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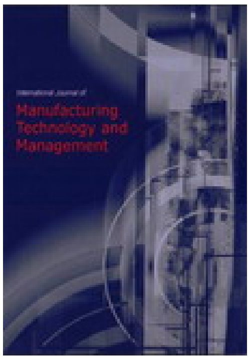

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An image detail enhancement of smart product UI interface based on stationary wavelet transform

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Abstract: To overcome the problems of low image segmentation accuracy, low image signal-to-noise ratio and long image enhancement time in traditional methods, an image detail enhancement method of smart product UI interface based on stationary wavelet transform is proposed. The Gaussian mixture model is used to obtain the image parameters of the UI interface of smart products, and the image of multiple pixels is divided into marked categories by the maximum posterior probability criterion, so as to realise the segmentation of image noise area and normal area. The two-dimensional stationary wavelet transform is performed on the noisy area, and the inverse stationary wavelet transform is performed on the stationary wavelet coefficients to obtain a reconstructed image with enhanced details. Experimental results show that the image segmentation accuracy of this method fluctuates in the range of 96%–98%, the signal-to-noise ratio is 55.3 dB, and the average image enhancement time is 66.9 ms.

Keywords: stationary wavelet transform; smart products; UI interface; image detail enhancement; Gaussian mixture model; image reconstruction.

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1 Introduction

At this stage, smart products can be seen everywhere in people's work and life, and their update speed is accelerating, while the manufacturing cost is decreasing. In order to improve the economic efficiency of intelligent product production, relevant enterprises regard user experience as an important design basis for intelligent product design (Jia, 2021). Smart products represented by mobile phones, computers and tablets all need to use related software to establish contact with other people, and UI interface design, as a bridge of communication, can closely integrate consumers with software and improve the ability of consumers to communicate with others, quality and efficiency (Alomari et al., 2020). The UI interface of intelligent products refers to an interface based on visualisation technology, which enables users to interact with others through related software, which can improve the controllability and convenience of communication (Purbasari et al., 2021). In the process of multi-party communication, many images are often sent, and the problem of image distortion is prone to occur in the process of sending images, which leads to a slight decline in the quality of communication. Therefore, in order to meet the needs of targeted customers, it is of great significance to design an image detail enhancement method for UI interface of intelligent products.

There are not many researches on image detail enhancement methods for UI interface of smart products; most of them transfer the research in the field of image detail enhancement to this direction. For example, Zou and Xia (2021) propose UI interface image detail enhancement method based on heterogeneous fusion network. Taking the heterogeneous fusion network as the research basis, the web crawler is used to collect relevant UI interface images, and the singular value model is constructed according to the image collection results, so as to realise the sparse representation of the data collection results, according to the difference between the noise area and the normal area. In order to find out the noise area in the image, the noise area is enhanced by the windowing process, but this method has the problem of low image segmentation accuracy, and the practical application effect is not good. Liu et al. (2020) proposes an improved frequency domain-based UI interface image detail enhancement method. The UI interface image is collected and Fourier transform is performed on the image. Perform frequency domain Gaussian filtering and inverse Fourier transform on the UI interface image Fourier transform processing result, so as to obtain the low-frequency part and high-frequency part of the UI interface image. For the low-frequency part of the UI interface image, the adaptive histogram equalisation method is used to enhance it. For the high-frequency part of the UI interface image, unsharp masking and greyscale transformation are used to obtain higher-quality high-frequency parts, so as to achieve high-frequency part enhancement, and the processing results of these two parts are weighted and fused to obtain high-quality UI interface image. However, this method is too complicated, and there is a problem that the UI interface image enhancement takes a long time. Xu (2020) proposes a UI interface image detail enhancement method based on histogram equalisation interpolation. The UI interface image is obtained by the cubic interpolation method, and the histogram equalisation is performed on the collected image. Insert a certain grey level SP into the histogram equalisation result to construct a new histogram, sort the result, map the sorting result to the original histogram, and obtain the UI interface image detail enhancement result. However, in practical applications, this method has the problem of low signal-to-noise ratio of UI interface images.

