International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-13

https://doi.org/10.70917/ijcisim-2026-0075
Article

Extraction of Traditional Chinese Patterns for Jewelry Design Innovation Using Computer Vision Technology

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Abstract: The use of traditional Chinese patterns in jewelry design has a long history, in order to realize the innovation of the design method, this paper uses computer vision technology to extract traditional Chinese patterns. After preprocessing the traditional pattern images, the edges of the images are detected by the improved Canny algorithm. Then the features of traditional Chinese patterns are extracted by the cascade fine segmentation algorithm in order to be integrated into modern jewelry design. The image extraction effect of the cascade fine segmentation algorithm in this paper is tested, and it is found that its extraction accuracy is far more than other image segmentation and extraction algorithms. The Chinese traditional pattern jewelry designed by this paper's computer vision technology gains "better" evaluation results among the viewer groups. The method proposed in this paper is feasible for the integration of Chinese traditional patterns into the jewelry design field.

Keywords: computer vision techniques; image segmentation; traditional Chinese patterns; jewelry design

1. Introduction

With the rapid development of the times, various new materials and modern manufacturing technologies have continuously emerged in jewelry design, accompanied by a steady influx of ideas and concepts pursuing trends and individuality [1-3]. The design industry is currently in a new era of clashing and converging ideas and concepts, particularly under the influence of Western values and cultural trends. Chinese design is subject to the "dual" influence of localization and internationalization, leading to issues such as inconsistent design stances, unclear design philosophies, and severe trends of imitation and repetition [4-5]. For a long time, China's jewelry design market has been overly focused on catering to mass tastes, neglecting the market's inherent role in leading and guiding trends. Without the foresight and guidance to lead fashion trends, design loses its inherent meaning [6-7]. Therefore, innovating while returning to tradition is the common demand of jewelry design in terms of form, style, content, and craftsmanship. It is believed that Chinese jewelry design can also take returning to tradition as an important path for design, thereby finding the essence and original intent of design.

As an art form beloved by people in China and around the world, traditional Chinese patterns bear the deep imprint of ethnic culture, exuding a strong sense of ethnic artistic flair. They represent the distillation of thousands of years of Chinese artistic thought and cultural heritage, the accumulation of ethnic culture, and the wisdom of ancient ancestors [8-9]. Patterns, or "decorative motifs," refer to the collective term for decorative designs on objects. The term "pattern" emphasizes the character "sample," indicating that it is intended for production and manufacturing purposes. It is not used directly as a design draft but undergoes craftsmanship processing to be manifested on crafts or daily necessities, thereby fulfilling its artistic function. As an indispensable part of Chinese traditional culture, patterns reflect the customs and practices of different periods and regions in China's historical development. The earliest patterns were simple and straightforward, such as the bold and powerful totem patterns on bronze ware, and the intricate and elaborate patterns of flowers, birds, fish, and insects on the utensils and clothing used by nobles and aristocrats, all of which reflect the unique artistic concepts of each period [10-12].

Traditional Chinese patterns are a category within traditional Chinese art, often drawing inspiration from flowers, birds, fish, insects, the sun, moon, stars, proverbs, folk sayings, and legends. They incorporate auspicious meanings into their designs to express beautiful wishes and blessings. This form of pattern creation, which uses homophones to convey deeper meanings, connects Chinese culture with the emotions of the Chinese people [13-15].

Therefore, combining traditional patterns with contemporary jewelry design is undoubtedly one of the most effective ways to return to tradition [16]. However, how to integrate the stylistic characteristics, aesthetic expressions, and forms of traditional patterns with contemporary design concepts and methods to create jewelry that is both traditional and contemporary is an important challenge facing the design community today.

In this context, Literature [17] takes traditional Chinese textile patterns as its research object. To address issues such as outdated pattern styles, lack of innovation, and high costs of manual design, it employs conditional generative adversarial network models and computer-aided technology to generate entirely new patterns with traditional pattern characteristics, while retaining the foundational structure of traditional patterns for innovative design. Literature [18] employs the directed gradient histogram method to extract density features from batik images and uses a multi-layer perceptron as a classification method to determine accuracy levels, thereby achieving feature extraction and classification of Indonesian batik patterns. Literature [19] proposes a traditional pattern segmentation algorithm based on a memory learning model to address the complexity of traditional pattern variations and material texture interference, enhancing segmentation robustness and accuracy. A traditional pattern dataset was constructed to validate its effectiveness. Literature [20] suggests that the coordinated effects of color, material, dyeing patterns/shapes, and narrative content can reveal the expressive value and emotional characteristics of jewelry design. These elements are integrated through the perception of representative images to design and create exquisite jewelry.

