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Application of Computer Vision in the Recognition of Intangible Cultural Heritage Patterns and Cultural and Creative Design

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Abstract With the rapid development of the digital era, the inheritance of intangible cultural heritage is facing the crisis of fading, and this problem is particularly prominent in Hainan Li brocade culture. Aiming at these problems, this paper constructs a set of non-heritage pattern recognition and reconstruction system based on computer vision, and innovatively designs a deep learning architecture. The architecture adopts a coding and decoding network structure, which effectively retains the high-level semantic information and the underlying feature information contained in the pattern through the deep fusion of multi-scale features between different layers. An asymmetric convolutional layer is introduced in the feature extraction process to avoid additional consumption of computational resources and significantly enhance the model's ability to capture pattern details. A pattern reconstruction architecture based on generative adversarial network is also developed, and a residual multi-head self-attention mechanism is incorporated into its generator, so that the reconstructed non-heritage patterns can maintain the original cultural characteristics and present a more delicate and realistic visual effect. In the specific application in the field of cultural and creative design, a complete digital resource library of non-heritage patterns is established to realize the intelligent matching between traditional cultural elements and contemporary design needs. The study proves that the deep learning-based pattern recognition and reconstruction method breaks through the limitations of traditional techniques in detail preservation and cultural characteristics inheritance, and realizes the two-way goal of digital protection and innovative application of non-heritage patterns. This research provides novel technical ways for the digital protection of intangible cultural heritage, and also indicates a brand-new direction for the innovative development of cultural and creative industries.

Index Terms intangible cultural heritage, computer vision, deep learning, generative adversarial network, cultural and creative design

I. Introduction

In today's rapid development of the information society, the protection and inheritance of traditional culture is facing unprecedented challenges. Intangible cultural heritage, as an important carrier of national spirit and cultural memory, is gradually marginalized by modern lifestyle and commercial entertainment culture [1], [2]. Especially in the context of the era of highly digitized visual cultural communication, ICH patterns, a traditional form of artistic expression, are undergoing a drastic change from physical to virtual [3]. Many precious traditional patterns are at risk of being lost, blurred or even misinterpreted due to the limited means of recording, poor preservation environment and unsound inheritance mechanism.

At the same time, cultural and creative industries are becoming an important hand of the country to promote the enhancement of cultural soft power and economic structure transformation [4]. Designers and creators have a growing demand for traditional cultural elements, however, existing NRL patterns are often difficult to be directly used in modern design creation, not only because of the low quality and aging form of the images, but also because of the lack of systematic and standardized digital resource management methods [5], [6]. How to protect the authenticity and integrity of NRL culture while integrating it with contemporary aesthetics and technical language has become a new proposition for NRL inheritance.

In this context, the development of artificial intelligence technology, especially computer vision and deep learning, provides a strong technical support to solve this problem. Through high-precision pattern recognition, intelligent reconstruction and style migration, it can not only digitally preserve the patterns of non-heritage, but also provide clear, high-quality and culturally rich image materials for cultural and creative design [7]. This way of embedding technological innovation into the cultural inheritance system not only enhances the accessibility of non-heritage culture, but also builds a bridge of innovative integration between tradition and modernity, which is of great significance and practical value of the times [8], [9].

This study aims to promote the digital protection of non-heritage patterns and the transformation of cultural creativity, and builds an overall methodological system around the three key aspects of “identification-reconstruction-design”. Firstly, through the construction of deep learning model, automatic identification and feature extraction of low-quality NRL patterns, to realize the accurate capture of their complex texture and cultural features; secondly, design pattern reconstruction algorithm integrating multi-scale information and attention mechanism, to improve the visual clarity and cultural integrity of the pattern; lastly, combined with the pattern digitization resource library and the generation of design system, to realize the intelligent matching between NRL elements and modern cultural and creative design. Finally, combining the pattern digitization resource library and design generation system, it realizes the intelligent matching between non-heritage elements and modern cultural and creative designs. On the basis of technical performance and cultural semantics, the whole study builds a set of closed-loop chain from heritage protection to creative design, and promotes the revitalization and dissemination of non-heritage culture in modern society.

