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Research on Target Trajectory Filtering and Risk Avoidance Strategy of Optimized Multilateration System

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ABSTRACT

In view of the large error of target state estimation in multi-point positioning system caused by traditional particle filter algorithm in the process of target tracking and positioning, thus increasing the risk of air traffic accidents, this paper analyzes the location update mechanism and operation process of firefly algorithm, and proposes to optimize particle filter algorithm by improving firefly algorithm. Firstly, following the global optimization idea of firefly algorithm, the position update formula of each particle is established, which effectively solves the particle dilution phenomenon and improves the operation efficiency Then, according to the change law of particle filter algorithm in each stage, the particle fixed-step movement mode is changed into dynamic step adjustment strategy by using nonlinear equation, which balances the ability of global search and local development and effectively avoids the premature convergence of the algorithm Finally, the improved firefly algorithm and particle filter mechanism are combined to make particles move to the high likelihood region and improve the effectiveness of particles. By analyzing the process of conflict resolution of multi-aircraft by multi-point positioning system, the direct influence of positioning efficiency on air traffic management is understood. The simulation results verify the effectiveness of the proposed algorithm, which shows that the algorithm has higher rapidity and better estimation accuracy, and improves the operation efficiency of the air traffic management system.

1. Introduction

With the rapid development of modern transportation modes, people are increasingly dependent on transportation, but no matter how diversified the transportation modes are, improving the positioning accuracy of transportation and tracking the moving target is the eternal research core. In recent years, the topic of air traffic management has become a hot topic for scholars all over the world. Facing the current complicated air traffic situation, the traditional radar surveillance system often has some problems such as abnormal positioning data, large positioning deviation and susceptibility to electromagnetic interference, which shows that it can no longer meet the needs of air traffic management, thus greatly limiting the development of air traffic, causing the stagnation of the global economy and increasing people's travel risks. A set of air traffic management system with real-time monitoring, accurate tracking, automation, intelligence and strong anti-interference ability is the focus of scientific research by scholars all over the world, and it is also an effective guarantee for future traffic management.

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Using multi-point positioning system to detect, locate, track and predict air targets is the basic data of air traffic management decision. However, the multi-point positioning system will be disturbed by various noises, resulting in the loss of positioning data, and the real-time performance of the positioning system will deteriorate, which will lead to misjudgment of air traffic management decisions. Therefore, ensuring the authenticity and integrity of aircraft tracking data is of far-reaching significance to ensure the stable operation of air traffic management.

Interactive Multi-model (IMM) algorithm is often used in the positioning and tracking system of moving targets, and its main feature is that it can calculate the continuous state and discrete state of the positioning system at the same time. IMM algorithm needs many iterative calculations to process data, and the variables can not be updated in time, which prolongs the time of tracking and forecasting air target trajectory. In the field of video tracking technology, Trucco and Plakas have studied in detail, and they have improved KLT algorithm to complete the tracking and positioning of three-dimensional space targets. However, as far as video tracking technology itself is concerned, there is a fundamental problem. When the target moves at a high speed or a long distance, its positioning effect will drop sharply, so it can not be applied well in practice. In air traffic management system, the flight state estimation of each target is an important basis for decision makers to issue instructions. However, in the face of complex air traffic conditions with different models, flight modes, flight states and flight environments, it is difficult for the positioning system to accurately provide the current traffic conditions. Obviously, the random filtering technology of multi-point positioning system can't effectively deal with complex air traffic data, while the particle filtering technology can simultaneously deal with the positioning data of multiple aircraft with high precision. The process of data processing by particle filter is the process of selecting high-quality particles and eliminating inferior particles. When the data jump range is large, the phenomenon of particle dilution will appear, which will affect the accuracy of target tracking. Therefore, this paper proposes an improved firefly algorithm to improve the particle dilution phenomenon in particle filter algorithm, which reduces the calculation amount of particle filter algorithm and makes the algorithm have higher rapidity and better estimation accuracy.

2. Numerical approach

2.1 target trajectory tracking principle of multi-point positioning system

Time difference of arrival (TDOA) positioning is used to locate all the equipment equipped with transponders with unified mode signals in the airport. Because the spatial positions of the four ground receiving stations are known, the time of arrival (TOA) of the target signal to each base station can be transmitted to the master station to calculate the TDOA, and the position of the target can be detected. The whole positioning process does not require high clock synchronization between the base station and the target. The base station layout and detection principle of detection target are shown in the following figure.

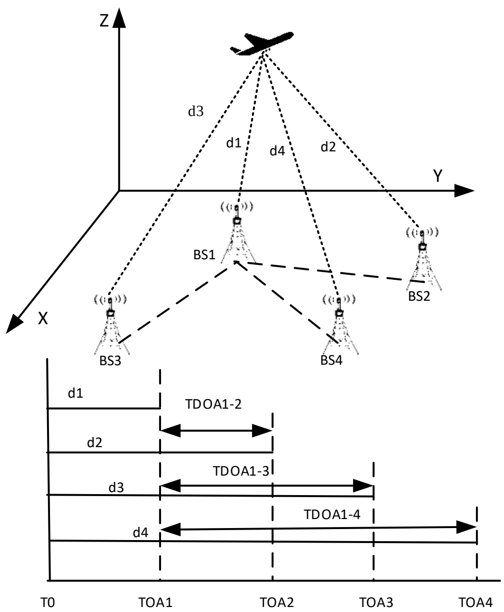


Fig. 1 Positioning principle of multi-point positioning system

The calculation process is:

$$\begin{cases} d_1^2 = (x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2 \\ d_m^2 = (x-x_m)^2 + (y-y_m)^2 + (z-z_m)^2 \\ d_{m,1} = d_m - d_1 = cn_{m,1} \\ (m = 2,3,4) \end{cases} \quad (1)$$

In the figure, bs1-bs4 represents the detection base station of MLAT system, BS1 is the master station, and the other three base stations are sub stations. Suppose the flight target location is (x, y, z), and the four base stations are (x_m, y_m, z_m). d_m represents the distance between the aircraft and the m base station, $d_{m,1}$ represents the distance difference between the signal and the m base station, that is, the difference between d_m and d_1. c represents the propagation speed of the signal, and $n_{m,1}$ represents the time difference between the m base station and the master station, namely $(d_m - d_1)/c$.

