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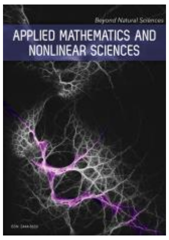

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Design and Application of SPOC Hybrid Teaching for College Basketball Teaching Based on Artificial Intelligence Technology

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Abstract

Students love basketball, but traditional teaching approaches are no longer able to suit their demands. In this article, artificial intelligence is combined with innovative teaching methods to create a new type of learning. Firstly, under the SPOC teaching mode, intelligent sensors are used to collect basketball sports data, and Kalman filtering is used for processing and segmentation. Then, through the definition of basketball sports gesture, the data division of basketball sports gesture, designing the basketball sports gesture feature extraction method based on unit division, and using the SVM method to analyze the basketball sports gesture features, designing intelligent SPOC hybrid basketball teaching. Finally, the experiments on data collection and motion attitude resolution in basketball are designed to investigate the effects of intelligent SPOC hybrid basketball teaching. The results show that the deviations of the collected acceleration and angular velocity are within 10^{-2} orders of magnitude and 1.8°/s deviation, respectively, and the average recognition effect of various basketball postures is 0.925, which is able to effectively carry out basketball motion recognition. The experimental class 1's physical quality improved by roughly seven after the teaching application was implemented, and the P-value for the improvement of different basketball sports was less than 0.05, indicating that the planned instruction can greatly enhance students' physical quality and basketball abilities.

Keywords: Smart sensor; Kalman filter; Feature extraction; SVM; SPOC hybrid teaching.
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1 Introduction

The mutual combination of relevant information technology and the field of education, along with the ongoing advancement of science and technology, fosters the ongoing development of education informatization. The integration of technology in the field of education can enhance student efficiency and classroom effects; in this regard, it also fosters the advancement of information technology in the field of physical education, which in turn directly advances the dissemination of the teaching methodology of the disciplines that combine education and physical education [1-2]. The benefits of information technology are demonstrated in the context of education through informatization, which can help students become more aware of and capable of independent innovation, as well as enhance their capacity to face and resolve challenges in their day-to-day study, employment, and personal lives [3].

China earnestly implements the guiding ideology of health first, takes enhancing students' physical fitness as one of the basic goals of school sports, and cultivates good sports habits and healthy lifestyles among young people [4]. In addition to putting health first, the fundamental ideas of physical education and health curricula also stress the importance of encouraging students' interest in sports and developing a lifetime understanding of sports. Basketball has always been a popular sport among young students and has been taught as a vital subject in physical education curricula at all levels and all kinds of schools. It also helps students develop lifelong physical exercise habits and the skills necessary to master sports exercise throughout their lives [5].

This paper examines the application of intelligent inertial sensor technology for basketball attitude recognition. The extended Kalman filtering algorithm is used to achieve data fusion from multiple sensors to improve accuracy and minimize noise interference during preparation and detection. Using a divided basketball motion posture unit, this paper extracts motion posture features by building a virtual human body model in the upper body, achieving human body motion posture reproduction, and solving the spatial limitation and complexity of optical motion capture data processing in sports training. After using the support vector machine algorithm to classify the basketball sports features, the resolution of basketball sports posture is realized after several trainings so as to design the intelligent SPOC hybrid basketball teaching mode. After collecting and calibrating the movement acceleration and angular velocity from the intelligent collection of basketball movement data and recognizing the basketball movement gesture features, the designed intelligent SPOC hybrid basketball teaching model is practically applied to explore its teaching effect.

2 Literature review

1) SPOC teaching and MOOC

SPOC, or small-scale restricted online course, is a new type of online course following the wave of MOOC, which restricts the teaching object to a small-scale learning group with a certain foundation and ensures the effectiveness of learning by providing high-quality teaching services and flexible and efficient learning modes. Rieber, L. P. In order to explore people's motivation for joining and engaging in MOOCs as well as their behavior and patterns of participation within MOOCs, descriptive statistics and analysis of 5079 people participating in MOOC teaching showed that MOOC courses can provide flexible learning for participants with different goals and needs. Participation behaviors and patterns, descriptive statistics and analyses of 5079 participants in a MOOC demonstrated that MOOC courses can provide flexible learning environments for participants with different goals and needs [6]. Gilly et al. examined the experiences of MOOC participants through surveys and interviews, describing the relationship between participant motivation and expectations in MOOCs, which in turn explored and improved the effectiveness of understanding and practice of MOOC learning design and participant motivation and expectations [7]. Wang, Y. et al. explored the effectiveness of private online course learning based on mobile internet and cognitive psychology and showed through comparative experiments that the learning effectiveness was significantly related to their online learning behaviors independently of their gender and that most of the students preferred the online mode of instruction [8]. A small private online course teaching model was created in conjunction with the traditional teaching model by Kang, Z., and He, L. based on the large-scale open online course teaching model, which entirely depends on independent student learning. This model is ideal for teaching because it enhances students' motivation to learn and the role that teacher-student interaction plays in education.

2) SPOC blended teaching mode

A hybrid teaching mode differs from a traditional teaching mode in that it combines traditional classroom instruction with online learning. The advantage of a hybrid teaching mode like SPOC is that it allows for the reorganization and implementation of teaching and learning activities, which ultimately improves teaching efficiency and effect. Hui, Y. said that the primary mode of educational change in colleges and universities is now hybrid teaching, or Internet + education. Hui, Y. suggested that Internet+education hybrid teaching has taken center stage in college and university education reform. Using the covariance analysis method, Hui examined the impact of deep learning and SPOC hybrid teaching modes on the teaching mode, allowing students' curiosity to run wild [10]. In order to enhance the political economy course's instruction and foster students' creativity and problem-solving skills, Fu, Y. developed the "Creative Education + SPOC" model, incorporating the offline teaching system and addressing the areas of teaching environment, process, and evaluation [11]. In order to calculate the specific value of the full assessment indexes of learning inputs, Zhang, Y. et al. built a learning behavior input model in the mixed teaching mode of college English. They then identified the specific learning input evaluation indexes and combined the index weights. Their findings demonstrated that the mixed teaching mode aids in improving English performance [12]. In order to gather data on the English flipped classroom's teaching quality evaluation and to enhance both student happiness and teaching quality even more, Liu, L. developed the SPOC-based IT English flipped instructional model [13].

