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A Kalman Filtering Algorithm Based on Pigeon-inspired Optimization for Target Tracking in Autonomous Aerial Refueling

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***Abstract*—In this paper, a new bio-inspired computation algorithm to optimize Kalman Filter (KF) for target tracking in autonomous aerial refueling (AAR) of unmanned aerial vehicles (UAVs) is proposed. The hybrid algorithm is based on KF, of which the measurement noise matrix *R* is optimized by the pigeon-inspired optimization (PIO). Experimental results of tracking a target demonstrate that the proposed method is efficient under dynamic environment, and it is better than Particle Swarm Optimization (PSO) in terms of time.**

Keywords—target tracking, pigeon-inspired optimization, Kalman Filter, unmanned aerial vehicle, autonomous aerial refueling.

I. INTRODUCTION

In autonomous aerial refueling (AAR) of unmanned aerial vehicles (UAVs), the computer vision theory is a foundation. One of the challenging problems for computer vision theory is to design an optimized robust control system with fast, accuracy, and stabilized responses. In AAR of UAVs, a UAV need to track a tanker in real-time, which can save time and fuel oil at the most extent. In order to increase battery life as much as possible, the factor of time appears to be significant especially.

In the process of AAR, it is necessary to accurately track moving targets (tanker). So it is very important to judge the next location of target ahead of time. But the current location of target must be known firstly, and the target must be recognized. Target recognition algorithm is the global search based on pixels, but this method has two obvious shortcomings: computationally intensive and time exhausting in the global search, while unable to meet the real-time control of maneuvering target tracking; Furthermore, in the respect of anti-interference, the global search can be easily interfered. The case of traditional filtering methods does not meet the practical application, while the Kalman Filter (KF) is a very efficient signal processing method[1], even in the case of weak noise, it still works well. Systematic and measured noise statistics need to be known exactly while performing standard KF. However, due to the great influences of various factors in sensors, it is difficult to get the noise statistics, so the Kalman filtering method is restricted. However, in real-time control of a mobile target tracking, real-time and accuracy of the algorithm is very high.

Recently, there are a boom of the bio-inspired optimization algorithms, which are derived from biological inspired self-organized systems such as ants, bees, pigeons, and so on. Holland et al. firstly put forward the genetic algorithm (GA) to study the self-adaptation behavior of natural system[2]. Inspired by the collective behavior on real ant system, Colorni et al proposed ant colony optimization (ACO)[3]. Particle swarm optimization (PSO) was developed by Kennedy and Eberhart[4], which were under inspiration of social behavior of bird flocking or fish schooling. Artificial bee colony optimization (ABC) was a bio-inspired optimization based on the intelligent foraging behavior of a honey bee swarm, proposed by Karaboga et al[5]. Moreover, there appeared many other algorithms including biogeography-based optimization (BBO)[6], brain storm optimization (BSO)[7], and so on.

To solve the problem, many scholars have made outstanding contributions using bio-inspired optimization algorithms. Wang et al. proposed that they used genetic algorithm (GA) and KF to track an object[8]. Ramakoti et al. used Particle Swarm Optimization (PSO) to improve the character of KF for tracking the object[9]. Combining with GA and PSO, Jatoth and Kumar proposed an algorithm using GA-PSO to track an object[10]. This paper proposes a Kalman filtering algorithm based on PIO [11] to predict the fast tracking of moving targets in AAR. Based on the study of the basis of the KF, this article introduces a PIO algorithm to improve the Kalman filtering method, and proposes a Kalman filter model based on PIO(called KF-PIO), and finally improves the accuracy of target tracking and sensor measurement data processing accuracy as well as reduces systematic noise and measured noise errors.

II. KALMAN FILTERING ALGORITHM

Kalman filtering algorithm is presented by Kalman[1] for the first time as a kind of linear minimum variance estimation theory, Kalman filtering algorithm adopts the time domain and recursive linear minimum variance, KF uses the recursion theory to process and filter random signal effectively.

With the development of science and technology, in the field of navigation, KF was more widely used. Kalman filtering algorithm can get the optimal estimate from the signal which is extracted, it is concluded that the optimal estimate mainly using the state variance, observation equation, Gaussian white noise's statistical characteristics and statistical properties of observation error.

