Packaging Beautification Design Based on Visual Image and Personalized Pattern Matching

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***Abstract*—Visual image technology is widely used in the field of product art design, enriching the visual beautification design effect of products. To improve the design effect of product packaging, a personalized packaging pattern matching technology is proposed based on computer vision image technology. Firstly, based on user needs, a pattern feature extraction technology is proposed, which uses the total variation model and GrabCut model to smooth and segment the image. Secondly, an improved style transfer generative adversarial network model is proposed for transfer training between feature elements and targets. Considering the problem of insufficient detail preservation in traditional transfer models, attention layers are incorporated into the transfer model for improvement. In the pattern feature extraction experiment, the proposed model had the best pixel accuracy in Image 1. In the pattern matching experiment, the proposed model had the lowest mapping loss in both pattern combinations, with a value of 0.135 in the Zhuang brocade pattern and 0.236 in the blue and white porcelain pattern, which was superior to other models. Comparing the effect of different model pattern combinations, in the blue and white porcelain pattern combination, the proposed model had an optimal peak signal-to-noise ratio of 32.32, which was superior to other models. The proposed model has excellent application effects in packaging design beautification. The research content will provide critical technical references for e-commerce product packaging design and intelligent image processing.**

Keywords*—*Visual images; personalized patterns; total variational model; GrabCut model; migration model

I. Introduction

Visual image technology is a technique that processes and analyzes images through computers. This includes image recognition, image processing, and image generation. Visual image technology is widely applied in multiple fields, such as medical image analysis, security monitoring, intelligent transportation, etc. [1]. In product packaging design, visual image technology can be used to enhance the design effect of packaging, making it more attractive to consumers [2]. Pattern packaging design refers to the use of various pattern elements and styles on the outer packaging of products to attract consumer attention. However, traditional pattern packaging design has shortcomings, such as the inability to meet the personalized needs of different users in packaging design, and the lack of innovation in pattern elements in traditional design, which cannot convey the connotation that the product needs to express [3]. Therefore, a packaging beautification design method based on the combination of visual images and personalized patterns is proposed. Images are processed through pattern feature extraction technology to achieve personalized matching of pattern elements and styles. The innovation of the research lies in the emphasis on considering the impact of different pattern elements on packaging design, proposing a multi-model fusion pattern feature extraction technology to effectively extract pattern features and preserve details. Secondly, an improved transfer model is introduced for pattern matching training, achieving optimization of pattern packaging design. This technology has important application value in the field of packaging. While meeting the requirements of packaging beautification design, it improves the detail retention ability of traditional transfer models. Research technology will drive the development of the e-commerce industry and provide new methods and ideas for the beautification design of product packaging.

The research content is composed of six sections. Section I and Section II introduces the application of relevant visual images and the latest cutting-edge technologies, and discusses and analyzes the application of visual image technology in fields such as image segmentation and image matching. Section III analyzes the characteristics of packaging design and proposes a feature extraction model and pattern matching model to achieve personalized design of packaging. Section IV is to apply the mentioned technology to specific scenarios and assess the performance of the proposed packaging beautification design technology in practical scenarios. Section V delves in to discussion and finally, Section VI concludes the paper.

II. Related Works

Computer vision image is a technique that utilizes computers to process, analyze, and understand images. It is widely applied in fields such as facial recognition, image processing, and object recognition, and researchers all over the world have organized relevant research on this. The study by Penumuru et al. aimed to propose a universal method for automatic material recognition using machine vision and machine learning techniques to enhance the cognitive abilities of material processing equipment such as robots deployed in machine tools and Industry 4.0. The study selected four common materials and prepared and processed their surface datasets. By extracting the red, green, and blue components of the three primary color model as features and applying support vector machines and other classification algorithms, the proposed method has been studied and verified to recognize different material groups [4]. The results indicated that the proposed method could be implemented in a manufacturing environment without significant modifications. Secondly, the research of Uthayakumar et al. focused on computer vision-based applications in wireless sensor networks. Research results showed that visual sensors generated a large amount of multimedia data in sensors, while image transmission consumes more computing resources. To address this issue, a study proposed an image compression model using neighborhood related sequences. This algorithm performed bit reduction operations and further compressed the image through a codec. The proposed NCS algorithm improved the compression performance of sensor nodes and reduced energy utilization while maintaining high fidelity. Through experimental evaluation on test images, the results showed a better compromise between compression efficiency and reconstructed image quality [5]. Finally, Huang et al.'s research aimed to raise the real-time performance of image segmentation. The study introduced a fruit fly model into image segmentation and obtained a fusion image processing technique. By using optimization strategies to search for the optimal segmentation threshold, the model could converge faster and consume less time without sacrificing segmentation accuracy. The research results indicated that this method significantly reduced segmentation time while keeping the segmentation effect basically unchanged [6].