However, since the above method does not segment the noise area in the design process, the problems of low image segmentation accuracy, low image signal-to-noise ratio and long image enhancement time appear. Therefore, this paper aims to solve various problems of traditional methods as research objectives, this paper designs an image detail enhancement method of smart product UI interface based on stationary wavelet transform. The overall technical route of the method is as follows:

1. Calculate the density function of the image pixels of the UI interface of the smart product in the Gaussian mixture model, and obtain the image parameters. According to the parameter estimation results, the images of multiple pixels are divided into marked categories through the maximum posterior probability criterion, so as to realise the image segmentation of the UI interface of smart products.
2. According to the image segmentation result, perform two-dimensional stationary wavelet transform on the noisy area, and perform inverse stationary wavelet transform on the stationary wavelet coefficients to obtain the reconstructed UI interface image of the smart product, and the details of the image are enhanced.
3. The image segmentation accuracy, image signal-to-noise ratio and image enhancement time are used as experimental indicators to verify the application effect of different methods.

2 Design of image detail enhancement method for UI interface of smart products

2.1 Smart product UI interface image segmentation

In order to ensure the image detail enhancement effect of intelligent product UI interface, this paper needs to divide the image noise region and non-noise region, so as to achieve image segmentation and lay a solid foundation for the subsequent image detail enhancement.

Assuming that the image pixel of the UI interface of the smart product is represented by x_i, $i = 1, 2, \ldots, N$, and the image of the UI interface of the smart product has $\Omega_1, \Omega_2, \ldots, \Omega_K$ marks, the total amount of which is represented by K. In the Gaussian mixture model (Hui et al., 2021; Hojjatinia et al., 2021), the density function of the image pixel x_i of the UI interface of the smart product is:

$$f\left(x_i \middle| D, \Theta\right) = \sum_{j=1}^{K} \pi_{ij} p\left(x_i \middle| \Theta_j\right) \tag{1}$$

In the formula, π_{ij} represents the prior probability of the image pixel x_i of the UI interface of the smart product, Θ_j represents the j^{th} Gaussian parameter, Θ represents the set of image parameters of the UI interface of the smart product, and $p(x_i| \Theta_j)$ represents the probability density function corresponding to the j^{th} category that is, which the Gaussian distribution is specifically described as:

$$p\left(x_i \middle| \Theta_j\right) = \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left(-\frac{\left(x_i - \sigma_j\right)^2}{2\sigma_j^2}\right) \tag{2}$$

For the prior probability distribution π_{ij}, its log-likelihood function is expressed by the following formula:

$$L(\Theta \mid D, X) = \sum_{i=1}^{N} \log\left(\sum_{j=1}^{K} \pi_{ij} p\left(x_i \middle| \Theta_j\right)\right) \tag{3}$$

Introducing Qinsheng's inequality into formula (3), formula (3) can be transformed into the following form:

$$L(\Theta \mid D, X) = \sum_{i=1}^{N} \log\left(\sum_{j=1}^{K} \pi_{ij} p\left(x_i \middle| \Theta_j\right)\right) \geq \sum_{j=1}^{N} \sum_{j=1}^{K} \pi_{ij} \log p\left(x_i \middle| \Theta_j\right) \tag{4}$$

Let $L(\Theta| D, X)$ be:

$$L(\Theta \mid D, X) = \sum_{i=1}^{N} \sum_{j=1}^{K} \pi_{ij} \log p\left(x_i \middle| \Theta_j\right) \tag{5}$$

Combined with $L(\Theta| D, X)$, the weight of the smart product UI interface image pixel x_i belonging to Ω_j categories is calculated, and the result is:

$$\xi_j\left(x_i\right) = \exp\left(-\frac{\left(x_i - c_j\right)^2}{2b_j^2}\right) \tag{6}$$

In the formula, c_j and b_j represent the original pixels and noise pixels of the UI interface image of the smart product, respectively. Taking the Gaussian kernel function as the constraint of the prior probability distribution (Dong et al., 2021; Ayiad et al., 2021), the prior probability distribution is:

$$\pi'_{ij} = \sum_{q \in N_i} \frac{h(i, q)}{Z_i} \xi_j\left(x_i\right) \tag{7}$$

In the formula, Z_i represents the normalisation factor, and its calculation formula is as follows:

$$Z_i = \sum_{q \in N_i} h(i, q) \tag{8}$$

In the formula, $h(i, q)$ represents the geometrical Euclidean distance between pixel i and pixel q of the UI interface image of the smart product. The geometric distance h is a Gaussian function of the magnitude of the relative position vectors of pixel i and pixel q (Graziani et al., 2022), and the Gaussian kernel function is expressed as follows:

$$h(i, q) = \exp\left(\frac{-\left\|u_i - u_q\right\|^2}{2\sigma_g^2}\right) \tag{9}$$

