Computer-Aided Integration of Wearable Sports Fitness Equipment in the Development of IoT-Enabled Public Sports Service System

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Abstract. In order to improve the effect of mass sports and fitness exercise, based on the basic concept of public sports services, this paper combines the Internet of Things technology and intelligent identification technology to construct a wearable sports fitness equipment based on the Internet of Things. Wearable clothes in this system are used as the front end of ECG and respiration signal collection, as well as the carrying platform of signal node and pulse node, and the inertial sensor MPU6050 is used to collect human gait information. Moreover, this paper distinguishes the exercise state through the target heart rate on the basis of the original energy consumption model, and compares the fit of the exponential and linear models to construct the entire system frame structure. Finally, this paper designs an experiment to evaluate the application effect of wearable sports fitness equipment based on the Internet of Things in the public sports service system. From the test results, it can be known that its application effect is good.

Keywords: Internet of Things; wearable; sports fitness equipment; public sports services; Computer-Aided Integration
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1 INTRODUCTION

With the continuous development of health informatization, residents continue to pay more attention to their own health, and emerging diagnosis and treatment methods and medical models such as smart medicine, mobile medicine, and telemedicine have emerged. We can completely imagine a medical scenario in which health and medical wearable devices or mobile medical APPs mounted on mobile communication devices are used to collect, mine, manage, and analyze personal health and physiological indicators and other related data, and to assist in providing medical decisions and solutions. These are completely subverting people's previous understanding of medical models. It is foreseeable that various medical subdivisions, from diagnosis, monitoring, treatment, and drug delivery, will fully open an era of intelligence, and traditional medical equipment may be completely subverted [3]. Moreover, the development of medical equipment will shift from complex large-scale equipment used in medical institutions to small wearable or even chip implantable equipment that can be used in hospitals and meet the needs of families and individuals [11]. Patients can use smart health and medical wearable devices to monitor various physiological indicators of their bodies, and use smart terminals or mobile communication devices to send them to doctors and medical institutions, which is conducive to reducing repetitive medical examinations, optimizing medical procedures, and improving the efficiency of medical services.

Because big data can be obtained, stored, searched, shared, analyzed, and even visualized, it implies huge social, economic, and scientific research value, which has attracted great attention from all walks of life [20]. With the in-depth research on big data, some social science issues such as public opinion analysis and sentiment analysis have tried to use big data related methods to analyze and solve. With the promotion of national fitness, sports and fitness big data issues have gradually received attention. In such a complex ocean of data, tidal currents of information wash our brains every day, and people understand the world through more colorful ways of perception, and display things three-dimensionally and “truthly” in front of us through multiple channels and multiple dimensions. The broadening of our horizons has allowed us to deepen our understanding of ourselves, and also made our material and spiritual needs no longer simple enough to meet in the past. The acceleration of the pace of life makes the application of time more efficient, and forces the pursuit of faster and more portable information acquisition and collection methods. The development of the wearable device industry has become an inevitable trend.

The National Fitness Program issued by the State Council pointed out that in the new development concept, it is necessary to improve the health of the people as the fundamental goal, and to incorporate the construction of a national fitness public service system into the country’s basic public service and modern public cultural service system, such as community sports equipment and the construction of public sports venues. At the same time, it is necessary to clarify the core indicators of national fitness, and formulate a series of evaluation methods and evaluation methods and standards for the construction of the national fitness public service system to judge the promotion of national fitness and the construction of the national fitness public service system, so as to promote the standardization and equalization of the basic public services of national fitness computer-aided technologies can assist in monitoring and evaluating the progress and effectiveness of the national fitness public service system. Wearable devices, such as fitness trackers and smartwatches, can collect data on individuals' physical activity levels, heart rate, sleep patterns, and other relevant metrics. This information can be analyzed to assess the impact of fitness programs, identify areas for improvement, and track the overall health and well-being of the population. Such monitoring and evaluation systems can provide valuable insights for policymakers, allowing them to make data-driven decisions and allocate resources effectively.

This article constructs a wearable sports fitness equipment under the Internet of Things environment, and applies it to the construction of a public sports service system to explore its practical effects.

2 RELATED WORK

Wearable devices, namely wearable computers, are computer devices that can be worn on the body or clothing and can send and transmit data or messages. It comprehensively uses various types of identification-related technologies, sensing technologies, data connections, and cloud computing technologies for data processing. Moreover, it allows the wearer to use wearable devices for infotainment, social sharing, and to monitor the wearer's personal physical condition [1]. Literature [4] believes that a wearable computer is a kind of wearable device that can serve the wearer and belong to the user's individual. This type of device is simply controlled by the wearer, and the wearer can use this wearable device to communicate and perform scientific calculations on related data. With the rapid development of technology and the continuous breakthrough of various difficulties, various functions have been developed and applied to wearable devices. A wearable device can meet the various needs of consumers. For example, Apple's products iwatch, Xiaomi bracelet, etc., can not only meet the convenience of users, but also ensure powerful and versatile functions. Moreover, it can also satisfy people’s pursuit of fashion and has the ability to perceive. In addition, it can use the built-in chip sensor to obtain relevant information of the user, and perceive the user’s surrounding environment and current sports conditions, which has become the most convenient way for wearers to obtain their own sports information [19].