With the development of visual image technology, it has important applications in fields such as image design, segmentation, and matching. Agarwal et al. found that with the development of image editing tools, image forgery activities are on the rise. To protect the authenticity of images, a deep learning-based detection, replication, movement, and forgery image technology was proposed. This technology involved processes such as segmentation, feature extraction, dense depth reconstruction, and ultimately identifying tampered areas. Finally, the technology was applied to specific scenarios, and it had good image visual processing effects [7]. Li et al. found that effective image segmentation in image design faced challenges, and proposed a convolutional neural network that combines attention mechanism (AM). The network structure studied consists of a basic feature layer and an attention module, which is utilized to capture global information and enhance features. The experimental outcomes showed that this method was superior to other existing mainstream image processing methods and had fewer parameters, improving the application of visual technology in related fields [8]. Chen et al.'s research focused on the importance of image matching in fields such as augmented reality, synchronous localization, and visual design. The study improved the accuracy of feature matching in visual design by incorporating instance aware semantic segmentation into visual feature matching for corner detection and rotation. Research used pixel level object segmentation and semantic information limitation to perform feature matching on adjacent images. The research findings indicated that this method improved the accuracy of feature matching and met the requirements of visual design [9]. Hu et al.'s research was dedicated to the study of image segmentation techniques. So, a parallel deep learning algorithm with mixed AM was proposed to enhance the effectiveness of pattern design work. This algorithm extracted pattern feature information from preprocessed images and inputs the images into a mixed AM and densely connected convolutional network module. The mixed AM consists of spatial AM and channel AM. The experiment outcomes denoted that this technology can significantly improve the image processing efficiency of design work, while also improving the processing effect of image data [10].

In summary, computer vision image technology has important applications in many fields. With the advanced visual image and machine learning techniques, problems such as image editing, segmentation, and matching in image design can be effectively solved. However, there are relatively few applications of visual image technology in the field of product appearance. In this regard, applying visual image technology to the packaging beautification design process provides relevant technical guidance for product packaging design and beautification.

III. Construction of Packaging Beautification Model based on Personalized Pattern Matching

This section mainly focuses on the research of product packaging beautification design, proposing pattern feature extraction models and pattern personalized matching models for product packaging design, and constructing relevant models separately.

A. *Extraction of Personalized Packaging Pattern Features*

In recent years, with the continuous improvement of people's quality of life and consumption ability, pursuing personalized consumption has become a social development trend. Personalized product packaging design can not only impress people, but also enhance the competitiveness of the product with personalized patterns. Therefore, in response to the growing demand for personalized packaging appearance, a personalized packaging pattern matching technology based on visual image technology is proposed [11]. To meet user needs, it is necessary to fully consider pattern design elements. Taking blue and white porcelain products as a case study, in the design of packaging patterns for blue and white porcelain, it is necessary to extract target features based on consumer needs and product attributes [12]. The process of product feature extraction technology is shown in Fig. 1.

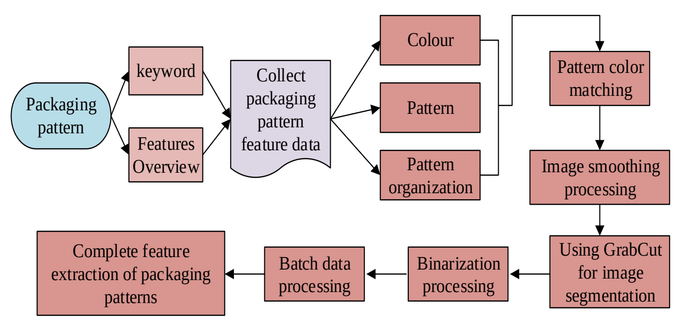


Fig. 1. Product feature extraction process.

According to the technical process in Fig. 1, feature extraction of patterns includes pattern, color, and tissue extraction. In the extraction of the above feature information, to meet the personalized design requirements of product packaging, it is necessary to process the above features accordingly. If the extracted pattern features contain a large number of organizational textures, it will have an impact on the personalized information processing of the pattern itself. Therefore, in the study, a Relative Total Variation (RTV) model is adopted to optimize the feature extraction. The RTV model can make the image texture smooth and highlight the main feature details needed [13]. In smoothing processing, any point in the product feature image is defined as p, and the RTV of the image's P points is calculated as shown in Eq. (1).

$$RTV(P) = \sum_{q \in N_P} w_{pq} \cdot \| I_P - I_{q_s} \|^2 \cdot \lambda_r \tag{1}$$

In Eq. (1), N_P is the set of points adjacent to P. λ_r represents the degree of smoothness. w_{pq} is the weight between point P and adjacent point q_s. I_P and I_q are the grayscale values of point P and adjacent point q. After completing the image smoothing process, it is also necessary to segment the image in order to better obtain different background features [14]. In the study, GrabCut was used as an image segmentation technique to perform local segmentation on the target image. The specific process is shown in Fig. 2.

