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Algorithm for Identifying Athlete Passing Trajectories in Team Competition Scenarios

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Abstract: *Existing athlete passing trajectory recognition algorithms primarily rely on traditional object detection and single-target tracking frameworks, and these algorithms match trajectories and determining passing events based on kinematic features. However, these approaches only perform local optimization for individual athlete trajectories and lack global modeling of spatio-temporal correlations among multiple trajectories, resulting in low recognition accuracy. To address this, we propose an athlete passing trajectory recognition algorithm for group-based competitive scenarios. The algorithm constructs composite model of multiple Gaussian distributions is constructed for each pixel to represent the temporal multi-state characteristics of background pixels. A weight-sorting mechanism is designed to selects Gaussian model combinations with cumulative probability thresholds to form the background model, effectively separating athletes from background regions. Then the algorithm adopts a Kalman filter algorithm constructs an athlete state space model incorporating position and velocity, utilizing a state transition matrix for temporal trajectory prediction. Process noise covariance adapts to the rapid directional changes characteristic of athletes in group confrontations, enabling pass trajectory prediction. Passing events are detected by establishing a dual-condition constraint: when two athlete trajectories satisfy spatial proximity and directional consistency within a spatiotemporal neighborhood, they are classified as potential passing events. By backwardly reconstructing the passer's trajectory segment and forwardly tracing the receiver's trajectory segment, the complete passing path is formed through temporal stitching. Finally, the algorithm applies nonlinear optimization globally corrects the merged trajectories by minimizing the sum of squared residuals between observed and predicted states, enabling pass trajectory recognition. Experimental validation confirms the proposed method's recognition accuracy. Comparative test results demonstrate that when applied to athlete pass trajectory recognition, the proposed approach achieves 92.5% match accuracy between predicted and actual trajectories, delivering highly satisfactory recognition performance.*

Keywords: *Team competition; Athletes; Passing trajectory; Recognition algorithm*

1. Introduction

In the realm of sports competition, team-based sports like soccer and basketball captivate global audiences with their intense physicality, strategic depth, and entertainment value. Passing serves as the cornerstone of teamwork in these disciplines; precise and skillful passes can breach defensive lines, create prime scoring opportunities, and ultimately sway the outcome of a match. Therefore, in-depth analysis of athletes' passing trajectories in team-based scenarios is crucial for understanding game tactics, enhancing training effectiveness, and supporting coaching decisions[1]. Accurate identification of passing trajectories enables coaching staff to thoroughly analyze game footage, uncover players' passing characteristics and patterns, thereby developing more targeted tactical strategies to elevate the team's overall competitive level.

Numerous scholars have already analyzed and explored motion trajectory recognition technologies. Early research primarily focused on tracking moving targets in simple scenarios, and the researchers used traditional image processing algorithms to locate moving objects and extract trajectories. However, group confrontation scenarios exhibit high complexity and dynamism. Frequent physical contact between athletes, rapid movements, and intricate tactical coordination make it difficult for traditional methods to accurately identify passing trajectories. Subsequent research gradually incorporated machine learning algorithms, and the researchers trained models with large amounts of annotated data to improve trajectory recognition accuracy. Some approaches achieved certain results in specific

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scenarios by constructing deep neural network models that automatically learn athletes' movement characteristics and passing patterns[2]. Nevertheless, these methods still face challenges such as target occlusion and motion blur when handling complex, dynamic group-based scenarios, leaving room for improvement in recognition accuracy and robustness.

This paper proposes an innovative algorithm for recognizing athlete passing trajectories in group-based competitive scenarios. The algorithm employs Kalman filtering combined with multi-condition passing event detection to comprehensively capture athletes' movement states. Simultaneously, the algorithm adopts background subtraction enables the model to automatically focus on critical temporal and spatial regions, effectively addressing target occlusion and motion blur.

2. Athlete Passing Trajectory Recognition Algorithm in Group Competition Scenarios

2.1 Background Subtraction for Athletes in Group Competition Scenarios

To achieve athlete pass trajectory recognition in group-based competition scenarios, this paper first employs a global shutter camera array to synchronously capture group-based competition video streams[3]. The paper then constructs Multiple Gaussian distribution combination models are then constructed for each pixel to characterize the temporal multi-state features of background pixels. The algorithm matches current frame pixel values are matched against existing Gaussian models for validation, with iterative model optimization achieved through dynamic adjustment of weight, mean, and variance parameters. The algorithm forms a background model is formed by selecting combinations of Gaussian models that meet cumulative probability thresholds through a weight-sorting mechanism. This effectively separates athletes from background areas, providing a precise foreground segmentation foundation for subsequent pass trajectory recognition.

