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Research on Basketball Shooting Action Based on Image Feature Extraction and Machine Learning

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ABSTRACT In modern sports training, collecting and analyzing basketball player's posture data is of great significance for improving the scientific of the coach's training plan and improving the athlete's training effect. The existing basketball action recognition technology has many challenges such as low efficiency and high error rate. In order to effectively identify the basketball player's sports posture and improve the athlete's training effect, this paper proposes a basketball shooting gesture recognition method based on image feature extraction and machine learning. First of all, the action posture data of basketball players is collected by image feature extraction method, and multi-dimensional motion posture features are extracted from time domain and frequency domain. Then, through the method of feature selection and Gaussian hidden variables, the accurate classification and recognition of basketball shooting gestures are realized. The actual case analysis and the assessment of shooting action recognition effect show the superiority of the achieved basketball shooting action recognition technology. This method can provide scientific reference and basis for the development of modern basketball training.

INDEX TERMS Basketball shooting, image features, machine learning, Gaussian hidden variables.

I. INTRODUCTION

In the process of basketball training and competition, coaches need to formulate corresponding training plans according to the individual conditions of different athletes to improve the basketball skills of athletes [1], [2]. The traditional training method is based on the coach's own training theory and training experience, combined with the basketball player's skill level to develop a training plan. This training mode is very subjective, and the coach needs to spend a lot of time to analyze the athlete's posture, and it is difficult to objectively evaluate the athlete's training effect [3]. The core of modern sports training is precision and efficiency. If the coach can accurately control the athlete's movement posture, it can greatly improve the training effect. Therefore, collecting and analyzing basketball player's posture data and accurately recognizing the sport posture are of great significance for improving the scientific of the coach's training plan and improving the athlete's training effect [4], [5].

Basketball gesture recognition is a kind of human gesture recognition. At present, the methods of human body gesture recognition mainly include two types. The basic idea of inertial sensor recognition is that the athlete's body wears a simple and lightweight data collection sensor, sends the collected data to the processing terminal in real time, and recognizes the athlete's posture based on various posture data. However, the disadvantage of this type of method is the large amount of equipment, which is not conducive to popularization and application [6]. Posture recognition based on image acquisition can be divided into monocular video recognition and multi-eye video recognition according to the number of image acquisition devices. The general idea of image acquisition gesture recognition is to first use the camera to collect the athlete's image or video, then extract the motion features hidden in the image and video, and finally design a classifier to recognize the athlete's athletic gesture [7]. Urtasun use a balanced Gaussian process dynamic model to guide the tracking of three-dimensional human motion in a monocular video sequence. The dynamic model is learned from fewer sports training data containing multiple modes [8]. Sigel et a1. In this paper, a Bayesian framework is proposed, which includes sequence importance sampling and annealing particle filtering, and multiple motion models are used in tracking [9]. In order to make the

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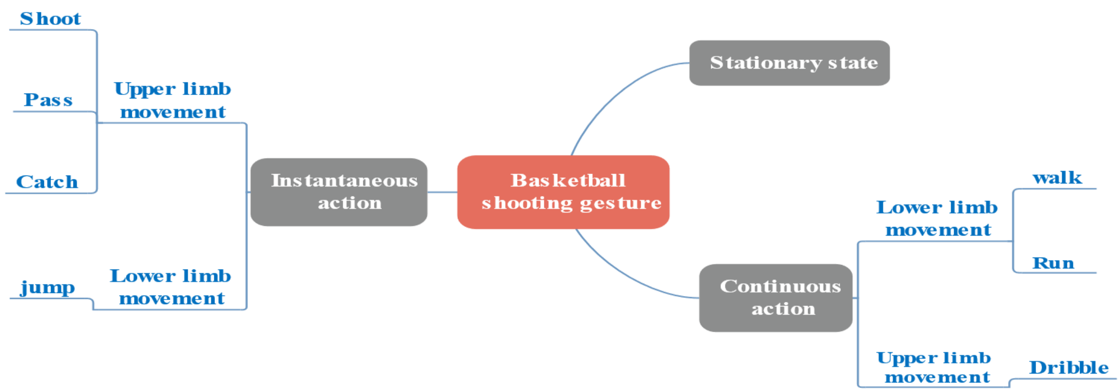

FIGURE 1. Classification structure of basketball shooting posture.

three-dimensional pose recovery more in line with anatomical joint constraints and reduce the search space dimension, the framework learns the motion model from the training data and uses the virtual marked Euclidean distance difference as the measurement error. Image acquisition gesture recognition technology is relatively mature, and the accuracy of gesture recognition is also high [10]. This kind of method can make up for the shortcomings of sensor collection and recognition, and has become a hot method of basketball gesture recognition research.

