Abnormal Signal Recognition Method of Wearable Sensor Based on Machine Learning

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Abstract. The recognition of abnormal signal of wearable sensor is of great significance to the application value of the device. In order to improve the accuracy of abnormal signal recognition of wearable sensors and indirectly ensure the safety of wearable sensor devices, a method of abnormal signal recognition of wearable sensors based on machine learning was proposed. According to the different abnormal types and principles of wearable sensors, the signal abnormal judgment criteria are set. The wearable sensor signal is collected, and the initial signal is preprocessed by Kalman filtering, normalization and weighted fusion. The machine learning algorithm is used to extract the features of sensor signals, and the recognition results of the abnormal type, abnormal semaphore and abnormal location of sensor signals are obtained through feature matching. Through the identification performance test experiment, it is obtained that the average abnormal type error detection rate of the optimization design identification method is 0.86%, and the average statistical error of abnormal semaphore is 0.22 db, lower than the preset value.

Keywords: Machine Learning · Wearable Sensor · Abnormal Signal · Signal Identification

1 Introduction

Sensor is a kind of detection device, which can feel the measured information, and can transform the sensed information into electrical signals or other required forms of information output according to a certain law, so as to meet the requirements of information transmission, processing, storage, display, recording and control. The characteristics of the sensor include miniaturization, digitalization, intellectualization, multifunction, systematization and networking. It is the primary link to realize automatic detection and automatic control [1]. The existence and development of sensors make objects have senses such as touch, taste and smell, and make objects slowly become alive. According to their basic sensing functions, they are usually divided into ten categories: thermal sensors, photosensitive sensors, gas sensors, force sensors, magnetic sensors, humidity

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sensors, sound sensors, radiation sensors, color sensors and taste sensors. In the environment of rapid expansion of information, more and more people have an increasing demand for the speed and frequency of information exchange. People are using mobile personal computers or mobile phones to receive, process and send all kinds of messages at any time. This dependence on electronic devices makes the relationship between people and machines become closer and closer, making portable wearable devices inevitable for the development of the times. The main application fields of wearable sensors include: medical fields represented by blood glucose, blood pressure and heart rate monitoring, health care fields represented by sports monitoring, consumption fields represented by information entertainment, and industrial and military fields represented by data acquisition and display. Relevant data points out that wearable devices in the health care and medical fields account for 60% of the market share this year, and the share may be further increased in the future.

Due to the aging of the internal components of the wearable sensor, the wrong installation of the sensor and other reasons, the abnormal state of the wearable sensor will not only affect the user's experience, but also may bring potential safety hazards such as electric leakage and magnetic leakage. Therefore, it is necessary to identify and detect the abnormal real-time signals of wearable sensors, so as to provide valuable reference data for the timely maintenance of sensors. Anomaly recognition is one of the important topics in the research of data analysis technology. Its main task is to find the anomaly in time, so that we can quickly take measures to early warn the anomaly and assist scientific decision-making. At present, the more mature sensor abnormal signal recognition methods include: abnormal recognition method based on the principle of electrical impedance, abnormal recognition method based on static fault tree and abnormal recognition method based on steady-state fault quantity. However, the above abnormal signal recognition methods can not recognize the type and location of abnormal signals at the same time, and the abnormal signal recognition results have large errors, which is lack of reference value for the maintenance of wearable sensors. Therefore, machine learning algorithm have been introduced.

Machine learning is an interdisciplinary subject involving probability theory, statistics, approximation theory, convex analysis, algorithm complexity theory and other disciplines. It specializes in studying how computers simulate or realize human learning behavior, so as to acquire new knowledge or skills, reorganize the existing knowledge structure and constantly improve its own performance. It is the core of artificial intelligence and the fundamental way to make computers intelligent. Machine learning methods based on statistical features can be divided into supervised learning and unsupervised learning according to learning methods. Supervised learning is to train the marked data, generate models, and then test and classify. This method has a high prediction accuracy, but it can not classify unknown categories. Common methods include Bayesian, decision tree, etc. The other is semi supervised learning, which can use labeled and unlabeled samples for training at the same time. Compared with it, it has more room for development, but it is still in the state of research. Select the appropriate machine learning algorithm and apply it to the optimization of the abnormal signal recognition method of wearable sensors, in order to improve the accuracy of abnormal signal recognition of wearable sensors and indirectly ensure the safety of wearable sensor devices.

