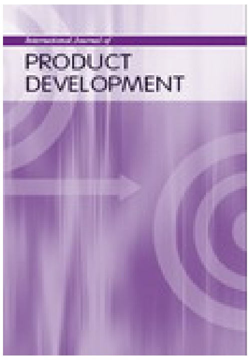

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Study on evaluation method of human-computer interface quality of intelligent products based on Bayesian classification

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Abstract: In order to improve the accuracy and efficiency of human-computer interaction interface quality evaluation, this paper proposes an intelligent product interaction interface quality evaluation method based on Bayesian classification. An adaptive Gauss filter is introduced to adjust the colour of intelligent product interaction interface through logarithmic operator, and the intelligent product interaction interface is formally described. Bayesian classification method is used to build the quality evaluation model of intelligent product interaction interface. According to Bayesian classification probability reasoning mechanism, the quality of intelligent product interaction interface is evaluated. According to the relevant verification results, the average significance of the proposed method is as high as 95.7%, the recognition accuracy is 96.4% and the evaluation time is only 7.2 s, which has a good evaluation effect.

Keywords: Bayesian classification; adaptive Gaussian filter; intelligent product; human-computer interaction interface; quality assessment.

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1 Introduction

In the current information age, users require that products not only meet the functions required for daily use, but also reflect the emotional care for users, which leads to the trend of 'user-oriented' design in product development (Machado et al., 2019; Hinsen, 2018; Ramakrishnan et al., 2021). The functions of smart products are becoming more and more complex and popular, and the demand for user interaction is also increasing. Complex smart product functions require more efficient interfaces. Popularisation requires an interface that is easy to grasp and adaptable to the needs of different users. This makes interface technology widely used in high-tech fields. In the interactive interface, new interactive channels, devices and interactive technologies such as vision, voice, gesture, line of sight tracking and avatar tracking are comprehensively used, so that users can conduct human-computer interaction naturally, in parallel and cooperatively through multiple channels (Guerrero-Vasquez et al., 2019; Erat et al., 2021; Nenadic, 2021). In the overall quality evaluation process, there are many factors affecting each other, including unknown or uncertain factors and the evaluation of the same interface. These characteristics make it difficult to evaluate the quality of interactive interface, and its scientific and reasonable evaluation is still in the exploratory stage.

At present, scholars in related fields evaluate the quality of the interactive interface. Wu et al. (2019) proposed an interactive interface quality evaluation method based on preference comparison, analyses the influence mechanism of interactive interface quality on user preference, establishes an evaluation index system of intelligent product interactive interface quality and constructs an objective evaluation model by using triangular fuzzy numbers. The objective evaluation index weight is determined through the objective evaluation index data to complete the evaluation of the quality of the interactive interface. Although this method can get the evaluation results, there is still much room to improve the evaluation accuracy. Zhang et al. (2019) proposed an interactive interface quality evaluation method based on visual perception characteristics. This method constructs a human-computer interaction interface visual perception intensity division model, uses the priority method to divide the importance levels of visual elements and obtains the weights of visual perception elements. Based on the study of the visual perception intensity of the interface, the evaluation results are obtained. However, the quality evaluation process of this method is complex, which leads to a long time for the overall evaluation. Hua et al. (2020) proposed an interactive surface quality evaluation method based on multi feature fusion. This method aggregates the extracted human-computer interface features through a random forest, constructs a 3D grid interactive interface quality evaluation model, obtains the evaluation scores and judges the quality of the human-computer interface according to the evaluation scores. However, the evaluation accuracy of this method still has much room for improvement.

In order to improve the effect, accuracy and efficiency of interactive interface evaluation, an interactive interface quality evaluation method based on Bayesian classification is proposed. The specific technical route is as follows:

1. Firstly, the adaptive Gaussian filter is used to pre-process the interactive interface, and the interactive interface, samples, saliency and quality of intelligent products are formally described.
2. Secondly, according to the results of pre-processing and formal description, combined with Bayesian classification probability reasoning mechanism, an interactive interface quality evaluation model is constructed to realise the evaluation of interactive interface quality.
3. Experimental verification.

