

Research Article

Multiperson Target Dynamic Tracking Method for Athlete Training Based on Wireless Body Area Network

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Aiming at the problems of large tracking error and long tracking time in traditional multiperson target dynamic tracking methods, a new method based on wireless body area network for athlete training multiperson target dynamic tracking is proposed. First, the microinertial sensor in the wireless body area network is used to collect the multiperson image data of the athlete training, and the sparse representation is performed after processing, which improves the reliability of the data and reduces the tracking error. Secondly, the multiperson target dynamic tracking method based on the adaptive search box is used, combined with target isolation and occlusion detection, to judge the athlete's training target. Finally, the nearest neighbor algorithm is used to construct an adaptive search box to achieve dynamic tracking of multiple targets. Experimental results show that this method can accurately measure the similarity of target features, with small tracking error and short tracking time. The minimum tracking error is only 0.11 frame.

1. Introduction

In modern life, sports competitions have been deeply loved by the majority of the audience. With the improvement of people's quality of life and the progress and development of science and technology, sports competitions, training videos, and images can no longer meet the requirements of all aspects of society [1]. For example, in the process of athlete training, many people are usually trained in a group, and many coaches guide on site. Therefore, when observing training videos and images, it is necessary to identify multiple or single targets from multiple targets [2].

Multiperson target detection and tracking technology for athlete training is the main content of many disciplines such as digital image processing, computer vision, and artificial intelligence. It has broad application prospects and important research value in many fields such as human-computer interaction, video image monitoring, and food retrieval [3–5]. Generally, the video image scene is composed of background and foreground target. The foreground target is an important part of the image sequence, is the research area of interest, and contains important information. Therefore,

how to quickly segment the multiperson target object and effectively locate and track it is the focus of the research.

Zheng et al. [6] proposed a multiperson target dynamic tracking method based on multifeature fusion, trained the filter model by using directional gradient histogram and color feature, and fused the feature results collected by the filter according to the peak sidelobe ratio and weighting ratio of different feature response diagrams. According to the peak sidelobe ratio of the final target position response map of each frame, judge whether the target is occluded. When occlusion occurs, the model will not be updated, and the current model will continue to be used for tracking in the next frame. However, this method has the problem of low accuracy of feature similarity measurement. Yikun et al. [7] proposed a multiperson target dynamic tracking method based on TLD and fdst. In order to strengthen the tracking accuracy of fdst algorithm in the case of rapid target movement, rapid deformation, and target disappearance, detectors and learners were added on the basis of fdst algorithm to modify and learn the tracking results; the positive and negative samples of the detector and the learner are used to evaluate the confidence of the tracking results, so as to

complete the dynamic tracking of the target. However, the tracking error of this method is large, which makes the needs of practical application difficult to meet. Jianqiang and Zhibing [8] proposed a multiperson target dynamic tracking method based on the fusion of mean shift and particle filter. Using the fast convergence of mean shift algorithm, the particle set is iteratively calculated, and the particles with the first 15% of weight are retained to form a new particle set, reducing the calculation cycle. The heavy particles are obtained by resampling, and the particle set is updated to improve the target positioning accuracy. However, the calculation of this method takes a long time.

In view of the poor effect of the existing multiperson target detection and tracking methods in the dynamic scene, taking the dynamic tracking of athlete training as the research object, based on the existing research theory, the multiperson images of athlete training are accurately collected by wireless body area network, and the collected images are sparse represented. Based on this, the adaptive search box is used to complete the dynamic tracking of athlete training multitarget.

The research contributions of the thesis include the following points:

- (1) The paper proposes a new method for athlete's training multiperson target dynamic tracking based on wireless body area network
- (2) The microinertial sensor in the wireless body area network is used to collect the multiperson image data of the athlete's training, and the sparse representation is performed after processing, which improves the reliability of the data and reduces the tracking error
- (3) The paper adopts a multiperson target dynamic tracking method based on an adaptive search box, combined with target isolation and occlusion detection, to judge the athlete's training target

2. Multiperson Target Dynamic Tracking of Athlete Training Based on Wireless Body Area Network

2.1. Athlete Training Data Acquisition Based on Wireless Body Area Network. Wireless body area network is a wireless network constructed by portable, wearable, or implantable sensor nodes that can perceive a variety of human physiological parameters. Wireless body area network provides a new means for human health monitoring and has great application significance and demand in the fields of disease monitoring, health recovery, special population monitoring, and so on [9]. Through the microinertial sensor worn on the body, the body area network can collect human motion signals and is widely used in human motion monitoring. It can realize the purposes of human motion recognition, abnormal motion detection, gait recognition and analysis, motion energy consumption analysis, and so on.

