Automatic Extraction and Reconstruction of Drawing Design Elements Based on Computer Vision and Neural Networks

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Abstract. The research aims to explore the vision and neural networks in painting and design and propose a method for automatic extraction of painting and design elements and computer-aided design (CAD) reconstruction based on recurring networks. Through this method, it is hoped that automatic extraction and reconstruction of painting design elements can be achieved while providing more creative inspiration. This article investigates how to use RNN to achieve automatic extraction of painting and design elements, including identification and extraction of lines, colours, composition, and other elements. Moreover, the study discusses in detail how to reconstruct the extracted painting design elements in CAD and achieve a parameterized representation of design elements for subsequent editing and modification. The pre-improvement image matching error rate is between 9% and 10%, while the improved matching error rate is between 3% and 5%. This indicates that the improved method significantly reduces the error rate of image matching. The minimum error rate before improvement was 9%, while the maximum error rate after improvement was 4.5%, further verifying the effectiveness of the improvement method. By constraining the model parameters, the regularization term prevents overfitting of the model on the training data, allowing the model to better generalize to the test data and improve the accuracy of matching.

Keywords: Computer Vision; Neural Networks; Painting and Design Elements; Automatic Extraction; CAD Reconstruction
DOI: https://doi.org/10.14733/cadaps.2024.S18.50-65

1 INTRODUCTION

In the field of painting design, artists do hand drawing or design work. With the rapid progress, computer vision and neural networks in the field of art have attracted more and more attention. Art is the crystallization of human civilization and wisdom; however, its complex details and subtle style often make its diagnosis and analysis challenging. We have the opportunity to explore the mysteries of art with new perspectives and methods. Amura et al. [1] explored how to apply these advanced technologies to achieve automatic extraction of design elements from artwork images and combine them with CAD (Computer Aided Design) systems for 3D reconstruction of artwork. Automatically extract features such as lines, colours, and textures from artwork images through algorithms, providing basic data for subsequent image analysis. Utilize trained neural network models to automatically classify artwork images, such as style, period, author, etc. By comparing the differences between artwork images and normal images, possible traces of repair, damage, or forgery can be automatically detected. Neural networks have powerful learning and generalization abilities. In art feature extraction, neural networks construct deep neural networks to learn complex features and representations in art images, improving the accuracy of image classification and recognition. By utilizing pre-trained neural network models on large-scale datasets and transferring them to other art datasets for fine-tuning, fast feature extraction and recognition can be achieved. By training generative adversarial networks, art images with specific styles or features are generated, providing new possibilities for artistic creation and restoration. These advanced technologies provide artists and designers with new tools and perspectives, making the process of artistic creation and design more intelligent. Designers can use these advanced technologies to realize the automatic extraction and reconstruction of painting design elements. Andriani et al. [2] explored how to optimize the automatic extraction of design elements in landscape painting drawings by combining technology. Firstly, the basic concepts of computer-aided process planning and pull production technology were introduced, and then how to combine these two and apply them to the extraction of design elements in landscape painting drawings was explained. Finally, the feasibility and advantages of this method were demonstrated through an example. CAD simulates and optimizes the manufacturing process of products, which can greatly improve production efficiency and quality. Pull production process is a customer-oriented production method that can quickly respond to market demand and reduce inventory costs. In the process of extracting design elements from landscape painting drawings, combining CAD with pull production technology can achieve more efficient and accurate extraction of design elements and improve production efficiency and quality. The pull production process is a customer-oriented production method that achieves the goal of quickly responding to market demand and reducing inventory costs through methods such as just-in-time production and lean production. The pull production process emphasizes flexibility, timeliness, and refinement in the production process. A certain landscape painting manufacturing company adopted the above method to optimize the production process. By combining CAD with the pull production process, the company has achieved more efficient and accurate extraction of design elements and production management. Its application, in combination with deep learning, makes the tasks of image identification, target detection, and image generation take a qualitative leap. In fields such as architecture, engineering, and manufacturing. However, the traditional CAD model creation process often requires manual input and adjustment; we can reconstruct CAD models by automatically extracting design elements from drawings, thereby improving design efficiency. Ben et al. [3] explored how to use computer vision technology to extract deformed surface meshes and further reconstruct CAD models. Deformable surface mesh extraction is one of the key steps in reconstructing CAD models. We first need computer vision analysis on the drawings to extract the deformed surface mesh. To verify the model reconstruction method for deformable surface meshes based on computer vision for automatic extraction of drawing design elements proposed in this article, we selected an actual case for experimentation. The experimental extract deformed surface meshes from drawings and successfully reconstructed CAD models. Compared with traditional manual input methods, this method greatly improves design efficiency and reduces error rates. This provides rich tools and methods for painting design, which enables designers to extract useful information from massive image data more conveniently and provide inspiration for creation. The growth of neural network technology also provides powerful tools for data analysis and pattern identification. However, currently, most BIM systems still rely on manual operations for data input, which undoubtedly limits their application in large and complex projects. Byun and Sohn [4] proposed a method for automatically generating building information models from 2D CAD drawings, focusing on the automatic extraction and reconstruction process of design elements. After extracting design elements, we need to reconstruct the building information model based on this information. This involves technologies such as 3D modelling and computer graphics. Specifically, we can use point cloud technology to perform a 3D reconstruction of each design element and then use BIM software to combine these elements. Compared with traditional manual input methods, this method greatly improves design efficiency and reduces error rates. From the initial perceptron to the current deep learning network, neural network technology has realized the transition from simple linear classification to complex pattern identification. Chowdary and Jaglal [5] discussed extracting design elements of rotating parts from 3D graphic drawings, reconstructing CAD models through reverse engineering methods, and further conducting rapid prototyping design. Computer vision is mainly used for image recognition and processing in this process, automatically extracting design elements of rotating parts from 3D graphic drawings, such as shape, size, texture, etc. By using image processing algorithms and deep learning techniques, these design elements can be effectively identified and extracted, greatly improving design efficiency. Reverse engineering is a technique that deduces the design principles or manufacturing process of a physical object in reverse. In the CAD model reconstruction of rotating parts, reverse engineering methods can help us convert design elements extracted from 3D graphic drawings into CAD models. The design elements of rotating parts from 3D graphic drawings were extracted, CAD models were successfully reconstructed through reverse engineering, and actual samples were manufactured using rapid prototyping technology. This method improves design efficiency, shortens the product development cycle, and has high practical value.