In recent years, with the continuous progress of computer vision technology, the recognition and reconstruction of non-heritage cultural patterns have gradually become one of the key areas of academic attention [10]. Through the careful analysis of related literature, it is obvious that the heat of this research direction continues to grow, especially in pattern quality improvement and its cultural value mining, which has made significant technical breakthroughs [11], [12]. Specific literature search data, as shown in Table 1, show the active exploration and innovation of domestic and foreign researchers in this field in recent years, reflecting the academic community's strong interest and increasing attention to this field.

Table 1: Statistics of relevant literatures

Database	Search for keywords	Initial literature quantity	The number of screened literatures
CNKI	Culture and intelligent technology, etc.	5098	1153
WOS	Digital Intelligence and Culture	-	473

II. Computer vision-based non-heritage cultural pattern recognition and reconstruction methods

II. A. Theoretical basis of the study

The research of non-heritage pattern recognition and reconstruction technology based on computer vision needs to rely on the theoretical support of multiple disciplines [13]. In recent years, deep learning has become a core technology in the field of computer vision and has made significant breakthroughs in the field of image processing. Its main principle lies in the construction of multi-level neural network structure, which enables it to automatically extract and learn deep features in images. In particular, convolutional neural network (CNN) has been widely used in many fields by virtue of its advantages in image processing [14]. CNN extracts local features in an image through convolutional operations and enhances its spatial feature extraction ability by stacking multiple convolutional layers [15]. In this process, the basic mathematical expression of convolution operation is:

$$y = f(\sum_{i=1}^{n} w_i \cdot x_i + b) \tag{1}$$

where w_i denotes the weight of the convolution kernel, x_i is the feature map of the input image, b is the bias term, and f is the nonlinear activation function. Such a structural design enables the CNN to effectively extract the detailed features when dealing with non-legacy patterns, while ensuring that the spatial information and local relationships of the patterns are not lost, laying a technical foundation for the accurate recognition of patterns. This is exactly where the value of convolutional neural network is applied in the recognition of non-heritage patterns, especially in the detail level of patterns, the powerful function of CNN is fully utilized.

On the other hand, Generative Adversarial Network (GAN) provides another powerful technical framework for image reconstruction [16]. Through adversarial learning between generators and discriminators, GAN is able to generate high quality images while maintaining high accuracy of cultural features. The loss function can be expressed as:

$$L = E_{x \sim P_{data}(x)}[\log D(x)] + E_{x \sim P_z(z)}[\log(1 - D(G(z)))] \tag{2}$$

This adversarial mechanism enables GAN to effectively preserve the details and cultural features of the original non-heritage patterns in image generation, which enhances the realism and detail expression of the image.

Especially in the reconstruction process of the non-heritage pattern, the discriminator of GAN learns the feature distribution of the real pattern by continuously adjusting the parameters, so as to guide the generator to continuously optimize the generated image and make it closer to the original pattern. This type of adversarial learning not only improves the clarity of the pattern, but also enhances the presentation of details, which greatly promotes the digital protection of non-heritage culture.

Therefore, deep learning technology has shown great potential in the protection and innovative development of non-heritage culture. Through the comprehensive application of technologies such as super-resolution reconstruction of images, style migration and intelligent creation, deep learning provides powerful technical support for the digital protection and creative inheritance of non-heritage culture. By establishing a complete technical system, we are able to realize the whole process of digitization from the collection, processing to application of non-heritage patterns, which not only promotes the inheritance of traditional culture, but also opens up a new path for its development in modern society.

II. B.Data Acquisition and Preprocessing

Constructing a high-quality dataset of non-heritage cultural patterns is the fundamental work of this research. In this paper, we carried out an in-depth study on representative non-heritage patterns such as Li brocade and Tantou New Year paintings, and collected more than 5000 original images as the basic dataset through the use of professional photographic equipment. In the actual acquisition process, we encountered problems such as uneven illumination and image distortion, for which we used professional light source control equipment and standard color cards for environmental light control, and at the same time repeatedly debugged the camera's aperture, shutter speed and other shooting parameters, so as to realize the acquisition of non-heritage images. Aiming at these original image data, this paper designs a set of pre-processing procedures including denoising, enhancement and standardization. The algorithm based on wavelet transform is used to eliminate the noise introduced by the environment and equipment, and the histogram equalization technique is used to improve the image contrast and detail performance. Then all images are uniformly adjusted to 512*512 pixel resolution and zero-mean normalization is performed to make the pixel value distribution more suitable for the training requirements of deep learning algorithms.