2.2 Multi-machine conflict resolution problem

The flight environment in low-altitude airspace is complex, so conflict resolution strategy is particularly important. On the basis of satisfying air traffic control and information exchange, the avoidance cost of each aircraft will be minimized, and the avoidance angle will be reduced as much as possible with the minimum safety distance as the restriction condition, so as to reduce the avoidance risk and avoid the situation of non-avoidance. Conflict resolution strategy is mainly to change flight direction and speed or change flight altitude to realize multi-aircraft avoidance. In this paper, the resolution strategy of dual-aircraft change direction is adopted. The specific conflict resolution process is shown in Figure 2.

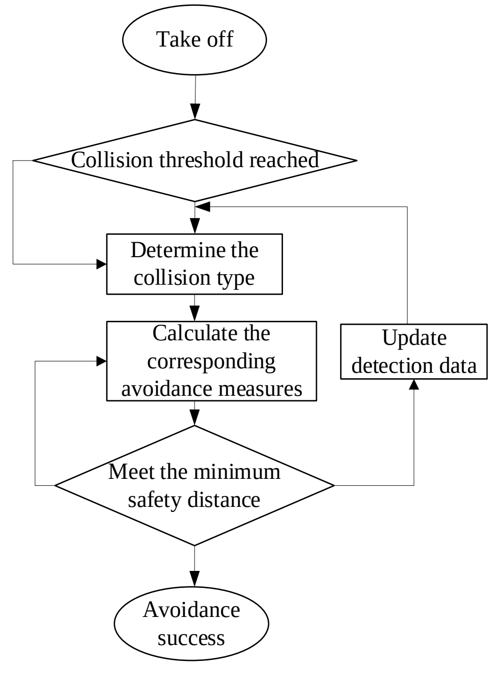


Fig.2 Conflict resolution process

When two aircrafts are flying in the same plane and the tracks cross, a conflict resolution model can be established to plan reasonable avoidance measures. It is assumed that the aircraft detection range is a circle with a diameter of 200km and the warning area is a circle with a diameter of 100km. All aircraft in the whole airspace carry out conflict detection, which can effectively avoid the secondary conflict of aircraft. The conflict detection model is shown in Figure 3.

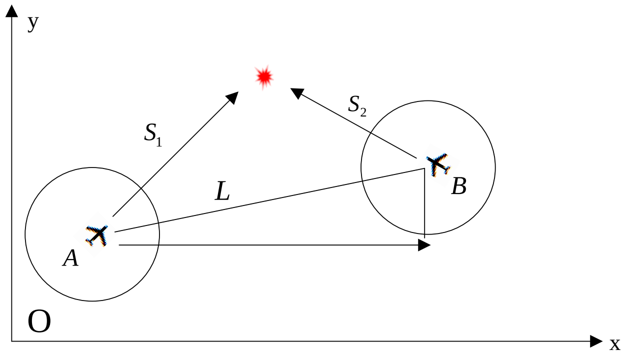


Fig.3 Conflict detection model

The initial coordinates of aircraft A are (x2, y2), the initial coordinates of aircraft B are (x3, y3), and the coordinates of collision points are (x1, y1). Because the speeds of the two aircrafts are consistent, when the distance between the two aircrafts and the intersection of flight paths is less than the minimum safe distance L, we can determine that the two aircrafts will collide at this time, that is, flight conflict. In which l is 10km, that is, flight conflict will occur when $s_1 - s_2 < L$ occurs.

$$\sqrt{(x_2-x_1)^2+(y_2-y_1)^2}-\sqrt{(x_3-x_1)^2+(y_3-y_1)^2}<L \qquad (2)$$

According to the flight rules of civil aviation and the operating characteristics of air traffic control, when building the model of aircraft conflict resolution, it can be simplified, so that the simulation platform can be built more simply without affecting the simulation results. For example, because the flying height of the aircraft is the same, the stereo map is changed to the plan map, the aircraft is assumed to fly at a constant speed, the conflict resolution is carried out in a geometrically optimal way, and the radius l of the safety area of the aircraft is fixed, and the conflict alarm distance is fixed as b.

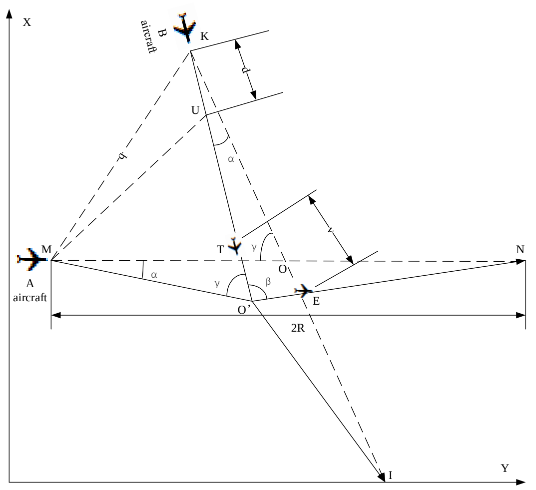


Fig.4 avoidance strategy of two aircraft

In order to avoid flight conflict, this paper puts forward a method of conflict relief, which mainly uses neural network algorithm to calculate the shortest flight distance between two aircraft and minimize the avoidance cost. The specific avoidance process is to make two aircraft turn their course at the same time to avoid collision, which is the most efficient of all avoidance strategies. As shown in fig. 4, aircraft a flies from point m to point n, and aircraft b flies from point k to point i. Assuming that the steering angles of both aircraft are α, a new trajectory intersection point will be formed after avoidance, and the distance between the two aircraft will be d after reaching O′, and then they can fly to their respective destinations. If at the initial point, the distance between two aircrafts is exactly equal to the warning distance, i.e b. The minimum safe distance is the radar control distance L .. Let them all have a flight distance of 2R.

