Texture Image Feature Enhancement Processing Method Based on Visual Saliency Model

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Abstract. To improve the feature visualization effect of texture images, a texture image feature enhancement processing method based on visual saliency model is proposed. After collecting texture images, use soft and hard threshold denoising algorithms to denoise the texture images. Extract and decompose the features of the denoised image based on the visual saliency model. Based on the results of feature decomposition, the resolution of the texture image is reconstructed using deep learning technology, and then the texture image is described using shear wave transformation method to enhance the expression of the image's feature information. According to the experiment, it can be seen that after applying this method, the distortion coefficient of the texture image is smaller and the clarity is higher, indicating the feasibility of this method.

Keywords: Texture Images · Feature Enhancement · Noise Reduction Processing · Visual Saliency Model · Feature Extraction

1 Introduction

As one of the visual foundations for human perception of the world, images are an important means for people to obtain, express, and transmit information. In the face of massive image data, how to enable computers to mine useful information to complete image analysis and understanding and provide effective decision making has become a current research focus [1].

Texture feature, as one of the underlying features of image, has been playing an important role in the fields of image analysis, machine vision and pattern recognition. No matter for natural images, medical images or remote sensing images, the extraction and analysis of texture features are the primary and basic problems to be solved [2]. Therefore, how to effectively obtain the representational texture features is the key to image analysis and understanding.

In response to this issue, relevant scholars have proposed enhancement processing methods for image features. A low illumination image enhancement method based on visual communication was proposed in reference [3], and an image enhancement method based on global and local multiple features was proposed in reference [4].

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The visual saliency model is a visual attention model designed based on the visual nervous system of early primates [5]. This model first uses Gaussian sampling method to construct a Gaussian pyramid for the color, brightness, and direction of the image. Then, the Gaussian pyramid is used to calculate the brightness feature map, color feature map, and direction feature map of the image. Finally, by combining feature maps of different scales, brightness, color, and direction saliency maps can be obtained, and the final visual saliency map can be obtained by adding them [6]. This method does not require the process of training and learning, and can only complete the calculation of saliency maps through pure mathematical methods.

Therefore, based on the traditional research mentioned above, this paper proposes a new texture image feature enhancement processing method based on the visual saliency model.

2 Texture Image Acquisition

Firstly, the texture 3D imaging system is established, and its structure is shown in Fig. 1.

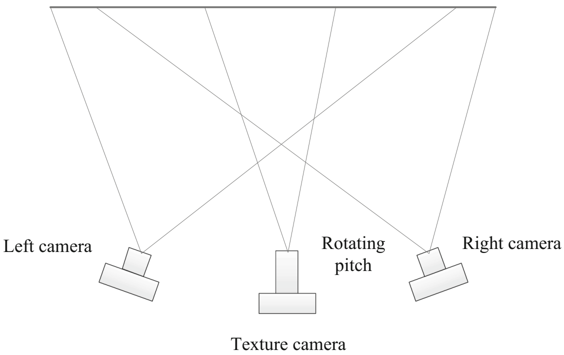

Fig. 1. Structure diagram of texture 3D imaging system

The texture 3D imaging system consists of three cameras, with the left and right cameras forming a binocular stereo vision system for reconstructing 3D point cloud models; The middle is a texture camera used to capture high-resolution texture images of objects. The texture camera is a telephoto camera that captures texture images from multiple perspectives by rotating and pitching.

Based on the texture 3D imaging system shown in Fig. 3, collect texture image information.

Before using multiple texture information to construct image information texture set, it is necessary to form local contour information feature vector of image first, including local edge contour information feature vector, image texture feature factor and enhanced information region coordinates, so as to construct image information texture set Q. Then, forward unification is used to decompose image texture feature information, and the feature equation of image edge state information feature matching can be obtained. The calculation formula is as follows:

$$a = \int_0^2 \rho^* \cos\theta^* \mathrm{d}\frac{\rho^*}{Q}, \rho^* \in [0, h] \tag{1}$$

In formula (1), h represents the set of edge contour pixels for low illumination images, θ represents the edge feature angle of the image.