2 Design of Abnormal Signal Recognition Method of Wearable Sensor

2.1 Set the Judgment Standard of Wearable Sensor Abnormality

Wearable sensor anomalies mainly include: complete failure anomaly, fixed deviation anomaly, drift deviation anomaly and accuracy degradation. Among them, failure anomaly refers to the sudden failure of sensor measurement, and the measured value has always been a certain constant; Deviation anomaly mainly refers to a kind of anomaly that the measured value of the sensor differs from the real value by a certain constant; Drift anomaly is a kind of anomaly that the difference between the measured value and the real value of the sensor changes with time; The decrease of accuracy refers to the deterioration of the measuring ability and accuracy of the sensor. When the accuracy level is reduced, the average value of the measurement does not change, but the variance of the measurement changes [2]. Both fixed deviation anomaly and drift anomaly are not easy to find, which will cause a series of unpredictable problems in the process of anomaly occurrence, so that the control system can not function normally for a long time. The types of abnormal signals of some wearable sensors and their causes are shown in Table 1.

Table 1. Description of abnormal signal types of wearable sensors

Serial number	Sensor abnormal signal type	Cause of abnormal signal
1	Stuck exception an exception caused by a stuck sensor running program	Stuck exception an exception caused by a stuck sensor running program
2	Abnormal gain: the working frequency or signal of the sensor changes with a constant gain due to the aging of the sensor element	Abnormal gain: the working frequency or signal of the sensor changes with a constant gain due to the aging of the sensor element
3	Abnormal deviation due to the abnormal connection of the sensor, the working signal has a fixed deviation	Abnormal deviation due to the abnormal connection of the sensor, the working signal has a fixed deviation
4	Abnormal short circuit the output signal is close to zero due to the short circuit of the sensor circuit and other reasons	Abnormal short circuit the output signal is close to zero due to the short circuit of the sensor circuit and other reasons
5	Abnormal open circuit. The output signal is close to the maximum value due to the open circuit of the sensor output circuit and other reasons	Abnormal open circuit. The output signal is close to the maximum value due to the open circuit of the sensor output circuit and other reasons

(*continued*)

Table 1. (*continued*)

Serial number	Sensor abnormal signal type	Cause of abnormal signal
6	The offset abnormal sensor is disturbed by a stable signal	The offset abnormal sensor is disturbed by a stable signal
7	The original output signal of the periodic abnormal sensor is interfered by the periodic signal of a certain frequency	The original output signal of the periodic abnormal sensor is interfered by the periodic signal of a certain frequency
8	Random abnormal sensor is disturbed by a random signal	Random abnormal sensor is disturbed by a random signal
9	The output signal offset signal caused by abnormal zero drift, temperature drift, sensitivity drift, etc	The output signal offset signal caused by abnormal zero drift, temperature drift, sensitivity drift, etc
10	Abnormal impact abnormal impact is caused by the interference of a pulse signal on the sensor	Abnormal impact abnormal impact is caused by the interference of a pulse signal on the sensor

The wearable sensor is stuck abnormally, the gain abnormally and the deviation abnormally meet the following characteristics:

$$x_{\psi}(t) = \begin{cases} c,\ \psi \in U_{\text{Stuck}} \\ \beta_i x(t),\ \psi \in U_{\text{gain}} \\ x(t) + \Delta\varepsilon,\ \psi \in U_{\text{deviation}} \end{cases} \tag{1}$$

where c is constant, β_i and $\Delta\varepsilon$ are constant gain and constant deviation respectively, and U_{Stuck}, U_{gain} and $U_{\text{deviation}}$ correspond to the set of stuck abnormal, gain abnormal and deviation abnormal signals. According to the above method, the standard characteristics of all abnormal signals of wearable sensors can be obtained, which can be used as the comparison standard to determine the signal type of wearable sensors.

2.2 Collect Wearable Sensor Signal

Wearable sensors are mainly divided into three parts from the physical structure: detection coil, analog circuit board and digital circuit board. In terms of circuit structure, it is mainly divided into: resonant input excitation resonant circuit, detection circuit, primary amplification and filtering, secondary amplification and filtering, AD sampling and digital signal processing, as shown in Fig. 1.

OP1, AD1, op2, OP3, ad2 and OP4 in Fig. 1 are the output signals that can be collected by the sensor. In practical engineering, only AD1 and ad2 signals are used. Since the four detection coils of the sensor are placed in space according to certain rules, the output of the four channel resonant circuit has a certain correlation. As described in Sect. 2, the output four channel OP signals differ by one quarter of the periodic phase in sequence, and the two channel ad signals differ by one half of the periodic phase [3].

