

Retraction

Retracted: Application Research on Roller Skater Detection, Tracking, and Trajectory Prediction Based on Video Stream

Scientific Programming

Received 8 August 2023; Accepted 8 August 2023; Published 9 August 2023

Copyright © 2023 Scientific Programming. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Peer-review manipulation

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] S. Duan, L. Meng, D. Ma, and L. Mi, "Application Research on Roller Skater Detection, Tracking, and Trajectory Prediction Based on Video Stream," *Scientific Programming*, vol. 2021, Article ID 2702272, 9 pages, 2021.

Research Article

Application Research on Roller Skater Detection, Tracking, and Trajectory Prediction Based on Video Stream

Shaolou Duan, Lingfeng Meng, Delong Ma, and Liangyu Mi 

Hebei Sport University, Shijiazhuang 050041, Hebei, China

Correspondence should be addressed to Liangyu Mi; miliangyu@hepec.edu.cn

Received 8 October 2021; Revised 30 October 2021; Accepted 10 November 2021; Published 7 December 2021

Academic Editor: Bai Yuan Ding

Copyright © 2021 Shaolou Duan et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

With the continuous progress of science and technology, the sport of roller skating has developed rapidly and the technical level of the game has become higher and higher. Its sport performance has been rapidly improved. However, China's roller skating is relatively late, and there is still a certain gap compared with many Western developed countries. In order to improve the performance of China's roller skating, this study takes the representative Chinese and foreign excellent speed skaters as the research object and compares the sprinting technology of Chinese and foreign excellent speed skaters by using image measurement and image analysis to obtain the kinematic parameters and data of the athletes' sprinting technology in the competition state. In view of the problem that the current video target tracking algorithm is easy to follow multiple targets, a video multiobject detection and tracking algorithm with improved tracking learning detection (TLD) is studied with the skater in the video as the research object. For the lost target, the prediction function of Kalman filter algorithm is used to track the trajectory of the typical target in the video, and the trajectory tracked by Kalman filter algorithm is used to compensate the lost part of TLD algorithm, so as to obtain the complete trajectory of the typical target in the video to improve the accuracy of video multiobject tracking. Since the existing trajectory prediction algorithms have the limitation of poor accuracy, a social-long short-term memory (Social-LSTM) network-based video typical target trajectory prediction algorithm is proposed to predict the trajectory sequences of typical targets to be detected by incorporating the contextual environment information and the interaction relationship between multiple target trajectories into the Social-LSTM network. The simulation results show that the proposed trajectory prediction algorithm outperforms the traditional LSTM algorithm, Hidden Markov Model Algorithm, and Hybrid Gaussian model algorithm, which is helpful to improve the accuracy of video roller skater target trajectory prediction, and the tracking success rate is 0.98.

1. Introduction

“Roller skating is also called roller skating; it is an ice sport in the land auxiliary training process gradually evolved in the formation of sport.” With the continuous development and growth of sports, roller skating has also been flourishing, and the new projects of modern roller skating have emerged and diversified, developing different forms of sports such as speed skating, roller skating ball, extreme roller skating, and figure skating, which are popular among people [1]. The International Roller Derby Federation was officially admitted as a member of the International Olympic Committee (IOC) at the IOC Session held in Prague, Czechoslovakia, in 2007 [2]. Speed skating is a

sport that uses roller skates or skating tools on the field or road to determine victory or defeat by speed, and as a component of roller skating, it is the sport that best reflects the characteristics of roller skating, such as competitiveness, skill, and fierce confrontation [3]. Speed skating is a relatively young sport, but in many Western countries, speed skating has been popularized.

At present, the world of speed skating has reached a fairly high level of competition, and sport performance is constantly improving [4]. In China, the sport of roller skating is in a maturing stage, and there is a big gap compared to many countries, especially in Western Europe. Although, in recent years, China's speed skating project has been developed rapidly, especially in the long-distance

project with very good results, such as a gold and a silver medal won by China's players in the World Roller Skating Championships marathon competition, relative to some high level countries, our gap is still very obvious [5, 6]. For example, in the men's individual time trial of the World Roller Skating Championships in 2007, our athlete He Xin only ranked first and did not enter the final. Therefore, it is very meaningful to study the short-distance project of speed skating in China, which can, on the one hand, provide certain training theoretical reference for China's speed skating coaches, so as to improve the technical level of China's speed skaters in the short-distance project and improve the sports performance, on the other hand, provide help for the popularization of China's speed skating technology, and can promote the further development of China's speed skating sport. It can also promote the further development of speed skating in China and play an indirect role in the implementation of the latest national fitness program in China [7, 8].

Because the individual time trial start has a certain uniqueness and the project is a competitive race project to determine the winner of the race, the start is particularly important and the individual time trial start is characterized by speed roller skaters not listening to the gunshot of the starter to start [9], but according to their own preparation in the coincidental seconds of time to decide to start, when the electronic timer infrared of the electronic timer is cut off by the runner's wheel, the timer will automatically calculate time [10]. This way, it is very advantageous for the runner, and there is sufficient time to self-adjust and to adjust the body to the best state, so that it is more conducive to start after the maximum impulse to start, with the shortest time to get speed. The sprint is an acceleration process after the start; the purpose is to quickly reach the dynamic from the static state, in the shortest time and the most energy-efficient way to get the best speed. It has a very important role in the generation of initial speed, so the study of sprinting technology is very important [11]. The technical movements in the sprinting process are very complicated, and the details of each technical movement are changed in the short-sprinting stage, such as body posture, pedal angle, stride frequency, stride length, and joint angle. These elements are the key to the sprinting technique, and the changes of these elements will directly affect the athletic level of the runner, and they interact with each other and are interrelated, the chain reaction of several factors.

