

Retraction

Retracted: Application of Improved Interactive Multimodel Algorithm in Player Trajectory Feature Matching

Complexity

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] X. Du, Q. Ao, and L. Qi, "Application of Improved Interactive Multimodel Algorithm in Player Trajectory Feature Matching," *Complexity*, vol. 2021, Article ID 2993675, 13 pages, 2021.

Research Article

Application of Improved Interactive Multimodel Algorithm in Player Trajectory Feature Matching

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The original target tracking algorithm based on a single model has long been unable to meet the complex and changeable characteristics of the target, and then there are problems such as poor tracking accuracy, target loss, and model mismatch. The interactive multimodel algorithm uses multiple motion models to track the target, obtains the degree of adaptation between the actual motion state of the target and each model according to the calculated likelihood function, and then combines the updated weight values of each filter to obtain a weighted sum. Therefore, the interactive multimodel algorithm can achieve better performance. This paper proposes an improved interactive multimodel algorithm that can achieve player tracking and trajectory feature matching. First, this paper proposes an improved Kalman filtering (IKF) algorithm. This method is developed from the unbiased conversion measurement Kalman filter, which can obtain more accurate target state and covariance estimation. Secondly, using the parallel processing mode of the IMM algorithm to efficiently solve the data association between multiple filters, the IMM-IKF model is proposed. Finally, in order to solve the problem of low computational efficiency and high mismatch rate in image feature point matching, a method of introducing a minimum spanning tree in two-view matching is proposed. Experimental results show that the improved IMM-IKF algorithm can quickly respond to changes in the target state and can find the matching path with the lowest matching cost. In the case of ensuring the matching accuracy, the real-time performance of image matching is ensured.

1. Introduction

There are various moving objects in the world, ranging from various insects to various celestial bodies, and their motion characteristics and behaviours are different. The traces left by moving objects in geographic space over time are called trajectories [1, 2]. The trajectory contains not only spatial information but also temporal information. People can mine and discover the trend or pattern of the movement of moving objects from the trajectory data [3, 4]. In recent years, the technical level of trajectory tracking has been significantly improved and has been widely used in various fields [5, 6]. However, the complexity of the target's environment and the variability of its own functions make the randomness of target position information in trajectory tracking still immeasurable, resulting in an increase in the technical difficulty of trajectory tracking [7, 8].

In order to accurately track players and improve the accuracy of player trajectories, this paper has carried out a research on the matching algorithm of player trajectories based on interactive multimodels. The research mainly includes three aspects:

- (1) Propose an improved Kalman filtering (IKF) algorithm. This method is developed from the unbiased conversion measurement Kalman filter, which can obtain more accurate target state and covariance estimation.
- (2) Using the parallel processing mode of the IMM algorithm to efficiently solve the data association between multiple filters, the IMM-IKF model is proposed.
- (3) Aiming at the problem of low computational efficiency and high mismatch rate in image feature point

matching, a minimum spanning tree is proposed in the two-view matching.

The rest of our paper was organized as follows. Related work was introduced in Section 3. Section 3 described the algorithm proposed in this paper. Experimental results and analysis were discussed in detail in Section 4. Finally, Section 5 concluded the whole paper.

2. Related Work

In recent years, many researchers have conducted a lot of research on the target motion model and have achieved remarkable results in the improvement of the target model. The earliest use of differential polynomials to approximate the target's motion trajectory, but this target model is difficult to match the real motion characteristics of the target [9]. When the target is maneuvering, the use of this model may result in the failure of target tracking. Zhang et al. [10] use adaptive turning model or curve model to accurately describe the true state of target motion. However, these simple models are also the basis for studying other new target motion models. Jia et al. [11] proposed a singer model, a zero-mean, first-order time-dependent maneuvering acceleration model for maneuvering targets. Nishikimi et al. [12] proposed a semi-Markov model based on the basic principles of the singer model. Feng et al. [13] proposed a new target normal acceleration statistical model in order to better reflect the change of the target acceleration and gave the simulation results of the real three-dimensional scene during the experiment to evaluate the interactive filtering.

The original target tracking algorithm based on a single model has long been unable to meet the complex and changeable characteristics of the target, and then there are problems such as poor tracking accuracy, target loss, and model mismatch. The key of the multimodel algorithm is to use multiple motion models to track the target, obtain the degree of adaptation between the actual motion state of the target and each model according to the calculated likelihood function, and then combine the weight values updated by each filter to weighted summation to obtain the final target state output result. With the development and innovation of interactive multimodel algorithm (IMM) algorithm [14] theoretical knowledge, the general recursive process of the IMM algorithm can be divided into three modules, namely, hybrid probability calculation, model mixing, and model matching filtering. The sum model probability is updated, and then the final filtering result is output through state and covariance estimation. Among the existing multimodel algorithms, the potential advantage of the IMM algorithm is that it is fused with related filtering algorithms and applied to the field of target tracking. Ahn et al. [15] proposed an interactive multimodel algorithm with Markov switching coefficients based on the generalized pseudo-Bayes algorithm. The core is to use multiple different motion models to match the different motion states of the target. We can estimate the weight value of

each single model and then use Markov chain to realize the switch between different target motion models.

Kalman filter (KF) is an algorithm that uses linear system state equations to optimally estimate system state through system input and output observation data. Therefore, many research contents have introduced the KF algorithm [16, 17]. In literature [18], the IMM algorithm is combined with two nonlinear filtering algorithms, EKF and UKF, respectively, and two nonlinear filtering algorithms based on interactive multiple models, IMM-EKF and IMM-UKF, are studied and designed. At the same time, for the scene of the target moving at a constant speed and turning motion, literature [18] compared and analysed four target tracking algorithms. In the application of conversion measurement Kalman filter, Radhika et al. [19] proposed the IMM-CMKF algorithm and compared the performance differences of the two algorithms, IMM-CMKF and IMM-UKF, and verified the mismatch in noise modelling. Under the circumstances, IMM-CMKF has better performance than IMM-UKF. However, for maneuvering targets, the CMKF filter still has the shortcoming of insufficient accuracy, and the selection of the filter still needs to be improved. Liang et al. [20] proposed a fusion strategy for pure bearing analysis. Then, based on the IMM algorithm, a multistation pure azimuth maneuvering target tracking method based on the least square method is proposed, and the performance of this method is verified to be better than the multistation CMKF filter in terms of convergence speed and tracking accuracy.