3) College basketball teaching

Regarding the method of teaching college basketball, traditional colleges and universities continue to use the same old "explanation-demonstration-practice-correction-consolidation-practice" approach without adopting any new teaching strategies.Li, S. The use of virtual reality technology to create a basketball teaching simulation system and establish a virtual simulation model is an attempt to improve the conventional methods of teaching basketball. This approach can help athletes quickly acquire the fundamental positions of sports skills and significantly increase the effectiveness of basketball players' training [14]. Li, S. Virtual reality is utilized to create a basketball teaching simulation system and virtual simulation model, which can help athletes master key sports skills as quickly as possible and significantly increase basketball players' training efficiency. This is an improvement over the traditional method of teaching basketball.14 Wang, Z. In conjunction with digital resources and information technology, which form the foundation of the network's development, we examined how innovative digital platforms and network resources are being applied in colleges and universities to teach basketball, correct basketball techniques, and spread the teaching of the game. Make basketball corrections and encourage creative basketball instruction [15]. By using video image processing technology, Lv, Y. et al. created an auxiliary training system for college basketball instruction. This system enhanced the quality of basketball instruction by identifying the pertinent parameters of students' fundamental basketball movements and technical behaviors based on the training's traditional basketball instruction [16]. In order to conserve energy through the habit of playing basketball, Zhang, N. et al. used contemporary teaching techniques in the Hide Markov and Motion Modeling for basketball collection. Their goals were to develop skills and understanding of movement and conservation as well as to utilize an active and healthy lifestyle in various activities [17].

3 Artificial Intelligence based SPOC hybrid basketball teaching design

SPOC Hybrid Basketball Teaching is to recognize the basketball playing techniques through artificial intelligence technology, upload the recognized movements backstage in real-time, and guide and correct them through the backstage professionals for better basketball teaching.

3.1 Smart sensor-based data acquisition and processing

When teaching basketball, intelligent acceleration sensors are utilized as a data acquisition tool. Smart sensors and posture assessment algorithms are employed to recognize basketball motion postures after pre-processing, feature extraction, and selection processing of human motion data [18].

3.1.1 Data Acquisition and Synthesis of 1D Acceleration

In this paper, data is collected using the JY-901 sensor, whose pin function is displayed in Table 1. The JY-901 module is equipped with a high-performance microprocessor, an internal voltage stabilization circuit, an operating voltage range of 3.3v to 5v, and an output rate of up to 200Hz. An attitude solver that is integrated can output the module's current attitude in dynamic environments. Finally, the module uses advanced digital filtering technology that effectively reduces measurement noise and can improve the sensor's measurement accuracy. 901 utilizes cutting-edge digital filtering technology, which effectively reduces measurement noise and enhances sensor accuracy.

Table 1. JY-901 module pin function

Order number	Name	Function
1	VCC	Module power supply cathode, 3.3v-5v
2	RX	serial data input
3	TX	serial data output
4	GND	Module power supply anode
5	SCL	12C clock line
6	SDA	12C data wire
7-10	D0-D3	Extended port

A total of motion data of different basketball movement postures were collected using JY-901 sensors, the sensors were worn on the waist during the process of collecting the motion data and keeping the Z-axis down, the data collection experiments were carried out at different times with a certain degree of variability.

In this paper, the values of three-axis acceleration during human movement are collected, which represent the acceleration values in the X, Y, and Z directions, respectively. In order to reflect the overall characteristics of each motion posture, its three-axis acceleration was synthesized into one-dimensional acceleration using equation (1).

$$acc = \sqrt{acc_x^2 + acc_y^2 + acc_z^2} \tag{1}$$

3.1.2 Kalman filtering

In the denoising filtering stage, the filtering method chosen in this paper is Kalman filtering [19].

From moment $k-1$ to moment k, the state prediction equation of the system is shown in equation (2):

$$X_k = AX_{k-1} + Bu_k + w_k \tag{2}$$

The state observation equation of the system is given in equation (3):

$$Z_k = HX_k + v_k \tag{3}$$

where A is the state transfer matrix, B is the input gain matrix, H is the measurement matrix, u_k is the system input vector, and w_k and v_k are the process noise and measurement noise obeying normal distribution with mean 0 and covariance matrices Q and R, respectively.

The a priori estimate of the current state $\hat{x}_k$ is shown in Eq. (4):

$$\hat{x}_{\bar{k}} = A\hat{x}_{k-1} + Bu_k \tag{4}$$

The error between the true value and the mismeasured value is shown in equation (5):

$$e_{\bar{k}} = x_k - \hat{x}_{\bar{k}} \tag{5}$$

Then the a priori estimated covariance P_k is as in equation (6):

$$\begin{aligned} P_{\bar{k}} &= E\left[e_{\bar{k}} e_{\bar{k}}^T\right] = E\left[\left(x_k - \hat{x}_{\bar{k}}\right)\left(x_k - \hat{x}_{\bar{k}}\right)^T\right] \\ &= E\left[\left(Ae_{k-1}\right)\left(Ae_{k-1}\right)^T\right] + E\left[\omega_k \omega_k^T\right] \\ &= AP_{k-1}A^T + Q \end{aligned} \tag{6}$$

The error between the true value and the estimated value is shown in equation (7):

$$e_k = x_k - \hat{x}_k = \left(I - K_k H\right)\left(x_k - \hat{x}_{\bar{k}}\right) - K_k v_k \tag{7}$$

Among them.

$$E\left[v_k v_k^T\right] = R \tag{8}$$

Then the updated error covariance P_k is as in equation (9):

$$\begin{aligned} P_k &= E\left[e_k e_k{}^T\right] \\ &= E\left[\left(I-K_k H\right)\left(x_k-\hat{x}_k\right)-K_k v_k\right]\left[\left(I-K_k H\right)\left(x_k-\hat{x}_k\right)-K_k v_k{}^T\right] \\ &= \left(I-K_k H\right) E\left[\left(x_k-\hat{x}_k\right)\left(x_k-\hat{x}_k\right)^T\right]\left(I-K_k H\right)^T+K_k E\left[v_k v_k{}^T\right] K^T \\ &= \left(I-K_k H\right) P_{\bar{k}}\left(I-K_k H\right)^T+K_k R K_k^T \end{aligned} \tag{9}$$

Since the essence of Kalman filtering is minimum mean square error estimation, the mean square error of P_k is as in equation (10):

$$tr\left(P_k\right)=tr\left(P_k\right)-2tr\left(K_k H P_k\right)+tr\left(K_k\left(H P_k H^T+R\right) K_k^T\right. \tag{10}$$

Also, since the optimal estimate K_k minimizes $tr\left(P_k\right)$, it can be obtained:

$$\begin{aligned} \frac{\partial tr\left(P_k\right)}{\partial K_k} &= \frac{\partial tr\left(2 K_k H P_{\bar{k}}\right)}{\partial K_k}+\frac{\partial tr\left(K_k\left(H P_{\bar{k}} H^T+R\right) K_k^T\right.}{\partial K_k} \\ &= -2\left(H P_{\bar{k}}\right)^T+2 K_k\left(H P_{\bar{k}} H^T+R\right) \end{aligned} \tag{11}$$

Making the above equation equal to 0 gives the Kalman gain factor K_k as in equation (12):

$$K_k=P_k H^T\left(H P_k H^T+R\right)^{-1} \tag{12}$$

Then the updated error covariance P_k is as in equation (13):

$$\begin{aligned} P_k &= P_{\bar{k}}-K_k H P_{\bar{k}}-P_{\bar{k}} H^T K_k^T+K_k\left(H P_{\bar{k}} H^T+R\right) K_k^T \\ &= \left(I-K_k H\right) P_{\bar{k}} \end{aligned} \tag{13}$$

The processed original acceleration signal is filtered and denoised using Kalman filtering, where the larger Q is, the more the measured value is trusted, the smaller R is, the faster the convergence is, and the parameter of Kalman filtering is set to $Q=0.06, R=1.0$.

