A Review of Target Tracking Algorithms Based on Traditional Filtering Methods

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Abstract: This paper conducts research on the field of the target tracking. Maneuvering targets tracking are of great significance in both military and civilian fields. First, this paper expounds on the key concepts and algorithms in this field. And we discuss the types of target motion and the classification of tracking algorithms. Second, we introduce the Kalman filter (KF) and its subsequent development, as well as the advantages and disadvantages of various algorithms. Third, we provide the detailed explanations of the multiple model (MM) algorithm, including the fixed structure of interacting multiple model (FIMM) algorithm and the variable structure of interacting multiple (VSIMM) model algorithm. Finally, the article sums up the evolution of maneuvering target tracking algorithms. It systematically outlines the content expounded earlier. Meanwhile, it looks ahead to the future development of algorithms in the field of maneuvering target tracking. For instance, by integrating with the artificial intelligence field and developing new sensors, the maneuvering target algorithms can be upgraded and improved. And this paper provides a theoretical reference for further research and applications in this field.

1. Introduction

With technological advancements and growing practical demands, target tracking has garnered significant research attention. In military applications, it enhances combat decision making, threat early warning, and weapon strike efficiency. Civilian domains leverage tracking technologies to ensure aviation or maritime safety and enable precision navigation. Maneuvering target tracking, a critical subset of this field, faces challenges due to increasingly agile target dynamics. Conventional single model tracking algorithms struggle to address these demands, driving the interacting multiple model (IMM) algorithm to emerge as a prominent research direction for robust state estimation in complex maneuvering scenarios.

The algorithms for tracking maneuvering targets have different classification methods according to various characteristics. One of the main classification methods is based on the motion type of the target. The motion models of the target include Constant Velocity (CV) Model; Constant Acceleration (CA) Model; Constant Turn (CT) Model, etc. The CV model posits that the target maintains a constant velocity; The CA Model posits that the target exhibits uniform acceleration during its movement; The CT Model posits that the target maintains a consistent turning rate during its movement. Single model algorithms employ a fixed dynamic model to predict and update target states in maneuvering target tracking. These methods assume the target's motion strictly follows a specific pattern, estimating state parameters via recursive filtering. On this basis, the Kalman filter (KF) algorithm was proposed. In order to solve the problem of noise correlation of the KF, R. Singer proposed the Singer model in 1969[1]. Zhou Hongren proposed the "current" statistical model, which focuses on the probability density of the instantaneous acceleration and can effectively constrain the future acceleration within the physical limits of the current state[2]. Mehrotra proposed the jerk model, which is committed to solving the limitations of tracking highly maneuverable targets. The approach is to introduce the jerk into the state vector and optimize the acceleration estimation by explicitly modeling the rate of change of the acceleration[3]. In order to address the limitation that the KF can only be used in linear systems, relevant scholars proposed algorithms such as the extended kalman filter (EKF). These are all single model algorithms. Single model filtering algorithms offer computational efficiency and simplicity,

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and they are suitable for low maneuver scenarios. These models exhibit notable limitations. They demonstrate a restricted capacity to adapt to abrupt maneuvers and intricate dynamics. Their operation hinges on fixed dynamic model assumptions and necessitates meticulous parameter adjustment. Moreover, model mismatch has the potential to induce substantial state estimation errors.

However, single model algorithms cannot solve the problem of tracking complex maneuvering targets. Drawing on the idea of multiple model adaptive control in the field of automatic control, relevant scholars successively proposed the multiple model algorithm (MM) and the IMM algorithm. The idea of the MM algorithm is to set up a model set M, add multiple models S to the model set M, and the output result of the algorithm comes from the fusion of the output results of the filters of a group of models in the set. This approach effectively addresses the challenges of target tracking that arise from model uncertainty due to the target's maneuvers.

