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# Review of the algorithms for radar single target tracking

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# Review of the algorithms for radar single target tracking

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**Abstract.** The research of radar single target tracking is a hotspot in science all the time. This paper recommends the basic principle of radar single target tracking firstly. Then, the algorithms for radar single target tracking are classified into two segments, namely state estimation and tracking model. And the development of the algorithms is reviewed. It also analyses and comments the methods, features, merit and demerit in the application of these algorithms. At last, this paper introduces new progress of the research field.

## 1. Introduction

In the modern war, radars are responsible for monitoring, early warning, tracking detection, navigation guidance and other multi tasks. Their information processing capacity directly determines the combat effectiveness of weapons and equipment [36]. In recent years, the research of maneuvering target tracking has been a hot issue in the field of radar. The key to the radar target tracking algorithm is the capacity to track the target accurately, that is, to ensure the accuracy of the algorithm. At the same time the realization time of the algorithm should be taken into account, that is, to guarantee the real-time performance in engineering applications. In general, the radar single target tracking algorithm consists of two parts: one part is the state estimation, namely real-time estimation of the movement state of the target through various methods; the other part describes the change law of the target moving state through establishing various models.

## 2. Single target tracking principle

Radar target tracking is to use the radar to observe and analyze the locked target, obtain the speed, location and other information of the target, and establish the corresponding dynamic model for the movement state of the target. Then the computer predicts and evaluates these information of the target at the next moment through a series of filtering methods to accurately, so as to establish the target trajectory. Target tracking algorithm is an important part of radar data processing, and its basic principle is shown in Figure 1. When the target maneuvers, the value of the residual V in the measurement will increase, this time maneuvering detection is based on the change of V. Then the computer determines the filter gain, the covariance matrix and other parameters, the filter outputs, thus completing the function for tracking maneuvering target.

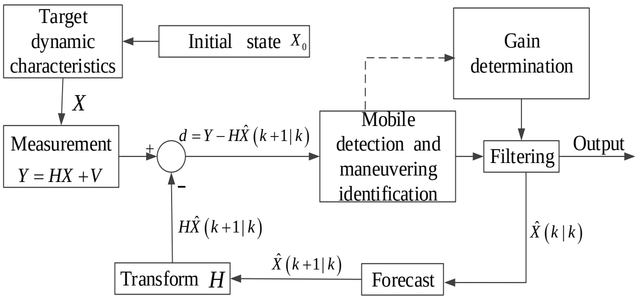


**Figure 1.** Schematic of radar single target tracking

## 3. State estimation algorithm

State estimation is the core problem of target tracking. The ability to achieve accurate estimation of target state is the prerequisite for the subsequent processing of the data. Usually, the target state estimation can be divided into two types: linear state estimation algorithm and nonlinear state estimation algorithm.

### *3.1. Linear state estimation algorithm*

The earliest state estimation algorithm should be traced back to the early nineteenth century. The mathematician Gauss put forward the least square method, and the method was first applied to observe the orbit of the planet. In 1940s, based on the needs of the radar system, Wiener designed and proposed the Wiener filter. The method used the Wiener-Hopf equation to solve the analytical solution of optimal transfer function to achieve signal gating and suppression. However, the Wiener filter cannot deal with non-stationary random process. It needs to store large amount of data in the application, and is not conducive to engineering. Then $\alpha-\beta$ filter was proposed for the analysis of the scanning edge tracking system. As a constant gain filter, it has been widely used for the advantages of small computation and easy engineering implementation. In 1960s, with the continuous improvement and development of the optimal estimation theory, for the application defects of Wiener filter, the American scholar Kalman derived Kalman filter (KF), which had milestone significance in the history of control theory. The algorithm introduces the concept of state space, uses the state equation to express the relationship between the input and the output, and estimates the required information from the measured data. In 1970s, Spaingarn proposed a linear autoregressive algorithm, but the algorithm ignored the impact of process noise, and failed to be applied in engineering. Kalman filter does not need to store all historical data and does not require the smoothness of the system strictly. The characteristics of the iterative recursive are also helpful for the computer to solve the problem, so KF gets the wide attention of scholars quickly, and has been applied in many fields such as navigation control. KF is simple designed, widely used, but because of the need to use the computer implementation, it will bring the rounding and truncation error of the cumulative problem, cause the filter results to be unstable. In this regard, Julier and Uhlmann proposed singular value decomposition Kalman filter and square root Kalman filter and other numerical robust filter, to improve the numerical stability of the algorithm [11].