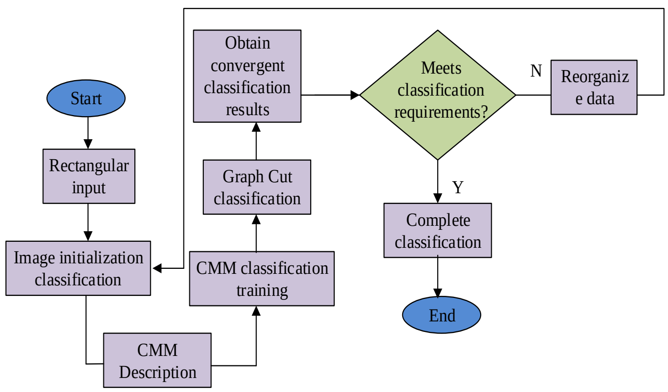


Fig. 2. GrabCut segmentation process.

In the target feature map, multiple targets containing T rectangles are defined, and the external background of the rectangle is set to T_B, while the internal area of the rectangle is used as the foreground area, which is T_F. This expression is shown in Eq. (2).

$$\begin{cases} T_F = \varnothing \\ T_U = T_B \end{cases} \tag{2}$$

In Eq. (2), $\varnothing$ represents an empty bag. If any pixel T_F within T_B is initialized with a label, then the label $a_n = 0$ represents the background pixel, and for each pixel in T_F, the T_F label is initialized with $a_n = 1$ as the possible target pixel. The foreground and background regions are clustered into K-type using a clustering model, and a Gaussian Mixture Model (GMM) is constructed for the foreground and background. The three primary colors of the target pixel n are brought into each Gaussian component of the GMM model, and the K_n th Gaussian component of pixel T_F is the target pixel, as shown in Eq. (3).

$$k_n := arg \min_{KN} D_n(\alpha_n, k_n, \theta, z_n) \tag{3}$$

In Eq. (3), θ represents the initial parameters of GMM, and z_n is the image matrix. For the given image data Z. D_n represents the Gaussian component. The GMM model is applied for parameter training, and the expression is shown in Eq. (4).

$$\theta' := arg \min_{\theta'} U(\alpha_n, k_n, \theta, z_n) \tag{4}$$

In Eq. (4), $U(\cdot)$ represents GMM parameter learning. The maximum minimum flow strategy is used to segment pixels and obtain the minimum energy, as shown in Eq. (5).

$$\min_{\{a_n, n \in T_U\}} = arg \min_K E(\alpha_n, k_n, \theta, z_n) \tag{5}$$

In Eq. (5), E represents the energy value. Repeating Eq. (3) and Eq. (5) until convergence is achieved to obtain the image segmentation result. Considering the issue of color difference in feature extraction, the Otsu segmentation method (OTSU) is adopted to handle the differences between extracted features. The OTSU idea is to segment a single feature, divide the target feature into foreground and background parts through grayscale features, and achieve black and white color gamut division by searching for grayscale levels and OTSU thresholds [15]. OTSU image segmentation is shown in Fig. 3.

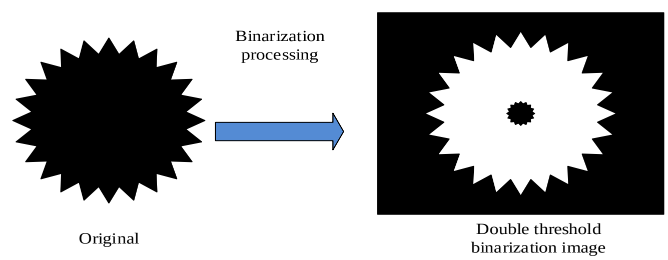


Fig. 3. Schematic diagram of OTSU image segmentation.

It defines the grayscale image as F, uses F as a matrix of $M \times N$, sets the pixel value to (0255), and uses n_i as the amount of pixels with a grayscale pixel level of i. The probability of selecting the grayscale pixel i is denoted in Eq. (6).

$$\begin{cases} p_i = \dfrac{n_i}{n_0 + n_1 + \cdots + n_{255}} \\ \sum_{i=0}^{255} p_i = 1 \end{cases} \tag{6}$$

In image segmentation, the foreground and background segmentation thresholds of the image are set to k_l. According to the segmentation threshold, there are a large number of pixels that are greater than or less than k_l, namely C_A and C_B. The probability of selecting the two types of pixels is set to P_A and P_B, and the grayscale mean of the two types of pixels is set to m_A and m_B. If the grayscale level accumulation value is set to m_l, the global mean of the image is shown in Eq. (7).

$$m_G = p_A(k_l)\times m_A(k_l) + p_B(k_l)\times m_B(k_l) \tag{7}$$

In Eq. (7), there is a relationship as shown in Eq. (8).

$$p_A(k) + p_B(k) = 1 \tag{8}$$

Then, the expression equation of variance is used to obtain the value of the image segmentation method, as shown in Eq. (9).

