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Research on Physical Fitness Prediction Model of Athletes Based on Computer Deep Learning

Abstract: - This project intends to study the sports monitoring system based on Android platform in combination with the current wide application of mobile terminal devices and the needs of athletes' daily sports monitoring. This project uses the currently popular head-mounted wireless headset as the main data acquisition terminal, and transmits and decodes data through the head-mounted cable and through the voice interface on the Android platform. Finally, these data are converted into the athletes' action data, and then the mobile terminal software evaluates the athletes' training effect. Simulation results show that the system improves the accuracy of sports training. Therefore, a low-cost athlete physical monitoring system is proposed in this paper, and its realization process is analyzed in detail.

Keywords: Physical Fitness; Monitor; Audio Class; Motion Monitoring.

I. INTRODUCTION

As an important research field of AI, computer vision is a new subject. Human-machine interaction is the process of information exchange between human and machine by using specific conversational language and machine through specific interaction mode. In recent years, with the rapid development of artificial intelligence, it has become an inevitable trend to introduce computer vision into human-computer interaction, and human posture recognition is a hot topic in current research, which has been widely used in road behavior monitoring and medical rehabilitation training. The core of physical fitness training system is to study how to identify and recognize human posture [1]. Human posture recognition refers to the accurate identification of the movement and posture of people in images or videos, which is a necessary condition for intelligent interaction and human-computer integration, and the integration of deep learning is a hot issue in the field of vision. Human posture detection is a key problem in machine vision, which is to obtain human posture from pictures or videos as the research object.

According to the difference of detection sequence, it can be divided into "Top-down" and "bottom-up". Top-down is to use the object detection network to locate the human body, and then introduce the part containing only the human body into the feature point extraction, so as to obtain the location information of the feature point [2]. The Bottom-up algorithm first locates the key points of the human body in each picture, and then forms multiple human body samples through the connection between these feature points. Compared with the Top-down method, the Bottom-up method is simpler, faster and more applicable [3]. It has been proposed that the integer linear optimization method is used for implicit de-noising of the candidate parts set, which can solve the pose problem of many people well, but the computational efficiency is very low. At present, some studies have proposed to improve the positioning algorithm of human body parts by using deep Cooter algorithm, and improve the positioning accuracy of human body parts by progressive algorithm, while reducing the calculation speed by 3 orders of magnitude. Some scholars correspond each key point to a "label", and then connect these key points with other key points in the same group, and then obtain the corresponding movement posture. Some researchers use heatmap as a feature extraction tool to obtain human local relevance by positioning regression of local closeness domains. Previous studies have used position intensity field (PIF) to locate various parts of the human body, and position correlation domain (PAF) to connect various parts of the human body, which is better in dealing with low resolution and complex background. Some studies use short distance movement to improve the accuracy of critical points, and then combine greedy decoding with Hough voting to combine multiple key points into a single pose estimation sample [4]. In the current machine learning, the commonly used classification methods are Naive Bayes, logistic regression, KNN,K-Means, decision tree, SVM, random forest and other seven methods. Naive Bayes is a classification method based on Bayes theory. This method assumes that each attribute is independent of each other, and can calculate the occurrence probability of each attribute in various situations,

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so it has strong practicability and practicability. Some researchers have studied data fusion algorithms based on pure Bayesian algorithms. The method predicts the probability of an accident. For binary classification problems that divide samples into "yes", "no", "qualified" and "unqualified", a common method is to perform Logistic regression analysis. KNN is a classification method using similarity measure [5]. The new sampling point is compared with the nearest K sampling point in the current sampling point, and the sampling points are divided according to their categories. At present, studies have shown that KNN is used for feature screening of gene chips to screen out small but most representative samples to improve the recognition rate. The decision tree algorithm is based on the tree structure to segment a group of decision nodes and leaf nodes. This method can effectively solve discrete and continuous problems, and has the characteristics of simple and easy to understand, adaptable to massive data, and effective solution to missing data. Among them, C4.5 algorithm, CART algorithm, ID3 algorithm is a more common algorithm. Support vector machine (SVM) is a classification method based on the maximum interval division, which searches the maximum value in this dimension by mapping the sample set. Many scholars have studied multi-class SVM algorithm. At present, some researchers have proposed AMSVM. An optimization algorithm based on multi-class support vector machine is proposed. Support vector machine (SVM) is an efficient and suitable machine learning method for high dimensions [6]. Traditional Bayesian methods are only suitable for standard types of data; The traditional linear regression method is prone to errors. Because random forest is a classifier composed of multiple decision trees, its modeling process is very complicated. SVM is easily disturbed by noise. K-Means method is susceptible to the interference of cluster center location and is insensitive to outliers. KNN method has the advantages of large computation and large computation, and it is easy to implement without presupposition or modeling. KNN is insensitive to outliers and has high accuracy [7]. In addition, KNN also has good scalability, and its computation depends only on the value of K and the size of the sample, so it is very suitable for massive or high-dimensional data. Various data and behaviors in the moving process are analyzed by means of motion capture. But this method is very difficult to use, and the cost is high. Therefore, a low-cost athlete physical monitoring system is proposed in this paper, and its realization process is analyzed in detail.