3.1.3 Data segmentation

In the process of collecting data, the experimenter is in continuous motion, so the length of the motion data needs to be processed in a certain way. The segmentation technique chosen in this paper is the sliding window segmentation technique, and the window size can be set to:

$$windowsize=2^{ceil\left(\log_2(2\times f)\right)} \tag{14}$$

When data segmentation is carried out, the length of the sliding window set in this paper is 200, and the motion data is processed by adding windows, and the neighboring windows need to be set up with overlapping areas, and the overlapping area set in this paper is half of the whole window, i.e., the length of 100, so that each segment of data afterward is composed of the first half of the window and half of the new window. Data segmentation can make the subsequent feature extraction steps more convenient.

3.2 Basketball feature extraction based on unit action segmentation

3.2.1 Basketball Stance

Basketball involves more complex human body movements; Figure 1 illustrates how basketball gestures are assembled. The basketball posture is classified into two states based on the condition of the limbs: the movement state describes the state of the limbs during basketball movements, and the static state describes the limb's posture when it is not changing. Unit actions are defined as the shooting, catching, passing, and dribbling of the upper limbs and the jumping, walking, and running of the lower limbs. In the movement state, the actions can be classified as instantaneous or continuous based on whether or not they are periodic. Therefore, it is important to recognize the division of upper and lower limb unit actions when recognizing basketball posture.

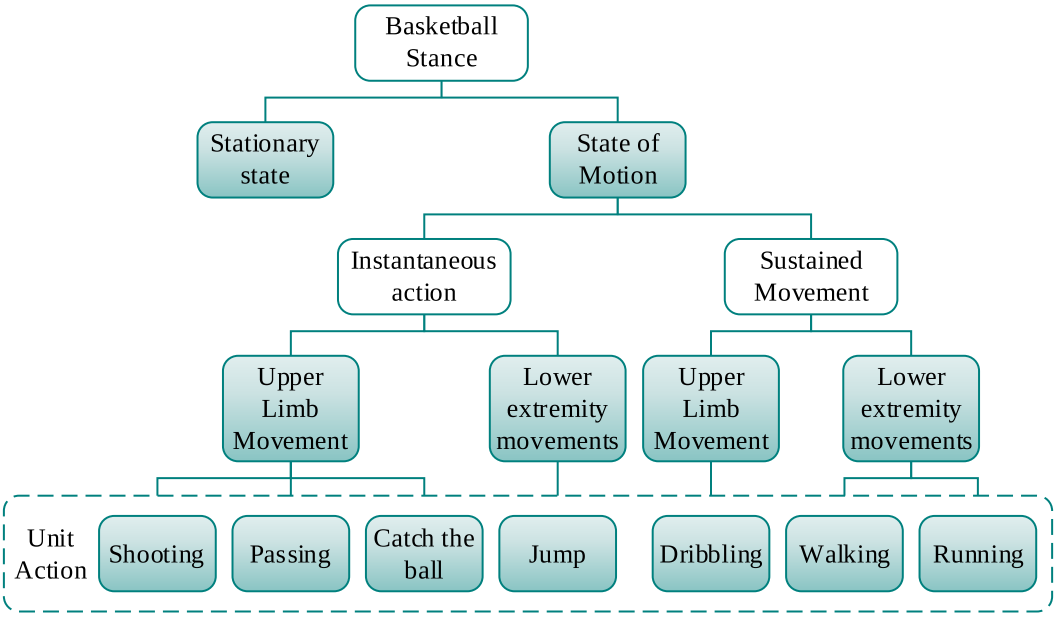


Figure 1. The basketball posture is made up

3.2.2 Data segmentation

The technique flow for the two steps of the data division is depicted in Figure 2. The extraction of the movement state data is finished in the first step of data division, and the extracted samples comprise both continuous and instantaneous motions based on the discrete degree features of the movement data in the two states. The extraction of upper and lower limb unit actions for the sustained action is finished in accordance with the angular change characteristics of the limbs throughout the movement process in the second stage of data division because the sustained action is made up of many consecutive unit actions.

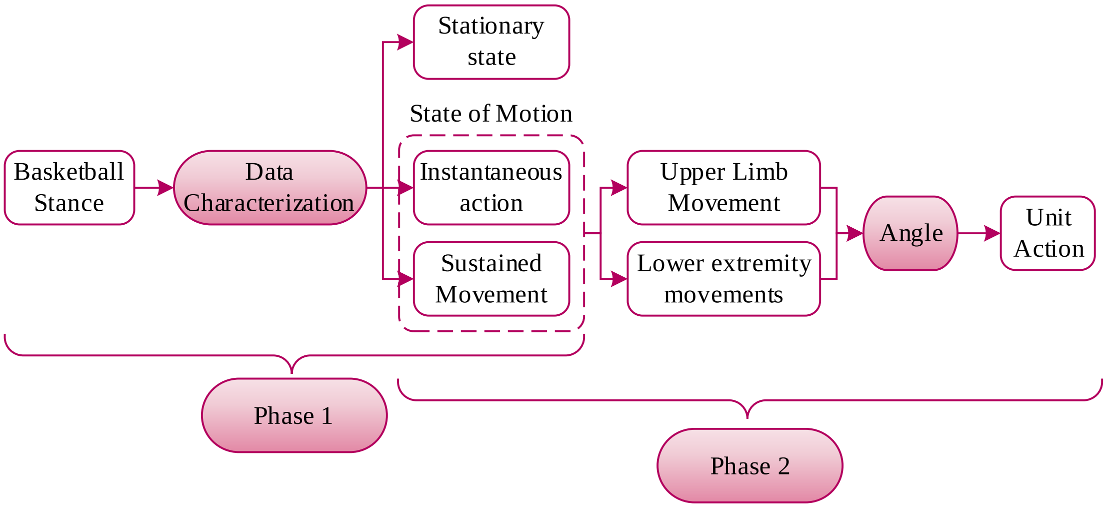


Figure 2. The flowchart of segmentation

1) Motion State Classification

The degree of dispersion is defined as the difference between the sample values of the sensor signals and reflects the degree of disparity between the values of the observed variables. Take the angular velocity as an example, ω_n^x indicates the x rd axis angular velocity data at the n nd moment, ω_{n-1}^x indicates the x th axis angular velocity data at the $n-1$ th moment, and d_n^x indicates the difference between the x th axis angular velocity of the sensor at the n th moment and the angular velocity at the previous moment, which can be used to find the dispersion degree of d_n^x by equation (15):