$$\sigma^2 = p_A(k_l)(m_A(k_l) - m_G)^2 + p_B(k_l)(m_B(k_l) - m_G)^2 \tag{9}$$

In Eq. (10), σ is the spatial scale adoption number, and the square difference is subjected to deformation processing. The result is shown in Eq. (10).

$$\sigma^2 = \frac{(m_G * p_A(k_l) - m_l)^2}{p_A(k_l)(1 - p_A(k_l))} \tag{10}$$

The traversal is used to obtain the maximum threshold k_l between variances, and then re-segment the image through binarization. The result is shown in Eq. (11).

$$img(i,j) = \begin{cases} maxval & ifimg(i,j) > threshold \\ 0 & othenuise \end{cases} \tag{11}$$

The extraction of pattern features is the key to packaging beautification design, and it is necessary to extract the main pattern feature elements from the target, including patterns, colors, and organization, to provide basic elements for subsequent packaging beautification design.

B. Construction of a Personalized Pattern Transfer Model Based on Packaging Beautification

In product packaging beautification design, it is necessary to combine the extracted multiple style features with the target product, meeting both the product style features and the visual aesthetic design requirements. To effectively match the elements in the pattern with the target product, a personalized pattern transfer model based on the Improved Style Transfer Generative Adversarial Networks for Image to Illustration Translation (GANILLA) was proposed in the study. By fusing the features of different styles of patterns with the target, personalized packaging matching was achieved [16]. The GANILLA model was proposed by Samet Hicsonmez et al. in 2020 as an image style transfer learning model. In image feature processing, the original image content details were preserved as much as possible to achieve different style feature transfer methods. Among them, the structural framework of the GANILLA model is shown in Fig. 4.

From Fig. 4, the GANILLA model used convolutional layers for downsampling. At the same time, the inverse convolutional layer was used for upsampling, and a concatenated residual layer was used in the model. The inverse convolutional layer was replaced by a sampling operator. In the given pattern element features, it was necessary to combine the extracted pattern elements with different styles to fuse and generate new design patterns [17].

The pattern features are independent data, and the product packaging data is target data. The GANILLA model sampled feature maps through a skip connection generator. At the same time, to better preserve the transmission pattern features, upsampling and skip connections were used to merge high-level and low-level features, thereby improving the image composition quality [18]. The distance between the synthesized image and the real image is defined as $L1$, where the number of samples is set to N, the predicted pixels are set to y, and the pixels of the real image are x. The comparison between the synthesized image and the real image is shown in Eq. (12).

$$L_{rec} = \frac{1}{N}\sum_{i}^{N}\frac{\| y - x \|}{WHC} \tag{12}$$

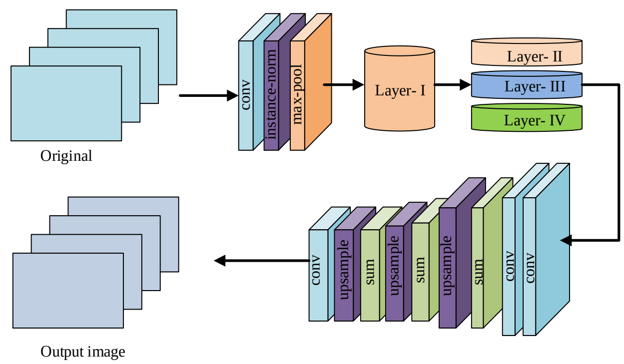


Fig. 4. GANILLA model structure.

In Eq. (12), W, H, and C respectively represent the width, height, and amount of channels of the image. Then, the discriminator adversarial loss is calculated, as shown in Eq. (13).

$$\begin{aligned} L_{GAN}(G,D) &= E\left[\log(Dx)\right] \\ &+ E\left[\log(1 - D(G(x^{'})))\right] \end{aligned} \tag{13}$$

In Eq. (13), $x^{'}$ means the input damaged image, G represents the output target, D is the discriminator, and E represents the energy loss value. Then the joint loss is calculated, as shown in Eq. (14).

$$L = \lambda_1 L_{rec} + \lambda_2 L1 \tag{14}$$

In Eq. (14), λ_1 and λ_2 are both loss optimization parameters. In the actual pattern transfer, although the GANILLA model has good adaptability to the processing of pattern texture features, there are still shortcomings in handling individual feature details, such as the problem of detail loss in the transformation of texture features. In this regard, improvements will be made from two methods: feature analysis and model performance. In the analysis of pattern features, attention SE block modules will be added to the Residual Block layer to improve the model's attention to key positions in the image. At the same time, the addition of AMs can improve the acquisition of useful features without suppressing useless features [19]. The SE block module structure framework is shown in Fig. 5.