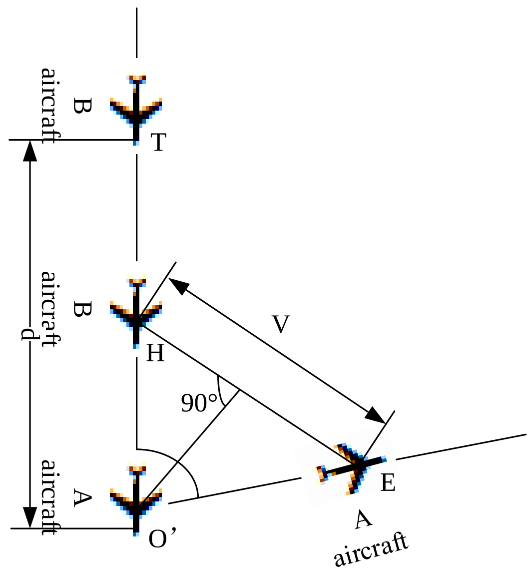


Fig.5 Two - engine avoidance trajectory calculation

In the figure, machine a arrives at O' point first, while machine b arrives at t point, and the distance between the two machines is d. Let's assume that when the B machine reaches the H point, the A machine reaches the E point, and the flight distance between the two machines is d/2, and the distance between the two machines is V. The calculation process of double-machine avoidance trajectory is as follows

$$\sin\frac{\beta}{2}=\frac{v}{d}\Rightarrow d=\frac{v}{\sin\frac{\beta}{2}} \qquad (3)$$

In ΔMOK ,the total flight distance of two aircraft can be calculated according to trigonometric function theorem:

$$\frac{MK}{\sin\gamma}=\frac{MO}{\sin(\frac{\pi-\gamma}{2})}\Leftrightarrow R=\frac{b}{2\sin(\frac{\gamma}{2})} \qquad (4)$$

In the model of conflict resolution, the sum of the intervals between the tracks of aircraft A and B is:

$$D=MO'+O'N+LO'+O'I \qquad (5)$$

It can be calculated by trigonometric function theorem in $\Delta MO'K$:

$$\frac{MK}{\sin\angle MO'K}=\frac{MO'}{\sin\angle MKO'}$$
$$\Leftrightarrow\frac{b}{\sin\gamma}=\frac{MO'}{\sin(\frac{\pi}{2}-\frac{\gamma}{2}-\alpha)} \tag{6}$$

The flight distance of a machine after avoidance can be calculated by cosine theorem in $\Delta MO'N$:

$$(O'N)^2=(MO')^2+(MN)^2-2\cos\alpha\cdot MO'\cdot MN \tag{7}$$

$$O'N=\sqrt{[\frac{b\cos(\alpha+\frac{\gamma}{2})}{\sin\gamma}]^2+4R^2-4R\cos\alpha\frac{b\cos(\alpha+\frac{\gamma}{2})}{\sin\gamma}} \tag{8}$$

In the same way, the flight distance of B aircraft after avoidance can be obtained:

$$KO'=\frac{s\cos(\frac{\gamma}{2}-\alpha)}{\sin\gamma} \tag{9}$$

$$O'I=\sqrt{[\frac{s\cos(\frac{\gamma}{2}-\alpha)}{\sin\gamma}]^2+4R^2-4R\cos\alpha\frac{b\cos(\frac{\gamma}{2}-\alpha)}{\sin\gamma}} \tag{10}$$

The steering angles of two aircraft can be calculated by trigonometric function theorem in ΔMNU :

$$\frac{MN}{\sin\angle MUN}=\frac{BU}{\sin\angle NMU}\Leftrightarrow$$
$$\frac{b}{\cos(\frac{\gamma}{2})}=\frac{d}{\sin\alpha}\Rightarrow\alpha=\arcsin(\frac{d\cos\frac{\gamma}{2}}{b}) \tag{11}$$

The intersection angle of two aircraft can be calculated by trigonometric function theorem in ΔMNU :

$$\frac{2R}{\sin(\gamma+\beta)}=\frac{O'N}{\sin\alpha}\Rightarrow\beta=\arcsin[\frac{2R\sin\alpha}{O'M}]-\gamma \tag{12}$$

Substitute (3)-(12) into (5) to get the expression of d. When the intersection angle of their flight path is constant, there are two aircraft that take the shortest distance from changing the flight path to restoring the original flight path for conflict relief, that is, the optimal flight path.

3. Numerical approach

3.1 Particle filter algorithm

Particle filter is often used to estimate the flight state parameters of the target in the positioning system. From the perspective of probability and statistics, particle filter takes the sample mean as the data processing method of the final parameter estimation. Its principle is to approximate the probability distribution function of random variables of the system on the sizing sleeve of discrete random sampling points, so as to obtain the minimum variance estimation of the state, instead of integrating the average value of samples, and the particle set of particle filter is appropriately weighted and recursively propagated according to Bayesian criteria.

According to the target tracking and positioning principle of multi-point positioning system, it can be judged that the system is nonlinear and non-Gaussian, so a nonlinear dynamic system model can be established as follows:

$$x_t=f\left(x_{t-1},w_t\right) \tag{13}$$

Among them, $f(\cdot)$ is a state function, which indicates the change process of system state with time; $w_t\in\mathbb{R}^{n_w}$ is the process noise of the positioning system; $x_t\in\mathbb{R}^{n_x}$ is the state value of the designated bit system at time t, x_{t-1} is the state value at time $t-1$.

$$y_t=h\left(x_t,v_t\right) \tag{14}$$

Where $y(t)\in\mathbb{R}^{n_y}$ is the measured value; $v_t\in\mathbb{R}^{n_v}$ represents measurement noise; $h(\cdot)$ is an observation equation, which represents the relationship between the measured data and the state equation.