2 Quality evaluation of human-computer interface for intelligent products

2.1 Interactive interface data pre-processing

The data types of the interactive interface quality assessment mainly include: brightness, sensitivity, colour conspicuousness, clarity, hue adaptation, etc. The above-mentioned related data are collected by visual perception method. In the human-computer interaction interface of pre-processing smart products, the adaptive Gaussian filter (Varghese et al., 2020; Xu, 2021; Hristov et al., 2019) must be used, and the *Q*-value of its gradient direction must be determined. The Gaussian function Q is used to perform horizontal and vertical differentiation, and convolute with the product interaction interface to obtain the vertical slope Q^{α} at position (w, e). Taken together:

$$R_w = \frac{\partial(w, e, Q)}{\partial w} \times T(w, e) \tag{1}$$

$$R_e = \frac{\partial(w, e, Q)}{\partial e} \times T(w, e) \tag{2}$$

$$Q^{\alpha} = \arctan\left[\frac{R_e(w, e)}{R_w(w, e)}\right] \tag{3}$$

In formulas (1) and (2), R_w is the derivative of Q in the horizontal direction, R_e is the derivative of Q in the vertical direction and $T(w, e)$ is the interactive interface of intelligent products.

Through the analysis of the above steps, the interaction surface of the smart product is obtained through Gaussian filter filtering:

$$Y(w, e) = \frac{T(w, e) - U(w, e)}{1 - U(w, e) \times Q} \tag{4}$$

In formula (4), $Y(w, e)$ is the filtered and clear human-computer interaction interface of the intelligent product, and $U(w, e)$ is the noise.

After correcting the clarity of the interface, the logarithmic operator (Shakirov, 2020; Rajiniganth, 2018) is used to adjust the colour tone of the interface. In smart products, the corresponding relationship between interface brightness and background brightness is as follows:

$$P_D = \frac{P_D^{\max} \times 0.01}{\lg\left(P_D^{\max} + 1\right)} \times \frac{\ln\left(P_O + 1\right)}{\ln\left(2 + \left(\frac{\beta \times P_O}{P_D^{\max}}\right)\right)} \tag{5}$$

In formula (5), P_O refers to the brightness adjustment threshold in the dark area of the interface, P_D refers to the interface brightness, $P_D^{\max}$ refers to the maximum brightness of the interface and β refers to the pixel value of the interface.

According to formula (5) and the calculation of the value β, the human-computer interaction interface image of the smart product after the brightness and colour tone improvement is obtained, and its expression is as follows:

$$I(w,e) = P_D \times P_O \times \beta \tag{6}$$

In formula (6), $I(w,e)$ is the interface after adjusting the hue and brightness.

Through the human-computer interaction interface filtering technology of intelligent products, the quality evaluation error of the product can be effectively reduced and the accuracy of the evaluation can be improved according to the colour difference.

2.2 *Formalisation of the interface*

Based on the above pre-treatment results, the human-computer interaction product interface is formalised. In this paper, before constructing an interface quality assessment model based on Bayesian classification (Zia et al., 2019; Kang et al., 2020; Zollanvari and Dougherty, 2019), we first need to describe the interactive interface in a vectorised manner, so as to use the computer to process the data. Therefore, this paper gives the following formal definition:

1) *Smart product interactive interface*:

$$I_i = (A(S_i)) \tag{7}$$

In formula (7), S_i refers to the interface characteristic data of article i, and A refers to the interface characteristic calculation function of the smart product.

2) *Interface sample data*:

$$D = \left[d_{ij}\right]_{m\times n} = \left(I_1, I_2, \ldots, I_i\right)^T \tag{8}$$

In formula (8), refers to the number of interfaces and refers to the number of interface features.

3) *Interface saliency*: In this paper, the method based on saliency is selected to formally define the interface quality, and the following definition formula is given:

$$F_i = \gamma_i \times I(w,e) \tag{9}$$

In formula (9), is the ratio of the maximum distance between each pixel in the interface and the middle.

