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Research Article

Design and Development of Smart Wearable Products for Basketball Dribble Teaching Training Posture Monitoring

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Basketball is one of the most popular sports, but apart from a small number of sports specialties, ordinary people rarely have the opportunity to receive professional basketball training, let alone coaches who provide one-on-one dribbling posture guidance. Dribbling is a very basic and important technique in basketball. Mastering the correct dribbling posture can help people further improve their basketball skills. In response to this problem, this article designed a smart wearable product to monitor the user's posture in basketball dribbling training. If the user has a wrong dribble posture, the product will automatically prompt and give relevant suggestions. This article focuses on user demand research, product conceptual design, prototype development, and dribbling posture determination experiments and elaborates the design and development process of the product. Based on the experimental data, this article believes that the optimal parameters of the monitoring standard for the "head down too long" during basketball dribbling are the x-axis angle value of the motion sensor is critical for -120°, and the duration of exceeding the critical value is 1 second. The optimal parameters of the "dribbling wrist flip" monitoring standard are the x-axis angle value of the motion sensor has a critical value of 105°, and the duration of exceeding the critical value is 0.4 seconds. Judging from the end user's experience and rating of the product's trial experience, it can be seen that the smart product can indeed play a very good auxiliary effect in the field of dribbling posture monitoring. Popularizing it in the daily training of basketball players can effectively promote the full informatization and intelligent development of sports.

1. Introduction

In recent years, the country has paid more and more attention to the cultivation of the people's comprehensive quality, hoping to promote the comprehensive development of people's morality, intelligence, and physical beauty. However, in the current campus, the lack of physical education teachers is very common, and it is difficult for students to conduct physical training under professional guidance. The product design and development of this article are mainly aimed at teenagers and students, hoping to improve the deficiencies in basketball teaching through smart dribbling training products. The advancement of Internet technology has brought tremendous changes to all aspects of people. Such as adding a lot of color and convenience to people's production and spiritual life, which of course also includes changes in the sports industry. If you want to change the rigid model in traditional physical education, it is undoubtedly a good attempt to develop new basketball training monitoring products based on smart motion sensors. Motion sensors can intelligently measure features such as free motion, acceleration, tilt, and rotation. The development of smart sensors allows wearable products to better monitor user posture.

Abroad, the evaluation and teaching research on basketball dribbling posture has been going on for many years. Conte et al. conducted research on the physiological and technical requirements of young basketball players' no-dribble game training. He asked 20 players to conduct no-dribble game training and regular training in a random order, and in the process collected the players' maximum heart rate percentage, perceived fatigue, hit rate, rebound rate, and turnover rate and other data for statistics. Although the research data is sufficient to reflect the importance of dribbling training, the lack of sample data affects the

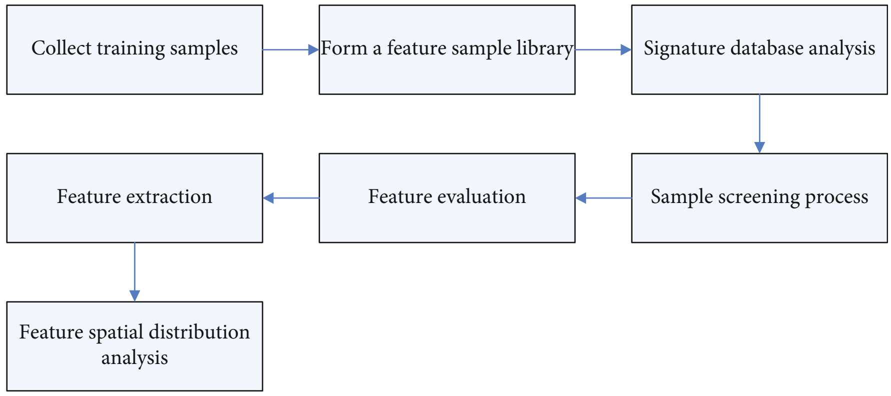

Figure 1: Feature selection and processing flowchart.

credibility of the results [1]. Jakovljevic et al. analyzed the relationship between basketball players' physical maturity and athletic ability. He divided the 32 basketball players into three categories: early, average, and late according to their maturity, and tested them from vertical jumps, 20-meter sprints, agility training, passing, ball control, and defense. From the results, the average mature person has a better performance, while the late mature person has the worst performance. Of course, if you want to make the data more convincing, you need more test items and test objects [2].

Domestic research on basketball dribbling training has also attracted a lot of attention and discussion. Ji explored the teaching evaluation of college public basketball courses. He believes that the single physical education model at this stage can easily lead to one-sided teaching content, and students do not have enough time to participate in basketball, which ultimately leads to more negative opinions in teaching evaluation. He proposed an intelligent sports training system and advocated introducing it into college public basketball teaching to improve the quality of classroom teaching. From the professional point of view of teaching data analysis and student classroom satisfaction survey, this intelligent system can play a good auxiliary effect in optimizing teaching content and improving teaching. If we can combine the actual situation and conduct more and sufficient user demand surveys, we can further improve the system's intelligent analysis and recommendation effect [3]. To sum up, basketball training has been deeply studied by many scholars. However, the development of the times has put forward more new requirements and new problems for basketball. For this reason, the design and development of intelligent wearable products for basketball dribbling teaching and training posture monitoring development research is urgent.