$$d_n^x = \left|\omega_n^x - \omega_{n-1}^x\right| \tag{15}$$

The motion data includes acceleration and angular velocity data; to achieve an accurate motion division, the properties of each sensor data must be taken into account in its whole. The dispersion of the acceleration sensor data at the n nd moment is represented by D_n^x, the dispersion of the angular velocity sensor data at the n th moment is represented by d_n^g, the dispersion of the acceleration and angular velocity of each axis is represented by $d_n^{a_x}$, $d_n^{a_y}$, $d_n^{a_z}$, $d_n^{g_x}$, $d_n^{g_y}$ and $d_n^{g_z}$, respectively, and the dispersion of the acceleration and angular velocity of each axis is obtained by Eqs. (16) and (17), respectively, in the D_n^a th and D_n^g th moment:

$$D_n^a = d_n^{a_x} + d_n^{a_y} + d_n^{a_z} \tag{16}$$

$$D_n^g = d_n^{g_x} + d_n^{g_y} + d_n^{g_z} \tag{17}$$

The dispersion of angular velocity and acceleration is maintained below the threshold values of λ_a and λ_g, respectively, in the stationary condition. During the motion state, the athlete's movements will cause the sensor's data to vary quickly. γ_n is used to indicate the state of the athlete's limb at the n th moment, γ_n is 0 to indicate the static state, and γ_n is 1 to indicate the motion state, which is defined as shown in equation (18).

$$\gamma_n = \begin{cases} 0, D_n^a < \lambda_a \text{ and } D_n^g < \lambda_g \\ 1, D_n^a \ge \lambda_a \text{ or } D_n^g \ge \lambda_g \end{cases} \tag{18}$$

Calculate the discrete degree of each sensor data, and each motion state can be recognized through the threshold.

2) Unit action segmentation

The split of movement states yields instantaneous and continuous movements, whereas the division of unit movements is the subsequent processing of continuous motions. It is discovered that the arm and leg movements during a continuous action are in a continuous cycle, and that the periodicity of these changes is more evident. As a result, it is possible to divide an action into units based on the movement data of the arm and leg. Through data comparison, it is discovered that the angular velocity data is the most intuitive in explaining the angular changes during the rigid body movement process, and this data is used as a benchmark for the division of the action.

3.2.3 Basketball posture feature extraction

After data division to get the unit action data, which consists of acceleration and angular velocity, a_n^x, a_n^y, a_n^z represents the acceleration of the three axes of the nth sampling point, g_n^x, g_n^y, g_n^z represents the angular velocity of the three axes of the nth sampling point. The acceleration vector sum and angular velocity vector sum are represented by a_n and g_n, respectively, and are obtained by Eqs. (19) and (20), respectively:

$$a_n = \sqrt{\left(a_n^x\right)^2 + \left(a_n^y\right)^2 + \left(a_n^z\right)^2} \tag{19}$$

$$g_n = \sqrt{\left(g_n^x\right)^2 + \left(g_n^y\right)^2 + \left(g_n^z\right)^2} \tag{20}$$

μ_a and δ^2 are used to denote the mean and variance of a component of the acceleration in the unit action, respectively, which are obtained by Eqs. (21) and (22):

$$\mu_a = E(a) = \frac{1}{N}\sum_{i=1}^{N} a_i \tag{21}$$

$$\delta^2 = \frac{1}{N}\sum_{i=1}^{N}\left(a_i - \mu_a\right)^2 \tag{22}$$

where a is some component of the acceleration.

$S_{DFT}(n)$ is used to represent the Fourier transform result of the nrd sampling point, and j represents the imaginary unit, which is calculated as shown in equation (23):

$$S_{DFT}(n) = \sum_{i=0}^{N-1} a_i e^{-j\frac{2\pi}{N}in} \tag{23}$$

According to the Fourier transform results to find its peak value of $S_{DFT}(K)$, where the peak of the Fourier transform corresponds to the sampling point of K, then the Fourier transform corresponds to the frequency of f by the formula (24) can be obtained, where f_s indicates the sampling frequency of the sensor:

$$f = K \times \frac{f_s}{N} \tag{24}$$

3.2.4 SVM-based Basketball Motion Posture Analysis

The SVM algorithm is utilized to construct a classification model for the collected acceleration data [20]. In this paper, we describe the sample set $D=\{(x_i, y_i), i=1,2,\dots l\}, x_i \in R^n$ is defined as the input quantity in the sample set, $y_i \in R^n$ is the target output quantity, i.e., it is the labeling category to which the support vector belongs, and l is the total number of training samples. In this model, the classification formula for the sample data is $f(x)=\omega^T x+b$ and the input quantity $x_i(i=1,2,\cdots,l)$ is defined as shown in equation (25):

$$x_i = \left(x_{avg_t}, y_{avg_t}, z_{avg_t}, x_{\max_t}, y_{\max_t}, z_{\max_t}, x_{dev_t}, y_{dev_t}, z_{dev_t}, sum_{a_t}\right) \tag{25}$$

In Eq. (25), $\left(x_{avg_t}, y_{avg_t}, z_{avg_t}\right)$ represents the average value of three-way acceleration collected within the time window t of the selected sample data set, which reflects the trend of the athlete's change in each direction of motion; $\left(x_{\max_t}, y_{\max_t}, z_{\max_t}\right)$ represents the maximum value of each direction of acceleration, which reflects the amount of acceleration change in the athlete's intense motion moment; $\left(x_{dev_t}, y_{dev_t}, z_{dev_t}\right)$ represents the maximum variance of three-way acceleration, which reflects the trend of the athlete's motion moment of the maximum change; sum_{a_t} represents the sum of the absolute values of the mean values of the three-way acceleration, which reflects the size of the three-way motion changes.