4) *Interface quality data output*:

$$G_i = \left(G_l, P\left(G_l \mid H_l = h_l\right)\right) \tag{10}$$

In formula (10), G_l refers to the discrete function, $P\left(G_l \mid H_l = h_l\right)$ refers to the probability that the *l*-th interface quality belongs to class G_l, H_l refers to the known characteristic variable, and h_l is its value.

2.3 *Quality assessment of human-computer interaction interface of intelligent products based on Bayesian classification*

According to the above formal processing results, Bayesian classification method is used to evaluate the quality of human-computer interaction interface of intelligent products. Bayesian classification is a directed acyclic graph consisting of a set of vertices and a set of directed edges, and on this graph, is the combined probability of a set of random variables. The Bayesian network classifier uses probability theory for reasoning, reduces the problem to be solved into a set of random variables, and then describes the problem to be considered as a joint probability distribution, and then classifies according to the Bayesian criterion.

Based on Bayesian classification, this paper builds an interface quality evaluation model, and uses the Bayesian classification probabilistic inference mechanism to evaluate the interface quality of smart products. First, the definition of the intelligent product interface quality evaluation model is given:

$$K = \left(J_R, \omega\right) \tag{11}$$

In formula (11), $J_R = \left(Z, X\right)$ and $\mathrm{Z} = \left(\mathrm{Z}_1, \mathrm{Z}_2, ..., \mathrm{Z}_\mathrm{n}\right)$ refer to the evaluation feature set containing the quality category of the human-computer interaction interface of the smart product, X refers to the set of directed edges, indicating the dependency between the evaluation features and ω refers to the human-machine interface of the smart product. A set of parameters for the interactive interface quality assessment model.

In this study, the dependencies between the interface features of smart products and quality research are obtained through Bayesian classification, and stored in a graph structure. Use the BIC scoring function to judge the quality of the smart product interface quality evaluation model *K* relative to the sample *D*. The detailed formula of the BIC scoring function is as follows:

$$BIC\left(K \middle| D\right) = \sum_{i=1}^{n} BIC\left(C_i, \pi\left(C_i\right) \middle| D\right) \tag{12}$$

In formula (12), C_i refers to the feature node of the human-computer interaction interface of the smart product, $\pi\left(C_i\right)$ refers to the parent node set of the feature of the human-computer interaction interface of the smart product and $BIC\left(C_i, \pi\left(C_i\right) \middle| D\right)$ refers to the family BIC score of C_i variables.

Once the scoring function has been selected, the structure search algorithm also needs to be determined. The K2 algorithm in Bayesian classification can make full use of the decomposition characteristics of the scoring function to share intermediate calculation results, and at the same time use certain qualifications to speed up the structure search process. Using the K2 algorithm in Bayesian classification, the optimal model K' is obtained as:

$$K' = \epsilon \times \theta \times \left(J_R, \omega\right) \tag{13}$$

In formula (13), ε refers to the feature sequence vector of a smart product human-computer interaction interface of *K*, and θ represents the upper bound of the number of parent nodes of each smart product human-computer interaction interface feature node.

After completing the structure learning of the intelligent product interface quality evaluation model, it is also necessary to obtain the parameter table of the intelligent product interface quality evaluation model according to this structure. The maximum likelihood estimation (Xie, 2021; Qi et al., 2021; Bahru and Zeller, 2022) is used to determine the parameter set of the smart product interface quality assessment model. Take as a sample to obtain the parameter table for each node in. The maximum likelihood estimate is as follows:

$$\omega = \frac{\varphi_k}{\sum_{k=1}^{n} \varphi_k} \tag{14}$$

In formula (14), φ_k refers to the number of intelligent product human-computer interaction interface samples in D that satisfy $\pi(C_i)$.