The author firstly continues the preprocessing of Chinese traditional pattern images, and detects the edges of the images using the genetic improvement Canny operator to obtain the Chinese traditional patterns. Then the cascade fine segmentation algorithm is used to extract the traditional patterns. The extracted traditional patterns are combined with modern jewelry design. In order to ensure the superiority of this paper's traditional pattern cascade fine segmentation algorithm in image extraction, it is experimented with other image segmentation and extraction algorithms to verify its effectiveness. In order to obtain the viewer's evaluation of the jewelry integrating traditional Chinese patterns, the evaluation index system is constructed, the evaluation data are obtained by questionnaire, and the final evaluation results are calculated by SPSS software.

2. Chinese Traditional Pattern Extraction

2.1. Characteristics of Traditional Patterns

Traditional Chinese patterns refer to a collection of decorative motifs and elements that have been handed down and widely used in a specific historical lineage and regional environment. They deeply reflect the social structure, religious beliefs, aesthetic concepts and artistic characteristics of the era in which they were created, and generally contain rich symbolism and cultural meanings. These patterns have evolved and developed over a long period of time, and have been displayed in a variety of media, such as clothing, architecture, utensils, paintings, etc. They not only serve the functional purposes of decoration and beautification, marking and differentiation, but also act as an important carrier of cultural symbols, carrying the uniqueness and diversity of different ethnic groups and regions and their cultural traditions.

Traditional patterns have diversity and complexity in form, color, size and arrangement, which contain rich cultural connotations and symbolic meanings. This complex and varied structure makes it difficult to accurately capture the boundaries and internal details of traditional tattoos in semantic segmentation, which leads to less precise segmentation results. In addition, the carriers of traditional tattoos are diversified, and each carrier has different characteristics and structures. This diversity makes it necessary to consider different backgrounds and environments when semantically segmenting traditional tattoos from different carriers, which increases the complexity of the segmentation task.

In view of the deep and complex semantic characteristics carried by traditional patterns, their rich cultural connotations, historical symbols and artistic expressions show remarkable uniqueness in the field of visual information processing, and their meanings often go beyond the pure visual forms and are deeply rooted in specific historical backgrounds, national customs and philosophical thoughts.

2.2. Pattern Image Preprocessing

2.2.1. Grayscaling

The tattoo information in the sample generally carries rich colors, and grayscaling serves to eliminate the influence and interference of colors. The graying formula is as follows:

$$A_{(i,j)} = 0.30R_{(i,j)} + 0.59G_{(i,j)} + 0.11B_{(i,j)} \tag{1}$$

where $A_{(i,j)}$ represents the gray value at image (i,j); $R_{(i,j)}$, $G_{(i,j)}$, and $B_{(i,j)}$ represent the original red, green, and blue color 3 components.

2.2.2. Image Smoothing Denoising

Due to the presence of noise in the captured image, which tends to blur the details of the pattern, a denoising model needs to be used to remove the noise. In this paper, the denoising model is designed based on Convolutional Neural Network (CNN), which can automatically learn the representation of features in the image without manually designing the features. Secondly, through convolutional operations and contextual information utilization, CNN can capture local and global features in images and better adapt to the denoising problem with noise and nonlinear attributes. In addition, CNN's large-scale data training and flexible network structure design enable the model to learn accurate robust denoising capabilities from a large amount of data. In addition, CNN supports fine-tuning and migration learning to accelerate the training process and improve the generalization performance. The CNN model in this paper is as follows:

$$C_{(i,j)} = f(A_{(i,j)}w_{ij} + a_{ij}) \tag{2}$$

where $C_{(i,j)}$ represents the smoothed filtered image; w_{ij}, a_{ij} represent the connection weights and thresholds, respectively; $f(\ )$ represents the excitation function; and $A_{(i,j)}$ represents the noisy texture-containing image after grayscaling.

The steps of model training are as follows:

(1) Prepare training samples: prepare a batch of image samples that do not contain noise as a training set.

(2) Add noise: add noise to the above image samples that do not contain noise to generate a noisy image.

(3) Define the model structure: choose CNN model to process the noisy image.

(4) Model training: take the noisy image as input, and calculate the prediction result of the denoised image through the model's operations of convolution, pooling and fully connected layers, and then compare the prediction result with the corresponding original image to calculate the signal-to-noise ratio between the two.

(5) Optimize model parameters: according to the signal-to-noise ratio calculated during training, adjust the weights and threshold parameters in the model.

(6) Completion of training: When the signal-to-noise ratio calculated during the training process of the model reaches the preset requirements, the training of the model can be considered complete.

(7) Application of the model: after the training is completed, the acquired image containing noise is input to the trained model, and the output of the model is the denoised smoothed filtered image.

2.2.3. Texture Removal

The different texture information presented on the texture image makes the texture structure intertwined with the texture, which increases the difficulty of texture extraction at a later stage, therefore, texture removal is especially necessary. Texture removal is a technique in computer graphics that focuses more on filtering out the high-frequency part of the texture, so that the details in the texture can be guaranteed even if the texture is removed.