Analyzing and understanding the shape of images is an important task. Complex geometric sketching, as a form of image, is of great significance for analysis and understanding due to its unique visual effects and artistic value. Đurić et al. [6] proposed a method for complex geometric sketching based on computer vision models in imaging, aiming to extract and analyze design elements and features in complex geometric sketching. Firstly, we need to preprocess the input complex geometric sketch image, including steps and image enhancement, to improve the quality and clarity of the image. Then, we use computer vision techniques such as edge detection and feature extraction to extract various features and elements from the image. These features include lines, shapes, colours, etc., which constitute the basic design elements of complex geometric sketching. After extracting the design elements, we need to perform shape analysis on them and reconstruct the corresponding two-dimensional model. This involves computer graphics and 3D modelling techniques. Specifically, we can use point cloud technology to convert each design element into 3D point cloud data and then use 3D modelling technology to convert these point cloud data into 2D models. In this process, we need to pay attention to maintaining the shape and features in the original image. Based on video streaming it has become an important means of modern art creation. However, traditional art drawing design methods often require designers to manually extract design elements. Therefore, Guo and Li [7] use neural network techniques such as Generative Adversarial Networks (GANs) to optimize and reconstruct the extracted design elements. Specifically, we train a generator network to generate new design elements and use a discriminator network to evaluate the quality of the generated design elements. Through continuous iteration and optimization, we can obtain more beautiful and high-quality design elements. This module is responsible for extracting keyframes from video streams and preprocessing them, such as denoising and enhancement, to improve the accuracy of subsequent processing. This module utilizes computer vision technology to automatically recognize and classify preprocessed keyframes, extracting key design elements such as lines, shapes, and colours. This module combines optimized design elements into multiple possible design solutions based on the needs and preferences of designers for designers to choose and modify. These research results show the extensive application and potential of computer vision and neural networks in the field of painting design and provide new tools and perspectives for artists and designers.