The research of this article aims to find feasible solutions for various problems existing in basketball dribbling teaching of physical education. The research mainly starts from the following parts: first, this article introduces the various technologies that need to be used in the development of basketball dribbling posture monitoring software, including smart motion sensor technology, human posture analysis technology, quaternion posture calculation method, and Kalman filter attitude angle estimation algorithm. Then, the article develops the functional prototype of the product and conducts an experimental study on the dribbling attitude determination. Finally, this article conducted a detailed analysis around the experimental data, which proved that the smart product can play an excellent role in monitoring the user's dribbling posture and providing posture correction. The research in this paper has practical guiding and practical significance in promoting the transformation and upgrading of basketball sports and improving the teaching level and can provide new ideas for the research of sports wearable devices.

2. Intelligent Product Development Technology Based on Basketball Dribbling Posture Monitoring

2.1. Smart Motion Sensor Technology. Motion sensors, also known as inertial sensors, include acceleration sensors and angular velocity sensors. The main difference between the two is the difference in the use of functions, the former is mainly responsible for acceleration in motion, and the latter is used for inclination velocity in motion. They are mainly used to detect and measure acceleration, tilt, shock, vibration, rotation, and multidegree-of-freedom motion. They are used to solve navigation, motion carrier control, and object or human spatial attitude [4, 5]. With the development of smart sensors, inertial sensors are becoming more miniature, lighter, more accurate, and cheaper. Because of this, motion sensing modules are increasingly used in research and commercial applications related to attitude assessment [6].

For the posture monitoring of objects, such as the interactive control system for mobile racing games, the steering wheel of a racing car can be accurately restored by simulating the spatial posture of the mobile phone to obtain a more realistic driving experience [7]. By monitoring the posture of objects, we can perform virtual simulation and experience of the scene. Human posture monitoring is mainly divided into three categories, bone-based, volume-based, and contour-based, such as the exercise pedometer function in the smart bracelet is to analyze the acceleration change of the human body during the walking process, then estimate the number of walking steps, display the invisible steps, and play the function of augmented reality [8]. In addition, human body posture analysis has always been a hot area in scientific research projects in universities, and the motion sensor module plays a pivotal role in the research on posture monitoring.

2.2. Human Posture Analysis Technology. In people's daily life, humans can easily find the human body and correctly recognize various movements of the human body through the naked eye, for example, waving, walking, standing up, accelerating, and other motion states, but it is difficult for computer vision systems to do this. At present, the development of human behavior analysis and recognition technology is still in its infancy. There are still many difficulties and challenges in data sources, human image segmentation, system real-time performance, and recognition algorithm robustness [9, 10].

The quality of human target detection is directly related to the accurate positioning of the human body area and subsequent human posture recognition, that is, it is related to the pros and cons and practicality of the entire system [11]. The smart wearable products designed in this paper are scattered in the head and wrist to help the system realize human body positioning and posture monitoring. Figure 1 is a flowchart of feature selection and processing.

Recognition is a process of connecting the unknown with the known. Appropriate selection of features is very important, because it is the only basis when recognizing object poses [12]. In practical applications, the general process of feature selection and processing is shown in Figure 1. The preliminary analysis of the sample feature library is to check whether the selected features are reasonable and whether classification can be achieved. The purpose of sample screening is to remove outliers and reduce the interference of these outliers to the classifier. The purpose of feature screening is to analyze the correlation between features, examine whether each feature factor is related to the target, and whether there is a correlation between feature factors. If there is a correlation, keep it, if the correlation is not large, delete it. By deleting those related factors, the overall performance of the classifier can be improved under the condition of not many samples, and the cost of the pattern recognition system can be reduced [13].

2.3. Quaternion Attitude Calculation Method

2.3.1. Coordinate Transformation and Attitude Angle. Attitude refers to the positional relationship between one coordinate system and another coordinate system. There are often a set of attitude angles: yaw angle, pitch angle, and roll angle to represent [14, 15]. The methods of attitude description include Euler angle method, direction cosine method, and quaternion method. Euler angle is a more intuitive method. Three angles are used to measure the attitude tilt between the body coordinates and the ground coordinates, but the representation method of quaternion and direction cosine matrix is more convenient in the coordinate conversion calculation involved in the UAV. Directly, both have applications. In this article, a smart product with a motion sensor is worn on the user's head and wrist. The carrier coordinate system consists of a horizontally right x-axis, a horizontally forward y-axis, and an upward z-axis perpendicular to the horizontal plane, which conforms to the right hand rule [16].

There is a certain positional relationship between different coordinate systems, and this positional relationship can be represented by a transformation matrix [17]. Set coordinate system $o-x1y1z1$ to become coordinate system $o-x2y2z2$ after rotating. The space vector r is projected in two coordinate systems, and the projected coordinates $[x1, y1, z1]^T, [x2, y2, z2]^T$ can be obtained, respectively. Assuming that the unit vectors of the two coordinate systems are, respectively $[ex1, ey1, ez1]^T, [ex2, ey2, ez2]^T$, the following formula exists:

$$r = x_1 e_{x1} + y_1 e_{x1} + z_1 e_{x1} = x_2 e_{x2} + y_2 e_{x2} + z_2 e_{x2}. \quad (1)$$

Rotate it around axis oz_1 and bring it in to get:

$$\begin{bmatrix} x_2 \\ y_2 \\ z_2 \end{bmatrix} = \begin{bmatrix} \cos\alpha & \sin\alpha & 0 \\ -\sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \\ z_1 \end{bmatrix}. \quad (2)$$