2.3. Image Edge Detection Based on Improved Canny Operator

2.3.1. Adaptation Function Design

Aiming at the shortcomings of the traditional Canny operator [21], this paper proposes a method based on the adaptive determination of thresholds by genetic algorithms, which automatically determines the double thresholds according to the features of each image. The key to optimize the effect of Canny operator image edge detection with genetic algorithm lies in the design of the fitness function. Drawing on the idea of Otsu algorithm to maximize the variance of gray value between classes to determine the threshold automatically, this paper sets the variance of gradient magnitude of pixel points in two classes, background and edge, as the fitness function. Adopting traversing all possible thresholds to calculate the objective function is computationally intensive, and the use of genetic algorithm to solve the optimal threshold can improve efficiency.

Otsu algorithm sets the threshold value to divide the pixel points into two categories of target and background regions [22-23], calculates the variance of the gray value between the two, and selects the threshold corresponding to the maximum variance as the image segmentation threshold. In the Canny operator edge detection algorithm, the determination of whether a pixel point is an edge point is based on the gradient magnitude of the pixel point, rather than the gray value. Therefore, in this paper, pixel points are classified into two categories of D_1, D_2 based on their gradient magnitude, where D_1 is a non-edge point in the original image, containing pixel points with gradient magnitude of $\{t_1, t_2, \cdots, t_k, t_{k+1}, \cdots, t_{m-1}\}$; D_2 is an edge point in the original image, containing pixel points with gradient magnitude of $\{t_{k+1}, t_{k+2}, \cdots, t_m, t_{m+1}, \cdots, t_l\}$ pixel points, and k and m are the low and high thresholds of the Canny operator, respectively. Let the total number of pixel points in the image be N, and the number of pixel points corresponding to a gradient magnitude of t_j be n_j, with probability $p_j = n_j / N, (j = 1, 2, \cdots, l)$. The gradient magnitude expectation of the whole image is:

$$E = \sum_{j=1}^{l} t_j \cdot p_j \quad (3)$$

expectation of the gradient magnitude within class D_1, D_2, respectively:

$$e_1(k,m) = \frac{\sum_{j=1}^{k} t_j \cdot p_j + \sum_{j=k+1}^{m-1} t_j \cdot p_j}{\sum_{j=1}^{k} p_j + \sum_{j=k+1}^{m-1} p_j} \tag{4}$$

$$e_2(k,m) = \frac{\sum_{j=k+1}^{m} t_j \cdot p_j + \sum_{j=m}^{l} t_j \cdot p_j}{\sum_{j=k+1}^{m} p_j + \sum_{j=m}^{l} p_j} \tag{5}$$

And define:

$$p_1(k,m) = \sum_{j=1}^{k} p_j + \sum_{j=k+1}^{m-1} p_j ; p_2(k,m) = \sum_{j=k+1}^{l} p_j + \sum_{j=m}^{l} p_j \tag{6}$$

The objective function is defined as:

$$\sigma^2(k,m) = p_1(k,m)[e_1(k,m) - E]^2 + p_2(k,m)[e_2(k,m) - E]^2 \tag{7}$$

Similarly, the k, m corresponding to the maximum of the interclass variance $\sigma^2(k,m)$ of the gradient magnitude of the two classes of pixel points is the optimal threshold for the Canny operator.

2.3.2. Genetic Algorithm to Optimize Canny Operator

The process of optimizing Canny operator edge detection by genetic algorithm is the process of solving the optimal solution of Eq. (7), and the optimal solution of Eq. (7) is the optimal threshold of Canny operator for each image. The main steps of genetic algorithm to optimize Canny operator edge detection are as follows:

(1) Population initialization. Set the population size n, the mutation probability P_m, the maximum number of evolutionary generations T, the maximum number of current generations G, and randomly generate n individuals as the initialized population P_0. Where the population size n if too large is easy to find the optimal solution, but the amount of computation becomes large, increasing the running time; if too small the amount of computation is small, the running time is short, and it is difficult to find the global optimal solution, it is appropriate to set it at 20~100. The variation rate P_m is generally small, 0.05~0.1 range is more appropriate. The maximum evolutionary algebra T is too small, the algorithm is not easy to converge, the population is not mature; the maximum evolutionary algebra T is too large, the algorithm is already skillful or the population is too precocious to converge, and it makes no sense to continue evolution, which will only increase the time expenditure and waste of resources. After many

experiments found that the algorithm iteration to about 10 times the maximum fitness has stabilized, the algorithm convergence, this paper will set the maximum number of iterations to 20.

(2) Encoding and Decoding. Gray code is used, as a kind of deformation of binary coding, which has all the advantages of binary coding and at the same time has a better local search ability. The value range of low threshold TL and high threshold TH is set to [0,255], corresponding to the length of each chromosome is 8.

(3) Adaptation degree evaluation. Equation (7) was used as the fitness function.