Guo and Wang [8] discussed how these two factors can play a role in sculpture space design, especially in the automatic extraction and expression techniques of design elements in drawings. Computer vision technology provides new possibilities for sculptural spatial design. Firstly, through image processing technology, designers can automatically recognize and analyze design drawings, thereby extracting key design elements. For example, designers can use techniques such as edge detection, colour separation, and shape matching to extract key information such as contours, textures, and colours of sculptures from drawings. In addition, computer vision evaluates the spatial effects of sculpture design. Designers can evaluate the visual effect of sculptures under different lighting conditions by simulating lighting on 3D models. Meanwhile, designers can also preview and evaluate the three-dimensional effects of sculpture design through computer vision technology. Although computer vision and neural networks have achieved some application results in the field of painting and design, there are still some challenges. For example, how to accurately extract useful design elements from complex images, how to effectively CAD reconstruct the extracted design elements, and how to improve the automation level of the entire process. An automatic extraction and CAD reconstruction method of painting and design elements based on RNN. By exploring the application of computer vision and neural networks in painting and design, this article helps to promote related technological innovation and provides more possibilities for the use of technology in the art field. The automatic extraction and CAD reconstruction method of drawing design elements based on RNN of drawing design reduces the workload of designers. By introducing advanced computer technology, research results can help expand the expression forms and styles of painting and design, providing artists and designers with more design ideas. This study includes the following innovations:

(1) The traditional methods for extracting elements from painting and design mainly rely on manual operations or simple image processing techniques. This article proposes the use of RNN for the automatic extraction of painting design elements, which improves the accuracy and efficiency of extraction by training models to recognize design elements such as lines, colours, and composition automatically.

(2) This article proposes a CAD-based reconstruction method for extracting painting design elements. Through parametric representation and digital processing, designers can flexibly edit and modify design elements in CAD software.

(3) Introducing advanced computer technology can bring more creative inspiration to artists and designers, helping to expand the forms of artistic expression.

Article organization:

Section 1: Introduction, introducing the research background and significance;

Section 2: Elaborate on the application of computer vision and neural networks in painting and design;

Section 3: Elaborate on the principles and model construction of RNN, as well as the identification and extraction methods of painting and design elements;

Section 4: Explore the principles, technical implementation, and application of CAD reconstruction;

Section 5: Experimental verification and performance evaluation, testing the application effect of the proposed method;

Section 6: Conclusion and Outlook, summarizing the content of the section and proposing future research directions.

2 RELATED WORK

The powerful functions and edits during the creative process greatly improve design efficiency. Jin and Yang [9] discussed visual and neural network-based art drawing design elements in art design teaching. CAD design software has precise graphic drawing capabilities, which can help students quickly draw accurate lines, shapes, and patterns. This helps students better understand the importance of precise measurement in art and design while also improving their design skills. Through CAD design software, students can create 3D models to better understand and present their design concepts. This three-dimensional perspective design approach can enhance students' sense of space and design ability. Thereby generating realistic visual effects. This helps students to make intuitive visual evaluations and adjustments during the design process. The importance of process planning in the production process is becoming increasingly prominent. Computer-assisted drawing design element automatic extraction process planning is a design method that utilizes artificial neural network technology. Krishnan and Gokulachandran [10] discussed the application of this method in process planning. Consisting of multiple interconnected neurons with powerful pattern recognition and prediction capabilities. Artificial neural networks can automatically extract features from input data through learning and training and perform tasks such as classification, prediction, and optimization based on these features. With the help of cloud computing technology, artificial neural networks can achieve efficient cloud collaboration and data sharing, improving the collaborative work efficiency and data utilization efficiency of design teams.