In order to enhance the scale and diversity of the dataset, we implemented systematic data augmentation and broadening processing on the original images. The original dataset is expanded to 25,000 images by performing geometric transformations such as rotating, flipping, and scaling the images, as well as adjusting visual parameters such as brightness, contrast, and saturation. During the enlargement process, special attention was paid to the preservation of cultural features. Through detailed comparative analysis of the images before and after the enlargement, it was verified that the enlargement operation did enhance the detailed expressiveness of the images while preserving the cultural features of the NRL patterns. The data set is divided into training set, validation set and test set according to the ratio of 7:1:2 by adopting the stratified sampling method, and the balanced distribution of various types of patterns is fully considered during the division to avoid the phenomenon of data distribution offset. A perfect data annotation system for non-heritage images is established, and the cultural features, types and quality levels of each image are carefully labeled.

Table 2: Image quality assessment data

Preprocessing stage	PSNR (dB)	SSIM	LPIPS	Processing time (ms)
Original image	25.32	0.7124	0.452	-
Denoising processing	27.65	0.7856	0.386	45
Enhanced processing	29.43	0.8235	0.312	38
Standardized processing	31.87	0.8647	0.284	32

In the data quality control link, an automated quality assessment system was developed, integrating functional modules such as clarity assessment, feature integrity detection and cultural feature retention analysis. The system can automatically identify and screen out image samples with substandard quality to ensure that the data entering the model training session have a high quality level. Table 2 shows the results of the image quality assessment in the super-resolution reconstruction of the Lijin pattern. By analyzing the objective evaluation indexes of the processed dataset, it is found that the pre-processed and quality-controlled images have gained significant improvement in the indexes of floating point parametric quantities (LPIPS), peak signal-to-noise ratios (PSNR), structural similarity (SSIM), and processing time, which provide a reliable basic support for subsequent algorithmic research and model training. In the experimental process, we found that image preprocessing has a decisive impact on the final recognition effect, especially when dealing with some non-heritage patterns that are old and poorly preserved, a suitable preprocessing method can effectively improve the recognizability and reconstruction quality of the patterns.

II. C.Pattern Recognition and Reconstruction Algorithm Design

To address the complex and variable characteristics of non-heritage patterns, this study constructs a deep learning recognition and reconstruction algorithm framework, which achieves its goal by combining the two-branch structure of convolutional neural network responsible for feature recognition and generative adversarial network dealing with pattern reconstruction. In the feature recognition branch, a network structure based on multi-scale feature extraction is designed to adapt to the multi-level cultural connotations embedded in the NRL patterns. The spatial attention mechanism is introduced in the study to enhance the model's ability to recognize cultural features, while the residual connection structure effectively alleviates the gradient vanishing problem caused by network deepening. In the generative adversarial branch, the detail reconstruction capability is enhanced by incorporating a multi-scale residual block and a channel attention module in the generator, and the loss function is optimized for the problem of training instability. Generator G and discriminator D enhance the reconstruction quality through adversarial learning, while incorporating a cultural feature preservation term to ensure the inheritance of artistic features.

In the experimental stage, a phased training strategy is adopted to achieve synergistic optimization of the two branches through the progressive training method of pre-training-reconstruction-fine-tuning. Table 3 shows the reconstruction comparison results between this paper's model and traditional methods. The experimental data show that this algorithm improves the recognition accuracy by 15.3% compared with the traditional method, reaching 92.7%, and the peak signal-to-noise ratio of the reconstructed image is improved to 33.56dB, and the structural similarity index reaches 0.948, which is especially good in dealing with the complex texture patterns such as Lai Jin. In the study, we also try to improve the model by group convolution and channel pruning techniques to lighten the model, which reduces the amount of parameters by 45% and improves the processing speed by 2.3 times while guaranteeing the performance. Although these optimizations are effective, the problems of insufficient data volume and overfitting are still found to be further solved during practical application, and more improvement schemes will be explored in the future to enhance the practicality of the algorithm.