### *3.2. Nonlinear state estimation algorithm*

Although Kalman filter has many advantages and is applied in many fields, it is limited to linear systems. Under the realistic conditions, the maneuvering of the target is usually nonlinear. In this regard, the scholars have studied the nonlinear filtering based on the Kalman filter. There are four main methods:

(1) improved algorithm based on function approximation

In 1970s, Bucy used the first-order Taylor expansion to linearize the nonlinear problem based on KF and proposed the extended Kalman filter (EKF). EKF has the advantages of simple structure, easy to implement and wide application. However, because of the linearization error in the process of EKF, the effect is poor or even diverging when the degree of nonlinearity is high. In order to reduce the errors in the process of linearization and improve the accuracy of EKF, scholars improved it and put forward many new algorithms. For example, Mahalanabis proposed the second-order EKF (SOEKF) algorithm. Bell derived the iterative EKF (IEKF) algorithm by using Gauss-Newton iteration, so that the accuracy of the filter was improved, but the drawback was not to make its convergence performance improved. Galkowski and Guerci proposed the modified gain EKF (MGEKF) algorithm [8, 9], which became difficult to generalize due to the lack of uniformity.

(2) improved algorithm based on deterministic sampling

In order to solve the problem of huge errors in the strong nonlinearity of EKF, Julier firstly proposed the unscented Kalman filter (UKF) algorithm [12] based on unscented transformation (UT) in 1997. The algorithm uses the probability density function to approximate the nonlinear function by selecting 2n+1 sigma points, and the accuracy of the evaluation can reach the second order. In the case of the same amount of computation with EKF, UKF is more accurate than EKF, does not need to calculate the Jacoby matrix, and its operation is more convenient. Since then, a series of improved algorithms have been developed for UKF. In order to solve the problem of non-local sampling and high-order cross matrix of UKF when the dimension of the system is high, Julier proposed a method to reduce the number of sample points in 2002 [11]. In order to improve the efficiency of the algorithm, Wan derived the square root UKF algorithm [31], which was numerical stable, so that the calculation was greatly reduced. Zhou Zhan-xin combined genetic algorithm with UKF, which improved the method of constructing sigma sample points and proposed adaptive weight approach UKF algorithm [37]. In view of the slow convergence rate of UKF, Zhan R H, Sibley G and Cheng Shui-ying proposed different forms of iterative UKF (IUKF) [6, 30, 35] algorithm to increase the convergence rate, but the amount of calculation increased correspondingly. Then Liu Da-peng put forward the hybrid iterative UKF algorithm [22], which guaranteed the convergence speed and reduced the computational complexity.

(3) improved algorithm based on cubature criterion

In 2009, Arasaratnam and Haykin proposed Cubature Kalman filter (CKF) [1, 2]. The algorithm was based on the third-order spherical-radial cubature criterion, and the derivation process was very rigorous. CKF has the advantages of simple realization, small calculation and high accuracy. Based on the superior performance of CKF, domestic and foreign scholars have conducted more in-depth research and improved to enhance CKF application space. In 2010, Arasaratnam and Haykin proposed the square root CKF (SCKF) algorithm to improve the stability of CKF and to ensure the nonnegative determinism of the covariance matrix. In order to reduce the influence of the nonlinearity of the initial error measurement equation on the state estimation, Mu Jing proposed the iterative CKF (ICKF) algorithm [26] by combining the Newton-Gaussian iteration with CKF, which improves the estimation accuracy. Liu Yang promoted the three-order CKF and deduced the generalized CKF algorithm [23], and verified it by five-order CKF. It was proved that the higher order can improve the estimation accuracy of the algorithm but increased the computational complexity.

(4) improved algorithm based on random sampling

All of the above algorithms can only deal with the noise statistic characteristics of Gaussian nonlinear system. For non-Gauss noise, it is necessary to implement the particle filter (PF), which is based on Monte Carlo method and Bayesian estimation. In 1950s, American scientist Hammersley creatively proposed the Sequential Important Sampling (SIS) algorithm. This algorithm was used to deal with the state estimation in physics and statistics, which laid a theoretical basis for the generation of PF. In 1970s, many experts studied the SIS so that it was developed. Experts have also found a problem, that is, the degradation of particles. The degradation of particles leads to the waste of computational resources and the deviation of the results directly. The problem has not been well handled until Gordon introduced resampling algorithm in the bootstrap in 1993, to a certain extent, to solve the problem of particle degradation, but made the calculation greatly improved. In 1999, Carpenter proposed the concept of Particle filter (PF) for the first time on the basis of summarizing the sequential importance sampling algorithm. Since then, PF has entered the stage of rapid development. Khan [13] introduced the Markov chain Monte Carlo process in PF, and proposed MCMCPF algorithm. For the resampling method, researchers conducted a series of improvements, mainly multi-pattern resampling, system resampling, hierarchical resampling [28], and residual resampling and so on. Similarly, Oshman introduced a genetic algorithm in resampling, and proposed the genetic particle filter method [7], which improved the accuracy to a certain extent, but the amount of calculation increased significantly when the number of iterations increased. In order to choose the importance probability density function, Mu Jing uses the CKF to produce the importance density function, and proposed the cubature particle filter (CPF) algorithm [27], which has the advantage of short operation time and small estimation error. Yuan Ze-jian used Gaussian-Hermite filter to produce Gaussian Hermite particle filter (GHPF) [33].

