Evaluation method of smart bracelet health monitoring accuracy based on multi-level data fusion

Weicheng Ma*

Institute of Physical Education,
Jilin Sports University,
Changchun 130000, China
Email: weicheng@mls.sinanet.com
*Corresponding author

Yanfei Lv

Teaching Affairs Office,
Jilin Sports University,
Changchun 130000, China
Email: 171385646@qq.com

Abstract: In the process of smart bracelet health monitoring, there are some problems, such as low efficiency of accuracy evaluation and high fusion error rate. An accuracy evaluation method of smart bracelet health monitoring based on multi-level data fusion. The intelligent bracelet is monitored by information collection, information judgment and information display. The v1.1 temperature acquisition sensor and pulse sensor are selected to measure the temperature, heart rate and blood oxygen saturation. The cloud design and fuzzy information clustering method are used to realise the effective integration of multi-level data and information, and the maximum likelihood estimation model of the health index of the intelligent bracelet is established to obtain the intelligent information evaluation results of the accuracy of health monitoring of bracelet. The experimental results show that the accuracy evaluation efficiency of the proposed method is always above 80%, and the fusion error rate is always below 0.1%.

Keywords: multi-level data fusion; smart bracelet; health monitoring; accuracy evaluation.

Reference to this paper should be made as follows: Ma, W. and Lv, Y. (2022) 'Evaluation method of smart bracelet health monitoring accuracy based on multi-level data fusion', *Int. J. Product Development*, Vol. 26, Nos. 1/2/3/4, pp.117–130.

Biographical notes: Weicheng Ma received his Master degree in education from Jilin Sports University in 2012. Currently he is a lecture in the college of Institute of Physical Education of Jilin Sports University. His research interests include physical education training, physical statistics, and football teaching.

Yanfei Lv received his Master degree in education from Jilin Sports University in 2012. Currently she is an assistant in the College of Institute of Physical Education of Jilin Sports University. His research interests include physical education training, physical statistics, and football teaching.

1 Introduction

The development of science and technology has improved the quality of people's lives. Most people are unable to undergo regular health check-ups in hospitals due to work reasons. In this situation, it is necessary to rely on intelligent health monitoring equipment to ensure that their lives and work are not affected. In order to monitor one's own health, smart bracelets are widely used due to their compact and portable characteristics (Yuan et al., 2019). By 2018, the development of domestic smart bracelets has reached a new height, and the sales of wearable devices have occupied the world's first place (Bouzón et al., 2019). The smart bracelet can monitor heart rate data in time, has good waterproof performance, and can transmit bioelectric signals, pressure values, and respiratory frequency signals generated during human activities (Roseland and Maturen, 2019). However, wearable devices mainly monitor human physiological parameters, and the amount of data collected is insufficient. A large number of human physiological parameters have a huge impact on the device, and the monitoring accuracy is greatly reduced. Therefore, relevant research is needed to improve the accuracy of smart bracelet health monitoring (Yazhu et al., 2019).

Huang et al. (2019) studied the accuracy measurement of blood pressure measurement function of a smart bracelet of a certain brand, and provided theoretical basis for the application of bracelet in the field of health monitoring. The research equipment is the brand's smart bracelet, combined with a mercury sphygmomanometer to measure the blood pressure measurement results of the two devices. The accuracy of the smart blood pressure test result of the brand bracelet reached 81.53%, the blood pressure measurement sensitivity was as high as 85.62%, the false negative rate and the positive rate were 22.83% and 13.81%, and the specificity was 77.97%. Obtain the receiver operating ROC curve, and calculate the area under the curve to reach 0.82 (95%CI = 0.786, 0.907). The research results prove that the bracelet has a high degree of accuracy in blood pressure monitoring, but the efficiency of accuracy evaluation in the monitoring process low. Chen (2019) proposed a smart bracelet health monitoring system based on the Android system, with the purpose of improving the health monitoring of the elderly. In this system, based on the open source software Android Studio, the Android system positioning device is installed on the smart bracelet. Realise timely monitoring of human heart rate, blood pressure and other conditions, upload data in time, and send rescue data to emergency contacts in case of emergency, and improve the monitoring system for the elderly. However, there is a high fusion error rate in the monitoring process. Zhang et al. (2020) proposed a health monitoring system based on smart bracelets and smart pill boxes. The main purpose is to monitor the physical condition of the elderly in time, and integrate body temperature measurement, heart rate measurement, and data on whether to fall. Upload the data to the terminal in time, optimise the structure of the smart pill box, which is convenient to carry, monitor whether the holder of the ring is taking the medicine according to the time, and transmit the specific situation to the relative's mobile phone, so that the child can understand the situation. However, in the monitoring process, there is a problem of poor appraisal index weight distribution.