The amount of data involved in public art design is increasing. How to process this data efficiently has become an important issue. Multi-core processors and computer vision technology provide new ideas for solving this problem. Multi-core processors and computer vision technology. Li [11] discussed how these two can play a role in big data public art design and improve the efficiency and quality of design. The visualization of public art design requires a large amount of computational resources, such as rendering building models, simulating lighting, etc. Multi-core processors can accelerate these calculations and improve design realism and detail. Art creation is a highly personalized activity. Every artist has their own unique style, viewpoint, and way of expression. Their creations are often based on their own life experiences, emotional experiences, aesthetic concepts, and personal skills. These factors make artistic creation highly personalized and unique, making it difficult to simulate through programming or automation fully. Secondly, artistic creation is an experiential judgment. During the creative process, artists not only need to consider the form, structure, colour, and other aspects of their works but also need to consider the audience's feelings and experiences. This experiential judgment requires artists to have sharp perception and imagination, which is also difficult to achieve through programming or automation. However, in recent years, the progress of deep learning and artificial intelligence has changed this situation. Liu and Yang [12] discussed how to use contemporary technologies such as deep learning and artificial intelligence to extract design elements automatically from drawings. By utilizing deep learning image recognition techniques, various elements in a drawing, such as lines, colours, shapes, etc., can be automatically recognized and segmented. Automatic extraction can be achieved. By combining image recognition and segmentation with feature learning, we automatically generate design schemes. For example, based on the identified lines and colour features, a design scheme for an abstract painting can be automatically generated. After achieving automatic extraction of design elements from drawing drawings, maintaining the creativity of the design has become an important issue. One possible solution is to introduce the creativity and judgment of human designers, combined with artificial intelligence technology, to achieve automatic extraction of design elements centred on creativity.

Tang tomb murals are an important component of the treasure trove of ancient Chinese art, and their clothing depictions have profound historical and cultural connotations. However, due to historical and natural factors, many Tang tomb mural costumes have been damaged and faded, requiring archaeological and restoration work. Therefore, Liu et al. [13] utilize human-computer interaction technology to model the costumes in Tang tomb murals in 3D, providing accurate 3D models for subsequent restoration work. Reverse engineering is a technique that deduces the design principles or manufacturing process of a finished product or phenomenon in reverse. Reverse engineering can help us deduce the original form and structure of Tang Dynasty costumes from existing murals. Human-computer interaction technology is a technology that enables interaction between humans and computers. In the restoration of Tang tomb mural costumes, human-computer interaction technology can help experts operate and monitor the restoration process more intuitively. Through interactive devices such as touch screens and mice, experts can intuitively operate computers for repair operations while monitoring real-time data during the repair process. Using computer vision technology to evaluate the effect of restored Tang tomb murals, including the integrity of colour, texture, and structure.

Art drawings are a form of art that is rich in information and contains a large number of design elements and details. How to effectively extract these design elements and perform 3D mesh reconstruction on them is currently a hot research topic. Liu et al. [14] proposed a method for automatic extraction of design elements from art drawing drawings based on original detection, which can achieve automatic extraction of design elements and 3D mesh reconstruction while maintaining clear features of the drawings. The original image detection technology was used to extract design elements from art drawings. Specifically, we first use image processing techniques to preprocess drawing sheets to enhance image quality and remove noise. Then, we use deep learning techniques to classify and segment images to identify and extract various design elements, such as lines, shapes, colours, etc. After extracting the design elements, we need to convert them into a 3D mesh model. For this purpose, we adopted point cloud technology for 3D mesh reconstruction. Specifically, we first use image segmentation techniques to convert each design element in the image into point cloud data. Then, we use point cloud reconstruction algorithms to convert these point cloud data into 3D mesh models. In this process, we need to pay attention to maintaining clear features and details of the drawings to ensure that the reconstructed model remains consistent with the original image. With the arrival of the Industry 4.0 era, the precision manufacturing field has put forward higher requirements for accuracy, reliability, and real-time defect detection. Traditional defect detection methods mainly rely on manual inspection, but this method is not only inefficient but also susceptible to fatigue and human factors. Therefore, it is imperative to develop an efficient and accurate automatic defect detection method. Ren et al. [15] explore the application of machine vision-based neural networks in precision manufacturing defect detection of drawing design elements. Machine vision is a technology that obtains, processes, and analyzes image information by simulating the human visual system. In defect detection, machine vision is responsible for image acquisition and analysis, while neural networks achieve automatic recognition and classification of defects through training and learning of image data. Train a neural network using a large number of known defect types of images to enable it to recognize and classify defects. In this process, the neural network gradually approaches the ideal solution by continuously adjusting the weight matrix. Apply the trained neural network to image data in actual production processes to identify and classify defects automatically. Based on actual detection results, optimize and adjust the neural network model to improve the accuracy and reliability of defect detection.