With the rapid development of high technology, fast matching algorithms have achieved good results in many research fields [21, 22]. For many problems in the field of computer vision, such as target recognition, target tracking, image registration and stitching, and three-dimensional (3D) reconstruction of targets or scenes, it is essential [23]. Most of them need to match multiple images before doing other types of processing. However, traditional matching algorithms generally only calculate all relevant and irrelevant feature points between two images, resulting in a high false matching rate and low efficiency. These problems are particularly prominent when dealing with complex and massive images.

Because the probability model can reflect the correlation between the items to be matched from many aspects, so that the matching algorithm has higher accuracy and robustness, it has been widely used in matching in recent years [24]. Ma et al. [25] proposed a feature matching method based on probability model. This method adopts the restarted random walk method to establish and solve the probability model, which improves the discrimination of matching and can be used in a variety of matching problems. However, this method also has certain shortcomings. For example, in the matching of random points, when serious geometric distortion occurs between points, the correct matching rate of the method will be greatly reduced. This shows that the method still has certain problems, and it cannot guarantee good matching accuracy under severe geometric distortion.

There are many image matching methods, and the most concerned one is the image matching method based on feature points [26]. Among the feature point matching

algorithms, the most influential ones are the SIFT and SURF algorithms, respectively. The SIFT algorithm [27] has a better effect on image splicing with different image scales, different rotations, and different brightness. At the same time, it has a strong antinoise ability, but the amount of calculation is very large, and the operation efficiency is very low. The SURF algorithm [28] is several times faster than the SIFT algorithm and has relatively good robustness to the differences in illumination, affine, and projection, and the computational efficiency has been significantly improved, but it is not stable enough. The MSER algorithm [29] is based on the maximum stable extreme value area, a grey-scale image is thresholded for binarization, and the threshold is increased sequentially, which solves the invariance of the affine change of the image grey. The ORB algorithm [30] combines the FAST feature point detection method [31] with the BRIEF feature descriptor. Although a faster calculation speed is achieved, the scale invariance is lost. The efficiency of the algorithm is between the SURF algorithm and the ORB algorithm. The BRISK algorithm [32] constructs an image pyramid for multiscale expression. The FREAK algorithm [33] is an improvement of the BRISK algorithm, and the sampling mode is improved to a sampling mode similar to the image information received by the retina of the human eye. In recent years, there have been many domestic researches on feature point matching. Malekabadi et al. [29] proposed an improved FREAK algorithm. Use the SURF algorithm to establish the scale-space model of the image, and then use the FREAK algorithm to sample and describe the feature points to establish the vector direction of each feature point. Chen et al. [34] proposed a matching algorithm based on improved ORB and symmetric matching. These methods are

all aimed at reducing mismatches based on the fast computing power of the ORB algorithm.

3. Improved Interactive Multiple Model Algorithm

Multimodel methods are mainly divided into three categories, namely, self-applicable multimodel methods, cooperative multimodel methods, and variable structure multimodel methods [35–40]. This paper mainly studies the IMM algorithm, which is the most representative of collaborative multimodel methods.

3.1. The Derivation Process of the IMM Algorithm. For the mixed estimation problem of m models, the posterior probability density function of the system state is

$$p(a_i|b_{1:i}) = \sum_{j=1}^n p(a_i|c_i(j), b_{1:i}, b_i) * \alpha_i(j). \quad (1)$$

In the formula, c_i is the model variable that acts on it from time $i - 1$ to i . This variable is usually described as a first-order Markov chain with all time and the state posterior conditioned on each model:

$$p(a_i|c_i(j), b_{1:i-1}, b_i) = \frac{p(b_i|c_i(j), a_i)}{p(b_i|c_i(j), b_{1:i-1})} p(a_i|c_i(j), b_{1:i-1}). \quad (2)$$

Using the full probability formula here for the second term in formula (2), there is

$$p(a_i|c_i(j), b_{1:i-1}, b_i) = \sum_{j=1}^n p(a_i|c_i(j), b_{1:i}, b_i) * \alpha_i(j) p(a_i|c_i(j), b_{1:i-1}). \quad (3)$$

If it is further assumed that the mixed form is a Gaussian mixture distribution and then a distance matching

approximation is used for a single Gaussian component, one can obtain

$$p(a_i|c_i(j), b_{1:i-1}) = \sum_{j=1}^n (a_i | (a_i, |c_i(j), \sum_k \mu_{i-1}[i|j]), \text{conv}(\alpha_i(j))). \quad (4)$$

Equation (4) takes advantage of the linear nature of the mixture Gaussian distribution and calculates the input value of the matched filter of model j from the interaction of k filters, where is the corresponding weight, also known as the mixed probability. Therefore, the multimodel filtering algorithm implemented by formula (4) is called an IMM algorithm.

According to the derivation process of the IMM algorithm, the realization structure of the IMM algorithm can be given as shown in Figure 1. Including i interactive filters

running in parallel, the mixing process is completed in the input stage of each filter, and with $b_{1:i-1}$ as the condition, the calculation of the mixing probability will be listed in detail in the specific algorithm steps. It can be seen from Figure 1 that the IMM algorithm assumes that multiple parallel interactive filters are used to completely describe different motion states, and the mixing probability calculation is completed at the input stage of each filter. In the filtering process, the model mixing is completed by calculating the model probability and the model transition probability, and the