The literature [7] used an acceleration sensor to identify human behavior. The experiment extracted the mean, variance, frequency domain entropy and correlation coefficient as behavior features, and used a decision tree classifier to identify 20 daily behaviors. The literature [12] extracted features such as interquartile difference, wavelet energy, and FFT coefficients, and used SVM (support vector machine) classifier to identify five gait patterns. The literature [5] started from the analysis of the motion data itself, extracts the average maximum (minimum), mean, variance and frequency domain characteristics, selected PCA (Principal Component Analysis) to reduce the dimensionality of the features, and finally used the J48 decision tree classifier. The literature [6] designed a distributed sparse representation classifier based on sparse representation and compressed sensing. The experimental results show that the algorithm can effectively identify 13 daily behaviors. The literature [15] designed a classifier based on compressed sensing, which can effectively recognize low-dimensional sampled data after random projection and has a recognition rate comparable to traditional recognition methods. Judging from the existing research work, it can be seen that researchers have a certain knowledge and understanding of the essential characteristics of behavior, and have accumulated a wealth of research experience. However, from an overall point of view, most of the current work is still in the preliminary exploratory stage. Human body movement itself contains many factors such as bones, muscles, and nerves [16], so there are still many difficulties to be overcome and solved both from the technical level and the theoretical level.

The behavioral data based on the inertial sensor system is the acceleration and angular velocity of various parts of the body. However, because the complexity of different actions is different, there are generally fewer sensor nodes needed to analyze and describe simple behaviors at the hardware level. However, the description of complex behavior requires more sensor nodes [9]. The SCUT-NAA database established in [14] uses only one sensor. The DSAD (Daily and Sports Activities Data set) database uses 5 sensor nodes [21]. The number of sensor nodes in the RARD (REALDISP Activity Recognition Data Set Data Set) database is 9 [13].

3 AN IMPROVED FVWNB CLASSIFIER

This article will introduce a Feature Value Weighted-Based Naive Bayes (FVWNB) classifier. This classifier weakens the influence of the conditional independence assumption of the classic naive Bayes model on the classification performance, and improves the accuracy of the model classification. The specific weighting method is a Correlation-based Attribute Value Weighting (CAVW) method. This method is simple and efficient, and is more suitable for the actual application scenarios emphasized in this paper.

The Bayesian Network Classifier (BNC) is a classification model based on probabilistic reasoning, and the Bayesian formula is the basis of the entire model. It is a model for supervised learning. A test instance x is represented by a feature vector $(a_1, a_2, \cdots, a_m)$, and BNC uses the following formula to classify x[10]:

$$c(x) = \arg\max_{c \in C} P(c) P(a_1, a_2, \cdots, a_m | c) \tag{1}$$

If it is assumed that all features are completely independent in a given category, the resulting BNC is called the Naive Bayes (NB) model. The NB model uses the following formula to classify x:

$$c(x) = \arg\max_{c \in C} P(c) \prod_{i=1}^{m} P(a_i | c) \tag{2}$$

Among them, the prior probability $P(c)$ and the conditional probability $P(a_i|c)$ are calculated by the following formula:

$$P(c) = \frac{\sum_{j=1}^{n} \delta(c_j, c) + 1}{n + l} \tag{3}$$

$$P(a_i|c) = \frac{\sum_{j=1}^{n} \delta(a_{ji}, a_i) \delta(c_j, c) + 1}{\sum_{j=1}^{n} \delta(c_j, c) + n_i} \tag{4}$$

δ is a binary function, which is represented by the following formula[8]:

$$\delta(a_1, a_2) = \begin{cases} 1 & a_1 = a_2 \\ 0 & else \end{cases} \tag{5}$$

The NB model is the simplest form of Bayesian network due to the assumption of the independence of its characteristic conditions. The advantage of this model lies in its simplicity and efficiency. At the same time, it is based on a solid mathematical theoretical foundation and has high reliability. , Is still one of the top ten data mining algorithms and a widely used classifier model. However, the hypothesis of feature condition independence is often difficult to achieve in practical problems. There are two main reasons: First, under the premise of a given category label, the features are often not independent of each other, and there is usually a certain degree between them. Second, the importance of different features for classification is not all the same. For the NB model, the classification decision should focus on the features that have a greater impact on the classification results and those features that have low dependence, although the NB model has been proved to be surprisingly robust under the condition of obvious violation of the independence condition. However, the influence of the assumption of independence on the results of classification decisions is still not negligible. Moreover, the Naive Bayesian (FVWNB) classifier based on eigenvalue weighting introduced in this article is an improvement of a more fine-grained weighting method of the NB model. Under the premise of ensuring the simplicity of the classification model, the maximum To improve the accuracy of classification.