(4) Selection. A tournament selection algorithm is used, which mimics the elimination tournament system by randomly selecting Tourn individuals in the population each time and letting them compete, and the one with the best fitness value will be selected as the parent. The operation is repeated until the size of the selected set reaches the number of individuals to be selected. The number of individuals participating in the tournament is Tourn, the size of the competition, and there are commonly binary and ternary tournaments. The tournament selection operator randomly selects participants for comparison, increasing the diversity and randomness of the population. The optimal individuals are prevented from dominating the population [100], avoiding premature convergence and falling into local optimal solutions.

(5) Crossover. Two-point crossover is used, i.e., two crossover points are randomly set in the coding strings of two individuals paired with each other, and part of the chromosomes of the two individuals between the two set crossover points are exchanged.

(6) Mutation. A mutation operation based on the polynomial variation operator is adopted to mutate each locus in the chromosome with probability P_m. In polynomial variation, the current element value is added with a certain probability plus a value that obeys a polynomial probability distribution to a neighboring value.

(7) Algorithm termination. When there is no significant improvement in adaptation in successive T_c generations, or when the maximum number of evolutionary generations T is reached, the iteration is terminated, the optimal threshold is obtained, and the edge detection is input into the Canny operator, and the edge map of the image of the weaving and embroidery artifacts is obtained in the end.

2.4. Pattern Acquisition

Expansion is one of the most fundamental morphological transformations and is used in many aspects of the image processing field, such as noise elimination, element segmentation, and concatenation. Expansion is an operation to find a local maximum, according to $A \oplus B = \{z \mid (\hat{B})_z \cap A \neq \varnothing\}$ morphological expansion. Where A is the image, B is a 3*3 rectangular solid kernel with its anchor point at the center, and $A \oplus B$ denotes that A is inflated by B. Its role is to fill the edge depressions, internal grooves, etc. of the segmented blemish image. Morphological expansion of the edge image solves the connection problem of the fractured region to a certain extent, and makes the contour of the pattern clearer so that the subsequent work can capture the most essential shape characteristics of the pattern.

2.5. Cascade Fine Segmentation Algorithm for Traditional Patterns

2.5.1. Pattern Feature Extraction

Traditional convolutional neural networks extract features from images through convolutional layers, and each convolutional kernel slides over the image and performs convolution operations, in which the convolutional kernel captures the local spatial correlation of the image, and uses the hierarchical structure formed by stacking different convolutional layers, each layer will extract features at different levels, from edges and textures to high-level abstractions. However, convolutional neural networks also have some inherent limitations, such as over-reliance on local features, limited detection ability of small targets, etc., in order to solve these problems, this paper uses ViT to extract image features, which does not rely on convolution operations, but uses a self-attention mechanism to consider all parts of the input image globally. The efficient capture of global features of images and the intuitive modeling of long-range dependencies are realized, which overcomes the limitations of traditional convolution in direct modeling of long-distance dependencies of images.

2.5.2. Token Clustering and Reconstruction

In order to solve the problem of excessive resource consumption in processing high-resolution texture images, this paper adds a nonparametric token clustering layer and a reconstruction layer on the basis of the existing ViT model [24], which realizes the path that the input of ViT is shifted from the high-resolution image to the low-resolution features, and then reconstructs the high-resolution features at last, so as to greatly improve the inference speed while maintaining the prediction performance, and does not need any additional training or fine-tuning parameters, and directly use the pre-trained ViT model weights to obtain a model with more efficient inference speed.

The token clustering layer is responsible for reducing the high-resolution token representation to a low-resolution representation. The clustering layer uses a clustering method based on the k-means algorithm, which can better describe the association relationship between samples and centers and capture the intrinsic structure in the feature space by calculating the probability of each sample to each center, and is computationally simple and efficient without learning any parameters.

In the first step, the initial clustering center is initialized, and the high-resolution feature maps are downsampled using adaptive average pooling (AAP) operation to obtain the initial clustering center at low resolution. In the field of image segmentation, the sizes of input images may vary greatly, and adaptive average pooling can effectively handle input data of different sizes and extract stable feature representations. As shown in Equation (8), Z_α represents the high-resolution feature map, and the low-resolution preliminary clustering center S_α is obtained after AAP operation:

$$S_\alpha = AAP(Z_\alpha, (h \times w)) \tag{8}$$

In the second step, iteratively update the clustering centers and calculate the similarity between each token Z_i and the surrounding λ clustering centers $S_{\alpha,j}$, and the probability of each token belonging to each clustering center $Q_{\alpha,i}$ is obtained by using softmax normalization calculation:

$$Q_{\alpha,i} = \frac{\exp\left(-\left\|Z_{\alpha,p} - S_{\alpha,j}\right\|^2 / \tau\right)}{\sum_{j=1}^{\lambda} \exp\left(-\left\|Z_{\alpha,p} - S_{\alpha,j}\right\|^2 / \tau\right)} \tag{9}$$

The third step, the maximization step, inputs the probability $Q_{\alpha,i}$ computed in the previous step, updates the position of each clustering center so that it is equal to the expected value, and finally outputs the updated low-resolution clustering center $S_{\alpha,i}$:

$$S_{\alpha,i} = \sum_{p=1}^{N} Q_{p,i} Z_{\alpha,p} \tag{10}$$

Repeat the above operation of steps 2-3 for several iterations to optimally update the cluster center position until the center position converges or the maximum number of iterations is reached, and output the final cluster in S_α as a low-resolution representation. S_α serves as the input to the subsequent module, replacing the original high-resolution features Z_α to complete the high- to low-resolution conversion.