Utilize the three-dimensional central coordinates of low illumination image information for feature aggregation processing of image information. Using $\rho^* - R$ as the displacement center point, the image information is optimized and sparsely identified, and then local contour image information is aggregated to obtain the texture image information collection model as follows:

$$b = \beta(g_l + f) \tag{2}$$

In Formula (2), b represents the acquisition model of low illumination image information; l represents the displacement distance of image information features, and the value range is $[1, R]$; f represents the aggregation model of image information; g_l represents the regional offset of image information; β stands for local contour scale.

3 Texture Image Denoising

After collecting the texture image mentioned above, the texture image is denoised using a soft and hard threshold denoising algorithm, and then the obtained wavelet coefficients are subjected to threshold processing. The soft threshold method needs to retract wavelet coefficients larger than the threshold to 0, and coefficients smaller than the threshold to 0; The hard threshold rule preserves coefficients that are greater than the threshold, and treats coefficients that are less than or equal to the threshold as 0. The constructed model is as follows:

$$\begin{cases} \hat{\delta}_{T2} = \begin{cases} sign(\delta)(|\delta| - T), |\delta| > T \\ 0, |\delta| \le T \end{cases} \\ \hat{\delta}_{T1} = \begin{cases} \delta, |\delta| > T \\ 0, |\delta| \le T \end{cases} \end{cases} \tag{3}$$

In Formula (3), $\hat{\delta}_{T1}$ and $\hat{\delta}_{T2}$ represent soft threshold and hard threshold respectively, and the sum of the deviations between them is E; $\hat{\delta}_T$ represents the wavelet coefficient after threshold processing; the wavelet coefficient of the original texture image is δ, and the selected threshold is T.

In the process of image denoising, if there are discontinuities or deviations in wavelet coefficients in the soft and hard threshold method during processing, it will cause vibration or blurring of the texture image [7]. Therefore, in order to avoid the occurrence of the above problems, the selected threshold function should have strong protection and scalability for edge coefficients, and also meet the requirement that the selected threshold is within the range of $\min E = \sum_k^n \left|\delta_{j,k} - \hat{\delta}_{j,k}\right|$. Among them, for wavelet coefficients with absolute values not less than the threshold, the above soft and hard threshold models are integrated and transformed as follows:

$$\begin{cases} \hat{\delta}_T = \begin{cases} 0, |\delta| \leq T_1 \\ sign(\delta)\dfrac{T_2(|\delta| - T_1)}{T_2 - T_1}, T_1 \leq |\delta| \leq T_2 \\ \delta, |\delta| < T_2 \end{cases} \\ \hat{\delta}_T = \begin{cases} sign\delta\left(|\delta| - \frac{2T}{1+\exp(m\delta^2)}\right), |\delta| \geq T \\ 0, |\delta| < T \end{cases} \end{cases} \tag{4}$$

In Formula (4), the adjustment coefficient in the model is m, and T_1 and T_2 represent the upper and lower limits of the threshold respectively. When $m = 0$, the threshold values in the threshold function can maintain continuity, and there are high order differentiability in the interval $\delta \geq T$, so as to solve the problem of threshold deviation. The specific denoising process is shown as follows:

Step 1: Set the wavelet bases and their decomposition levels in the image based on the type of noise in the image to obtain the wavelet coefficient $\delta_{j,k}$ of the texture image.

Step 2: Based on the characteristics of the obtained wavelet coefficients, select an appropriate threshold to calculate the wavelet coefficients in the image, and obtain the wavelet estimation coefficient $\hat{\delta}_{j,k}$ of the texture image, while keeping the difference between $\hat{\delta}_{j,k}$ and $\delta_{j,k}$ in a minimum state.

Step 3: Use the obtained wavelet estimation coefficients to perform wavelet reconstruction on the texture image, thereby completing the denoising process of the texture image.

4 Feature Extraction and Decomposition of Texture Image Based on Visual Saliency Model

In this paper, a significance analysis algorithm based on graph theory is used to extract the visual significance of texture image features. Saliency analysis algorithm extracts visual saliency through Markov chain, whose properties are:

$$P(X_{n+1} = x | X_0, X_1, \cdots, X_n) = P(X_{n+1} = x | X_n) \tag{5}$$

In Formula (5), x represents the process of a state, and X_n represents the state of time n [8].