To sum up, this paper proposes an evaluation method of intelligent Bracelet health monitoring accuracy based on multi-level data fusion. Through the collection of relevant information, and the collection of information for multi-level fusion, improve the accuracy of intelligent Bracelet health monitoring evaluation effect. The technical route of this paper is as follows:

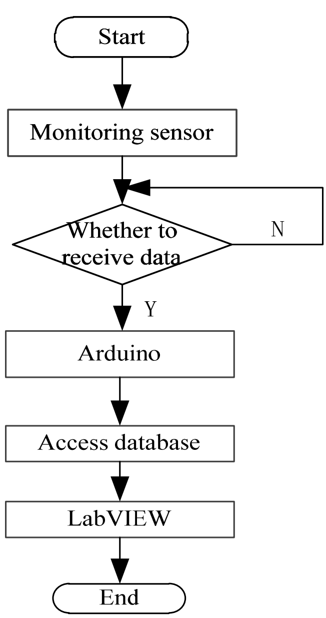
1. Through information collection, information judgment and information display, intelligent Bracelet monitoring was carried out. V1.1 temperature acquisition sensor, pulse sensor heart rate sensor and max31000 sensor were selected to measure body temperature, heart rate and blood oxygen saturation.
2. Cloud design and fuzzy information clustering method are used to realise the effective integration of multi-level data information. Combined with the analysis of visual spectrum characteristics, multi-source data are fused to establish the maximum likelihood estimation model of smart Bracelet health index.
3. Combined with analytic hierarchy process, the accuracy evaluation results of health monitoring of smart Bracelet were obtained.
4. Experimental analysis.

2 Data collection of health monitoring information of intelligent bracelet

In the method of accuracy evaluation of intelligent hand ring health monitoring, in order to realise the detection of human health, it is necessary to analyse the health data such as body temperature, heart rate and other data. Therefore, the data are extracted by smart Bracelet firstly. In order to ensure the accuracy of extraction, they are extracted many times.

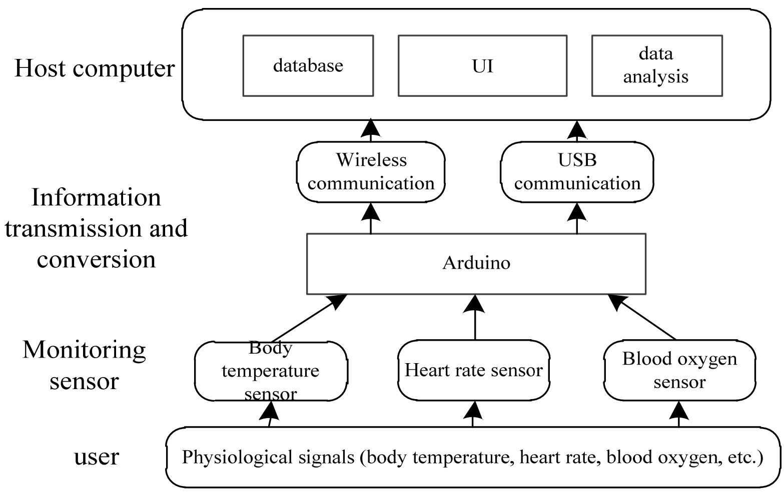
Smart bracelets are mainly used to monitor the health information of families and individuals in their daily lives, and provide timely feedback on whether the human body is in a healthy state. Smart bracelet monitoring is mainly divided into three parts, namely information collection, information judgment and information display. The smart bracelet monitoring process is shown in Figure 1.