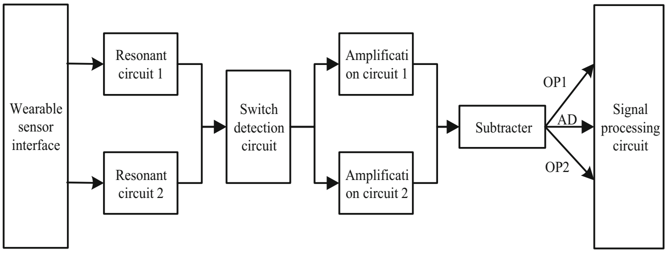


Fig. 1. Circuit structure diagram of wearable sensor

The output signal of a normal sensor is a sinusoidal like periodic signal. When the gap between the sensor and the track is certain, the amplitude of the sensor output signal remains unchanged. If the amplitude of the sensor output signal changes, or there is no output signal, it indicates that the sensor has failed. Take the wearable sensor shown in Fig. 1 as the target to collect the real-time data generated by the sensor, and the acquisition process of angular velocity and acceleration signals is shown in Fig. 2.

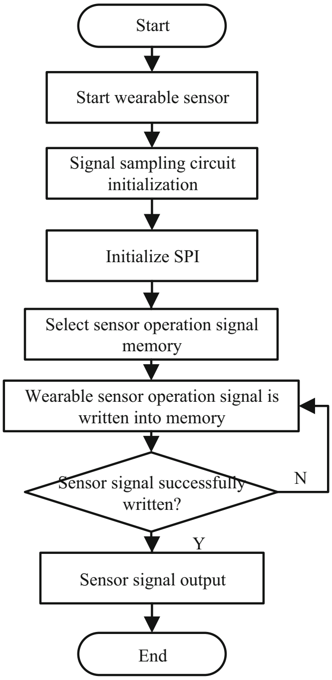


Fig. 2. Flow chart of wearable sensor signal acquisition

Similarly, the acquisition result of wearable sensor position signal can be obtained, which can be quantitatively expressed as:

$$\begin{cases} X = (R + H)\cos\delta\cos\sigma \\ Y = (R + H)\cos\delta\sin\sigma \\ Z = \left(\frac{\kappa_1^2}{\kappa_0^2}R + H\right)\sin\delta \end{cases} \tag{2}$$

In the above formula, the variables R and H respectively represent the height of the radius of curvature charge relative to the surface of the ellipsoid, δ and σ correspond to latitude and longitude, κ_0 and κ_1 are the long and short semi axis parameters describing the earth as a reference ellipsoid. According to the above methods, the real-time acquisition results of wearable sensor operation signals can be obtained.

2.3 Fusion Processing of Wearable Sensor Signals

Wearable sensor signal acquisition process will be polluted by different degrees of noise, so that the obtained sensor data is also mixed with noise information, so that useful signals can not be directly detected [4]. Kalman filter can be used to estimate the necessary useful signals, so as to detect the abnormal occurrence of sensor data. Kalman filter adopts linear minimum variance estimation, which encapsulates the state quantity in the corresponding state space in the filtering process, and then obtains the state estimator in real time through continuous iteration. This method is very suitable for dealing with the estimation of multi-dimensional random variables. And only through the state equation of the observation system and the statistical characteristics of noise can be used to express the statistical characteristics of the actual state quantity and noise, which does not need to grasp the error changes between the observation and the real state quantity in real time. The Kalman filter processing process of wearable sensor signals can be expressed as:

$$\begin{cases} X_k = BX_{k-1} + An_{k-1} \\ Y_k = GX_k + N_k \end{cases} \tag{3}$$

In the above formula, X_k and Y_k are the state variables and observation variables of the wearable sensor signal respectively, B, A, G and N correspond to the state transfer matrix, interference transfer matrix, observation noise matrix and observation matrix, and n_{k-1} represents the input noise value in the signal [5]. By substituting all the signal acquisition data into formula 3, the noise signal suppression processing in the initial acquisition signal can be realized. Normalize the noise signal, and the processing process can be expressed as:

$$x = \frac{x_{\max} - x}{x_{\max} - x_{\min}} \tag{4}$$

$x_{\max}$ and $x_{\min}$ correspond to the maximum and minimum values of wearable sensor signals. On this basis, the data processing results are fused, and the processing results are as follows:

$$x_{\text{fuse}} = \frac{\kappa_{\text{fuse}}\left(x_i + x_j\right) + (\kappa_{\text{fuse}} - 1)^2 x_i x_j}{1 + \kappa_{\text{fuse}}^2 - (\kappa_{\text{fuse}} - 1)^2\left(x_i - x_j\right)^2} \tag{5}$$

where x_i and x_j are the i and j signal processing results of the wearable sensor respectively, and κ_{fuse} is the fusion coefficient between the data. Complete the fusion and processing of wearable sensor signals according to the above process.