II. Design of athlete physical fitness prediction system

A. Architecture

In view of the characteristics of high data dimension, marked data set and fitting, KNN method is used to classify them. When the data dimension is high and the data scale is large, principal component analysis is used to reduce the dimensionality. In order to meet the requirement of real-time performance of this system, the paper chooses the Blythe Bose algorithm which is more suitable for mobile phone terminal, and greatly accelerate the detection speed through improved human posture tracking strategy and lightweight human posture estimation network [8]. The system is mainly composed of two modules: physical counter and body multi-class classifier. A method of human feature parameter recognition based on Blythe wave pattern is proposed, and then the key points of human body in video are extracted and compared with the sampled data to recognize the specific posture. The image data containing different categories of behaviors are transformed into feature point correlation vectors, and the principal component analysis method is used to reduce the dimensionality processing, thus reducing the computational complexity and ensuring the accuracy of the detection results. Finally, the best K is selected through the test, so as to achieve high-precision target recognition. In this paper, the overall architecture of the system is designed as shown in Figure 1 (the picture is quoted in Ultra Low Power DSP for Health Care Monitoring). This paper divides the entire software architecture into three parts: wearables, interface programs and Android applications. The function of wearable device is to complete the acquisition of basic information; Wearables can be linked to application software through interface software.

Due to the high complexity and degree of freedom of the measured object's motion trajectory, if the conventional NMS method is used for object detection, many candidate frames meeting the IoU threshold will be generated, and the detection complexity is high and the accuracy is poor [9]. Because of the high contrast of the human face and the small change in shape, a lot of the time, the movement information of the facial muscles comes from the face. BlazeFace model is used to automatically extract the face edge frame, and extract the face edge frame, including the middle point of the hip, the circular size around the whole body and the tilt Angle.

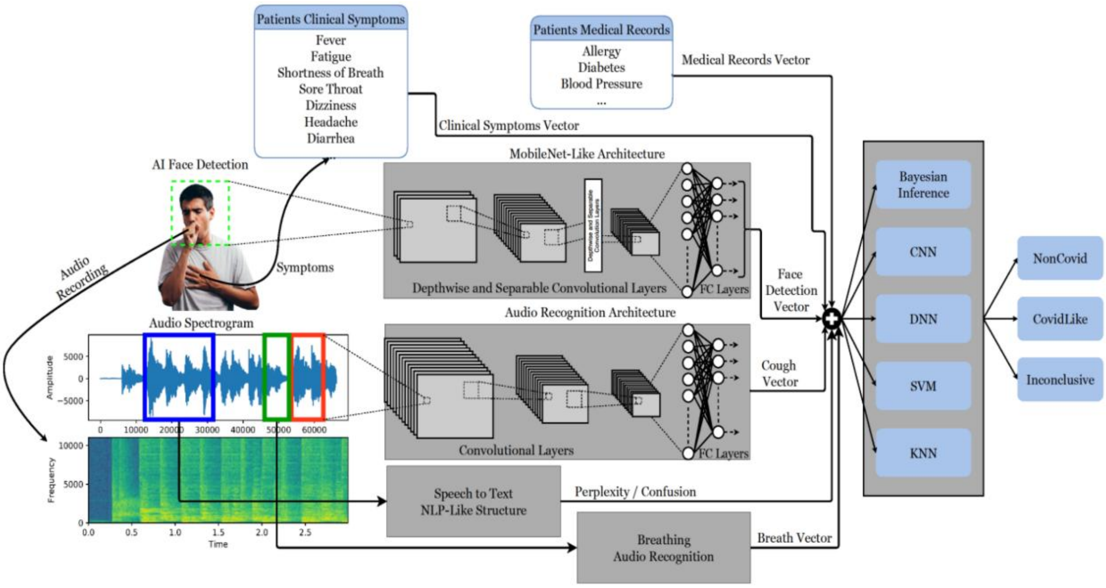

Fig.1 Overall architecture of physical fitness monitoring system

B. Design of data acquisition module

At present, most information acquisition relies on wearable devices. It's too much trouble for an athlete to wear such a big outfit. Therefore, in the process of playing the game, be sure to pay attention not to interfere with the daily activities of the athletes, such as the use of smart bracelets [10]. In view of the characteristics of athletes wearing headphones during the basic exercises, this paper intends to implant an intelligent data acquisition device on the headset to obtain movement information. Among them, in the wearable device, the MMA4755 chip is used, which can detect acceleration in three directions. For ordinary physical exercise, their acceleration will not change much, and for the accuracy of acceleration, more precision is required. With the topological relation of 33 joints on the human body surface as input, a 3D spatial pose detection model is established [11]. The pose detection network is established by heatmap, deviation set and regression, and its network structure is shown in Figure 2. The heat balance chart heatmap based on each node and equidistant deviation setloss are used to learn the center, left and right nodes of the network. The corresponding output layer is removed before the inference process, so as to realize the efficient application of the lightweight interpolation vector based on thermodynamics. MediaPipePose is a highly accurate human posture tracking algorithm developed by Google, which can extract 33 three-dimensional landmarks according to the three-dimensional characteristics of the human body, and classify the background of the human body. This architecture is shown in Figure 2 (image cited in the Improvement of Human Pose Estimation and rocessing With the Intensive Feature Consistency Network). The tracking program was used to predict 33 postural critical point coordinates. If the tracker determines that no one is present in the frame, the detector is executed again in the next frame.