2. Related Work

2.1. Starting Technique. "The kinematics of the knife starting technique of China's excellent male speed skating athletes research" in [12] reveals the athletes in the starting phase of the lower limbs of the ice stirring process contained in the kinematic law, to enrich the technical theory of speed skating, for teaching, training, and scientific research to provide reference basis short-track speed skating starting technology analysis; the article introduced the short-track speed skating is China's dominant project, and the work in [13, 14] introduces that short-track speed skating is the

dominant sport in China, especially the female athletes have long been the world leaders in this sport. Their advantage lies in the starting phase, which is highlighted in the reaction speed, explosive power, and starting technique. In the training through continuous summary, the starting technology should have a deeper understanding. In [15], through the analysis of the domestic and foreign excellent mobilization starting technology, an in-depth description of the short-track speed skating starting technology essentials and its training methods is given. Combined with the competition rules of the project, it puts forward rationalized suggestions to give full play to its characteristics and advantage [16]. The Key Points of Starting Technique and Training for Short-Distance Projects of Youth Speed Skaters "sums up that youth athletes should seize the key technical points in training practice and constantly improve training methods and means in order to improve the starting technique level continuously. A Trial on Starting Technique of Claypool Ice Skating" predicts that, with the improvement of technical proficiency and mastery, there is potential for the Claypool Ice Skaters to improve their starting performance again [17].

2.2. Sports Biomechanics Research. "Biomechanical Analysis of Starting Techniques of Excellent Speed Skaters" in [18] is a comparative analysis of the old and new ice skate starting techniques of domestic excellent speed skaters using photomechanical methods, and the following conclusions are drawn. At present, the distance from the center of gravity projection to the front support point of the new type of ice skate standing start by our athletes is large at the moment of starting, and the forward leaning angle and back pedaling angle of the new type of ice skate are generally large. Angle and backstroke angle are generally large, which leads to the instantaneous horizontal speed drop of the athletes' sprint phase. Athletes are using high-frequency skating to quickly complete the sprint phase and into the gliding phase [19]. This article starts from the comparative photomechanical analysis of the old and new ice skating starting techniques of domestic outstanding speed skaters, trying to find out the photomechanical parameters and respective characteristics of both, in order to improve the speed skating starting technique and improve the speed skating training level. "A Comparative Study on the Starting Movements of Chinese and Japanese Men's Speed Skaters in Meters" in [20] aims to reveal the characteristics of the starting movements of Chinese and Japanese athletes. The authors came to the result that the Chinese athletes' starting preparatory posture has small support point spacing and small front stability angle and their center of gravity is more forward, which creates favorable conditions for completing the transition from the static state to the fast starting stirring state, and their stability is slightly lower than that of Japanese athletes. Kinematic analysis of an excellent speed skater Yu Fengtong's starting technique in [21] shows that a higher stride frequency in the starting phase is an important factor for Yu Fengtong's fast starting speed. In the starting process, the center of gravity is less fluctuating, and the angle of stirrups

is closer to the angle of forward leaning of the upper body so that a larger center of gravity speed is obtained, and the starting stirrups are completed with a higher frequency [22].

2.3. Algorithm of This Paper. In this paper, we propose a video multiobject detection and tracking algorithm based on improved TLD to obtain the complete trajectories of moving targets. The moving trajectory data are analyzed, and a Social-LSTM-based video typical target prediction algorithm is proposed to improve the accuracy of prediction by combining contextual feature information.

2.4. Improved TLD-Based Video Multiobject Detection and Tracking Algorithm. Video target trajectory acquisition mainly includes video target detection and video target tracking, detecting the position of video targets [23]. Then, the video targets are tracked and the position of video targets in each image frame is marked to form the motion trajectory of targets in the video. Video target trajectory acquisition methods can be mainly classified into tracking methods based on deep learning combined with correlation filtering, tracking methods based on prediction, and tracking methods based on optical flow [24]. The classical algorithms corresponding to the three methods are efficient convolution operator ECO [25] algorithm for tracking combined with depth features and correlation filtering [13], Kalman filtering algorithm, and Lucas–Kanade (LK) [26] optical flow algorithm. Although these three algorithms can detect video target trajectories in a specific environment well, there are still some problems in detecting video target trajectories.

Robust tracking algorithms need to be designed in complex scenes to solve the unavoidable problems in practical applications such as lighting changes and obstacle occlusion. Depth features obtained by deep learning methods are more accurate than traditional manual features, but the tracking real-time performance is low. Correlation filtering transforms the computation to the frequency domain, which substantially improves the tracking speed. Combining deep learning with correlation filtering can fully utilize the advantages of both methods.

When there are multiple targets in a video scene, effective tracking of multiple targets is not feasible by relying solely on one of the current tracking algorithms [15]. It is necessary to select a reasonable tracking algorithm from the current mainstream tracking algorithms and combine several different tracking algorithms to complement the advantages and disadvantages to study and design the moving target trajectory tracking algorithm.

The TLD algorithm is a kind of tracking-while-detecting algorithm; when there are occluding objects in the video, the target will not be detected and lost; when there are no occluding objects, the algorithm is a stable and effective algorithm. In order to improve the accuracy of video target tracking, this paper proposes a video multiobject trajectory acquisition algorithm with improved TLD to track and obtain the running behavior trajectory of the target in the case of target movement. The TLD algorithm is used as the basic tracking algorithm, and the Kalman filtering algorithm

is used as the auxiliary tracking algorithm. The trajectory obtained by the Kalman filtering algorithm is used to supplement the missing part of the trajectory obtained by the TLD algorithm, and the complete trajectory of the video target is obtained. The specific steps of the algorithm are as follows:

Step 1: video is input.