FVWNB tries to decompose the importance of features. The evaluation of importance is not only on the features, but also more fine-grained evaluation of the importance of each feature value. According to the different value of the feature value, different feature values are assigned. Weight, this weighting method is called Feature Value Weighted (FVW). The basic assumption of the FVW method is that each feature value has a different contribution when classifying test cases. This more fine-grained weighting method can further relax the constraints of the conditional independence assumption of the NB model [18].

The improved FVWNB classifier is expressed as:

$$c(x)=\arg\max_{c\in C} P(c)\prod_{i=1}^{m} P(a_i|c)^{w_{a_i}} \tag{6}$$

Among them, $c(x)$ represents the predicted value of FVWNB for the test instance x, w_{a_i} represents the weight of the eigenvalue a_i. For a given feature, the importance of the impact of different values on the classification result may be different, and the feature value with high importance should be assigned more weight. On the contrary, eigenvalues that have little effect on the results should have relatively low weights. The best eigenvalue should be such that the eigenvalue is closely related to the class attribute and is completely independent of other eigenvalues. Therefore, the CAVW method attempts to decompose the importance of eigenvalues, and defines the weight of each eigenvalue as the difference between the cross-correlation between the eigenvalue and the class attribute and the average redundancy between the eigenvalues, which is expressed as[2]:

$$w_{a_i}=I(a_i;C)-\frac{1}{m}\times I_d(a_i;a_j) \tag{7}$$

Among them,

$$I_d(a_i;a_j)=\frac{1}{m-1}\sum_{j=1\wedge j\neq i}^{m} I(a_i;a_j) \tag{8}$$

Among them, $I(a_i;C)$ is a normalized value, which represents the correlation between the characteristic value a_i and the class attribute variable, and $I(a_i;a_j)$ is also a normalized value, which represents the degree of redundancy between a_i and other characteristic values. For a certain feature value, when it provides more effective information for the classification result, its importance should be higher. Therefore, for an important high predictive feature value, it should have a higher $I(a_i;C)$ and a lower $I(a_i;a_j)$.

The weight w_{a_i} of each eigenvalue should be a certain value belonging to the interval $[0,1]$. The value of w_{a_i} may not be within the restricted range. Therefore, the sigmoid function is used to convert the value range into a valid range. The sigmoid function is expressed as[17]:

$$f(x)=\frac{1}{1+e^{-x}} \tag{9}$$

The value range of the sigmoid function is 0 to 1, that is, the calculation formula of the final eigenvalue weight after conversion is expressed as:

$$w_{a_i} = \frac{1}{1+e^{-\left[I(a_i;C)-\frac{1}{m}\times I_d\left(a_i;a_j\right)\right]}} \tag{10}$$

The distance criterion is a measure of the degree of difference between two random variables, or the degree of similarity between two distributions. In the distance measurement criteria, the commonly used distances are roughly divided into two categories: geometric distance and probability distance. The Kull-back-Leibler (KL) distance in the probability distance is used for estimation, and the KL distance of eigenvalues and class attributes is expressed as:

$$KL\left(C|a_i\right) = \sum_c P\left(c|a_i\right)\log\frac{P\left(c|a_i\right)}{P(c)} \tag{11}$$

Secondly, another quantity that needs to be estimated is the degree of correlation between eigenvalues. KL distance is expressed as:

$$KL\left(a_j|a_i\right) = P\left(a_j|a_i\right)\log\frac{P\left(a_j|a_i\right)}{P\left(a_j\right)} \tag{12}$$

The calculation result of the above formula is normalized and expressed as:

$$I\left(a_i;C\right) = \frac{KL\left(C|a_i\right)}{\frac{1}{m}\sum_{i=1}^{m} KL\left(C|a_i\right)} \tag{13}$$

$$I\left(a_i;a_j\right) = \frac{KL\left(a_j|a_i\right)}{\frac{1}{m(m-1)}\sum_{i=1}^{m}\sum_{j=1\wedge j\neq i}^{m} KL\left(a_j|a_i\right)} \tag{14}$$

4 CONSTRUCTION OF SMART SYSTEMS FOR WEARABLE SPORTS EQUIPMENT BASED ON THE INTERNET OF THINGS

According to the functional requirements of the testing equipment, the testing equipment should include the following modules: control module, communication module, body temperature detection module, pulse detection module, display module, control button, power detection module, voltage stabilization module and power supply module. The corresponding detection equipment structure is shown in Figure 1.

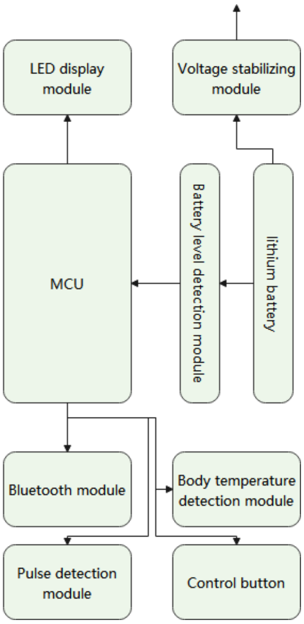

Figure 1: The Structure Diagram of the Physiological Parameter Detection Equipment.