## 4. Target motion model

For a target tracking system, to ensure the filter performance stable and consistent convergence, we must ensure that the system model of unbiased [15] firstly. Therefore, to establish the mathematical model for the good performance of the target tracking process is important. The maneuvering target motion model is divided into Single Model and Multi-Model [4] according to the number of models.

### *4.1 Single model algorithm*

In 1973, Bridgewate and Friedland successively proposed the Constant Velocity (CV) model and the Constant Acceleration (CA) model. CV model considers that the target does linear motion, the speed is constant, and the acceleration is in the form of Gauss white noise. The CA model assumes that the target is linear motion and the acceleration is constant. CV and CA model are the most basic models in target tracking. Singer argued that the maneuvering model was a correlated noise model rather than a normally assumed white noise model. He assumed that the acceleration was a first order zero means stochastic process with exponential autocorrelation, and that the time correlation function satisfied the exponential decay conditions, thus put forward the Singer model. The model has a good effect in dealing with slow maneuvering in both constant and uniform acceleration ranges, but its drawback is that the acceleration is 0 at any time, and there is a serious error in the face of strong maneuvering problem. Helferty made full use of the idea of Singer model, generalized it into circular motion, and proposed the Helferty model. The model describes the motion of the maneuvering target by selecting instructions that obey the semi-Markov process, and the magnitude of the acceleration is determined by the transition probability. In 1983, Professor Zhou Hong-ren believed that at the next moment the target acceleration can not be completely out of the value of the previous moment, but the value was in the current acceleration of the neighborhood interval. Therefore he proposed the "current" statistical model, also called mean adaptive acceleration model. The model is only one more than the Singer model, but it is more realistic to reflect the scope of the target maneuver. In 1992, Waston and Blair established the Coordinated Turn (CT) model. They firstly assumed that the target to do uniform circular motion, then used the relationship between velocity and acceleration to select a transfer matrix whose parameter was the angular velocity to describe the trajectory of the target in order to determine the movement of the target. Subsequently, Best and Norton put forward the arc model based on the CT model [3]. The model is more general. Matsuzaki put forward the CAV model, which is based on the characteristics of circular motion. In this model, the curve motion is decomposed into a uniform linear motion along the velocity direction and a constant angular velocity motion about the two axes perpendicular to the velocity direction [24]. It is often used to describe the three-dimensional circular motion of a spatial target. Mehrotra pointed out that the limit of the order of the state vector derivative was an important reason why all models could not accurately characterize the complex movement of the target [25]. So Mehrotra introduced the rate of change in acceleration (Jerk) when he established the target motion model, and established the Jerk model to accommodate the stronger maneuvering..

*4.2 Multi-model algorithm*

*4.2.1 First generation multi-model algorithm.* In 1965, Magill proposed the first generation of multi-model algorithm, which was based on different models of filters working in parallel and then merging the outputs. The working process is shown in Figure 2. Compared to the single model, when the selected model set can cover all forms of motion, the algorithm can achieve the best filtering effect. However, the obvious disadvantage is that the number of model is fixed. It didn't consider the transition between the system modes and unable to fully select the appropriate model. When the model is more, the tracking efficiency becomes low, and there is a lack of interaction between models.

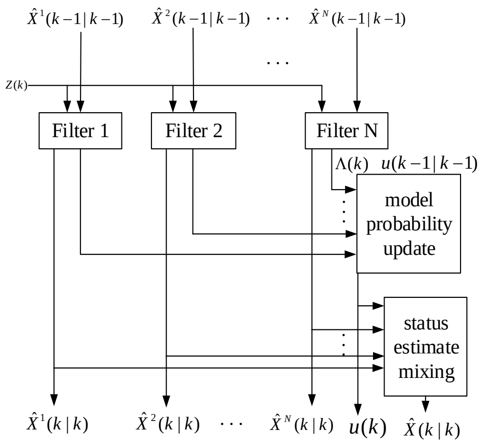


**Figure 2.** Schematic diagram of the first generation MM algorithm

*4.2.2 Second generation multi-model algorithm.* The number of models of the second generation multi-model algorithm is still fixed, but the selected model has interaction. There are mainly GPB algorithm and IMM algorithm.

(1) GPB algorithm

In 1970, Ackerson proposed the Generalized Pseudo-Baysian (GPB) algorithm. The algorithm considers that each of the selected models conforms to the target's motion state and performs the same input for each model. However, the algorithm does not consider the characteristics of each model, nor dose it use the model information, therefore it can not be widely applied.