The transformation relationship between coordinates in the same rectangular coordinate system after a basic rotation satisfies

$$r2 = c_1^2 r2. \quad (3)$$

According to the properties of the orthogonal matrix, the projection matrix of the final coordinate system $o-x3y3z3$ in the original coordinate system can be obtained:

$$\begin{bmatrix} x_0 \\ y_0 \\ z_0 \end{bmatrix} = C_3^0 \begin{bmatrix} x_3 \\ y_3 \\ z_3 \end{bmatrix}. \quad (4)$$

Let each element of the posture transformation matrix C_3^0 be represented by the letter T with a subscript, then, the matrix can be rewritten as

$$C_3^0 = \begin{bmatrix} T_{11} & T_{12} & T_{13} \\ T_{21} & T_{22} & T_{23} \\ T_{31} & T_{32} & T_{33} \end{bmatrix}. \quad (5)$$

From $T_{32} = \sin\beta$, the roll angle, yaw angle, and pitch angle can be obtained:

$$\beta = \arcsin\,(T_{32}), \quad (6)$$

$$\phi = \arctan\left(-\frac{T_{12}}{T_{22}}\right), \quad (7)$$

$$\psi = \arctan\left(-\frac{T_{31}}{T_{33}}\right). \quad (8)$$

2.3.2. Quaternion Pose Solution. An element number is composed of a real number element plus three complex number elements i, j, k, which can be expressed as

$$Q = q0 + q1i + q2j + q3k, \quad (9)$$

$$Q = (q0, qv). \quad (10)$$

Among them, $q0, qv$ represents the scalar part and the vector part of the quaternion, respectively. The matrix representation of the quaternion is

$$Q = (q0, q1, q2, q3). \quad (11)$$

Euler's theorem states that the position of the carrier coordinate system relative to the reference coordinate system is equivalent to the rotation of the carrier coordinate system around an equivalent axis by an angle θ [18]. If u is a unit vector representing the direction of the equivalent axis of rotation, the orientation of the dynamic coordinate system is completely determined by these two parameters. Then, the quaternion constructed with these two parameters is

$$Q = \cos\frac{\theta}{2} + u\sin\frac{\theta}{2}. \quad (12)$$

2.4. Kalman Filter Attitude Angle Estimation Algorithm. Starting from simple and practical requirements, this paper proposes a combined posture estimation scheme based on Kalman filtering, which is verified by experiments to meet the requirements for human posture estimation. The attitude angle calculated by the gyroscope is used as the predicted value of the Kalman filter, and the process noise covariance Q is estimated; the attitude angle calculated by the magnetometer and accelerometer is used as the measurement value, and the gyroscope error is used to estimate the measurement noise covariance matrix R [19, 20]. The Kalman filter realizes the fusion of multisensor information and ensures the accuracy of attitude estimation.

The state x to be estimated by the Kalman filter is determined by the following linear stochastic difference equation:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}. \quad (13)$$

Among them, A, B, C represent the state transition matrix, the incidence matrix, and the process noise matrix, respectively. z, H, v are the measurement vector, correlation matrix, and measurement noise matrix [21]. Then, the measurement method satisfies

$$Z_k = Hx_k + v_k. \quad (14)$$

In the process and metering variables, we treat the process and metering noise as independent white noise, satisfying a normal distribution [22]. In practice, both the procedure interference variation matrix Q and the measurement interference variation matrix R will vary depending on the time and the moment of application. It is presumed here that they are permanent.

The Kalman controller uses return regulation to approximate a constant status of the flow: the controller estimates the state of the flow at a given moment, and the return adjusts the estimated state by means of noise measurements [23]. The Kalman filtration method includes two components: a temporal renewal method and a reckoning method. The temporal renewal function is concerned with estimating the present condition and calculating the a priori estimated coupling; the measurement renewal function is concerned with gaining control, that is, combining the updated results with the a priori estimate to obtain an improved a posteriori estimate [24].

The process of calculating the attitude angle according to the output angular velocity value of the gyroscope is regarded as the prediction of the current state, and the state equation of the filtering system is established. According to the quaternion differential equation, the attitude angle is reversed, and this attitude angle is used as the current predicted value, the formula can be obtained:

$$\dot{Q} = \frac{1}{2} Q \cdot \omega, \quad (15)$$

$$\begin{bmatrix} \dot{q}_0 \\ \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix} = \frac{1}{2}\begin{bmatrix} 0 & -\omega_x & -\omega_y & -\omega_z \\ \omega_x & 0 & \omega_z & -\omega_y \\ \omega y & -\omega_z & 0 & \omega_x \\ \omega_z & \omega_y & -\omega_x & 0 \end{bmatrix}\begin{bmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{bmatrix}. \quad (16)$$

The output predicted angle can be regarded as the combination of the true angle and the error angle, satisfying the formula:

$$\theta_G^k = \theta_T^k + \Delta\theta_G^k. \quad (17)$$

According to the three-axis gravitational field acceleration measured by the accelerometer and the three-axis magnetic field strength obtained by the magnetometer, the current attitude angle is calculated as the observation [25]. Among them, a three-axis accelerometer is used as a static inclinometer to obtain the pitch and roll angles in the attitude angle by measuring the gravitational field; the magnetometer is used to calculate the heading angle in the horizontal direction. When the carrier is in any attitude, the ground is calculated. The components of the magnetic field are along the x-axis and y-axis, and then find the heading angle. The attitude angle calculated by accelerometer and magnetometer satisfies the formula:

$$\theta_{AM}^k = \theta_T^k + \Delta\theta_{AM}^k. \quad (18)$$

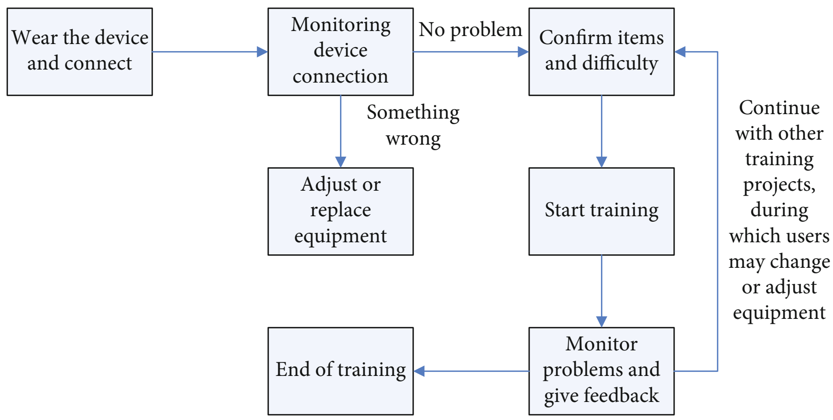

Figure 2: Logical structure of scene when the user uses software.

Figure 3: Data survey based on eight bad dribbling habits.

Table 1: Iterative process of parameter combination when dribbling is too long.

Group	Parameter	Monitoring times	Recognition times	Effective ratio
1	0.5 s, -100°	288	65	22.57%
2	1.0 s, -100°	140	75	53.57%
3	1.0 s, -110°	98	50	51.02%
4	1.0 s, -120°	81	73	90.12%
5	1.0 s, -130°	46	44	95.65%
6	1.5 s, -120°	39	37	94.87%

3. Basketball Dribbling Posture Judgment Experiment

3.1. Experimental Background. Before carrying out the basketball dribbling posture determination experiment, this article made extensive preparations for the design of wearable basketball dribbling posture training products. After user survey and demand analysis, this article conducts research and investigation from the following perspectives. These include collecting and determining the pain points in the dribble training scenario, determining the basic functions of the product, analyzing product opportunities, and determining the content that should be presented in the product data report [26]. When conducting user research, this article hopes to understand the current public awareness and acceptance of basketball smart equipment and summarize the common problems in youth basketball dribbling training. This survey is only conducted for groups who have participated in basketball or have a certain basic understanding of the game.

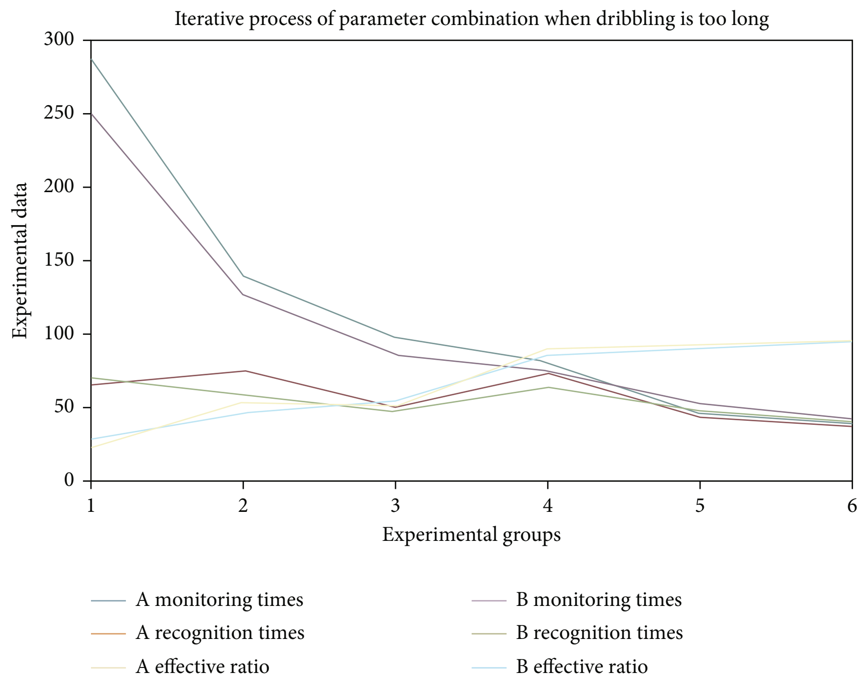

FIGURE 4: Iterative process curve of parameter combination for too long bowing time.

TABLE 2: Iterative process of parameter combination of dribble and wrist.

Group	Parameter	Monitoring times	Recognition times	Effective ratio
1	0 s, -90°	152	21	13.82%
2	0.2 s, -100°	54	20	37.04%
3	0.2 s, -110°	42	22	52.38%
4	0.4 s, -120°	33	27	81.82%
5	0.4 s, -130°	6	6	100%
6	0.6 s, -120°	9	9	100%

Through analyzing the literature, consulting experts, and youth surveys, this article finally determined the following common wrong postures or habits in dribbling training:

(1) The bowing time is too long-affecting the observation of the form on the field

(2) The nondominant hand is too weak-do not pay attention to the practice of the nondominant hand

(3) Blindly imitating gorgeous movements-insufficient basic training, more results with less effort

(4) The dribble is too high-easy to be intercepted by the opponent and affect the start speed

(5) The dribbling power is too small-the ball is slow and easy to be intercepted by the opponent

(6) Dribbling over the wrist-easy to be whistled for "carrying the ball" violation

(7) Touching the ball in the palm of the hand-affects the force of the fingers during dribbling

(8) Raise the central foot before the ball leaves the hand-it is easy to be called for "walking" violation

When designing wearable products, this article will focus on the higher priority and technically achievable parts of the function development. Since there is no more mature method of using motion sensors to accurately obtain the dribble strength and dribble height, the "low dribbling force" and "dribbling too high" cannot be directly obtained, but in essence, both are one of the factors leading to "slow dribbling," so it was decided to use "slow dribbling rate" as an alternative monitoring point.