Among them, $x_{dev_t} y_{dev_t}, z_{dev_t}$ and sum_{a_t} can be expressed as:

$$x_{dev_t} = \max\left(x_t - x_{t-1}\right), t=1\cdots,k \tag{26}$$

$$y_{dev_t} = \max\left(y_t - y_{t-1}\right), t=1\cdots,k \tag{27}$$

$$z_{dev_t} = \max\left(z_t - z_{t-1}\right), t=1\cdots,k \tag{28}$$

$$sum_{a_t} = \left(\left|x_{avg_t}\right| + \left|y_{avg_t}\right| + \left|z_{avg_t}\right|\right), t=1\cdots,k \tag{29}$$

In Eqs. (26)-(29), k is used to denote the number of sample points collected in the sample set time window t. Meanwhile, in order to find the optimal classification hyperplane, the original problem can be transformed into the dyadic problem of convex quadratic programming through the duality of Lagrangian function, and the dyadic function model is shown in Eq. (30):

$$\begin{cases} \max\limits_{\alpha} \quad \sum_{i=0}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K\left(x_i, x_j\right) \\ s.t. \sum_{i=1}^{l} \alpha_i y_i = 0 \\ \sum_{i=1}^{l} \alpha_i \geq 0, i = 1, 2 \cdots, l \end{cases} \tag{30}$$

Eq. (30) the pairwise function model formula, $\alpha_i..0$ is the Lagrange multiplier, function K is the kernel function:

$$K\left(x_i, x_j\right) = \exp\left(-\frac{\left\| x_i - x_j \right\|^2}{(2\sigma)^2} \right) \tag{31}$$

Where σ is the width parameter of the kernel function, which can be adjusted dynamically, and the kernel matrix is a positive definite matrix that can satisfy Mercer's theorem, the steps for realizing the classification of data using the established classification model of SVM algorithm are as follows:

The mathematical model of equation (29) to find the optimal solution, the optimal classification decision function is:

$$f(x) = \operatorname{sgn}\left(\sum_{i=1}^{l} a_i^* y_i K\left(x_i, x_j\right) + b^* \right) \tag{32}$$

(32), $\operatorname{sgn}()$ represents the sign function, α_i^* is not 0 sample data, that is, the support vector, b^* is the classification threshold, α_i^* and b^* represent the optimal solution when the classification interval is maximum, which can be derived from the classification conditions of the convex programming problem introduced by Eq. (30), and the classification conditions are shown in Eq. (33):

$$\alpha_i y_i \left[\sum_{i=1}^{l} \alpha_i^* y_i K\left(x_i, x_j\right) \cdot x_i + b \right) - 1 \right] = 0 \tag{33}$$

According to equation (33) can be solved for b^*. Using this classification rule and by calculating the value of $\operatorname{sgn}\left[f_k\left(x_i\right) \right]$ can be obtained classification decision function. However, in the construction of the classification model, the sample set is often not completely separated by the optimal classification hyperplane, that is, the classification surface can not completely separate the sample set at this time through the introduction of the relaxation factor $\xi_i\left(\xi_i..0, i = 1, 2, \ldots l\right)$, allowing the existence of fault-tolerant samples, in order to improve the ability of the model to promote and reduce the empirical risk, which results in the model of the optimal classification hyperplane to meet the following formula (34):

$$y_i\left(\omega^T x_i + b\right) \geq 1 - \xi_i \tag{34}$$

For different sample data, if $0<\xi_i<1$, input sample data x_i can be classified correctly; if $\xi_i \geqq 1$, input sample data x_i cannot be classified correctly. Therefore, the optimization objective function is introduced, as expressed in equation (35):

$$\phi(\omega)=\frac{1}{2}\|\omega\|^2+C\sum_i^l \xi_i \tag{35}$$

In Eq. (35), C is a constant, which is called the penalty factor, and when the relaxation factor is introduced into the classification model, a weight parameter needs to be added in front of the relaxation factor in order to avoid an increase in sample misclassification, and ω is the corresponding normal vector in the classification model, which determines the direction of the classification hyperplane. The optimal classification hyperplane can be found by transforming Eq. (35) into a quadratic programming problem.

The motion attitude feature's mean acceleration value in each of the three directions of the acceleration data components in the X, Y, and Z axes, added to its maximum, mean, variance, and absolute values, is what, using the feature extraction function, creates the feature vector. The data is transmitted to the control host for processing and analysis once the device has gathered the three-direction acceleration data. The best classification function is created in the higher dimensional space for the identification and resolution of the basketball sports posture after the input feature vectors are mapped into a higher dimensional feature space using the RBF kernel function.

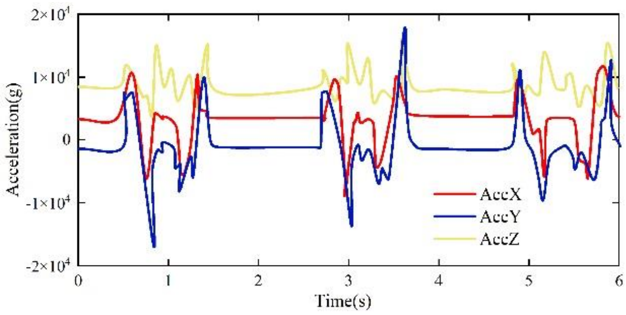
4 Intelligent SPOC Hybrid Basketball Teaching Application and Analysis

4.1 Basketball sports data intelligent acquisition effect and analysis

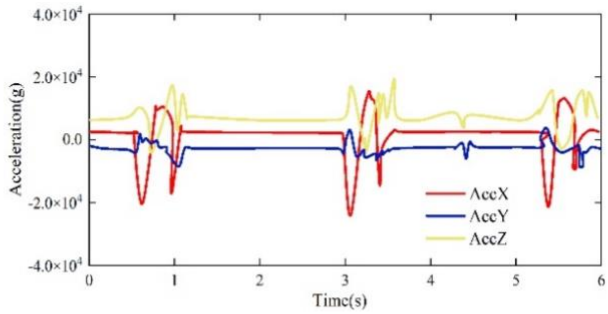
The pressure value produced when performing basketball actions varies depending on the weight of the player. Therefore it cannot be a reliable source of information for recognizing basketball actions and is not particularly useful for the subsequent feature extraction stage. Combining the elements mentioned above, this experiment simply uses the acceleration and angular velocity data of basketball actions, such as dribbling, shooting, passing, and defense, as the foundation for recognizing basketball motion.

4.1.1 Motion acceleration collection results

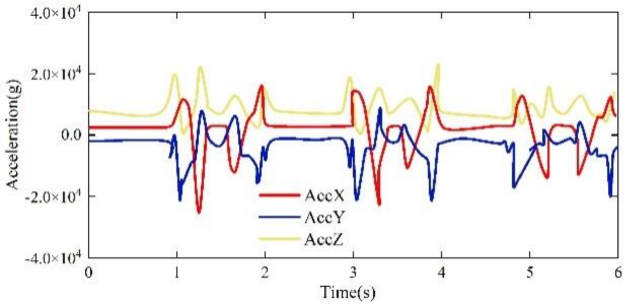
Three basketball players in total had their data collected; each of the three basketball players had 200 sets of sensor data collected from them, for a total of 600 sets of data. The information in each set of data was derived from the smart insole sensor module and included information about the basketball players' stepping movements. Finally, 150 dribbling data, 150 shooting data, 150 passing data and 150 defense data were obtained, and Fig. 3 shows the acceleration data curves under different movements. (a)~(e) are the acceleration curves of dribbling, shooting, passing and defending, respectively. The waveforms of the acceleration data of the four basketball actions can be visualized through the waveform plots of the four actions with obvious differences, and the waveforms of the X-axis, Y-axis and Z-axis are different, and the acceleration collected in 6S are all in the range of (-2×10^4g, 2×10^4g). In addition, the shooting acceleration curve fluctuation is relatively smooth. The acceleration curve fluctuation degree of dribbling and passing is significantly higher than that of defense acceleration curve fluctuation within 6S. Both are higher than the shooting acceleration curve fluctuation through the intelligent acceleration sensor can accurately collect the acceleration curve of the basketball player's action and, to a certain extent, can distinguish different types of actions.