Based on the above analysis, this paper combined with machine learning and image feature extraction and other new technologies to build a basketball shooting gesture recognition model. Through the feature selection method and machine learning to achieve the basketball player's posture recognition, the experimental results verify the effectiveness of the method. This method can provide a scientific reference and basis for the development of modern sports training.

II. RESEARCH ON BASKETBALL SHOOTING ACTION

The research of basketball shooting movement belongs to the field of human motion tracking. In the field of computer vision, human motion tracking has become an urgent research topic in the past two decades. Human motion tracking is an important branch of computer science and technology and artificial intelligence. The purpose of machine vision is to enable electronic systems composed of various computer imaging elements to obtain visual information like the human eye, and the machine realizes the understanding and analysis of visual perception and feeds it back to humans. Simply put, it is to make the machine have human visual discrimination ability [11]. A complete visual perception system should generally contain these contents: visual information collection, visual information processing, feature expression, storage and transmission of visual information. Generally, electronic devices or systems with control and sensing are used to collect the initial visual data, and then the captured visual information is deeply characterized and compressed by the computer system, and then processed and analyzed, and finally the processed visual data is stored And carry out the necessary network transmission, so as to realize all the functions of a complete human biological vision system [12]. The computer system forms a clear and meaningful expression of the captured visual information, so as to achieve visual perception of the objective world. Throughout the process, the processing of visual signals is the focus and difficulty of research in the field of machine vision.

A. BASKETBALL SHOOTING

The classification structure of basketball postures is shown in Figure 1. The process of basketball involves very complicated human movements. Before designing a basketball sport posture recognition algorithm, it is necessary to establish a basketball sport posture classification [13].

The classification structure of basketball postures is shown in Figure 1. The process of basketball involves very complicated human movements. Before designing a basketball sport posture recognition algorithm, it is necessary to establish a basketball sport posture classification [13]. Scientific and reasonable posture classification is the basis for accurate recognition of basketball postures. In order to effectively recognize the posture of basketball, according to the physical state of the basketball player, the posture is first divided into a sport state and a static state. The sports state corresponds to the state of the athlete when he completes various basketball actions, at which time the athlete's limbs are in motion. The static state refers to the strict static state of the athlete's limb processing, without any movement. The key point of basketball posture recognition is the recognition of various sport postures. In order to effectively identify the various sports postures of basketball, the sports postures are divided into two levels progressively. The first layer divides the posture into two categories according to whether the movement state is cyclic: continuous movement and instantaneous movement. The second layer further divides the posture into seven postures of walking, running, dribbling, jumping, shooting, passing and

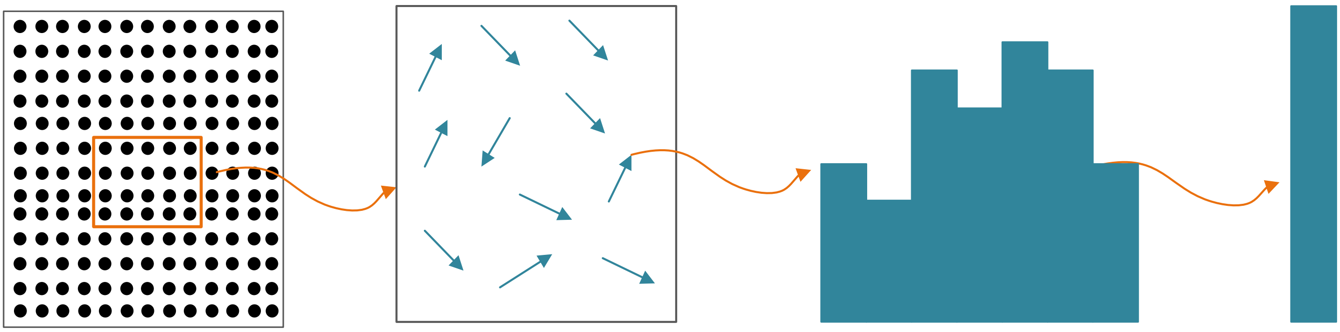

FIGURE 2. Schematic diagram of statistical feature extraction methods such as SIFT and HO.

catching according to whether the upper limb movement or the lower limb movement is in operation. Basketball sport posture recognition is the automatic recognition of seven sports postures of basketball players [14].