According to Bayesian decision principle, the prediction of flight path of aerial vehicle is to calculate and deduce the authenticity of current flight state $y_{1:t}$ of aircraft according to the change trend of positioning data x_t measured by positioning system, and the degree of judging authenticity is expressed by probability formula $p(x_t\mid x_{t-1})$, which needs the following two steps to calculate.

A. Forecast

The system model is used to predict the prior probability density of the state, and the probability density at the previous time is obtained as follows:

$$\begin{aligned}p\left(x_t\middle|y_{1:t-1}\right)&=\int p\left(x_t,x_{t-1}\middle|y_{1:t-1}\right)dx_{t-1}\\&=\int p\left(x_t\middle|x_{t-1},y_{1:t-1}\right)p\left(x_{t-1}\middle|y_{1:t-1}\right)dx_{t-1}\\&=\int p\left(x_t\middle|x_{t-1}\right)p\left(x_{t-1}\middle|y_{1:t-1}\right)dx_{t-1}\end{aligned} \tag{15}$$

B. Update

The latest posterior probability density function can be obtained by further modifying the prior probability density through the newly obtained measured values, which is an extension of the change trend of the previous measured data, and its expression can be as follows:

$$\begin{aligned}p\left(x_t\middle|y_{1:t}\right)&=\frac{p\left(y_t\middle|x_t,y_{1:t-1}\right)p\left(x_t\middle|y_{1:t-1}\right)}{p\left(y_t\middle|y_{1:t-1}\right)}\\&=\frac{p\left(y_t\middle|x_t\right)p\left(x_t\middle|y_{1:t-1}\right)}{p\left(y_t\middle|y_{1:t-1}\right)}\end{aligned} \tag{16}$$

The above two expressions illustrate the optimal solution of Bayesian filtering, but in the face of complex actual operating environment, the system belongs to nonlinear non-Gaussian distribution, and the optimal solution of posterior probability density function cannot be expressed by the above methods. Faced with this problem, Monte Carlo sampling is proposed, which collects weighted particle sets from posterior probability and expresses posterior distribution with particle sets, which can avoid integral operation and improve calculation efficiency. The expression of posterior probability is as follows:

$$\hat{p}\left(x_{0:t}\left|y_{1:t}\right.\right)=\frac{1}{N}\sum_{i=1}^{N}\delta_{x_{0:t}}\left(dx_{0:t}\right) \tag{17}$$

Where $\left\{x_{0:t}^{(i)}:i=1,2L,N\right\}$ is a random sample set collected from posterior probability distribution; $\delta(\cdot)$ is Dirac function.

First, sample from the reference distribution $q(x_{0:t}\mid z_{1:t})$ (the reference distribution data is known and the sampling is simple), and then the posterior probability distribution function can be obtained. Finally, the particle set obtained according to the sampling result is weighted and summed to approximate the posterior distribution $p(x_{0:t}\mid z_{1:t})$, namely:

$$\begin{aligned}E\left[g_t\left(x_{0:t}\right)\right]&=\int g_t\left(x_{0:t}\right)p\left(x_{0:t}\left|y_{1:t}\right.\right)dx_{0:t}\\&=\int g_t\left(x_{0:t}\right)\frac{p\left(x_{0:t}\left|y_{1:t}\right.\right)}{q\left(x_{0:t}\left|y_{0:t}\right.\right)}q\left(x_{0:t}\left|y_{0:t}\right.\right)dx_{0:t}\end{aligned} \tag{18}$$

If the calculation process of system parameter estimation is optimal and the probability density function of reference distribution depends on x_{t-1} and y_t, the calculation of system state estimation only includes sample point $x_t^{(i)}$. By sampling and assigning weights $w_t^{(i)}$ to each sample, a reasonable probability density update formula can be further obtained:

$$w_t^{(i)}=w_{t-1}^{(i)}\frac{p\left(y_t\left|x_t^{(i)}\right.\right)p\left(x_t^{(i)}\left|x_{t-1}^{(i)}\right.\right)}{q\left(x_t^{(i)}\left|x_{t-1}^{(i)},y_{1:t}\right.\right)} \tag{19}$$

Expression of status output:

$$x_t=\sum_{i=1}^{N}w_t^i x_t^i \tag{20}$$

The update process of particle prediction of particle filter can be divided into the following steps: The first step is to initialize the original data at the initial time, so that each particle is in the initial state, and then estimate the prior probability density of the state by using the positioning system model; Secondly, the state of particles is transferred by the system state transfer equation to spread the state of each particle, and then the system observation value can be obtained, and then the weight of each particle is calculated and weighted, so as to obtain the output of posterior probability; In the third step, on the premise of completing the first two steps, the process of system state transition is not finished after resampling, which will make the system form a cycle.

3.2 Principle of firefly algorithm

Firefly algorithm (FA) is a bionic algorithm, which was originally inspired by international famous scholar Xin-she Yang by observing the rule of firefly flashing tail light, and formed by further research and development. The flash of fireflies can attract the same kind, so it can be regarded as a signal system, and the group activities in a fixed area constitute a complete communication system. According to the swarm behavior mechanism of fireflies, an intelligent optimization algorithm is designed. For the positioning system, the three-dimensional space in the positioning area can be subdivided into points, and these points are the positions of fireflies. Using the process of positioning, tracking and forecasting a certain point in space by the positioning system as the process of attracting and moving fireflies to the same kind, the system optimization can be completed by continuously updating the brightness and attraction ability of taillights. Firefly algorithm can effectively solve the problem that there are multiple local optimal solutions in a large range of feasible solutions, and it has obvious advantages in the process of optimization in a small range. The whole optimization calculation process is simple and easy to implement, with few process parameters, and the parameters have little influence on the algorithm. To improve FA based on particle filter and firefly algorithm, the improvement of firefly algorithm must be based on the following criteria:

A. it is assumed that fireflies in a certain area can attract each other, and there is no difference between individuals except the brightness intensity of taillights, and individuals will move closer to the same kind with high brightness of taillights, thus completing position iteration in space.

