Dynamic Recognition Method of Track and Field Posture Based on Mobile Monitoring Technology

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Abstract. The recognition technology using conventional sensors or image processing is effective for static gesture recognition, but for dynamic gesture recognition, the moving object can not be tracked in time, resulting in low recognition accuracy and efficiency. In order to optimize the above problems, the dynamic recognition method of track and field posture based on mobile monitoring technology is studied. Set up mobile monitoring equipment in the movement area and the movement track to acquire the data of track and field movement posture. After de-noising the track and field posture data, a Gaussian model is established to segment the image background. Based on the human skeleton model, the motion posture features are extracted. Using BP neural network improved by artificial fish swarm to classify the input movement posture data, the recognition of track and field movement posture is realized. The test results show that the recognition accuracy of the proposed methods is higher than 95%, the recognition efficiency is greatly improved, and it has good practical value.

Keywords: Monitor · Track and field sports · Dynamic attitude recognition · Gaussian model · BP neural network · Artificial fish swarm algorithm

1 Introduction

There are many kinds of track and field sports, and the training methods of each sport are different in different degrees, but the most important thing in track and field sports training is whether the athletes' movement posture is standard or not. The standard and scientific posture can improve athletes' competitive ability and physical quality, and prevent sports injuries, which is the fundamental guarantee for athletes to achieve good competitive results. The continuous development of science and technology has promoted the diversification of training methods and the scientific process of training means in track and field events. Using related technologies to guide and adjust athletes' body posture can avoid physical injuries caused by improper sports posture, and lay a foundation for improving athletes' track and field performance.

The definition of standard movement posture during exercise is mostly based on pictures or oral guidance, which leads to the lack of quantitative evaluation criteria for

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standard movement posture. At present, there are many methods to study the human motion posture recognition, and the two main methods are: human posture recognition based on image and video analysis and human posture recognition based on motion sensor [1]. Early human motion recognition needs the assistance of external equipment to perceive the change of human posture and then recognize human motion. With the development of machine learning and deep learning, there are many different research directions in academic circles, such as image processing, SVM classifier and deep neural network. With the development of these technologies, computers can sense human movements only through cameras and other devices, thus greatly reducing the number of external sensors. In document [2], the laser sensor is used to collect the motion signal data of the moving target, and the characteristic values of the initial motion signals after segmentation are extracted by the time domain signal analysis method, which are input into the BP neural network to obtain the motion recognition results. Literature [3]. Machine learning is used to identify the local feature points of human movements. By using the differences of human bodies in space-time state and the changes of motion frequency, multi-scale local space-time domain features are constructed, mathematical models of human behaviors are constructed, and neural network parameters are trained to reduce the recognition error of local feature points of human movements. The above methods are effective for static movement recognition, but there are some limitations for dynamic track and field movement recognition with space-time continuity.

When athletes do track and field sports, the posture change from the beginning to the end can be regarded as a dynamic sequence composed of several static postures [4]. Although using sensors to monitor the movement can accurately obtain the movement posture data, wearable sensors will affect athletes' movements and are not suitable for daily training. The types of data collected by non-contact sensors are relatively simple, and it is difficult to meet the identification requirements. Using mobile monitoring technology to collect images of athletes' postures in track and field training can simultaneously achieve the acquisition of athletes' postures from the whole to the local, and reduce the influence of data collection stage on posture recognition. Based on the above analysis, this paper will aim at improving the efficiency and accuracy of athletes' attitude recognition in track and field training, and study the dynamic recognition method of track and field sports attitude based on mobile monitoring technology, which can be used to assist athletes' training and improve the efficiency of track and field training. Aiming at the problem of insufficient efficiency and accuracy of dynamic motion recognition, this paper applies mobile monitoring equipment to collect motion trajectory information. When processing the information, it first removes noise to avoid noise interference, and then improves the recognition accuracy. It uses the improved BP neural network algorithm of artificial fish to solve the pose, so as to avoid falling into local optimization and improve the efficiency of motion pose recognition.