3.2. Preparation for the Experiment. This experiment requires the following equipment: (1) a full set of functional prototypes, including headsets, wristbands, Witte intelligent motion sensor modules, and mobile phones equipped with functional prototype software APP and stopwatch software; (2) video recording equipment; (3) basketballs used in experiments; and (4) notebooks used to record scenes computer.

The purpose of this experiment is to obtain the judgment conditions for the software to monitor the dribbling posture function, including the judgment conditions of "being too long," "dribbling rate too slow," and dribbling over the wrist.

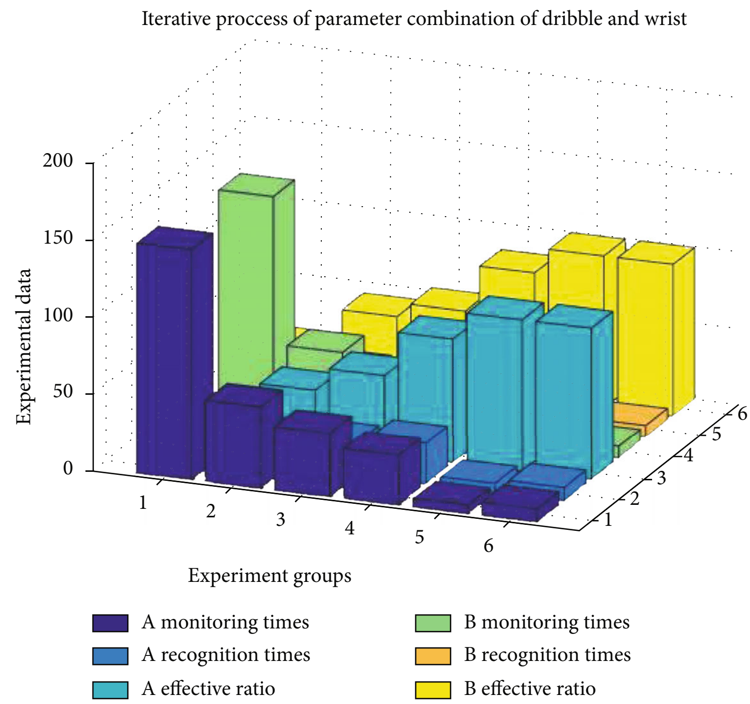

Figure 5: Iterative process of parameter combination of dribble and wrist.

Table 3: Comparison of judgment conditions for different dribbling rates.

	Underhand dribble	Cross dribble	Crotch dribble	Back dribble	Two-handed dribble
Simple	1.84	1.97	2.01	2.05*	2.03
Medium	1.36	1.40*	1.15	1.45	1.42
Difficult	1.13	1.15	1.08	1.24	1.18

The expert members participating in the experiment consist of 3. It consists of coaches of youth basketball training courses, 3 university professors majoring in physical education, and 1 professional basketball referee. The test subjects are 50 basketball enthusiasts of different levels, of which 10 are more professional and excellent level recommended by the coach basketball player.

3.3. Experimental Process Design. The dribble grip monitoring software is organized into the procedural philosophy of two lines, consisting of the strategy for controlling grip and the strategy for selecting and checking reporting visualization of current data, referred to below as the supervision and testing mechanism. The surveillance strategy is the procedure for completing movement routines and stance detection and automatically saves statistical evidence regarding this practice; the scope of monitoring includes "frequent bowing," "dribbling rate too slow," "dribbling over wrist," four common problems of "nondominant hand is weaker," and give corresponding feedback; among them, "nondominant hand is weaker" can only be detected by certain training items. Figure 2 shows the logical structure of the scene when the user uses the software.

4. Smart Wearable Product Based on Basketball Dribble Teaching Training Posture Monitoring

Through the analysis of relevant literature, this article clarifies the eight common bad habits of young people and other people receiving grassroots physical education in dribbling training. Through interviews with experts, the rationality of these eight habits is confirmed and supplementary explanations are provided and finally developed a list of common bad habits in dribbling training for teenagers and other people receiving basic physical education. Figure 3 is a data survey based on eight bad dribbling habits. In Figure 3, 1 represents the time to bow the head too long, 2 represents the nondominant hand is too weak, 3 represents blindly imitating gorgeous movements, 4 represents too high dribbling, 5 represents too little dribbling power, 6 represents dribbling over wrist, 7 represents palm when the heart touches the ball, and 8 means that the ball is lifted from the center of the foot.