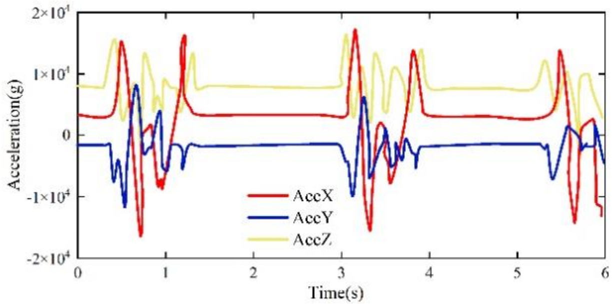
(a) Dribble acceleration curve



(b) Shooting acceleration curve



(c) Passing acceleration curve

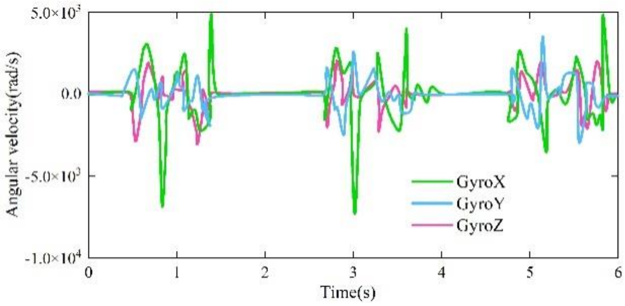


(d) Defensive acceleration curve

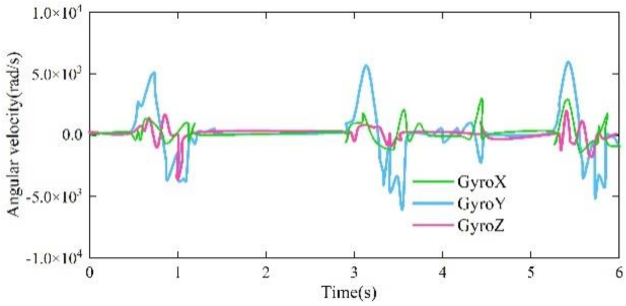
Figure 3. The acceleration data curve under different action

4.1.2 Motion Angular Velocity Collection Results

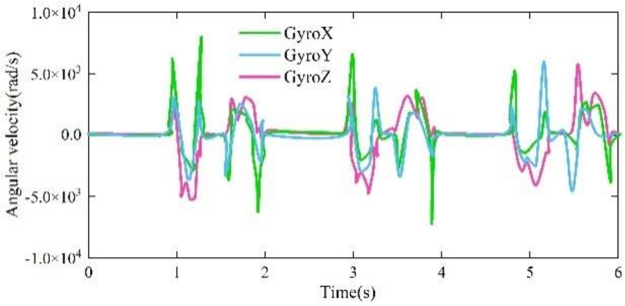
The sensor signal is readily influenced by the player's body and the surrounding surroundings when they are playing basketball. The acceleration, magnetic field strength, and angular velocity data are fused when computing the angle during limb movement using the Kalman filter technique, which can lessen the impact of outside noise. The angular velocity data curves under various movements are displayed in Figure 4. The angular velocity curves for dribbling, shooting, passing, and defending are represented by the letters (a) through (e). After processing the collected angular velocity signal curves using Kalman filtering, the curves are clearer, the dribbling angular velocity fluctuates more times in the X-axis, and the fluctuation amplitude in 6s is between (-7500rad/s, 5000rad/s), and the basketball angular velocity fluctuates more obviously in the Y-axis, and its amplitude is between (-6000rad/s, 5000rad/s). The angular velocity of passing and defense have some fluctuation in X, Y, Z axis, the peak value of fluctuation is not more than ±10000rad/s, similar to the results of acceleration collection, and the curve fluctuation amplitude is the smallest in the case of shooting. The angular velocity data of the four different types of basketball actions can be seen to have distinct waveforms, and it is evident that the motion signal exhibits strong regularity around the zero point of the variation following the removal of the gravitational component.



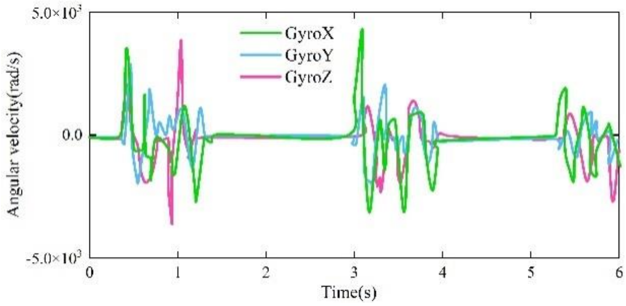
(a) Dribble angular velocity curve



(b) Shooting angular velocity curve



(c) Passing angular velocity curve



(d) Defensive angular velocity curve

Figure 4. The angular velocity data curve under different action

4.1.3 Data calibration

Following the completion of collecting basketball motion and acceleration data, the data is analyzed, and the terminal's data is calibrated upon successful analysis. The terminal is positioned horizontally during the calibration procedure, and the horizontal plane is checked against the horizontal plane of the mobile phone. Two measurements are required to determine the scale factor of the Z-axis. The sensor data calculated after two acquisitions is shown in Table 2. Since the acceleration Z-axis out of the other axial information about motion should theoretically be 0g or 0°/s, the mean value of the statistics can represent its zero bias error. Each reading takes 30 seconds of stationary data and reverses the terminal to get the information processed when the Z-axis is downward. The table's data indicates that the acceleration sensor's standard deviation is stable at (0.001~0.003) orders of magnitude, the extreme deviation is stable at 0.0007 to 0.02 orders of magnitude, the offset is also stable at 10-2 orders of magnitude, and the acceleration sensor's sampling accuracy in this study is 0.0001 g. Both the extreme deviation and the standard deviation of the angular velocity are steady at (0.05~0.93) orders of magnitude. The offset is likewise in the range of 0.01 to 100, the maximum deviation not to exceed 1.8°/s, and the extreme deviation is stabilized at 10-1 order of magnitude. The standard deviation of angular velocity is stabilized at (0.05~0.93) order of magnitude. Since the angular velocity's writing error is 0.1°/s, there will be some interference from the zero-value deviation with the observed data. The data obtained by the terminal can be calibrated once the actual measurement has been compensated, yielding a number that is more in line with the real situation.