2 Research on Dynamic Recognition Method of Athletic Attitude Based on Mobile Monitoring Technology

2.1 Acquisition of Dynamic Monitoring Data of Athletic Attitude

Athletes' body posture changes rapidly in training or competitive state. Using mobile monitoring equipment to monitor athletes' posture in sports can quickly and accurately acquire the whole process of athletes' movements in the whole track and field events. In order to meet the requirement of high-speed capture of athletes' movement posture in track and field, this paper uses mobile monitoring technology to obtain the dynamic posture of athletes when they make corresponding track and field movements.

According to the difference of track and field events, mobile monitoring terminals are set up within the effective training range of track and field events. The mobile terminal consists of signal transceiver, high-speed camera, communication module, etc. When athletes enter the effective monitoring range of track and field sports, the tracking camera is started, and a series of movement posture data of athletes within the monitoring range are collected, and a dynamic movement sequence composed of several static image frames is generated [5].

The process of human movement is the process of human posture change, which is continuous. The camera with higher frame rate can capture more images of athletes' postures per second, which will not miss the postural changes of athletes' postures during strenuous exercise and reduce dynamic blur. Therefore, the posture change of human body is not obvious in the images collected by the camera with high frame rate in continuous time intervals. According to the sampling theorem, in the process of discretization of continuous signals, when the sampling frequency is more than twice of the highest frequency in the signal, the sampled discrete signal can completely retain the information in the original signal. Therefore, in the design process of the human posture evaluation system, by selecting the appropriate frame rate and setting the appropriate sampling interval. Try to make the sampling frequency more than twice the frequency of human motion.

The acquired motion posture data is transmitted to computer equipment for subsequent processing by WIFI and ZigBee wireless transmission. In order to realize the dynamic real-time monitoring of track and field posture, H.264 video compression format is selected as the basic format of mobile monitoring video compression, and RTP/RTCP advanced protocol is used to assist wireless transmission UDP protocol when monitoring video transmission, so as to provide some data traffic congestion adjustment services and network traffic deployment control services in the process of information and image transmission [6]. The transmission flow of H264 mobile surveillance video format in IP/UDP/RTP protocol is shown in Fig. 1 below.

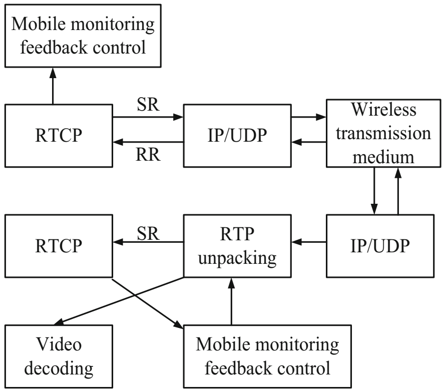

Fig. 1. Mobile surveillance video transmission process

As can be seen from Fig. 1, H.264 video data is first encapsulated by RTP protocol. After encapsulation, the merged data packet is transmitted through the network through the appropriate network protocol, and the data information is unpacked and decoded by RTP protocol to obtain the decoded form of the collected data. RCTP protocol, as an auxiliary protocol of UDP protocol, can adjust and control the traffic in real time during the process of data encapsulation and unpacking, ensure the quality of data encapsulation and unpacking, and improve the fault tolerance of data. After monitoring and collecting the athletes' track and field postures in the training area, the monitoring data is transmitted to the data processing computer according to the above protocol flow, and then used to identify the movement postures after processing.

There are many kinds of human body postures, each of which seems relatively simple from the visual point of view, but actually quite complicated. Human body movements involve many parts (such as legs, waist, arms, etc.), and the intensity and characteristics of each posture are different, and each person's physiological data and exertion methods of track and field events are also different, which increases the difficulty of track and field posture recognition. Therefore, it is necessary to preprocess the image data of track and field movement monitoring before the movement gesture recognition, so as to improve the efficiency of the movement gesture dynamic recognition.