Kalman filtering algorithm generally has the following characteristics:

(1)Firstly, Kalman filtering algorithm is obtained by iteration and Kalman filter is designed and implemented by using state space method in the time domain, so the Kalman filtering algorithm is very applicable for the estimate in multidimensional stochastic process.

(2)Secondly, dynamic change regulation of the KF's estimator is described using dynamic equation and state equation, the statistical information and dynamic equation of Gaussian white noise determines the dynamic statistical information of the variable. In practice, the dynamic equation is usually known in advance, and Gaussian white noise is often stable .Therefore, KF's estimator can be divided into two kinds: the stationary and the non-stationary.

(3)Kalman filtering algorithm can be either applied in a continuous system or a discrete system, and discrete algorithm can be easily implemented on a digital computer, the following is to introduce basic modal of the Kalman filtering algorithm.

A. The basic model of the Kalman filtering algorithm

In the process of the description of the Kalman filtering algorithm, it will involve some basic concepts associated with Kalman filtering algorithm. Mainly include: Probability, random variables, the normal distribution, the space model, etc.

First of all, a discrete control system is introduced. The system with linear stochastic differential equation can be formulated as follows:

$$Y(i) = AY(i-1) + BC(i) + W(i) \tag{1}$$

The second is the system measured value:

$$X(i) = HY(i) + V(i) \tag{2}$$

where $Y(i)$ is system state at i moment. $C(i)$ is the controlled variable of system at i moment. A and B are systematic parameters, and in multiple model systems, A and B can be expressed by matrix. $X(i)$ is the observed value at i moment. H is the parameter of measurement system, and in multiple model systems, H can be expressed by matrix. Process noise and measurement noise are expressed by *W(i)* and *V(i)*.Assuming that the current state of the system state is i, according to the model of the system, the current state can be predicted according to the last state of the system:

$$Y(i\,|i-1) = AY(i-1|i-1) + BC(i) \tag{3}$$

The last state is used to predict $Y(i\,|i-1)$, $Y(i-1|i-1)$, is the optimum at i-1 moment. $C(i)$ is the controlled variable at current moment. Then, the result of the system has been updated, but the system variance P of $Y(i-1|i-1)$ is not updated.

$$P(i\,|i-1) = AP(i-1|i-1)A' + Q \tag{4}$$

where $P(i\,|i-1)$ is variance of $Y(i|i-1)$,and $P(i-1|i-1)$ is variance of $Y(i-1|i-1)$, A' is transposition of A. Q is the system process variance. The first two formulas of Kalman Filter is formula (3) and (4). Up to now, the predicted value at current state has been gotten, then combined with the current state of the measured values, the optimum at moment can be gotten.

$$Y(i|i) = Y(i|i-1) + Kg(i)(X(i) - HY(i|i-1)) \tag{5}$$

where $Kg(i)$ is Kalman gain.

$$Kg(i) = P(i|i-1)H' / (HP(i|i-1)H' + R) \tag{6}$$

The optimum $Y(i|i)$ at i moment can be obtained. However, Kalman filter must be continuous running down until the end of the process of the whole system, therefore, the variance of at moment can be updated.

$$P(i|i) = (I - Kg(i)H)P(i|i-1) \tag{7}$$

where I is identity matrix.

According to the above formulas, the design of Kalman Filter can be implemented easily. The block diagram of traditional KF is given in Fig. 1.

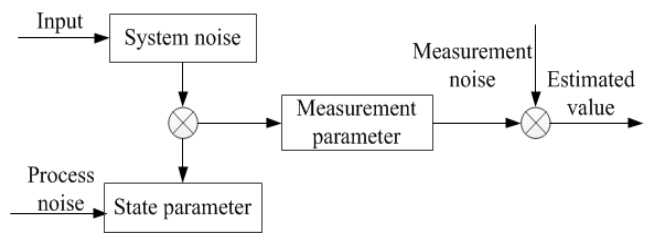


Fig. 1. Block diagram of traditional Kalman filter

In this work, only the measurement noise matrix R is optimized.

B. Pigeon-inspired optimization algorithm

Pigeon is a popular kind of bird in the world. Pigeons once presented as an important communication tools, which can be not only applied to the daily life, but also to the military fields. During the First World War and the Second World War, pigeons played an important role in the military as well, because of their safety and veracity in seeding military intelligence. Thus, a lot of scientists devote to making research on the pigeons. They discover that pigeons can easily find their destinations by using three tools: magnetic field, sun and landmarks. Inspired by the homing pigeons, PIO algorithm was firstly proposed by Duan in 2014 [11], which has been applied to solve various problems in many fields[12-14].

