Visual perception-based human-computer interaction information classification method for intelligent products

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Abstract: This paper proposes a new intelligent product human-computer interaction information classification method based on visual perception. Design smart product human-computer interaction information collection device to realise rapid and accurate collection of smart product human-computer interaction information, and fusion processing of the collected information. The ISA model is built according to the principle of visual perception, and the model is optimised by the gradient descent method. The optimised model is used to extract the information attribute characteristics, and the intelligent product human-computer interaction information classification is carried out according to the information attribute characteristics. The experimental results show that the accuracy of information classification of this method is always above 94.7%, and the average classification time is 0.53 s, which verifies the superiority of the method.

Keywords: visual perception; intelligent products; man-machine interaction; information classification; ISA model.

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1 Introduction

With the further improvement of information technology, many types of intelligent products have emerged in the market. In general, intelligent product refers to a kind of product that takes artificial intelligence technology as the theoretical basis, can accept, understand and execute user instructions by using relevant software and hardware and can also reason and process user requirements according to historical data and real-time situation (Zong et al., 2017). Especially so far, with the rapid development of artificial intelligence technology, a variety of new technologies have been integrated into the development process of such products, so that their functions are no longer simple, but show the characteristics of diversification and high intelligence. In the process of intelligent product design, human-computer interaction page design is a very important content. In the human-computer interaction page, it establishes contact with users, and achieves the purpose of smooth communication between the two sides through the interaction between man and machine (Yang and Tao, 2018). In the process of intelligent products put into use, there are a lot of interactive information, so in order to make the machine can better understand the user instructions, need to categorise the human-computer interaction information processing, in order to enhance the comprehensive performance of intelligent products, so the product of a kind of intelligent human-computer interaction information classification method has very important significance (Liu, 2018; Hu, 2017).

So far, the research progress of human-computer interaction information classification method for intelligent products is slow, but there are some excellent research results. For example, Dai et al. (2019) proposed a binary coded human-computer interaction information classification method for intelligent products. This method mainly solves the defects of traditional information classification methods as the research goal, in order to improve the follow-up intelligent product human-computer interaction information classification effect. The specific process is: The 64-bit binary value is used to code the human-computer interaction information of intelligent products, and different information classification foundations are built according to the different attributes of information codes, and the information classification hierarchy is built. Based on this, the information is allocated to different human-computer interaction information sets of intelligent products, so as to complete the information classification. However, this method has the problem of low classification accuracy of human-computer interaction information of intelligent products, and the practical application effect is not good. Lu et al. (2020) proposed a classification method of human-computer interaction information for intelligent products based on Text-CRNN+ Attention architecture. Quickly get smart products using CNN interactive information and local characteristics, the attention mechanism was developed for the RNN was used to model the sequence characteristics, to realise the human-computer interaction information weighted processing, to ensure the CNN extract local features in the process of its key characteristics are not lost, combined several weighted intelligent human-computer interaction products information extraction results overall characteristics. According to the result of feature extraction, the information classification model is built to obtain the information classification result of human-computer interaction of intelligent products. However, this method has the problem that it takes a long time to classify the human-computer interaction information of intelligent products. Wang (2020) proposed a hierarchical and optimised man-computer interaction information classification method for big data centres. This method firstly collects the background data of intelligent products to extract the attribute characteristics of human-computer interaction information and obtain its key features. On the basis of the characteristics of does not have the key to deal with the redundant information, and calculate the information key characteristic coefficient, according to the coefficient of human-computer interaction information hierarchical processing, get the ultimate interactive information classification results, but the methods to solve the problem of low accuracy of feature extraction in information classification efficiency declined dramatically.