The IMM methodology is theoretically grounded in the generalized pseudo-Bayesian estimation framework. The IMM framework incorporates various filters that correspond to distinct tracking models. The probabilities associated with these models can be adjusted. Interaction among the different models is facilitated via a Markov matrix, and the resultant outputs are integrated based on the likelihood function of each model. The IMM can be divided into the fixed structure interacting multiple model algorithm (FIMM) and the variable structure of interacting multiple model algorithm (VSIMM)[4]. The VSIMM algorithms can be divided into the active digraph algorithm (AD), the digraph switching algorithm (DS), and the adaptive grid algorithm (AG).

In summary, target tracking holds substantial importance in both military and civilian sectors. Maneuvering target tracking presents significant challenges due to the intricate dynamic variations of the targets. Although traditional single model tracking algorithms have the advantages of computational efficiency and simplicity in low maneuver scenarios, when faced with complex maneuvers, they rely on the assumption of a fixed dynamic model, require high parameter adjustment, and are prone to model mismatch, making it difficult to meet the requirements. To solve this problem, MM, IMM algorithms, and others have emerged successively. Next, the specific types and characteristics of these algorithms will be introduced in detail.

2. Single model target tracking algorithm

The Wiener filter is an optimal linear filter utilized for discrete-time signals. Its primary objective is to reduce the mean square error (MSE) between the output signal and the target signal. The Wiener filter has limitations. It requires that the input signal is wide sense stationary (WSS)[5]. It also requires that the desired signal be known or that some characteristics of the signal be known. Vaseghi introduces the theory of Wiener filters and their alternative formulations, with discussions on applications in channel equalization, time delay estimation, and additive noise suppression[6].

State estimation in stochastic dynamical systems is effectively performed through KF, recognized as a computationally efficient recursive estimator under noisy conditions. Its main approach is to combine the model prediction with measurements to obtain an optimal state estimate. As a linear filter, it performs exceptionally well in continuously changing linear systems. The prerequisite for the KF is that the system is a linear Gaussian system. The motion equations and observation equations should be linear, and the system noise to follow the Gaussian distribution. Mahfouz proposes a methodology integrating machine learning with KF to estimate the instantaneous position of maneuvering targets, where the implementation enables accurate estimation of both target acceleration and positional states[7]. Patel applies KF to the tracking of individual moving objects within security surveillance systems, with experimental validation conducted on video datasets[8]. Lerro proposed an accurate method for tracking using debiased consistent converted measurements and took into account the sensor errors under all practical geometries and precisions[9].

KF is limited by the linear requirements of both the state transition equation and the observation equation. However, in practical applications, many nonlinear systems are encountered. To address the non linearity issues of the KF, some scholars proposed the EKF. The EKF uses local linearization to tackle non linear problems by differentiating the non linear prediction and observation equations and employing a tangent approximation for linearization. The EKF linearizes the motion and observation equations through Taylor series expansion. Both the KF and the EKF share the same algorithmic structure, describing the posterior probability density in a Gaussian form and obtaining it through the calculation of Bayesian recursive formulas. The use of the EKF also has limitations. It assumes that the motion and observation models are approximated into linear models using the first or second order expansion of the Taylor series, ignoring higher order terms, which inevitably introduces linearization errors and may even lead to filter divergence. The calculation of the first order Jacobian matrix and the second order Hessian matrix is difficult, resulting in a large computational load. However, EKF still has some valuable applications, Hostettler applies the EKF to vehicle tracking based on road surface vibration measurements[10]. Habib employs the EKF for spacecraft orbit estimation and control using GPS measurements[11].