In the formula, σ_g represents the width parameter of the Gaussian kernel function, and u_i and u_q represent the positions of pixel i and pixel q, respectively. Taking the value in this model, it can be seen from the above formula that when the distance $\|u_i - u_q\|$ increases, the $h(i, q)$ function will decrease. The closer the geometric distance between two pixels is, the higher the probability that the two pixels belong to the same class and the farther the geometric distance between two pixels is, the smaller the probability that the two pixels belong to the same class (Rong et al., 2021; Yoo and Jeong, 2020). Based on this idea, introduced a Gaussian kernel function, which can also ensure that the prior probability π_{ij}' satisfies the conditions of formula (3). Then the log-likelihood function can be written as:

$$\begin{aligned} L^*(\Theta \mid D, X) &= \sum_{i=1}^{N}\sum_{j=1}^{K}\sum_{q\in N_i}\frac{h(i,q)}{Z_i}\xi_j\left(x_q\right)\log p\left(x_i \middle| \Theta_j\right) \\ &= \sum_{i=1}^{N}\sum_{j=1}^{K}\sum_{q\in N_i}\frac{h(i,q)}{Z_i}\xi_j\left(x_q\right)\exp\left(\frac{-\left(x_i-c_j\right)^2}{2b_j^2}\right) \end{aligned} \tag{10}$$

Combined with the above analysis, this paper mainly estimates the smart product UI interface image parameter $\Theta = (\mu_j, \sigma_j, c_j, b_j)$ by maximising the log-likelihood function (Tian et al., 2020; Babcock, 2020), then the negative logarithm of the likelihood function is:

$$E(\Theta \mid D, X) = -\sum_{i=1}^{N}\sum_{j=1}^{K}\sum_{q\in N_i}\frac{h(i,q)}{Z_i}\exp\left(\frac{-\left(x_i-c_j\right)}{2b_j^2}\right) \tag{11}$$

Now maximising the log-likelihood function is equivalent to minimising the negative log-likelihood function. Using the gradient descent algorithm to adjust the parameters to minimise the negative log-likelihood function, the specific process is as follows:

1 Use the k-means algorithm to initialise the parameter mean μ_j and variance σ_j, $c_j = \mu_j$, $b_j = \sigma_j$ to obtain the initialisation parameter $\Theta^{(t)}$ at this time.

2 Calculate the Gaussian distribution $p\left(x_i \middle| \Theta_j^{(t)}\right)$ and the prior probability distribution $\pi_{ij}^{(t)}$ respectively, and then calculate the posterior probability $z_{ij}^{(t)}$:

$$z_{ij}^{(t)} = \frac{\pi_{ij}^{(t)} p\left(x_i \middle| \Theta_j^{(t)}\right)}{\sum_{k=1}^{K}\pi_{ik}^{(t)} p\left(x_i \middle| \Theta_k^{(t)}\right)} \tag{12}$$

3 According to the gradient descent method, update parameter $\Theta = (\mu_j, \sigma_j, c_j, b_j)$, and obtain new parameters through the following rules:

$$\Theta^{(t+1)} = \Theta^{(t)} - \eta\nabla E\left(\Theta^{(t)}\right) \tag{13}$$

In the formula, η represents the learning rate, also called the step size, which controls the size of each drop. $\nabla E(\Theta^{(t)})$ represents the gradient of the current parameter, and:

$$\nabla E\left(\Theta^{(t)}\right) = \left[\frac{\partial E}{\partial u_j}, \frac{\partial E}{\partial \mu_j}, \frac{\partial E}{\partial c_j}, \frac{\partial E}{\partial b_j}\right] \tag{14}$$

4 Check whether the negative log-likelihood function or the parameter value converges. If it does not converge, set the parameter to the current parameter and set it to the parameter $\Theta^{(t)}$ of the current t + 1-step, and return to step (2).

After the parameters are estimated, class labels are assigned to each smart product UI interface image pixel through the calculated posterior probability. For each pixel x_i, its corresponding posterior probability for each class label is given by z_{ij}. The N-pixel image is divided into K marked categories by the maximum a posteriori probability criterion to complete the image segmentation of the UI interface of smart products, which is specifically expressed as:

$$x_i = \Omega_j, z_{ij} > z_{ik}, j, k = 1, 2, ..., K \tag{15}$$

To sum up, this paper calculates the density function of intelligent product UI interface image pixels in Gaussian mixture model and obtains image parameters. According to the result of parameter estimation, the image of multiple pixels is segmented into labelled categories by maximum posterior probability criterion, and the image noise region and normal region can be segmented. Therefore, this method has the characteristics of high precision and short segmentation time.