2.4 Extracting Sensor Signal Characteristics Using Machine Learning Algorithm

BP neural network in machine learning is selected as the technical support for feature extraction of sensor signals. The network topology of BP neural network is composed of three parts, which are input layer, hidden layer and output layer respectively. The connection relationship is shown in Fig. 3.

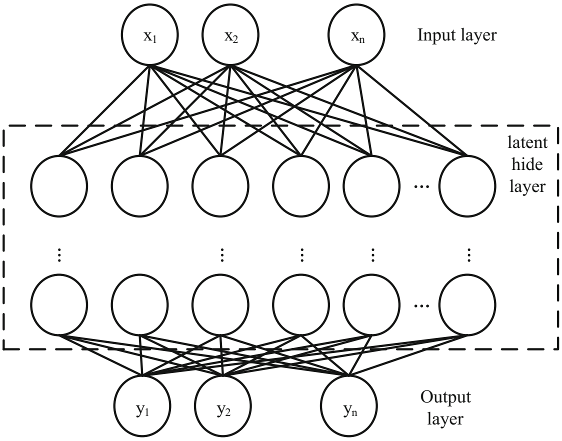


Fig. 3. Internal structure of BP neural network

The calculation process of each neural unit in Fig. 3 can be expressed as:

$$\begin{cases} u_1^{(2)} = g\left(\varpi_{11}^{(1)} x_1 + \varpi_{12}^{(1)} x_2 + \lambda_1^{(1)}\right) \\ u_2^{(2)} = g\left(\varpi_{21}^{(1)} x_1 + \varpi_{22}^{(1)} x_2 + \lambda_2^{(1)}\right) \\ u_3^{(3)} = g\left(\varpi_{31}^{(1)} x_1 + \varpi_{32}^{(1)} x_2 + \lambda_3^{(1)}\right) \\ u_1^{(3)} = g\left(u^{(2)} + u_2^{(2)} + u_3^{(2)} + \lambda_1^{(2)}\right) \end{cases} \tag{6}$$

The output result $u_i^{(j)}$ of formula 6 represents the i neural unit of the j layer in BP neural network, ϖ and λ represent the weight value of the neural unit respectively, and $g()$ is the activation function. Its numerical expression is as follows:

$$g(x) = \frac{1}{1 + \exp^{-e}} \tag{7}$$

The calculation result of formula 7 is substituted into formula 6. After integration, the relationship between the input and output of BP neural network is as follows:

$$u^{(l+1)} = g\left(\varpi^{(l)} x^{(l)} + \lambda^{(l)}\right) \tag{8}$$

In the network training phase, wearable sensors train the network weights according to the given training mode in four processes: "forward propagation of mode" → "reverse propagation of error" → "memory training" → "learning convergence". In the working stage of the network, according to the trained network weight value and the given input vector, the solution of the output vector corresponding to the input vector is obtained in the way of "mode forward propagation". The input signal is transmitted from the input layer node to each hidden layer node in turn, and then to the output layer node. If the expected output cannot be obtained at the output layer, it will turn to reverse propagation, return the error signal along the original path, and modify the weights of neurons at each layer through learning to minimize the error signal. In the process of BP network learning, first adjust the connection weight between the output layer and the hidden layer, then adjust the connection weight between the intermediate hidden layer, and finally adjust the connection weight between the hidden layer and the input layer. In the actual training and learning iteration process, the fusion processing results of wearable sensor signals are substituted into the input layer of BP neural network, and these information is continued to be transmitted to the hidden layer nodes of the middle layer connected later. The middle layer loads the internal information processing of neural network, which is the core part of the network. It mainly transforms the input information according to the requirements of information change, The number of intermediate layers can also be changed according to the requirements of transformation, using a single hidden layer or multiple hidden layers structure; The last hidden layer transmits the processed information to the nodes of the output layer. After further conversion and processing, the output layer finally outputs the information processing results of this neural network forward learning to the outside world [6]. When the output value of the neural network does not match the expected output value, the neural network will carry out error back propagation to change the learning process of the network connection weight. The error starts from the output layer, and the weight of each layer in the network is modified according to the gradient descent method of the error, and gradually passes back to the hidden layer and input layer of the network. After repeated cycles and multiple above learning processes, the connection weights of each layer of the network are continuously adjusted according to the difference between the network output and the actual output of the sample, so that the output of the network is closer to the actual value of the system. This process is the training and learning process of the neural network. In neural networks, the steepest descent method is widely used as its learning rule, and the network parameters are continuously adjusted through the back propagation of the difference between the network output and the actual output of the sample. This process takes the sum of squared errors of the network output as the evaluation standard, and this process will not be terminated until the difference between the network output and the actual output of the sample meets the accuracy requirements or the number of network learning and training reaches the preset value [7]. In the process of multiple learning iterations, the weights and offsets of neurons will change dynamically, so it is necessary to use formula 9 to update all neural units in BP neural network.

