Fault data extraction of human-computer interaction interface for music electronic products based on improved second generation wavelet algorithm

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Abstract: In order to solve the problems of low extraction accuracy and high time cost in human-computer interface fault data extraction, a method of human-computer interface fault data extraction for music electronic products based on improved second generation wavelet algorithm is proposed. The probability of data encounter in the human-computer interaction interface of adjacent music electronic products is calculated, and the interface data is collected with the help of probability distribution function, judging by the function interval of data points. The similar fault data points are processed by sliding window to complete fault data similarity fusion. The second generation wavelet algorithm is improved by discrete wavelet transform. The energy distribution of fault data in different frequency bands is extracted, and the fault data is extracted in different scale space and wavelet subspace. The results show that the highest accuracy of fault data extraction is about 95%.

Keywords: improved wavelet algorithm for generation 2; music electronics; human-computer interface; fault data extraction.

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1 Introduction

With the continuous development of electronic information technology, many kinds of electronic products continue to appear. Among them, music electronic products are the important representative products. Music electronic products with its large capacity, convenient operation and other advantages, for people's lives increased (Yang and Huo, 2020). At present, the common music electronic products on the market are mainly video and mobile. Tablet computer is a typical representative, it is small, easy to carry, anytime and anywhere use (Ma et al., 2019). The human-computer interaction interface of music electronic products is an important factor affecting the user experience. The degree of human-machine interaction process can enhance the user's sense of experience. But people have higher and higher requirements for music electronic products, and more complex function development seriously affects the fluency of human-computer interaction interface of music electronic products, leading to its failure (Dong et al., 2019). Fault data generally refers to the data generated after system failure, loss and destruction. In the human-computer interaction interface fault of music electronic products, it refers to the data that leads to poor interface and affects user experience. The analysis of these fault data can improve the quality of human-computer interface of music electronic products.

Therefore, in order to improve the fluency of human-computer interface of music electronic products, researchers have done a lot of research on the extraction of fault data.

In Wang (2020), an attribute recognition method of interface fault data based on human-computer interaction is proposed. Firstly, the human-computer interaction interface data is obtained with the help of relevant equipment, and the outlier entropy is used to denoise the fault data obtained above, then the fault data is reconstructed, and the fault data is identified with the help of distance pixel factor. This method can effectively improve the accuracy of fault data identification, but the amount of data obtained in the noise reduction process is less, and the result is more one-sided. Guan et al. (2019) proposed fault feature extraction based on inherent time scale decomposition and multi-scale morphological filtering. In this method, the fault data signal is analysed by ITD method, and the decomposed data is analysed by correlation analysis. The above data is denoised by multi-scale morphological filtering algorithm, and the fault data feature is extracted. The speed of feature extraction is fast, but the accuracy is poor. Jiang et al. (2020) proposed a data-driven fault extraction method based on xgboost feature extraction. In this method, the loss function is designed according to the type of fault data, and the fault tree is constructed based on the sample data. The hidden fault features are expressed, and the fault diagnosis is classified by SVM algorithm to complete the feature extraction of fault data. This method can represent the hidden features, but it still has the problem of low extraction accuracy.

In order to make up for the shortcomings of the above methods, this paper proposes a method to extract the fault data from the human-computer interface of music electronic products based on the improved second generation wavelet algorithm. Firstly, the human-computer interface data of music electronic products are collected, and the acquired data are effectively classified and fused. Discrete wavelet transform (DWT) is used to improve the second generation wavelet algorithm. The energy distribution of fault data in different frequency bands is extracted, and different frequency band sets of fault data are constructed. The fault data is extracted in different scale space and wavelet subspace. The technical route of this paper is as follows

Firstly, the probability of data encounter in the human-computer interaction interface of adjacent music electronic products is calculated, and the distance between data pairs is determined;

Then, the interface data is classified by judging the function interval of data points; With the help of sliding window, the similar fault data points are slided to complete the fault data similarity fusion;

Finally, the second generation wavelet algorithm is improved by discrete wavelet transform (Vamvoudakis-Stefanou et al., 2018). With the help of the improved second generation wavelet algorithm, the energy distribution in different frequency bands of fault data is extracted, and different frequency band sets of fault data are constructed. The fault data is extracted in different scale space and wavelet subspace.