Markov chain is used in graph theory significance extraction, texture image features can be written in the form of $M : [n]^2 \rightarrow R$. Define $M(i, j)$ and $M(p, q)$ as feature vectors, and the difference between the two vector values is represented by $d((i, j)\|(p, q))$, thus:

$$d((i, j)\|(p, q)) \triangleq \log\left|\frac{M(i, j)}{M(p, q)}\right| \tag{6}$$

Therefore, texture images can serve as directed graphs with interconnected pixels, as the nodes of the image are represented by pixel points, and the two adjacent nodes in the graph are $M(i, j)$ and $M(p, q)$. Set the two nodes $M(i, j)$ to $M(p, q)$ as weights ω_1, which can be expressed as:

$$\omega_1((i, j), (p, q)) \triangleq d((i, j) \| (p, q)) \cdot F(i - p, j - q) \tag{7}$$

$$F(a, b) \triangleq \exp\left(-\frac{a^2 + b^2}{2\sigma^2}\right) \tag{8}$$

where σ is a free parameter in the algorithm. Therefore, the distance from node $M(i, j)$ to $M(p, q)$ is proportional to the weight ω_1 of node $M(i, j)$ to $M(p, q)$ and the difference between them. The initial texture image is represented by the pixel value of each node, and the node mode is used to represent the pixel of each node. All the weighted values and original significance values are added together respectively to calculate the probability of transfer. The original significance graph of the node is represented by the newly obtained significance value, and all nodes in the Markov chain are normalized. The excitation information obtained converges to many main places, thus creating a graph GN (including n^2 nodes), setting the two adjacent nodes in the graph as the new weight ω_2, which can be expressed as:

$$\omega_2((i, j), (p, q)) \triangleq A(p, q) \cdot F(i - p, j - q) \tag{9}$$

In formula (9), $A(p, q)$ represents the original saliency map.

The nodes of Markov chains correspond to the states and have limited characteristics. Markov chains are also constrained by higher excitation nodes, resulting in a saliency map that further normalizes $A(p, q)$.

After extracting texture image feature $M : [n]^2 \rightarrow R$, the feature information is decomposed. The texture image information fusion model is generated by decomposing the information features of the image, and the multi-scale high frequency of the image information is decomposed by the Gaussian filter pixel detection method.

The sequence of nonlinear feature distribution chaotic function of image information is:

$$P = \sum_{k=1}^{n} I_{(k)}(x, y) \times 2^l / b \tag{10}$$

In formula (10), I represents the scale decomposition function of texture image information; k represents the edge grayscale pixel feature set of texture image information; b represents the collection model of texture image information; (x, y) represents a multi-scale input pixel chaotic sequence.

By fusing the distribution sequence of texture information, the feature fusion function obtained is:

$$W = P\big[2(x - 1) + u, 2(y - 1) + v\big] \tag{11}$$

In Formula (11), u represents the information intensity of image information edge extraction; v represents the information integration degree of image information distribution.

The amount of information distributed in adjacent domains of image information is:

$$r_\lambda^* = \begin{cases} \dfrac{W}{cs_k}, 1 \leq \lambda \leq x - y \\ \varepsilon_\lambda, \text{others} \end{cases} \tag{12}$$

In formula (12), λ represents the blur factor for image information enhancement; c represents the standardized component set of image information; s_k represents the grayscale information of the image; ε_λ represents the Gaussian filter coefficient of digital images of different levels.

Based on the above content, establish a set of regional feature decomposition vectors for image information as follows:

$$E = \frac{r_\lambda^* \sum_{i=1}^{p} \rho^* \times r_\lambda^* \sum_{j=1}^{p} \rho^*}{\sqrt{\int_1^p \left(\rho_i^* - R\right) \mathrm{d}\rho^* + \int_1^p \left(\rho_j^* - R\right) \mathrm{d}\rho^*}} \tag{13}$$

5 Using Deep Learning Technology to Reconstruct the Resolution of Texture Images

After the feature extraction and decomposition of the texture image is completed based on the visual saliency model, the resolution of the texture image is reconstructed by using deep learning technology, which lays a foundation for the subsequent feature enhancement processing.

Deep learning evolved from traditional neural networks, but it has deeper network results and more efficient training methods [9]. In the process of deep learning, loss functions can be optimized as far as possible to mine learning rules, and learning results can be obtained by directly inputting data, without manual design of learning rules. Deep learning can apply the learned rules in deeper network combinations to build complex models, distinguish and simplify different categories of problems, and further extract more complex features to replace artificial feature extraction [10]. Therefore, this study utilizes deep learning processes to construct a numerical imaging model for texture images and reconstruct image resolution.