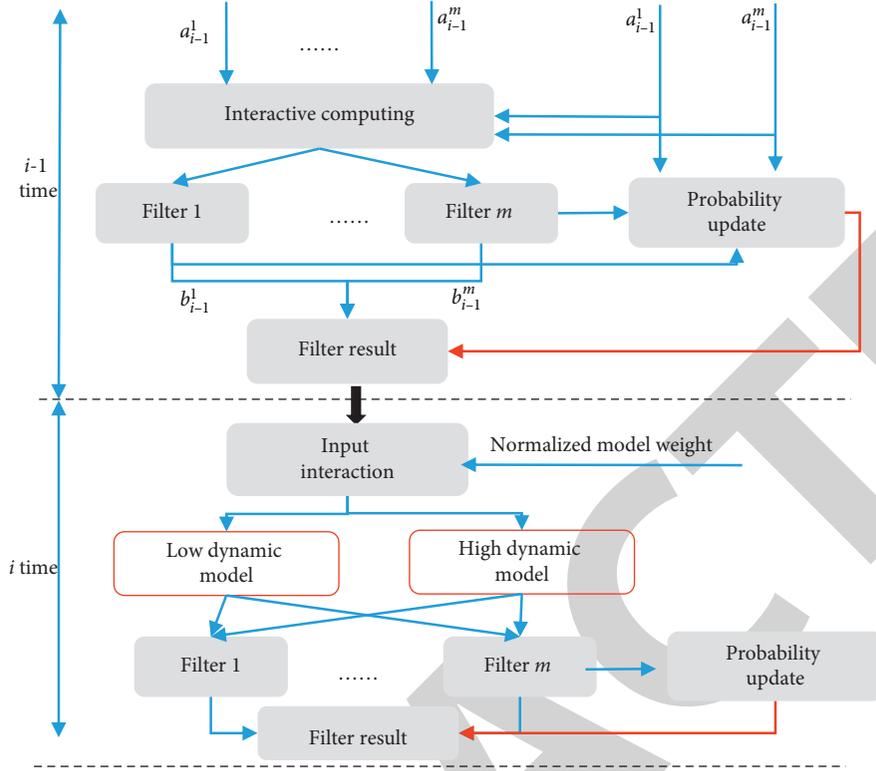


FIGURE 1: Structure diagram of IMM algorithm.

input data of the IMM model are calculated interactively. The model probability is updated by using the likelihood function of each filter and finally in the iterative update process. After that, recalculate the state and covariance estimates based on the model, and output the final result.

The dynamic model refers to a model that describes the balance relationship between the various components of the system and between the system and the outside world and the movement process of these relationships. The low dynamic model is a dynamic model through low-speed movement. The high dynamic model is a dynamic model through high-speed movement. Because the players have low speed and high speed in the process of running, we divide the dynamic model into low speed and high speed.

3.2. Improved Kalman Filtering Algorithm (IKF Algorithm).

For the tracking system, because the target speed is getting higher and higher and the maneuverability is getting stronger and stronger, it is very important to develop a robust and fast tracking algorithm. In view of this, this paper proposes an improved Kalman filtering algorithm (IKF algorithm). This method is developed from the unbiased conversion measurement Kalman filter, which can obtain more accurate target state and covariance estimation. Compared with traditional target tracking methods, the method proposed in this paper has potential advantages in tracking accuracy. Numerical simulation and experimental results verify the correctness and effectiveness of the new method.

The iterative method can speed up the convergence speed of the target tracking method to certain extent. Therefore, if the iterative processing can be added to the filtering algorithm with better consistency, there is a large room for improvement in its performance. Because the iterative process of the traditional algorithm has some defects, we will consider adding some special processing steps to make the iterative filter work well. This paper proposes an improved Kalman filtering algorithm whose iterative process will be different to solve the potential problems in the iterative process of traditional algorithms.

The IKF algorithm includes the following steps.

First, before starting the iterative process, redefine the measurement vector:

$$\begin{aligned} Q &= \{p, q\} \sim N(g(x), \{R, 0, 0, P\}), \\ g(x) &= \{h(x), x\}. \end{aligned} \quad (5)$$

Among them, p and q are the value obeying the Gaussian distribution, and x is the measurement vector.

The estimated value of the target state x' is obtained by minimizing the cost function, written in the form of a matrix:

$$\min (1/2)M(Q - g(x))^2. \quad (6)$$

Among them, S is the crouch decomposition of Q^{-1} ($S * S = Q^{-1}$).

Equation (6) is a nonlinear optimization problem, and it is usually impossible to obtain an analytical solution. The Newton optimization method has a second-order descent

speed, and its convergence performance is good. This is an iterative algorithm, and its update calculation is as follows:

$$x'_{i,j+1} = x'_{i,j} - it_j H_j^{-1} G_j, \quad (7)$$

Among them, it_j is the iteration step length of the j -th step, H_j is the Hessian matrix of x , and G_j is the gradient to x . The calculation of the gradient and the Hessian matrix uses the value of $x'_{i,j}$. Then, the update can be written as

$$x'_{i,j+1} = it_j x'_{i,j} + (1 - it_j) x'_i + it_j [c - g(x'_{i,j}) - H(x'_{i,j})]. \quad (8)$$

Compared with the traditional method, the termination condition of the newly proposed IKF method ensures that the iterative process moves upward along the surface of possibility, that is, to ensure that the iteration moves toward the most possible solution.

The method in this paper can make corrections based on the measured value and adjust the state estimation to make it adaptively close to the true value. Therefore, when the iteration is terminated, the state estimation error can be controlled to a very low level. In addition, the new method can quickly respond to the new information contained in the new measurement value by adjusting the state estimation and its covariance matrix. When the initial value error is large, the new method can achieve faster convergence speed.

3.3. Conversion Measurement Kalman Filtering Algorithm Based on Interactive Multiple Model. The IMM algorithm uses parallel processing to efficiently solve the data association between multiple filters. Among them, the filter is different, the target state space model is also different, and the corresponding target motion mode is also very different. In this section, combined with the IKF filter proposed above, the IKF algorithm based on interactive multiple models is further proposed. The block diagram of the entire module of the IMM-IKF algorithm is shown in Figure 2.

The IMM-IKF algorithm first initializes the position information and then filters the initialized position information. Use parallel processing to solve the data association between multiple filters. At the same time, make corrections based on the measured values and adjust the state estimation to make it adaptively close to the true value.

3.4. Application of Improved Interactive Multimodel Algorithm in Player Trajectory Feature Matching. The IMM-IKF algorithm uses parallel processing to efficiently solve the data association between multiple filters. At the same time, this paper uses the IKF algorithm to correct the measured value and adjust the state estimation to make it adaptively close to the true value. Because the iterative process of the traditional algorithm has some defects, we will consider adding some special processing steps to make the iterative filter work well. Compared with the traditional method, the KF method differs mainly in two points. One aspect is that the termination condition ensures that the iterative process moves upward along the surface of possibility; that is, it ensures that the iteration moves toward the optimal solution. The other

aspect is the adjustment of the step size. The introduction of the attenuation factor weakens the influence of the last correction value, making the two iteration values closer, thus accelerating the convergence of the iteration. The characteristic matching of the player's trajectory requires obtaining the tracking image of the player and obtaining the trajectory of the player according to the tracking image, so as to realize the characteristic matching of the trajectory.