It can be seen from Figure 3 that among the various problems, the long time to bow the head, the blindly imitating gorgeous movements, and the weak dribbling with nondominant hands are bad habits that professionals think need to be corrected most urgently, and they are also some of the more difficult problems to correct. The survey data reached more than 0.15, respectively. But comprehensively considering the feasibility of motion sensor technology, this article will analyze the system's judgment conditions from four

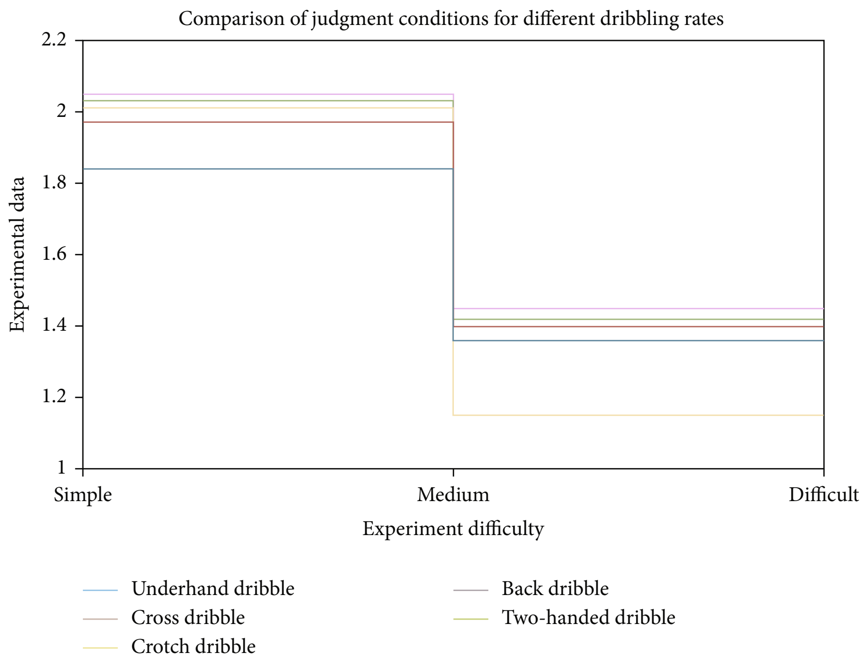

Figure 6: Comparison of judgment conditions for different dribbling rates.

Table 4: Tester's left and right hand data performance.

Tester	Test items	Wrist flip trigger rate	Rate trigger rate	Lower head trigger rate
A	Left	2.6	3.7	5.1
	Right	2.1	2.2	4.0
	Ratio	1.24	1.68	1.275
B	Left	1.7	3.2	5.9
	Right	1.8	1.4	3.7
	Ratio	0.94	2.29	1.59
C	Left	1.5	4.8	6.1
	Right	0.4	2.5	2.7
	Ratio	3.75	1.92	2.26

aspects: too long time to bow, dribbling over the wrist, slow dribbling speed and weak nondominant hand, and give play to the intelligent product The auxiliary effect is when monitoring bad dribble posture.

4.1. Judgment Conditions for "Head Down Too Long" when Dribbling. In order to preset a stricter monitoring standard for "bending the head for too long" when dribbling, this article puts the test subject on the head-mounted device during the experiment and asks him to try to lower his head. At this time, the coach will conduct real-time observation on the side. Once the instructor feels the need to advise the student, the researcher will observe the relevant posture readings of the hardware on the head through the "Debug" page of the product function prototype. If the angle between the student's head device and the surface is essentially fixed at approximately 45° and 60° at this point, then, 70° is selected as a stricter monitoring standard in this article.

At the end of the dribble, the quantity and time of occurrence of the starting problem and the video logged by the feature archetypes are given to the genuine boccia trainers, integrated with the moment of the issue, by looking back at the video to determine the problem of the functional prototype monitoring. Which ones are effective and which ones are ineffective, and are there any missing or undetected "head down time." Through coaching, the supervision is amended, and the mentioned criteria are revised. Effective records are recorded in the effective ratio, and invalid ones are eliminated, strictly according to the monitoring standards, and the sequence is cycled until the manager has a high level of awareness of the system to supervise poor positions and there are no further slips. Table 1 and Figure 4 show the iterative process of parameter combination when dribbling is too long.

As can be seen in Table 1 and Figure 4, the smallest changes in the "critical value of the X-axis angle value of the motion sensor" and the "duration above the critical value" were found when the "head down too long" parameter was varied by a minimum of 5° and 0.2 seconds. If the value changes step by step, there is no big difference in the recognition ratio of the results of different parameter combinations. Therefore, when the parameters of "head down time is too long" are iterated, "motion sensor threshold X-axis angle value" and "duration exceeding threshold" were adjusted to 10° and 0.5 seconds, respectively. Taken together, the optimal parameters of the "head down time is too long" monitoring standard are the X-axis angle value threshold of the motion sensor is -120°, and the duration of exceeding the threshold value is 1 second.