Step 2: TLD algorithm and Kalman filtering algorithm are initialized.

Step 3: the video target is tracked and detected using the TLD algorithm, and it is determined whether the target profile is detected in the current video frame; if so, Step 4 is executed; otherwise, the state equation of the Kalman prediction stage is updated, and Step 6 is executed.

Step 4: it is determined whether the detected target contour is complete; if so, Step 5 is executed; otherwise, the equation of state in the Kalman prediction phase is updated and Step 6.1 is executed.

Step 5: the training parameters are updated in the TLD learning model.

Step 6: the location of the video target is recorded, and it is determined whether the video is finished. If the video is over, the video target trajectory data are output; otherwise, Step 1 is executed.

2.5. Video Target Trajectory Prediction Algorithm Incorporating Contextual Features. Motion trajectories of video typical targets have temporal dependencies between adjacent frames, while different motion targets may have mutual effects in the same frame. If these two problems cannot be solved reasonably, the accuracy of video typical target motion trajectory prediction will be affected. In order to solve the abovementioned problems, this paper proposes a Social-LSTM-based algorithm for video target trajectory prediction [27]. The algorithm uses LSTM to process the temporal relationship between the same type target motion trajectory in different video frames. When dealing with multiple typical targets, the LSTM is used to predict the trajectory of each target separately, and a social-pooling layer is added between multiple LSTMs to deal with the interaction between multiple targets, so as to predict the trajectory of the typical targets of the video more accurately.

2.6. Social-LSTM Construction Method. Social-LSTM is an improvement of LSTM, which is a network model that adds an S-Pooling to the LSTM structure to predict the trajectory of a target considering the influence of neighboring targets in the same frame on its trajectory. This S-Pooling allows the LSTMs of spatial proximal sequences to share the hidden states of each network with each other. The Social-LSTM model effectively considers the influence of video typical target running rules and other targets in the same scene and jointly predicts the motion trajectories of all typical targets in that scene [28]. The structure of the Social-LSTM network is shown in Figure 1. In Figure 1, h_i ($i = 1, \dots, n$) denotes the

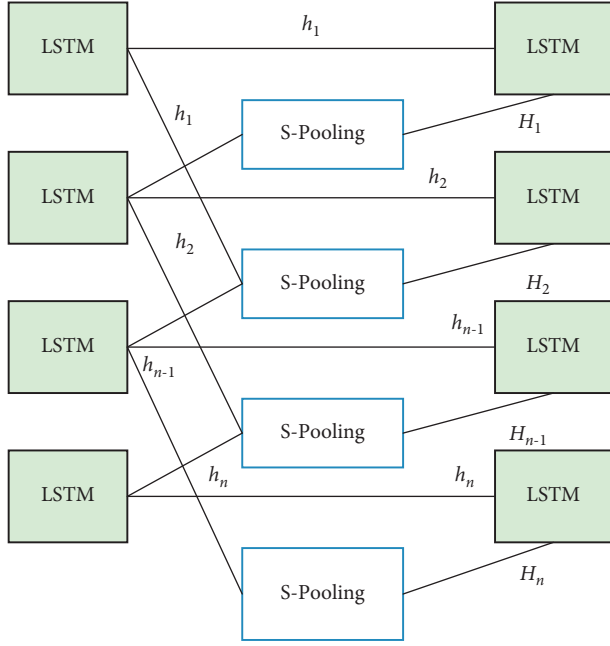


FIGURE 1: Social-LSTM network structure.

predicted trajectory of the LSTM corresponding to the i th video target in the same scene and n is the number of video targets in the same scene and is the hidden state of the i th video target in the same scene.

Figure 1 represents an LSTM neural network, and each LSTM is used to predict the trajectory of a typical target in the video. Since LSTM networks use unsupervised learning, each LSTM needs to learn historical trajectory data to obtain its weight parameters and use the network to predict the coordinate trajectory of the video target at future moments. Since the trajectory of a target in a video may be affected by the motion of its neighboring targets, this paper connects the LSTM network of the target to be detected with the LSTM network of its neighboring targets through an S-Pooling layer to form a new network, namely, Social-LSTM, and uses this network to predict the trajectory of the target to be detected.

The role of S-Pooling is to translate the influence of its neighboring targets on the motion of the target to be predicted (i.e., contextual information), H_i^t and H_i^t the formula is given by

$$H_i^t(m, n, :) = \sum_{j \in N_i} I_{mn}(x_j^t - x_i^t, y_j^t - y_i^t) h_j^{t-1}, \quad (1)$$

where H_i^t represents the hiding state of the i th video target corresponding to the LSTM network at time t ; $I_{mn}(x, y)$ represents the indication function. If the trajectory coordinates (x, y) are in the (m, n) neurons of the grid, the $I_{mn}(x, y)$ value is 1; (x_i^t, y_i^t) represents the trajectory coordinates of the i th video target at time t , (x_j^t, y_j^t) represents the trajectory coordinates of the j th video target at time t , and $(x_j^t - x_i^t, y_j^t - y_i^t)$ represents the difference between the trajectory coordinates of the j th and i th video at time t ; N_i represents the motion attribute of the i th adjacent video target; and h_j^{t-1} represents the LSTM prediction trajectory corresponding to the j th video target at time $T-1$.