The token reconstruction layer is responsible for reconstructing the low-resolution representation output from the token clustering layer into a high-resolution representation. Specifically, it takes the low-resolution tokens output from the token clustering layer as input, uses an encoder-decoder structure to encode the low-resolution tokens into high-dimensional features, and finally reconstructs the features into high-resolution representations semantically similar to the original high-resolution inputs by means of a decoder. By inserting this layer, it is possible to improve the efficiency by utilizing the low-resolution representation while obtaining the detail information through reconstruction, recovering the high-resolution representation, and to some extent recovering the spatial structure information lost in the clustering process.

The token reconstruction layer mainly uses the classical self-encoder framework of Encoder-Decoder. The encoder uses a multilayer perceptron as the encoder to encode the low-resolution token representation into high-dimensional features, and the decoder also uses a multilayer perceptron as the decoder to decode and reconstruct the high-dimensional features into the same size of the original high-resolution representation, and then uses a reconstruction loss function, L2, to measure the difference between the decoded output and the input as the loss, and uses the gradient descent method to optimize the encoder and decoder's parameters of the encoder and decoder to minimize the loss, and finally output the reconstructed representation with the same size as the original high-resolution token:

$$L2 = \sum_{i=1}^{n} (y_i - f(x_i))^2 \tag{11}$$

3. Use of Traditional Cultural Patterns in Jewelry Design

3.1. The Significance of Traditional Patterns in Modern Jewelry Design

From ancient times to the present, human ancestors to explore their own ingenuity, to create a brilliant pattern symbols, each period has the representative pattern of the period, through the pattern we can peep out of the period of history and culture and people's aesthetic consciousness. These rich pattern gallery for our jewelry design today provides unlimited creative ideas, but also for the world jewelry culture to add a thick ink.

Mention of traditional patterns, people will generally associate with ancient ceramics on the blue and white pattern, bronze Taotie pattern, etc., but the modern jewelry design is not contrary to the traditional culture and patterns, but often from the traditional pattern of borrowing from the available elements, borrowing from traditional patterns to design and produce jewelry works than commercial models of the many products obviously have more highlights, in the modern exudes In modernity, there is a sense of simplicity and culture, and in tradition, there is a sense of fashion. Just as in the opening ceremonies of many famous film festivals or major fashion shows, Chinese elements can often be seen, and the reason why it can be clearly identified that this set of clothing or this piece of jewelry comes from the ancient East is because of the forms and patterns of symbols borrowed from the epitome of traditional culture that is deeply rooted in our minds. It is the international stage that gives us an international display platform, the use of traditional patterns and symbols of jewelry works will have a higher cultural and visual recognition, Chinese culture and tradition to the world, so that the world through the window of traditional patterns to understand China. Therefore, modern jewelry design is walking on the road of combining traditional jewelry design patterns with modern jewelry design trends.

In modern jewelry design, there is also a contradiction between tradition and trend, we can not abandon the traditional patterns, beautiful symbols, but also in today's highly informative and modern society. Traditional patterns need to be protected, but this does not mean that we should be addicted to the traditional swaddling clothes, to find a suitable material carrier to carry on its heritage and development, is the meaning of the combination of traditional patterns and modern art design.

3.2. The Use of Traditional Patterns in Modern Jewelry Design

This paper mainly takes the traditional patterns of plants and geometric patterns as an example to talk about its combination with modern jewelry design.

3.2.1. Combination of Traditional Plant Motifs and Jewelry Design

As early as in the primitive society, people will have close contact with plants, often found in colored pottery plant patterns and seed patterns, in the Miaodigou culture has been unearthed in the petal pattern pottery. In the Wei, Jin, North and South Dynasties era of plant patterns are mostly manifested in the Lonicera, Eight Treasures, Lotus pattern, the traditional pattern by the deeper influence of Buddhist culture, patterns of many subjects, most of the content is related to the Buddhist scriptures. Sui and Tang dynasties, the high degree of economic and cultural prosperity, plant pattern modeling full and rounded, smooth and generous lines, floral pattern, scroll pattern became the mainstream pattern. To the two Song dynasty plant pattern pursuit of natural beauty, the overall natural, dexterous, elegant, beautiful style, showing a subtle, static beauty. To the Ming and Qing Dynasties, the types and themes of plant motifs further increased, due to the frequent exchanges between the Ming and Qing Dynasties, foreign plant motifs were also imported into China, and traditional plant motifs are integrated, the overall plant motifs give a more lively feeling, plant motifs are also used in a large number of forms of art, the use of a variety of ways of processing to produce a variety of plant-themed jewelry.