The basic PIO includes two operators: Map and compass operator and Landmark operator. The map and compass operator model is based on magnetic field and sun, while

the landmark operator model is based on landmarks. Therefore, the process of basic PIO is as follows: Map and compass operator. When the evolutionary iteration is less than the map and compass maximum iteration, the algorithm relies on the map and compass operator as Fig. 2, which means the pigeons are far from the destination. Each pigeon has a position and a velocity of evolution. Suppose the position and the velocity of pigeon i are X_i, V_i. For a n-dimension search space, $X_i = \left[x_i^1, x_i^2, \ldots, x_i^n\right]$, $V_i = \left[v_i^1, v_i^2, \ldots, v_i^n\right]$. X_i and V_i are updated in every iteration. The new position X_i and velocity V_i of pigeon i at the t-th iteration are updated as follows (Duan and Qiao,2014):

$$V_i(t) = V_i(t-1) \cdot e^{-rt} + rand \cdot \left(X_g - X_i(t-1)\right) \tag{8}$$

$$X_i(t) = X_i(t-1) + V_i(t-1) \tag{9}$$

where r is the map and compass factor which makes the velocity of evolution slow down as the iteration goes. *rand* is a rand number within [0,1]. X_g is the global best position, which means the best (the minimum or the maximum) fitness value among all the pigeons.

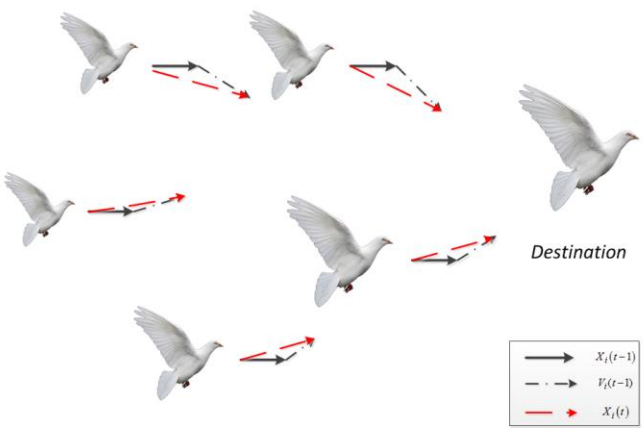


Fig. 2 The process of map and compass operator evolution

In landmark operator, as Fig. 3, pigeons would fly straight to their destination if they are familiar with the landmarks. However, suppose the pigeons are still far from the destination, they are unfamiliar with the landmarks. And the pigeons far from the destination (pigeons outside the big circle at Fig. 3) would follow those that are familiar with the landmarks. In landmark operator, half of the pigeons would regard the center of the pigeons as their destination and they would fly straight to the center, as the pigeons in the big circle at Fig. 3. Thus, the number of pigeons would be decreased a half in every iteration. Let $X_c(t)$ be the center of some pigeons at the t-th iteration. The position of pigeon i at the t-th iteration can be calculated by the following equation:

$$N_p(t) = \frac{N_p(t-1)}{2} \tag{10}$$

$$X_c(t) = \frac{\sum_{Np} X_i(t) \cdot fitness\left(X_i(t)\right)}{\sum fitness\left(X_i(t)\right)} \tag{11}$$

$$X_i(t) = X_i(t-1) + rand \cdot \left(X_c(t) - X_i(t-1)\right) \tag{12}$$

where $fitness()$ is the fitness function as Table 1, which can determine the quality of each pigeon .