After calculating the hidden state of the S-Pooling layer, the hidden state of the target to be detected and its own motion state are fused with the S-Pooling layer to calculate the trajectory of the target to be detected, and the calculation formula is shown as follows:

$$\begin{cases} e_i^t = \phi(x_i^t, y_i^t; \mathbf{W}_e), \\ a_i^t = \phi(H_i^t; \mathbf{W}_a), \\ h_i^t = \text{LSTM}(h_i^{t-1}, e_i^t, a_i^t; \mathbf{W}_{\text{LSTM}}), \end{cases} \quad (2)$$

where \mathbf{W}_e , \mathbf{W}_a is the weight matrix of embedding; \mathbf{W}_{LSTM} is the weight matrix of LSTM; a_i^t and e_i^t are the pooled social hidden state tensor and coordinates, respectively; and h_i^t denotes the predicted LSTM trajectory of the i th video target at time t .

The Social-LSTM-based video target trajectory prediction algorithm uses LSTM to deal with the temporal relationship of the same target motion trajectory between different frames. When dealing with multiple targets, the LSTM is used to predict the trajectory of each target separately, and an S-Pooling layer is added between multiple LSTMs to deal with the interaction between multiple targets, so that the trajectory of a typical target of the video can be predicted more accurately [29].

Social-LSTM can take into account the influence factors between neighboring target trajectories and add the influence factors to S-Pooling. This network model can take into account the video target's own trajectory pattern and the influence of other neighboring targets on its trajectory and fuse the two to predict the trajectory of the video target, which helps to improve the accuracy of typical target trajectory prediction.

2.7. Contextual Feature Extraction Methods. The biggest difference between video and image is the possession of temporal dimensional information. Contextual features, i.e., the dependence of video motion targets in the two frames before and after the video image and the influence of other motion targets in the same frame on the trajectory of the target, are to be detected. In order to accurately predict the trajectory of a typical target and eliminate the influence of other neighboring targets on its trajectory, this paper adds an S-Pooling to LSTM to extract the contextual features of a typical target in the same frame, and the network can take into account the influence of other moving targets in a grid on its trajectory in the same frame.

Since the memory unit in the LSTM network can store the operational status of the typical target in the previous frames, the operational status of the typical target in the current frame can be taken into account by the self-looping unit in the LSTM network. In this paper, we use the memory unit in the LSTM network to extract the dependency relationship between the typical target in the previous and the next two frames.

2.8. Social-LSTM-Based Algorithm for Predicting the Typical Target Trajectory of Video. In this paper, we propose a Social-LSTM-based video typical target trajectory prediction

algorithm to predict the trajectories of typical targets in videos. Since LSTM uses unsupervised learning, the weight parameters in the network can only be obtained by learning the training data. To calculate the weight parameters in this network, a bivariate Gaussian distribution with mean $\mu_i^{t+1} = (\mu_x, \mu_y)_i^{t+1}$, standard deviation $\sigma_i^{t+1} = (\sigma_x, \sigma_y)_i^{t+1}$, and correlation coefficient ρ_i^{t+1} is used to predict the trajectory coordinates of the video target at $t + 1$ using the hidden state, and the mean, standard deviation, and correlation coefficient in the bivariate Gaussian distribution can be found by a $5 \times D$ order weight matrix \mathbf{W}_p . The calculation of the trajectory of the video target at time t predicted by the hidden state is shown as follows:

$$(\hat{x}, \hat{y})_i^t \sim N(\mu_i^t, \sigma_i^t, \rho_i^t), \quad (3)$$

where $(\hat{x}, \hat{y})_i^t$ denotes the trajectory coordinates of the typical target of the video at time t predicted by using the hidden state; $N(\mu_i^t, \sigma_i^t, \rho_i^t)$ denotes the bivariate Gaussian distribution. The mean, standard deviation, and correlation coefficients of the bivariate Gaussian distribution are calculated as follows:

$$(\mu_i^t, \sigma_i^t, \rho_i^t) = \mathbf{W}_p h_i^t. \quad (4)$$

In order to find the weight parameters in this network, the negative log-likelihood loss function is defined in this paper, and the unknown weight parameters in this network are obtained by finding the minimum value of the negative log-likelihood loss function, and the negative log-likelihood loss function is defined in the following form:

$$\text{loss}_i(\mathbf{W}_e, \mathbf{W}_1, \mathbf{W}_p) = - \sum_{t=T_s}^{T_e} \ln(P(x_i^t, y_i^t | \mu_i^t, \sigma_i^t, \rho_i^t)), \quad (5)$$

where loss_i is the loss function of each video target trajectory; T_s is the predicted start time; T_e is the predicted end time; and $P(x_i^t, y_i^t, \mu_i^t, \sigma_i^t, \rho_i^t)$ is the conditional probability of the predicted trajectory with respect to a bivariate Gaussian distribution [30].

Since the added S-Pooling does not introduce additional unknown parameters, the network only needs to find the weight parameters in the LSTM structure. Based on the historical trajectory data of the video target and the minimum value of the loss function, the unknown \mathbf{W}_1 , \mathbf{W}_e , and \mathbf{W}_p weight parameters in the LSTM structure can be found.

After the network learning is completed, the test data of the video target trajectory is input, and the predicted trajectory of the video target is derived according to equation (4); using the predicted trajectory, the hidden state of the video target is derived according to equation (3), and the trajectory of its neighboring targets in the video scene is obtained.