Figure 1 Smart bracelet monitoring process



The collected information mainly includes body temperature, heart rate, and blood oxygen saturation. Based on body temperature, heart rate and blood oxygen sensor to collect human body related information (Cai et al., 2019). AD conversion is performed by Arduino hardware, the collected information is displayed through LabVIEW, and the collected information is synchronised into the Access database. The collected data is determined based on JAVA, and the user is judged whether the user is in a healthy state. The judgment result is stored in the Access database, and the human health information is fed back in real time. The human health monitoring process is shown in Figure 2.

Figure 2 Human health monitoring process



According to the above monitoring process, it can be seen that it is based on the human-computer interaction mode between the user and the health monitoring sensor. On the host computer interface, users can input their own information and place sensor devices on corresponding parts of the human body. Collect, display, and store data of human body parts by starting the upper computer. The information transmission and conversion module undergoes AD conversion through Arduino hardware.

2.1 Temperature information data collection

The V1.1 body temperature acquisition sensor from Huaqiang Electronics Factory is selected, which is temperature sensitive and highly accurate. As the core of the body temperature acquisition module, as the body temperature rises, the sensor voltage decreases (Lao et al., 2021). Under the influence of a variety of external interference factors, the subtle changes in human body temperature can be captured, and the relationship between temperature and sensor voltage changes is shown in Figure 3.

It can be seen from Figure 3 that the temperature changes between 30 and 44°C, the voltage changes linearly, and the information collected by the sensor is converted through A/D analogue to digital. The resolution range of the converter is controlled within 0–1022, the analogue input voltage is within the range of 0–5 V, and the conversion relationship is shown in Table 1.

Figure 3 Temperature curve change

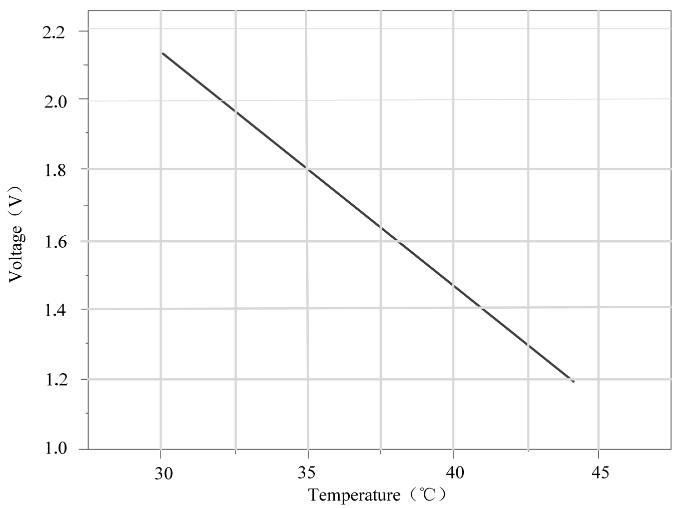


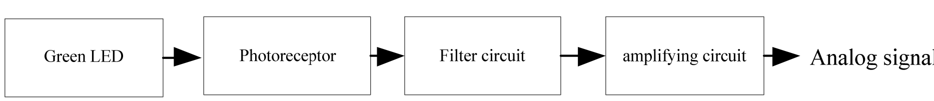
Table 1 Temperature, voltage and digital signal conversion relationship

Body temperature/°C	*Voltage/V*	*Digital signal data*
30	2.126	434.6025
45	1.187	245.3125

2.2 Data acquisition of heart rate and oxygen saturation

Heart rate information can reflect the heart health of the human body. Normal people's heart rate range is generally 60-100 beats/min. The type of heart rate sensor in this article is Pulse Sensor, and the basic working principle is photo volume method. Because the pulse signal changes slightly, it is easily affected by external interference factors. The pulse signal is processed by filtering and amplifying the circuit board. Based on the resistance divided power supply voltage, the method signal is collected through the single-chip AD interface (Bacciu et al., 2021). The collection process is shown in Figure 4.