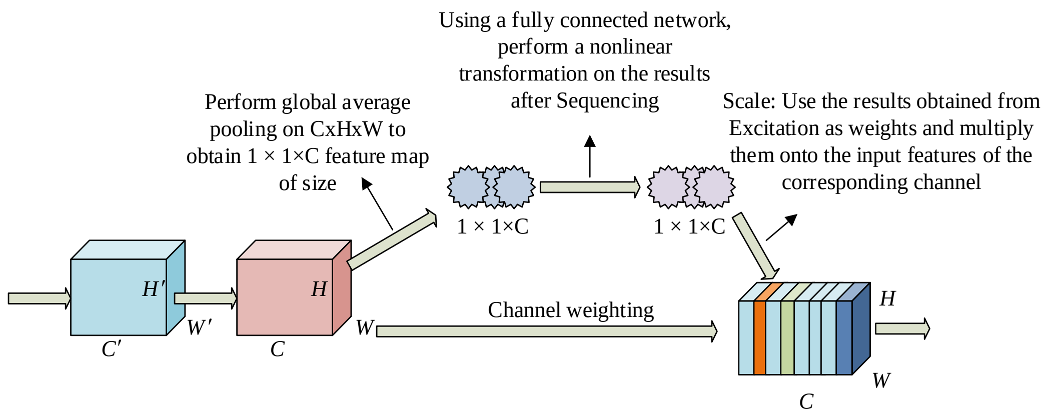


Fig. 5. SE block module structure framework.

In terms of model performance, considering the addition of AM, the computational complexity of model parameters is increased, and a parameter compression model, Residual block, is introduced to reduce network parameters and floating-point computational complexity in the model. Two generators and discriminators are included in the generative adversarial loss function of the improved GANILLA model. Firstly, the adversarial loss is adopted in the mapping network, and the target mapping relationship is expressed as Eq. (15).

$$G^*, F^* = arg\min_{G,F}\min_{D_X,D_Y} L(G,F,D_X,D_Y) \tag{15}$$

In Eq. (15), F represents the mapping target, and F and D_Y are the discriminators corresponding to the X domain and Y. The image $G(X)$ generated by G will continuously approach Y, enhancing the similarity between the two sides of the mapping. D_Y can be used to distinguish the two targets y and $G(X)$. Simultaneously, the minimum target in the target G mapping relationship is applied to counter the discriminator. In adversarial training, learning training can be used to learn the mapping relationship between G and D [20]. Finally, the various loss functions are combined, and the loss optimization parameter λ is introduced to optimize the real image pixel x. The target loss is shown in Eq. (16).

$$\begin{aligned} L(G,F,D_x,D_y) &= L_{GAN}(G,D_Y,X,Y) \\ &+ L_{GAN}(F,D_X,X,Y) + \lambda L_{cyc}(G,F) \end{aligned} \tag{16}$$

In Eq. (16), the larger the loss optimization parameter value λ, the closer each pair of discriminators will be. Through the above techniques, the extracted personalized pattern elements can be style transferred to achieve personalized design of packaging patterns.

IV. Algorithm Model Simulation Testing

This section conducted performance tests on the two proposed models to evaluate their practical application effects. The main evaluation indicators included pixel accuracy (PA), signal-to-noise ratio (SNR), peak signal-to-noise ratio (PSNR), and loss.

A. Experimental Analysis of Pattern Feature Extraction

To improve the proposed packaging beautification design model, experimental testing was conducted on the Windows 10 64 bit platform. The processor was a Zhiqiang 64 core processor, the graphics card was NVIDIA RTX4060ti, and the running content was 64G. The experimental data was sourced from the integrated packaging graphic design website, which included 15564 image feature data, including pattern, color, tissue and other feature data. The initialization parameters of the experimental model are expressed in Table I.

TABLE I. Model Initial Parameters

Parameter indicator type	Numerical value
Smoothness parameter r λ_r	0.005 to 0.03
Spatial scale parameter σ	0 to 6
Model iteration times	100
Float	Le-3
Execute initialization times	1

PA and SNR were introduced as evaluation indicators. 12 patterns were selected for feature extraction, and some pattern samples are shown in Fig. 6.

(a) Image 1 (b) Image 2 (c) Image 3 (d) Image 4
(e) Image 5 (f) Image 6 (g) Image 7 (h) Image 8
(i) Image 9 (j) Image 10 (k) Image 11 (l) Image 12

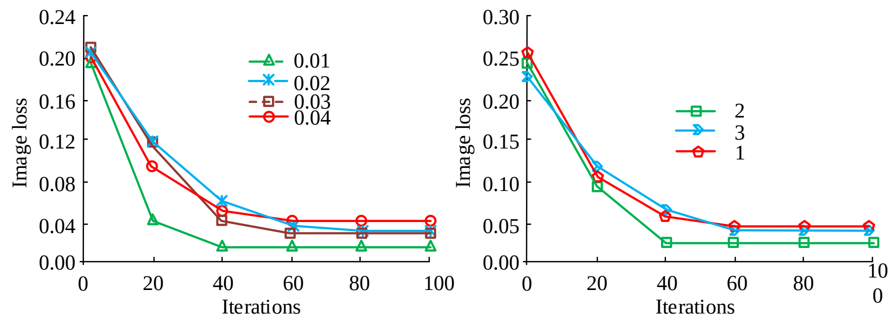
Fig. 6. Partial pattern data.