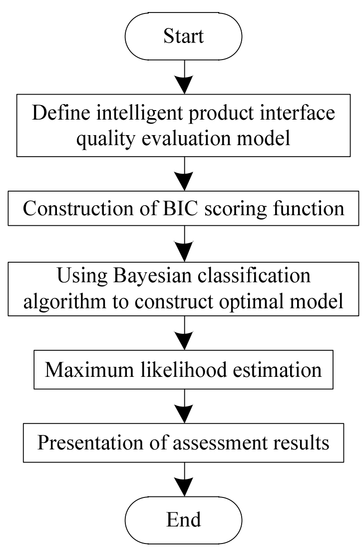
Based on the obtained quality evaluation model of human-computer interaction interface of intelligent products, the quantitative relationship between quality was evaluated by using the probabilistic inference method of Bayesian classification. The quality evaluation results of human-computer interaction interface of intelligent products are expressed as:

$$V = \frac{\sum B_Q}{K' \times \omega} \tag{15}$$

In formula (15), B_Q refers to a probability function that includes G_i.

The human-computer interaction interface quality assessment process of intelligent products based on Bayesian classification is shown in Figure 1.

Figure 1 Evaluation process



Based on the above calculation process, the intelligent product interface quality evaluation based on Bayesian classification is realised.

3 Evaluation performance analysis

3.1 Scheme setting

In order to verify the practical application performance of the proposed Bayesian classification-based quality assessment method, a quality assessment performance analysis is carried out. Based on Python 2.7, this thesis develops a robot application software for NAO. All programs use .NET technology on a PC with Intel 2.20 GHz, 2.19 GHz CPU and 8 GB RAM, the operating system is Windows 10. Select 70 intelligent product interface features as experimental data to verify and analyse the quality evaluation performance.

3.2 Experimental data and scheme

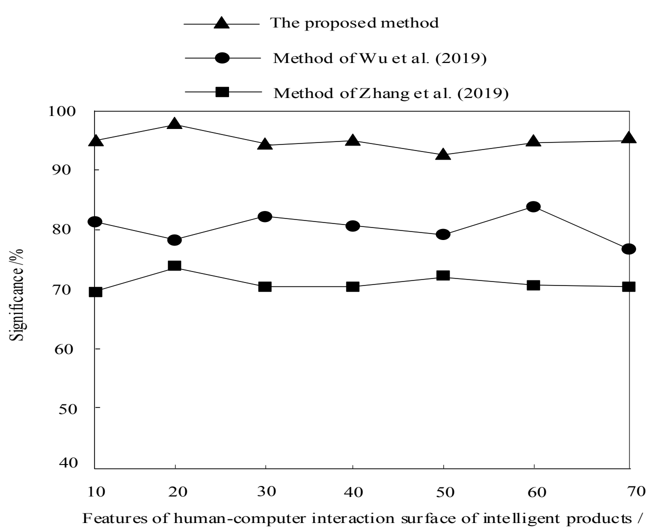
Experimental data: The interface data is collected by visual perception method. The data types mainly include brightness, sensitivity, colour conspicuousness, sharpness and hue adaptation. The amount of data collected is 1.2 GB. After pre-processing and formalisation, the remaining sample data that can be used for experiments is 1.0 GB.

Set the experimental plan, and analyse the significance, evaluation accuracy and evaluation time as performance indicators in the experiment. The method of Wu et al. (2019), the method of Zhang et al. (2019) and the proposed method are used to compare the actual evaluation performance of the method in this paper.

3.3 Analysis of the effect of quality assessment

Since the interface quality evaluation mainly involves images, the image saliency results will have a serious impact on the final evaluation results. The comparison results of the quality assessment results are shown in Figure 2.