In order to solve the problems of the above methods, improve the classification accuracy of intelligent product human-computer interaction information, and reduce the classification time, this paper proposes a new intelligent product human-computer interaction information classification method based on visual perception. The overall design scheme of the method is as follows:

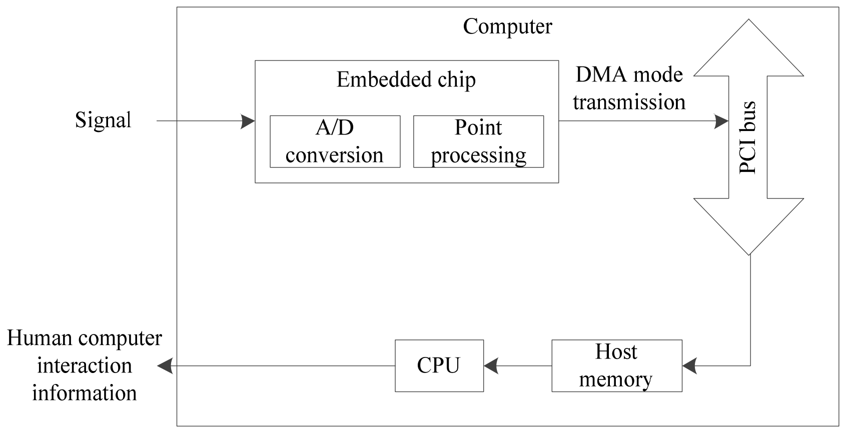
- First, design a smart product human-computer interaction information collection device to achieve rapid and accurate collection of smart product human-computer interaction information, and fusion processing of the collected information.
- Secondly, build an ISA model based on the principle of visual perception, and use gradient descent to optimise the model, use the optimised model to extract information attribute features and classify intelligent product human-computer interaction information based on the information attribute features.
- Finally, through experiments, different methods of intelligent product human-computer interaction information attribute feature extraction error rate, intelligent product human-computer interaction information classification accuracy rate and classification time are compared.

2 Human computer interaction information classification of intelligent products based on visual perception

2.1 Information collection and fusion processing

Because the sources of human-computer interaction information of intelligent products are relatively complex, including line of sight and viewpoint in the process of eye movement interaction, touch point and click judgment in tactile interaction, voice dialogue, gesture tracking, etc. (Jing et al., 2018; Czarnecki and Tabor, 2017), this paper designs a new human-computer interaction information acquisition device for intelligent products, so as to realise the rapid and accurate acquisition of human-computer interaction information of intelligent products. The specific structure of the intelligent product human-computer interaction information collection device is shown in Figure 1.

Figure 1 Human-computer interaction information collection device of intelligent products



The sampling frequency should be greater than or equal to 2 times of the highest frequency of the signal to ensure that the data is not distorted. Based on the sampling data, wavelet transform is used to filter the original data. The information acquisition device is mainly to add embedded chip into intelligent products, and use the device to collect human-computer interaction information of intelligent products through multiple channels. In this process, there will be A digital processing process of human-computer interaction information of intelligent products, including A/D conversion processing and point processing. A/D conversion is used to convert the collected data into A form that can be recognised and read by the computer. Point processing requires clarifying the pixels of the collected image information so as to improve the image quality, and DMA is used to transfer the collected data to the PCI bus (Ding et al., 2017). On this basis, the collected information is stored in the cloud database by the PCI bus for the computer to analyse and process the collected data. Therefore, the device has many characteristics, such as simple operation, low energy consumption, high integration, etc., which can improve the classification and processing efficiency of human-computer interaction information of subsequent intelligent products.

Owing the high complexity of human-computer interaction information of intelligent products, multiple channels should be used for information collection. The information collection results of a single channel can be expressed by the following formula:

$$y^t = f\left(x^t - x^{t-1}, \dots, x^{t-l}\right) \tag{1}$$

In the above formula, x^t represents the input signal of an information collection channel when the sampling time is t, and l represents the maximum information length that the information collection channel can accommodate (Borriello and Walker, 2017; Partridge et al., 2018).

Assuming that the signal of the k-th information acquisition channel obeys the Gaussian distribution, then the mean value of the Gaussian distribution is (u_k, δ_k), then the Gaussian distribution satisfies the following formula:

$$s_k \sim N(u_k, \delta_k) \tag{2}$$

In the above formula, s_k represents the maximum likelihood estimation result of the signal, and N represents the number of signals.

According to the above formula, the confidence of each information acquisition channel signal is calculated (Zhang and Han, 2020). The specific calculation formula is as follows:

$$w_k = \frac{\frac{1}{\delta_k^2}}{\sum_k \frac{1}{\delta_k^2}} \tag{3}$$

In the above formula, δ_k represents the signal spectrum of the information acquisition channel.

