarios with superior performance to the traditional GM-PHD filter.

The proposed method has achieved some improvements oriented on the multi-UAV target tracking field but there are still some limitations. In the multi-UAV target tracking process, we assumed that the observation information is strictly organized by time series. However, the observation value is often obtained by sensors or radars in the real situation. Thus, there must be a large amount of preprocessing during the information transferring, which may lead to chaotic timing of the observation information. It is an important problem that should be considered in further work. In addition, how to utilize the obtained trajectory information for subsequent processing, and with the development of the sensor, how to realize tracking using multiple sensor measurement data will be discussed in future research.

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