The multiview feature point matching of the player trajectory is obtained by matching the high-dimensional feature points of the extracted player tracking image to obtain the multiview feature point matching trajectory, which is then transformed into the correspondence between multiple images. Multiview feature point matching is to obtain the corresponding relationship of point features in multiple images. The direct method is to first establish the pairwise matching relationship between the views, then expand to multiple views, and perform a breadth search on the results of the pairwise matching set. However, for large-scale image sets, this feature trajectory calculation method is to perform feature point matching between a large number of unrelated images, which is very time-consuming.

In order to improve the efficiency of multiview feature point matching, based on the interactive multimodel algorithm, this paper proposes a fast multiviewpoint feature matching algorithm based on the minimum spanning tree (MST). On the basis of calculating the matching cost of the pairwise views, the minimum spanning tree path with the lowest matching cost is found, so that most of the feature point matching process only runs in the relevant image, and the calculation cost is reduced. Different from the traditional multiview "violent" pairwise matching, the minimum spanning tree is used to predetermine the image pairs that may have a matching relationship to ensure that most feature matching processes only run on related images.

Let $I = I_1 \cup I_2 \cup \dots \cup I_n$ be the point feature set extracted from each image in the image set containing n images. Among them, I_i corresponds to the image feature points extracted from the image i . For each feature point in I_j , first search for its nearest neighbour in I/I_j , and then calculate score matrix s_m , where each element $s_m_{i,j}$ is all the feature points in the image I_j . The number that appears in the image i , the diagonal element of the matrix s_m is 0. The image feature description vector is 64-dimensional, and the feature is approximated by the nearest neighbour search. Define the matching cost between two images as

$$\text{loss} = 1 - \frac{s_m_{i,j}}{\sum_k s_m_{i,k}}. \quad (9)$$

After obtaining the pairwise matching cost between the two images, create an undirected complete image. Each vertex in the graph represents an image, and the weight of each edge is the matching cost of the two images connected by the edge. After calculating the initial matching cost graph, the algorithm is used to traverse the graph with a minimum spanning tree. The algorithm selects a certain node as the start and adds the node with the smallest edge weight adjacent to it to the node set of the smallest spanning tree. At

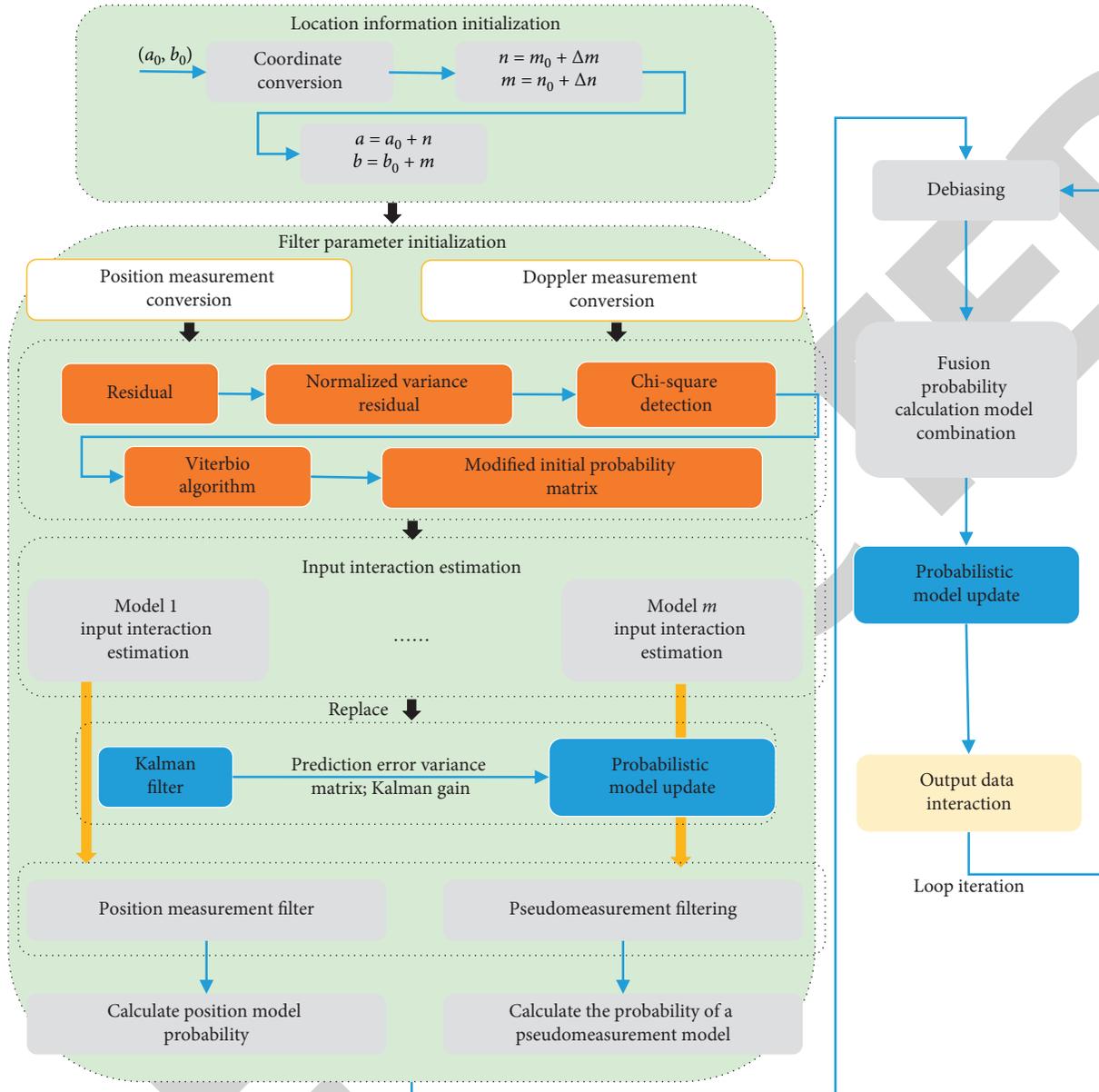


FIGURE 2: Block diagram of IMM-IKF algorithm module.

the same time, the edge corresponding to the minimum weight is added to the edge set of MST, and so on, until all the nodes are added to the point set of MST, and the images in the multiview have constructed corresponding connections. Figure 3 shows the process of constructing MST. The distance between any two nodes in the minimum spanning tree is the smallest path distance between two nodes in the original undirected graph.

Using MST to define the similarity of feature points between two images is the most intuitive way. If the distance between two images in the MST is close, they have a larger number of matching feature points. On the contrary, if the two images are farther apart in the MST structure, the number of pairs of their matching feature points is less. The biggest advantage of using MST as the matching cost is to reduce the time for feature points to be matched in irrelevant

images, and it also facilitates the generation of subsequent multiview feature point trajectories.