3. Data Preprocessing

Canny edge detection is a very popular edge detection algorithm, which was proposed by [31]. It is a multistage algorithm, i.e., it consists of multiple steps. First is image noise reduction. We know that the gradient operator can be

used to enhance an image, essentially by enhancing the edge contours; i.e., it is possible to detect the edges. However, they are all heavily affected by noise. Then, our first step is to think of removing the noise first because noise is where the gray scale changes a lot, so it is easy to be identified as a pseudoedge. The purpose of doing this is to keep only strong edge contours then. Some edges may not be closed and need to be supplemented from the point that meets between low and high to make the edges as closed as possible, as shown in Figure 2.

4. Roller Derby Forecast

4.1. Analysis of the Correlation between the Sprint Phase and Final Performance. As the individual time trial is a segment distance project and it is a project to decide the winner of the race by the time, the initial speed has a relatively important impact on the final result [23]. Sprint technology is mainly reflected in the distance of the stage after the start and before entering the skating run. The distance is around the new rules of the World Skating Federation from the starting point to the distance of entering the curve in meters. The correlation coefficient can directly show that the speed skating sprint is significantly correlated with the performance of the meter, which directly affects the performance of the meter. The correlation coefficient of this study can be calculated by the sprint performance and the meter performance, and the correlation coefficient, therefore, shows that the sprint performance in speed skating has a significant correlation with the final performance of an individual time trial, which can directly affect the performance of this project. It can be seen through Table 1 that our speed skaters' sprint speed in the first meter is significantly lower than that of the world's best athletes, the average performance of the world's best speed skaters in the sprint stage in meter, and the average performance of our speed skaters in the sprint, which is different from the world level. The best short-distance skater in China, He Xin, has a worse sprint than the world average, and Liu Zhicong has a worse sprint than the world average, so there is still some room for improvement. Through the improvement of technology, body strength, and flexibility, it is possible to improve the sprint speed, which is more conducive to the improvement of the meter performance.

4.2. Analysis of Stride Frequency, Stride Length, and Sprint Speed

4.2.1. Comparative Study of Step Frequency. Step frequency is one of the important factors to determine the speed, and step frequency is the number of times the two legs alternate in a unit of time, mainly by the impact of factors such as pedal time and support time; in addition, the athlete's body coordination, strength, flexibility, height, and many other factors have a certain impact on the step frequency [14].

From Table 2, we can see that speed skaters are using high-frequency isochronous techniques in the sprint phase, which is in line with the technical characteristics of speed skating sprint. Our skaters' stride frequency is in

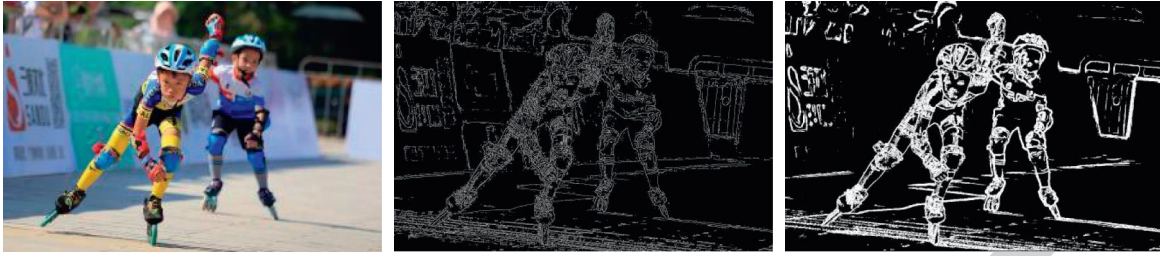


FIGURE 2: Different treatment effects.

TABLE 1: Six male athletes from China and abroad before the results and gamma statistics.

Full name	8 m	300 m
Joey	1.25	24.250
Perdo	1.22	24.265
Song Qingyang	1.27	24.499
He Xin	1.37	25.395
Liu Zhicong	1.42	25.666
Yuan Jianjin	1.40	25.622

TABLE 2: World's best athletes' sprint phase step frequency statistics in subseconds.

Full name	Step frequency
Joey	3.22
Perdo	3.25
Song Qingyang	3.46
\bar{x}	3.31
S	0.26

subseconds, and the standard deviation is in subseconds. The analysis of the table shows that the difference between our speed skaters and the world average is in subseconds. Although the stride frequency is related to the innate individual conditions, however, from another aspect, it reflects that there is a certain gap between the body strength and coordination of speed skaters in China, and the step frequency of Song Qingyang in the same Asian region can reach subseconds, and the height is in meters.

So, in comparison, our athletes are still lacking in this area, which can be improved through the training of the body's first power, and there is a lot of room for improvement, as shown in Table 3. However, attention should be paid to the intensity of the load in training; too much load will affect the speed of completion of the action, if the weight is too small, it will be difficult to realize the rapid power, and athletes should try to experience the maximum force and maximum speed of the feeling.

4.3. A Comparative Study of Stride Length. The stride length is mainly influenced by the force and speed of the stirrup, while the height, leg length, and flexibility of the athlete are all factors that affect the stride size. The sport effect of sprinting is mainly reflected through the stride speed. A reasonable combination of stride frequency and stride length can improve the performance of athletes in sprinting.

TABLE 3: Domestic outstanding athletes' sprint phase step frequency statistics in subseconds.