First, the researchers deploy multi-angle cameras based on field size and monitoring requirements. The researchers utilize a global shutter camera array to synchronously capture video streams, ensuring no jelly effect distortion in motion footage[4]. To address athletes' high-speed movement, this study employs a high-frame-rate capture mode to prevent trajectory discontinuities caused by insufficient temporal sampling. Considering that background pixels in group-competition scenarios may exhibit multimodal state changes—such as spectators waving flags or flickering lighting—this study initializes multiple Gaussian distributions per pixel to cover diverse dynamic patterns. Simultaneously, frequent background changes caused by athletes' rapid movement necessitate dynamic model parameter adjustments to prevent misclassifying athletes as background[5].To address this, the paper adopts a strategy where the weight of the Gaussian distribution matching the current pixel value increases, while the weights of other distributions decay. The specific weight update expression is as follows.

$$\omega_{k,t} = (1-\alpha)\omega_{k,t-1} + \alpha \cdot M_{k,t} \tag{1}$$

Where α represents the learning rate, and $M_{k,t}$ denotes the matching indicator function. Background models in group adversarial learning must balance stability and dynamic adaptability[6]. Thus, the algorithm prioritizes distributions with high weights and low variance are prioritized for background models. The algorithm sorts distributions are sorted in descending order of weight, and the top `B` distributions with cumulative weight exceeding the threshold `T` form the background model. The specific expression is as follows.

$$B = \arg\min_{b}\left(\sum_{k=1}^{b}\omega_k \geq T\right) \tag{2}$$

If the current pixel value does not match any background distribution, the algorithm classified as foreground, i.e., the athlete region[7]. The specific foreground detection expression is as follows.

$$F(x,y) = \begin{cases} 1,,if\,\forall k \in B, \left|I_t - \mu_{k,t}\right| \geq \lambda\sigma_k \\ 0, otherwise \end{cases} \tag{3}$$

Among these, I_t represents the current pixel value, $\mu_{k,t}$ denotes the mean of the *k*-th Gaussian distribution at time *t*, and σ_k signifies the standard deviation of the *k*-th Gaussian distribution,

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characterizing the range of pixel value fluctuations covered by this distribution. B represents the set of Gaussian distribution indices identified as background, where λ denotes the parameter controlling the sensitivity of foreground detection.

2.2 Athlete Passing Trajectory Prediction

Building upon the aforementioned athlete detection, this paper employs the Kalman filter algorithm to construct an athlete state space model incorporating position and velocity. The algorithm utilizes a state transition matrix to achieve temporal trajectory prediction[8]. The algorithm adapts the process noise covariance is adapted to account for the rapid directional changes characteristic of athletes in group competition scenarios[9]. The algorithm takes the actual position obtained from foreground detection serves as the observation value. By integrating the observation matrix with the predicted state, the algorithm realizes pass trajectory prediction is realized.

An athlete's movement in group competition scenarios involves states such as position and velocity. Accordingly, this paper constructs a dynamic model[10]. Assuming the athlete's state vector at time t is X_t , the following modeling expression is derived.

$$X_t = \begin{bmatrix} x_t \\ y_t \\ v_{x,t} \\ v_{y,t} \end{bmatrix} \tag{4}$$

Here, $\left(x_t, y_t\right)$ represents the position in the image coordinate system, and $\left(v_{x,t}, v_{y,t}\right)$ denotes the velocity components[11]. Assuming athletes move at constant velocity within extremely short time intervals, the algorithm can apply the Kalman prediction step can be applied. This involves using the detected athlete position as an observation value, fusing the predicted position with the actual detection results, and optimizing the state estimation[12]. The specific expression is as follows.

$$P_t = \left(I - K_t H\right) P_{t|t-1} \tag{5}$$

Here, P_t represents the updated state covariance matrix, characterizing the uncertainty of the passing trajectory. I denotes the identity matrix, K_t represents the Kalman gain, and H signifies the observation matrix.

2.3 Athlete Passing Trajectory Identification

This paper detects passing events by establishing a dual-condition constraint: the algorithm identifies a potential passing event is identified when two athlete trajectories satisfy both spatial proximity and directional consistency within a spatiotemporal neighborhood[13]. By reconstructing the passer's trajectory segment backward and the receiver's trajectory segment forward, the algorithm forms a complete passing path is formed through temporal stitching.

In group-opposed scenarios, the algorithm only classifies a pass event is only classified when the predicted positions of passer k and receiver l at time t are sufficiently close and their passing directions form an acute angle[14]. The distance and angle constraint expressions formulated in this paper are as follows:

$$\begin{cases} d\left(\hat{x}_{t|t}^{k}, \hat{x}_{t|t}^{l}\right) \le \varepsilon_d \\ A\left(\hat{x}_{t-1|t-1}^{k}, \hat{x}_{t|t}^{k}, \hat{x}_{t|t}^{l}\right) \le \varepsilon_\theta \end{cases} \tag{6}$$

Where, $\hat{x}_{t|t}^{k}$ and $\hat{x}_{t|t}^{l}$ represent the optimal position estimates of trajectories k and l at time t, respectively, as updated by the Kalman filter algorithm. $d\left(\cdot\right)$ denotes the distance calculation

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function, quantifying the spatial proximity between the two players' positions. ε_d represents the distance threshold, defining the spatial validity boundary for pass events. $A\left(\hat{x}_{t-1|t-1}^{k}, \hat{x}_{t|t}^{k}, \hat{x}_{t|t}^{l}\right)$ denotes the formed angle, verifying the geometric consistency between the movement direction and the receiver's position. ε_θ represents the angular threshold, controlling the matching precision between the passing direction and the receiver's position.