4. Results and Discussion

4.1. IKF Algorithm Simulation. In order to verify that the IKF algorithm has a faster convergence speed and higher target tracking accuracy than the traditional conversion measurement algorithm, this section uses the root mean square error (RMSE) criterion to evaluate the performance of each player tracking algorithm. Under the same simulation conditions, each algorithm filters a set of measurement data to evaluate the effectiveness of the algorithm. In addition, in order to highlight the performance difference of the filtering algorithm, this simulation uses a more common CA model to verify the feasibility and effectiveness of the algorithm. All

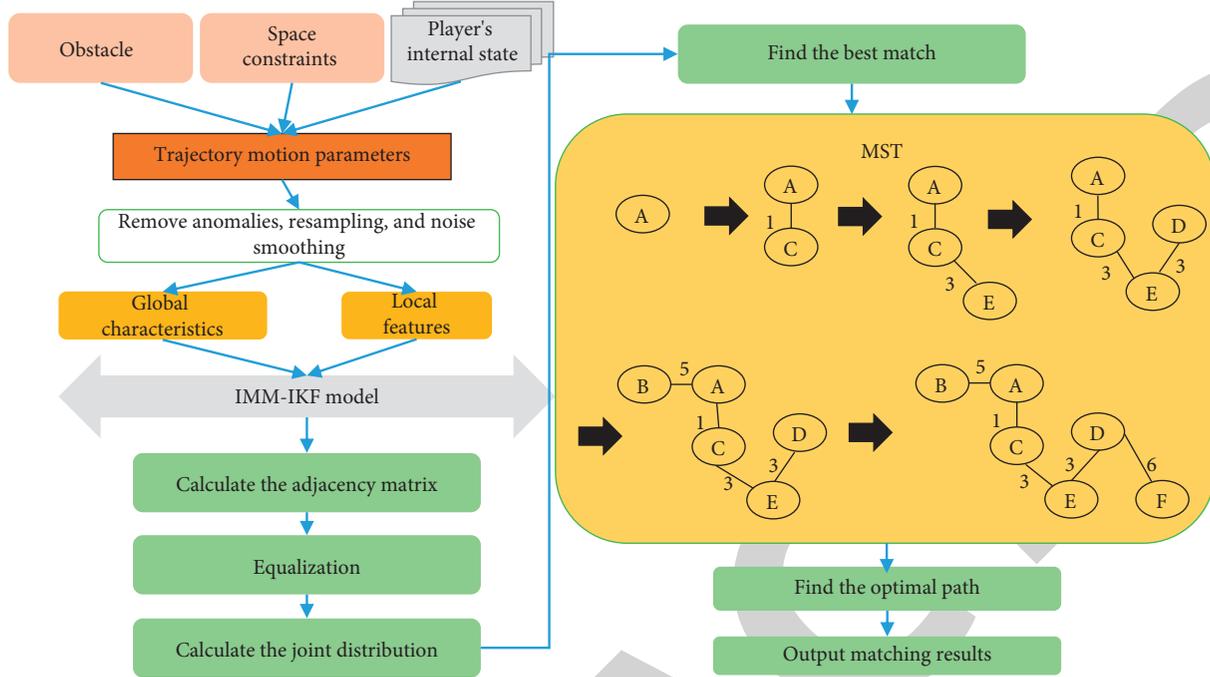


FIGURE 3: Process diagram for constructing the MST.

simulation results are performed with 50 Monte Carlo experiments. Using the CA model as the player tracking simulation model, the simulation results of the position root mean square error and the overall position root mean square error in the X and Y directions are shown in Figures 4 and 5, respectively. Among them, the calculation formula of RMSE is as follows:

$$\text{RMSE} = \sqrt{\frac{1}{m} \sum_{i=1}^m (y_i - y'_i)^2}. \quad (10)$$

Among them, m is the number of measurements. The variable y_i represents the true result of the i -th time. The variable y'_i represents the i -th prediction result.

When using the CA model to match the target trajectory, according to Figure 5, it can be understood that the three algorithms can track the target better and can provide different tracking effects. Among them, the IKF algorithm is slightly better in convergence, stability, and accuracy. The UCMKF algorithm performs poorly in terms of convergence. When tracking the target, it cannot converge in time and enter a steady state. However, when UCMKF converges into a steady state, its tracking effect on moving targets is equivalent to that of IKF. In addition, it can be seen from Figure 4 that, in the X direction, the tracking effects of the three algorithms are sorted from high to low as $\text{IKF} > \text{UCMKF} > \text{CMKF}$, where the tracking accuracy of IKF and UCMKF is equivalent. In the Y direction, compared with UCMKF, IKF is different only in the initial stage of tracking, and the IUCMKF algorithm can quickly converge and enter a steady state. Therefore, under such simulation conditions, based on the CA model, the IKF algorithm has the best tracking effect on moving targets, followed by UCMKF.

4.2. IMM-IKF Algorithm Simulation. The simulation experiment uses three filtering algorithms (IMM-CMKF, IMM-DCMKF, and IMM-IKF) to analyse the differences in player tracking performance. When the CA model and the CS model are used as the model set for the IMM algorithm simulation, the simulation results of the position root mean square error comparison in the X and Y directions, the overall position root mean square error, and the normalized estimated variance are shown in Figures 6–8, respectively.

When the CA model and the CS model are used as the model set of the IMM algorithm, Figures 6 and 7 show that these three algorithms can accurately track the target, and Figure 8 shows that the filter estimation results of the three algorithms have consistency. In the early stage of target tracking, the advantages of the IMM-IKF algorithm are more obvious. Among them, in the X direction, the superiority of the IMM-IKF algorithm is more prominent. In other sections, the IMM-IKF algorithm has a great advantage in convergence speed. Although the computational complexity increases, through the combination of iteration and IMM algorithm, compared to traditional IMM, the IMM-IKF algorithm has better filtering effects and fast convergence characteristics.

4.3. Performance Analysis of Target Tracking and Trajectory Feature Matching. In order to fully test the effectiveness of the algorithm, two typical continuous maneuvering scenarios are selected, and the IMM-CVCA, IMM-CVCACT, IMM-CVCS, IMM-CVSTMIE, and the IMM-IKF algorithm proposed in the paper are used for tracking, respectively. The root mean square error (RMSE) is used as the performance evaluation index.