The research field of wireless body area network is shown in Figure 1.

Figure 1 summarizes the research fields involved in the existing wireless body area network. From the existing research, data fusion technology, situation awareness technology, and WBSN energy control are the technical research hotspots of WBSN, and the research of WBSN for multitarget dynamic tracking in athlete training accounts for a large proportion [10].

When the wireless body area network is used for multitarget dynamic tracking of athlete training, the microinertial sensor in the wireless body area network needs to be used to identify the movement information of multitarget of athlete training [11]. The multiperson target movement information recognition of athlete training based on microinertial sensor is a series of image sampling sequences arranged in a chronological order, including all the movement information of athlete training.

The field of athlete training multiperson target dynamic tracking based on microinertial sensors is a new field. Its essential content is to first obtain the motion signal generated during athlete training through one or more inertial sensors and then sparse represent the sampled image, so as to facilitate the follow-up athlete training multiperson target dynamic tracking [12]. The specific processing process is shown in Figure 2.

Generally, the sample image collected by inertial sensor contains not only the motion signal generated by athlete training but also various noises. Therefore, the collected sample image must be preprocessed first. Preprocessing methods generally include smoothing and denoising, normalization, resampling, windowing, and tilt correction.

Smoothing and denoising are often used in the image processing of human motion samples based on inertial sensors. Therefore, in the process of sample image acquisition, the noise generated by the jitter of athletes' training and the measurement noise of sensors will be included in the collected images, so these interference noises should be removed first [13].

In addition, normalization and resampling are also technologies often used in preprocessing. In multiperson target dynamic detection, because the action amplitude of athletes is not fixed and different athletes are doing different actions, the influence of signal amplitude on sampling results must be eliminated. Normalization can usually be used to adjust the amplitude difference of signals [14].

After the preprocessing of the sampled image, the sparse representation model of the sampled image is constructed. In the multiperson target detection process of athlete training based on inertial sensor, the acceleration values of three axes in the athlete training process can be collected through inertial sensor, and (x, y, z) represents the acceleration values measured by inertial sensor in x , y , and z directions, respectively, so the once collected sample of a target dynamic detection is the time sequence of acceleration data. The sampling value of the sensor at time t is

$$s(t) = (x(t), y(t), z(t)). \quad (1)$$

Then, the l -time sampling value obtained corresponding to a complete athlete's training posture for a short period of

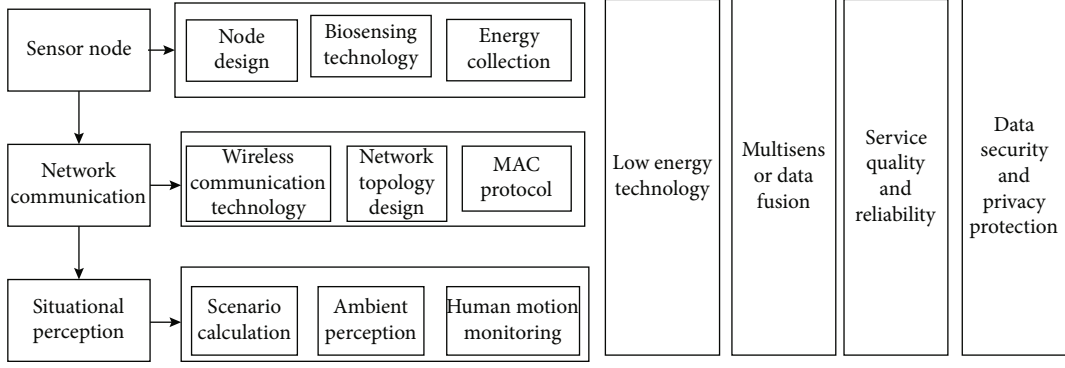


FIGURE 1: Research area of wireless body area network.