B. Attraction among fireflies is related to brightness and distance, but has nothing to do with other factors, and attraction is proportional to brightness and inversely proportional to distance.

C. the target equation to be corrected specifies the brightness of firefly taillights.

The mathematical expression for optimizing firefly algorithm is as follows:

1) the relative brightness of two fireflies i 、j

$$L=L_0\times e^{-\gamma r_{i,j}} \tag{21}$$

L_0 represents the initial fluorescence intensity of fireflies; γ represents the light intensity attenuation coefficient. Assuming that the media among fireflies are consistent, the luminous brightness of fireflies is inversely proportional to the distance. $r_{i,j}$ represents the distance between two fireflies i 、j, and the expression is as follows:

$$r_{i,j}=\left\|x_i-x_j\right\|=\sqrt{\sum_{k=1}^{d}\left(x_{i,k}-x_{j,k}\right)^2} \tag{22}$$

2) It can be assumed that the expression of attraction strength between two fireflies i 、j is as follows:

$$\beta_{i,j}=\beta_0\times e^{-\gamma r_{i,j}^2} \tag{23}$$

In the formula, β_0 represents the attractive force when $r_{i,j}$=0 is used; γ is the absorption coefficient of light intensity; $r_{i,j}$ is the spatial distance between fireflies i 、j.

3) Firefly i will be attracted and approached by the same kind of j with higher brightness than itself, so as to update its own spatial position, thus generating a position update equation, the specific expression is as follows:

$$X_{t+1}^{i}=X_{t}^{i}+\beta_{i,j}\left(X_{t}^{j}-X_{t}^{i}\right)+\eta\times\left(rand-\frac{1}{2}\right) \tag{24}$$

In the formula, X_t^j, X_t^i is the position of two fireflies at t time; $\eta\in[0,1]$ is the step factor; $rand$ is a rando $[0,1]$ factor that obeys uniform distribution in $[0,1]$ interval.

3.3 Optimize particle filter position update strategy

According to the position update equation, each firefly in the specified area will approach the same kind with higher brightness in the decision range, so the brightness of the same kind is the main parameter in the optimization process of fireflies within the decision radius. If fireflies need to compare and calculate with the same kind within the decision radius every time they move, the amount of calculation is huge. For the positioning system, the positioning time is increased, resulting in a large error in target positioning. The idea of firefly algorithm is applied to particle filter algorithm, in which the particles in particle filter can be regarded as fireflies, and the update of particle position is calculated by firefly position update equation in the previous section. This is a problem of seeking global optimum . Through iterative calculation, the results of each iteration calculation are compared, and each calculation result represents the global optimum solution experienced by particles at this time. Through comparison, the real optimum solution can be found, and data interaction can be carried out on behalf of the globally optimum particles. In the improvement of firefly algorithm, the distance formula is used to calculate the distance between optimal particles i 、j:

$$r_{i,j}^{best}=\sqrt{\left(x_i-x_{best}\right)^2+\left(y_i-y_{best}\right)^2+\left(z_i-z_{best}\right)^2} \tag{25}$$

Define the location update formula as follows:

$$X_{t+1}^{i}=X_{t}^{i}+\beta_{i,j}e^{-\gamma r_{i,j}^{best}}\left(G_{best}-X_{t}^{i}\right)+\eta\times\left(rand-\frac{1}{2}\right) \tag{26}$$

In which X_{t+1}^i, X_t^i represents the spatial position of particles at two adjacent moments; $r_{i,j}^{best}$ represents the optimal distance between two particles i 、j; $\eta\in[0,1]$ represents the global optimal value; $rand$ represents step factor; $[0,1]$ represents a random factor that obeys uniform distribution within HH.

The location updating formula can continuously improve the particle movement optimization process until the global optimal result is found. On the time axis, fireflies will reach the global optimal value by moving, so the particles in particle filter need to compare with the optimal solution at the previous moment to quickly calculate the optimal value, thus avoiding a large number of calculations, improving the global optimization ability, and having a good effect in the application of the actual positioning system.

3.4 Optimize the dynamic adjustment step size mechanism of particle filter

According to the principle of firefly algorithm, the attraction between fireflies is inversely proportional to the distance between them. For particle filter, the step size set by each particle is consistent, which may lead to local optimum, thus falling into premature convergence. According to the firefly attraction formula, when the two fireflies are far away from each other, i.e. SS, the attraction between the two fireflies is set to 0, and the position update expression is adjusted as follows:

$$X_{t+1}^{i}=X_{t}^{i}+\eta\times\left(rand-\frac{1}{2}\right) \tag{27}$$

According to the adjusted position update expression, the position update of particles at a certain time has nothing to do with other particles with higher brightness, and the whole particle optimization process can be summarized as follows:

At the initial stage of calculation, the firefly algorithm has a large population distribution space, and there will be many $r_{i,j}\to\infty$ cases. If the set step size is small at this time, the particles with poor position in the space will not be attracted by the high-quality particles, and only a simple position update strategy can be used to update the particle position and perform local optimization with a small step size.

When the distance between two mutually attractive individuals is very small, then the light intensity attraction coefficient is set to $\gamma\to 0$ to get $\beta_{i,j}\approx\beta_0$, and the particle position updating formula is the same in this case.