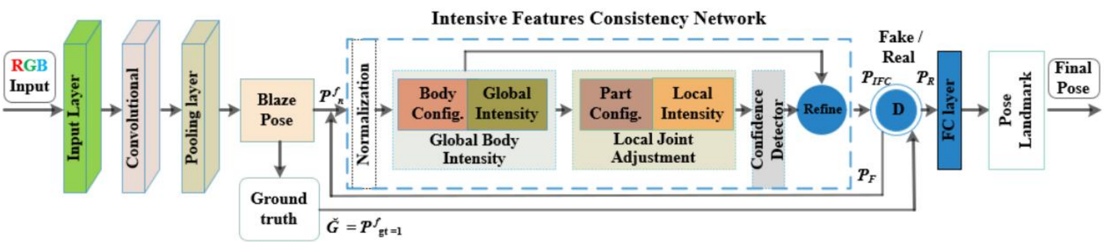

Fig.2 Media PipePose process architecture

Using Python programming to achieve a fire physical fitness training of intelligent speech recognition software, the specific implementation of the following steps. Firstly, the image data is imported into the training use case generation and testing, and then the key words are extracted and normalized encoded to obtain a set of multi-class pose recognition algorithm based on principal component analysis. The algorithm flow is shown in Figure 3 (see Sensors 2022, 22(7), 2489).

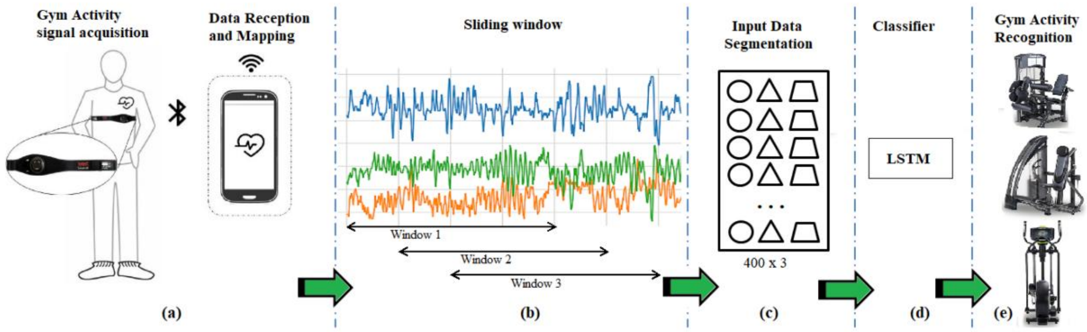

Fig.3 Overall process of physical training identification system

C. Function Design

This paper puts forward a kind of development trend of sports monitoring software which is different from the conventional sports monitoring software, that is, it mainly monitors the physical condition of athletes. So in terms of function, it is very different from ordinary motion monitoring software. The overall function of the system is designed as shown in Figure 4 (the picture is quoted in Appl.Sci.2019, 9(19), 3986).