TABLE 1 THE TARGET TRACKING METHOD, FITNESS( ) FUNCTION

```
Begin
    fitness=0;
    for i=1:N;
      d=sqrt((x(i)-X(i))^2+(y(i)-Y(i))^2);
      fitness=fitness+d;
    end
End
```

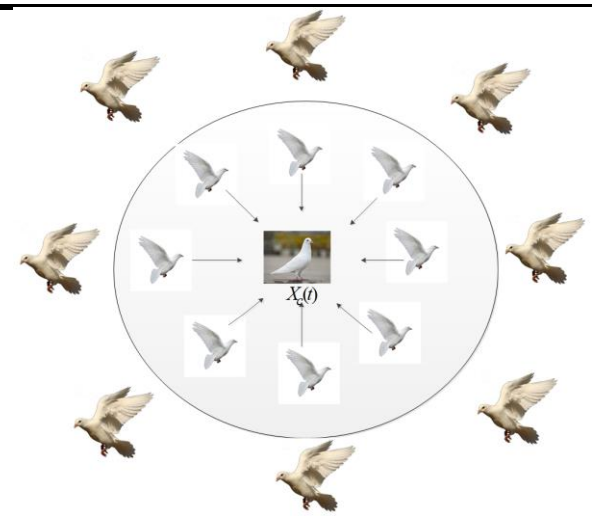


Fig. 3 The process of landmark operator evolution

III. KALMAN FILTERING ALGORITHM BASED ON PIO.

A. The process of KF-PIO algorithm

In order to evaluate the quality of each pigeon (solution), the fitness function is often defined. The pigeon at the better position has the smaller fitness value. The pigeons with big fitness value fly to those with smaller fitness value. In addition, all the pigeons fly to the position where it has the minimum fitness value. The smaller fitness value is, the better target tracking result is. In this work, the fitness function is chosen as Table 1, which is simple and easy programming.

KF-PIO combines the PIO algorithm and Kalman filtering algorithm to solve the target tracking problem. Our proposed method has better properties with high accuracy and efficiency.

The process of KF-PIO is described as follows:

Step 1: Trajectory pre-processing.

Obtain the trajectory of the target at different moments. A simulative trajectory can be obtained, and then Gaussian white noises are added as vibration.

Step 2: Initialization of the pigeons, and initialize the parameters of KF.

Step 3: Calculate each pigeon's fitness value according to Table 1.

Step 4: Update the pigeons.

When $NC \le NC1_{\max}$, update the pigeons using the map and compass operator. The velocity and position of each pigeon by Eqs. (8) and (9). When $0 < NC - NC1_{\max} \le NC2_{\max}$, update the pigeons by using the landmark operator. The velocity and position of each pigeon are updated by Eqs. (10)-(12).

Step 5: Calculate each pigeon's fitness value according to Table 1. Calculate the minimum fitness and the best position for the trajectory.

Step 6: Terminate when the current number of iterations NC reaches the $NC_{\max}$, output the results. Otherwise, go to Step 4.

B. Comparative experimental analysis

Firstly, because the process of AAR of UAVs is a straight line motion approximately, so a curve: $y = 2x$ which is added a Gaussian white noise respectively to x and y as the measurement value can be used to simulate the trajectory of the target.

Initialize pigeon's positions, velocities, and the parameters of this algorithm as Table 2. Initialize KF's parameters as Table 3.

The initial value of system parameter matrix P is I. Measurement noise matrix R is unknown and waits to be optimized.