In the manufacturing industry, process drawings are important documents that guide production and contain various information during the product manufacturing process. The traditional process of designing process drawings is cumbersome and prone to errors, which cannot meet the efficiency and accuracy requirements. The emergence of computer-aided process drawing design element automatic extraction and planning technology has brought revolutionary changes to the manufacturing industry. The application of computer-aided process drawing design elements, automatic extraction, and planning in manufacturing systems is becoming increasingly widespread. Soori and Asmael [16] discussed the research status, application classification, and important role of computer-aided process drawing design element automatic extraction and planning in manufacturing systems. Automatically recognize and extract design elements from process drawings through preset rules and algorithms. This method is suitable for process drawings with relatively fixed and simple rules. By training a large amount of sample data, machine learning algorithms can learn the features and patterns of design elements in process drawings, thereby achieving automatic extraction. This method is suitable for process drawings with complex and variable rules. The application of computer-aided process drawing design element automatic extraction and planning technology is especially important in fields such as architecture, engineering, and manufacturing. However, despite the powerful design and modelling capabilities of CAD software, its use often requires specific training and skills. We are exploring a new method that combines computer vision and neural network technology to automatically extract design elements from a 360-degree library and perform programmatic CAD reconstruction. Willis et al. [17] explored the dataset and runtime environment required to achieve this goal. In order to extract design elements from a 360-degree library, we first need to build a dataset containing various design elements. This dataset needs to contain various types of design elements, such as lines, shapes, colours, etc., and each element should have a clear label. In addition, for each element, we also need to obtain its spatial position and orientation information in order to perform correct reconstruction in CAD software. For the creation of a dataset, we can take the following steps: First, we collect various types of design drawings from various sources. Then, image processing and computer vision techniques are used to preprocess these drawings to extract various design elements. Finally, annotate and organize the extracted design elements to construct our dataset.

During the creative process, greatly improve design efficiency. Yeo et al. [18] explore the application of CAD design software in visual and neural network-based art drawing design element art design teaching. CAD design software has precise graphic drawing capabilities, which can help students quickly draw accurate lines, shapes, and patterns. This helps students better understand the importance of precise measurement in art and design while also improving their design skills. Through CAD design software, students can create 3D models to understand better and present their design concepts. This three-dimensional perspective design approach can enhance students' sense of space and design ability. Engines that can simulate various lighting and material effects, thereby generating realistic visual effects. This helps students to make intuitive visual evaluations and adjustments during the design process. Zhao et al. [19] explore the application of CAD design software in visual and neural network-based art drawing design element art design teaching. CAD design software has precise graphic drawing capabilities, which can help students quickly draw accurate lines, shapes, and patterns. This helps students better understand the importance of precise measurement in art and design while also improving their design skills. Students can create 3D models through CAD design software to better understand and present their design concepts. This three-dimensional perspective design approach can enhance students' sense of space and design ability. Engines that can simulate various lighting and material effects, thereby generating realistic visual effects. This helps students to make intuitive visual evaluations and adjustments during the design process.

3 AUTOMATIC EXTRACTION METHOD OF PAINTING DESIGN ELEMENTS BASED ON RNN

Neural networks are becoming more and more widely used in painting design. The introduction of these technologies makes the process of artistic creation and design more intelligent. This section will discuss the application of computer vision and neural networks in painting design.

(1) Application status of computer vision technology.

Computer vision technology is a technology that uses computers and related equipment to analyze and understand images and videos automatically. In painting design, computer vision is mainly used in image identification, object detection, image generation and so on. Through computer vision, we can realize the automatic identification and extraction of lines, colours, composition and other elements in paintings, which provides convenience for designers to edit.

⊖ Image identification: Through training and learning a large number of paintings, computer vision technology can realize automatic identification and classification of paintings with different styles and themes. This technology can help designers quickly browse and filter a large quantity of paintings.

⊜ Target detection: Computer vision technology can automatically detect and locate specific targets in paintings. Through the detection of specific targets, such as faces and gestures, designers can realize the automatic identification and extraction of characters.