Filigree inlay is China's traditional jewelry processing technology, its long history, the processing of works produced by the extremely fine, but also one of the eight jewels of Yanjing. In ancient times, filigree inlay was mainly used for the royal family, mostly using gold and silver as raw materials, through pinching, filling, piling, basing, weaving, knitting, saving, welding and other techniques for production, the finished product for the exclusive use of the royal family.

Ancient Chinese painters gave life to the trees in their many forms in nature, and highly summarized and refined their patterns, so that the branches and trunks, the thick and the thin, could reach harmony and unity. We can also find a match with jewelry, which is beneficial to our jewelry design and decorative art creation today. Noble wood can also be combined with jewelry, perhaps because of their small size can not play its role in furniture design, but in another way, they can be used as a “jewel” in jewelry design. The strong texture contrast between wood and metal, together with the collision of colors, will get a new visual experience, and the noble wood can continue to shine in another new carrier.

Traditional patterns can also be produced through modern jewelry processing and production methods, and can achieve the visualization of the parameters, controllable, through the modeling of jewelry, can be convenient to retain the parameters of jewelry, dynamic jewelry design, and can be used in modern production equipment for fast and accurate production, mass production.

3.2.2. Combination of Traditional Geometric Patterns and Shapes with Jewelry Design

Geometric patterns include plane geometric patterns and three-dimensional geometric patterns, and various geometric patterns can often be seen in ancient artifacts excavated in China, such as circular patterns, triangular patterns, back-shaped patterns, etc. Geometric patterns are more modern and fashionable in today's society. Geometric patterns are relatively simple and modern, and the use of geometric patterns in jewelry design has become fashionable in today's society.

The design and composition of traditional geometric patterns pay attention to the sense of wholeness and details, emphasize the organic combination of points, lines and surfaces, and pursue changes in the regular whole. There are distinctive embodiments in the arts and crafts works of various historical periods in China, and the use of traditional geometric patterns should also pay attention to the use of points, lines and surfaces, so that the whole of the jewelry is more hierarchical and rhythmic.

4. Pattern Extraction and Jewelry Design Effect Analysis

4.1. Analysis of Traditional Pattern Extraction

In order to verify the effectiveness and accuracy of this paper's algorithm, the automatic image segmentation algorithms of Gaussian mixture model clustering (LGMM, SGMM, LSGMM) are analyzed experimentally with the traditional texture cascade fine segmentation algorithm proposed in this paper, as well as a variety of other segmentation algorithms, and other segmentation comparison algorithms selected in this section are the background a priori salient graph segmentation method (SO, adopting OTSU method to complete the segmentation), GC segmentation method (subjective selection of seed points, 5 iterations), using three datasets including BSD, ASD and CGO, segmentation metrics using accuracy, recall, F-value and other evaluation indicators of the dimensions of the comparative analysis, to validate this paper's traditional texture cascade segmentation algorithms, the experimental environment is configured for MacOS Mojave, 2.3 GHz Intel The experimental environment is configured as MacOS Mojave, 2.3 GHz Intel Core i5, 8GB 2133 MHz LPDDR3, Matlab R2017b. The experimental results show that the traditional texture cascade fine segmentation algorithm not only reduces the cost of manpower and time, but also the segmentation results are relatively complete, retains more details, and is more robust to changes in illumination.

4.1.1. Comparison with Gaussian Mixture Model Clustering Image Segmentation Algorithm

The image automatic segmentation algorithm based on Gaussian mixture model clustering adopts the center-periphery assumption when calculating the saliency map, and fails to make full use of the boundary information of the image, so the segmentation algorithm needs to be improved. In this paper, the traditional pattern cascade fine segmentation algorithm makes full use of the boundary information of the image to calculate the saliency map by combining the idea of center-periphery assumption and background prior assumption, and optimizes the saliency map by the texture operator with strong robustness to the lighting change. In this subsection, the traditional pattern cascade fine segmentation algorithm of this paper and the automatic image segmentation algorithm based on Gaussian mixture model clustering are experimented on the selected images in the CGO dataset to compare and analyze the segmentation results and validate the algorithm of this paper. The F-value comparison results of the segmentation results of this paper's algorithm and the three algorithms (LGMM, SGMM, LSGMM) for automatic image segmentation based on Gaussian mixture model clustering are shown in Table 1. From Table 1, it can be seen that this paper's algorithm has a higher F-value relative to the LGMM, SGMM, and LSGMM algorithms, showing a more obvious advantage.

Table 1. F value comparison results.