Table 3: Model comparison results

Index	Traditional method	This method
Accuracy rate	77.4%	92.7%
PSNR (dB)	20.11	33.56
SSIM	0.826	0.948
LPIPS	0.944	0.519

II. D.Practical Application Cases and User Experience Evaluation

Taking Tantou New Year's Paintings as the core research object, this study, through in-depth cooperation with Tantou New Year's Paintings Non-Genetic Inheritance Base, digitally captures and reconstructs 50 typical and representative traditional New Year's Paintings. In the process of practice, it was found that the reconstructed patterns not only completely retained the flavor of traditional art, but also achieved significant improvement in image clarity and detail presentation, which provided a high-quality digital material base for the subsequent cultural and creative design. Based on these high-quality reconstruction results, the research team has developed a cultural and creative product line covering a wide range of categories such as home accessories, stationery products, clothing accessories and digital artwork, etc. Especially in the field of digital artwork, augmented reality technology realizes the in-depth fusion of traditional New Year's Paintings with the modern media, allowing users to feel the charm of the dynamic rendition of New Year's Paintings in real time through mobile devices.

Through multi-dimensional evaluation methods such as questionnaires, in-depth interviews and user behavior analysis, the research team collected data from 2,547 valid questionnaires and 128 in-depth interviews during the 6-month market testing cycle. Table 4 shows the results of the user experience assessment. The assessment results show that the cultural and creative products are highly recognized by users in terms of visual performance, cultural value and usage experience, with a high user satisfaction score of 4.71 (out of 5) for digital artworks, and young consumer groups aged 18-35 showing great interest in such innovative products. Market performance data further confirmed the commercial value of the products, with sales growth of 188.6% in the digital artwork category, and sales growth of 165.8% and 153.2% in the stationery and clothing accessories categories respectively. Market data verified the feasibility of this technology route, with the market acceptance of digital artwork reaching 94.5%, nearly doubling that of traditional products. Based on the analysis of user feedback on social media and e-commerce platforms, it is found that “cultural heritage”, “design innovation” and “practical value” constitute the main dimensions of positive evaluation by users, and these dimensions are consistent with this study's promotion of NRL. These dimensions are highly compatible with the original purpose of this study, which is to promote the innovative development of NRL culture. Users' suggestions on product price and personalized customization also provide important references for future optimization, and these practical experiences fully prove the great potential of computer vision technology in promoting the innovative development of traditional culture.

Table 4: User experience assessment results

Product type	Design quantity	Market recognition (%)	Sales growth rate (%)	User satisfaction
Home decorations	38	86.5	142.3	4.32
Stationery	45	92.7	165.8	4.56
Clothing and accessories	42	88.9	153.2	4.28
Digital artworks	35	94.5	188.6	4.71

III. Conclusions and outlook

This study has achieved significant results through in-depth exploration of computer vision-based pattern recognition and reconstruction methods for non-heritage culture. At the technical level, the deep learning framework proposed in this study effectively breaks through the bottleneck of traditional pattern reconstruction techniques, and the combination of multi-scale feature extraction and spatial attention mechanism adopted significantly improves the clarity and detail restoration of patterns. The cultural feature preservation module introduced in the Generative Adversarial Network (GAN) ensures that the original cultural features are preserved in the pattern reconstruction process, which makes the pattern not only have high-quality visual effects, but also faithfully inherit the traditional cultural elements. The experimental results show that the peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) of the reconstructed images are significantly improved, which proves the effectiveness and superiority of the method.

From the application point of view, the lightweight model designed in this study has great practical value, which reduces the amount of model parameters by 45% while maintaining high recognition accuracy, and improves the processing speed by 2.3 times, which provides a realistic and feasible technological solution for the large-scale processing of digitization of non-heritage cultural patterns. Especially in the application of cultural and creative design of Tantou New Year's Paintings, the market performance of the digital artwork is outstanding, with a sales growth rate as high as 188.6%, which verifies the commercial potential of this technical solution in the cultural and creative industry.

However, this study still faces some challenges. First, the existing dataset is not large enough to cover more rare and dated patterns, which affects the generalization ability of the model. Second, despite the optimization of existing techniques, high-resolution pattern processing still suffers from the problem of long time consumption, and there is still room for improvement in inference speed. In addition, there are differences in marketing and consumer acceptance, especially the middle-aged and old-aged groups have low acceptance of digital cultural and creative products.

To address these issues, future research can be carried out in the following directions: first, expanding the size of the dataset, especially by obtaining more rare samples through cross-regional cooperation; second, exploring lightweight deep learning architectures to reduce the computational overhead and improve efficiency; and third, optimizing the marketing strategy, especially by expanding the market penetration of the cultural and creative products through the differentiation of the product experience and promotion methods. These directions will further improve the effect of digital protection and application of non-legacy patterns and promote the digital transformation of cultural and creative industries.

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