2.2 Image enhancement based on stationary wavelet transform

According to the image segmentation results, the two-dimensional stationary wavelet transform is performed on the noisy area, and the inverse stationary wavelet transform is performed on the stationary wavelet coefficients to obtain the reconstructed UI interface image of the smart product, and the details of the image are enhanced.

According to the image segmentation results, two-dimensional stationary wavelet transform is carried out on the noisy area, and the stationary wavelet coefficient is inverse stationary wavelet transform, and the reconstructed UI interface image of intelligent product is obtained, and the details of the image are enhanced. The stationary wavelet transform is obtained by modifying the wavelet transform, that is, the output coefficients of the low-pass and high-pass filters are not down-sampled (Chellappan et al., 2021), so as to ensure the data denoising effect, improve the image quality and achieve rapid image enhancement. Let the one-dimensional signal be $f(x)$ and let $c_0 = f(x)$, the discrete wavelet transform of the signal can be expressed as:

$$\begin{cases} c_{j+1} = D_\varepsilon H c_j \\ d_{j+1} = D_\varepsilon G c_j \end{cases} \tag{16}$$

In the formula, c_{j+1} is the discrete wavelet scale coefficient, d_{j+1} is the normal wavelet coefficient, H is the low-pass filter, G is the high-pass filter, and D_ε is the down-sampling operator. The inverse discrete wavelet transform of the signal is:

$$c_j = Z_\varepsilon H^* c_{j+1} + Z_\varepsilon G^* d_{j+1} \tag{17}$$

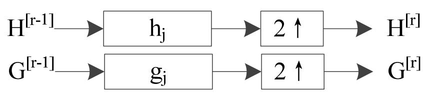
In the formula, * represents the conjugation, H^* and G^* represent the dual operators of H and G, respectively, and Z_ε represents the zero-padding interpolation operator. Then formula (17) can be transformed into the following form:

$$c_j = R_\varepsilon \left(c_{j+1}, d_{j+1} \right) \tag{18}$$

In the formula, R_ε represents the reconstruction operator. However, the signal cannot approach the signal after discrete wavelet transform, and the length of detail signal is inconsistent with the original signal, which can be perfectly solved by stationary wavelet transform. The main advantage of Gibbs transform is to avoid the size invariance of the original image, which is the same as that of Gibbs transform in the process of image reconstruction. It can also be understood that the amount of data contained in the coefficients of each sublayer decomposed is the same as the total number of pixels of the original image, so as to ensure that enough coefficients participate in the inverse stationary wavelet transform, which greatly improves the visual effect of the reconstructed UI interface image of intelligent product (Dwivedi et al., 2021).

If the coefficients of filters H and G in the discrete wavelet transform are h_j and g_j, respectively, then let the coefficients of filters $H^{[r]}$ and $G^{[r]}$ in the stationary wavelet transform be $Z^r h$ and $Z^r g$, respectively, and $Z^{[r]}$ is the filter zero-filling interpolation operator. The relationship of the filter $H^{[r-1]}$, $H^{[r]}$, $G^{[r-1]}$, $G^{[r]}$ is shown in Figure 1, and 2↑ in the figure represents the zero-padding interpolation at every other point.

Figure 1 Interpolation process of every-point zero-filling filter



Let the one-dimensional signal be $f(x)$, $a_0 = f(x)$, $H^{[0]} = H$, $G^{[0]} = G$, the stationary wavelet transform of $f(x)$ is:

$$\begin{cases} a_{j+1} = H^{[j]} a_j \\ b_{j+1} = G^{[j]} a_j \end{cases} \tag{19}$$

In the formula, a_{j+1} represents the stationary wavelet scale coefficient.