2 Pretreatment of human-computer interaction interface fault data for music electronics

2.1 Data acquisition of human-computer interface for music electronics

In order to extract the fault data of the music electronic products' interaction interface, the data of the human-computer interaction interface of music electronic products are collected first. Because of the large number of human-computer interaction interface data and different attributes of music electronic products, the data of human-computer interaction interface of music electronic products is collected comprehensively. The probability of meeting between adjacent data in the human-computer interface data of music electronic products can be regarded as fixed value. Therefore, the probability of meeting of human-computer interface data of adjacent music electronic products is determined first.

When the number of human-computer interaction interfaces a adjacent music electronic products and the neighbour data b meet, they remain independent of each other, and the minimum relationship is as follows:

$$A = \min\left(a_i, b_j\right) \tag{1}$$

At this time, the distance between the human-computer interface data of adjacent music electronic products is the smallest, and the relationship between the two data is as follows:

$$B\left(A \le a\right) = C\left(\min\left(a_i, b_j\right) \le a\right) \tag{2}$$

There are many close data in the human-computer interface data of music electronic products. The two data are regarded as one data pair and the distance between the data pairs is determined, that is:

$$S_i = v - G \tag{3}$$

In the formula, S_i represents the distance difference between human-computer interface data pairs of music electronic products, v represents the initial location of the data, G represents the actual running distance.

After obtaining the distance between the human-computer interaction interface data pairs of music electronic products, the probability distribution function is used to describe the probability (Alian et al., 2019) of the existence of the human-computer interaction interface data pairs of music electronic products, and the data collection of the human-computer interaction interface data of music electronic products is completed. That is:

$$f(t)=\frac{N(S_i \le t)-A(S_i \le 0)}{1-G(T_x \le 0)} \tag{4}$$

In the formula, N represents the amount of human-computer interface data for music electronics, T_x represents the persistence factor of neighbour data points.

2.2 Data classification of man machine interface of music electronic products

In this paper, the extraction of fault data refers to the data generated after system failure, loss and destruction. In the human-computer interaction interface fault of music electronic products, it refers to the data that leads to poor interface and affects user experience. The analysis of these fault data can improve the quality of human-computer interface of music electronic products.

According to the man-machine interface data of music electronic products obtained above, because it contains two kinds of main data, one is normal data, the other is fault data. In order to realise the extraction of human-computer interaction interface fault data of music electronic products, it is necessary to classify them in detail and lay the foundation for subsequent extraction.

In the classification of human-computer interaction interface data of music electronic products, this paper puts the interaction interface data of music electronic products collected above are placed in a hyperplane, and their categories are judged according to the distance between the data in the plane. Set the hyperplane to:

$$P=F^T X+C \tag{5}$$

In the formula, P stands for hyperplane, X represents the distance between different points in the hyperplane, T represent full-time symbols, C marks representing the data.

According to the hyperplane of the above settings, the positive and negative values of the music electronic products are classified (Liang et al., 2020). At this point, the training set of human-computer interaction interface data of music electronic products is defined first, and the set data set is set to Y, the function interval of the data points of the human-computer interaction interface of the sample music electronic products in this plane as follows:

$$\varepsilon_i=Y_i\left(F^T X+C\right)\mu \tag{6}$$

In the formula, ε_i function interval values representing the data points of the human-computer interface of the sample music electronic product, μ represent interference factors.

According to the function interval of the data points of the human-computer interaction interface of the sample music electronic product, the minimum interval between the sample data is determined. If the minimum interval between the two sample data is within a reasonable range, it is judged to be normal data. Conversely, it is fault data, that is:

$$\tau_k = \begin{cases} \varepsilon_i \sum Y_i \left(F^T X + C\right)\mu & \mu > 1 \\ \varepsilon_i \sum Y_i \left(F^T X + C\right)\mu & \mu < 1 \end{cases} \tag{7}$$

In the formula, τ_k represents the data classification results of the human-computer data of sample music electronic products.