The process of deep learning mainly includes preprocessing, feature learning, model training, and model construction. The specific content is as follows:

(a) Pre processing. Due to factors such as improper human operation and system errors, if noise data from some data samples is input into the deep learning network without processing, it will lead to phenomena such as unclear data features in the output results. Therefore, the process of processing data is very important. In the previous study, based on the processing of texture image features, a structure parallel to the linear shape was selected to process the corrosion reflection component, thereby effectively eliminating interference information in the image.
(b) Feature learning. The main goal of feature learning is to make the model more accurate, improve operational efficiency, and master more complex texture image features.

(c) Model training. After applying deep learning to construct a numerical imaging model for texture images, the optimal imaging model that meets the expectations and goals is ultimately generated through multiple training and calculation of data.
(d) Model construction. Using the feature regions obtained from the above processing, a numerical imaging model is constructed using deep learning as follows:

$$F(x, y) = -\frac{(x^2 + y^2)}{2\pi\lambda^2} \tag{14}$$

In Formula (14), $F(x, y)$ represents the constructed numerical imaging model, λ represents the range compression parameters in the texture image region, and x and y respectively represent the pixel points in the imaging region.

There is a compromise processing method of spatial proximity of pixels in the texture image region, which leads to the blurring of image edge details in the reconstruction of the resolution in the image. Therefore, guided filtering is used to establish the linear constraint relationship between pixels, forming the linear transfer of edge pixels. The local window is used to guide pixels to generate edge gradient, control pixels to form forward rotation, and control artifacts generated by image edges.

After the edge artifacts of the texture image are processed, the local window function is used to calculate the image cost generated by forward rotation [11, 12]. The reverse imaging process of the visual image is used to construct a downsampling numerical model to minimize the image cost formed by the processing. When reconstructing image resolution, the LR image reconstruction method is used to set interpolation functions between texture image pixels, randomly select a pixel, use a cubic polynomial to construct a correlation function between neighboring pixels of the pixel, and use the back projection method to project the pixel interpolation into the numerical imaging model constructed above. The changes in projection parameters during the projection process are shown in Fig. 2.

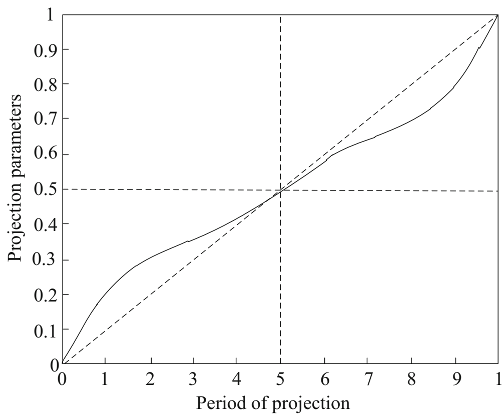

Fig. 2. Changes in projection parameters

As can be seen from the parameter changes shown in Fig. 2, the projection parameters show a changing process of increasing continuously within the range of calibrated projection cycle. In order to ensure the reconstruction accuracy of texture image resolution, SRCNN model is used to extract image block features and process them into corresponding high-dimensional vectors. The numerical relationship can be expressed as:

$$F(Y) = \frac{\max(Y)}{B_1} \tag{15}$$

In formula (15), $F(Y)$ represents the constructed high-dimensional vector, $\max(Y)$ represents the preprocessed image block, and B_1 represents the Bicubic preprocessing parameter. By integrating the high-dimensional vectors constructed above into the constructed numerical imaging model, the resolution in the visual image can be reconstructed.

6 Texture Image Feature Enhancement Processing

Since wavelet, curve wave and other transform methods can not best describe the texture image information [13], this study adopts the Shearlet transform method to describe the texture image. This method is roughly the same as curve wave and contour wave, and has the characteristics of multi-resolution and multi-direction, and has the best nonlinear approximation characteristics, which is more suitable for image feature expression, and makes the results more close to the real situation.