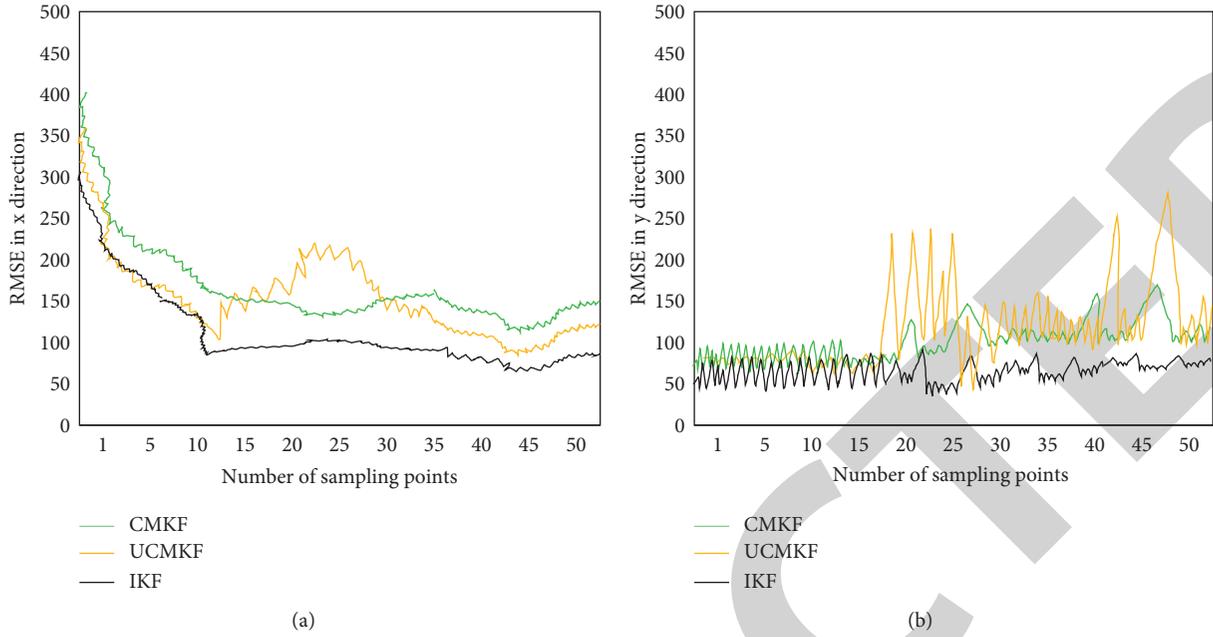


FIGURE 4: Comparison of root mean square error of position in X and Y direction. (a) Root mean square error of position in x direction. (b) Root mean square error of position in y direction.

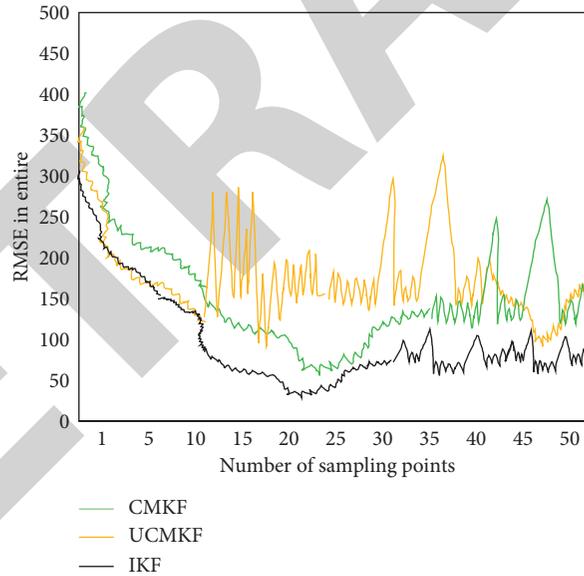


FIGURE 5: Position root mean square error comparison.

The IMM-IKF algorithm proposed in the paper and the above four algorithms are used to track the target, and the root mean square error curve of its position and velocity is shown in Figure 9. At the same time, the average root mean square error during the observation period and the peak error after stabilization (starting after 20 s) are counted. The results are given in Table 1.

From Figure 9 and Table 1, it is easy to know that, in the nonmaneuvering section, all algorithms can achieve better tracking results. In the maneuvering section, the tracking error rises rapidly. But generally speaking, the

IMM-IKF and IMM-CVSTMIE algorithms have higher tracking accuracy and lower peak error, and they respond faster to state changes. Among them, the average error of IMM-IKF is 26.4%, 42.9%, 28.5%, and 20.1% lower than other algorithms. The peak error of IMM-IKF is 24.1%, 45.2%, 17.5%, and 23.3% lower than other algorithms. The reason is that the unknown maneuver input is estimated online in real time, so that the filter can be adjusted in time when the target state changes, which reduces the model mismatch. Therefore, the algorithm in the paper has stronger mobile adaptability.