Due to pulse pulsation, the hyperemia volume in the blood vessel will change. When the light emitted by the light source transmitter passes through the peripheral blood vessels of the human body, the photoelectric transducer will receive the light reflected by the human tissue and convert it into an electric signal to amplify and output. The change period of the electrical signal output by the photoelectric converter is the pulse rate. the heart rate signal is converted into an electrical signal by a photoelectric reflective heart rate sensor as shown in Figure 2.

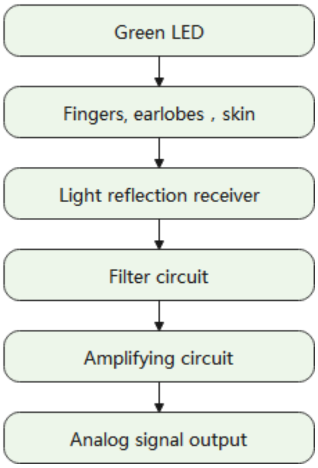

Figure 2: The Process of Collecting Heart Rate Signals by the Photoelectric Reflective Heart Rate Sensor.

Transmissive heart rate sensors are mostly pinch-finger and ring-type. The finger is placed in the middle of the infrared photoelectric sensor. As the heart beats, the blood flow in the blood vessel will change, and the change of blood saturation will affect the photoelectric receiver's light reception. The intensity of the received light is indirectly reflected as the current of the infrared receiving diode. Therefore, the current signal and the heart rate signal outputted after the signal output by the infrared receiving diode are amplified, filtered, and reshaped have a corresponding relationship. The flow chart of the transmissive infrared photoelectric heart rate sensor converting the heart rate signal into an electrical signal is shown in Figure 3.

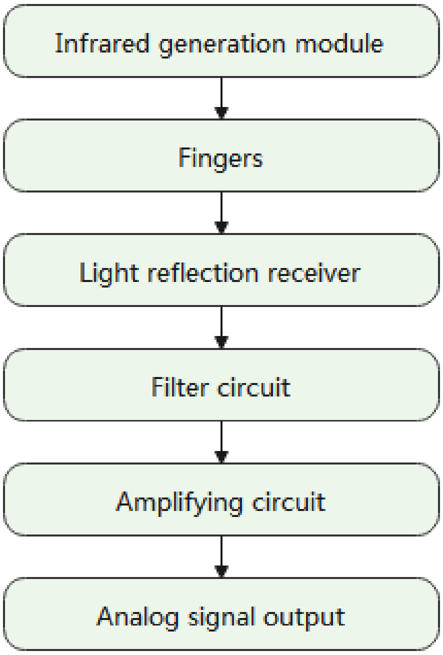

Figure 3: The Process of Collecting Heart Rate Signals by the Transmissive Infrared Photoelectric Heart Rate Sensor.

This system uses the inertial sensor MPU6050 to collect human gait information. The heart rate sensor SON1205 directly outputs pulse waveforms. When calculating the heart rate value, this system designs two timers, one way to count and one time to calculate the heart rate value data. The software scheme design flow chart is shown in Figure 4.

According to the kinematics algorithm of human body, in order to calculate the spatial attitude relatively accurately, the sending end node needs to be able to collect data including acceleration, angular velocity and magnetometer. At the same time, for some medical applications, it is hoped that the system can provide simple vibration feedback. The system architecture is shown in Figure 5.

The standardization work for all aspects of health informatization will build a data standard system framework for health and medical wearable devices from the three dimensions of "X-life cycle", "Y-business area" and "Z-standard type", as shown in the figure below. The Overall Structure Diagram is shown in Figure 7.

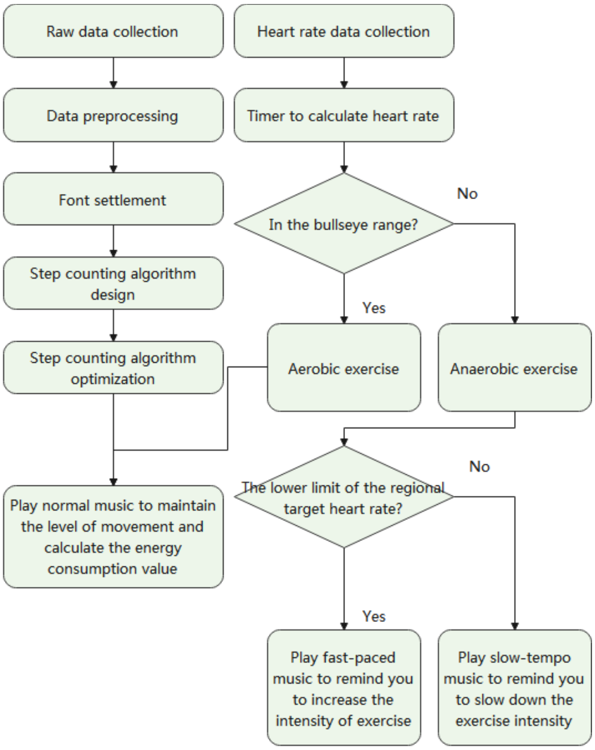

Figure 4: Flow Chart of Software Scheme Design.