In actual feature extraction, the difference between λ_r

value and σ would directly affect the effect of image detail texture processing. Therefore, it is necessary to compare the image feature extraction under different parameters, as shown in Fig. 7.

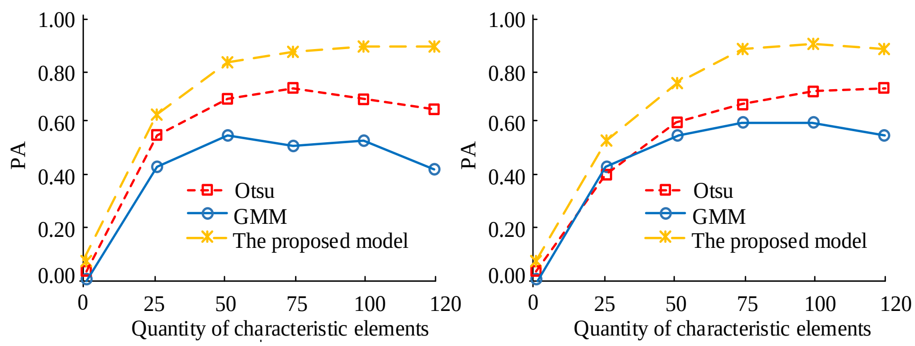
Fig. 7(a) and Fig. 7(b) express the comparison outcomes of λ_r and σ, respectively. Among them, when the λ_r parameter was set to 0.01, the model training image loss was the lowest, which was 0.012. At the same time, comparing the σ parameter settings of the model, when σ was set to 2, the training loss of the model was the lowest and the convergence effect could be achieved the fastest. Therefore, in subsequent experimental testing, the parameters were set to 0.01 and the σ parameter was set to 2. Image 1 and Image 2 were selected for feature extraction testing, and the test results are shown in Fig. 8.

Fig. 8(a) denotes the feature extraction test outcomes of Image 1. According to the results, when the amount of image elements was 120, the PA was the highest, at 0.903. Compared to this, both OTSU and GMM had a decrease in feature extraction performance after the number of pattern elements was 75. When the amount of image elements was 120, the PA of OTSU and GMM was 0.689 and 0.403, respectively. Fig. 8(b) shows the feature extraction test results of Image 1. The proposed model realized the highest PA of 0.909 when the number of pattern elements was 120, while the GMM model gradually decreased in PA after the amount of pattern elements was 100. The highest PA of OTSU and GMM were 0.786 and 0.526, respectively. Finally, the SNR was used to reflect the quality of feature extraction for different model elements. The effect of extracting cluster features for multiple models is shown in Fig. 9.



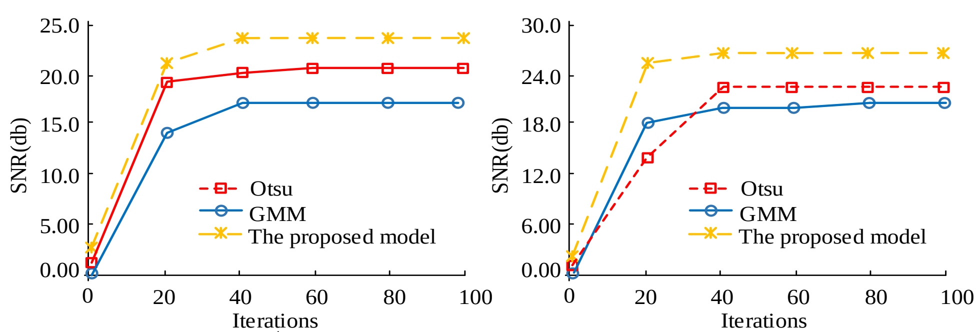
(a) Comparison of values for λ_r (b) Comparison of values for σ

Fig. 7. Comparison of image loss under different parameters.



(a) Image 1 (b) Image 2

Fig. 8. Comparison of pixel accuracy among different models.