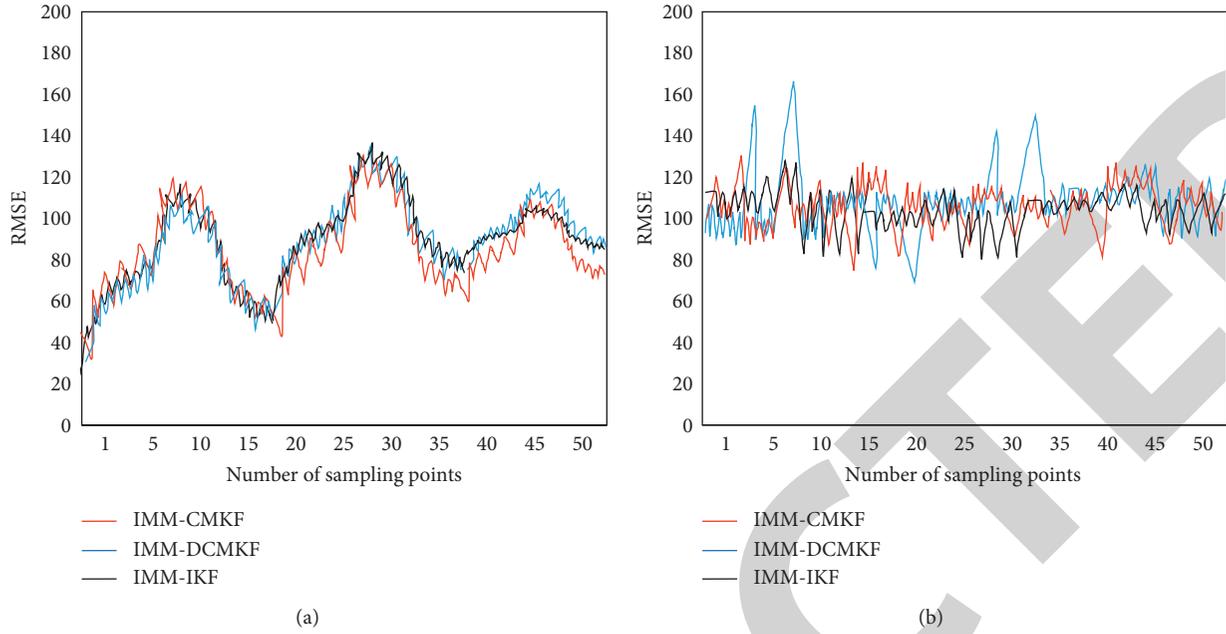


FIGURE 6: Comparison of the root mean square error of position in the X and Y directions on the CA model. (a) Root mean square error of position in x direction. (b) RMSE of position in y direction.

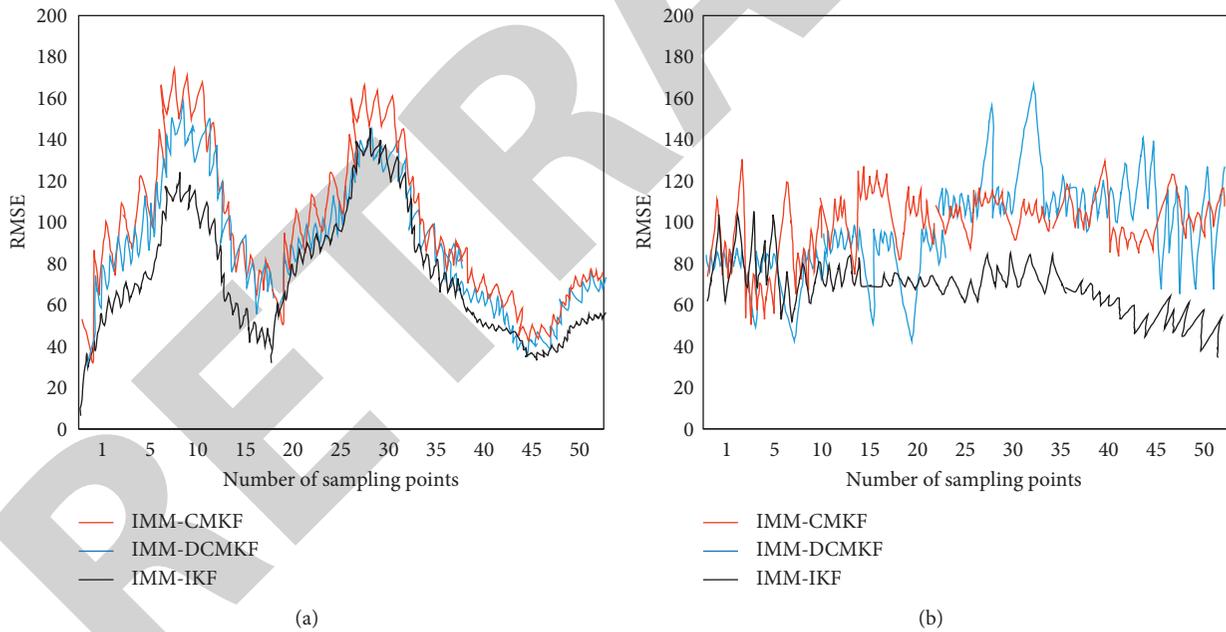


FIGURE 7: Comparison of the root mean square error of the position in the X and Y directions on the CS model. (a) Root mean square error of position in x direction. (b) Root mean square error of position in y direction.

In order to test and analyse the performance of the minimum spanning tree multiview feature point matching algorithm, the efficiency of the MST algorithm and the traditional pairwise matching algorithm to generate multiview feature trajectories was compared. The experiment selects three different iteration times N_t ($N_t = 1, 2, 3$) of the MST algorithm and the pairwise matching scheme for comparison experiments. The experimental test results are

shown in Figure 10. It can be seen from Figure 10 that when $N_t \geq 2$, the number of feature trajectories successfully extracted by the MST multiview feature point matching algorithm is more than 95% of the number of feature trajectories obtained by the traditional pairwise matching method.

Figure 10(a) describes the number of image matching pairs under different image numbers for each image

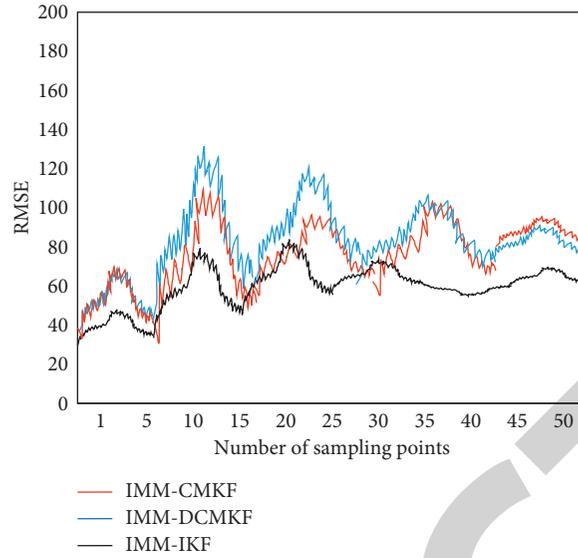


FIGURE 8: Normalized estimation variance comparison.