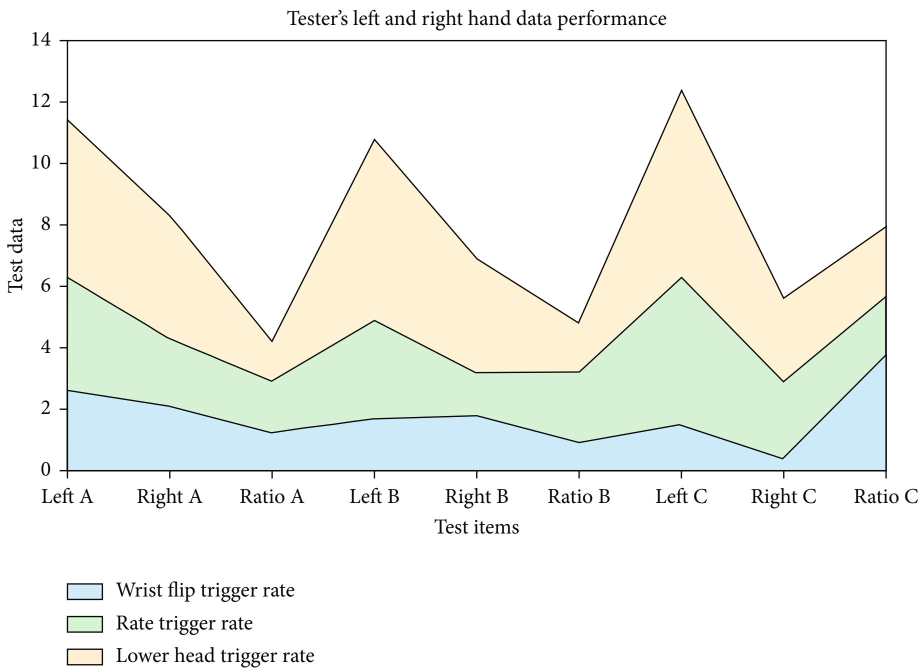

Figure 7: Tester's left and right hand data performance.

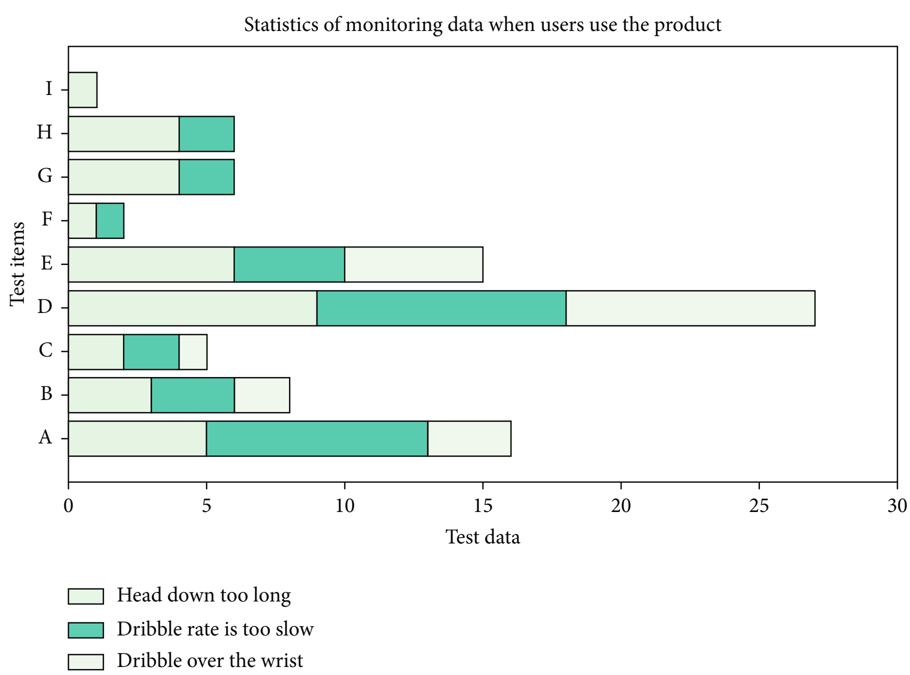

Figure 8: Statistics of monitoring data when users use the product.

4.2. Judgment Conditions for "Dribbling over Wrist" and "Dribbling Too Slow." The monitoring standard of "dribbling over the wrist" is carried out in the scene of "entry-difficult in-situ cross or crotch dribble." "Dribbling Over Wrist" is a condition that tends to cause problems when reversing orientation. In this case, the athlete's dribbling difficulty increases, which can effectively simulate the movement state during real training. The pertinent statistics can be measured with greater precision than in other cases. In "introductory" situations of relatively minor challenge, for the same reason that below-level learners tend to produce more errors, the pertinent information can be managed more usefully. Due to the amount of supervision required, the experts assign a competent person to stochastically imitate dribbling errors and make prototype judgments as required.

In the parameter iteration of the "dribbling wrist flip" detection standard, 90° and 0 seconds are used as the initial

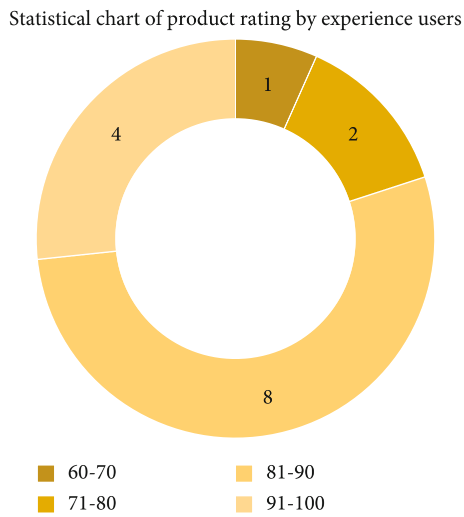

Figure 9: Statistical chart of product rating by experience users.

values of the "X-axis angle value critical value of the motion sensor" and the "duration exceeding the critical value" as the initial values. For monitoring, each student under test will conduct dribbling training for no less than 3 minutes. Basketball assistants at the camp were then asked to work with the playback film and the duration of the undesirable positions recorded from the featured protagonist to validate the captured undesirable positions. Table 2 and Figure 5 show the combination of parameters for carrying the ball and flipping the wrist in an iteration procedure.

It can be seen from Table 2 and Figure 5 that the smallest changes in the "Critical point of the movement transducer X-axis perspective valued" and "Duration over the continuous threshold" data during the argumentation were 5° and 0.2 seconds, respectively. The identification rate of maximum of individual grouping of variables is group 4, with more omissions in groups 5 and 6. Although the recognition rate is high, they are abandoned. Taken together, the ideal specification for the "dribbling wrist flip" surveillance criterion is a limit of 105° for the X-axis perspective function of the kinematic transducers and 0.4 seconds for the time to exceed the limit.