Algorithm	LGMM	SGMM	LSGMM	Ours
F value	0.7256	0.7514	0.8065	0.9278

4.1.2. Performance Comparison with Other Algorithms

In order to further illustrate the effectiveness of the traditional pattern cascade fine segmentation algorithm in this paper, the algorithm in this paper is compared with SO and GC. The accuracy, recall and F-value of this paper's algorithm and other algorithms on ASD, BSD and CGO datasets are shown in Table 2, which shows that this paper's algorithm has better segmentation results compared to other algorithms, with higher accuracy, recall and F-value. Compared with SO algorithm, the F-value of this paper's algorithm on each dataset is improved by 2.85%, 13.97% and 9.42%, in which the F-value on the BSD dataset is significantly improved, the reason is that the threshold segmentation method in the segmentation of unevenly illuminated images has greater limitations, resulting in a reduction in the accuracy of segmentation, and also proves that this paper's traditional ripple cascade fine segmentation algorithm is more robust to changes in lighting It also proves that the traditional grain cascade fine segmentation algorithm in this paper is more robust to light changes.

Table 2. Algorithm comparison results.

		Ours	SO	GC
ASD	Precision	0.9785	0.9702	0.9234
	Recall	0.9364	0.9015	0.9564
	F	0.9489	0.9204	0.9346
BSD	Precision	0.9689	0.9274	0.8936
	Recall	0.9052	0.7122	0.8941
	F	0.9365	0.7968	0.8735
CGO	Precision	0.9475	0.9602	0.9311
	Recall	0.9423	0.7829	0.9452
	F	0.9516	0.8574	0.9366

The F-value comparison results of this paper's traditional tattoo cascade fine segmentation algorithm with SO and GC algorithms on BSD, ASD, and CGO datasets are shown in Tables 3 to 5, from which it can be seen that the computational accuracy of this paper's algorithm has a more obvious advantage over SO algorithm, and this paper's algorithm is able to maintain a higher accuracy without the help of manual labeling, compared with GC algorithm.

Table 3. F value comparison in BSD dataset.

Experiment number	Ours	SO	GC
1	0.9408	0.8845	0.6403
2	0.9314	0.9044	0.6819
3	0.9022	0.8787	0.7107
4	0.9215	0.8459	0.7676
5	0.9178	0.8957	0.8092

Table 4. F value comparison in ASD dataset.

Experiment number	Ours	SO	GC
1	0.8878	0.8731	0.8755
2	0.9632	0.8846	0.8839
3	0.9602	0.8355	0.9719
4	0.9687	0.9657	0.9282
5	0.9131	0.8794	0.8208
6	0.8673	0.8754	0.8659
7	0.7565	0.7953	0.8062
8	0.9761	0.9832	0.9329
9	0.8313	0.7909	0.8039
10	0.9513	0.9496	0.9174

Table 5. F value comparison in CGO dataset.

Experiment number	Ours	SO	GC
1	0.9147	0.7702	0.8854
2	0.9781	0.7639	0.8317
3	0.9789	0.6978	0.8747
4	0.9495	0.9632	0.9236
5	0.8974	0.7781	0.8934
6	0.9555	0.9282	0.9405
7	0.7969	0.7899	0.8526
8	0.8994	0.6771	0.8227
9	0.9561	0.9002	0.8872
10	0.9664	0.9641	0.9396
11	0.8285	0.6059	0.7994
12	0.9624	0.8718	0.9146
13	0.9009	0.7454	0.8814
14	0.8115	0.7664	0.8592
15	0.9634	0.8633	0.8843

4.2. Analysis of Subjective Perception of Jewelry Design Effects

In order to understand the audience's perception of traditional Chinese patterns applied to modern jewelry design, this paper first constructs a subjective evaluation index system of jewelry design effect as shown in Table 6.

Table 6. Evaluation index system for jewelry design effect.

	Primary index	Secondary index
Jewelry design effect	Artistic and aesthetic value (X1)	Originality and uniqueness (X11)
		Formal beauty and balance (X12)
		Color collocation and application (X13)
		Material texture and expression (X14)
		Topic expression and narrative (X15)
		Style consistency (X16)
	Wearability and ergonomics (X2)	Comfort (X21)
		Stability and security (X22)
		Proportion and scale sense (X23)
		Wearability convenience (X24)
		Daily applicability (X25)
	Craftsmanship and quality (X3)	Structural rationality (X31)
		Metal machining accuracy (X32)
		Gem mosaic craftsmanship (X33)
		Surface processing quality (X34)
		Detail processing refinement (X35)
		Material authenticity (X36)
	Commercial value and market fitness (X4)	Target audience fitness (X41)
		Cost control and pricing rationality (X42)
		Identification (X43)
		Market trend fitness (X44)
		Productability and efficiency (X45)
		Packaging and presentation effect (X46)
	Emotional resonance and symbolism (X5)	Emotional arousal ability (X51)
		Cultural significance (X52)
		Personalized potential (X53)
		Sense of value(X54)
		Treasure willingness (X55)

In order to follow up the evaluation survey, the index weights are calculated for the above jewelry design effect evaluation index system, and the results are shown in Table 7.