(a) Image 1 (b) Image 2

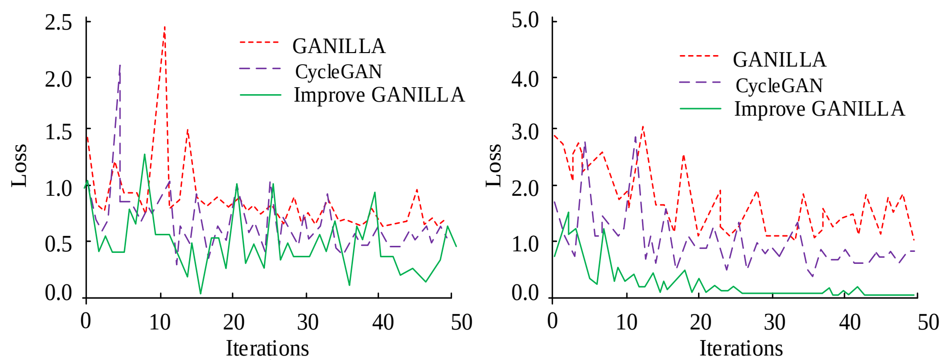
Fig. 9. Comparison of optimal SNR among different models.

Fig. 9(a) shows the feature extraction quality results of Image 1. From the data outcomes, as the amount of iterations increased, the image quality of all three models continued to improve. The best performing model was the one proposed, with an optimal SNR of 23.56 at convergence, followed by OTSU with an optimal SNR of 20.65, and GMM with an optimal SNR of 17.56. Fig. 9(b) shows the feature extraction quality results of Image 2. Before 40 iterations, the GMM model performed better than the OTSU model in extracting pattern features. In the early training, the GMM model had better feature extraction performance than the OTSU model. After training, the OTSU model could retain more black and white details during training, which was better than the GMM model. Overall comparison showed that the proposed model had the best feature extraction performance, followed by OTSU, and finally the GMM model. The optimal SNRs for the three models, from high to low, were 25.65, 22.86, and 19.98, respectively.

B. Experimental Analysis of Personalized Packaging Pattern Matching

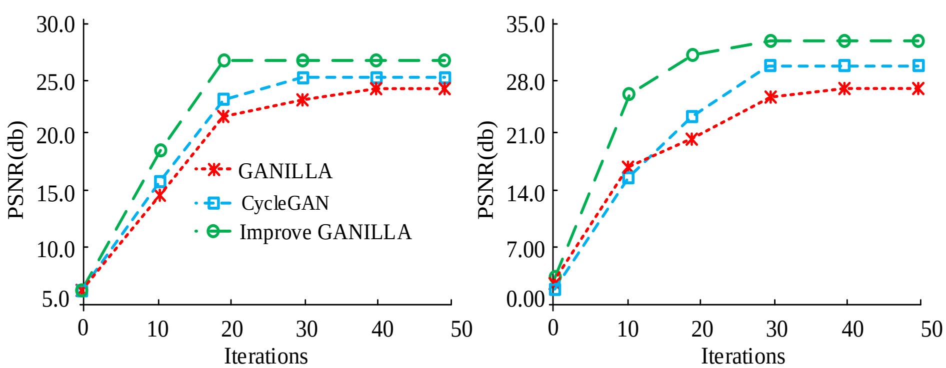
In the personalized packaging matching experiment section, the selected pattern features would be used as experimental data, and the proposed improved GANILLA model would be used as the pattern matching model. Meanwhile, the Cycle-Consistent Generative Adversarial Networks (CycleGAN) and GANILLA were introduced as experimental testing benchmarks. In the parameter settings, the Bachsize was 1, the optimization algorithm was Adam, the initialization step factor was 0.0002, and the experimental analysis was completed using the Pytorch platform. Mapping loss (Loss) and PSNR were introduced to reflect the quality of reconstructed images in the model. Two types of styles, Zhuang brocade pattern and blue and white porcelain pattern were selected for packaging matching. Fig. 10 shows the Loss results of different models.

Fig. 10(a) shows the packaging matching test results under the Zhuang brocade pattern. In the early stage of testing, both the CycleGAN model and the GANILLA model showed significant fluctuations. Considering the overall situation, it was possible that the two models were unable to accurately recognize the color of the pattern during the early training, resulting in a decrease in image transfer quality. Compared to this, the proposed model had smaller overall fluctuations during training and lower Losses. When GANILLA, CycleGAN, and improved GANILLA converged, the Losses were 0.542, 0.512, and 0.135, respectively. Fig. 10(b) shows the packaging matching test results under the blue and white porcelain pattern. Due to the presence of more feature elements in the blue and white porcelain pattern, it further tested the model's ability to recognize features. Overall, the proposed improved GANILLA model performed the best with a Loss of 0.236 at convergence, while the CycleGAN model and GANILLA model had Losses of 0.956 and 12.35 at convergence, respectively. Finally, the PSNR was used to reflect the quality effect of pattern matching, as shown in Fig. 11.



(a) Zhuang brocade pattern (b) Blue and white porcelain pattern

Fig. 10. Comparison of mapping loss results for different models.



(a) Zhuang brocade pattern (b) Blue and white porcelain pattern

Fig. 11. Comparison of peak signal-to-noise ratio for different model pattern combinations.