Based on the different surveillance levels, the trainer picked 5 prototypical trainees for an individual level, each dribbling the ball 99 times, and figured out the estimated duration of the 5 deliveries as a guideline for judging the condition of monitoring the slow dribbling speed of the standard. From the data, the criterion for measuring the latitude of initiating a low-hand carry in situ is "1.84 seconds to complete 3 successive full deliveries." Table 3 and Figure 6 compare the judging conditions at different dribbling speeds.

From Table 3 and Figure 6, we can see the comparison values of all 15 dribbling speed judgment conditions. The data with "$*$" shown in Table 3 appears because the average time used by 1 person in the test of this difficulty is compared with other 4 people have big differences, so we exclude them when calculating the average and only take the average of the other four people.

Compared with the long time of bowing the head and turning over the dribble, the judgment conditions of too slow dribbling rate appear more detailed classification. This is because players of different levels have a larger average time when using different dribbling methods. In order to improve the intelligence of dribble monitoring products, more monitoring standards must be artificially given to the system.

4.3. Judgment Conditions for Dribbling "Nondominant Hand Is Weaker." In the "nondominant hand weakness" judgment condition experiment, a sample of participants were selected to accomplish the training with the identical degree of complexity and items with their combined right and left hands, and a physical monitoring stance was added to the previous three experiments with the former judgment condition's operational archetypes. The number of triggering of the monitoring point determines the judgment condition of "nondominant hand is weaker."

The coach recommended 3 students who have a certain dribbling basis and have mild "weak nondominant hand" problems. Under the condition of moderate difficulty in dribbling with low hands in place, 3 participants used the product to train for 2 minutes and obtained corresponding data. Table 4 and Figure 7 show the tester's left and right hand data performance.

As can be seen from Table 4 and Figure 7, this experiment will eventually use "weak nondominant hand" as the trigger condition. After every low-hand dribbling training in place, mistakes are made due to problems such as too long bowing time, too slow dribbling speed, and dribbling over the wrist.

4.4. User Trial Results. In order to test the main functions of the product, this article invited 15 young people as experience users to feel the monitoring effect of this product during dribbling posture monitoring and collected users' evaluations of the product, hoping to find the shortcomings and make further improvements to the product. These 15 experience users are very fond of basketball and will play basketball at least once a week. Figure 8 is a statistical diagram of monitoring data when users use the product.

It can be seen from Figure 8 that, in summary, during the dribble training process, the intelligent system issued a total of 27 reminders, while the coach only reminded the collective 7 times due to the large number of people. By comparison, in the group training scenario, the prompting efficiency of the monitoring posture wearing smart products is higher than that of the coach, which can more effectively compensate for the shortcomings caused by the low teacher-student ratio in the group training. Figure 9 is a statistical chart of the ratings of products by experience users.

It can be seen from Figure 9 that among the 15 product experience users, 80% of the users gave a score of more than 80 points, and only one user thought that wearing the head device caused a strong discomfort, so the rating was lower. This means that wearable devices have yet to be optimized in terms of user experience design. In subsequent research, this article will also focus on improving user wearing experience.

5. Conclusions

This article analyzes the judgment conditions of "head down too long" and "dribbling over wrist" when dribbling. In order to make the problems detected by the product meet the judgment vision of professional coaches in real applications, this paper has obtained the monitoring standards recognized by real coaches through experiments. The expert members participating in the experiment consisted of 3 coaches of youth basketball training classes, 3 university professors majoring in physical education, and 1 professional basketball referee. Through communication with the professor group, this article sorted out the general idea of the experiment and formulated a parameter model of an approved monitoring point. From the experimental results, the optimal parameters of the "head down time too long" monitoring standard are finally identified in this article as: the threshold value for the x-axis angular rating of the kinematic transducer is -120° and the maximum length of time beyond the boundary is 1 second; the ideal characteristics for the "ball turning wrist" surveillance concept are the threshold value for the x-axis angular rating of the kinematic transducer is 105° and the maximum length of time beyond the boundary is 0.4 seconds.

This article analyzes the judgment conditions of "slow dribbling rate" and "weak nondominant hand." This article asks the coaching staff to recommend a number of "benchmarking students" from all the students. The recommended rule is that the coach believes that the student's dribbling rate under the training item and difficulty can be used as the "dribbling rate too slow" monitoring standard for the training item and difficulty. After repeated experiments, the comparison values of all 15 dribbling speed judgment conditions were finally obtained. In order to ensure that the reference standard is strict and closer to the true level, this article removes data that is significantly lower than other testers when calculating the average data. After discussing with experts, it was concluded that the "weak nondominant hand" was caused by too long pauses, too slow dribbling speed, and dribbling over the wrist after the in situ dribbling training. And the trigger rate of any two monitoring points is 1.2 times higher than the trigger rate of the corresponding monitoring point of the other hand during the last low-hand dribbling training.

In this study, limited by experimental conditions, it was impossible to obtain a product-level miniaturized motion sensor module, resulting in a low degree of design reduction in the hardware part of the wearable device. In addition, due to the limited time, the number of people tested during follow-up product trials is small, resulting in insufficient persuasiveness of the final user score. I believe that in the future, as people continue to deepen the research on smart motion sensors, they will be able to develop more excellent smart auxiliary software to provide professional and humanized services for all aspects of life.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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