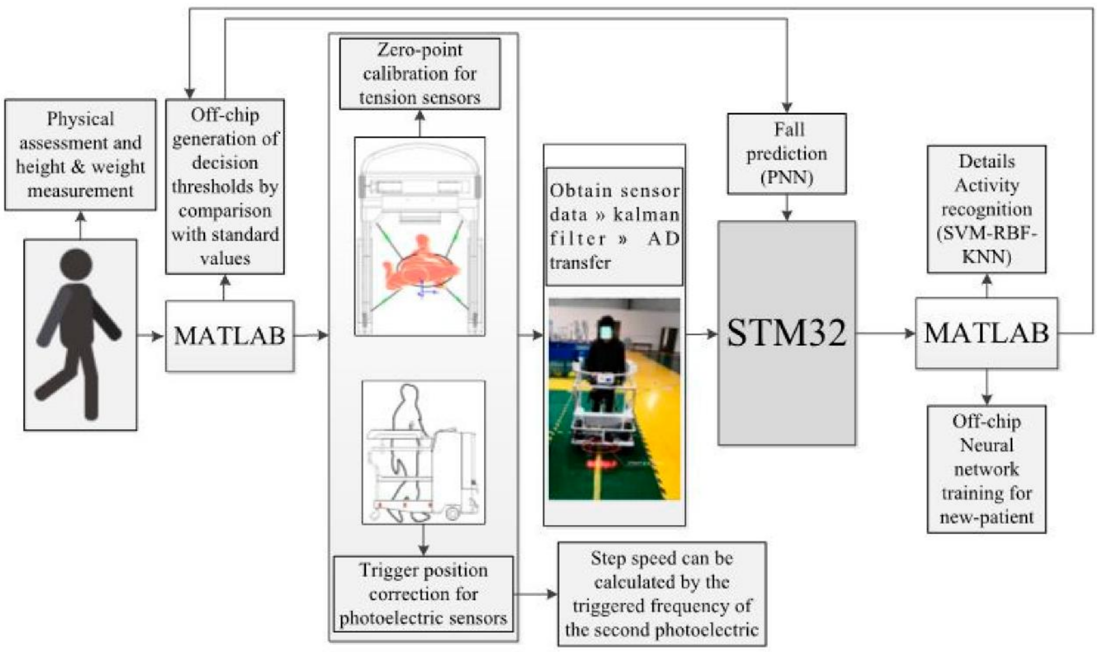

Fig.4 Overall functional design of physical fitness monitoring system

In the whole architecture, the functions such as system are divided into three levels: presentation layer, logic layer and hardware layer. A complete training system is designed, which includes personal data, respiration monitoring and movement monitoring. At the bottom of this architecture is Android, whose main function is to use it for voice systems [12]. The software uses the built-in sound processing device of Android to obtain the athlete's breathing, movement and other information in real time, and completes it through the human-machine interface.

D. Communication Design

At present, the main communication methods of smart phones are Bluetooth, hot spot, USB and so on. Each method of communication has its own advantages and disadvantages. For example, WIFI is now widely used. According to the 802.11 standard, designed a wireless communication technology with 802.11 as the core, and, due to the development of WIFI, can communicate between two different smart phones. However, whether it is Bluetooth, or wifi, they need more energy [13]. In addition to wireless transmission, there is cable transmission. On smartphones, the USB port and 3.5mm sound transmission are at the heart of it. For the two methods, the former consumes less energy, and the latter is faster. However, if you use USB, you must have a special USB interface. In this case, people recommend using earbud wire to transmit. In addition, the headset and Android phone communicate with 2 FSK, using the built-in interface software AudioRecod class to extract the voice signal, and then use 2 FSK to demodulate, and then use error correction coding to recover the original data.

III. IMPLEMENTATION OF ALGORITHM

The core problem of RBF network is how to determine the center and radius of the data set of RBF network. The center selection of RBF network generally includes: random choice center method, self-organizing choice center method, supervised choice center method, and orthogonal least square method [14]. Although based on Kolot's omogorov theorem, the number of middle-level nodes in the forward neural network is theoretically 2+1, the existing researches are all based on the existing prior information. However, this theory does not achieve ideal results in the selection of radial basis functions, because the number of cores has been determined, but it is difficult to determine how many sampling points in a large sample set, and the number of cores in this method is not only related to the number of nodes in the input layer of the network, but also to the number of input and output samples.

A. RBF neural network

RBF network is composed of three orthogonal layers, including input layer, intermediate layer and output layer. The intermediate layer uses a radiating basis function as the excitation factor, and obtains the following output:

$$g_n(U) = \varepsilon_0 + \sum_{i=1}^{n} \varepsilon_0 + \sum_{i=1}^{n} \varepsilon_i \phi(\| U - z_i \|) \tag{1}$$

ε_0 represents the threshold of the input, ε_i represents the weight of the input, and $\| * \|$ represents the Euclidean distance. $\phi(u)$ is a radial basic function, usually a Gaussian function:

$$\phi(\| U - z_i \|) = \exp\left(-\frac{\| U - z_i \|^2}{2\delta_i^2} \right) \tag{2}$$

z_i represents the center of the radius basis function, and δ_i represents the radius coefficient. Therefore, when selecting the RBF neural network with Gaussian function as radius, the center z_i, width δ_i, number of centers n and the weight of each node must be determined first [15]. The input end of the system is a linear element, and the weight is obtained by least square method. Therefore, how to choose the appropriate parameters is a very important problem in the construction of RBF network.

B. Subtraction clustering

The difference cluster method is a single method for the number and distribution of clusters in a sample set. Firstly, the sampling value $\{u_1, u_2, \cdots, u_n\}$ of the n dimensional cluster is taken as the central candidate point of the cluster. The density index of each cluster center is calculated. The density index on u_i is restricted to:

$$S_i = \sum_{j=1}^{n} \exp\left(-\frac{\| u_i - u_j \|^2}{(c_\gamma / 2)^2} \right) \tag{3}$$

c_γ is expressed as the neighbor radius of u_i. After calculating the concentration index of each sample point, the sample with a larger concentration index is selected as the clustering center. Suppose u_{z1} is the selected data and S_{z1} is its density index. Then, you need to use the following formula to represent the density index of each data u_i:

$$S_i = S_i - S_{zi} \exp\left(-\frac{\| u_i - u_{zi} \|^2}{(c_\zeta / 2)^2} \right) \tag{4}$$

c_ζ is a neighbor, and its density exponential function is significantly reduced. Clusters of clusters are usually represented by $c_\zeta = 1.5 c_\gamma$ to prevent clusters from being too tightly distributed [16]. After modifying the density index of each data, select the center u_{z2} of the next cluster to recalibrate all the density index of the data. This is repeated until the operation of $\frac{S_{z_k}}{S_{z_z}} < \delta(\delta = 0.5)$ terminates, and the number of clusters is obtained. Taking $U = \{u_1, u_2, \cdots, u_N\}$ as N G dimensional feature vectors of the measured sample set, formula (5) is used as the objective function of clustering to approximate the minimum value of this objective function during iterative optimization

$$F_m(A,B) = \sum_{j=1}^{N} \sum_{i=1}^{z} a_{ij}^m s_{ij}^2 \tag{5}$$

A is a membership matrix, B is the group center set of U cluster; Where a_{ij} is the degree of membership between sample u_j and the cluster center v_i of class i, and s_{ij} is the Euclidean distance $\| u_j - v_i \|$.