The following describes how to perform an inverse stationary wavelet transform on a one-dimensional signal. The reconstruction operators used in this process are introduced. Perform $D_{\varepsilon_1}, ..., D_{\varepsilon_j}$ downsampling on a_j and b_j in turn for a total of j times, and you will get $a_j(\varepsilon_1, \ldots, \varepsilon_j)$ and $b_j(\varepsilon_1, \ldots, \varepsilon_j)$. Since the downsampling is divided into parity, ε_j can take the value of 0 or 1, so that $\varepsilon_1, \ldots, \varepsilon_j$ has 2^j combinations. When $\varepsilon_j + 1 = 0$, the reconstruction operator can be expressed as:

$$R_0^{[j]} = \left(a_{j+1}, b_{j+1}\right) = H^* a_{j+1}\left(\varepsilon_1, ..., \varepsilon_j, \varepsilon_{j+1}\right) + G^* b_{j+1}\left(\varepsilon_1, ..., \varepsilon_j, \varepsilon_{j+1}\right) \tag{20}$$

When $\varepsilon_j + 1 = 1$, the reconstruction operator can be expressed as:

$$R_1^{[j]} = \left(a_{j+1}, b_{j+1}\right) = H^* a_{j+1}\left(\varepsilon_1, ..., \varepsilon_j, \varepsilon_{j+1}\right) + G^* b_{j+1}\left(\varepsilon_1, ..., \varepsilon_j, \varepsilon_{j+1}\right) \tag{21}$$

With the reconstruction operator, it is easy to obtain the stationary wavelet inverse transform formula of the one-dimensional signal:

$$a_j\left(\varepsilon_1, ..., \varepsilon_j\right) = \frac{1}{2}\left[R_0^{[j]}\left(a_{j+1}, b_{j+1}\right) + R_1^{[j]}\left(a_{j+1}, b_{j+1}\right)\right] \tag{22}$$

Similarly, the stationary wavelet transform is extended from one-dimensional to two-dimensional, and the two-dimensional signal is set to $f(x, y)$, and $a_0 = f(x, y)$, then the stationary wavelet transform of the two-dimensional signal is:

$$\begin{cases} a_{j+1} = H_r^{[j]} H_c^{[j]} a_j \\ b_{j+1}^1 = H_r^{[j]} G_c^{[j]} a_j \\ b_{j+1}^2 = G_r^{[j]} H_c^{[j]} a_j \\ b_{j+1}^3 = G_r^{[j]} G_c^{[j]} a_j \end{cases} \tag{23}$$

In the formula, a_{j+1} means that the scale coefficient reflects the low frequency subband, and b_{j+1}^i, i = 1, 2, 3 means that the stationary wavelet coefficient reflects the high frequency subband. In the process of two-dimensional signal stationary wavelet inverse transformation, when $\varepsilon_j + 1 = 0$, the reconstruction operator can be expressed as:

$$\begin{aligned} R_0^{[j]} = \left(a_{j+1}, b_{j+1}^1, b_{j+1}^2, b_{j+1}^3\right) &= H_r^* H_c^* a_{j+1}\left(\varepsilon_1, ..., \varepsilon_j, \varepsilon_{j+1}\right) \\ &+ H_r^* G_c^* b_{j+1}^1\left(\varepsilon_1, ..., \varepsilon_j, \varepsilon_{j+1}\right) + G_r^* H_c^* b_{j+1}^2\left(\varepsilon_1, ..., \varepsilon_j, \varepsilon_{j+1}\right) \\ &+ G_r^* G_c^* b_{j+1}^3\left(\varepsilon_1, ..., \varepsilon_j, \varepsilon_{j+1}\right) \end{aligned} \tag{24}$$

When $\varepsilon_j + 1 = 1$, the reconstruction operator can be expressed as:

$$\begin{aligned} R_1^{[j]} = \left(a_{j+1}, b_{j+1}^1, b_{j+1}^2, b_{j+1}^3\right) &= H_r^* H_c^* a_{j+1}\left(\varepsilon_1, ..., \varepsilon_j, \varepsilon_{j+1}\right) \\ &+ H_r^* G_c^* b_{j+1}^1\left(\varepsilon_1, ..., \varepsilon_j, \varepsilon_{j+1}\right) + G_r^* H_c^* b_{j+1}^2\left(\varepsilon_1, ..., \varepsilon_j, \varepsilon_{j+1}\right) \\ &+ G_r^* G_c^* b_{j+1}^3\left(\varepsilon_1, ..., \varepsilon_j, \varepsilon_{j+1}\right) \end{aligned} \tag{25}$$

With the reconstruction operator, it is easy to obtain the inverse stationary wavelet transform formula of the two-dimensional signal:

$$a_j\left(\varepsilon_1, ..., \varepsilon_j\right) = \frac{1}{2}\left[R_0^{[j]}\left(a_{j+1}, b_{j+1}^1, b_{j+1}^2, b_{j+1}^3\right) + R_1^{[j]}\left(a_{j+1}, b_{j+1}^1, b_{j+1}^2, b_{j+1}^3\right)\right] \tag{26}$$

After determining the stationary wavelet, it is necessary to calculate the wavelet threshold in the image enhancement process of the UI interface of the smart product. Assuming that X and Y are the Gaussian distribution of the stationary wavelet coefficients of the UI interface image of the smart product, there are:

$$X \sim \left(0, \sigma_x^2\right), Y / X \sim \left(X, \sigma_x^2\right) \tag{27}$$

In the formula, σ_x represents the noise variance.