Starting from the moment t when the pass event occurs, the algorithm trace the pass thrower k's trajectory forward and track the receiver l's trajectory backward[15]. The algorithm merges These two segments are merged to form the pass trajectory. Finally, the algorithm applies a nonlinear optimization method is applied to refine the pass trajectory, minimizing the error between the trajectory and the observed values. The specific optimization objective function is expressed as follows.

$$J = \min x \sum_{i=t_1}^{t_2} \left\| z_i - Hx_i \right\|^2 \tag{7}$$

Where $X = \left[x_{t1}, x_{t1+1}, \ldots, x_{t2}\right]$ represents the trajectory to be optimized, t_1 denotes the start time of the pass trajectory, and t_2 denotes the end time.

3. Experimental Setup

3.1 Experimental Preparation

The experimental dataset of group-competitive sports video streams comprises 300 independent video clips covering scenarios such as soccer and basketball, with each clip averaging 3-5 minutes in length. In terms of settings, the dataset images encompass indoor basketball courts and outdoor soccer fields, while also covering diverse lighting conditions including sunny and overcast days. The dataset includes scenarios simulating sudden lighting changes account for 10% of the dataset. Each frame averages 8 athletes, with the experiment annotating 5,000 passing events—each marked with corresponding spatiotemporal coordinates. Additionally, the experiment performed sub-pixel-level annotations on 12,000 athlete trajectories involving passes. The study divides the trajectory length distribution is as follows: 55% are short trajectories (1-3 seconds), 30% are medium-long trajectories (3-5 seconds), and 15% are long trajectories (over 5 seconds). The specific dataset distribution is shown in Table 1.

Table 1 Distribution of the Experimental Dataset

Parameter Category	Parameter Item	Numerical/Distribution Settings
Overall Parameters of the Dataset	Resolution	1920×1080 (Full HD)
	Frame Rate	30 fps
	Total Frames	45,000 frames
Scene Distribution	Motion Type Ratio	Soccer: 60% (90 segments) / Basketball: 40% (60 segments)
	Lighting Conditions	Sunny 50% / Cloudy 30% / Artificial Lighting 20%
Interfering Factors	Occlusion Scene Ratio	30% (Player Overlap / Crowd Intrusion)
	Camera Shake Ratio	5% (Simulated Handheld Shake or Impact Disturbance)
	Motion Blur Ratio	8% (Frame-to-Frame Blur from High-Speed Movement)

In addition to the proposed algorithm, the study selected two conventional motion trajectory recognition algorithms were selected as control groups. The researchers applied all three methods to identify passing trajectories in the experimental dataset, the accuracy differences among the recognition algorithms were compared.

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3.2 Experimental Results

The experiment measured the actual recognition accuracy of each method using trajectory matching degree as the comparison metric. This metric represents the degree of alignment between the pass trajectories identified by the algorithm and the actual trajectories. Specific comparison results are shown in Figure 1.

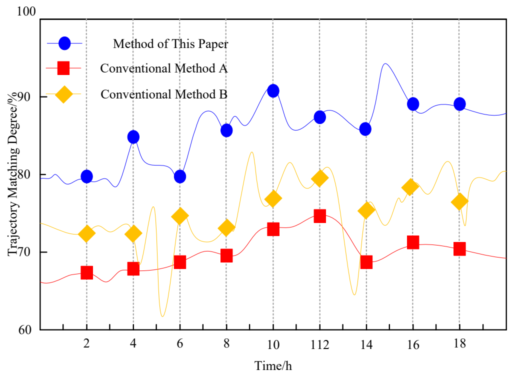

Figure 1 Trajectory Matching Accuracy of Different Recognition Algorithms

The experimental results demonstrate that the proposed method maintains consistently high matching accuracy throughout, with an average of 92.5% and a minimum value never falling below 85%. The method delivers stable performance even during complex confrontations. This indicates that the synergistic optimization of Kalman filtering and multi-condition pass event detection minimizes trajectory continuity errors in complex dynamic scenarios, and this optimization achieves high pass trajectory recognition accuracy.

4. Conclusion

The core focus of this research lies in multidimensional technical synergy and scenario-adaptive optimization. This study establishes an athlete motion state model via Kalman filtering and incorporating a constant-velocity dynamic assumption, precise prediction of complex movement patterns—such as high-speed direction changes and brief pauses—is achieved. Building upon this foundation, the study proposes a pass event detection mechanism based on dual constraints of spatial distance and motion direction is proposed, enhancing interference resistance in event determination through dynamic threshold adjustment. The study employs nonlinear optimization was employed to globally correct merged trajectories and minimize cumulative errors between observations and predicted states, ensuring the physical plausibility of output trajectories.

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