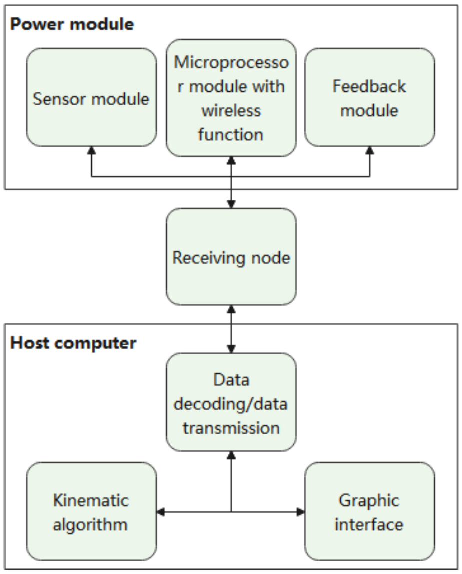

Figure 5: Wearable System Architecture.

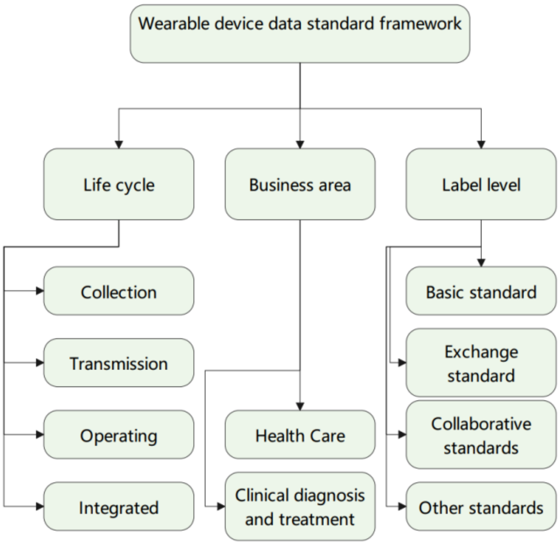

Figure 6: The Framework Structure of the Data Standard System for Health Sports Wearable Devices.

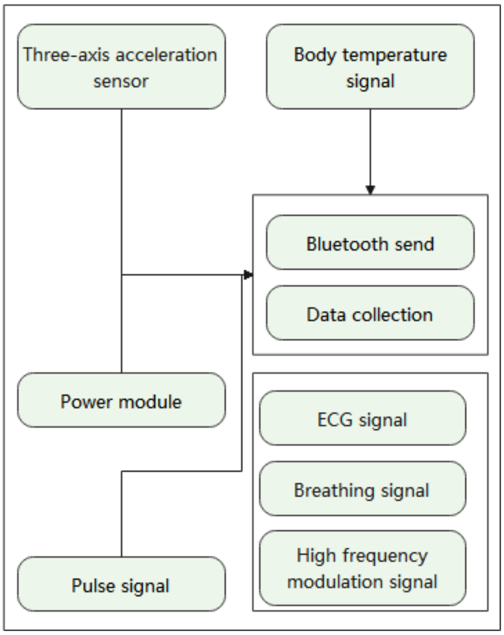

Figure 7: The Hardware Structure of the Signal Node.

The body temperature data output by the DS18B20 temperature sensor DQ bus is collected through the universal input and output port of the main control chip; the output data of the ADS1292R ECG breathing module is controlled and collected through the serial peripheral interface; the movement is controlled and collected through the two-wire serial bus The data of the module's three-axis acceleration sensor; the signal output by the pulse node is collected through the internal ADC of the chip; the power module is responsible for providing a stable voltage for each module and the main control chip, and it also integrates a charging circuit for charging the lithium battery.

The wearable clothes in this system are used as the front end of ECG and respiration signal acquisition, as well as the carrying platform of signal node and pulse node. Therefore, wearing clothes should ensure the convenience and comfort of users, and can be reused, so that various modules and nodes work together to truly form a complete signal acquisition system to realize the wearing of human body physiological signals such as ECG, respiration, pulse, and movement status.

The structure of the wearable clothe is shown in Figure 8 below.

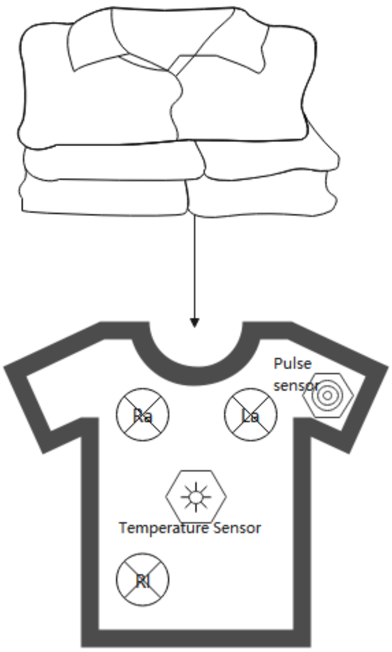

Figure 8: Structure Design of the Wearable Clothe.