B. IMAGE LOCAL FEATURES

Most of the existing learning-based visual recognition methods use local image descriptors such as HOG or SIFT, which mainly rely on the calculation of the local gradient changes of video images or other natural images, or the local area image. The histogram is used for voting statistics, and finally a feature description with statistical properties for the entire image is formed [15]. The specific schematic diagram is shown in Figure 2.

Another origin of local image feature is inspired by biology. The biological visual system is naturally based on local visual features. Wiesel and Hubel proposed the biological visual receptor, which is a processor of natural local visual features [16]. Marr's visual theory also believes that the processing of the bottom layer of the image should be attributed to the acquisition of local visual features of the image. Elements of Mart's visual theory include edges, corners, trunks, lines, and terminal points [17]. Therefore, the traditional idea is to study the information extracted from ridges, spots, and edges. At present, some research institutions want to prove that the use of these local features can also restore the information of the original video image. The result is that under certain conditions, all the information of the original image can be expressed by edges or spots, which has become the current the necessary theoretical basis for image compression and texture simplification. At the same time, the HMAX model proposed by Pugio Vision Lab, which was originally a global feature, is now gradually being combined with the local image features studied in machine vision [18]. Compared with the global image feature, the advantage of the local image feature is that the processing of the local image information improves the robustness to illumination changes, posture deformation, and viewing angle changes. The disadvantage is that compared with the global special extraction, the extraction of points of interest is more time-consuming, and the local feature points need to be located and matched [19]. In the research of local image features, a current mainstream direction is to study new image descriptors and study new local feature learning models. For the visual model itself, it has a certain layering or interrelated characteristics, and the model itself can also be regarded as a sub-feature of a larger model, so that a batch of image features are formed.

III. MOTION TRACKING BASED ON IMPROVED SGPLVM

In previous studies, the Gaussian latent variable model and its variants have been widely used to learn a priori poses from training data for 3D pose estimation and human motion tracking. But most of the methods are plagued by the following two difficulties: 1) a good initialized hidden variable; 2) large-scale observation data processing. Unfortunately, these two points will always exist in human motion tracking [20].

This paper proposes a method based on random initialization of hidden variables to solve these two problems. The motion tracking method based on the improved random Gaussian latent variable model has the following two advantages. 1) In the initialization phase of the hidden variable, use the K-means algorithm to cluster the randomly generated hidden variable, select the cluster center as the initial reference point, and select the nearest neighbor point of the point as the element of the gradient calculation in the hidden variable [twenty one]. 2) After selecting the reference point, LPP (Locality Preserving Projection) projects the original three-dimensional hidden variable into N-dimension, and selects the nearest neighbor point of the reference point. The improved algorithm has made great improvements in the selection of initial points and computational complexity, making the tracking results more robust and accurate.

A. HUMAN MOTION TRACKING

The main task of human body motion tracking is to detect the human body contour from the video image, and then locate the joint points of the human body, on this basis, recognize the human body motion posture, and finally reconstruct the three-dimensional human body motion posture. Since the current video image is the projection of

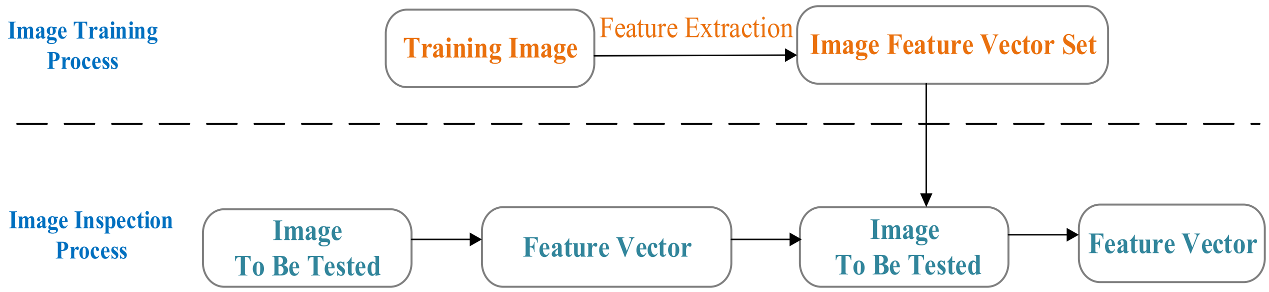

FIGURE 3. Learning-based human motion tracking framework.

the human silhouette in the three-dimensional scene on the two-dimensional image, a large amount of depth information is lost, and during the movement of the human body, the self-occlusion of the human limbs often occurs, and the video image is ambiguous, which makes It is difficult to recover human motion posture from unmarked monocular video [22]. However, because human motion tracking based on monocular video has potential applications and economic value in various aspects such as medical treatment, sports training, animation production, and intelligent monitoring systems, it has attracted the attention of many scholars. So far, video-based human motion tracking methods are mainly divided into the following two categories.