$$\begin{cases} \varpi_{new} = \varpi - \frac{\partial \varphi}{\partial \varpi} \\ \lambda_{new} = \lambda - \frac{\partial \varphi}{\partial \lambda} \end{cases} \tag{9}$$

In the above formula, φ is the update cost function. Finally, according to the process shown in Fig. 4, the forward and back propagation are repeated to complete the learning iteration process of BP neural network.

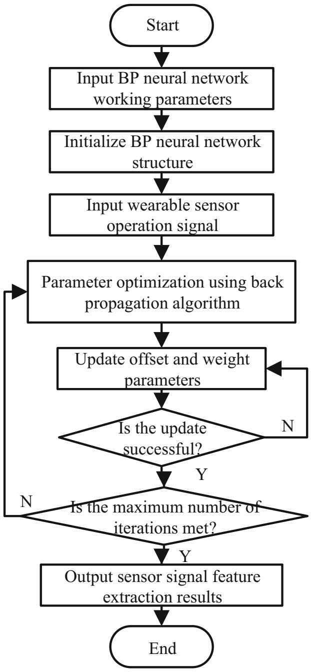


Fig. 4. Flow chart of BP neural network propagation and learning

For the sensing signal with the overall downward depression of signal amplitude, take the ordinate value of the peak point with higher value as the baseline, and take the area covered between the data curve between the two peaks and the baseline. The calculation formula of this characteristic parameter is as follows:

$$\chi = \sum_{t=1}^{N_{\text{collection}}} \{x(t) - \min[x(t)]\} \tag{10}$$

where $N_{\text{collection}}$ represents the collected signal quantity of the wearable sensor, and min() is the minimum value calculation function [8]. Similarly, the feature extraction results of signal peak value, valley value, average value, valley spacing, peak spacing, signal area, signal surface energy, signal length, signal width and so on can be obtained and output in the form of feature vector.

2.5 Realize Abnormal Signal Recognition of Wearable Sensor

Combined with the sensor signal characteristics extracted by machine learning algorithm, the abnormal signal type, signal quantity and abnormal location of the current wearable sensor are determined through feature matching, signal statistics and other technologies.

Identify the Abnormal Type of Signal
The identification of abnormal type of wearable sensor signal is to match the real-time collected and extracted operation signal with the set abnormal standard, and calculate the similarity between them using formula 11.

$$\phi = \sqrt{(\chi_{set} - \chi_{\text{draw}})^2} \tag{11}$$

where χ_{set} and χ_{draw} correspond to the set abnormal signal characteristics and the extracted wearable sensor signal characteristics [9]. Set the determination threshold of the abnormal signal type as ϕ_0. if the calculation result obtained from formula 11 is higher than ϕ_0, it is determined that the current wearable sensor signal characteristics are consistent with the abnormal signal characteristics, so that the abnormal recognition result of the current wearable sensor signal is the abnormal type corresponding to the χ_{draw} feature. Otherwise, it needs to be re determined until the determination conditions are met.

Statistical Abnormal Semaphore
The statistical process of abnormal semaphores of wearable sensors can be expressed as:

$$M_{\text{abnormal}} = \sum_{i=1}^{num_{\text{satisfy}}} m_i \tag{12}$$

In the above formula, m_i is the number of the i signal that meets the abnormal condition. The wearable sensor signals identified as abnormal state are counted according to formula 12, and the quantitative statistical results of abnormal signal quantity are obtained.

Determine the Abnormal Position of the Signal
Figure 5 shows the identification principle of abnormal signal position of wearable sensor.