Figure 4 Heart rate sensor collection process



The sensor can be placed on the wrist and earlobe of the human body for heart rate test collection, and feedback the human health status. The signal conversion between the heart rate sensor and the single-chip microcomputer is based on the 5 V voltage for power supply, the pulse signal is collected, converted into a digital voltage by the converter, the heart rate value is calculated, and the heart rate test and display are realised based on program programming.

Blood oxygen saturation represents the concentration of blood oxygen in the blood, which can reflect the human respiratory status (Dai et al., 2019). The human body can ensure normal activities in a sufficient oxygen environment. The calculation is based on the current amount of haemoglobin bound to oxygen and the proportion of all haemoglobin bound to oxygen:

$$SpO_2 = \frac{[HbO_2]}{[HbO_2] + [Hb]} \times 100\% \tag{1}$$

The normal range of blood oxygen saturation is between 95% and 99%. If the blood oxygen saturation is between 90% and 95%, the human body will have insufficient oxygen supply. If it is less than 90%, mild hypoxemia will occur. If it is less than 80%, hypoxemia is severe (Yu et al., 2019).

This article selects MAX30100 model sensor to measure blood oxygen saturation, and monitors blood oxygen saturation by photoelectric measurement method. This type of sensor has the advantages of simple structure, sensitive response and small error. Using 5V voltage as the power-on voltage, the pin interface description is shown in Table 2.

Table 2 Pin interface situation of blood oxygen saturation module

Pin	*Definition*	*Description*
1	VIN	Power positive
2	GDN	Grounded
3	SCL	12C serial data line
4	SDA	12C serial data line
5	INT	Interrupt pin

The oxygen saturation value is displayed by sensor program programming. Through information collection, information judgement and information display, intelligent bracelet monitoring is carried out. V1.1 temperature acquisition sensor, PulseSensor heart rate sensor and MAX30100 type sensor are selected to measure body temperature, heart rate and oxygen saturation.

3 Evaluation of health monitoring accuracy of smart bracelet based on multi-level data fusion

In order to evaluate the accuracy of intelligent bracelet health monitoring, on the basis of the above determined health data, the data are fused at various levels, and the accuracy evaluation of intelligent bracelet health monitoring is realised according to the data such as health index.

3.1 Multi-level data fusion

Use cloud design and fuzzy information clustering method for multi-level data information to achieve effective integration, and use 5G network to realise real-time data update for the data returned by sensor perception (Shu et al., 2020), build a multi-level data load balancing model, expressed as:

$$S_{j,k} = \frac{\hat{D}_{j,k} - \mu S_{j,k}}{S_{j,k}} \tag{2}$$

In the formula, $S_{j,k}$ represents the similarity feature distribution of multi-level data fusion. Combining periodic sample fusion and feature clustering analysis, and fusion with the GIM model, a fuzzy state equation $N\left(z^*\right) = N\left(z\right)$ of multi-level data fusion is obtained. Using the method of multi-dimensional information entropy fusion, the associated information distribution result of multi-level data fusion is obtained as:

$$K = \frac{\left[P\left(A_i \middle| B_1 \wedge \cdots B_k \cdots \wedge B_m\right) - I\right] S_{j,k}}{\tau} \tag{3}$$

In the formula, τ represents the key node on the GIM, and the feature quantity of the scene where the online sensor is mounted. According to the multi-level data information sampling result, the statistical information distribution set is $u_i \epsilon R^m$. For the result data obtained by multiple sensors, the information transfer function obtained is:

$$M = \frac{\sqrt{u_i N\left(z^*\right)}}{K} \tag{4}$$

In the formula, u_i represents the detection threshold of multi-level data. Assuming that the statistical probability density is $\rho(t)$, the filter analysis function of multi-level data information is established through the method of fusion of GIM and real scene 3D model:

$$\varphi\left(t\right) = \max_{t/I} \int_0^1 \left|M \times \rho\left(t\right)\right| dt \tag{5}$$

Based on the above analysis, a reliable random distribution sequence of multi-level data is constructed to improve the online management capability of multi-level data. Through the database structure and data feature extraction of the multi-level data, combined with the visualisation map feature analysis method, the spectral density of the multi-level data is obtained as:

$$\rho_N = \left|\sum_{i=1}^{n} \varepsilon X_i + K'\left(\hat{N}\right)\varphi\left(t\right)\right| \tag{6}$$