Physiological parameter monitoring clothing is mainly composed of wearing clothing, ECG and respiratory signal collection electrodes, fabric wires, signal node interface, and pulse node interface. Three ECG breathing signal acquisition electrodes, LA (Left Arm) and RL (Right Leg) are respectively arranged on the left lower sternum clavicle, right lower sternum clavicle, and right abdomen on the inner side of the wearing clothes. The three electrodes are gathered to each other through three fabric wires. At the signal node interface under the chest; the pulse signal acquisition node is installed at the left wrist radial artery, and is connected to the signal node interface through three GND, VCC, PPG signal wires, which are respectively used for the common ground, power supply and pulse of the pulse acquisition module circuit Signal transmission. The temperature sensor is also fixed on the inside of the chest garment, and the signal node and pulse node are connected and fixed with the garment through the interface at the corresponding position, which together constitute the hardware platform of the human body's multi-physiological parameter collection system.

5 EVALUATION OF THE APPLICATION EFFECT OF WEARABLE SPORTS FITNESS EQUIPMENT BASED ON THE INTERNET OF THINGS IN THE PUBLIC SPORTS SERVICE SYSTEM

Next, this paper evaluates the application effect of wearable sports fitness equipment based on the Internet of Things in the public sports service system, and designs experiments with statistical methods to verify the effects. Moreover, this paper evaluates the fitness effect of the wearable sports fitness equipment constructed in this paper through multiple groups of testers, and the results obtained are shown in Table 1 and Figure 9.

Num	*Fitness effect*	*Num*	*Fitness effect*	*Num*	*Fitness effect*
1	*92.61*	*28*	*91.75*	*55*	*88.87*
2	*91.57*	*29*	*86.45*	*56*	*91.53*
3	*90.79*	*30*	*88.40*	*57*	*89.75*
4	*92.28*	*31*	*92.61*	*58*	*92.32*
5	*93.61*	*32*	*90.34*	*59*	*92.49*
6	*86.48*	*33*	*93.40*	*60*	*88.26*
7	*89.68*	*34*	*90.65*	*61*	*89.23*
8	*86.87*	*35*	*88.12*	*62*	*88.45*
9	*88.51*	*36*	*87.05*	*63*	*91.58*
10	*88.67*	*37*	*86.67*	*64*	*93.95*
11	*90.96*	*38*	*87.00*	*65*	*90.49*
12	*89.86*	*39*	*87.82*	*66*	*86.27*
13	*86.75*	*40*	*91.55*	*67*	*88.32*
14	*91.30*	*41*	*86.91*	*68*	*86.95*
15	*87.74*	*42*	*92.43*	*69*	*86.42*
16	*92.71*	*43*	*86.01*	*70*	*89.10*
17	*91.99*	*44*	*86.95*	*71*	*92.39*
18	*91.85*	*45*	*92.34*	*72*	*88.92*
19	*92.63*	*46*	*87.86*	*73*	*93.53*
20	*92.34*	*47*	*88.66*	*74*	*89.22*
21	*86.88*	*48*	*88.95*	*75*	*89.20*
22	*86.04*	*49*	*86.10*	*76*	*86.79*
23	*86.71*	*50*	*86.12*	*77*	*87.26*
24	*89.53*	*51*	*92.56*	*78*	*86.58*
25	*86.38*	*52*	*89.46*	*79*	*93.78*
26	*87.04*	*53*	*90.30*	*80*	*92.82*
27	*88.31*	*54*	*86.37*	*81*	*89.86*

Table 1: Statistical Table of the Evaluation of the Fitness Effect of Wearable Sports Fitness Equipment.

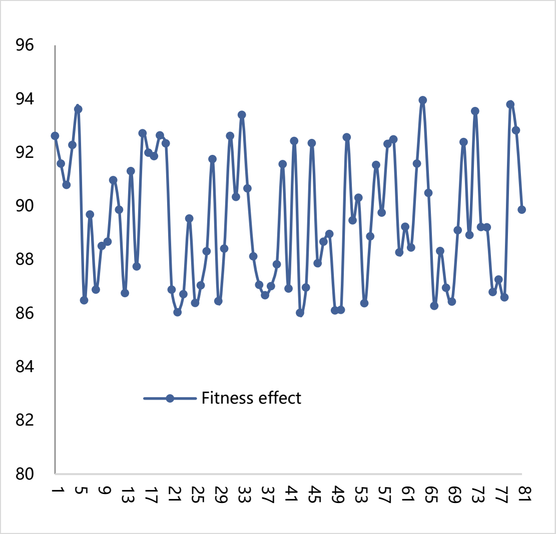

Figure 9: Statistical Diagram of the Evaluation of the Fitness Effect of Wearable Sports Fitness Equipment.

Through the above research, it can be known that the wearable sports fitness equipment based on the Internet of Things constructed in this paper can effectively improve the fitness effect of the masses. On this basis, the application effects of wearable sports fitness equipment based on the Internet of Things in the public sports service system are evaluated through expert evaluation methods, and statistics are made through scoring methods. The results are shown in Table 2 and Figure 10.