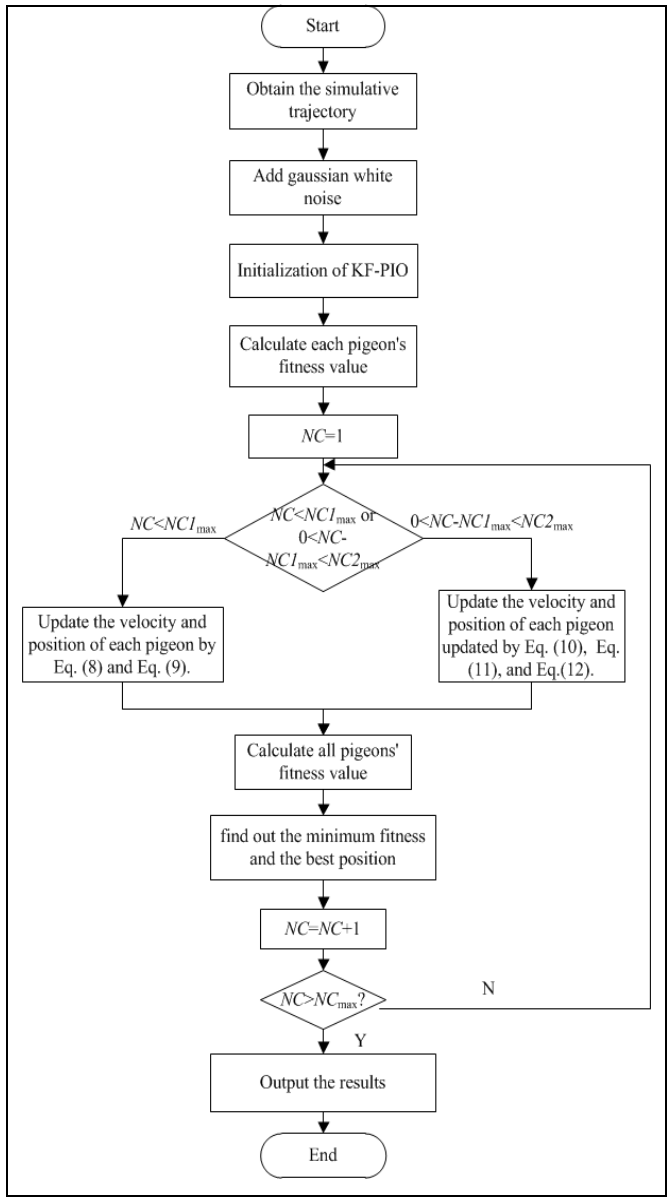


Fig. 4 The KF-PIO algorithm flow

TABLE 2 THE PARAMETERS OF PIO ALGORITHM

Parameter	Description	Value
n	Number of pigeons	200
$NC_{\max}$	Maximum times of iteration	150
$NC1_{\max}$	The iteration of map and compass operator	100
$NC2_{\max}$	The iteration of landmark operator	50
r	The map and compass operator	0.2
D	Dimension of the search problem	4

TABLE 3 THE PARAMETERS OF KF

Parameter	Description	Value
A	State-transition matrix	[1,0;0,1]
Q	Process variance matrix	[1,0;0,1]
H	Measurement matrix	[1,0;0,1]
P	Covariance matrix	Initial value I
B	System parameter matrix	[1,0;0,1]
C	Controlled variable matrix	[1,2]
R	Measurement noise matrix	Optimized

Experiment 1: The trajectory of the target only using Kalman filtering algorithm is given in Fig. 5.

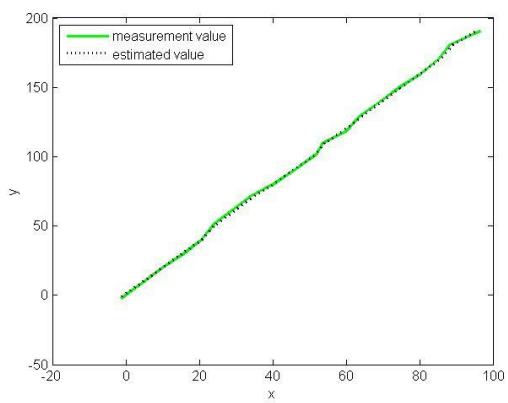
Experiment 2: The trajectory of the target using Kalman filtering algorithm based on PIO is shown in Fig. 6.

Comparing the results of the two experiments, it is obvious that the trajectory of target only using Kalman filtering algorithm is worse than the trajectory of target using Kalman filtering algorithm based on PIO. As the fitness value of only using KF is 70.44, which is bigger than the fitness value 44.25 of KF-PIO.

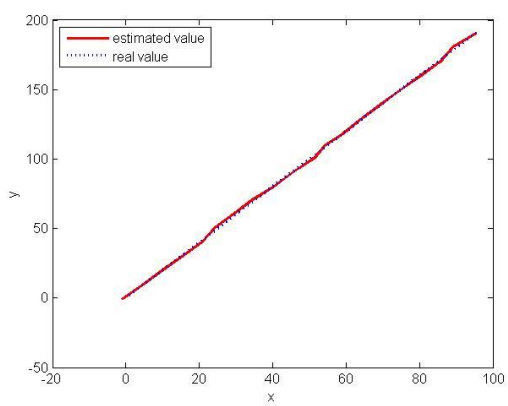
Experiment 3: The trajectory of the target using Kalman filtering algorithm based on PSO (KF-PSO) is shown in Fig. 7.

The fitness value of Experiment 2 and Experiment 3 can be compared, and the result is shown in Fig. 8.