Full name	Step frequency
He Xin	2.77
Liu Zhicong	2.79
Yuan Jianjin	2.65
\bar{x}	2.73
S	0.13

Domestic and foreign outstanding athletes sprinting stage stride length statistical comparison is as shown in Table 4. The stride length and stride frequency are comprehensive factors that determine the stride speed in the sprinting process, which can directly reflect the effect of the athlete's sprinting and is one of the important indicators to evaluate whether the speed skater's sprinting technique is reasonable. Excellent athletes can highlight the characteristics of stride frequency and stride length in the competition through training and their own physical conditions.

As shown in Figure 3, the large stride length in the game can seize the opportunity, but from the speed skating start after the sprint phase to analyze, the first step should not be too large, and if the stride length is too large, it will certainly cause the body's center of gravity to be too high and the pedal angle becomes large, resulting in the reduction of the horizontal force of the pedal. The initial speed and acceleration of the sprint are affected, which in turn affects the starting speed. The first step of the start should be small; in the starting stirrup, the stirrup angle is small to try to make the body thrust forward, and stirrup reaction force in the horizontal direction of the force will be larger, conducive to the start of a greater thrust.

In the speed skating sprint process, the position of the foot support point is always changing; when the foot hits the ground after the start of the stirring process, it changes to forward skating, and the direction of power propulsion is not backward but lateral; although inertial skating can increase the stride length, but because there is not enough inertia after the start, speed skaters in the sprint process increase the friction coefficient between the wheel and the track, so as to obtain a relatively high speed. However, it is necessary to accelerate the frequency to overcome the frictional resistance generated by the contact between the wheels and the track, so that, in the speed skating sprint process, the appropriate way to reduce the stride length is more conducive to the improvement of sprint speed. Therefore, if you keep the same pedaling force per step in the

TABLE 4: Domestic and foreign outstanding athletes sprinting stage stride length statistical comparison table (m/s).

	First step	Step 2	Step 3	Step 4	Step 5	Step 6
Domestic athletes	0.42	0.55	0.69	0.93	1.25	1.32
Foreign athletes	0.33	0.46	0.84	1.22	1.38	1.46

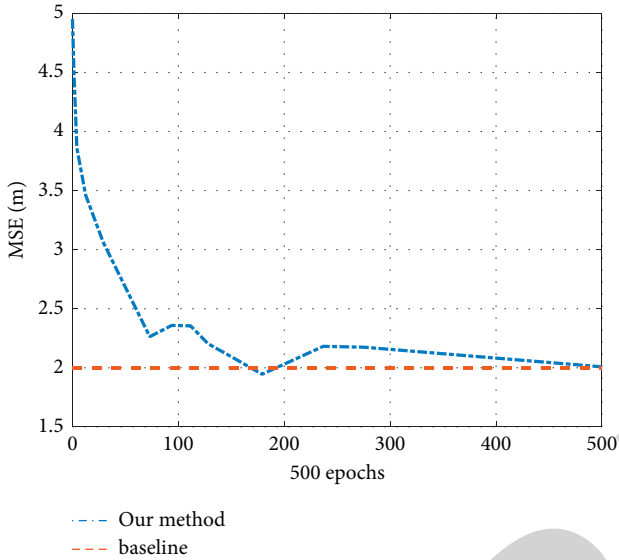


FIGURE 3: Tracking error curve of the arm coordinate position by different methods.

sprinting phase, you can control the sprinting speed by changing the pedaling frequency.

From a comparative analysis of Chinese and foreign speed roller skaters' sprint phase stride frequency, stride length, and the first six steps of the sprint, it can be seen that China's outstanding male speed roller skaters have a certain gap in the sprint phase stride frequency and stride length compared to foreign outstanding athletes; in the first two steps of the sprint phase after the start, the average value of our athletes is the first step and the second step is meters, while the first two steps of the sprint phase of foreign athletes are relatively small. The first two steps of the sprint phase are relatively smaller than the first two steps of foreign athletes. Therefore, the main factors that lead to the difference of speed skaters' performance in the sprint phase are stride frequency and stride length.

4.4. Simulation Proof. In order to prove the effectiveness of the proposed algorithm of the roller skating process arm skating image trajectory tracking method, it is necessary to conduct a simulation; the experimental object is selected from 15 male excellent athletes of our school of physical education, with professional training time of about 8 years; these athletes in the experimental stage are without sports injuries and are proficient in roller skating basic action essentials and are a good representative, as shown in Figure 4. The entire roller skating process was filmed with a



FIGURE 4: Images of the skating process of the athlete.

fixed camera, and the marker points were put on the roller skating arms within 5 meters of the filming range to get a complete roller skating action of each athlete, totaling 50 images. The simulation is mainly implemented in the MATLAB software environment under the Windows7 system using different methods to detect and track the skating image targets during the skating process of skaters [7, 17].

Firstly, the error curves of the skating arm coordinate position and the real position of the skating arm during the skating process under the method of this paper, the template update method, and the least-squares line method are given, as shown in Figure 3.

Analysis of Figure 3 shows that the corresponding coordinate positions of the template update method and the least-squares linear method deviate from the real position, while the corresponding coordinate position tracking error curve of the skating process of the skating arm of this paper has a smaller error, indicating that the method of this paper is closer to the real skating process of the skating arm trajectory and the tracking effect is better.

The tracking success rates of the three different methods are compared in Table 5. The tracking success rates (%) of the three methods were compared, and the results are shown in Table 5, where the tracking success rate = total number of pixels accurately tracked N /total number of pixels in the target area of the skating arm target.

Analysis of Table 5 shows that the tracking success rate of the skater's skating arm target is much higher than that of the template update method and the least-squares linear method, which is mainly because this method first extracts the outline of the skater's skating arm target, constructs the global matching approximation function of the skating arm target based on the position and size of the skater's skating arm target, and thus, determines the skating arm target tracking success rate. This makes the tracking success rate of the roller skater's roller skating arm target higher.