2.2 Image Processing of Mobile Monitoring Posture

Track and field training is usually conducted outdoors. Outdoor environment interferes with the motion video collected by mobile monitoring technology to varying degrees, which affects the accuracy of gesture recognition. Therefore, firstly, the track and field movement monitoring video is denoised. In this study, the threshold method of multi-wavelet transform is used to smooth the motion posture and movement surveillance video. Because multiwavelet does not have translation invariance, it will produce obvious Gibbs phenomenon in the neighborhood of signal singularity (image discontinuity). Two different thresholds T_1 and T_2 are adopted, of which $T_1 = \sigma(2\ln N + 2\ln\ln N)^{1/2}$, $T_2 = \mu\sigma(2\ln N + 2\ln\ln N)^{1/2}$, of which μ is an adjustable parameter, $\mu \in [0, 1]$. If the multiwavelet coefficient of the pixels of the track and field movement monitoring video image is greater than T_1, the coefficient remains unchanged; If the multiwavelet coefficient value of the image pixel is less than T_2, the coefficient is set to zero. For multiwavelet coefficients between T_1 and T_2, the new slope threshold function is used to shrink [7].

The calculation formula of the slope function is as follows:

$$\dot{W}(i,j) = \begin{cases} W(i,j), W(i,j) > T_1 \\ W(i,j) - \delta T_1, T_2 < W(i,j) < T_1 \\ 0, \ \ else \end{cases} \tag{1}$$

where, δ represents the quantity related to multiwavelet coefficients of pixel points. The coefficient is determined by the ratio of the minimum to maximum value of the median value of the pixel in the 3×3 neighborhood. After the original image is converted into a gray image, the decomposition number of multiwavelet is $\mathrm{K} = 2$, and the odd/even pre-filtering is used to convert two adjacent pixels in a row or column of the monitoring image $J(i,j)$ with size $M * N$ into a vector pixel of $C(i,j)$, which is 2×1 or 1×2. The row-column conversion formats are as follows:

$$C(i,j) = \begin{vmatrix} J(i, 2j) \\ J(i, 2j + 1) \end{vmatrix} \tag{2}$$

$$C(i,j) = \begin{vmatrix} J(2i, j) \\ J(2i + 1, j) \end{vmatrix} \tag{3}$$

After preprocessing, the noise image is subjected to K-times multiwavelet transform, and the multiwavelet transform coefficients of the image are obtained. The threshold of wavelet denoising is obtained by thresholding the coefficients of multi-wavelet transform with the existing wavelet denoising threshold method. The threshold process is reconstructed by wavelet, and the intermediate image is obtained. According to the inverse process of pre-filtering, the intermediate image is post-filtered, and the final denoised motion monitoring image is obtained. After the image is denoised, Gaussian background segmentation is performed on the image where the gesture recognition object, that is, the individual athlete, is located to reduce the influence on the recognition accuracy.

2.3 Attitude Recognition Background Segmentation

In track and field training, athletes' instantaneous explosive force is strong, and their postures change rapidly, so the recognition of athletes' postures will be influenced by shadows. Therefore, Gaussian background model is used to segment the detected object and background in surveillance video.

When building Gaussian background model, we should also consider the influence of background shadows on the detection effect. When building background model in RGB color space, if the pixels in RGB space are covered by shadows, in which the values of R, G and B are linearly attenuated, the shadows can be detected by calculating the posterior probabilities of pixel background, moving objects and moving shadows. However, this method is not suitable for rapid and accurate detection of targets because of its large computation. However, it is easier to remove the influence of shadows when building a background model in HSV space. In HSV space, when the pixels are covered by shadows, the brightness wallpaper of the pixels is approximately linear, and shadows will not greatly change the chroma of the background pixels and can reduce the saturation of the background pixels. This method can simply and quickly suppress shadows. Therefore, this paper establishes a background model in HSV color space to suppress shadows, and the specific algorithm is as follows [8]:

$$SP(i,j) = \begin{cases} 1, r \le \dfrac{I_V(i,j)}{B_V(i,j)} \le R \\ |I_S(i,j) - B_S(i,j)| \le -1 \\ |I_H(i,j) - B_H(i,j)| \le 4 \\ 0, \ else \end{cases} \tag{4}$$

where, $I_H(i,j)$, $I_S(i,j)$, $I_V(i,j)$ respectively represents the component of the pixel; $B_H(i,j)$, $B_S(i,j)$, $B_V(i,j)$ represents the component of the background pixel respectively. In which parameters $0 < r < R < 1$, The value of R is related to the light intensity in the environment. The stronger the light, the smaller the value. The value is taken according to the light intensity of the environment. $SP(i,j)$ is the shadow pixel mask at pixel coordinate point (i,j) of the image, $SP(i,j) = 1$ if pixel $J(i,j)$ is judged as shadow, otherwise $SP(i,j) = 0$.

Gaussian background model is established. For each pixel in the image, Q states are used to represent the color of the pixel. Each of the Q states is represented by a corresponding Gaussian function. If each pixel is represented by J_t, its probability density function is represented by Q three-dimensional Gaussian functions as:

$$g(J_t = j) = \sum_{i=1}^{Q} w_{i,t}\eta\left(j, \bar{j}_{i,t}, \overline{G}^2\right) \tag{5}$$

Among them, $\eta\left(j, \bar{j}_{i,t}, \overline{G}^2\right)$ is the first Gaussian distribution, $\bar{j}_{i,t}$ is the mean value of the i Gaussian model at t times, $\overline{G}^2$ is the covariance of the Gaussian model, and $w_{i,t}$ is the weight of the i Gaussian distribution at t times. A Gaussian mixture model is established in each color channel to improve the real-time performance of the algorithm. The mixed Gaussian model is initialized, and the gray mean and variance of each pixel in the video sequence image in a period of time are calculated as the next Gaussian distribution parameters. When establishing the initial background model, if the pixel satisfies the following formula, it is judged as the background pixel, otherwise it is the foreground pixel.

$$\left|J_t - \bar{j}_0\right| \le 2/5 * \overline{G}_0^2 \tag{6}$$

When the background light or background objects have not changed, the background model is consistent, and the corresponding background model can be obtained without realizing the background update process. During the detection process, the background model should be updated due to the changes of the moving target and the background light in the environment, and the updating process is updated by updating the model parameters. The updated production data of the model is updated by the downward gradient method. The larger the value of the update learning rate, the faster the update speed, and the smaller the value, the slower the update speed. After segmenting the background in the surveillance image, the gesture features of track and field movements are extracted for gesture recognition.

2.4 Feature Extraction of Athletic Attitude

People are non-rigid objects, and different people have different postures at different times and places, so it is necessary to extract human posture features. Feature extraction is a primary operation on the original data, the purpose of which is to transform the original information representing the categories of sports behaviors into features with more obvious physical or statistical significance. Feature extraction is a very important step in the whole process of motion gesture recognition. It converts the collected original behavior data into the data form after preprocessing, and obtains the feature vector that can better represent the behavior category, which is used by the classifier to learn, identify and classify. Therefore, the selection of features directly affects the classification performance and accuracy of the classification model. Features that are widely used now mainly include three categories: time domain features, frequency domain features and time-frequency features.

Time domain features show the characteristics of the movement behavior information in the time dimension, which can be obtained by directly calculating the features of the movement data collected by sensors. Time domain features are widely used in human motion behavior recognition because of their simple calculation and small amount of computation. Frequency domain feature is also a common feature, which reflects the frequency domain features of motion signals. Generally, it is necessary to transform the original signal from time domain to frequency domain by fast Fourier transform, so as to extract the corresponding frequency domain features. In this paper, the feature extraction method based on principal component analysis is used to extract the posture features of track and field sports.