The expression for the generalised Gaussian distribution is as follows:

$$GG_{\sigma_x,\beta}(x) = C\left(\sigma_x, \beta\right)\exp\left\{-\alpha\left(\sigma_x, \beta \mid x\right)^{\beta}\right\} \tag{28}$$

In the formula, β represents the formal parameter.

The specific description of Bayes risk is as follows:

$$r(T) = E\left(\hat{X} - X\right)^2 \tag{29}$$

In the formula, E represents the risk prediction function, and $\hat{X}$ represents the Gaussian distribution mean.

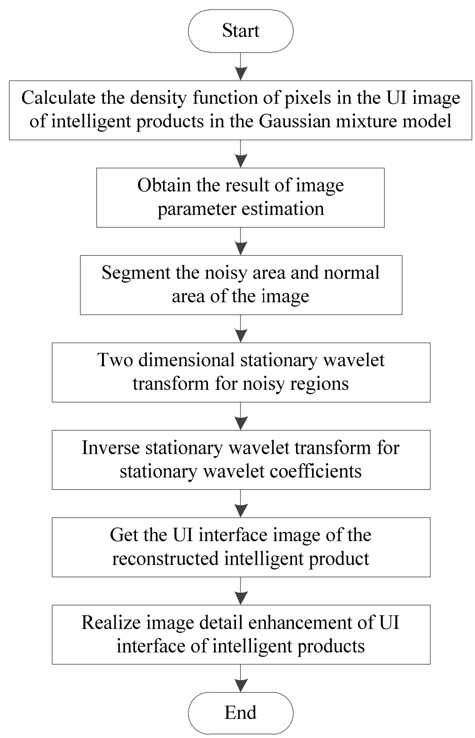
Calculate the optimal threshold to minimise the Bayes risk. The specific calculation formula is as follows:

$$T^*(\sigma_x, \beta) = \arg\min_T r(T) \tag{30}$$

Using the spatial adaptive method, the adaptive threshold is determined for each stationary wavelet coefficient, and the value is calculated by the following formula:

$$T_B(i, j) = \frac{\sigma_n^2}{\sigma_x(i, j)} \tag{31}$$

Figure 2 UI image detail enhancement process of intelligent products based on stationary wavelet transform



To sum up, the steps of image detail enhancement method of smart product UI interface based on stationary wavelet transform as follows:

1 Perform two-dimensional stationary wavelet transform on the noisy image to obtain stationary wavelet coefficients.

2 Thresholding the detail subband stationary wavelet coefficients based on inter-scale neighbourhood dependencies, replacing the general threshold $T = \sigma_n \sqrt{2 \log n^2}$ with $T_B(i, j)$.

3 Perform an inverse stationary wavelet transform on the processed stationary wavelet coefficients to obtain a reconstructed image of the UI interface of the smart product, and realise the enhancement of the UI interface image of the smart product.

The process of UI image detail enhancement of intelligent products based on stationary wavelet transform is shown in Figure 2.

To sum up, this paper obtains image parameters by calculating the density function of intelligent product UI interface image pixels in Gaussian mixture model. The image of multiple pixels is segmented into labelled categories by maximum posterior probability criterion, and the image noise region is segmented from normal region. According to the image segmentation results, two-dimensional stationary wavelet transform is carried out on the noisy area, and the stationary wavelet coefficient is inverse stationary wavelet transform, and the reconstructed UI interface image of intelligent product is obtained, and the details of the image are enhanced. Therefore, this method has the characteristics of high efficiency and good enhancement effect, and can be further promoted in practice.