C. Learning algorithm of RBF neural network based on mixed clustering

It is A key problem to determine the number of centers n, center z_i and width δ_i in RBF neural network training. In the traditional method, by equating the number of middle-level nodes of the neural network with the number of training samples, each training sample is divided into its own core, thus reducing the learning speed and accuracy of the model. The difference cluster and fuzzy C-mean clustering method are used to classify the samples with similar characteristics [17]. The optimal number of clusters is the number of nodes in the middle layer, and the center of each cluster is the center of the basis function. The algorithm proposed in this project does not need to pre-test samples, and can automatically determine the number of middle-level nodes through the algorithm, greatly reducing the number of middle-level nodes, and achieving the purpose of reducing the complexity of the network.

IV. System implementation

A. Implementation of respiratory monitoring module

Through the detection of various indicators of the human body, people can better guide the training status of athletes [18]. In this system, the sound information obtained from the headsets is converted into the respiratory rate of the human body through calculation, so as to realize the monitoring of human respiration. The implementation process of the respiratory monitoring module is shown in Figure 5 (image quoted in arXiv preprint arXiv:2303.15585, 2023.). The whole algorithm formula is as follows:

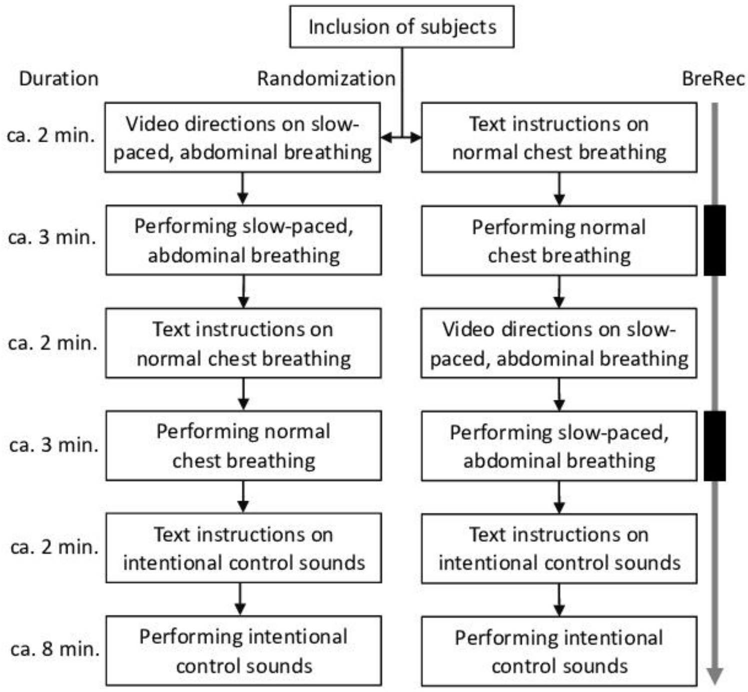

Fig.5 Breathing module algorithm

Because the athlete's breath cannot be measured through sound acquisition, it needs to be converted into a sound-to-respiratory frequency conversion [19]. In order to achieve the amount of sound converted into a breath, this paper adopts a method based on discrete Fourier transform, since this method is only suitable for discrete types of signals. By taking the Fourier transform in the time domain, cutoff it in the frequency domain, and then sampling it in the frequency domain, it is finally converted into a discrete array of finite length.

B. Implementation of motion monitoring module

In the design of motion model, the rotational speed is calculated by the three-way acceleration. The movement of the athlete is regarded as a three-dimensional space, in each dimension, by solving the acceleration in each direction, this process can be converted into the calculation of running steps. The detailed algorithm and implementation steps of this method are shown in Figure 6 (the picture is quoted in Automation in Construction, Volume 84, December 2017, Pages 214-230).