The first is a learning-based human motion tracking method. This method first extracts accurate image features from the training video image and target video image databases, then learns the mapping between the image features of the training video image database and the motion capture data, and finally uses the human features directly on the target video image to recover the three-dimensional attitude. Such as Urtasun et a1. It is to use a balanced Gaussian process dynamic model to guide the tracking of three-dimensional human motion in a monocular video sequence. The dynamic model is learned from fewer sports training data containing multiple modes [23]. Sigel proposed a Bayesian framework, which includes sequence importance sampling and annealing particle filtering, and uses a variety of motion models in tracking. In order to make the three-dimensional pose recovery more in line with the anatomical joint constraints and at the same time reduce the dimensionality of the search space, the framework learns the motion model from the training data and uses the virtual marked Euclidean distance difference as the measurement error [24]. The disadvantage of this method is that it takes a lot of time to extract accurate image features, and video tracking is limited by whether there is a learning database. If there is no learning database, video tracking cannot be completed. Human motion tracking based on learning can be represented in Figure 3.

The second is a model-based human body motion tracking method. This method does not need to learn a database, directly extract image information from the target video image, establish a similarity function between the target image and the model, and then optimize the similarity function to search for the optimal state in the high-dimensional state space, thereby obtaining Accurate human posture [25]. For example, C of the French National Institute of Information and Automation (INRIA) Smirches and A. Jepson used this method in his article to achieve motion tracking using multiple human models [26]. In the article, Detacher et a1 used boundaries and silhouettes as image features to construct a weighted similarity function, and applied annealing particle filtering to achieve human body motion tracking [27]. Since this method only establishes a similarity function, the method used to optimize the similarity function is easy to fall into the local optimum when searching for the optimal result, resulting in inaccurate tracking of the posture of the human body, and the algorithm has high time complexity. A complete model-based human motion tracking framework is shown in Figure 4.

B. GAUSSIAN LATENT VARIABLE MODEL

First, a brief review of the Gaussian latent variable model. The Gaussian latent variable model was developed by Neil in 2004. Lawrence proposed a non-parametric model for solving high-dimensional complex regression problems. He interpreted PCA as a special Gaussian process from a low-dimensional hidden variable to a high-dimensional observation space [28]. With prior knowledge, the covariance function is used to constrain the mapping to linear, so that the Gaussian model can be regarded as a special PCA. For the traditional Gaussian latent variable model, first make an assumption: the high-dimensional data that has been observed can be represented by some unobserved low-dimensional latent variables, which constitute what we call latent variables [29].

To understand the Gaussian latent variable model, you must know some basic variable expressions. The first is the representation of observation data. Generally, $Y = [y_1, \cdots, y_n]^T, (y_i \in R^D)$ is used to represent observation data, where D is the dimension of the observation space. The unobserved hidden variables are denoted by $X = [x_1, \cdots, x_n]^T, (x_i \in R^Q)$, and Q is the dimension of the hidden variables. The relationship between the observation space and the hidden variable can be represented by a