Num	*Practical effect*	*Num*	*Practical effect*	*Num*	*Practical effect*
1	*93.93*	*28*	*88.48*	*55*	*93.30*
2	*90.65*	*29*	*90.68*	*56*	*89.20*
3	*90.93*	*30*	*86.35*	*57*	*88.38*
4	*91.72*	*31*	*89.20*	*58*	*86.68*
5	*91.31*	*32*	*88.02*	*59*	*90.86*
6	*87.27*	*33*	*88.23*	*60*	*88.15*
7	*91.65*	*34*	*92.23*	*61*	*87.55*
8	*91.35*	*35*	*90.07*	*62*	*92.73*
9	*92.08*	*36*	*93.22*	*63*	*89.90*
10	*92.57*	*37*	*91.51*	*64*	*91.61*
11	*86.49*	*38*	*88.83*	*65*	*89.88*
12	*88.85*	*39*	*91.27*	*66*	*92.26*
13	*92.56*	*40*	*93.63*	*67*	*86.58*
14	*91.63*	*41*	*88.66*	*68*	*87.26*
15	*91.35*	*42*	*88.65*	*69*	*86.61*
16	*91.29*	*43*	*89.56*	*70*	*86.09*
17	*87.91*	*44*	*86.51*	*71*	*93.31*

18	*88.86*	*45*	*92.83*	*72*	*88.66*
19	*89.34*	*46*	*92.93*	*73*	*89.30*
20	*87.34*	*47*	*88.04*	*74*	*93.53*
21	*89.00*	*48*	*86.81*	*75*	*87.94*
22	*87.12*	*49*	*93.67*	*76*	*90.67*
23	*89.81*	*50*	*91.00*	*77*	*92.22*
24	*86.04*	*51*	*87.59*	*78*	*92.87*
25	*91.94*	*52*	*92.43*	*79*	*87.55*
26	*92.95*	*53*	*89.12*	*80*	*92.97*
27	*92.70*	*54*	*92.82*	*81*	*92.70*

Table 2: Statistical Table of the Evaluation of the Application Effect of Wearable Sports Fitness Equipment Based on the Internet of Things in the Public Sports Service.

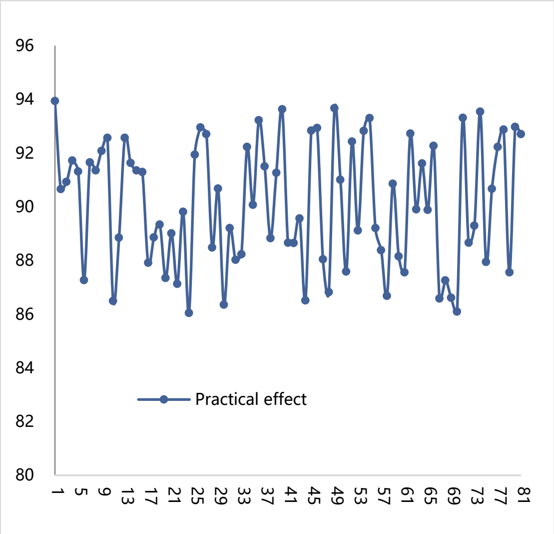

Figure 10: Statistical Diagram of the Evaluation of the Application Effect of Wearable Sports Fitness Equipment Based on the Internet of Things in the Public Sports Service System.

From the above experimental research, it can be seen that the application effect of wearable sports fitness equipment based on the Internet of Things in the public sports service system is relatively good, which verifies that the method proposed in this paper has a certain practical effect.

6 CONCLUSION

In recent years, the application of the Internet of Things has gradually integrated into all aspects of people's lives, and it has a very mature product market in the fields of gesture recognition, gait recognition, and smart home. As one of the applications of inertial sensors, wearable devices were first used in smart games. With the improvement of living standards, people's attention to their own health has gradually increased, and the products of wearable devices in health detection have received more and more attention.

This article mainly studies a wearable sports fitness equipment based on the Internet of Things, which uses inertial sensors to collect gait information, and designs a step-counting algorithm to display the user's exercise steps in real time. Through experimental research, it can be seen that the application effect of wearable sports fitness equipment based on the Internet of Things in the public sports service system is better.