(2)IMM algorithm

In 1988, Blom and Bar-Shalom proposed a new algorithm to approximate the target motion state by probabilistic weighting of multiple models based on the GPB algorithm, namely the Interacting Multiple Model (IMM) algorithm. Figure 3 is the schematic diagram of the IMM algorithm. The IMM algorithm treats the transition between models as a Markov process, and transforms them through a probabilistic transfer matrix. The algorithm has been widely used because of its advantages such as no need of maneuvering detection, simple structure, moderate computation and so on. Many scholars devoted themselves to the study of IMM algorithm and its improvement. Such as in literature [34], Zaveri combines genetic algorithm with IMM. In literature [14, 16, 32], the fuzzy theory is introduced into the IMM algorithm. In the literature [5, 29], the neural network is used in IMM. These improvements have improved the performance of IMM to varying degrees.

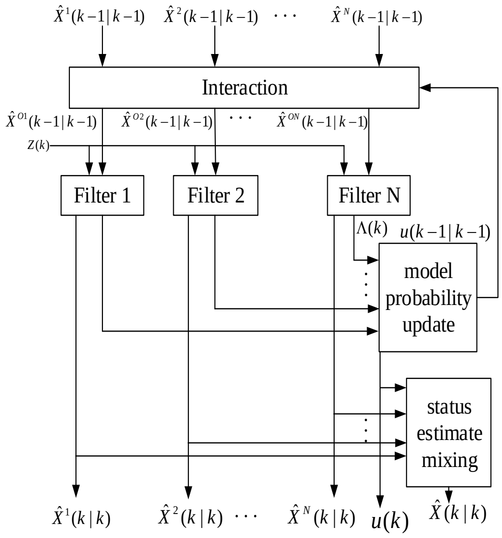


**Figure 3.** Schematic diagram of the IMM algorithm

*4.2.3. Third generation multi-model algorithm.* Although IMM has made great progress compared to the first generation of multi-model algorithm, but there are still some shortcomings. When the target takes a variety of maneuvering methods, the small model set can not accurately describe the maneuver situation. In addition, when the number of model increases, the computational complexity will be greatly improved. Moreover, the increase in the number of model also makes the competition between the various models increasing, so that it affects the performance negatively. In order to solve the above problems, in 1992 Li X R proposed the Variable Structure Multi-Model (VSMM) [32] algorithm with a time-varying model set adaptive switching to replace the fixed structure of the restrictions, in which the key part is the adaptive mechanism of the model set. For the problem of how to determine the candidate model set and select the optimal model set, Li X R proposed four commonly used algorithms in the literature [17-21]: model group switching(MGS), likely model set(LMS), adaptive grid(AG) and expectation model algorithm (EMA).

MGS is earliest proposed, and the representation is the digraph switching (DS) model set adaptive algorithm. Its performance is superior to the IMM algorithm, but the algorithm may be due to activation of the wrong model set and performance degradation. The representative of LMS is the active digraph model set adaptive algorithm, whose cost efficiency is low and easy to realize. The disadvantage is that if the topology design is not appropriate, the conversion algorithm may not be able to handle two different patterns and lead to greater error. Adaptive grid interacting multiple model (AGIMM) algorithm is a typical case of the adaptive grid (AG) algorithm which is proposed by Jilkov in the literature [10]. EMA can generate the model matching the pattern in real time. The estimation accuracy of EMA is very high, but the amount of calculation is large, and relatively difficult to achieve.

Overall, the performance of VSMM algorithm is better than IMM algorithm. Moreover, the stronger the mobility of the target is, the more favorable advantages VSMM will show.

## 5. Summary and Prospect

From the above review of the radar single target tracking algorithm can be seen, because of a solid theoretical basis and after decades of continuous development, algorithm research has become increasingly mature. In recent years, the research of radar single target tracking algorithm has been moving in the direction of engineering application development, emphasizing the real-time and stability of the algorithm, being more inclined to all kinds of adaptive algorithm research and the development of multi-model and nonlinear state estimation fusion algorithm. When the external environment is complex and changeable, the statistical characteristics of the prior measurement noise often cannot accurately describe the real noise characteristics. At this time, the result of the standard tracking algorithm will be affected and even divergent. Some scholars introduced the adaptive mechanism in the filter algorithm which has a certain effect to solve this problem. There were also scholars applying the nonlinear filter to the second and third generation multi-model algorithm, which had a good effect for long-term continuous maneuvering target tracking. These various forms of algorithm were not only reused in the field of target tracking, but also extended to other areas, such as fault diagnosis, artificial intelligence, computer vision, etc, and fully demonstrated the broad prospects for research.

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