Shear wave transform has a unique bionic system, and its mathematical expression can be described as:

$$\begin{aligned} \Psi_{XY}(\psi) &= \{\psi_{c,d,e}(a) \\ &= |\det X|^{c/2}\psi(Y^d X^c a - e) : c, d \in Z, e \in Z^2\} \end{aligned} \tag{16}$$

In formula (16), $\psi \in L^2R^2$ and L represent the length of the wavelet, R represents the wavelet transform coefficients, c, d, and e represent the shear wave transform parameters, Z represents the set of real numbers, and X and Y can form a $2 \times$ The invertible matrix of 2, $|\det X| = 1$. If $\Psi_{XY}(\psi)$ conforms to the Parseval framework, i.e. a compact framework, then the elements of $\Psi_{XY}(\psi)$ are considered as synthesized wavelets.

Assuming the continuous Shearlet transformation of function $f \in L^2R^2$ is set to:

$$SH_{\psi}f(c, d, e) = < f, \psi_{(c,d,e)} > \tag{17}$$

According to formula (16) and (17), the texture image is divided into two parts: low frequency information and high frequency information. Among them, the low frequency component is the image irradiation component, namely brightness, contrast, gray value, etc. The high frequency component is the texture and detail features of the image, i.e. the average gradient, spatial frequency, etc.

On this basis, the multi-scale Retinex method was used to solve the low frequency coefficient after separation, and the best estimated radiation component was obtained. However, the result of low frequency coefficient may be positive or negative. If it is negative, the enhancement effect of the image will be affected to some extent. In this way, linear mapping method is used to map the coefficient $F(x, y)$ to the interval [0,125], which is also an enhancement processing of the texture image.

$$F'(x, y) = \frac{F(x, y) - F_{\min}}{F_{\max} - F_{\min}} \times 125 \tag{18}$$

In formula (18), $F_{\max}$ and $F_{\min}$ represent the two extreme values of the low-frequency subband coefficients, while $F'(x, y)$ represents the normalized result, which is treated as an input image and then enhanced according to the multiscale Retinex formula. In order to better reconstruct this part of the image, the multi-scale Retinex processed coefficients are mapped to the interval of $[0, F_{\max} - F_{\min}]$.

Since the details and noise of the texture image are basically retained in the high-frequency subband after the shear wave transformation, the separation of noise and image can be solved by selecting the appropriate threshold value. The scale will become more refined with the increase of decomposition level, and the shear wave allows different sizes and directions of each scale [14]. In order to solve the problem of noise amplification in the process of fuzzy image enhancement, the threshold method is used to suppress the high frequency subband coefficient of shear wave, so as to remove the noise formed in the process of decomposition and the noise of texture image itself. There is a direct correlation between image enhancement effect and threshold value, so the following formula is used to determine the threshold value, namely:

$$T = \lambda\varepsilon \tag{19}$$

In formula (19), λ represents a constant quantity, and its value satisfies [0, 2] between [0,2]; ε represents the minimum value of the variance of shear wave noise in different directions at the minimum scale, namely:

$$\varepsilon = \min\left(\varepsilon_{x,y}\right) \tag{20}$$

The noise variance of the high-frequency subband is obtained using the robust median value, i.e.

$$\varepsilon_{x,y} = mediam|D_{x,y}| \tag{21}$$

In formula (21), $D_{x,y}$ represents the coefficients of each high-frequency subband. In this paper, the decomposition layer of the shear wave transformation is 3, and the number of directions is 2, 5, and 7. According to the hard threshold T shrinkage method, denoise the high-frequency coefficients, and the calculation process is as follows:

$$D'_{x,y} = \begin{cases} D_{x,y}, & D_{x,y} \geq T \\ 0, & D_{x,y} < T \end{cases} \tag{22}$$

The texture image processed by the above steps basically removes the interference of light and noise, but the contrast of the image is low and the sense of hierarchy is not good. Therefore, the fuzzy contrast method is used in this paper to process the multi-scale Retinex reconstructed image. The fuzzy contrast formula is set as:

$$F = |\mu_{x,y} - \overline{\mu}_{x,y}|/|\mu_{x,y} - \overline{\mu}_{x,y}| \tag{23}$$