Then, at any sampling moment, the signals of multiple information acquisition channels are fused, and the results are as follows:

$$S = \oplus_{k=1}^{K}(s_k) \sim N\left(\sum_{k=1}^{K} w_k u_k, \sum_{k=1}^{K} w_k \delta_k\right) \tag{4}$$

Then, the joint probability distribution of information acquisition channel signals at a certain moment can be expressed in the following form:

$$P_s(S) = P_s(s_1, s_2, \ldots, s_D) \tag{5}$$

In the above formula, D represents the number of human-computer interaction information collection channels of intelligent products.

Assuming that the probability of edge distribution of the observed signal in a certain information acquisition channel is $P_D(d_{obs})$, the following relationship exists:

$$P_D(d_{obs}) = P_D(d_{obs}|S) \times P_s(S) \tag{6}$$

In the above formula, d_{obs} represents the observed value of the d-th intelligent product human-computer interaction information acquisition channel signal, and $P_D(d_{obs}|S)$ represents the joint probability distribution of the signal inferred by the Bayesian formula (Xiao et al., 2020). Then, when the joint probability distribution of some signals is known, the following relationship exists:

$$(S|d_{obs}) = \frac{P_D(d_{obs}|S) \times P_s(S)}{P_D(d_{obs})} \tag{7}$$

$$P_D(d_{obs}) = \int_s^S P_D(d_{obs}|S) \times P_s(S) \times dV_s \tag{8}$$

The above formula can be used to complete the missing information V_s and obtain a more accurate joint probability distribution result of the signal of the information collection channel.

According to the joint probability distribution results of the signals of information acquisition channels, the information acquisition results of multiple channels are integrated and the human-computer interaction information acquisition results of all intelligent products are fused. The specific forms are as follows:

$$y_i^t = P_s(S)\left[\oplus_{k=1}^{K}\left(x_k^t\right), \oplus_{k=1}^{K}\left(x_k^{t-1}\right), \ldots, \oplus_{k=1}^{K}\left(x_k^{t-l}\right)\right] \tag{9}$$

2.2 Information classification based on visual perception

Based on the above intelligent product human-computer interaction information collection and fusion processing results, the human-computer interaction information of intelligent products is classified by visual perception method, in order to improve the classification accuracy and classification efficiency.

Human visual system is a very efficient method of information processing, which mainly extracts useful information according to different responses of the brain. The human-computer interaction information classification of intelligent products is mainly based on psychology and related theories of visual perception, and maps the low-level visual features of information to the high-level emotional semantics according to certain rules. On this basis, the attribute characteristics of human-computer interaction information of intelligent products are extracted and applied to information classification to improve the accuracy and efficiency of classification by this method.

It is assumed that and respectively represent adjacent cells in the optic nerve. Since the orientation of visual perception of simple cells is similar in the actual system of human beings (Xie, 2018; Wang, 2019), the following formula exists in the case of similarity with topology.

Assuming that x_i and x_j represent adjacent cells in the optic nerve respectively, since in the actual human system, the orientation of visual perception of simple cells is similar, the following formula exists when the topologies of x_i and x_j are similar:

$$cov\left(x_i^2, y_i^2\right) = E\left\{x_i^2, y_i^2\right\} - E\left\{x_i^2\right\} E\left\{y_i^2\right\} \neq 0 \tag{10}$$

In the above formula, $cov\left(x_i^2, y_i^2\right)$ represents the evaluation function of topology similarity between x_i and x_j, and $E\left\{x_i^2, y_i^2\right\}$ represents the response characteristics of neurons.

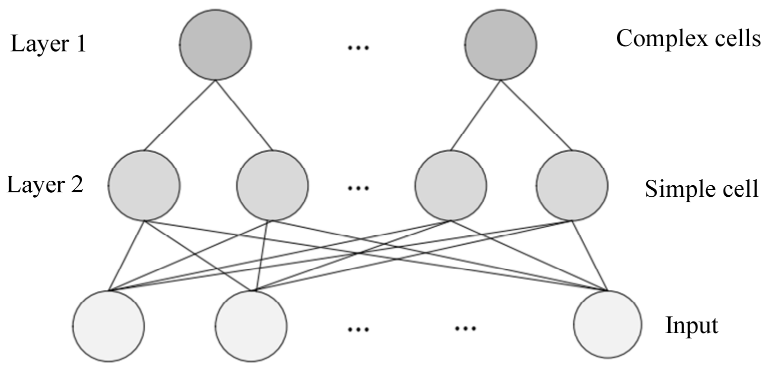
Compared with simple cells, complex cells can accurately describe the visual perception characteristics of human brain, so this paper mainly analyses the response characteristics of complex cells in the presence of stimuli, as follows:

$$\left|y_i\right| = \left(\sum_{j=1}^{n} v_{ij} x_i^2\right)^{\frac{1}{2}} \tag{11}$$

In the above formula, n represents the number of simple cells in the optic nerve (Chen et al., 2020), and v_{ij} represents the connection weight between the *i*-th complex cell and the *j*-th simple cell.

Based on the above analysis, this article mainly uses the ISA model as the main method to extract the characteristics of the human-computer interaction information attributes of smart products. The ISA model is essentially a two-layer artificial neural network. The ISA model structure is shown in Figure 2.

Figure 2 ISA model structure



According to the ISA model, the human-computer interaction information attribute feature extraction function of intelligent products is constructed. The specific description of the function is as follows:

$$J(W)=\frac{1}{N}\sum_{i=1}^{N}\sum_{i=1}^{m}\sqrt{\sum_{j=1}^{c}\left(s_j^t\right)^2}+log\left|det(W)\right|=\frac{1}{N}\sum_{t=1}^{N}\sum_{i=1}^{m}\sqrt{\sum_{j=1}^{c}\sum_{J=1}^{S_i}v_{ij}\left(\sum_{k=1}^{n}W_{jk}x_k^t\right)^2}+log\left|det(W)\right| \quad (12)$$

In the above formula, W represents the connection weight matrix, s_j^t represents the response characteristics of simple cells in the model (Guo and Cai, 2018), N represents the amount of human-computer interaction information of intelligent products after information fusion processing, m and c respectively represent the number of neurons in the first and second layers, and $det(W)$ represents the initial weight. W_{jk} represents the connection weight between the *i*-th simple neuron and the *j*-th complex neuron, and x_k^t represents the *i*-th subspace of ISA model.

To extract more human-computer interaction information attributes of intelligent products, it is necessary to make W meet the orthogonal constraint, that is, to make W an orthogonal matrix, then the value of $log\left|det(W)\right|$ is 0. Therefore, the above formula can be simplified as:

$$J(W)=\frac{1}{N}\sum_{t=1}^{N}\sum_{i=1}^{m}\sqrt{\sum_{j=1}^{S_i}\left(s_j^t\right)^2} \quad (13)$$

In order to reduce the model output error, this paper chooses the gradient descent method to optimise the model. It is necessary to obtain the partial derivative of W with respect to the simplified feature extraction objective function (Wang et al., 2020; Chen and Guo, 2020), and the calculation formula of the conventional gradient is:

$$\Delta_w J(W) = \frac{\partial J(W)}{\partial W} = \frac{1}{N}(R \times F) \times X^T + \left(W^{-1}\right)^T \tag{14}$$

In the above formula, R and F, respectively represent the response eigenmatrix of simple cells in the first and second layers of ISA model, X^T represents the Eigen response matrix of complex cells and T represents matrix transpose.

The optimised ISA model is used to extract the human-computer interaction information attribute characteristics of smart products, and the human-computer interaction information classification of intelligent products is carried out according to the information attribute characteristics. The results are as follows:

$$K(X_i, Y_i) = exp\left(-\frac{1}{2D}\sum_{k=1}^{K}\frac{\left(X_{ik} - X_{jk}\right)^2}{X_{ik} + X_{jk}} + J(W)\right) \tag{15}$$

In the above formula, X_{ik} and X_{jk}, respectively represent the human-computer interaction information attribute characteristics of key intelligent products and repetitive intelligent products.

3 Simulation experiment design and result analysis

3.1 Experimental scheme

In order to verify the reliability and scientific nature of the human-computer interaction information classification method of intelligent products based on visual perception proposed in this paper, experimental design is needed. The specific experimental scheme is as follows:

1) Experimental environment: the PC processor used in this experiment is Inter Pentium G460 (3.0 GHz), the memory is 16 GB, the operating system is Windows 10, the simulation software is Matlab 7.2 and the data analysis and processing software is SPSS13.0.