The trajectory tracking experiments with the skating arm motion target during the skating process were conducted by this paper, the template update method and the least-squares linear method, respectively. The track time (s) of the three methods is compared, and the results are shown in Figure 5.

TABLE 5: Comparison of the target tracking success rate of different methods of roller skating arm.

Method	Number of image pixels (piece)	Total number of target pixels (piece)	Number of tracking pixels (piece)	Tracking success rate (%)
Paper method	500	357	350	98
Template update method	500	357	284	79
Least-squares linear method	500	357	268	76

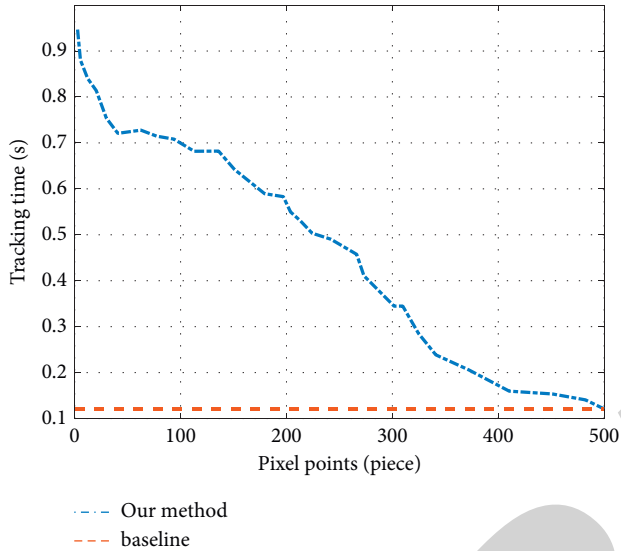


FIGURE 5: Time spent tracking the trajectory of different methods of roller skating arm movements.

This is mainly because this method extracts the target trajectory of the skater's skating arm by estimating the Gaussian model parameters of the skating arm differential image and introducing the boundary detection operator to construct the skating arm motion boundary image and then extracts the target trajectory of the skater's skating arm during the skating process. Based on this, the morphological operator is used to calculate the body ratio and tightness of the target region of the skating arm. This process solves the contradiction between the amount of computation and the amount of information to a certain extent, which makes this paper's method to track the target trajectory of the skating arm during the skating process of the skater in a shorter time. Athletes should strengthen leg training and other links.

5. Conclusions

In this paper, we use video measurement and image analysis to obtain kinematic parameters and data of athletes' sprinting techniques in competition and conduct a comparative study on the sprinting techniques of excellent speed skaters in China and abroad. In this paper, video multi-objective detection and tracking algorithm with improved TLD is investigated with the skaters in the video. The experimental results show that the proposed trajectory prediction algorithm is better than the traditional LSTM algorithm, Markov model algorithm, and hybrid Gaussian

model algorithm, which is helpful to improve the accuracy of target trajectory prediction of video skaters, and the tracking success rate is 0.98.

Data Availability

The dataset used in this paper is available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest regarding this work.

Acknowledgments

This work was supported by the Research Project of Sports Science and Technology in Hebei Sports Bureau, China, investigation and test analysis on the present situation of the basic physical ability of winter sports teams in Hebei Province (Grant no. 20211001).

References

- [1] M. Archana and G. Kalaisevi, "Object detection and tracking based on trajectory in broadcast tennis video - ScienceDirect [J]," *Procedia Computer Science*, vol. 58, pp. 225–232, 2015.
- [2] W. Marynowsky, S. Ferguson, A. Fraietta, and O. Bown, "The ghosts of roller disco', a choreographed, interactive performance for robotic roller skates," in *Proceedings of the Fourteenth International Conference on Tangible, Embedded, and Embodied Interaction*, pp. 631–637, New YorkNYUnited States, February 2020.
- [3] K. Kardiyono, S. Soegiyanto, and T. Rahayu, "Roller skating activities as a reflection of the community life style in semarang municipality[J]," *The Journal of Educational Development*, vol. 6, no. 2, pp. 265–271, 2018.
- [4] X. Yu, H. W. Leong, C. Xu, and Q. Tian, "Trajectory-based ball detection and tracking in broadcast soccer video," *IEEE Transactions on Multimedia*, vol. 8, no. 6, pp. 1164–1178, 2006.
- [5] C. Zhang, T. Xie, K. Yang et al., "Positioning optimisation based on particle quality prediction in wireless sensor networks," *IET Networks*, vol. 8, no. 2, pp. 107–113, 2019.
- [6] Z. Huang, J. Wang, L. Pi, X. Song, and L. Yang, "LSTM based trajectory prediction model for cyclist utilizing multiple interactions with environment," *Pattern Recognition*, vol. 112, p. 107800, 2021.
- [7] D. Bronzi, Y. Zou, F. Villa, S. Tisa, A. Tosi, and F. Zappa, "Automotive three-dimensional vision through a single-photon counting SPAD camera[J]," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 3, pp. 782–795, 2015.