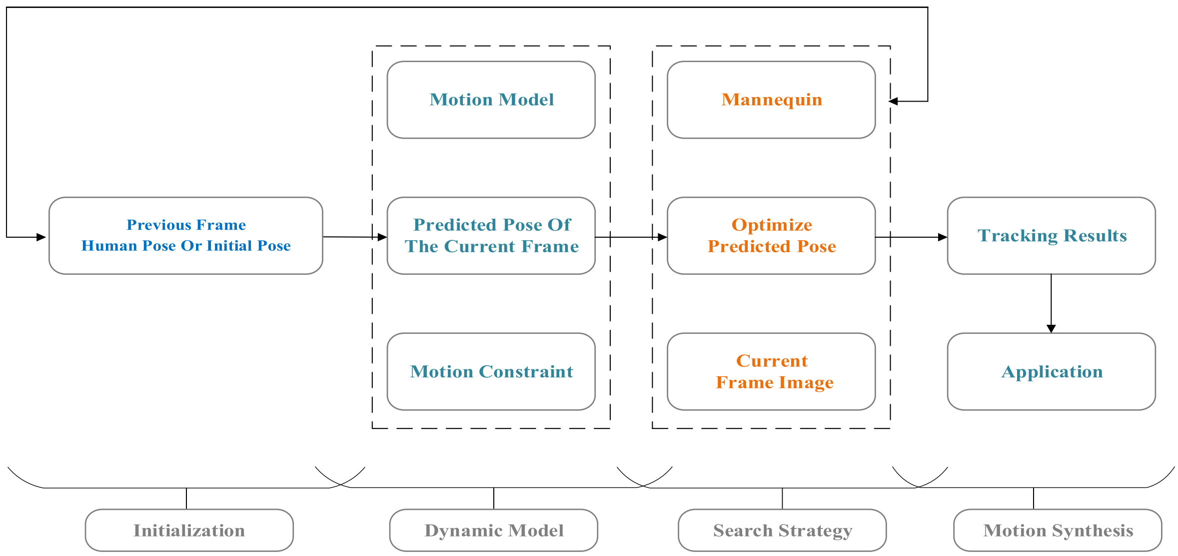

FIGURE 4. Model-based human motion tracking framework.

non-linear mapping: $y^{(d)} = f(x) + \varphi$, in this equation φ is zero-mean Gaussian noise. $y^{(d)}$ is the d observation vector in the observation space. From Bayesian point of view, the mapping can be expressed by the following formula.

$$f(Y|X,\beta)=\frac{1}{\sqrt{(2\pi)^{ND}|Ker|^{D}}}\exp(-\frac{1}{2}tr(K^{-1}YY^{T})) \quad (1)$$

In which, Y is the observation data, X is the hidden variable of the observation data, β is the nuclear hyperparameter, is the number of samples of the observation data, and N is the dimension of the observation space. D is a kernel function, which is used to determine if Ker is very close in the observation space, then the corresponding hidden variable y_i, y_j is very close to the position of the hidden variable [30].

$$\bar{L}_{Los}(h)=32.5+20\log_{10}(f)+10\gamma\log_{10}(h)+A\times h \quad (2)$$

A layer of Sigmoid function mapping is added to the feature-to-result mapping to limit the predicted value to [0, 1], and the probability of different categories can be output. Probability $p(y = 1|x, \theta)$ represents the probability that y belongs to 1 given the characteristic variable x, and $h_\theta(x) = p(y = 1|x, \theta)$, there is a logistic regression model.

$$h_\theta(x) = [1 + exp(-\theta^T x)]^{-1} \quad (3)$$

In which, $\theta = \{\theta_0, \theta_1, \cdots \theta_p\}$ represents the coefficient value corresponding to each feature. The value of θ can be obtained by solving the maximum likelihood estimation function. It is assumed that each sample in the data set is independent of each other [31].

$$l(\theta) = \prod_{i=1}^{n}[h_\theta(x)]^{y_i}\cdot[1-h_\theta(x)]^{1-y_i} \quad (4)$$

The elements in the Ker function can be represented by $Ker_{ij} = ker(x_i, x_i)$.

$$ker(x_i, x_j) = \beta\exp(\beta_2\left\|x_i - x_j\right\|^2) + \beta_3 + \beta_4\delta_{x_i x_j} \quad (5)$$

This is a general radial basis function with Gaussian noise, where the vector is a kernel hyperparameter, which can help control the output variance. The radial basis function RBF (Radial Basis Function) controls the kernel width through additional noise [32]. In fact, the Gaussian latent variable is a process of estimating the position of the latent variable and nuclear hyperparameters. According to Neil D. According to Lawrence's theory, the latent variables and nuclear hyperparameters can be determined through maximum resolution estimation, which means that the negative logarithmic resolution function needs to be minimized.

$$\begin{aligned}\zeta &= -\ln p(Y|X,B)\\ &= -\frac{DN}{2}\ln 2\pi - \frac{D}{2}\ln|Ker| - \frac{1}{2}tr(Ker^{-1}YY^T)\end{aligned} \quad (6)$$

In general, in order to solve X and β by using the gradient descent method, the gradient of the negative logarithmic resolution function is obtained for X and β, respectively.