Because the information between features overlaps to some extent, this paper uses principal component analysis (PCA) to analyze the extracted features. When PCA is used, it is necessary to calculate the covariance matrix and its eigenvalues of data, and then select the eigenvector with the largest eigenvalues to form a new matrix and transform it into a new space, so as to realize the dimension reduction of data features. The main process is as follows:

Before extracting human posture features, firstly, the coordinate system of human posture skeleton points under different track and field events is established. Firstly, the human contour model is established according to the feature vectors of the human contour, and the skeleton model under the human motion posture is obtained according to the skeleton information. As the support of the human body, bones are an important part of the human movement system, providing support in movement is the foundation of movement. Human skeleton sequence can be modeled by joint points and bones. There are 18 skeleton points in the human skeleton point model, which refers to the traditional human posture model. Including nose, neck, right shoulder, right elbow, right wrist, left shoulder, left elbow, left wrist, right hip, right knee, right ankle, left hip, left knee, left ankle, left eye, right eye, left ear and right ear. According to the sample image data of track and field movement posture, the skeleton feature sequence of track and field movement posture is obtained according to the human skeleton state under different movement postures.

In order to extract the motion characteristics of skeleton, it is necessary to extract skeleton sequence from video, and construct Shi Kongtu to input the nodes related to skeleton sequence according to the connection between joints. There are two kinds of joint connection edges, one is the skeleton edge formed by the internal connection nodes according to the natural connection order of human bones, the other is the inter-frame edge formed by the connection of the same joint point in consecutive frames according to the time order, thus obtaining a Shi Kongtu containing the natural connection of human bodies and the same joints between frames.

The gesture data of human body is expressed as matrix form X, and the initial matrix is linearly transformed to obtain a new matrix Y. Calculate the orthogonal matrix of the new attitude feature matrix, $Y = UX$. Therefore, matrix U is a matrix composed of the eigenvectors of the correlation coefficient matrix of l random variables.

Because the transformed points have the maximum variance on the y_1 axis and the minimum variance on the y_1 axis. At the same time, the covariance of all points for different y_i axis and y_j axis is zero. Let all l eigenvalues be non-negative 0, the eigenvector corresponding to λ_i is ζ_i, let $U = [\zeta_1, \zeta_2, \cdots, \zeta_i]$, then the variance of y_1 is:

$$Var(U_1X) = U_1XX^TU_1^T = \zeta_1 \tag{7}$$

y_1 has the largest variance, y_2 has the second largest variance, and there is covariance:

$$\mathrm{cov}\left(U_i^TX^T, U_jXX\right) = U_i^TRU_j \tag{8}$$

If the eigenvalues are arranged from large to small, the expression of the contribution rate of principal components is:

$$P_i = \frac{\zeta_i}{\sum_{k=1}^{l} \zeta_k} \tag{9}$$

Generally, the principal components with cumulative contribution rate greater than 80% and characteristic value greater than 1 are selected. For the original feature set, after dimensionality reduction by PCA, the new feature vectors obtained are pairwise uncorrelated. By orthogonal transformation of high-dimensional features, a new feature set is obtained. Then use formula (8) to calculate the contribution rate of different new features, and select new features with high contribution rate to form new feature vectors. The extracted motion posture features are used as the input of recognition classifier, and the dynamic recognition of track and field motion posture is realized through classifier processing.

2.5 Realize Dynamic Recognition of Motion Posture

When BP neural network algorithm adjusts the weights and thresholds of the network based on the negative gradient direction of error, it is easy to fall into local extremum. Artificial fish swarm algorithm is used to optimize the neural network. The core idea of artificial fish swarm algorithm is to simulate the behavior of fish swarm. It is a new strategy that can be used for global optimization. The realization of the algorithm is mainly to simulate the behavior of fish looking for food, which is an application based on animal behaviorism. When fish are looking for food, they mainly swim to places where there is more food. In the process of searching, they usually take the initiative to search or follow other schools of fish. In AFS algorithm, its main purpose is to search for places where there is more food, and the highest density through searching is the global optimal value. The algorithm mainly achieves the result of local optimization through several behaviors of fish, which mainly include foraging, clustering and rear-end collision. AFS algorithm has good convergence, can save the whole process time, has strong robustness and can achieve the effect of overcoming local extremum.