In formula (23), $\mu_{x,y}$ represents the grayscale value of the pixel; $\overline{\mu}_{x,y}$ represents 2 $\times$ 2 windows remove the average value of the central domain. This calculation process is similar to the low-frequency component, and the grayscale value of the reconstructed image is transformed to the range of [0125] through formula (18). Due to the fast processing speed of this process, the image enhancement effect is average and the contrast is low. Taking into account the above factors, a linear membership function is used to further improve it. The reconstructed image is transformed into a fuzzy domain, and $x_{a',b'}$ describes the grayscale situation of any pixel, which is represented as follows:

$$\mu_{x,y} = \frac{x_{a',b'}}{L+1} \tag{24}$$

Then, the fuzzy contrast of the reconstructed image is obtained according to the threshold formula, and the nonlinear transformation of F can be obtained:

$$F' = \psi(F) \tag{25}$$

After transforming $\psi(F)$, make $\psi(0) = 0$, $\psi(1) = 1$, and the selected nonlinear enhancement function is represented as:

$$\psi(a') = \frac{1 - e^{-ka'}}{1 - e^{-k}} \tag{26}$$

The membership function adjusted by F' can be described in the following form:

$$\mu_{a',b'} = \begin{cases} \bar{\mu}_{a',b'}(1 - F'), & \mu_{a,b} \le \bar{\mu}_{a',b'} \\ 1 - (1 - \bar{\mu}_{a',b'})(1 - F'), & \mu_{a,b} > \bar{\mu}_{a',b'} \end{cases} \tag{27}$$

Finally, the fuzzy domain is converted into the space domain, and then the image with enhanced contrast is obtained, that is, the enhanced texture image. The calculation process is as follows:

$$a'_{a',b'} = \mu'_{a',b'} \times (L+1) \tag{28}$$

In formula (28), $a'_{a',b'}$ is the enhanced texture image.

In summary, the design of a texture image feature enhancement processing method based on visual saliency model has been completed, and the framework structure of this method is summarized, as shown in Fig. 3.

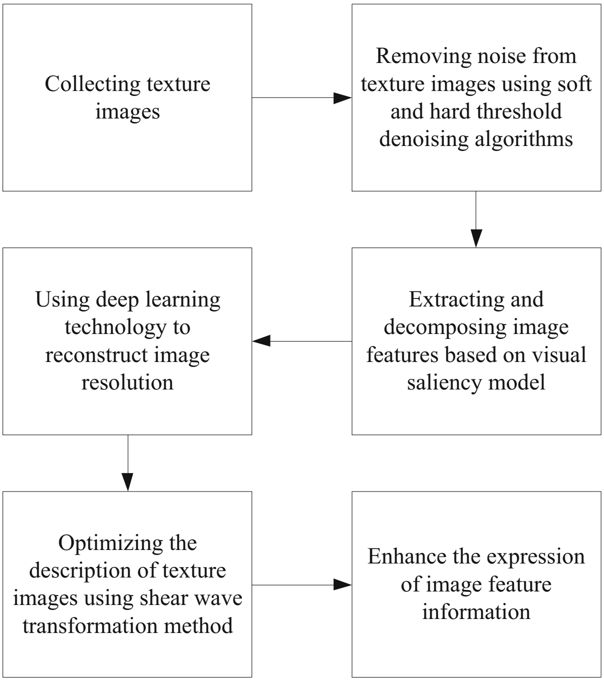

Fig. 3. Framework structure diagram of the method

7 Experiment and Analysis

To verify the feasibility of the texture image feature enhancement processing method based on visual saliency model designed above, the following experiments are designed.

The method proposed in this article will be used as the experimental group, with traditional visual communication based image enhancement methods and global and local multi feature based image enhancement methods as control group A and control group B, respectively. Use three processing methods to enhance the same set of texture images.

The obtained images are all taken in low light and shaded areas. Number the 10 texture images obtained as JPG-#1, JPG-#2, JPG-#3, JPG-#4, JPG-#5, JPG-#6, JPG-#7, JPG-#8, JPG-#9, and JPG-#10. Strictly follow the implementation steps of the three processing methods to complete the image enhancement processing.

To objectively evaluate the three processing methods, firstly, the distortion of the processed image is selected as the evaluation indicator, which can be calculated using the following formula:

$$LOE = \frac{1}{m}\sum_{x=1}^{m} RD(x) \tag{29}$$

In Formula (29), *LOE* represents the distortion coefficient of the texture image after enhancement; m represents the number of pixels in the image; $RD(x)$ represents the relative order difference between the original image and the enhanced image. According to this formula, the distortion coefficient *LOE* of the texture image processed by the three groups of processing methods is calculated. In terms of image enhancement effect, if the value of *LOE* is smaller, it means that its features are more natural and the distortion rate is lower. According to the above discussion, the brightness distortion results of the three processing methods are counted, as shown in Table 1.