3 Experimental design

3.1 Experimental scheme

In order to verify the effectiveness of the image detail enhancement method of smart product UI interface based on stationary wavelet transform designed in this paper, relevant experimental tests are carried out. The experimental scheme is as follows:

1 Experimental data: using web crawler technology to randomly grab 1,000 UI interface images of intelligent products from the network, and integrate the data collection results to build an enhanced data set of UI interface image details of intelligent products. In this process, the data set is divided into experimental set and test set, and the images in the test set are input to the simulation platform for trial operation, so as to obtain the optimal operation parameters of the platform. This parameter has been used in the experimental process, so as to improve the accuracy of the simulation experiment.

2 Evaluation index: the accuracy of UI interface image segmentation of intelligent products, the signal-to-noise ratio of UI interface image of intelligent products and the image enhancement time are taken as the evaluation indexes to verify the practical application effect of Zou and Xia (2021) method, Liu et al. (2020) method and this method.

The image segmentation accuracy refers to the ratio of the size of the noise area segmented by different methods to the actual noise area. The calculation formula of this index is as follows:

$$C = \frac{z_i}{z_j} \times 100\% \tag{32}$$

where z_i represents the size of the noise area segmented by different methods, and z_j represents the size of the actual noise area.

The signal-to-noise ratio of intelligent product UI interface image is an important standard to measure the image enhancement quality of intelligent product UI interface. The higher the index, the better the image quality. The calculation formula of this index is as follows:

$$SNR = 10\log_{10}\left[\frac{\sum_{i=1}^{M}\sum_{j=1}^{N} g(i, j)^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}\left[g(i, j) - f(i, j)\right]^2}\right] \tag{33}$$

where M and N respectively represent the total number of pixels on the length and width of the UI image of the intelligent product, $g(i, j)$ represents the grey value of the original image, and $f(i, j)$ represents the grey value of the image after denoising.

The image enhancement time of intelligent product UI interface is the most important index to measure the image quality. The shorter the enhancement time, the higher the efficiency. The calculation formula of this index is as follows:

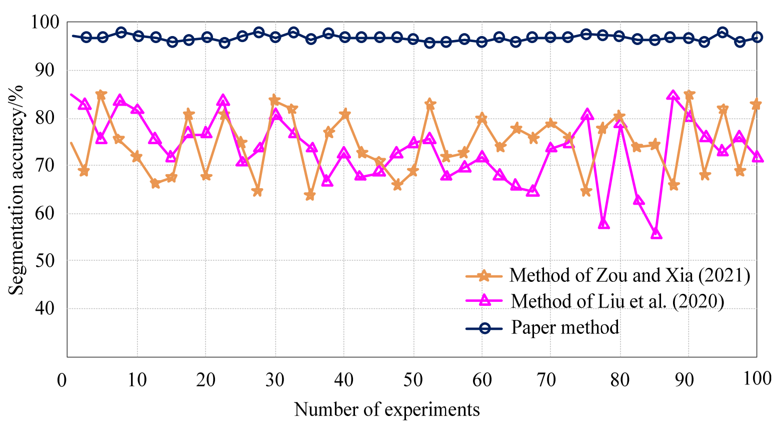
$$T = \sum_{i=1}^{n} t_i \tag{34}$$

where t_i represents the time consumption of the i^{th} intelligent product UI interface image enhancement step.

3.2 Analysis of experimental results

In order to verify the image segmentation accuracy of different methods, the image segmentation accuracy of intelligent product UI interface of different methods is compared. The comparison results are shown in Figure 3.

Figure 3 Segmentation accuracy (see online version for colours)



By analysing the results in Figure 3, we can see that the image segmentation accuracy of intelligent product UI interface of Zou and Xia (2021) method fluctuates in the range of 63%–85%, and the image segmentation accuracy of intelligent product UI interface of Liu et al. (2020) method fluctuates in the range of 55%–85%. Compared with these two methods, the image segmentation accuracy of intelligent product UI interface of this method fluctuates in the range of 96%–98%, which is always higher than these two methods, and the image segmentation accuracy curve of this method is more stable, which proves that this method has high image segmentation accuracy, and the segmentation process is more stable, which can lay a solid foundation for subsequent image detail enhancement. The reason is that the method segmented multiple pixel images into labelled categories by maximum posterior probability criterion, and realised the segmentation of image noise region and normal region. The reason is that the method segmented multiple pixel images into labelled categories by maximum posterior probability criterion, and realised the segmentation of image noise region and normal region.

The signal-to-noise ratio of intelligent product UI interface images of the three methods is compared, and the comparison results are shown in Table 1.