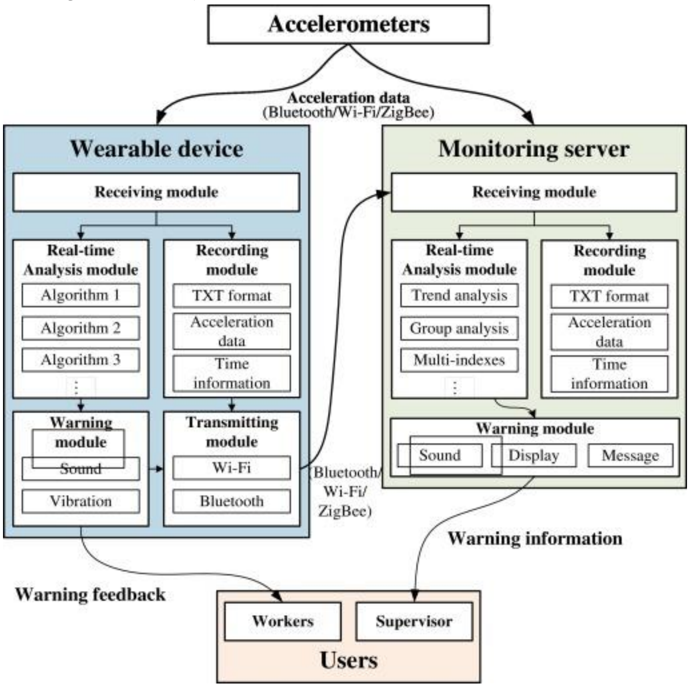

Fig.6 Algorithm of the motion monitoring module

C. Physical counting is realized

The function of the physical counter is to input the video of the firefighter's physical exercise or to monitor the whole process of training in real time through the video call camera, such as bending leg sit-ups, lying straight legs up at both ends, prone and upright at both ends, etc., through the real-time detection and identification of the body movement data, complete the detection and statistics of the body movement, which is divided into: Training set and inspection correction module, human key point standardized coding module, human posture standardized coding module, classification result smoothing module, classification result visualization module, action counting module, video detection module and video detection module. The essence of timing is the extraction and accumulation of movement behavior.

Taking the straight leg hard pull exercise as an example, the whole movement is broken down into two instantaneous states, namely up and down. The body bends the waist, leans forward, extends the hips back, lowers the two hands and grabs the bar handle, that is, presses down; When you're done, stand up straight and bring the bar back to your waist [20]. The method takes the image set images_in as the training sample and stores a fixed number of two state images. Each sample image covers the maximum number of photographic perspectives to enhance the accuracy and universality of the classifier. Media pipe software was introduced to build a pose model, and the image was simply processed to obtain 33 features of the human body (Figure 7).

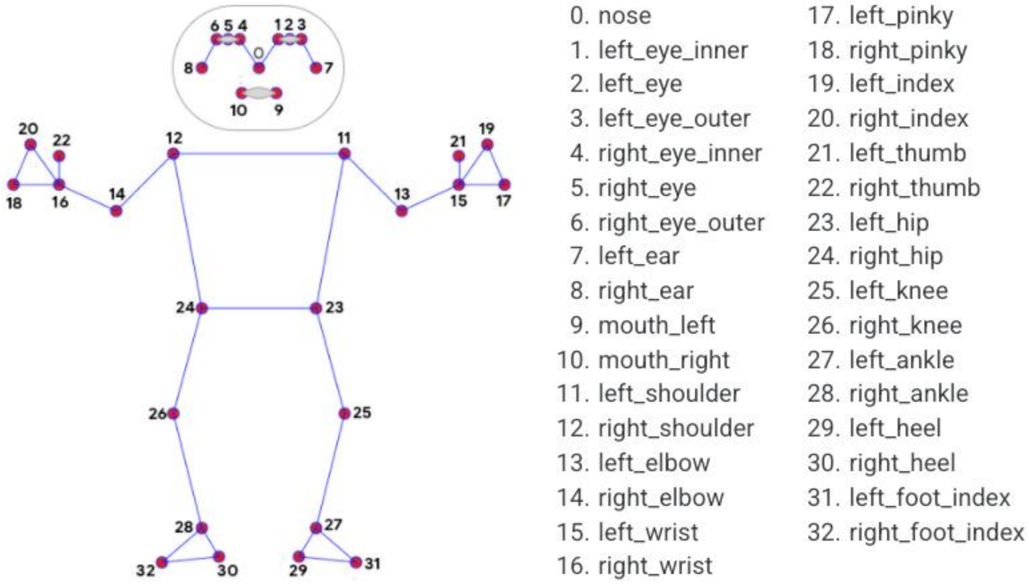

Fig.7 Human critical point identification results

The coordinates information is stored in a CSV file and key points on the output image are identified and linked. In each image, the position and proportion of the figure are not the same, that is, the starting point and rotation Angle of the coordinate axis on each image are not the same. The difference in scale will cause the difference in different dimensions, and the proportion of human body in the training sample will directly affect the final classification effect, resulting in great classification errors. Therefore, it is very necessary to standardize the spatial position of feature points. Discrete normalization is used to make a linear transformation of the original data, and the line with the left_hip and right_hip lines with 23,24 is taken as the horizontal axis, and a point in the line is taken as the starting point of the coordinates [21]. Calculate the distance between the midpoint and the interval of the left-shift sequence and right-shift sequence lines to determine their size. Finally, the space position between the key points is standardized to obtain the distance between the key points, so as to obtain the corresponding image feature vector. When performing various body exercises, the difference between the upper and lower parts of the body is larger than the difference between the left and right parts.