In order to monitor the condition of each sensor, the following three decision functions can be formed by using formula 13:

$$\begin{cases} F_1 = d_1 d_3 \\ F_2 = d_1 d_2 \\ F_3 = d_2 d_3 \end{cases} \tag{13}$$

When the wearable sensor operates in the normal state, the error of the state variable estimated by the filter is very small, so the value of d_i fluctuates around zero, and the

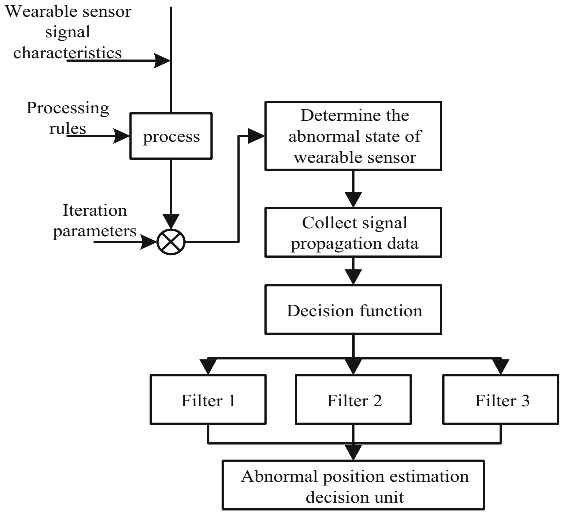


Fig. 5. Schematic diagram of abnormal signal positioning of wearable sensor

value of F_i also fluctuates around zero. When a sensor is abnormal at a certain time, the error of the state variable estimated by the state variable estimated by the first filter will be large, so the values of d_1 and d_3 will increase correspondingly, and the value of F_1 will also increase a lot compared with F_2 and F_3. Similarly, when sensor 2 is abnormal, the value of F_2 will also increase a lot compared with F_1 and F_3, so that the abnormal position of the sensor can be determined by the change of the decision function, realize the positioning of abnormal wearable sensors.

3 Experimental Analysis of Recognition Performance Test

In order to test the recognition performance of the optimized wearable sensor abnormal signal recognition method based on machine learning, different types of wearable sensors are selected as the research object for testing. Through the control of sensor working parameters and working environment, the setting samples of sensor abnormal signals are obtained. Through the comparison between the output results of the design recognition method and the setting data, the test results reflecting the performance of the abnormal signal recognition method of the optimized wearable sensor are obtained.

3.1 Prepare Wearable Sensor Research Samples

Wearable heart rate sensor, temperature sensor, gyroscope and pressure sensor are selected as the research objects in this experiment. The model of heart rate sensor is KEYENCE and the model of temperature sensor is PT100. In addition, the models of gyroscope and pressure sensor research samples are pa-arc-0050 and pt124g-111 respectively. The total number of research samples prepared for this experiment is 80, and the number of samples of each wearable sensor is 20. Before starting the experiment, they debug the prepared wearable sensor research samples to ensure that the initially prepared research samples are in a normal state.

3.2 Configure the Experimental Environment

The test bench is equipped with a secondary coil, which is connected in series with the Programmable Potentiometer on the hardware circuit of the control box. The control box controls the resistance of the Programmable Potentiometer to change regularly through the hardware program, and the programmable potentiometer is used as the load to affect the equivalent load of the coil of the relative position sensor. At the same time, the control box collects data in real time from the sensor communication interface, and sends it to the upper computer in real time through serial port to USB interface after simple digital signal processing. The upper computer displays and stores the received sensor data in real time and diagnoses the sensor fault. The test bench is mainly used to load the relative position sensor and the secondary coil. The size design of the test bench refers to the overall size of the potting coil at the bottom of the relative position sensor, with a width of 114mm. Wearable sensors are always a pair of redundant structures, which can be used to switch sensors when the train is too long stator track joints, so as to ensure the reliability of positioning and speed measurement signals. The interval between each pair of sensors is just the width of one sensor. Therefore, in order to better simulate the actual working conditions of the sensors, this test platform has designed the same installation position size as the sensors on the train, and is conducive to the development of off-line test experiments of wearable sensor signal switching. The excitation frequency of the coil of the relative position sensor is 3.2 MHz and 2.5 MHz high-frequency signals. The test bench works in a high-frequency electromagnetic field environment, so the material of the test bench cannot be metal materials with strong conductivity and magnetic conductivity. At the same time, in order to consider the convenience of processing, the test environment selected polyoxymethylene resin as the material. Polyoxymethylene resin has good insulation performance and high hardness, which is suitable for machining and meets the needs of testing environment.