In the later stage of firefly algorithm calculation, the distance between each particle in the population will $\gamma\to 0$ generally decrease, that is, ll. At this time, the algorithm will tend to converge. When the step size is set very large, particles in bad positions will jump and update their positions, which will lead to missing the optimal position. Repeatedly, the algorithm will oscillate and improve the error of the positioning system.

In the traditional firefly algorithm, the step size of firefly's non-directional movement is often fixed. According to the above principle analysis, this does not conform to the running rules of dynamic system, which will lead to the loss of the optimal solution and prolong the operation time of the system. Therefore, different step values can be dynamically set at different stages of firefly algorithm calculation. In this study, the idea of setting variable step size is adopted to optimize firefly algorithm. The dynamic setting expression of step η is:

$$\eta(L)=\frac{0.4}{\left(1+\exp\left(0.015*\left(L-Maxgeneration\right)/3\right)\right)} \tag{28}$$

In the formula, L represents the current iteration times of firefly algorithm, and $Maxgeneration$ represents the highest iteration times.

According to the above discussion of firefly algorithm in different operation stages, it can be known that the step size of the linear equation decreases with the passage of operation time. This step size setting is helpful to avoid the loss of optimal solution and a large number of calculations, and improve the system operation efficiency.

4. Simulation analysis

Establish the positioning space model of the multi-point positioning system, specify that the flight plane of the target is oxz and oy as the yaw direction of the target, and the position of the target in the specified three-dimensional space is (x, y, z) . Assuming that the target only moves in a straight line and the sampling time of the positioning system is T_0, the position of the aircraft tT_0 in the three-dimensional space at the moment is denoted by S_t, and the detection value of the positioning system at the moment tT_0 is denoted by y_t. Its detection model is:

$$y_t = s_t + v_t \tag{29}$$

In the formula, v_t represents positioning error, and it is a σ_v^2 that the environment in which the positioning system is located is white noise with zero mean variance of σ_v^2, and the estimation of s_t is obtained from a large number of positioning data of each ground base station in the multi-point positioning system. Assuming that the detected aircraft moves in a straight line with uniform acceleration, a mathematical model corresponding to tT_0 is established. The flight speed and acceleration of the aircraft at $\dot{s}_t T_0$ time are a_t, and the target motion equation expression is as follows:

$$s_{t+1} = s_t + \dot{s}_t T_0 + \frac{1}{2} T_0^2 a_t \tag{30}$$

$$\dot{s}_{t+1} = \dot{s}_t + T_0 a_t \tag{31}$$

The acceleration of aircraft is composed of maneuvering acceleration u_t and random acceleration w_t, and its expression is as follows:

$$a_t = u_t + w_t \tag{32}$$

In the formula, u_t represents the control signal for controlling the power output of the aircraft itself, which is a known maneuver signal; w_t represents the influence of external resistance on aircraft, and it is assumed that random acceleration is white noise with zero mean and variance of σ_w^2, which is independent of v_t. The expression of the system space model is as follows:

$$\begin{bmatrix} s_{t+1} \\ \dot{s}_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & T_0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} s_t \\ \dot{s}_{t+1} \end{bmatrix} + \begin{bmatrix} 0.5T_0^2 \\ T_0 \end{bmatrix} u_t + \begin{bmatrix} 0.5T_0^2 \\ T_0 \end{bmatrix} w_t \tag{33}$$

$$y_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} s_t \\ \dot{s}_t \end{bmatrix} + v_t \tag{34}$$

In the process of positioning and tracking the target in the specified area by the multi-point positioning system, if $X_t = [x \ v_x \ y \ v_y \ z \ v_z]^T$ and $Y_t = [x \ y \ z]^T$ are set, the state space variable model expression of the positioning system is as follows:

$$X_{t+1} = \Phi X_t + \mathrm{B} u_t + \Gamma w_t \tag{35}$$

$$Y_t = \mathrm{H} X_t + v_t \tag{36}$$

In the process of positioning and tracking the target in the specified area, the multi-point positioning system generally does not consider the control signal of the aircraft itself to control the power output, so the expression of the state equation at this time is as follows:

$$X_{t+1} = \Phi X_t + \Gamma w_t \tag{37}$$

among them: $\Phi = \begin{bmatrix} 1 & T_0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T_0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & T_0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

$$\Gamma = \begin{bmatrix} \frac{T_0^2}{2} & T_0 & \frac{T_0^2}{2} & T_0 & \frac{T_0^2}{2} & T_0 \end{bmatrix}^T.$$

The measurement equation is:

$$Y_t = \sqrt{(x_t - x_0)^2 + (y_t - y_0)^2 + (z_t - z_0)^2} + v_t \tag{38}$$

The running process of the whole algorithm is as follows:

$Step1$: initialization processing, in which the initialization state $p(x_0)$ is extracted from the prior probability distribution $x_0^{(i)}$, and N particles $\{x_0^{(i)}, i = 1, 2, 3L \ N\}$ are selected as initial sampling samples.

$Step2$: According to the idea of firefly algorithm, calculate the attraction between two particles i 、j, that is, $\beta_{i,j} = \beta_0 \times e^{-\gamma r_{i,j}^2}$, and assume that the global optimal value is $G_{best} = \max\{x_t, x_{t+1}\}$.

$Step3$: the position of each particle in space is updated by the attraction formula between particles and the dynamic step strategy, and the expression is:

$$X_{t+1}^i = X_t^i + \beta_{i,j} e^{-\gamma r_{i,j}^{best}} (G_{best} - X_t^i) + \eta(t) \times (rand - \frac{1}{2})。$$

$Step4$: According to the changing position of each particle, the weight of each particle is also updating

$$w_t^{(i)} = w_{t-1}^{(i)} \frac{p\left(y_t \middle| x_t^{(i)}\right) p\left(x_t^{(i)} \middle| x_{t-1}^{(i)}\right)}{q\left(x_t^{(i)} \middle| x_{t-1}^{(i)}, y_{1:t}\right)}.$$

$Step5$: Calculate whether the current iteration number is the same as the maximum iteration number, and return $Step2$ if it is different

$Step6$: Calculation system error! You cannot create an object by editing the field code. The estimated value of the state at the time, and the expression is $x_t = \sum_{i=1}^{N} w_t^i x_t^i$.