Figure 2 The significance comparison results of different methods

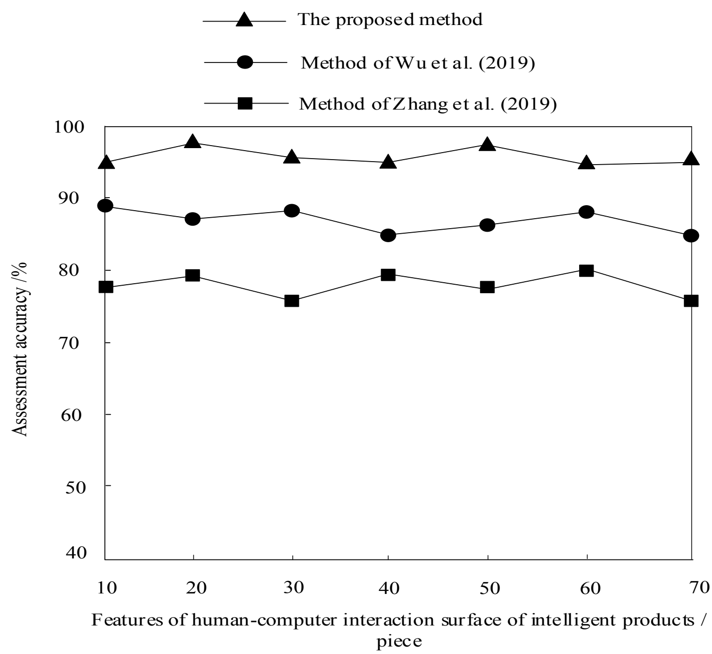


According to Figure 2, when the number of interface features is 70, the mean significance of the method in Wu et al. (2019) is 80.6% and the mean value of the method in Zhang et al. (2019) is 82.3%. The mean significance of the proposed method is as high as 95.7%. It can be clearly seen from the above saliency data results that the saliency of the method in this paper is the highest, so it shows that the proposed method can improve the evaluation effect.

3.4 Evaluation accuracy analysis

On this basis, verify the evaluation accuracy ability of this method, take the evaluation accuracy as the performance evaluation index and also use the three methods for comparative verification. The higher the evaluation accuracy, the stronger the evaluation ability of the method. The comparison of evaluation accuracy is shown in Figure 3.

Figure 3 Evaluation accuracy



According to Figure 3, when the number of interface features is 70, for the average evaluation accuracy, Wu et al. (2019) method is 87.5%, Zhang et al. (2019) method is 78.2%, the proposed method is as high as 96.4%. Compared with the two traditional methods, the evaluation accuracy of this method is improved by about 9–18%. Therefore, it shows that the proposed method can greatly improve the evaluation accuracy and meet the evaluation requirements.

3.5 Evaluation efficiency analysis

To further verify the evaluation performance of the method in this paper, due to the huge amount of data on the interface in the actual application process, higher requirements are put forward for the efficiency of the evaluation method and practical application can only be carried out if the accurate evaluation can be achieved quickly. Therefore, taking the evaluation time as the performance indicator. The comparison results of the evaluation time of different methods are shown in Table 1.

Table 1 Evaluation time

Human-computer interaction interface characteristics of intelligent products/unit	*The proposed method/s*	*Wu et al. (2019) method/s*	*Zhang et al. (2019) method/s*
10	0.8	3.8	6.8
20	1.9	5.4	8.9
30	2.6	7.6	11.2
40	3.8	9.3	13.7
50	5.1	10.9	15.4
60	6.3	12.3	17.6
70	7.2	14.6	19.3

According to Table 1, as the number of interface features continues to increase, the evaluation time increases. In the experiment, when there are 70 interface features. For the evaluation time, Wu et al. (2019) method is 14.6 s, Zhang et al. (2019) method is 19.3 s, and the proposed method is only 7.2 s. The evaluation time of the proposed method is shorter, indicating that the method in this paper can improve the evaluation efficiency.

4 Conclusion

In this paper, Bayesian classification method is introduced to evaluate the quality of intelligent product interface. Analyse the factors affecting the interface quality, collect various data related to the interface quality and pre-process the collected data to improve the data quality and ensure the reliability of the later evaluation results. After the formal description of the whole interface, the quality is evaluated based on the probabilistic reasoning mechanism of Bayesian classification method. The simulation results show that this method has a good evaluation effect when the number of interface features is the same, and the mean value of significance reaches 95.7%; the evaluation accuracy is significantly improved, about 9–18% higher than that of the traditional method; The evaluation efficiency is high, and the maximum time is only 7.2 s. The performance of the method is verified from many aspects, which highlights the high application value of the method in this paper. In the future research work, we should further improve the accuracy of the assessment to improve the effectiveness of the assessment.

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