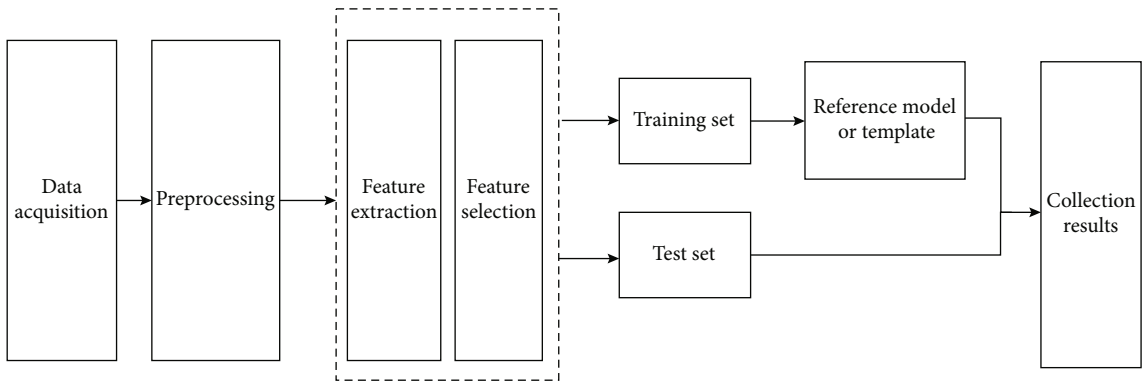


FIGURE 2: Multiperson target image sampling process of athlete training based on microinertial sensor.

time can be represented by a one-dimensional vector, which is recorded as

$$g = (s(1), s(2), \dots, s(l))^T. \quad (2)$$

From a geometric point of view, many data classes to be detected can be characterized by specific subspaces, and each subspace represents a data category [15]. It is assumed that the spatial distribution of a variety of different motion trajectory data satisfies the mixed subspace model, and different motion trajectory data are approximately distributed in different subspaces. For the collection of dynamic trajectory data, as long as the appropriate dynamic trajectory is selected to meet the mixed subspace model and each subspace represents a trajectory data category, the motion trajectory recognition problem can be transformed into a sparse representation classification model.

The problem of motion trajectory data acquisition is to judge the motion category of a motion trajectory vector $g_{k,\text{test}}$ to be collected given the training set of class C motion target samples. The acquisition based on sparse representation mainly has two steps: sparse coding and sparse representation. Using the super complete dictionary atom composed of training samples, the motion trajectory vector to be collected is expressed as the linear combination of these atoms, so the motion trajectory acquisition problem

is transformed into the acquisition problem of multiple linear regression models.

Assuming that the class i training sample contains n_i motion tracks, the training sample is transformed into a column vector, and the column vector $g_{i,j} \in R^m$ is used to represent the j motion track of class i , where m is the dimension of the motion track vector; then, all one-dimensional motion directions in the training set corresponding to the class i motion track constitute a motion track subspace, which is recorded as

$$G_i = [g_{i,1}, g_{i,2}, \dots, g_{i,n_i}] \in R^{m \times n_i}. \quad (3)$$

According to the principle of linear subspace, if the motion trajectory vector $g_{k,\text{test}}$ to be collected belongs to class k motion, the motion trajectory vector can be represented by the linear combination of trajectory vectors of all training motions in the subspace, that is

$$g_{k,\text{test}} = \alpha_{k,1}g_{k,1} + \alpha_{k,2}g_{k,2} + \dots + \alpha_{k,n_k}g_{k,n_k}. \quad (4)$$

In the formula, $\alpha_{i,j}, j = 1, 2, \dots, n_k$, is the sparse representation coefficient.

All the training samples of all C kinds of motion tracks in the whole training sample set are formed into redundant

dictionary matrix G . Each base vector in the dictionary represents one training sample, as follows:

$$G = [G_1, G_2, \dots, G_k] = [\mathcal{g}_{1,1}, \mathcal{g}_{1,2}, \dots, \mathcal{g}_{c,n_c}] R^{m \times n}. \quad (5)$$

In the formula, $n = n_1 + n_2 + \dots + n_c$, and the number of columns in dictionary G is greater than the number of rows. Such a dictionary is called an overcomplete dictionary.