$$\begin{aligned}\frac{\partial\zeta}{\partial X} &= \frac{\partial\zeta}{\partial Ker}\cdot\frac{\partial Ker}{\partial X}\\ &= -(Ker^{-1}YY^TKer^{-1} - DKer^{-1}) * \frac{\partial Ker}{\partial X}\end{aligned} \quad (7)$$

$$\begin{aligned}\frac{\partial\zeta}{\partial \beta} &= \frac{\partial\zeta}{\partial Ker}\cdot\frac{\partial Ker}{\partial \beta}\\ &= -(Ker^{-1}YY^TKer^{-1} - DKer^{-1}) * \frac{\partial Ker}{\partial \beta}\end{aligned} \quad (8)$$

However, in most cases, when calculating the logarithmic resolution function with respect to gradients, there is usually a very difficult problem: the training data is too large. The calculation complexity of the gradient will increase with the increase of the sample number, and the geometric series will increase, which is unbearable for the calculation of the inverse function of the kernel function. Therefore, solving

TABLE 1. The specific status of the test database.

Database		Human Eva Subject 1 C1			
Pose		Jogging	Gesture	Walking	Boxing
Size	Train Set	X=220*768	X=401*768	X=588*768	X=400*768
		Y=220*60	Y=401*60	Y=588*60	Y=588*60
	Test Set	X=220*768	X=401*768	X=588*768	X=400*768
		Y=220*60	Y=401*60	Y=588*60	Y=400*60

the Gaussian latent variable model is a very challenging problem [33].

To solve this problem, Angle Yao and Raquel Urtasun proposed a Gaussian latent variable method of stochastic gradient descent to reduce the computational complexity and avoid falling into the local optimum [34]. The idea of this method is to randomly extract the points near the reference point as the hidden variable of the gradient when calculating the gradient, so as to replace all the hidden variables. It can be expressed by the following formula.

$$\frac{\partial \zeta}{\partial \beta} \approx -(Ker_R^{-1} Y_R Y_R^T Ker_R^{-1} - DKer_R^{-1}) * \frac{\partial Ker_R}{\partial \beta_R} \tag{9}$$

$$\frac{\partial \zeta}{\partial \beta} \approx -(Ker_R^{-1} Y_R Y_R^T Ker_R^{-1} - DKer_R^{-1}) * \frac{\partial Ker_R}{\partial \beta_R} \tag{10}$$

In which, Ker_R is the kernel matrix relative to the neighbor space X_R, is the relevant observation vector, and Y_R is the selected reference point.

However, the disadvantage of this method is that for randomly selecting initialization reference points, the results obtained in different trials are quite different. Sometimes there is an unexpected attitude error. The selection criterion for the neighbor points is too simple. Only the point with the closest Euclidean distance is selected as the neighbor point, while ignoring other distances from the reference point, but it has a greater impact on the gradient [35].

IV. CASE ANALYSIS OF BASKETBALL SHOOTING BASED ON GRAPHIC FEATURE EXTRACTION

Action analysis through actual basketball shooting images is an effective method to study the characteristics and effects of basketball action. The test data can be used to analyze the relevance of basketball players' shooting rate and personal movements, work norms and other aspects. Since the 21st century, there have been a large number of literature reports on the research of basketball shooting, mainly in Europe, the United States and Japan [36], [37]. The above describes the theoretical basis of basketball shooting action research based on image feature extraction and machine learning. This section analyzes and verifies the practicability and efficiency of the method by analyzing actual case tests.

A. TEST ENVIRONMENT AND DATA SOURCES

This paper uses simulation experiment condition settings: this experiment is compiled on Python, and the execution environment is HP workstation under Windows 10 framework. The video images used in this experiment come from the Human Eva database of Brown University in the United States. The original image size is 640∗480. After preprocessing, the original image contains the human body size of 64∗192. The original video human motion posture used in this experiment is shown in Table 1.

B. PACKET LOSS RATE AND RESPONSE TIME TEST

In the technical performance testing process, the system response time and packet loss rate are used to test the system's concurrent performance and customer response performance. Limited to the network environment and server performance have a greater impact on performance indicators. The network environment during the test was selected as the internal network. The server was a stand-alone server with a brand-new system and a cluster with two stand-alone servers. The test tool was Mercury LoadRunner. This article uses the Mercury LoadRunner tool to create concurrent accesses and perform performance tests on systems in a single server environment and systems in a cluster environment. By sorting the recorded data, the results shown in Figure 5 and Figure 6 are obtained.