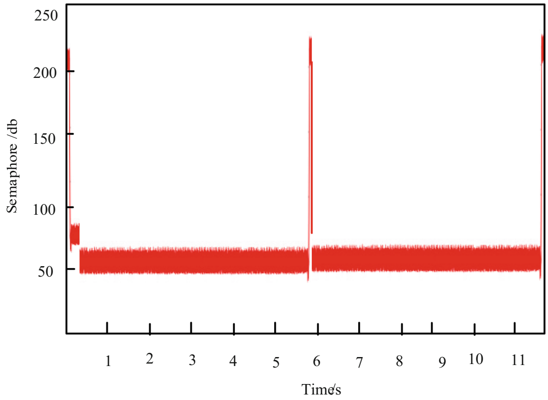
3.3 Generate Wearable Sensor Signal

By controlling the working parameters and environment of the wearable sensor, the abnormal signal of the wearable sensor is generated. The initial signal generation results of the heart rate sensor numbered A01 and the temperature sensor numbered B01 are shown in Fig. 6.

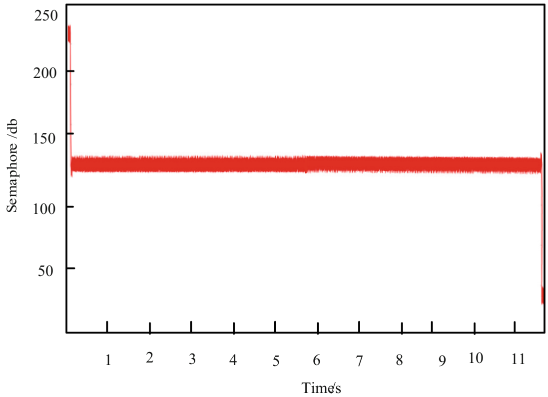
Before data analysis, it is necessary to normalize the sample data. Neural network trains and predicts the network based on the statistical distribution probability of samples in events. Normalization is the statistical coordinate distribution unified between intervals $[-1,1]$. In addition, normalization is also to speed up the training speed of neural network and the convergence of network.

3.4 Input Machine Learning Algorithm Working Parameters

Because the optimized wearable sensor abnormal signal recognition method uses the BP neural network algorithm of machine learning algorithm, it is necessary to set the



(a) A01 heart rate sensor



(b) B01 temperature sensor

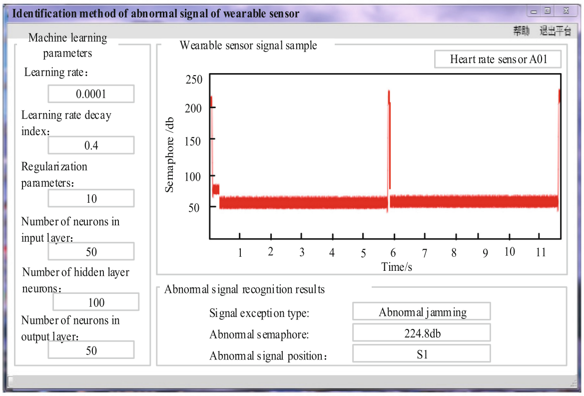
Fig. 6. Initial signal setting diagram of wearable sensor

relevant working parameters. Set the learning rate and attenuation index of BP neural network to 0.0001 and 0.4 respectively, the regularization parameter to 10, the number of neurons in input layer and output layer to 50, the number of neurons in hidden layer to 100, and the number of neural network layers to 5. The maximum number of iterations of BP neural network is 20, and the weight initialization is 0.2. Finally, the above working parameters are input into the operation program of the wearable sensor abnormal signal recognition method.

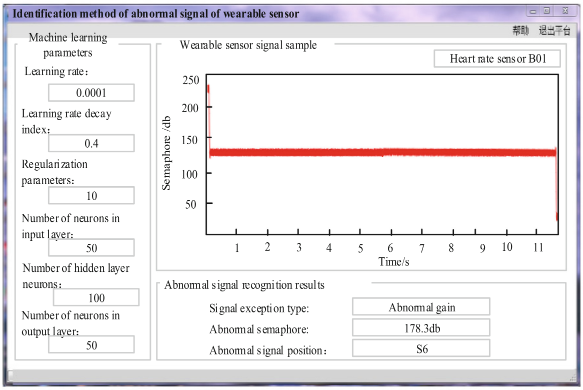
3.5 Describe the Performance Test Process

Use the synchronous data acquisition instrument to collect data, use the designed circuit board to analyze the collected data through programming, and display the analysis results on the 256*128 LCD screen. Figure 7 shows the abnormal signal output results of the heart rate sensor numbered A01 and the temperature sensor numbered B01.