Table 2. Sensor data calculated after two collection

First acquisition	gyrox(°/s)	gyroy(°/s)	gyroz(°/s)	accelx(g)	accely(g)
standard error	0.13	0.05	0.07	0.0023	0.0003
range	0.93	0.31	0.39	0.0232	0.0084
mean	0.68	0.61	-1.61	0.04551	-0.0198
offset	-0.68	-0.61	1.61	-0.04551	0.0198
Second collection	gyrox(°/s)	gyroy(°/s)	gyroz(°/s)	accelx(g)	accely(g)
standard error	0.05	0.02	0.0253	0.0002	0.0015
range	0.2	0.15	0.1133	0.0073	0.0201
mean	0.67	1.38	-1.5368	-0.0252	0.0175
offset	-0.67	-1.38	1.5368	0.0252	-0.0175

4.2 Basketball posture recognition effect and analysis

4.2.1 Feature extraction

The above four time domain features were extracted for the four basketball motion data after the basketball motion posture data was collected because there were a total of six axes for the accelerometer and the angular velocity meter, so there were twenty-four features extracted for each segment of the basketball gait data. The twenty-four statistical features initially extracted are shown in Table 3. Here are examples of the twenty-four features that were originally retrieved for the basketball step data: Max stands for maximum value, Min for minimum value, Mean for average value, and Std for standard deviation.

Table 3. The two fourteenth statistics of the initial extraction

Number	Feature	Number	Feature	Number	Feature	Number	Feature
1	AX-Max	7	AY-Mean	13	GX-Max	19	GY-Mean
2	AX-Min	8	AY-Std	14	GX-Min	20	GY-Std
3	AX-Mean	9	AZ-Max	15	GX-Mean	21	GZ-Max
4	AX-Std	10	AZ-Min	16	GX-Std	22	GZ-Min
5	AY-Max	11	AZ-Mean	17	GY-Max	23	GZ-Mean
6	AY-Min	12	AZ-Std	18	GY-Min	24	GZ-Std

4.2.2 Algorithm Recognition Effect

The algorithm in this research is used to conduct the feature vector usage frequency trials, and Fig. 5 displays the attribute usage frequency of SVM with a 90% accuracy guarantee. A useful tool for comparing two classification models is the ROC curve, which illustrates the trade-off between a model’s true positive case rate and false positive case rate. The algorithm in this paper’s ROC curve is displayed in Fig. 6.

AX-Mean, AZ-Max, and GY-Std have a comparatively big percentage, as seen in Figure 5. According to statistics, there are 5200 times that all attributes are used overall, and 1170 times are used for AX-Mean, AZ-Max, and GY-Std, or 22.3% of all attributes. Of these, AZ-Max is the most frequently utilized feature; AX-Mean and GY-Std are also used more frequently than or as frequently as the other features; and a feature is considered more significant the more times it is used as a segmentation feature. Consequently, the recognition of human posture depends on these three feature vector sets. Random guessing is represented by the diagonal line in the ROC curve; the closer the model's ROC curve is to this line, the less accurate it is. When the true example tuple is encountered, the algorithm in this chapter's curve begins to rise steeply as the tuple moves to a higher number. Later on, however, the curve flattens and becomes more horizontal, with a ROC value of 0.942, indicating an accurate classification prediction. As more false positive example tuples are encountered, the number of true example tuples decreases.

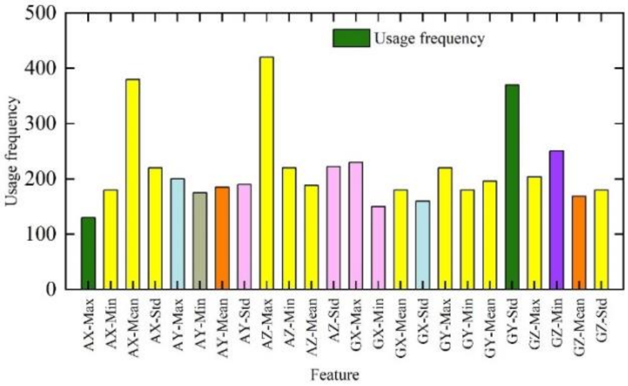


Figure 5. SVM attribute usage frequency

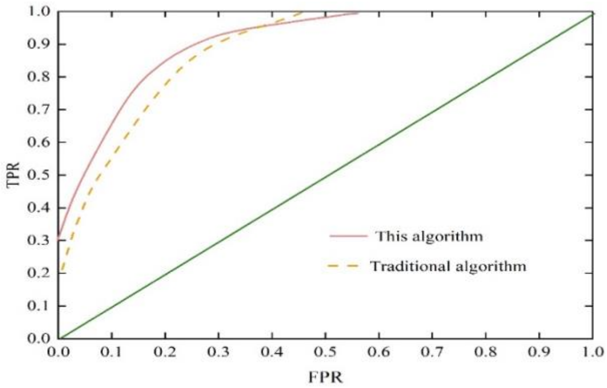


Figure 6. Roc curve of this algorithm

4.2.3 Basketball gesture recognition results

The basketball dataset was used to conduct ten experiments to test the impact of each penalty factor on algorithm performance. The results showed a relationship between the algorithm's maximum accuracy, average accuracy, and penalty factor, as well as between the size of the penalty factor and accuracy, which is depicted in Figure 7. The accuracy rate of the method used in this study varies as the size of the penalty factor changes. When the penalty factor's size is less than 200, the accuracy rate generally increases as the penalty factor's size increases. When the penalty factor size is greater than 200, the accuracy rate tends to decrease as the penalty factor increases. The algorithm's maximum accuracy and average accuracy are at their highest when the penalty factor is 200. The penalty factor's size is set to 200 due to the algorithm's maximum accuracy being 0.92.

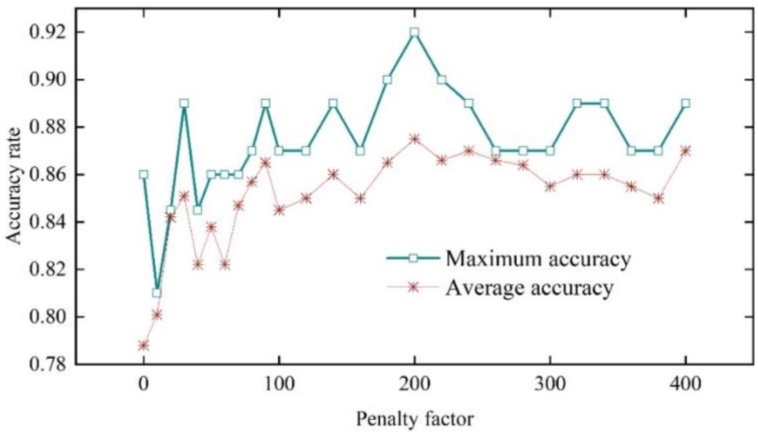


Figure 7. The relationship between the size of the penalty and the accuracy

The confusion matrix related to this paper's algorithm to get the maximum accuracy rate in the experiment is analyzed in order to further analyze the classification results and determine the recognition rate of each class. Table 4 displays the confusion matrix of the recognition results of basketball sports gestures. The four actions—dribbling, shooting, passing, and defending—have recognition effects using the SVM algorithm that are all above 0.90, with an average gesture recognition effect of 0.925. This means that the algorithm in this paper can accurately identify the basketball gesture, allowing for action corrections and the advancement of basketball instruction.