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REFERENCES

[1] Abanazir, C.E: sport and the EU: The View from the English Bridge Union, The International Sports Law Journal, 18(3), 2019, 102-113. https://doi.org/10.1007/s40318-018-0139-6
[2] Budde, H.: Koutsandréou, F.: Wegner, M.: Aerobic Exercise Training Reduces Anxiety in children, European Psychiatry, 33, 2016, S139-S139.
[3] Ferguson, L.J.; Carlson, K.T.; Rogers, D.: Moving towards Reconciliation Through Sport: Sharing Our Process of Exploring Team Saskatchewan Experiences at the North American Indigenous Games, Journal of Exercise, Movement, and Sport (SCAPPS Refereed Abstracts Repository), 51(1), 2019, 99-99.
[4] Gerke, A.; Babiak, K.; Dickson, G.: et al. Developmental Processes and Motivations for Linkages in Cross-Sectoral Sport Clus-Ters, Sport Management Review, 21(2), 2018, 133-146. https://doi.org/10.1016/j.smr.2017.05.005
[5] Giulianotti, R.; Numerato, D.: Global Sport and Consumer Culture: An Introduction, Journal of Consumer Culture, 18(2), 2018, 229-240. https://doi.org/10.1177/1469540517744691
[6] Gurinovich, A.G.: Petrova, G.V.: Key Priorities of Physical Education and Sport Sector Budgeting Laws and Regulations in the Russian Federation, Theory and Practice of Physical Culture, (4), 2019, 34-34.
[7] Ilies, D.C.; Buhas, R.; Ilies, M.: et al. Sport Activities and Leisure in Nature 2000 Protected Area-Red Valley, Romania, Journal of Environmental Protection and Ecology, 19(1), 2018, 367-372.
[8] Jarani, J.; Grntved, A.; Muca, F.: et al. Effects of Two Physical Education Programmes on Health- and Skill-Related Physical Fit-Ness of Albanian Children, Journal of Sports Sciences, 34(1), 2015,1-12. https://doi.org/10.1080/02640414.2015.1031161
[9] Jie, Z.; Xiao-Xia, L.I.; Department, P.E.: et al. Inhibitory Effect of Aerobic Exercise on Left Ventricular Remodeling and Sympa-Thetic Neural Remodeling in Rats with Heart Failure After Myocardial Infarction, Chinese Journal of Pathophysiology, 31(6), 2015, 973-979.
[10] Josh, L.; Secomb; Jeremy, M.; Sheppard; Ben, J.: Dascombe. Time-Motion Analysis of a 2-Hour Surfing Training Session, int j Sports Physiol Perform, 10(1), 2015, 17-22. https://doi.org/10.1123/ijspp.2014-0002
[11] Kimasi, K.; Shojaei, V.; Boroumand, M.R.: Investigation of Safety Conditions at Gymnasia in Different Organizations, Journal of Humanities Insights, 3(02), 2019, 70-74.
[12] Kondrukh, A.I.: Practical shooting sport in Russian Sport System: Essential Specifications and Features, Theory and Practice of Physical Culture, (5), 2017 27-27.
[13] Korobeynikov, G.; Korobeynikova, L.: Iermakov, S.: et al. Original Article Reaction of Heart Rate Regulation to Extreme Sport Activity in Elite Athletes, Journal of Physical Education and Sport, 16(154), 2016, 976-981.

[14] Lembe, G.; Mboungou, Z.; Alongo, G.Y.R.: et al. The Teaching of the Traditional Physical Activities and the Physiologicals Adaptations in the Congo Pupils, Current Research Journal of Social Sciences, 8(3), 2016, 34-38. https://doi.org/10.19026/crjss.8.2915

[15] Liu, Y.Q.: Operative Correction of Judoists' Training Loads on the Base of on-Line Monitoring of Heart Beats Rate, Chinese Journal of Tropical Crops, 19(2), 2015, 13-21. https://doi.org/10.15561/20755279.2015.0203

[16] Lyyra, N.; Heikinaro-Johansson, P.; Lyyra, M.: Exploring in-Class Physical Activity Levels During Physical Education Lessons in Finland, Journal of Physical Education and Sport, 17(2), 2017, 815-820.

[17] Queiroz, M. G.; de Araújo, J. A.; Rezende, D.A.N.; et al. Heart Rate Variability Threshold Estimates Ventilatory Threshold in Young People with Different Body Mass Index: 1524 Board #177, AM, Medicine & Science in Sports & Exercise, 48(5S Suppl 1), 2016, s415.

[18] Kocić, M.; Bojić, I.; Aleksandrović, M.; et al.: Physical Activity in Adolescent with Mental Retardation: Is Adapted Basketball Training Adequate Stimulus to Improve Cardiorespiratory Fitness and Sport Skills Performance?, Nephron Clinical Practice, 34(2), 2017, 159-168. https://doi.org/10.1515/afmnai-2017-0018

[19] Pogrebnoy, A.I.; Komlev, I.O.: Sport Institutions Reporting to Ministry of Sport of Russian Federation: Intellectual Property, Invention Activity, Patenting and Legal Consulting Service analysis, Theory and Practice of Physical Culture, (2), 2018, 2-2.

[20] Reinhart, K.; Wichmann, B.: The TuS Fortschritt Magdeburg-Neustadt (soccer section) in the GDR-an Example of Amateur Socialist Sport, Soccer & Society, 21(4), 2020, 408-420. https://doi.org/10.1080/14660970.2020.1751466

[21] Sebastián del Rosso; Fábio, Y.: Nakamura Boullosa, D. A.: Heart Rate Recovery After Aerobic and Anaerobic Tests: Is There an Influence of Anaerobic Speed Reserve?, Journal of Sports ences, 35(9), 2016, 820-827. https://doi.org/10.1080/02640414.2016.1166391