Fig. 11(a) and Fig. 11(b) respectively show the packaging matching test results of Zhuang brocade pattern and blue and white porcelain pattern. In the combination of Zhuang brocade patterns, the proposed improved GANILLA converged the fastest and had the highest PSNR of 25.65 among the three models. The GANILLA model performed the worst, with the best PSNR of 24.15 during convergence. In the combination of blue and white porcelain patterns, the best performance was still the proposed improved GANILLA model. The improved GANILLA, CycleGAN, and GANILLA had the best PSNRs at convergence of 32.32, 29.32, and 27.03, respectively. From the above experiment, the proposed model had better testing performance in packaging pattern matching. The matching effect of the final packaging pattern is shown in Fig. 12.

Fig. 12. Packaging pattern matching effect.

V. Discussion

In recent years, with the rapid development of the e-commerce industry, product packaging has played an increasingly important role in attracting consumer attention and increasing sales. The diversification and personalization of packaging design have become one of the important strategies for brand competition. The packaging beautification design based on the combination of visual images and personalized patterns is an innovative design method proposed to meet this demand. The study will conduct in-depth discussions on it. Visual image technology refers to an interdisciplinary technology that utilizes computer vision and image processing techniques to analyze, process, and apply images. It mainly includes image acquisition, processing, analysis, and application. In the field of design, visual image technology has been widely applied in product, web, advertising designs, and other aspects. By processing and analyzing images, functions such as image enhancement, restoration, segmentation, and detection can be achieved, thereby improving design effectiveness and user experience. Packaging beautification design refers to the design and adjustment of the appearance, pattern, color, form, and other aspects of product packaging to meet the aesthetic needs and brand image of consumers, and to attract the attention of target consumers, enhancing the market competitiveness of the product. Packaging beautification design includes various contents, such as the selection and design of packaging patterns, color matching, material selection, position and size of patterns, etc. By cleverly utilizing these design elements, product packaging can be made more attractive, unique, and effectively convey the brand's value and characteristics.

A visual image-based packaging beautification design technology was proposed in the study, which utilized advanced image segmentation processing technology and image transfer technology to achieve personalized and efficient development of packaging images. In the experiment of pattern feature extraction, by comparing the image feature extraction under different parameters, it was found that the proposed model achieved the best training loss and convergence effect when the parameters were set to 0.01 and 2. Meanwhile, compared with traditional OTSU and GMM models, the proposed model performed better in PA and SNR, and had higher feature extraction quality. This indicated that visual image technology had significant advantages in packaging image data processing compared to similar technologies, laying the foundation for subsequent packaging beautification design. In the personalized packaging pattern matching experiment, by comparing the proposed improved GANILLA model with CycleGAN and GANILLA models, it was found that the improved GANILLA model achieved better Loss and PSNR ratio results in the packaging matching of Zhuang brocade patterns and blue and white porcelain patterns. This meant that the proposed model could more accurately transfer the colors and features of patterns during the pattern matching process, improving the quality and effect of pattern matching.

It can be seen that by using visual image technology, accurate extraction and analysis of image features can be achieved, providing scientific basis and guidance for packaging beautification design. The proposed technology also has significant advantages compared to similar technologies. In the experiments of pattern feature extraction and pattern matching, the proposed techniques have shown excellent results. Therefore, research-proposed technology can make packaging design more creative and personalized, improving the attractiveness and competitiveness of packaging.

VI. Conclusion

Product packaging design is one of the important means to showcase product functions and concepts, and the effectiveness of product packaging design has a significant impact on product competitiveness. Traditional packaging design faces problems such as long design cycles and single packaging design. An intelligent packaging pattern beautification technology was proposed for this. Firstly, based on product positioning, a pattern feature extraction method was proposed, which preserved the main features of pattern elements through pattern smoothing, segmentation, and binarization processing. Secondly, a pattern matching technique was proposed, which used the GANILLA model to train features and experiment with the transfer of pattern features. Simultaneously, AM was introduced to improve the model and enhance image details. In the feature extraction experiment of Image 1, when the number of image elements was 120, the PA of OTSU, GMM, and the proposed model were 0.689, 0.403, and 0.903, respectively. In the SNR test, the optimal SNRs of the proposed model, OTSU, and GMM models in Image 2 were 25.65, 22.86, and 19.98, respectively.

In the packaging pattern matching experiment, the Losses of different models were compared. Under the Zhuang brocade pattern, the sound losses of CycleGAN, GANILLA, and improved GANILLA were 0.542, 0.512, and 0.135, respectively. Finally, the matching effects of different model patterns were compared. In the PSNR test of blue and white porcelain patterns, the improved GANILLA, CycleGAN, and GANILLA had the best PSNRs at convergence of 32.32, 29.32, and 27.03, respectively. The proposed model had excellent application effects in packaging beautification design. However, the study did not provide personalized design for different target groups. However, there are also limitations to the research technology. This technology has a slower efficiency in image processing, and in the future, model parameters can be optimized to improve image processing efficiency. At the same time, image data can be preprocessed to improve the application effect of the technology.

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