Similarly, the abnormal signal recognition results of all wearable sensor research objects can be obtained.



(a) A01 heart rate sensor



(b) B01 temperature sensor

Fig. 7. Recognition results of abnormal signals of wearable sensors

3.6 Set Identification Performance Quantitative Test Indicators

In the experiment, two indicators, the false detection rate of abnormal types of sensors and the statistical error of abnormal signals of sensors, are set as quantitative test indicators to test the recognition performance. The numerical results of the false detection rate of abnormal types are as follows:

$$\eta_w = \frac{n_e}{n_{all}} \times 100\% \tag{14}$$

In the formula, the variables n_e and n_{all} are the semaphore of the sensor abnormal type identification error and the total amount of sensor signal samples prepared. The specific value of n_e is determined by comparing the identification output results with the setting data. In addition, the test result of the statistical error of the abnormal signal of the sensor can be expressed as:

$$\varepsilon_{\text{signal}} = M_{set} - M_{\text{distinguish}} \tag{15}$$

In the above formula, M_{set} and $M_{\text{distinguish}}$ are the set abnormal semaphore and the actually recognized abnormal semaphore respectively. In order to ensure the optimization effect of the wearable sensor abnormal signal recognition method based on machine learning, it is required that the error detection rate of the abnormal type of the design method should not be higher than 1%, and the statistical error of the abnormal signal should not be higher than 0.5 dB.

3.7 Analysis of Experimental Results

Through the statistics of relevant data, the test results of the false detection rate of sensor abnormal types are obtained, as shown in Table 2.

Table 2. Test data of sensor abnormal type and false detection rate

Wearable sensor number	Total sensor signal /db	Abnormal type identification correct semaphore /db	Abnormal type identification error semaphore /db
A01	240	237.3	2.7
A02	180	178.6	1.4
A03	220	217.9	2.1
B01	250	248.3	1.7
B02	270	267.5	2.5
B03	190	188.5	1.5
C01	150	148.7	1.3
C02	260	257.8	2.2
D01	170	168.6	1.4
D02	200	198.4	1.6

Numbers a, B, C and D in Table 1 represent heart rate sensor, temperature sensor, gyroscope and pressure sensor respectively. By substituting the data in Table 1 into formula 14, it is calculated that the average false detection rate of sensor abnormal type is 0.86%, which is lower than the preset value. The error detection rate of the design method shall not be higher than 1%. This is because the method in this paper sets the signal anomaly judgment standard according to different types and principles of wearable sensors. The wearable sensor signals are collected, and the initial signals are preprocessed through Kalman filtering, normalization and weighted fusion. In addition, the test results of the statistical error of the abnormal signal of the sensor are shown in Table 3.

By substituting the data in Table 2 into formula 15, the average value of the statistical error of the abnormal signal of the sensor in the optimal design method is 0.22 db. The statistical error of the abnormal signal of the design method is not higher than 0.5 dB. This is because the method in this paper uses machine learning algorithm to extract the

Table 3. Test results of statistical error of sensor abnormal signal

Wearable sensor number	Set sensor abnormal semaphore /db	Identify sensor abnormal semaphore /db
A01	225.0	224.8
A02	178.5	178.3
A03	204.2	204.0
B01	238.7	238.5
B02	266.4	266.1
B03	179.5	179.2
C01	144.9	144.6
C02	252.6	252.4
D01	158.4	158.2
D02	188.2	188.1

features of sensor signals, and obtains the recognition results of the abnormal types, abnormal signals and abnormal positions of sensor signals through feature matching.

4 Conclusion

Wearable sensors have important application value in medical monitoring, human motion recognition, medical rehabilitation and other fields. Abnormal signal is an important embodiment of the real-time running state of wearable sensors. The key of abnormal data recognition is how to form a characteristic contour of the normal activity of the sensor. The self-learning habit and adaptability of neural network have attracted more and more scholars to study how to apply it to anomaly detection. It mainly trains a large number of samples, constantly learns and adjusts the subject's feature pattern, so as to build an adaptive feature contour. On this basis, the wearable sensor real-time running signal features are matched with the normal active feature contour to obtain accurate anomaly recognition results. From the experimental results, it can be seen that the recognition method of optimized design meets the preset requirements in two aspects: the false detection rate of abnormal signal types and the statistical error of abnormal semaphores, so it can be applied to the daily maintenance and monitoring of wearable sensors.

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