In the formula, $K'\left(\hat{N}\right)$ represents the estimated amount of multi-level cloud data fusion deviation. A computer is used to perform multi-level fusion of IoT data obtained by multiple sensors, and the output modulus of the data fusion meets $K\left(\hat{N}\right) \neq K'\left(\hat{N}\right)$. In the finite field distribution area, combining the sensor information tracking results of different nodes, a multi-level data fusion linear matrix $R_{A\times B}$ is obtained, and its form is:

$$R_{A\times B}=\begin{bmatrix}\mu_{11} & \cdots & \mu_{1n}\\ \vdots & \ddots & \vdots\\ \mu_{m1} & \cdots & \mu_{mn}\end{bmatrix} \tag{7}$$

In the formula, μ_{ij} represents the coding parameters of multi-level data fusion. Combining sensor equipment at different nodes and 5G network to build the Internet of Things, and fusion with the GIM model, to obtain the exponential feature quantity of data fusion output: $m^{\varphi(n)}=1\bmod n$, so there is $m^{1+\varphi(n)}=m\bmod n$. According to the above model design, establish a multi-level data fusion arithmetic coding model, Obtain the identification bit feature distribution sequence:

$$Q_i=m^{1+\varphi(n)}+\sum_{i=1,2,\ldots,n}\mu_i\left[\rho_N+\beta\left(1-\left|R_{A\times B}\right|\right)\right] \tag{8}$$

In the formula, β is the forward three-dimensional map information of multi-level data, with $2\beta=2\rho_N$ or $2\beta=2\rho_N\pm 255$, but since 2β is an even number, combining feature clustering and technology, the data fusion rules are as follows:

$$R_I=\left(1-\rho_N\right)^{-1}\sum_{i=1}^{n}\prod_{1\le i\le n}Q_i \tag{9}$$

In the process of multi-level data fusion, combined with the visual map feature analysis method, the reliability random distribution sequence of multi-level data is constructed. In the finite domain distribution area, the sensor information tracking results of different nodes are combined to realise the multi-source data fusion processing.

3.2 Evaluation of health monitoring accuracy of smart bracelet

Based on the use of cloud design and fuzzy information clustering methods to achieve the effective integration of multi-level data and information, combined with the visualised map feature analysis and fusion processing of multi-source data, the maximum likelihood estimation model of the smart bracelet health index is established. Combined with the method of piecewise linear fitting estimation, the least square fitting function to construct the health index distribution of the smart bracelet is:

$$z(t)=x(t)+iy(t)=a(t)e^{i\theta(t)} \tag{10}$$

Among them, $a(t)$ is the difference between the predicted data points of the smart bracelet health index x_i and x_j, and $\theta(t)$ is the amount of mutual information of the smart bracelet (Hauguel-Moreau et al., 2020). According to the correlation between the quality indicators of the smart bracelet, the health of the smart bracelet is obtained. The output AC component of the index prediction is:

$$\Psi_2\left(d_2(t)\right)=\Psi+\left(h_2-d_2(t)\right)L\left(Z_2+Z_3\right)^{-1}L^T+d_2(t)M^T\left(Z_2+Z_3\right)^{-1}M^T \tag{11}$$

Constructed a high-frequency feature distribution model of the health index, and established an unbalanced stability distribution model. In the Bochner-Riesz time-frequency space (Qu et al., 2020), the output directivity coefficient of the *j* type of smart bracelet health index prediction is defined as *C*, when $\Psi\left(d_1\left(t\right),d_2\left(t\right)\right)<0$:

$$V\left(t\right)\leq\xi^T\left(t\right)\Psi\left(d_1\left(t\right),d_2\left(t\right)\right)\xi\left(t\right)<0 \tag{12}$$

According to the distribution of characteristic harmonics and switching sub-harmonics, the effective prediction model of the distribution equipment health index in the equivalent model of the DC power supply system is described as:

$$\begin{pmatrix} x_1\left(t\right) \\ \vdots \\ x_m\left(t\right) \end{pmatrix}=\begin{pmatrix} a_{1i} \\ \vdots \\ a_{mi} \end{pmatrix}s_1\left(t\right)=\frac{x_1\left(t\right)}{a_{1i}}=\cdots=\frac{x_m\left(t\right)}{a_{mi}}=s_i\left(t\right) \tag{13}$$

In the formula, $x(t)$ represents the smart bracelet health index time series.