2) Experimental data: the experimental data comes from intelligent product manufacturers and user background. Web crawler is used to capture human-computer interaction information and related product parameter information of intelligent products, and the captured data is cleaned and sorted to improve the accuracy of simulation experiment. The amount of experimental data is 10 GB, and sine cosine transform is used to filter the experimental data.

3) Experimental methods: This paper method, Dai et al. (2019) method, Lu et al. (2020) method and Wang (2020) method were selected as experimental comparison methods.

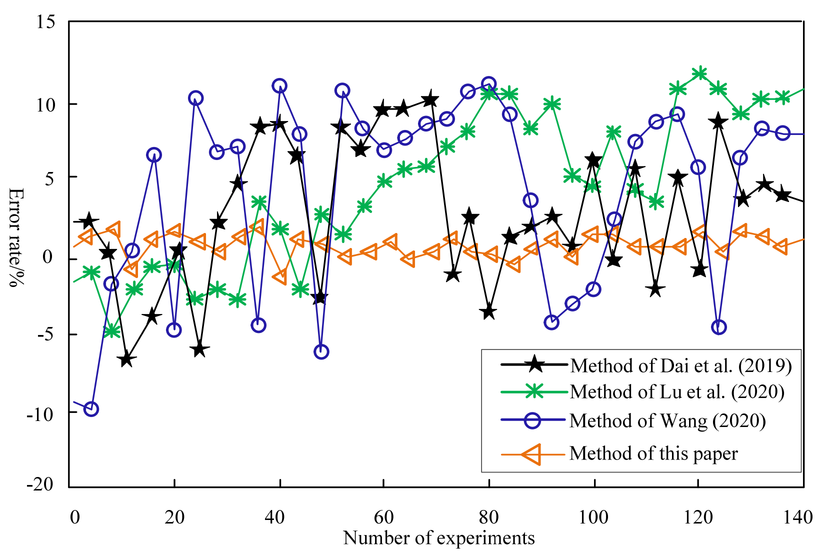
4) The error rate of the feature extraction, the accuracy of the classification and the classification time of the information are taken as the evaluation indexes. Among them, the lower the error rate of feature extraction of human-computer interaction information attribute of intelligent products, the higher the accuracy of feature extraction; the higher the classification accuracy of human-computer interaction information of intelligent products, the more accurate the classification results, the better the classification effect; the shorter the classification time of human-computer interaction information of intelligent products, the higher the classification efficiency, the better the practical application effect.

3.2 Analysis of experimental results

3.2.1 Feature extraction error comparison

According to the above experimental scheme, firstly, the error rate of attribute feature extraction of human-computer interaction information of intelligent products based on the method of this paper, the method of Dai et al. (2019), the method of Lu et al. (2020) and the method of Wang (2020) is compared. The error comparison results of the four methods are shown in Figure 3.

Figure 3 Comparison of feature extraction error rates



As can be seen from the data in Figure 3, the error rate of intelligent product human-computer interaction information attribute feature extraction by the method in this paper is between –2% and 2%, and the error rate of intelligent product human-computer interaction information attribute feature extraction by Dai et al. (2019) method is between –7% and 11%. The error rate of human-computer interaction information attribute feature extraction of intelligent products based on Lu et al. (2020) method is between –5% and 13%, and the error rate of human-computer interaction information attribute feature extraction of intelligent products based on Wang (2020) method is between –10% and

12%. In summary, the error rate of intelligent product human-computer interaction information attribute feature extraction based on the method in this paper is lower, so the result of information attribute feature extraction is more accurate, which can lay a solid foundation for the follow-up intelligent product human-computer interaction information classification.

3.2.2 Comparison of information classification accuracy

On the basis of comparing the error rate of feature extraction of the four methods, the accuracy rate of human-computer interaction information classification of intelligent products based on the method of this paper, the method of Dai et al. (2019), the method of Lu et al. (2020) and the method of Wang (2020) is compared. The comparison results of information classification accuracy are shown in Table 1.