In the data classification of human-computer interaction interface of sample music electronic products, the probability of meeting data of adjacent human-computer interaction interface of music electronic products and the distance between data pairs are first calculated. The probability distribution function is used to describe the probability of human-computer interaction interface data pair of music electronic products, and collect the data of human-computer interaction interface of music electronic products.

2.3 Fault data fusion of man machine interface of music electronic products

Because there is a lot of data in the fault data of the human-computer interface of music electronic products, but there are some similarities between the fault attributes, the fault data is similar to the fusion. Reduce the complexity human-computer interface fault data extraction (Aucejo et al., 2019) music electronic products.

The fault data of human-computer interaction interface of music electronic products are classified (Xue and Zheng, 2019) effectively by random forest algorithm, which are divided into important fault data and secondary fault data, and trained N times. The important fault data set and the secondary fault data set are as follows:

$$Z_i = \{z_1, z_2, \ldots z_m\} \tag{8}$$

$$L_i = \{l_1, l_2, \ldots l_m\} \tag{9}$$

According to the fault data type of formula (8) and formula (9), the influence degree of the data is calculated, that is, the proportion of his influence factor, that is:

$$J(x) = \arg u \sum_{i=1}^{n} Z_i L_i \delta \tag{10}$$

In the formula, δ represents the ensemble classifier, u represents the underlying classifier.

In order to ensure the accuracy of the above fault data, the convergence control of the data in formula (10) is carried out. The control formula is as follows:

$$K(Z_i,\ L_i) = avk\tau \prod J(x) \tag{11}$$

In the formula, τ represents the convergence function, *avk* represents the data mean.

Based on the above analysis, the similar data in the human-computer interface fault data of music electronic products are fused (Guo and Liu, 2020). In view of the possible data loss problems in the fusion process, it is necessary to control the quality of similar data, namely:

$$R(X,Y)=\frac{R_{xy}\times \overline{xy}}{R_{xy}{}^{2}\left(\overline{xy}\right)^{2}} \tag{12}$$

In the formula, R_{xy} represents similar data on human-computer interface failures of music electronics, $\overline{xy}$ represent the fault data covariance of human-computer interface of music electronic products respectively.

In the actual fusion of human-computer interaction interface fault data similarity of music electronic products, the data fluctuates greatly. Therefore, this paper uses sliding window to slide the similar fault data points to complete the fusion of fault data similarity of human-computer interaction interface of music electronic products, that is:

$$H=\frac{1}{M}\sum_{i=1}^{M}R(X,Y) \tag{13}$$

In the formula, M represents the number of window slips in fusion.

In the process of fault data similarity fusion, the random forest algorithm is used to divide the fault data to different degrees and control its convergence. On this basis, the sliding window is used to slide the similar fault data points to complete the fusion of fault data similarity in the human-computer interface of music electronic products.

3 Fault data extraction of human-computer interaction interface for music electronic products based on improved second generation wavelet algorithm

On the basis of wavelet algorithm, the second generation wavelet algorithm reduces the volatility of the method in feature extraction, but there are still large fluctuations in the practical application process, which leads to certain errors in the extraction results. Therefore, the second generation wavelet algorithm needs to be improved before it is applied.

The second generation wavelet algorithm is evolved from the first generation wavelet algorithm, which is an effective data extraction method. This method decomposes the data of the research object in a certain space, and obtains different signals of the research object after decomposition, so as to realise the research purpose (Ji and Wang, 2020). In each wavelet packet decomposition process, the signal of the research object will be reduced by half, and the decomposed signal will be decomposed into the non-frequency band of the signal. The second generation wavelet decomposition mainly studies the research data through different levels of filters.

$$\begin{cases} U(X)=1-E(X)^{2}P(X) \\ G(X)=-P\left(X^{2}\right)+X^{-1} \end{cases} \tag{14}$$

In the formula, $U(X)$ represent high-level filters, $G(X)$ represent low-frequency filters, E represents wavelet coefficients.

Although the second generation wavelet algorithm can effectively extract the human-computer interface fault of music electronic products, the extracted structure is affected by different frequency filters, resulting in the human-computer interface fault result of music electronic products is not the optimal result (Li et al., 2018). Therefore, this paper improves the second generation wavelet algorithm with the help of discrete wavelet transform to improve the accuracy of fault data extraction of music electronic product man-machine interface.