Considering that some errors will inevitably be included in the actual calculation process, when the redundant dictionary G is used to represent the motion trajectory vector $\mathcal{g}_{k,\text{test}}$ to be measured, it can be expressed by the following formula:

$$\mathcal{g}_{k,\text{test}} = G\alpha + e \in R^m. \quad (6)$$

In the formula, $\alpha = [0, \dots, 0, \alpha_{k,1}, \alpha_{k,2}, \dots, \alpha_{k,n}, 0, \dots, 0]^T \in R^n$ represents the coefficient vector, $e \in R^m$ represents the observation noise, and the noise tolerance is $\|e\|_2 < \varepsilon$. Ideally, the samples to be collected should only be linearly represented by the training samples from the same category in the dictionary; that is, in the coefficient vector α , only the representation coefficients of the training samples belonging to the same category as the samples to be collected are not 0, and the rest are 0; then, when the number of categories is enough, compared with the whole dictionary, this representation will show the characteristics of sparsity. Therefore, based on the prior knowledge that the super complete dictionary has sparsity in the representation of test samples, the most sparse linear combination in the super complete dictionary is found to represent test samples.

α is a coefficient vector with $1/C$ sparsity. When the number of categories C reaches a certain degree, the solution of the equations has enough coefficients. According to the compressed sensing theory, α can be solved by minimizing the l_1 norm under quadratic constraints. The specific calculation formula is

$$\begin{aligned} \hat{\alpha} &= \arg \min \|\alpha\|_1 \\ \text{s.t.} \quad &\|\mathcal{g}_{k,\text{test}} - G\alpha\|_2 \leq \varepsilon. \end{aligned} \quad (7)$$

Ideally, the non-0 elements in the sparse coefficient vector $\hat{\alpha}$ obtained by formula (7) will only appear in the position corresponding to the samples of the same class as the motion trajectory vector $\mathcal{g}_{k,\text{test}}$ to be collected, so the category of the test sample can be determined according to the distribution of these non-0 elements. However, due to the existence of noise, in practice, non-0 elements may also appear in the corresponding positions of other categories. Then, calculate the linear weighted difference between the motion vector to be collected and all motion vectors in each category, and the calculation formula is

$$r_i(\mathcal{g}_{k,\text{test}}) = \|\mathcal{g}_{k,\text{test}} - G\delta_i(\hat{\alpha})\|_2, \quad i = 1, 2, \dots, C. \quad (8)$$

In the formula, $\delta_i(\hat{\alpha})$ means to extract the coefficients corresponding to all motion vectors of class i in sparse representation coefficient $\hat{\alpha}$, and the other coefficients are 0. Select the category of $r_i(\mathcal{g}_{k,\text{test}})$ with the smallest difference, and record it as the final acquisition result.

Through the above calculation, the multitarget motion data is collected according to the microinertial sensor in the wireless body area network, which lays the foundation for the subsequent multitarget dynamic tracking of multiplayer training.

2.2. Multiperson Target Dynamic Tracking. The multiperson target dynamic tracking method using an adaptive search box uses the separation processing of target isolation and target occlusion, extracts target features through an efficient multiperson target detection algorithm, and maintains a real-time updated tracking area search box. When each target is in an isolated motion state, the nearest neighbor algorithm based on the search box is adopted. When the target is occluded, a feature matching algorithm based on the central area is used to dynamically track the target. The block diagram of multiperson target dynamic tracking is shown in Figure 3.

It can be seen from the multiperson target tracking block diagram flow shown in Figure 3 that this method is a multiperson target dynamic tracking method based on detection. This method maintains a good search box and target feature information base by implementing accurate multitarget detection. Multiperson target detection and marking technology, data association technology, and feature matching technology are adopted. Taking whether the target is occluded as the branch point, the hybrid algorithm is used to deal with target tracking in time-sharing.

It should be noted that when several measurements appear in the target search box, that is, there are several targets in a search box, switch the tracking algorithm immediately and switch from the nearest neighbor algorithm to the feature matching algorithm. This usually occurs in the separation process after the target is blocked. When a target suddenly stops after being blocked and another target crosses, at this time, the target breaks away from the occlusion state and enters the isolated motion of the target. At this time, the nearest neighbor algorithm will inevitably lead to the wrong tracking of the target.