According to the disturbance-type fluctuation characteristics, the smart bracelet health index time series $x(t)$ is reconstructed in two dimensions, and the voltage imbalance evaluation method is adopted. The smart bracelet health index distribution satisfies the discriminant function $\alpha_k\geq 0$. When $\sum_{i=1}^{K}\alpha_k=1$, the fuzzy constraint vector obtained for the health index prediction evaluation is:

$$F\left(x\right)=\sum_{q=1}^{Q}e_q^Te_q=\sum_{q=1}^{Q}\sum_{k=1}^{m}e_{kq}^2=\sum_{i=1}^{N}v_i^2 \tag{14}$$

In the formula, the assessment results are $F(x)$, e represents the fuzzy constraint vector factor, v_i represents the health index distribution state.

In the case of continuous changes within the fluctuation range of the health index, the piecewise linear fitting method is used to predict and optimise the smart bracelet health index.

The process of evaluating the accuracy of smart bracelet health monitoring combined with analytic hierarchy process is to calculate the largest eigenvalue and eigenvector of the judgment matrix. The weights of the elements of each layer of the evaluation index system can be obtained from the eigenvector components after normalisation of the maximum eigenvalue of the judgment matrix of each layer:

$$AU=\lambda_{\max}U \tag{15}$$

Normalise each component of the feature vector to get:

$$\sum_{i=1}^{n}U_i=1 \tag{16}$$

Obtain the relative target layer weight of each element of the criterion layer and the relative criterion layer weight of the scheme layer according to the above formula, and obtain the relative target layer weight of each element of the scheme layer, as shown in the following formula:

$$U_{P_i}=\sum_{j=1}^{m}U_{PB_{ij}}U_{B_j} \tag{17}$$

In the formula, U_{P_i} is the weight of the i-th element P_i of the scheme layer to the target layer; $U_{PB_{ij}}$ is the weight of the element P_i of the scheme layer relative to the j-th element B_j of the criterion layer; U_{B_j} is the weight of the criterion element B_j relative to the target layer.

According to the obtained weight results and expert scores, the formula for evaluating the accuracy of the smart bracelet health monitoring accuracy is calculated as follows:

$$Z = \frac{1}{n}\sum_{i=1}^{m}\left(U_i\sum_{j=1}^{n}F_{ij}\right) \tag{18}$$

In the formula, Z represents the evaluation result of the health monitoring accuracy of the smart bracelet, n is the number of experts participating in the accuracy evaluation, F_{ij} is the evaluation result of the index i by the j-th expert, and U_i is the weight of the health monitoring accuracy of the smart bracelet.

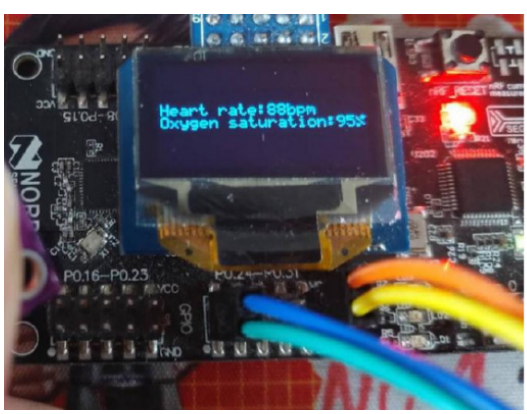
In summary, this article uses cloud design and fuzzy information clustering methods to achieve effective integration of multi-level data information, combined with visual map feature analysis and fusion processing of multi-source data, and establishes the maximum likelihood estimation model of the smart bracelet health index. Combined with the analytic hierarchy process, the evaluation results of the accuracy of the smart bracelet health monitoring are obtained.