- [8] D. Wu, C. Zhang, L. Ji, R. Ran, H. Wu, and Y. Xu, "Forest fire recognition based on feature extraction from multi-view images," *Traitement du Signal*, vol. 38, no. 3, pp. 775–783, 2021.
- [9] C. H. Song, "Exploring and predicting the knowledge development in the field of energy storage: evidence from the emerging startup landscape[J]," *Energies*, vol. 14, 2021.
- [10] G. Liu, X. Tang, H. D. Cheng, J. Huang, and J. Liu, "A novel approach for tracking high speed skaters in sports using a panning camera," *Pattern Recognition*, vol. 42, no. 11, pp. 2922–2935, 2009.
- [11] X. Yu, H. W. Leong, C. Xu, and Q. Tian, "Trajectory-based ball detection and tracking in broadcast soccer video," *IEEE Transactions on Multimedia*, vol. 8, no. 6, pp. 1164–1178, 2006.
- [12] G. Yang, J. Li, Y. He, and Z. Kang, "An information hiding algorithm based on intra-prediction modes and matrix coding for H.264/AVC video stream," *AEU - International Journal of Electronics and Communications*, vol. 65, no. 4, pp. 331–337, 2011.
- [13] T. Xie, C. Zhang, Z. Zhang, and K. Yang, "Utilizing active sensor nodes in smart environments for optimal communication coverage[J]," *IEEE Access*, vol. 7, pp. 11338–11348, 2018.
- [14] H. Li, D. Zeng, L. Chen, Q. Chen, M. Wang, and C. Zhang, "Immune multipath reliable transmission with fault tolerance in wireless sensor networks," in *Proceedings of the International Conference on Bio-Inspired Computing: Theories and Applications*, pp. 513–517, Springer, Singapore, October 2016.
- [15] J. Harting, M. J. Harvey, J. Chin, and P. V. Coveney, "Detection and tracking of defects in the gyroid mesophase," *Computer Physics Communications*, vol. 165, no. 2, pp. 97–109, 2005.
- [16] H. Yu, G. Li, W. Zhang et al., "The unmanned aerial vehicle benchmark: object detection, tracking and baseline," *International Journal of Computer Vision*, vol. 128, no. 5, pp. 1141–1159, 2020.
- [17] J. Lee, Y. Lee, E. Lee, and S. Hong, "Hand region extraction and gesture recognition from video stream with complex background through entropy analysis," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society*, pp. 1513–1516, San Francisco, CA, USA, September 2004.
- [18] K. Thirusittampalam, M. J. Hossain, O. Ghita, and P. F. Whelan, "A novel framework for cellular tracking and mitosis detection in dense phase contrast microscopy images," *IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 3, pp. 642–653, 2013.
- [19] Q. Zhao and D. H. Zhou, "Leak detection and location of gas pipelines based on a strong tracking filter," *Transaction on Control, Automation and Systems Engineering*, vol. 3, no. 2, pp. 89–94, 2001.
- [20] S.-H. Zhang, X.-Y. Li, S.-M. Hu, and R. R. Martin, "Online video stream abstraction and stylization," *IEEE Transactions on Multimedia*, vol. 13, no. 6, pp. 1286–1294, 2011.
- [21] B. Masberg and A. Eklund, "Benefits of roller derby: the roller girl perspective[J]," *ACTIVE: Journal of Physical Education, Sport, Health and Recreation*, vol. 7, no. 3, pp. 133–141, 2018.
- [22] P. A. Thomas, "Dancing muses, roller disco and the phantasmagoric feminine: r," *Studies in Musical Theatre*, vol. 13, no. 1, pp. 53–65, 2019.
- [23] V. Kapoor, W. G. Hirst, C. Hentschel, S. Preibisch, and S. Reber, "MTrack: automated detection, tracking, and analysis of dynamic microtubules," *Scientific Reports*, vol. 9, no. 1, p. 3794, 2019.
- [24] H. T. Ngo, V. K. Asari, M. Z. Zhang, and L. Tao, "Design of a systolic-pipelined architecture for real-time enhancement of color video stream based on an illuminance-reflectance model," *Integration*, vol. 41, no. 4, pp. 474–488, 2008.
- [25] Z. Zhang, C. Zhang, M. Li, and T. Xie, "Target positioning based on particle centroid drift in large-scale WSNs," *IEEE Access*, vol. 8, pp. 127709–127719, 2020.
- [26] V. Bhushan, S. Ng, D. Spiller, H. Gang, and S. Inamdar, "Detecting children's passive exposure to cocaine and marijuana," *American Journal of Public Health*, vol. 84, no. 4, pp. 675–676, 1994.
- [27] S. Sowmiya, K. Valarmathi, S. Sathyavenkateshwaren, M. Gobinath, and S. Thillaisivakavi, "Snag detection robot for visually impaired steering and blind individuals," in *Proceedings of the 2018 International Conference on Inventive Research in Computing Applications (ICIRCA)*, pp. 167–171, IEEE, Coimbatore, India, July 2018.
- [28] L. Wang, C. Zhang, Q. Chen et al., "A communication strategy of proactive nodes based on loop theorem in wireless sensor networks," in *Proceedings of the 2018 Ninth International Conference on Intelligent Control and Information Processing (ICICIP)*, pp. 160–167, IEEE, Wanzhou, China, January 2018.
- [29] R. Domeij, J. Hollman, and V. Kann, "Detection of spelling errors in Swedish not using a word list En Clair*," *Journal of Quantitative Linguistics*, vol. 1, no. 3, pp. 195–201, 1994.
- [30] Y. Sakurai, Z. Fujita, and Y. Ishige, "Automatic identification of subtechniques in skating-style roller skiing using inertial sensors," *Sensors*, vol. 16, no. 4, p. 473, 2016.
- [31] E. Castillo, *Roller Derby as a Form of Self-Empowerment: An Examination of Female Athletes' Resilience to Intimate Partner Violence*, The University of Texas Rio Grande Valley, United States, 2018.