In the actual athlete training scene, the state between targets in multiperson target tracking is the basis of preanalysis and the premise of the realization of tracking method. According to the actual situation of multitarget movement, the multitarget movement state mainly includes four situations: the emergence of new targets, occlusion between targets, mutual occlusion, separation of multitarget, and disappearance of old targets. Among them, the occlusion between multiple human targets is divided into partial occlusion and severe occlusion. Whether the target occlusion is serious or not is judged according to the accuracy of the algorithm. When the tracking algorithm cannot effectively realize the independent tracking of occluded targets, the occluded multiple human targets are combined. Otherwise, some non-severely occluded targets are tracked independently.

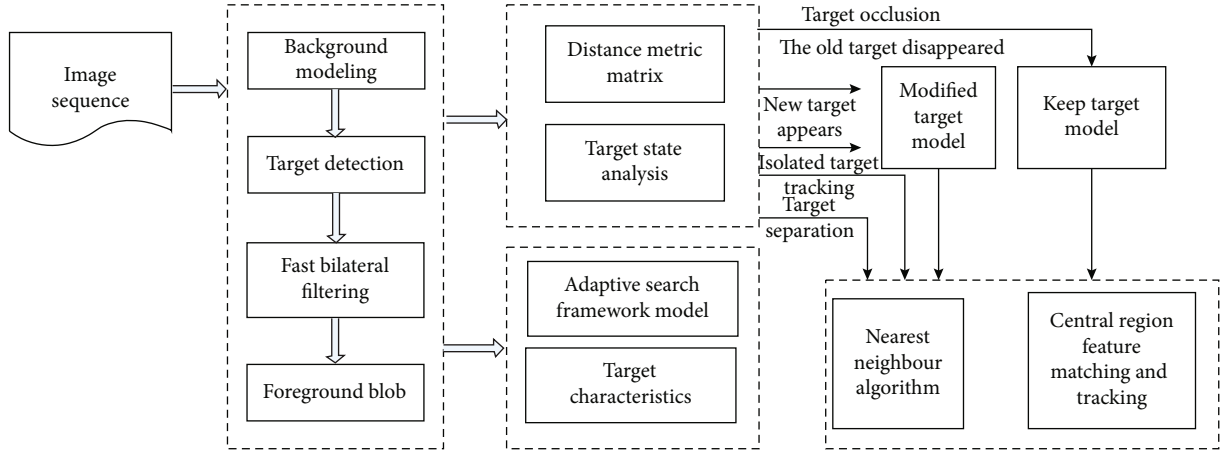


FIGURE 3: Multiperson target dynamic tracking block diagram.

In general, the position change of the moving target on the two adjacent frames of images is very small relative to the image space distance. Therefore, set a distance threshold r . When a target position is in a circle whose origin is the target centroid of the current frame and radius is r , it is judged as the same target, and the circle is defined as the nearest neighbor circle. Therefore, a distance measurement matrix P is proposed, P is $M \times N$ matrix, M represents the number of targets detected in $t-1$ frame, N represents the number of blobs segmented in $t-1$ frame, and the multitarget state is determined according to the number of targets in two adjacent frames in a nearest neighbor circle:

$$P(m, n) = \begin{cases} 1, & \text{if } |o_t^n(x, y) - o_{t-1}^m(x, y)| < r, \\ 0, & \text{else.} \end{cases} \quad (9)$$

In the formula, $o_t^n(x, y)$ represents the centroid position of the n th blob detected in the t frame image, and $o_{t-1}^m(x, y)$ represents the centroid position of the m th target in the $t-1$ frame image.

According to the matrix definition, we can get

$$\begin{aligned} P_m &= \sum_{n=1}^N P(m, n), \\ P_n &= \sum_{m=1}^M P(m, n). \end{aligned} \quad (10)$$

In the above formula, P_m represents the number of foreground blocks matched with the m th target, and P_n represents the number of targets matched with the n th foreground block.

- (1) When a new target enters the scene (including target splitting), $P_m = 0$, that is, the n th blob detected in the current frame fails to find a matching target in the $t-1$ frame. In order to judge whether the target is new or split, it is necessary to extract the color data-

base information for matching. If it is a new target, number the target; record the static characteristic parameters such as centroid, minimum circumscribed rectangle, and color information of the new target; and obtain the dynamic characteristic parameters such as motion speed and direction from the second frame