The image is divided into two levels, and 69 dimensions composed of 23 feature vectors are analyzed respectively, and the rotated feature vector is compared with the original image, so as to avoid the influence of the difference of perspective and orientation on the recognition effect. By inverting the center point on the yz plane, the eigenvector composed of the point set centered on the yz plane is obtained. The first maximum distance excludes an outlier in the training set, which is similar to a particular pose, but one of the nodes is tilted in the other direction, which is actually a pose type. Compare the maximum distance between the feature vector of the tested sample, the feature vector of the tested sample and the rolling feature vector. In order from largest to smallest, the best 30 samples will be taken as the next learning objects. The second step is to use the result of the average distance identification. By comparing the average distance between the 23 feature vectors of the 23 tested samples and the 23 flipped feature vectors, 10 samples with the minimum average distance are selected. Ten samples are counted, where the largest number of marks is the sample's classification value "up" or "down".

The counting module counts the number of times that a certain kind of posture is identified to get the counting result. Divide a video into a picture, and then treat it as a sample to be tested, and then specify a type to be tested is "up" or "down", and then count the number of identified classes in each picture, that is, the number of physical training you have completed. Finally, the final image detection effect is obtained through image smoothing and visualization (Figure 8 is quoted in Scaling up SoccerNet with multi-view spatial localization and re-identification).

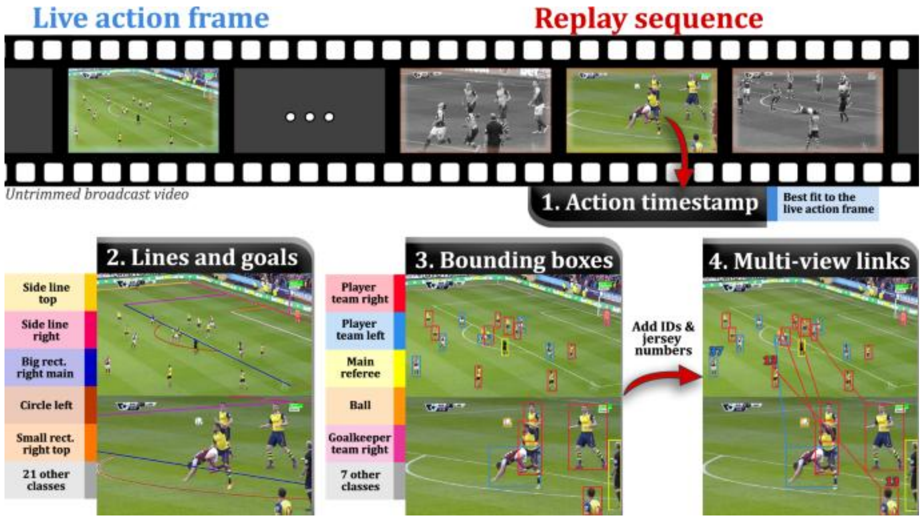

Fig.8 Video detection and counting results

V. CHECK THE SYSTEM

The function of the body classifier is to classify various body behaviors, and through the input of a certain behavior, it can be determined to belong to the type. These include straight leg hard pulls, pull-ups, push-ups, squats, lying on your back straight leg ends, parallel bar arm flexion. The image data included: 61 straight leg hard pull, 64 pull-ups, 74 parallel bars extension, 92 push-ups, 101 squatting, 54 straight leg two starts on the back, a total of 446. By keyword extraction and feature vector coding, six csv files were obtained. A set of behaviors is associated with a csv file. Each row has a behavior, each behavior has a category tag, and each behavior has a 23x3d feature vector. Finally, all CSv documents are integrated to form a labeled category set. With the increase of behavior types, it is necessary to reduce the dimension of behavior. In this method, only the upper two dimensions of the 3-dimensional information corresponding to each feature vector are saved, which is divided into the xy plane and becomes 46 dimensions. The dimensionality was reduced from 46 to 3 by PCA method, so as to achieve multi-dimensional visualization effect. The distribution of the six types of behaviors in 2-D dimension and 3-D space is shown in Figure 9. The same color dots represent the same types of behaviors, which verifies the correctness of this method.