4 Experimental study

4.1 Experimental program

In order to test the application performance of the method in this paper to realise the evaluation of the accuracy of the smart bracelet health monitoring, the simulation experiment analysis was carried out, and the experiment was designed by Matlab. The experimental data comes from TalkingData (the database website is http://www.talkingData.com). Collect relevant parameters of the health index of the smart bracelet during the sampling period. The results are shown in Figure 5.

Figure 5 Heart rate blood oxygen data display results



The data collected by the LIS3DH three-axis acceleration sensor is displayed on the OLED display and the results are as follows. Because the OLED display area is limited, only the current real-time sensor data can be displayed.

4.2 Experimental indicators

1 *The efficiency of health index prediction*: The expression of the smart bracelet health index is as follows:

$$h_i(t) = \sum_{j=1}^{m} \rho_{ij} h_{ij}(t) \tag{19}$$

In the above formula, $h_i(t)$ represents the health index of the smart bracelet i; m represents the number of feature parameters; ρ_{ij} represents the weight of the feature parameter x_j, reflecting the influence of the parameters on the state of the smart bracelet.

2 Perform multi-level data fusion processing on the current smart bracelet, and get the data fusion performance test. The average absolute percentage error formula is as follows:

$$MAPE = \left(\sum_{i=1}^{n} \left(\frac{\left| X_{pi} - x_{mi} \right|}{x_{mi}} \right) \right) / n \times 100\% \tag{20}$$

In the formula, X_{pi} and x_{mi} also represent the forecast and actual values respectively, and the reference *MAPE* is mainly to measure the difference between the overall forecast data and the actual data.

3 Perform simulation comparison experiments based on the established experimental environment, set experimental procedures, and determined evaluation experts, and calculate the reasonableness of the evaluation index weight distribution based on the obtained experimental data. The formula is expressed as:

$$\Psi = \frac{\sum_{i=1}^{n} W_i}{\lambda_i} \tag{21}$$

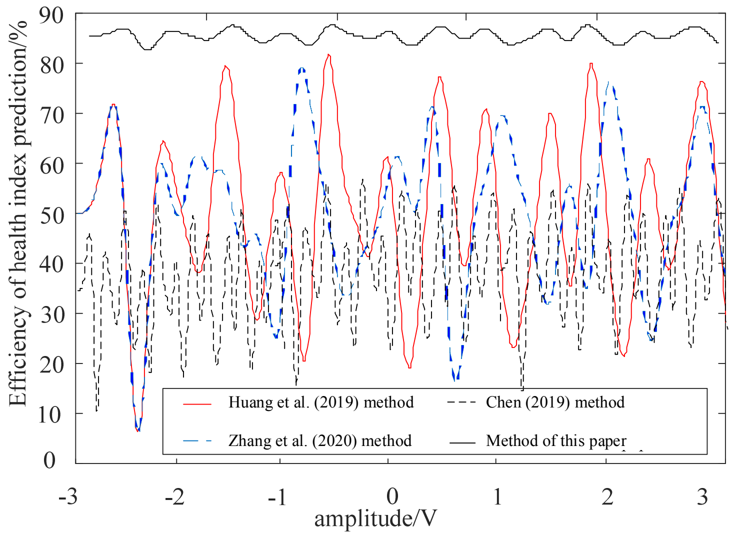
Among them, ψ represents the parameter value of the rationality of the evaluation index weight distribution. Under normal circumstances, the larger the parameter value, the better the rationality of the evaluation index weight distribution. On the contrary, the worse the rationality of the evaluation index weight distribution. λ_i represents the calculation factor for the rationality of the evaluation index weight distribution.

4.3 Analysis of results

Test the efficiency of different methods for smart bracelet health index prediction, and the comparison results are shown in Figure 6.