Table 4. The recognition result of the game attitude is confused by the matrix

Categories	Dribbling	Shooting	Passing	Defense	Total	Recognition rate
Dribbling	135	2	5	8	150	0.900
Shooting	2	140	5	3	150	0.933
Passing	3	7	138	2	150	0.920
Defense	2	3	3	142	150	0.947
Total	150	150	150	150	600	0.925

4.3 Effectiveness of Intelligent SPOC Hybrid Teaching Application

The experimental subjects in this paper are students in the college physical education basketball option class. Specifically, there are 32 students in the experimental 1 class, 30 students in the experimental 2 class, and 32 students in the control class. This paper utilizes the intelligent SPOC hybrid teaching method for its teaching application. To determine whether there is a statistically significant difference between the physical characteristics of students in the experimental class 1, experimental class 2, and control class before and after the experiment, statistics of the various physical attributes of students in each class before and after the experiment are tested. Figure 8: Before and after the experiment, physical fitness levels in the experimental and control groups are compared. The overall level of fitness in experimental class 1 was the highest; it increased by approximately 7 points, and the overall level of the experimental class 2 increased by approximately 5 points. There was no significant improvement in the control class. This is because the students in the experimental class 1 could take the physical fitness training seriously in the final portion of each class, were able to clearly recognize the advantages of physical fitness training, and completed the preparatory activities prior to the test, through the designed intelligent SPOC blended instruction can improve students' physical fitness.

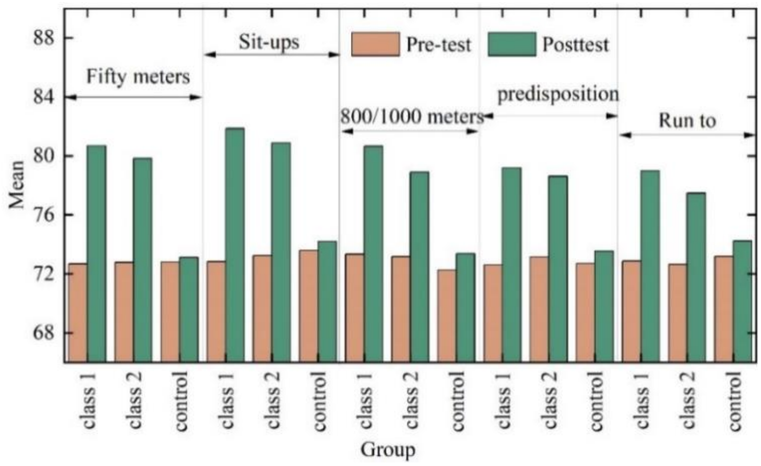


Figure 8. The physical quality was compared before and after the experiment

Statistics prior to and following the experiment of each student class in basketball technology and the technical and tactical application of ability performance, test the students in experimental classes 1, 2, and the control class prior to and following the experiment of basketball technology and the technical as well as tactical application of ability of the existence of significant differences. Table 5 displays the differences in the comparison prior to and following the experiment on basketball technology. The volleyball technical and tactical use ability scores of the students in Experiment 1, Experiment 2, and Control Classes were compared before and after the experiment using a paired samples t-test. The analysis revealed that, in the four areas of full-court dribble-passing, shooting, dribbling, and defense, Experiment 1 Classes had p-values less than 0.05, indicating substantial discrepancies between the students in Experiment 1 Classes in terms of these abilities. There are notable variations in the four basketball talents and the technical and tactical application abilities among the students in Experiment 2. The use of intelligent SPOC in a hybrid mode can greatly enhance basketball instruction in colleges and universities, and it can also help with basketball movement correction. There was no noticeable improvement in dribbling or defense skills in either the Experiment 2 class or the control class.

Table 5. Comparison of basketball technology

Index	Group	Pre-test	Posttest	T	P
		Mean	Mean		
Dribble	Class 1	63.16	74.82	-1.462	0.001
	Class 2	62.86	69.81	-2.281	0.135
	Control	62.47	65.64	-3.014	0.075
Shoot	Class 1	61.63	75.66	-5.151	0.002
	Class 2	61.73	68.98	-1.943	0.000
	Control	62.71	64.82	-1.983	0.188
Passing	Class 1	62.21	72.26	-1.181	0.000
	Class 2	63.13	70.15	-3.222	0.001
	Control	62.96	64.34	-4.664	0.088
Defense	Class 1	62.65	69.89	-2.855	0.000
	Class 2	63.08	67.42	-1.943	0.288
	Control	63.35	64.25	-6.288	0.145

5 Conclusion

In this paper, intelligent sensors are used to collect motion data from students playing basketball in colleges and universities so as to divide and extract the features of basketball gestures, combine with the algorithm of support vector machine for motion gesture recognition, and carry out intelligent correction of basketball motion, so as to realize the hybrid SPOC teaching of basketball in intelligent colleges and universities and to carry out applications.

In the processing of basketball movement data, the acceleration collected in 6S using the intelligent sensor were all in (-2×10^4g, 2×10^4g), the angular velocity fluctuation range was in ±10000rad/s, and the waveforms of the angular velocity data of the four basketball maneuvers had obvious differences. The acceleration *offset* were all on the order of 10^{-2}, and their angular velocity *offset* were all on the order of 0.01 to 100, with a maximum deviation of no more than 1.8°/s. The data collection was satisfactory.

AX-Mean, AZ-Max, and GY-Std are employed 1170 times in the basketball sports posture identification; this represents a proportion of 22.3%, a ROC value of 0.942, and an accurate classification prediction effect. The maximum and average accuracy of the algorithm reach their maximums when the penalty factor is 200. At this point, the algorithm's maximum accuracy is 0.92, and its average gesture recognition effect is 0.925. The algorithm in this paper can accurately identify the basketball gesture, which allows for movement corrections and the advancement of basketball instruction.

In terms of physical quality, the experimental class 1's overall level improved by roughly 7 points, the experimental class 2's overall level improved by about 5 points, and the control class did not significantly improve. Additionally, the experimental class 1's P-value for each of the four full-court dribble and pass drills—shooting, dribbling, defense, and dribbling—was less than 0.05, and the control class did not significantly differ. The teaching method outlined in this paper can significantly improve physical quality and basketball technology, as suggested by these results.

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