Table 7. Evaluation index weight for jewelry design effect.

	Primary index	Weight	Secondary index	Weight
Jewelry design effect	Artistic and aesthetic value (X1)	0.2304	X11	0.1584
			X12	0.1665
			X13	0.2049
			X14	0.1715
			X15	0.1438
			X16	0.1549
	Wearability and ergonomics (X2)	0.1826	X21	0.2011
			X22	0.2045
			X23	0.1993
			X24	0.2065
			X25	0.1886
	Craftsmanship and quality (X3)	0.2121	X31	0.1812
			X32	0.1554
			X33	0.1562
			X34	0.1635
			X35	0.1672
			X36	0.1765
	Commercial value and market fitness (X4)	0.1645	X41	0.1762
			X42	0.1535
			X43	0.1495
			X44	0.1691
			X45	0.1756
			X46	0.1761
	Emotional resonance and symbolism (X5)	0.2104	X51	0.2205
			X52	0.1404
			X53	0.2257
			X54	0.2111
			X55	0.2023

Based on the evaluation index system constructed in this paper to design the survey questionnaire, will use the method designed in this paper to integrate the traditional Chinese patterns of jewelry for display, the questionnaire is issued to the visitors, the effective questionnaires recovered for data collation and statistics. A total of 300 questionnaires were issued, 276 questionnaires were recovered, with a recovery rate of 92%, of which 264 were valid questionnaires, with an effective rate of 88%. With 20, 40, 60, 80, 100 represent very poor, poor, average, good, very good respectively as the rating standard. SPSS analysis software was used to statistically analyze the visitors' evaluation of jewelry incorporating traditional Chinese patterns, and the results are shown in Table 8.

As can be seen from the results in Table 8, the Chinese traditional pattern jewelry designed by the method of this paper received an overall rating of 87.3, which is a “better” evaluation result among the visitors. In the five primary indicators of artistry and aesthetic value, wearability and ergonomics, craftsmanship and quality, commercial value and market fit, emotional resonance and symbolism, the scores were 88.2, 84.2, 88.6, 84.1 and 90.4, respectively, and the evaluation of the five primary indicators were all “better”. In the evaluation of secondary indicators, only the proportion and size sense (X23), wearing convenience (X24), cost control and pricing reasonableness (X42) are below 80 points, which belongs to the category of “general” evaluation, and the rest of the indicators get “better” evaluation. Results.

Table 8. Evaluation results for jewelry design effect.

	Primary index	Score	Evaluation	Secondary index	Score	Evaluation
Jewelry design effect (87.3)	Artistic and aesthetic value (X1)	88.2	Good	X11	92.8	Good
				X12	82.7	Good
				X13	94.2	Good
				X14	86.6	Good
				X15	86.4	Good
				X16	84.8	Good

	Wearability and ergonomics (X2)	84.2	Good	X21	90.8	Good
				X22	82.9	Good
				X23	78.6	Normal
				X24	76.8	Normal
				X25	92.4	Good
	Craftsmanship and quality (X3)	88.6	Good	X31	89.1	Good
				X32	89.7	Good
				X33	83.4	Good
				X34	90.9	Good
				X35	93.8	Good
				X36	84.8	Good
	Commercial value and market fitness (X4)	84.1	Good	X41	86.0	Good
				X42	73.1	Normal
				X43	85.4	Good
				X44	85.2	Good
				X45	90.7	Good
				X46	83.1	Good
	Emotional resonance and symbolism (X5)	90.4	Good	X51	90.6	Good
				X52	85.3	Good
				X53	94.6	Good
				X54	93.0	Good
				X55	86.3	Good

5. Conclusion

This paper uses computer vision technology to extract traditional Chinese patterns, and then integrates traditional patterns with modern jewelry design. The effect of this paper's pattern extraction technology is explored, and the subjective perception of the viewers on the jewelry designed by this paper's method is statistically analyzed.

The traditional pattern cascade fine segmentation algorithm of this paper has an F-value of 0.9278 in comparison with the automatic image segmentation algorithms (LGMM, SGMM, LSGMM) with Gaussian mixture model clustering.The algorithms of this paper have the optimal extraction effect in comparison with SO and GC algorithms, with 0.9489, 0.9365, and 0.9516 on ASD, BSD, and CGO datasets.

The overall score of the jewelry works designed by this method with traditional Chinese patterns was 87.3, and the evaluation result was "good". All Level 1 indicators were scored above 80 points, which fell into the "good" category, and the highest score was "emotional resonance and symbolism" with 90.4. Among the secondary indicators, only the proportion and size sense (X23), wearing convenience (X24), cost control and pricing rationality (X42) belong to the "average" category, and the rest of the indicators all exceed 80 points.

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