The signal to be processed in the second generation wavelet algorithm is set to $\beta(t)$, during which the displacement occurs is *O*, the transformation in the process of wavelet decomposition is transformed into continuous change, and the fluctuation of the second generation wavelet algorithm can be stabilised at this time, that is:

$$\epsilon_{jk}(t) = \alpha^{-\frac{1}{2}} \vartheta(\alpha_0 t - \sigma t) \tag{15}$$

In the formula, α represent scale factors, ϑ represent discrete coefficients, σt represents power-level discrete processing.

Based on obtained α, in order to complete the signal acquisition in the second generation wavelet algorithm, it is necessary to set the limited conditions for the frequency of its occurrence, and to complete the improvement of the algorithm, that is:

$$w(t) = \alpha \int f_{jk}(t) \gamma dt \tag{16}$$

In the formula, γ represents discrete wavelet functions.

Based on the improvement of the second generation wavelet algorithm, according to the human-computer interface fault data of music electronic products obtained in the second chapter, it is effectively extracted. Firstly, the energy distribution of fault data in different frequency bands is extracted, and the decomposed energy of human-computer interface fault data of music electronic products is set as follows:

$$\theta_e = \sum_{i=1}^{N} \left| E_N^2 \right| \tag{17}$$

In the formula, E_N^2 represents the sequence amplitude of the human-computer interaction interface fault data of music electronic products.

On the basis of this, the fault data of human-computer interaction interface of music electronic products are set up for each different frequency band data, that is:

$$E_N^2 = \left[E_{N1}^2, E_{N2}^2, \ldots E_{Nm}^2 \right] \tag{18}$$

In the formula, $E_{N1}^2, E_{N2}^2, \ldots E_{Nm}^2$ represent data energy values on different frequency bands.

The energy value of the above fault data is normalised to unify the characteristics of the fault data, that is:

$$G = \left(\sum_{N}^{M} \left| E_N^2 \right| \right) \beth \tag{19}$$

In the formula, $\beth$ represents the normalised dimension value.

According to the characteristics of the unified fault data, the discrete time of the fault data (Hu et al., 2019) is by wavelet transform, the energy value of fault data is normalised to unify the fault data, which is regarded as the limiting condition of wavelet transform, that is:

$$W(n) = G\sum_{j=1}^{i=1}\beta(\tau_o + p) \tag{20}$$

In the formula, τ_o represents the base discrete binary wavelet transform value.

On this basis, the fault data is extracted in the new space, and the different scale space is set to U_i, wavelet subspace as the B_i, to extract in these two spaces, and the final fault data of the human-computer interaction interface of the music electronic product is obtained, that is:

$$S_{Ui} = \sum_{i=1} v_k(2j - l) \tag{21}$$

$$S_{B_i} = \sum_{i=1} u_k(2j - l) \tag{22}$$

In the formula, S_{Ui} represents fault data results in different scales, S_{B_i} represents the fault data result value in the wavelet subspace.

The second generation wavelet algorithm is improved by discrete wavelet transform to maintain the fluctuation extracted by the second generation wavelet algorithm, extract the energy distribution of fault data in different frequency bands, obtain the decomposed energy of human-computer interface fault data of music electronic products, and collect and construct each different frequency band data of human-computer interface fault data of music electronic products, The fault data is extracted in different scale space and wavelet subspace.

4 Experimental analysis

4.1 Experimental environment

In order to verify the effectiveness of the proposed method, experimental analysis was carried out. The experiment takes a brand of music electronic products as the research object. The experiment is carried out on the MATLAB platform and runs a WINDOWS XP system of 8 GB. In order to ensure the accuracy of the research data, the data is counted through the professional data statistics software.

4.2 Experimental parameters

The verification performance of the method is considered in the experimental parameter setting, and the experimental sample test parameters are set on the basis of ensuring its performance. The relevant parameters in the test are shown in Table 1.