- (2) When the old target leaves the scene (including severe occlusion of the target). At this time, $P_m = 0$, that is, when the m th target in frame $t-1$ fails to find a matching blob in the current frame. When the m th target is at the boundary of the video scene, it is judged that the old target disappears; delete the m th target, and refresh the target chain; otherwise, judge that the target is seriously occluded, ensure the m th target message, and record the target state at time $t-1$, so as to realize effective tracking of the target when the target is split
- (3) Target occlusion judgment. As shown in Figure 4, r_1 is the minimum inscribed circle radius centered on the centroid of the target contour, and r_2 is the maximum circumscribed circle radius centered on the centroid of the target contour. Considering the shape characteristics of human body, when the centroid distance $d_{i,j}$ of two or more adjacent targets meets $d_{i,j} < r_1^i + r_1^j$, where $i, j \in [1, m]$ and $i \neq j$, judge that the targets block each other and stop updating their characteristic parameters; when $P_n > 1$, that is, when the number of targets matched with the n th block is greater than 1, it is judged that multiple targets block each other. Tracking the smallest outer circumscribed rectangle and the inside and outside circles is shown in Figure 4

As can be seen from Figure 4, the adaptive search frame is based on the extraction of target motion information and makes full use of the target area detected in the previous frame to predict the target search range in the next frame. When the new target enters the image, the minimum

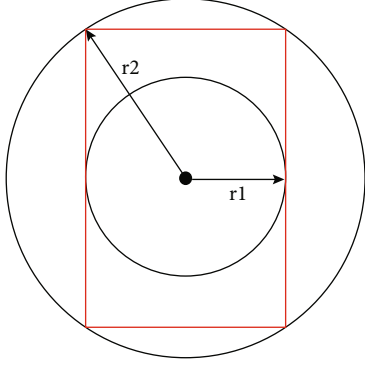


FIGURE 4: Tracking the smallest outer circumscribed rectangle and the inside and outside circles.

circumscribed rectangle of the target is obtained through the target detection and state evaluation algorithm, that is, the length and width of the target, the centroid, and other static parameters. The centroid of multiperson moving target is obtained through the marked target blob. The centroid calculation formula is as follows:

$$\begin{aligned} X(i) &= \frac{\sum f(x, y)x}{\sum f(x, y)}, \\ Y(i) &= \frac{\sum f(x, y)y}{\sum f(x, y)}. \end{aligned} \quad (11)$$

In the formula, $f(x, y)$ represents the value of the blob (0 or 1), x and y represent the index positions of the image pixels, and $X(i)$ and $Y(i)$ represent the centroid of the i th target in the K th frame of the image. In the same way, the length and width of the target can also be obtained through the connected domain of the target.

The dynamic parameters of the target are acquired from the second frame when the target is detected, which mainly include the movement speed and the movement direction. The calculation principle of the target movement direction θ is shown in Figure 5.

As shown in Figure 5, the motion direction is obtained by the centroid position of the current frame and the previous frame. According to the position information of the moving target, the following calculation formula can be obtained:

$$\begin{aligned} \theta &= \arctan \left(\frac{x_t^n - x_{t-1}^n}{y_t^n - y_{t-1}^n} \right), \\ \theta &\in [0, 360). \end{aligned} \quad (12)$$

It is easy to know that when θ is at four special angles of 0, 90, 180, and 270, it is necessary to decompose the movement in the direction of the target centroid (x, y) . When $x_t^n = x_{t-1}^n$ and $y_t^n > y_{t-1}^n$, judge $\theta = 0$; similarly, $y_t^n = y_{t-1}^n$ and $x_t^n > x_{t-1}^n$, then $\theta = 90$; $y_t^n = y_{t-1}^n$ and $x_t^n < x_{t-1}^n$, then $\theta = 180$; and $y_t^n > y_{t-1}^n$ and $x_t^n < x_{t-1}^n$, then $\theta = 270$. In order to reduce the computational complexity and improve the

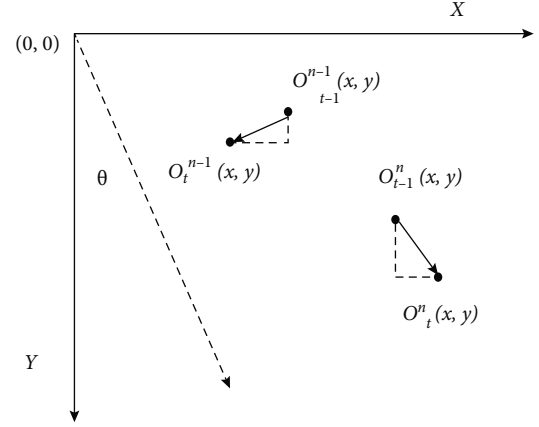


FIGURE 5: The calculation principle of target movement direction θ .