From Fig. 8, it is obvious that the fitness value of PSO is smaller than PIO, the fitness value of PSO is 37.62, and the fitness value of PIO is 44.25, which shows the result of KF-PSO is better than KF-PIO. However, the curve shows that the iterations of KF-PIO that the fitness value reach stable almost the same to KF-PSO, the iteration of KF-PSO is 59 and the iteration of KF-PSO is 54. Under circumstance of the same time-consuming, the accuracy of target tracking is more important, and our proposed KF-PIO algorithm is superior to KF-PSO algorithm.

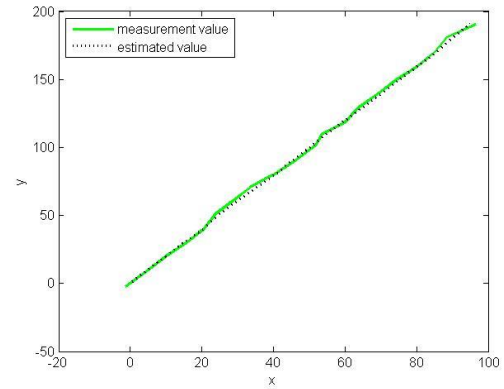


(a)Measurement value and estimated value

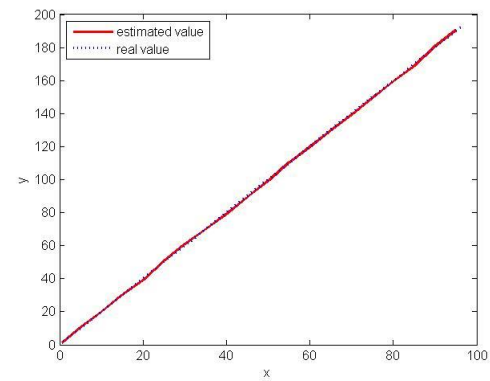


(b)Estimated value and real value

Fig. 5 The trajectory of the target only using Kalman filtering algorithm

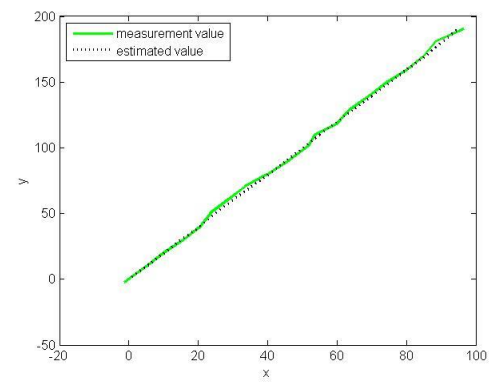


(a)Measurement value and estimated value

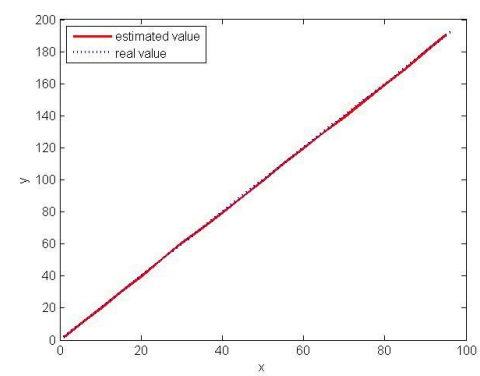


(b)Estimated value and real value

Fig. 6 The trajectory of the target using Kalman filtering algorithm based on PIO



(a)Measurement value and estimated value



(b) Estimated value and real value

Fig. 7 The trajectory of the target using Kalman filtering algorithm based on PSO

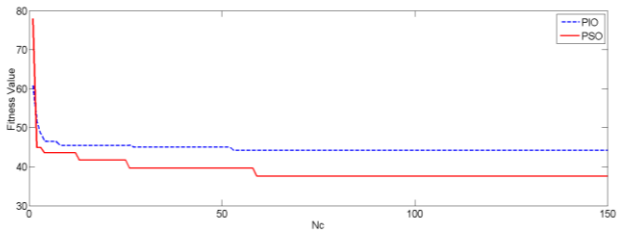


Fig. 8 Fitness value of KF using PSO and PIO

IV. CONCLUSIONS

This paper presents a hybrid algorithm of PIO and KF for the target tracking in AAR. This paper utilizes the PIO to optimize the process noise covariance *R* and then use KF to get more accurate estimated value from the observed value. The results of this paper show that the effect of KF-PIO is better to tracking the target than only using KF but worse than KF-PSO, but better than KF-PSO in terms of time.

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