When using AFS to optimize BP neural network, it is necessary to combine the advantages of both. The process of fish searching for food in AFS algorithm is to find the global optimum. Combining it with the local searching ability in BP algorithm can achieve the effect of overcoming the local extremum. At the same time, it can accelerate the convergence speed of BP neural network and have better generalization ability. The implementation steps are as follows:

(1) Parameters of BP neural network are randomly initialized. After determining the main parameters, network training can be carried out.
(2) The parameters of AFS algorithm are randomly initialized. The main parameters include state s_i, quantity N_s, dimension D, crowding factor ϑ and so on. Each artificial fish represents a neural network, and its initial solution is a D-dimensional vector. If the number of neurons in the input layer is N_{i}, the number of neurons in the hidden layer is h and the number of neurons in the output layer is m, then the dimension of D is as follows:

$$D = (N_{\mathrm{i}} + 1) \times h + (h + 1) \times m \tag{10}$$

Calculate the fitness of food concentration of artificial fish.

The fitness of artificial fish's food concentration ρ_F is set as the reciprocal of total error E in BP algorithm, and the point with the largest food concentration is the point with the smallest error in BP algorithm. Fitness value of food concentration:

$$\rho_F = E^{-1} \tag{11}$$

(4) Each artificial fish simulates the second step and the third step of AFS, calculates the fitness of food concentration in the current position, and performs the behavior with better fitness, and the default way is foraging behavior.
(5) After each action, each artificial fish will be calculated and compared with the adaptive value of the previous step, and if it is better than that, it will be replaced by itself.

(6) When the number of cycles exceeds the maximum number of cycles, the training is finished. Otherwise, return to step 4.

Optimize the BP neural network, form a network identification model, input the processed track and field movement monitoring movement data, and identify the human movement posture data. According to the above process, the purpose of dynamic identification of athletes' track and field posture by using mobile monitoring technology is realized.

To sum up, the design of dynamic recognition method of track and field posture based on mobile monitoring technology is completed. The process of this method is shown in Fig. 2 below:

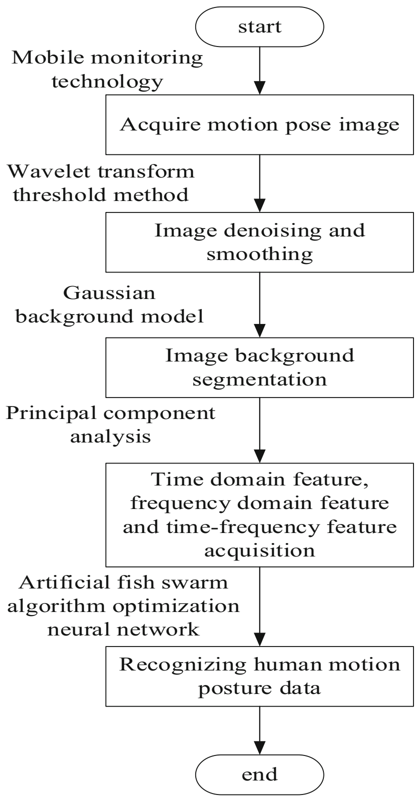

Fig. 2. Flow chart

3 Test Experiment

A dynamic identification method of track and field posture based on mobile monitoring technology was proposed above. Before applying this method to actual track and field training, the usability of this method was tested as follows.

3.1 Experimental Content

In this paper, the dynamic attitude recognition method of track and field based on mobile monitoring technology is compared with the attitude recognition method based on machine learning and sensor. Three kinds of recognition methods are used to dynamically recognize the posture of the motion posture data set with known results, and the recognition accuracy and recognition efficiency are selected as the comparison indexes. The experimental data set is the posture images of track and field sports shot by professional athletes. In the shooting process, the computer is used to establish the theoretical optimal model according to human physiological data to guide athletes' movements, so as to avoid interference with the experimental results. By analyzing the index data, the experimental verification is completed.