In the process of locating and tracking the target in the specified area, the multi-point positioning system uses Matlab software to simulate the previous process, so that the number of particles is $N = 30, N = 100$, the sampling period of the positioning system is $T_0 = 1s$, and the method of considering the advantages and disadvantages of the filtering algorithm is often expressed by the parameter root mean square error RMSE, namely:

$$RMSE = \left[\frac{1}{T} \sum_{t=1}^{T} (x_t - \hat{x}_t)^2 \right]^{\frac{1}{2}} \tag{39}$$

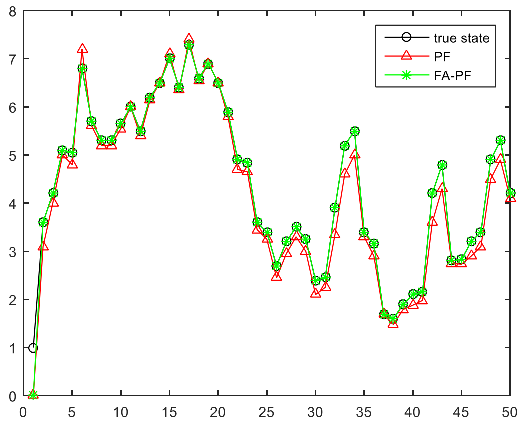


Fig. 6 Comparison of state estimation between two algorithms

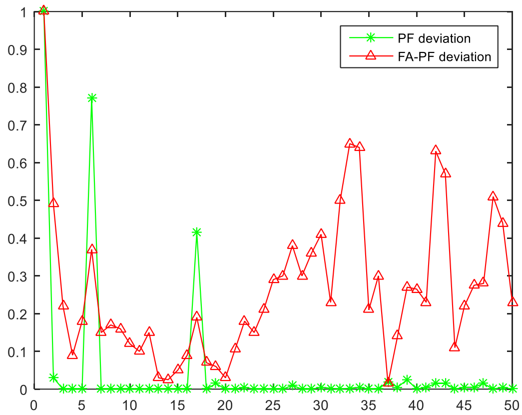


Fig. 7 Comparison of algorithm deviation

From the above two matlab simulation diagrams, it can be seen that the improved particle filter algorithm can more effectively approach the original state of the system in state estimation. The relative estimation error of FA-PF algorithm is much lower than that of traditional particle filter algorithm. The main reason is that the global optimization idea of firefly algorithm and the strategy of dynamically adjusting step size are introduced into the particle position update strategy of particle filter algorithm, which can effectively solve the problem of particle dilution and make the distribution of particles better.

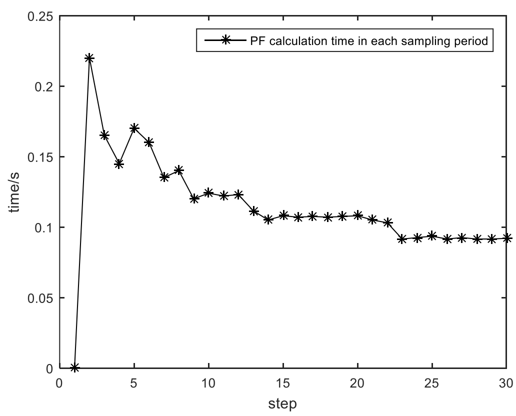


Fig. 8 PF calculation time per sampling period

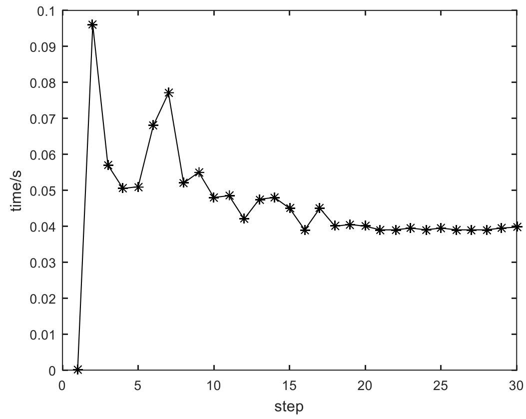


Fig. 9 Calculation time of FA-PF in each sampling period

Simulation figures 8 and 9 respectively show the calculation time of traditional particle filter and improved particle filter in each sampling period. By comparison, it is intuitively found that the improved particle filter algorithm is faster in tracking and positioning the target in the positioning system. When the particle filter algorithm processes the positioning data, it uses the global optimization mechanism of firefly algorithm to make the particle set move intelligently to the high likelihood region, thus effectively improving the diversity and moving efficiency of particles. This greatly reduces the number of particles when processing positioning data by particle filter, which effectively reduces the positioning time and improves the positioning accuracy.