Table 1 Image signal-to-noise ratio (unit/dB)

Number of experiments	*Zou and Xia (2021) method*	*Liu et al. (2020) method*	*Paper method*
10	35.6	39.6	51.6
20	32.4	45.2	54.7
30	37.8	46.3	58.6
40	39.6	47.5	56.2
50	35.5	42.1	57.1
60	38.7	39.6	54.6
70	36.4	35.7	56.8
80	36.7	41.8	53.7
90	34.8	45.7	51.8
100	35.9	41.3	57.6
Average value	40.1	42.5	55.3

By analysing the results in Table 1, it can be seen that with the increase of the number of experiments, the signal-to-noise ratio of UI interface images of intelligent products of different methods shows a fluctuating trend. Among them, the average signal-to-noise ratio of UI interface images of intelligent products of Zou and Xia (2021) method is 40.1 dB, the average signal-to-noise ratio of UI interface images of intelligent products of Liu et al. (2020) method is 42.5 dB, and the average signal-to-noise ratio of UI interface images of intelligent products of this method is 55.3 dB, Compared with the experimental comparison method, the intelligent product UI interface image signal-to-noise ratio of this method is the highest, which shows that the image quality of the intelligent product UI interface enhanced by this method is higher and clearer. The reason is that according to the segmentation result of image noise region and normal region, the method carries out two-dimensional stationary wavelet transform on the noisy region, and carries out inverse stationary wavelet transform on the stationary wavelet coefficient to obtain the reconstructed intelligent product UI interface image, and the image completes the detail enhancement.

The image enhancement time of intelligent product UI interface of the three methods is compared, and the comparison results are shown in Table 2.

Table 2 Image enhancement time (unit/ms)

Number of experiments	*Zou and Xia (2021) method*	*Liu et al. (2020) method*	*Paper method*
10	125.6	98.6	56.8
20	114.7	110.3	84.7
30	125.6	99.7	67.4
40	175.1	104.7	75.6
50	125.9	106.5	74.3
60	147.6	104.7	69.6
70	135.7	97.2	64.7
80	116.3	96.3	58.7
90	147.2	100.4	59.6
100	139.8	94.1	57.3
Average value	135.4	101.3	66.9

By analysing the data results in Table 2, it can be seen that the average time of UI interface image enhancement of intelligent products in Zou and Xia (2021) method is 135.4 ms, the average time of UI interface image enhancement of intelligent products in Liu et al. (2020) method is 101.3 ms, and the average time of UI interface image enhancement of intelligent products in this method is 66.9 ms. Compared with the experimental comparison method, the UI interface image enhancement time of intelligent products in this method is shorter and the efficiency is higher, it shows that this method can achieve the goal of rapid enhancement of UI interface image of intelligent products. The reason is that the method can estimate the image parameters, divide the image noise area and normal area, and reconstruct the intelligent product UI interface image by stationary wavelet transform, so that the image can complete the detail enhancement.

To sum up, the segmentation accuracy of intelligent product UI interface image in this method fluctuates in the range of 96%–98%, and the average signal-to-noise ratio of intelligent product UI interface image is 55.3dB, and the average enhancement time of intelligent product UI interface image is 66.9ms, which is characterised by high segmentation accuracy, high image signal-to-noise ratio and short image enhancement time. Ensure image enhancement quality.

4 Conclusions

At this stage, digitisation and intellectualisation have become an important symbol of today's society. Therefore, various intelligent products emerge in endlessly and occupy an important position in various fields such as life and learning. The UI interactive interface is an important index to test the functions and services of intelligent products. In order to effectively improve the customer experience and meet the customer requirements, it is necessary to make the UI interface of intelligent products clearer, so it is necessary to study the image enhancement method of UI interface of intelligent products. However, the traditional methods have the defects of low signal-to-noise ratio and long increase time of intelligent product UI interface image, so this paper proposes a new image detail enhancement method of smart product UI interface based on stationary wavelet transform. The experimental results show that the image segmentation accuracy of intelligent product UI interface fluctuates in the range of 96%–98%, the average signal-to-noise ratio of intelligent product UI interface image is 55.3dB, and the average image enhancement time of intelligent product UI interface is 66.9 ms. It has the characteristics of high segmentation accuracy, high image signal-to-noise ratio and short image enhancement time. It can be applied to the field of digital intelligent product design in order to further improve the level of intelligent product design, it also provides guarantee for the full implementation of follow-up intelligent management and control.

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