Table 1. Distortion coefficients of images processed by three methods

Image number	AImage distortion coefficient *LOE*		
	Experimental group	Control group A	Control group B
JPG-#1	0.325	0.624	0.742
JPG-#2	0.314	0.664	0.756
JPG-#3	0.315	0.650	0.826
JPG-#4	0.327	0.671	0.845
JPG-#5	0.315	0.681	0.825
JPG-#6	0.326	0.692	0.791
JPG-#7	0.313	0.674	0.783
JPG-#8	0.326	0.682	0.925
JPG-#9	0.317	0.634	0.921
JPG-#10	0.325	0.665	0.846

From the data in Table 1, it can be seen that after enhancing the five images, the image distortion coefficients of the experimental group were controlled between 0.313 and 0.327, while the image distortion coefficients of the control group A fluctuated between 0.624 and 0.692, while the image distortion coefficients of the control group B all exceeded 0.700. Through the comparison of the experimental results obtained above, it can be concluded that the distortion coefficient of the texture image is the lowest in the experimental group after enhancement processing, indicating that after the experimental group method processing, the natural characteristics of the image are maintained well, and the distortion rate is effectively controlled.

To further compare the clarity of texture images processed by three different processing methods, the average gradient was chosen as the evaluation index to reflect the changes in clarity of the original image after enhancement processing. The calculation formula for the average gradient is:

$$G(x, y) = I(dxi + dyj) \tag{30}$$

In Formula (30), $G(x, y)$ represents the average gradient of the image after enhanced processing; I represents pixel value; (i, j) stands for pixel coordinates. The higher the average gradient $G(x, y)$, the clearer the image.

According to the above formula (30), taking JPG-#3 of the above five pedestrian action images as an example, the average gradient of the images processed by the three enhancement processing methods was compared with the original image, and the experimental results as shown in Fig. 4 were obtained.

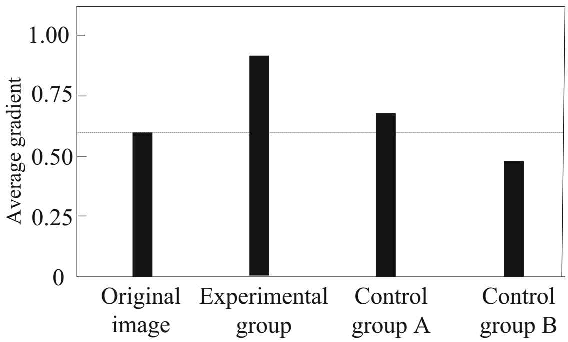

Fig. 4. Comparison of processing effects of three enhancement processing methods

From the bar chart shown in Fig. 4, it can be seen that the average gradient of the experimental group and the control group A treatment method has been slightly improved compared to the original figure, while the average gradient of the control group B treatment method has actually decreased compared to the original figure. Therefore, the above experiments can further prove that the experimental group method can effectively improve the clarity of texture images.

Based on the above experimental results, it can be concluded that the method proposed in this paper not only maintains good feature naturalness in the processed texture image, but also improves the clarity of the image. This indicates that the method proposed in this paper effectively achieves comprehensive optimization of visual effects on texture images.

8 Conclusion

In this paper, a feature enhancement method of texture image based on visual saliency model is designed. Firstly, after the texture image is collected, the texture image is denoised. Then, the features are extracted and decomposed based on the visual saliency model, and the resolution of the texture image is reconstructed using deep learning technology. Finally, shear wave transform is used to describe the texture image to enhance the expression of feature information.

The experimental results show that the enhanced texture image has lower distortion coefficient and higher clarity, which indicates that the proposed method achieves the design expectation effectively.

In practical applications, this method can enhance the features of texture images by utilizing visual saliency models, thereby improving the visibility and discrimination of texture features. By highlighting the most significant texture regions in the image, this method can help analysts better understand and recognize texture images. For example, in texture image classification tasks, using this method can make texture features more vivid and clear, reduce background noise interference, and thus improve the accuracy and stability of classification. This is of great significance for many application scenarios such as texture recognition, material classification, medical image analysis, etc.

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