It can be seen that the number of concurrent services closest to the system is 400 in a single-server server environment, and 700 is closest to the system in a cluster environment with two servers. The test results show that the performance of the system can meet the demand, and can be reused in a multi-system environment, and the performance can be further improved through later expansion. Analysis of simulation results. The improved random Gaussian latent variable model tracks the video images of different motion states basically the same as the real human motion posture. This method effectively solves the ambiguity problem of human motion tracking, and improves the accuracy and stability of tracking. The main reason is that this method uses K-means clustering to find the initial reference point and LPP to find the neighbors of the reference point, which makes the learned model highly stable and can accurately track different motion states.

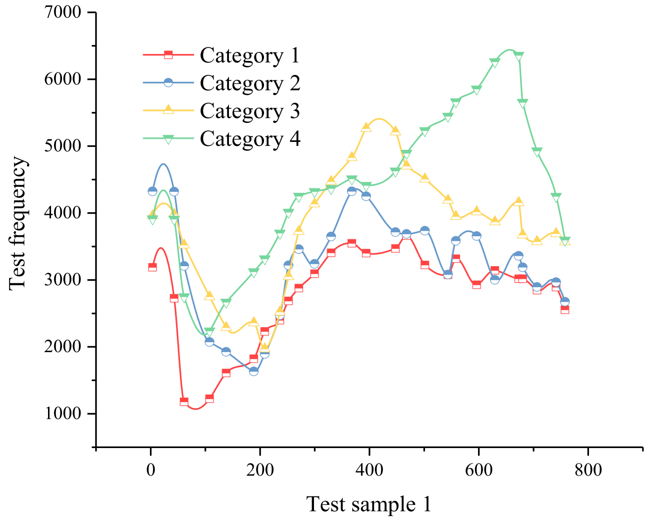

FIGURE 5. Basketball shooting action technical response time test.

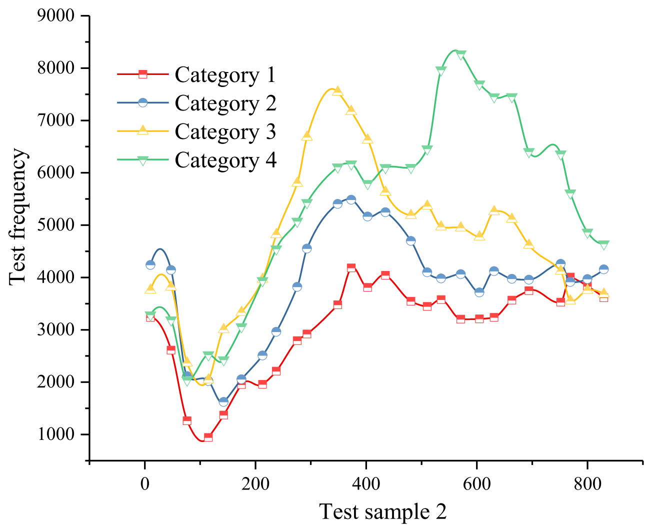

FIGURE 6. Basketball shot action technology packet loss rate test.

C. COMPARISON OF BASKETBALL SHOT RECOGNITION EFFICIENCY

Basketball player's sport posture recognition is to construct a classifier that can recognize the player's posture based on the image recognition collected data features, input the extracted posture features into the classification, and the classifier outputs a specific basketball action. After feature extraction, a three-dimensional feature parameter set that recognizes the attitude of basketball players is obtained. However, some of these characteristic parameters are features that are not related to the basketball player's posture or have low correlation, and some of the information expressed between the features is redundant. If these features are input into the classifier at the same time, it will not only reduce the recognition performance of the classifier, but also seriously affect the recognition efficiency of the classifier. Therefore, before performing basketball sport gesture recognition, feature selection is required. The purpose of feature selection is to filter out feature parameters that are highly relevant to basketball player's posture recognition while reducing data dimension. After experimental testing, the main component analysis method is selected to realize the selection of characteristic parameters. In the 32-dimensional feature, the optimal feature is selected based on the principal component analysis method. Next, a classifier is constructed to recognize the attitude of the basketball player. At present, there are many classifiers applied to human posture recognition, and theoretically it is difficult to analyze which classifier is more suitable for the gesture recognition of basketball players. To this end, we choose the widely used random forest, support vector machine, SOM neural network and Bayesian network to recognize the attitude of basketball players. Experimentally verify the performance of the classifier to select the best classifier.

To this end, according to the characteristics of the upper limb movement and lower limb movement of the athlete, a classifier is constructed to recognize the attitude of the basketball player. Random forest, support vector machine, SOM neural network and Bayesian network four-type classifiers recognize the results of upper limb movements and lower limb movements as listed in Table 2 and Figure 7 and Figure 8.