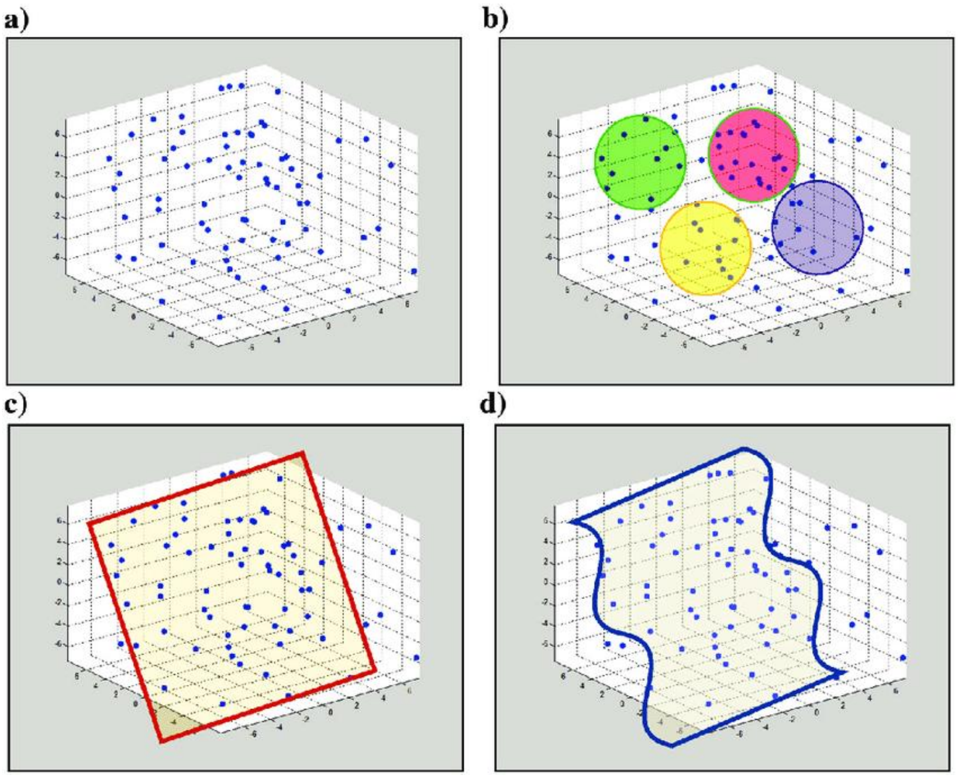

Fig.9 Data distribution in two-dimensional space and three-dimensional space

Through the reduced data, the KNN of 5-20 interval K is selected, a set of data is saved in sequence, the marks are deleted, and the rest is the training sample. By comparing with the real label, the corresponding scatter plot is obtained, and the best value of K is selected. In the case of K=6, the prediction accuracy is 99.25%. The performance of athletes is reflected through technical and tactical data during training and competition. For example, in a single match, four technical and tactical indicators, such as the player's service score rate, the success rate of receiving service, the score ratio of the bottom line strike, and the score ratio of the middle and front court interception, can show the player's competitive status. The index data collected by an athlete in the training process of the first phase are taken as the research object (Table 1).

Table 1. Various technical and tactical indicators and expert evaluation status of an athlete

Serial number	Serve /%	Serve received /%	Bottom line /%	Centre-front /%	Status
1	22.2	94.9	18.3	4.5	1
2	17.4	56.6	16.0	4.0	-1
3	18.5	92.8	14.9	2.8	0
4	23.0	87.4	13.8	4.3	1
5	20.1	69.9	14.2	2.9	0
6	16.3	63.6	15.2	4.9	-1
7	18.6	80.5	12.8	3.3	-1
8	20.5	47.6	17.4	5.0	0
9	21.5	84.8	16.0	3.6	0
10	27.4	81.6	14.3	3.0	0
11	26.5	81.8	13.8	3.9	0
12	23.0	84.6	14.5	3.3	0
13	14.8	91.6	14.0	4.2	0
14	23.1	81.7	18.5	4.4	1
15	25.7	95.0	16.4	4.7	1
16	21.7	94.0	16.0	4.2	1
17	22.1	91.1	17.6	3.6	1

Firstly, a hybrid clustering method is used to classify 17 samples, and the cluster centers of 6 clusters are obtained. The results are shown in Table 2.

Table 2. Shows the center of neural network obtained by clustering algorithm

Type I center	21.899	92.603	15.939	4.171
Type ii center	25.768	82.336	14.053	3.595
Type III center	22.699	88.004	18.193	4.394
Type IV center	21.347	85.154	15.845	3.628
Category v center	19.020	79.958	13.505	3.262
Type vi center	17.639	58.724	15.926	4.653

Then, the set of learning samples is obtained through the formula: $c_i = \frac{1}{|1_i|}\sum_{u \in 1_i} \|u - u_{zi}\|$ to find the width of the network center, namely the parameter value of the radial basis function. In a mesosphere network, the number of centers of clusters is the number of one node. This paper presents an RBF neural network based on multiple inputs, multiple inputs, multiple intermediate layers and one output. Through the study of 17 samples, a new RBF neural network is obtained. The method only uses 11 steps to achieve the goal, and the deviation is only 0.01. Through testing the 5 samples listed in Table 1, Table 3 is obtained by comparing with the conventional radial basis function. Satisfactory prediction effect is obtained. The forecast results are basically consistent with the measured data, and the forecast accuracy decreases from 0.083 to 0.0432. The fitting accuracy and prediction accuracy of this model are reasonable evaluation and prediction techniques.

Table 3. RBF prediction results after improved training algorithm

Serial number	Actual value	Traditional RBF prediction	Improved RBF prediction
1	1	0.992	1.035

3	0	-0.081	-0.096
7	-1	-1.190	-1.064
14	0	0.013	0.008
17	1	1.214	1.134

VI. CONCLUSION

The basic physical parameters of athletes are collected and processed in real time by means of voice and wearable, so as to achieve a simple physical fitness information acquisition purpose. The difference clustering method is used to classify the samples, obtain the number of clusters of the samples, and then re-optimize the cluster center using the fuzzy C-mean clustering algorithm, and finally determine the central width and middle layer structure of the RBF network. Experiments show that the algorithm proposed in this project has the characteristics of fast convergence, high classification accuracy, and the learning process is not easy to fall into the local minimum. This provides a new way of thinking for event prediction in sports competition.

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