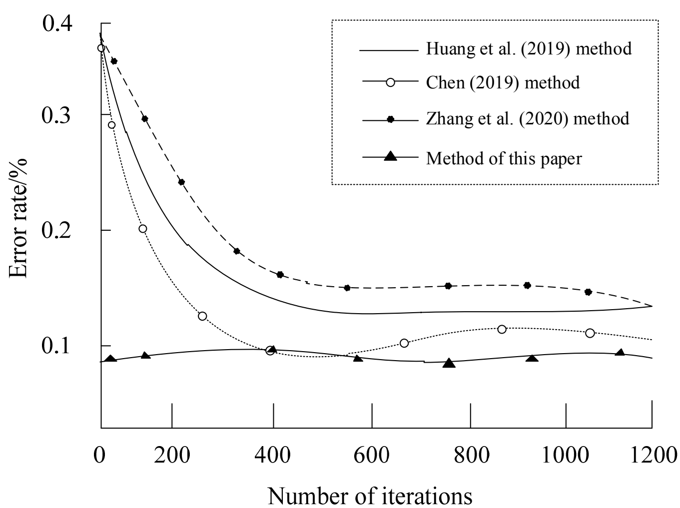
As can be seen from Figure 6, as the monitoring time changes, the efficiency of the smart bracelet health monitoring accuracy evaluation method in this paper is always above 80%, and the fluctuations are small. The main reason is that this article introduces multi-level data fusion, and uses the 5G network to realise real-time data updates on the data sent back from sensor perception, and improves the efficiency of smart bracelet health index prediction.

Figure 6 Comparison of the efficiency of smart bracelet health index prediction



According to the experimental results, the smaller the error value obtained, the more accurate the monitoring effect. The fusion error effect diagram is shown in Figure 7.

Figure 7 Effect of fusion error



Analysis of Figure 7 shows that the four methods can reduce the error. The method in Huang et al. (2019) reduces the error rate to a stable value after 400 iterations, but the fusion error is large before 400 iterations; the method in Chen (2019) has the largest error. From the beginning to the end of the method in this paper, the fusion error is always the best, and then as the number of iterations increases, the fusion error of the demand can always be tracked well.

Table 3 shows the comparison of the reasonableness parameters of the evaluation index weight distribution obtained through experiments.

Table 3 Comparison of parameters for the rationality of evaluation index weight distribution

Number of experiments	*Method of this paper*	*Huang et al. (2019) method*	*Chen (2019) method*	*Zhang et al. (2020) method*
20	23.26	10.03	12.26	9.12
40	24.59	12.10	13.31	8.45
60	25.00	12.03	14.25	10.02
80	25.99	11.11	15.02	9.45
100	26.38	12.12	15.89	9.99
120	26.79	15.41	16.52	9.56
140	27.01	13.51	17.00	9.12
160	27.06	12.45	12.00	10.03
180	27.34	16.25	13.02	11.23
200	29.45	10.05	10.03	16.45

As shown in the data in Table 3, the rationality parameter of the evaluation index weight distribution of the proposed method is much higher than the existing three methods, and the maximum value can reach 29.45. The main reason is that the method in this paper adopts cloud design and fuzzy information clustering method to achieve effective integration of multi-level data information in the hand ring, and uses 5G network to realise real-time data update for the data sent back from sensor perception, which improves the rationality of the weight distribution of evaluation indicators.

5 Conclusion

In this paper, an evaluation method of health monitoring accuracy of smart Bracelet based on multi-level data fusion is proposed. In the process of monitoring accuracy evaluation, v1.1 body temperature acquisition sensor, pulse sensor heart rate sensor and max31000 sensor are selected to measure body temperature, heart rate and blood oxygen saturation. Cloud design and fuzzy information clustering method are used to realise the effective integration of multi-level data information. Combined with the characteristics of visual atlas, multi-source data are analysed and fused to establish the intelligent Bracelet health index system Combined with the analytic hierarchy process (AHP), the maximum likelihood estimation (MLE) model is used to obtain the accuracy evaluation results of smart Bracelet health monitoring. Compared with traditional methods, this method has the following advantages:

1 The efficiency of the proposed method is higher than 80%, and the evaluation efficiency is better;

2 The fusion error rate of the proposed method is always less than 0.1%, and the maximum rationality of the evaluation index weight distribution can reach 29.45, which can give timely feedback on whether the human body is in a healthy state.

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