Table 1 Test parameters

Parameter	*Data*
Sample Fault Data/GB	2
Number of sample failure data	2000
Total sample data	5000
Number of iterations/times	100

4.3 Experimental indicators

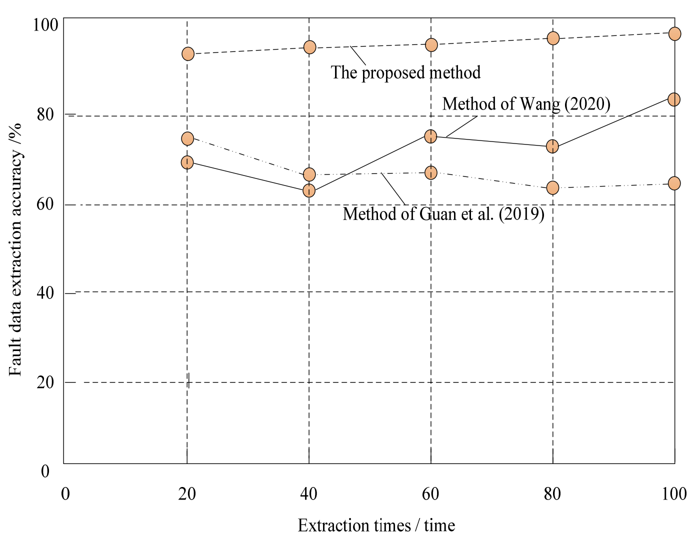
To highlight the research advantages of the method in this paper, in the experiment, by comparing the proposed method, Wang (2020) method and Guan et al. (2019) method, the accuracy of fault data extraction and the time consuming of extraction are taken as the research indexes. the experiment times and the average value is obtained.

4.4 Experimental result

4.4.1 Analysis of fault data extraction precision of human-computer interaction interface of music electronic products

The experimental comparison of the proposed method, Wang (2020) method and the accuracy of Guan et al. (2019) method for sample fault data extraction, the results obtained are shown in Figure 1.

Figure 1 Comparison of fault data extraction accuracy of human-computer interaction interface for music electronic products



By analysing the data in Figure 1, it can be seen that the proposed method, Wang (2020) method and Guan et al. (2019) method are used to extract sample fault data. Among them, the highest accuracy of the proposed method is about 95%, while the extraction accuracy of the other two methods is always lower than that of the proposed method, which verifies the reliability of the proposed method.

4.4.2 Time-consuming analysis of human-computer interaction interface fault data of music electronic products

The method, Wang (2020) method and Guan et al. (2019) method are time-consuming for sample fault data extraction. The experimental results are shown in Table 2.

Table 2 Time-consuming analysis of fault data extraction of human-computer interface for music electronics by different methods (s)

Number of withdrawals/times	*Proposed methodology*	*Wang (2020)*	*Guan et al. (2019)*
20	1.2	2.2	3.6
40	1.3	2.6	2.9
60	1.5	3.2	3.5
80	0.8	3.6	3.4
100	0.5	3.4	3.8

From the analysis of the data in Table 2, it can be seen that there are some differences in the time-consuming of the three methods in extracting sample fault data in the same experimental environment. Among them, the shortest time for the proposed method to extract sample fault data is about 0.5 s, the shortest time for the method in Wang (2020) to extract sample data is about 2.2 s, and the shortest time for the method in Guan et al. (2019) to extract sample data is about 2.9 S. in contrast, the extraction time of the proposed method is shorter, which verifies the effectiveness of the proposed method.

5 Conclusion

Aiming at the shortcomings of fault data extraction, this paper proposes a method of fault data extraction based on improved second generation wavelet algorithm. With the help of probability distribution function to collect data, the collected data is placed in the hyperplane, and the human-computer interface data classification of music electronic products is completed by judging the interval of data point function; the influence degree of fault data is divided by random forest, and the similarity fusion of fault data is completed by sliding the similar fault data points with the help of sliding window; the discrete wavelet transform method is adopted The second generation wavelet algorithm is improved to extract the energy distribution in different frequency bands of fault data, construct different frequency band sets of fault data, and complete the extraction of fault data in different scale space and wavelet subspace. Compared with the traditional methods, this method has the highest accuracy of about 95% and the shortest extraction time is about 0.5 s.

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