EKF may have linearization errors, and the Jacobian matrix is generally difficult to implement, increasing the computational complexity of the algorithm. The unscented Kalman filter (UKF) does not use Taylor series expansion to linearize nonlinear systems. Rather, it employs the unscented transform (UT) to address the nonlinear propagation of means and covariances. It estimates the probability density distribution of a nonlinear function by utilizing a collection of deterministic samples to approximate the posterior probability density of the state. A collection of sigma points is chosen to represent the probability distribution of the initial state. These points are then mapped to a new state space through the nonlinear function, and the new state probability distribution is approximated by using the mapped points. This method allows highly nonlinear systems to be propagated through the nonlinear function while maintaining the accuracy of the state's mean and covariance. Ding proposes an adaptive UKF framework is implemented for visual tracking, demonstrating improved real-time processing and localization precision [12]. Kim investigates the UKF for spacecraft attitude estimation by addressing nonlinear dynamic models through unscented transformation. The experimental results demonstrate that the UKF achieves superior estimation accuracy and robustness compared to the EKF, particularly in highly dynamic environments[13]. Liu proposes a modified IMM algorithm based on the UKF for target tracking, which operates under a time difference of arrival (TDOA) framework[14]. The UKF also has its drawbacks. The computational complexity is relatively high because it needs to handle multiple sigma points, and it may be less efficient in some high dimensional problems.

The particle filter (PF), a probabilistic inference method based on Monte Carlo sampling, is widely adopted in nonlinear and non Gaussian scenarios. The primary approach involves estimating the posterior probability distribution of the target state by utilizing a substantial collection of random samples. The procedure involves three stages: first, predicting particle swarm positions via motion models; second, updating particle weights by integrating observational data; finally, resampling to retain high-weight particles while eliminating low-weight ones, thereby iteratively converging toward optimal state estimation. The PF has strengths. It can handle complex noise profiles and nonlinear motion models well. It also adapts to multimodal distributions. However, it has limitations. Computational costs rise proportionally to the particle population. Particle diversity may degrade during resampling. This can reduce tracking robustness in abrupt state transitions. Arulampalam presents a systematic framework for PF based online tracking in nonlinear or non Gaussian systems, leveraging Monte Carlo methods to approximate intricate probability distributions[15].

Based on above algorithms, some scholars have developed specialized models tailored to diverse operational conditions. Wan introduced the unscented particle filter (UPF), which combines the advantages of the UKF and PF by employing unscented transformation to create importance sampling distributions. The UPF exhibits improved estimation accuracy and computational efficiency in systems characterized by significant nonlinearity and non-Gaussianity[16]. Särkkä introduced a refined UKF algorithm for state estimation in continuous-time nonlinear systems. By discretizing the nonlinear dynamics, this approach achieves an improved trade off between estimation precision and computational efficiency[17]. Huang developed a novel adaptive extended Kalman filter (AEKF) based on online expectation maximization (EM) methods to address the inherent challenge of unknown noise covariance matrices in autonomous underwater vehicle (AUV) cooperative localization[18]. Kotecha formulated a Gaussian particle filter (GPF) that reduces computational complexity through Gaussian approximation, exhibiting superior computational efficiency and estimation accuracy in target tracking and signal processing applications[19].

3. Multiple model target tracking algorithm

The single model target tracking algorithm fails to accommodate time varying target motion patterns, frequently resulting in tracking loss. To address this limitation, IMM was proposed by Blom in 1984[20]. As a filtering technique for systems with complex dynamics, IMM employs multiple motion models to match diverse state transitions of maneuvering targets, ensuring broad coverage of potential motion modes. This method is particularly effective in scenarios involving significant target maneuverability or model uncertainty.

IMM contains multiple models, and each model represents a motion form. Thus, IMM would generate multiple filter results, and the final result is their convex combination. The algorithm is categorized into two variants: FIMM algorithm and VSIMM algorithm. FIMM maintains a fixed set of models throughout the estimation process, while VSIMM dynamically adjusts the model set.

4. Fixed structure interacting multiple model algorithm

The IMM algorithm has a basic idea. At each moment, assume a specific model is valid currently. The state estimates of all previous filters are mixed to get the initial conditions of the filter matching this model. Then, prediction and correction filtering operations are performed in parallel for each model. Finally, the model probabilities are updated according to the model matching likelihood function. We sum up the state estimates after correcting all filters with weights to obtain the final state estimate.