Table 1 Comparison of information classification accuracy

Number of experiment	*Accuracy rate of information classification/%*			
	Method of this paper	*Dai et al. (2019)method*	*Lu et al. (2020) method*	*Wang (2020) method*
10	96.3	86.3	78.5	85.2
20	98.5	85.2	77.4	87.4
30	97.4	87.4	72.4	79.3
40	95.2	87.0	75.6	78.5
50	96.4	85.6	78.2	72.1
60	98.1	82.3	79.3	78.5
70	94.8	84.9	71.5	74.4
80	95.6	85.2	72.5	72.6
90	94.7	87.6	74.6	84.1
100	95.2	86.4	74.3	82.2
110	96.1	83.2	76.8	86.3
120	97.4	79.6	77.3	78.6
130	95.6	78.5	74.9	71.2
140	97.3	84.1	75.5	75.4

By analysing the data in Table 1, it can be seen that the classification accuracy of human-computer interaction information of the method in this paper is always above 94.7%, while that of Dai et al. (2019) method fluctuates between 78.5% and 87.6%, and that of the Lu et al. (2020) method fluctuates between 71.5% and 79.3%. The classification accuracy of human-computer interaction information based on Wang (2020) method fluctuates between 71.2% and 87.4%. In summary, the classification accuracy of human-computer interaction information of intelligent products based on the method in this paper is higher and the practical application effect is better.

3.2.3 Comparison of information classification time

On the basis of comparing the classification accuracy of human-computer interaction information of intelligent products of four methods, the classification time of human-computer interaction information of intelligent products of this method, Dai et al. (2019), Lu et al. (2020) and Wang (2020) is compared. The comparison results of information classification time are shown in Table 2.

Table 2 Comparison of information classification time

Number of experiment	*Information classification time/s*			
	Method of this paper	*Dai et al. (2019) method*	*Lu et al. (2020) method*	*Wang (2020) method*
10	0.54	2.56	1.69	3.66
20	0.48	2.35	1.52	3.85
30	0.52	2.85	1.84	2.59
40	0.66	2.47	1.47	5.84
50	0.47	2.96	1.63	2.74
60	0.58	2.35	1.85	3.66
70	0.41	2.84	1.95	4.85
80	0.58	1.96	1.64	4.96
90	0.62	2.66	1.75	2.55
100	0.47	2.38	1.36	2.74
110	0.37	2.75	1.65	2.84
120	0.68	2.59	1.85	2.96
130	0.55	2.36	1.84	3.64
140	0.49	2.47	1.87	5.31
Average	0.53	2.54	1.71	3.73

By analysing the data in Table 2, it can be seen that the average classification time of intelligent product human-computer interaction information based on the method in this paper is 0.53 s; the average classification time of human-computer interaction information of intelligent products in Dai et al. (2019) method is 2.54 s; the average classification time of human-computer interaction information of intelligent products in Lu et al. (2020) method is 1.71 s. The average classification time of human-computer interaction information of intelligent products in Wang (2020) method is 3.73, which is the longest classification time among the four methods. In summary, compared with the other two methods, the classification time of human-computer interaction information of intelligent products in this paper is shorter and the classification efficiency is higher, so it can be widely used in practice.

4 Conclusion

With the common progress of economy and science and technology, products are gradually developing in the direction of intelligence and automation. In the process of its development, the importance of human-computer interaction is gradually highlighted, so it is necessary to collect the human-computer interaction information of these intelligent products purposefully, and classify it, in order to provide corresponding services according to different user needs. However, the traditional human-computer interaction information classification method of intelligent products has many problems, such as low classification accuracy and long classification time. Therefore, this paper proposes a new human-computer interaction information classification method of intelligent products based on visual perception, and completes the overall design of this method through a series of demonstration. The experimental results show that the error rate of the intelligent product human-computer interaction information attribute feature extraction is between –2% and 2%, and the feature extraction accuracy is high. The classification accuracy of human-computer interaction information is always above 94.7%, and the classification results are more accurate. The average classification time of human-computer interaction information of intelligent products is 0.53 s, which is shorter and more efficient in classification. This method can fully solve the problems existing in traditional methods and promote the further development of intelligent product design and manufacturing.

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