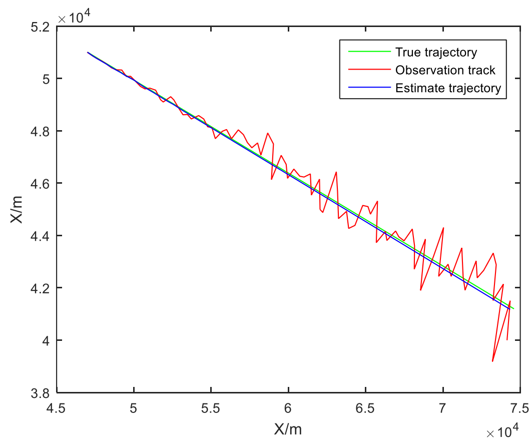
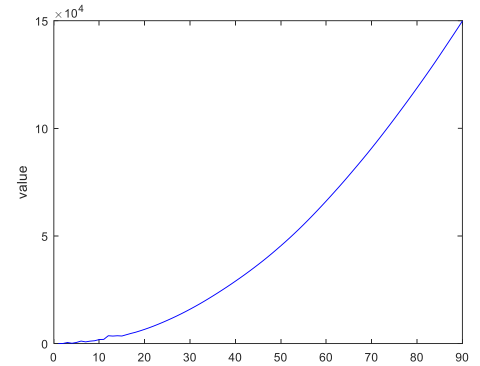
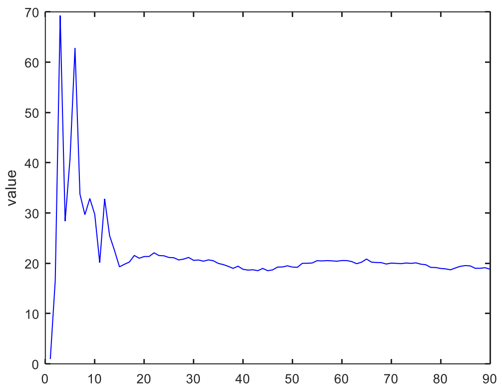


Fig. 10 Trajectory prediction based on FA-PF algorithm

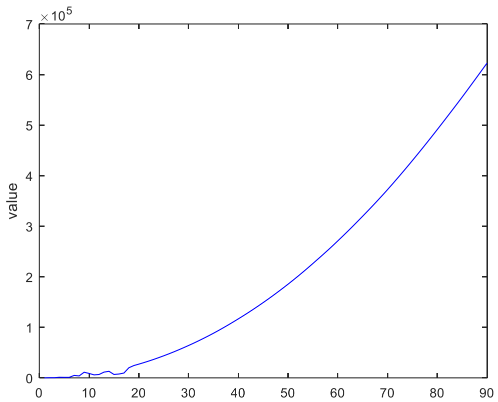
From the simulation figure 10, we can see the real trajectory, estimated trajectory and observed trajectory of the aircraft. The positioning system first obtains the observed trajectory through a large number of positioning data, and then processes the observed trajectory through the improved particle filter algorithm to obtain the estimated trajectory. Through the simulation comparison results of the three trajectories, it can be seen that the FA-PF algorithm has a good monitoring and tracking effect on the aircraft.



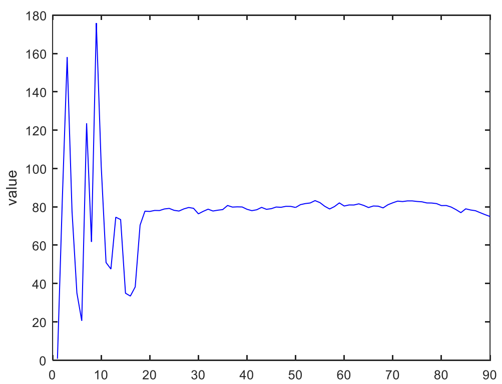
(a) Root mean square curve of position estimation error in x direction



(b) Root mean square curve of velocity estimation error in x direction



(c) Root mean square curve of position estimation error in y direction



(d) Root mean square curve of velocity estimation error in y direction

Fig. 11 Mean value curve of position estimation error and mean value curve of velocity estimation of multi-point positioning system in x and y directions respectively

Simulation Figure 11 shows the average curves of estimation errors and velocity estimation errors in X and Y directions of the positioning system. The positioning and tracking errors tend to increase slightly, which is related to the enhancement of noise in the environment where the positioning system is located. However, the errors in both directions are within the range specified by air traffic management, which fully conforms to the air traffic safety rules. It also proves that the improved algorithm can effectively deal with non-Gaussian and nonlinear problems.

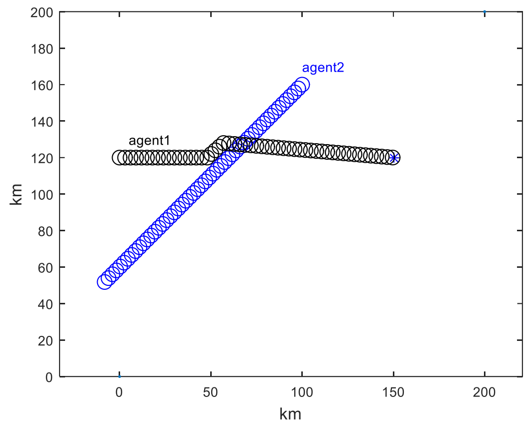


Fig. 12 Tracking process of double-machine avoidance trajectory in multi-point positioning system

Simulation Figure 12 shows the trajectory tracking of the multi-point positioning system during the conflict relief process between two aircraft in the air. From the figure, we can see that when the tracks of the two aircraft collide, the climbing angle of the aircraft with low avoidance level is too large, which requires high positioning accuracy of the multi-point positioning system and trajectory tracking accuracy of the aircraft. However, by improving the firefly algorithm to optimize the particle filter algorithm, the target trajectory is tracked and displayed, and it is found that the tracks of the two aircraft are clear, which effectively improves the control ability of air traffic management.

5. Summary

According to the similar operation mechanism of particle filter algorithm and firefly algorithm, this paper proposes to optimize particle filter algorithm by improving firefly algorithm. According to the firefly position update mechanism in firefly algorithm, the position update mode of each particle in particle filter algorithm is optimized. On this basis, according to the variation law of particle swarm in different stages in the application of particle filter in target location, a dynamic step adjustment strategy is introduced. The particle filter algorithm effectively alleviates the problem of particle degradation by improving the above two aspects, and uses the global optimization idea to guide the particle movement process, thus simplifying the calculation process. The variable step size strategy effectively balances the ability of global search and local search. Simulation results show that the proposed FA-PF algorithm effectively improves the accuracy of target tracking and positioning and the operation efficiency of air traffic management system.

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