The FIMM algorithm has four main stages:

Model Set Initialization: A finite set of motion models is defined, with initial probabilities assigned to each.

Parallel Filtering: KF execute state prediction and update for each model using its respective dynamic equations.

Model Probability Update: Probabilities are recalculated based on prediction observation residuals and measurement likelihoods.

State Interaction and Fusion: Estimates and covariances from all models are mixed via Markovian transitions, followed by probability weighted averaging to yield the final output.

Compared to single model KF, FIMM exhibits enhanced robustness, accuracy, and dynamic tracking performance. However, its computational complexity and parameter tuning requirements limit practical applications. Performance degrades when predefined models inadequately represent target maneuvers.

These advancements collectively demonstrate progressive adaptations to address evolving challenges in target motion characterization and estimation precision. Wang designs a hybrid IMM algorithm that integrates KF with mean shift filtering to address target occlusion scenarios. This architecture enhances robustness against partial or complete visual obstructions in cluttered environments[21]. Zhuzheng proposes a novel IMM variant leveraging likelihood function theory to dynamically update both model probabilities and Markovian transition matrices based on real time target state distributions. This approach achieves significant improvements in real-time adaptability compared to conventional static transition frameworks[22]. Dongying introduces a feature dependent IMM algorithm incorporating adaptive tuning parameters linked to target characteristics. By iteratively optimizing the state gain matrix and error covariance matrix, this method achieves sub-meter-level tracking precision in complex maneuvering scenarios[23]. Luo develops an IMM algorithm grounded in CV and CT motion models, specifically optimized for radar-based aerial maneuvering target tracking[24]. Kaempchen analyzed the Stop&Go situations and systematically parameterized the IMM method based on these statistical data, which can be applied to the maneuvers in high-dynamic driving scenarios[25].

5. Variable structure of interacting multi model algorithm

The VSIMM algorithm, developed from the FIMM framework, addresses the limitations of fixed model sets in FIMM, where computational load grows significantly with the number of models. Performance degrades due to excessive competition among redundant models when overpopulated. Estimation accuracy is constrained by model mode mismatch under unknown or infinite system mode sets. Inflexible model set adaptation fails to leverage real time measurements, reducing robustness. VSIMM algorithm can adjust the model set in real time based on measurements and system states. It also balances performance and computational cost well, and is less sensitive to model selection with strong adaptability. This structural flexibility enables VSIMM to refine state estimation precision under diverse maneuvering conditions. According to the way of adjusting the model, VSIMM is divided into three categories: AD, DS, AG. They achieve the dynamic adjustment of the model set from different perspectives. The AD algorithm adjusts based on subgraph selection of the overall graph and pattern classification. The DS algorithm adapts by switching among multiple pre-determined directed graphs. The AG algorithm undergoes adaptive changes for the parameter grid.

AD utilizes directed graphs to represent model transition relationships, where nodes denote motion models and edges indicate permissible transitions. By activating localized subgraphs through online residual analysis and model probability thresholds, AD reduces computational load while maintaining tracking fidelity in scenarios with complex but locally correlated model transitions. However, its performance depends critically on threshold selection, requiring careful trade-offs between subgraph coverage and computational efficiency. Li introduced a VSIMM approach known as the "likely model set (LMS) algorithm," which is broadly applicable to various hybrid estimation challenges and is straightforward to implement[26].

DS algorithm switches between predefined digraphs using posterior probabilities or residual covariance metrics. This approach suits systems with predictable mode transitions but suffers performance degradation when target dynamics exceed predefined patterns. Jilkov evaluates and compares the performance of DS algorithms and AG filters across diverse flight scenarios via Monte Carlo simulations, demonstrating the superiority of VSIMM frameworks over FIMM approaches in terms of tracking accuracy and computational adaptability[27]. Quanxin introduces an adaptive variable structure multiple model (AVSMM) algorithm that utilizes turn rate estimation, which dynamically adjusts the supporting digraph topology through improved turn rate prediction[28]. Li proposed a VSIMM estimation method called the model group switching (MGS) algorithm[29].