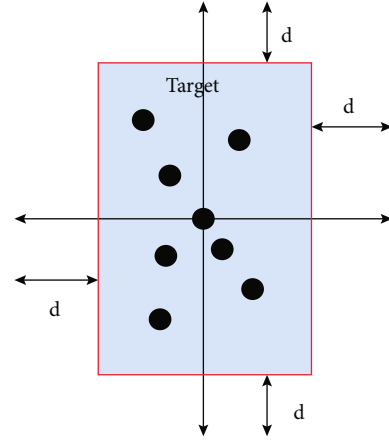


FIGURE 6: Multihuman target dynamic search model.

motion efficiency of the algorithm, according to the principle of computer operation, consider removing the arcsine calculation and converting the θ unit accordingly.

The multitarget dynamic search model is shown in Figure 6.

As shown in Figure 6, build a search box model for each moving target. The establishment of the search box starts from the acquisition of target motion parameters. When a new target appears, initialize its search box from the second frame to complete the dynamic tracking of multiperson targets.

3. Experimental Verification

In order to verify the proposed multiperson target dynamic tracking method for athlete training based on wireless body area network, simulation and comparative verification experiments are carried out.

The environment used in the experiment is the Matlab environment, and the test sequence used is the image sequence. The athlete training wireless body area network multiperson target image data used in the experiment is stored in the PETS-ECCV database, the image

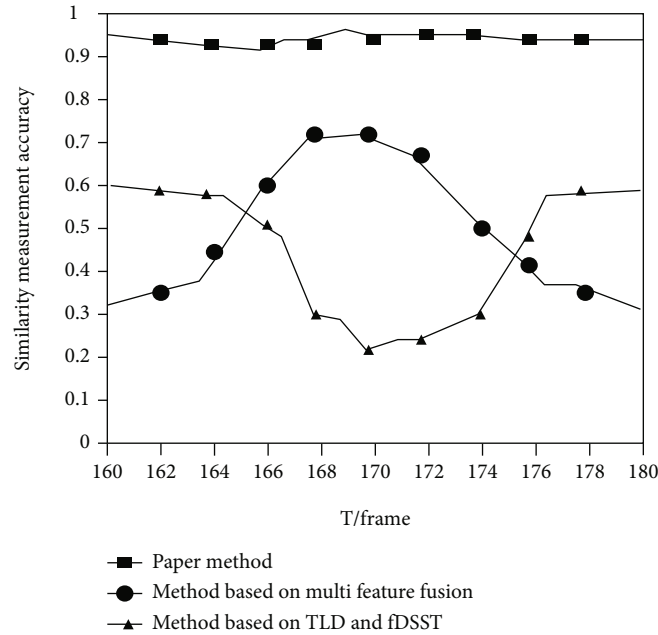


FIGURE 7: Comparison results of feature similarity measurement accuracy.

size is 320×240 , the number of images is 500, and the total number of image frames is 180.

The experimental scheme is as follows: taking the accuracy of feature similarity measurement, tracking time, and tracking error as experimental comparison indexes, this method is compared with the multifeature fusion method proposed in reference [6] and the TLD and fdst methods proposed in reference [7]. The specific experimental results are as follows.

3.1. Accuracy of Feature Similarity Measurement. In the process of multiperson target dynamic tracking, it is necessary to dynamically track the training characteristics of different athletes, so it is necessary to judge the characteristics of different athletes. Feature similarity measurement has become an important means of feature judgment. Therefore, taking the accuracy of feature similarity measurement as the experimental comparison index, this method is compared with two traditional methods [16]. The comparison results of feature similarity measurement accuracy of the three methods are shown in Figure 7.