3.2 Experimental Result

The comparison data of the recognition results of the three gesture recognition methods on the gesture images of track and field sports are shown in Table 1.

Table 1. Comparative results of track and field gesture recognition

Number of identification objects	Identification method in this paper		Sensor-based identification method		Recognition method based on machine learning	
	Accuracy rate/%	Identification duration/ms	accuracy rate/%	Identification duration/ms	accuracy rate/%	Identification duration/ms
10	99.5	65.8	90.2	73.6	93.5	78.1
20	98.7	72.3	90.3	78.1	94.7	79.6
30	96.8	70.9	84.5	82.4	90.1	84.3
50	97.4	74.2	83.1	96.5	86.7	106.7
60	95.6	75.5	73.4	107.3	88.4	119.9
70	96.3	78.6	79.8	119.9	85.9	125.3
80	97.2	83.4	87.9	137.4	89.6	139.8
90	98.1	84.1	78.2	152.6	87.3	141.3
100	97.5	84.8	79.9	174.8	85.8	146.9

From the data analysis in Table 1, it can be seen that the identification accuracy of the identification methods proposed in this paper is higher than 95%, while the identification accuracy of the sensor-based identification method is obviously reduced in track and field events with strong light interference, which lowers the identification accuracy of the overall method. The recognition accuracy of the recognition method based on machine learning is affected by the training samples, and it is impossible to recognize the dynamic and continuous motion posture. From the recognition time of the method, the recognition time of this method is shortened by about 31.56% compared with the other two comparison methods, and the recognition efficiency is higher.

Taking the average recognition rate as the index, on the basis of the above experiments, we continue to use different methods to test, and the results are shown in Fig. 3 below:

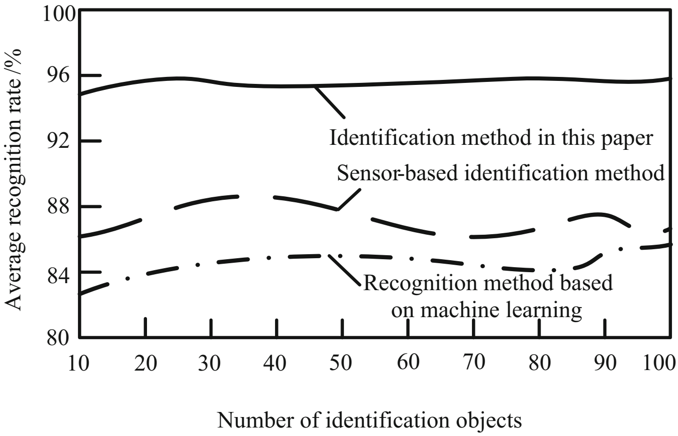

Fig. 3. Average recognition rate of different methods

It can be seen from Fig. 3 that when using this method for action gesture recognition, it can still maintain a high level, with an average of 95.6%, under different numbers of recognized objects, while the average recognition rate of other methods is below 89%, and the recognition effect of dynamic actions is far less than that of this method.

According to the above analysis, it can be seen that the dynamic recognition method of track and field movement posture based on mobile monitoring technology has higher recognition effect for track and field movement posture.

4 Concluding Remarks

If track and field athletes want to achieve excellent results, they must go through systematic training for many years. Among many high-level sports teams, many excellent athletes who can win gold medals are plagued by injuries and injuries, which is the most difficult problem that coaches need to face. The standard and scientific sports posture is the foundation of athletes' sports career, which can maintain and expand the competitive state of excellent athletes and achieve more excellent sports results in future competitions. In this paper, a dynamic identification method of track and field movement posture based on mobile monitoring technology is proposed. By using the mobile monitoring technology, the moving posture of athletes during track and field training in the training ground can be effectively dynamically identified after image analysis and processing. Compared with other gesture recognition methods, the experimental results show that the proposed gesture dynamic recognition method has higher recognition accuracy and efficiency, and can assist the daily development of track and field training.

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