AG dynamically discretizes continuous parameter spaces into adaptive grids, refining resolution in high probability regions and coarsening it in low probability areas. While AG eliminates the need for fixed model sets and autonomously covers high likelihood parameter regions, its computational complexity escalates with grid density. Li proposed a new class of VSIMM, which is called the expected mode augmentation (EMA) algorithm[30].

Collectively, these mechanisms enable VSIMM to balance adaptability, precision, and computational tractability, outperforming FIMM in highly nonstationary tracking environments. Du proposes an adaptive interacting multiple model (AIMM) algorithm for integrated navigation systems in unmanned underwater vehicles (UUVs) utilizing inertial navigation systems (INS), Doppler velocity logs (DVL), magnetometer compasses (MCP), and terrain aided navigation (TAN)[31]. Guo develops an adaptive structure multiple model (ASMM) algorithm incorporating fuzzy control theory to accelerate model probability updates[32]. Wang designs an adaptive grid multiple model (AGMM) algorithm combining strong tracking filters (STF) with fuzzy interaction logic. Comparative analyses against generalized pseudo Bayesian (GPB), IMM, and conventional VSMM algorithms demonstrate its superiority, with 0.12m RMS positioning error in 3D maneuvering target tracking[33]. Kirubarajan introduced a VSIMM estimator designed to leverage moving target indicator (MTI) reports collected from airborne sensors for tracking groups of ground targets along constrained trajectories[34].

6. Conclusion

In the context of continuous technological iteration and expanding application scenarios, target tracking, as a key technology in multiple fields, has drawn significant attention in the research and development of its algorithms. This paper comprehensively and deeply reviews target tracking algorithms based on traditional filtering methods.

Traditional single model target tracking algorithms, such as the Wiener filter, KF and its derivatives EKF, UKF, PF, each have unique advantages and limitations. In low maneuver scenarios, they can play a certain role with the characteristics of high computational efficiency and simple implementation. However, when facing complex maneuvers of targets, these algorithms rely on fixed dynamic model assumptions, require strict parameter adjustment, and are prone to model mismatch. As a result, the tracking accuracy and reliability are greatly reduced, making it difficult to meet the actual application requirements. To effectively address the above challenges, MM target tracking algorithms have emerged, with the IMM algorithm being a representative one. FIMM algorithm can adapt to multiple target motion patterns to some extent by processing multiple models in parallel. It has significantly improved robustness, accuracy, and dynamic tracking performance compared with single model algorithms. However, FIMM has problems such as high computational complexity and a high degree of dependence on predefined models. When the target motion patterns exceed the predefined range, its performance will decline significantly. VSIMM algorithm further develops based on FIMM. By adjusting the model set in real time, it effectively balances the performance and computational cost of the algorithm, is less sensitive to model selection, and has stronger adaptability. Whether it is the AD algorithm based on sub graph selection, the DS algorithm based on directed graph switching, or the AG algorithm based on adaptive grids, they all achieve dynamic optimization of the model set from different perspectives and exhibit superior performance to FIMM in highly non-stationary tracking environments.

In the future, with the continuous progress of technology, the research on target tracking algorithms is expected to make breakthroughs in the following directions: First, for the increasingly complex practical application scenarios, the researchers should further optimize the existing algorithms, reduce the computational complexity, and improve the real-time performance and adaptability of the algorithms. Second, they need to explore the organic combination of traditional filtering methods and emerging technologies such as deep learning and artificial intelligence to give full play to the advantages of both and enhance the intelligent recognition and precise tracking capabilities of target tracking algorithms for target motion patterns in complex environments. Third, it is necessary to strengthen the application research of multiple sensor fusion technology in the field of target tracking, integrate information from different sensors, obtain more comprehensive and accurate target state information, and thus achieve more reliable target tracking.

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