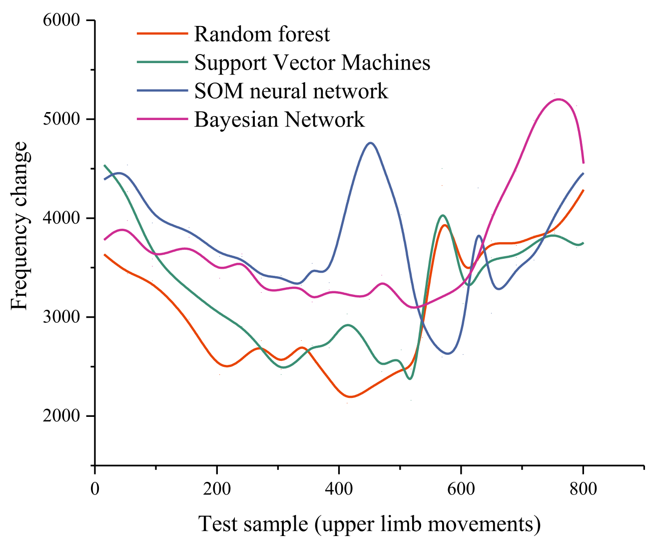

FIGURE 7. Comparison of basketball shooting action recognition effect (upper limb movement).

By analyzing the experimental results, we reached the following conclusions. For the upper limb recognition of basketball gestures, the Bayesian algorithm has the highest recognition accuracy rate, and the average recognition accuracy rate reaches 91.2%. For the lower limb recognition of basketball postures, the random forest algorithm has the highest recognition accuracy rate, and the average recognition accuracy rate reaches 94.1%. The experimental results verify the effectiveness of the proposed basketball recognition method based on multi-feature fusion and

TABLE 2. Basketball shooting recognition effect comparison table.

Attitude	*Random Forest*	*Support Vector Machines*	*SOM Neural Network*	*Bayesian Network*
Shoot (%)	85.3	82.6	86.9	91.4
Pass (%)	87.6	88.8	89.4	91.6
Catch (%)	91.3	94.1	93.5	92.2
Dribble (%)	92.0	89.9	91.8	89.9
Average (%)	89.05	88.85	90.4	91.275

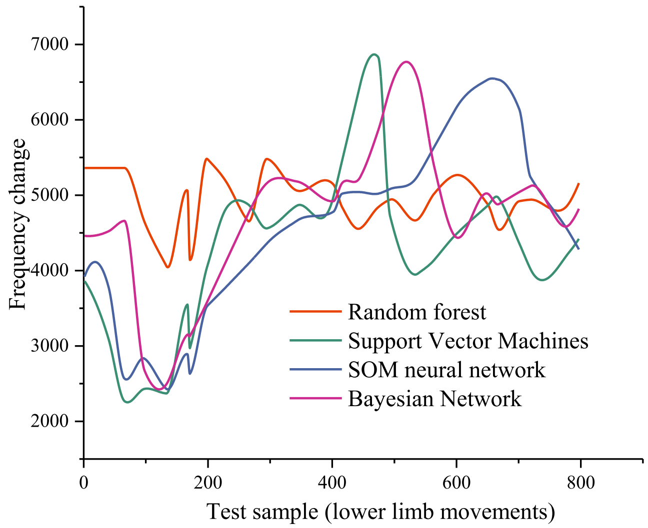

FIGURE 8. Comparison of recognition effects of basketball shooting movements (lower limb movements).

machine learning. The experimental results show that the Bayesian algorithm can be used to identify the upper limb posture of basketball, and the random forest algorithm can be used to identify the lower limb posture of basketball.

V. CONCLUSION

This paper mainly studies the gesture recognition of basketball shooting. Human motion tracking and posture recovery have many important applications in the field of machine vision. However, due to the inherent variability of human posture, the dimensionality of the observation data space is too large, the expression of human video image features is complex, and the influence of different experimental environments, etc., resulting in human motion tracking is still an open urgent need in the field of machine vision solved problem. In view of the above problems, this study starts from the action principle of basketball shooting, and firstly elaborates the background, reasons and current status of the research. After elaborating the theory of image feature recognition and Gaussian hidden variables, the accurate recognition of basketball shooting movements is realized. Practical case analysis and vibration impact assessment illustrate the superiority of the gesture recognition technology achieved. Due to the numerous methods of motion tracking analysis, the methods used in this article are still very limited. Therefore, using more abundant methods to study more representative basketball moves is the focus of future research.

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