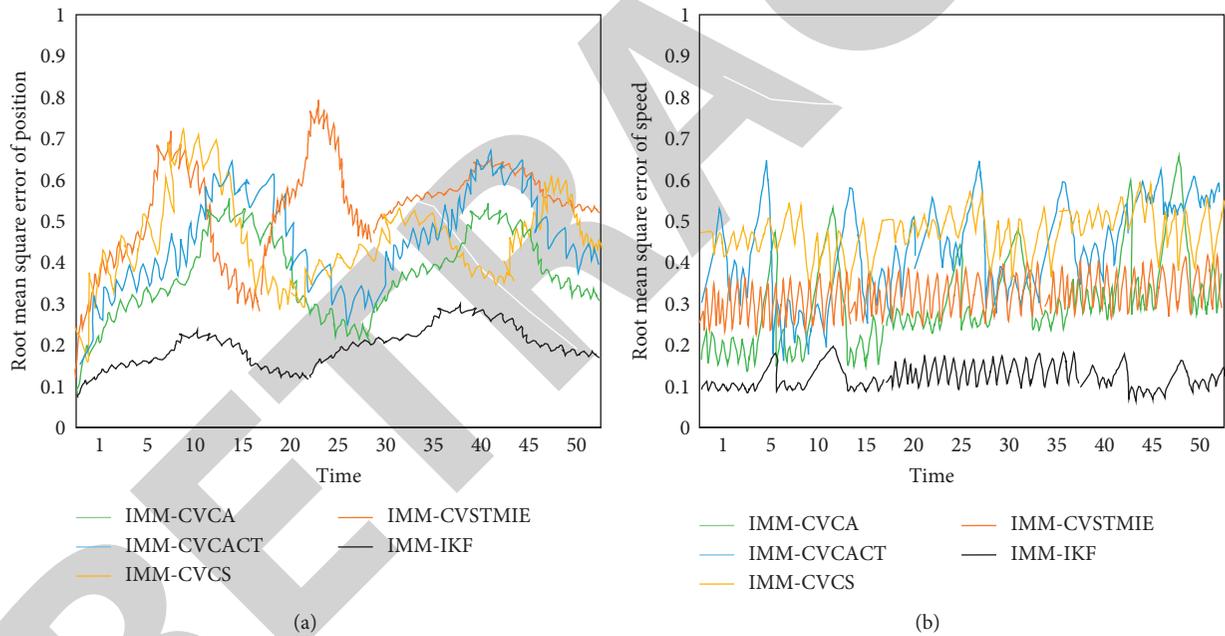


FIGURE 9: Root mean square error curve of position and velocity. (a) Root mean square error of position. (b) Root mean square error of speed.

TABLE 1: Comparison of tracking performance of each algorithm.

Method	Average error		Peak error	
	Position/m	Speed/m ⁻¹	Position/m	Speed/m ⁻¹
IMM-CVCA	96.1	42.5	1159.7	83.1
IMM-CVCACT	123.9	45.8	1653.2	115.2
IMM-CVCS	98.9	41.9	117.5	76.5
IMM-CVSTMIE	88.5	43.2	1131.9	82.3
IMM-IKF	70.7	34.5	91.2	63.1

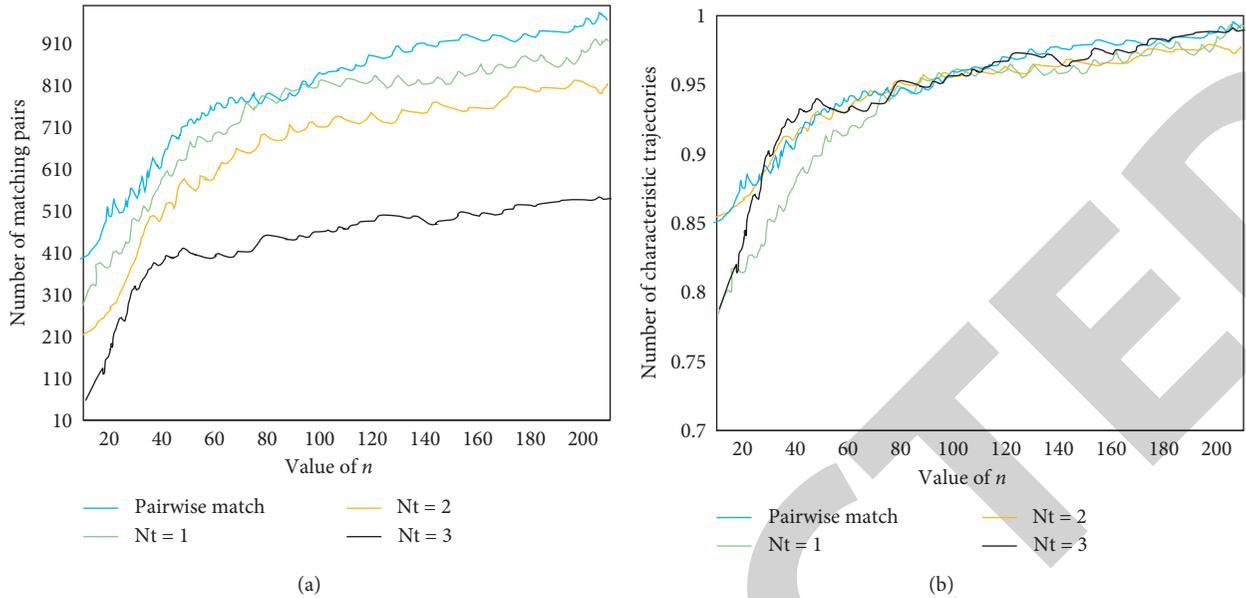


FIGURE 10: Test of multiview feature point matching under different number of images. (a) Number of image matching pairs. (b) Number of characteristic trajectories.

matching scheme. Under the four experimental schemes, the number of image matching pairs generally increases with the increase of the number of images. But under the traditional pairwise matching method, as the number of images increases, the number of matched image pairs has an obvious continuous linear increase. As for the MST algorithm, after the number of images increased to 60, the increase stopped. This is because the image matching of this algorithm is mainly carried out between the images that have an obvious correlation with each other.

Figure 10(b) shows the number of feature trajectories obtained under different image numbers for each experimental scheme. Compared with the pairwise matching scheme, the number of image matching pairs of the MST algorithm is reduced, but the number of effective feature trajectories obtained is the same as the number of feature trajectories obtained by the pairwise matching scheme, which verifies that the MST algorithm can find almost all effective features of trajectory.

5. Conclusion

The interactive multimodel algorithm uses multiple motion models to track the target and can achieve better performance. Therefore, this paper first proposes an improved Kalman filtering algorithm. This method is developed from the unbiased conversion measurement Kalman filter, which can obtain more accurate target state and covariance estimation. Secondly, using the parallel processing mode of the IMM algorithm to efficiently solve the data association between multiple filters, the IMM-IKF model is proposed. Finally, in order to solve the problem of low computational efficiency and high mismatch rate in image feature point matching, a method of introducing minimum spanning tree in two-view

matching is proposed. Experimental results show that the improved interactive multimodel algorithm proposed in this paper can achieve player tracking and trajectory feature matching. And under the condition of ensuring the matching accuracy, the real-time performance of image matching is ensured.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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