From the comparison results of the feature similarity measurement accuracy shown in Figure 7, it can be seen that the accuracy of the three methods of similarity measurement shows a distinct trend when the test frame sequence continues to increase. The measurement accuracy of the method in this paper is always maintaining a high level, basically above 0.9. The multifeature fusion method started to rise from the beginning of the experiment, but when the frame sequence reached 168, it began to gradually decrease and finally even reached 0.3. The measurement accuracy based on the TLD and fDSST method shows a trend of first decline and then rise, but the highest measurement accuracy of this method does not exceed 0.7. Therefore, it is explained that the method in this paper accurately measures the similarity

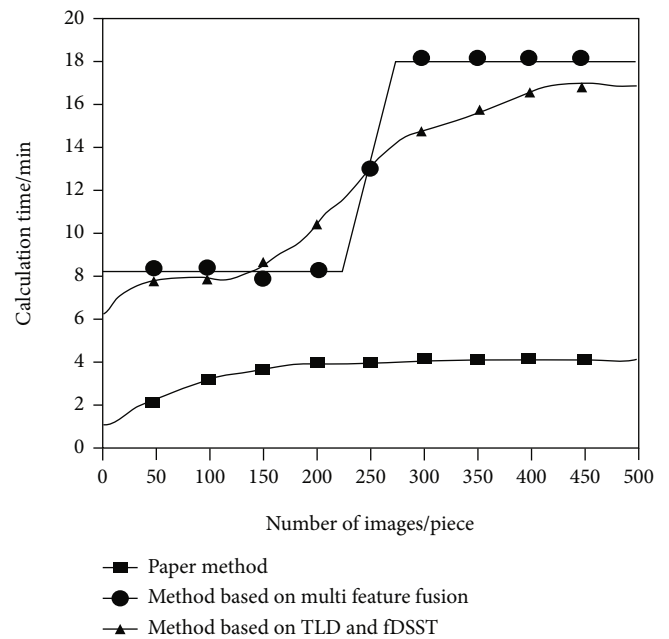


FIGURE 8: Comparison results of tracking time.

of multiperson target features to improve the reliability of tracking [17].

3.2. Tracking Time. Tracking time is one of the key indicators to judge the overall performance of the tracking method. The shorter the tracking time is, the stronger the tracking performance of the method is [18]. The tracking time comparison results of the three methods are shown in Figure 8.

TABLE 1: Comparison of tracking errors.

Number of iterations	Paper method	Tracking error/frame	
		Method based on multifeature fusion	Based on TLD and fDSST method
100	0.13	6.71	4.85
200	0.15	5.67	5.61
300	0.11	5.23	4.56
400	0.12	4.62	5.76
500	0.14	6.32	6.34
600	0.12	4.69	6.47
700	0.12	6.63	4.39
800	0.13	6.16	6.48
900	0.15	5.96	6.31
1000	0.11	7.32	7.45

Observing the tracking time comparison results shown in Figure 8, it can be seen that with the increase of experimental images, the tracking time of the method in this paper shows a slight upward trend, but the maximum time is no more than 5 min. The tracking time of the two literature comparison methods increases seriously, and the maximum time is more than 15 min. Therefore, this method can reduce the tracking time and improve the tracking efficiency [19, 20].

3.3. Tracking Error. Tracking error is used as an index to directly verify the dynamic tracking method, and its results can intuitively show the performance of different tracking methods. The more obvious the tracking error is, the better the tracking performance of the method is. The tracking error comparison results of the three methods are shown in Table 1.

Observing the tracking error comparison results shown in Table 1, we can see that in the process of full iterative verification, the tracking error of the text method is significantly lower than that of the two traditional comparison methods. The minimum tracking error of the method and the method based on TLD and fDSST are 4.62 frames and 4.39 frames, respectively. Therefore, it is proved that the method in this paper can improve the accuracy of tracking.

4. Conclusion and the Future Work

In order to improve the reliability of multiperson target dynamic tracking in athlete training, a wireless body area network-based dynamic tracking method of athlete training multiperson target is proposed, and the performance of the method is verified from both theoretical and experimental aspects. This method has shorter tracking time and lower tracking error when performing multiperson target dynamic tracking during athlete training. Specifically, compared with the method based on multifeature fusion, the tracking time is significantly reduced, and the maximum tracking time is less than 5 minutes; compared with the method based on TLD and fDSST, the tracking error is significantly reduced, and the minimum error is only 0.11 frames. Therefore, it fully shows that the proposed tracking method based on

wireless body area network can better meet the requirements of athlete training multiperson target dynamic tracking. The real-time update of the athlete's status is the current research hotspot. How to capture the athlete's sports data in a shorter time and update their sports status in real time has become the research goal.

Data Availability

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

Conflicts of Interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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