⊛ Image generation: Through computer vision technology, the automatic generation and creation of painting works can be realized. Through the study and analysis of a large quantity of paintings, the computer can automatically generate new works with similar styles.

(2) The growth of neural network technology in the field of art

Simulates human brain neurons and has strong learning and reasoning abilities. Neural network technology is mainly applied in art appraisal, artistic creation, and design.

⊖ Art appraisal: Through training and learning of artworks, neural networks can achieve automatic appraisal and classification of artworks. This technology can help collectors and investors quickly and accurately identify the authenticity and value of artworks.

⊜ Art creation: By training neural network models, new works of art with specific styles or themes can be generated. By learning and analyzing artworks, neural networks can automatically generate new works with similar themes, providing inspiration for artists to create.

⊛ Design scheme generation: Through neural network technology, the design scheme can be optimized. Neural networks can automatically generate new solutions that meet design requirements and optimize existing solutions.

(1) Basic principle and model construction of RNN

RNN is a neural network used for processing sequence data, characterized by its memory function and the ability to capture temporal dependencies in sequence data. In RNN, the output of each time step is dependent not only on the current input but also on the hidden state of the previous time step. This structure enables RNN to process sequence data effectively.

In order to construct an RNN-based automatic extraction model for painting design elements, it is necessary to first collect a large number of painting works as training data. Then, preprocess these paintings and convert them into sequence data suitable for RNN processing. Represent each element in a painting as a vector and then combine these vectors in a certain order to form a sequence. In this way, RNN can be used to model and learn this sequence.

In traditional neural network models, each layer is interconnected, and the nodes between each layer are unconnected. Therefore, this type of neural network structure can only handle limited problems and cannot handle data with temporal relationships. Due to the special construction of temporal memory, RNN is often used in natural language processing tasks. The RNN model and its expanded model structure are shown in Figure 1.

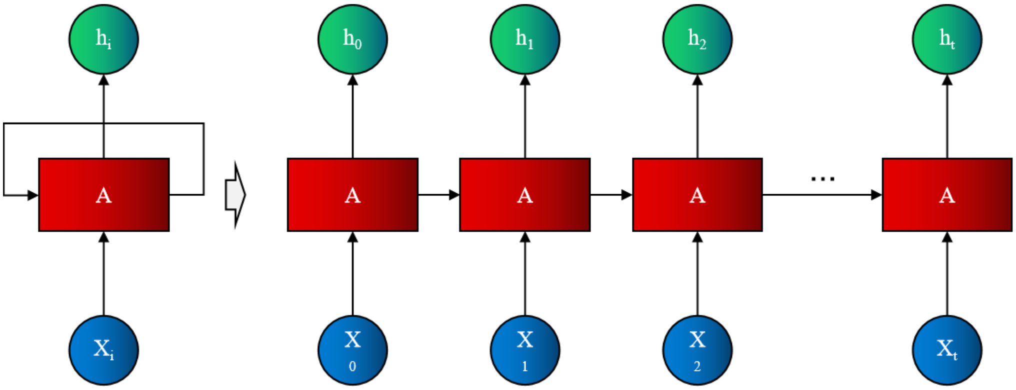


Figure 1: RNN structure diagram.

The current time step is through a circular connection, so there will still be an output in each time step. The forward propagation updating equation of the network is as follows:

$$a_t = b + Wh_{t-1} + Ux_t \tag{1}$$

$$h_t = \tanh(a_t) \tag{2}$$

$$o_t = c + Vh_t \tag{3}$$

$$\hat{y}_t = soft\max(o_t) \tag{4}$$

The weight matrix U,W and the offset vector b correspond to the connection input to the hidden unit, while the weight matrix V and the offset vector c correspond to the connection from this time step to the next time step on the hidden unit.

(2) Identification and extraction methods of painting design elements

Once RNN training is completed, researchers can use its output to extract and reconstruct design elements from the artwork automatically. By setting thresholds or clustering methods, they can identify key design elements from the output of RNN, such as the direction of lines, colour distribution, etc. The automatic extraction architecture of painting design elements is shown in Figure 2.

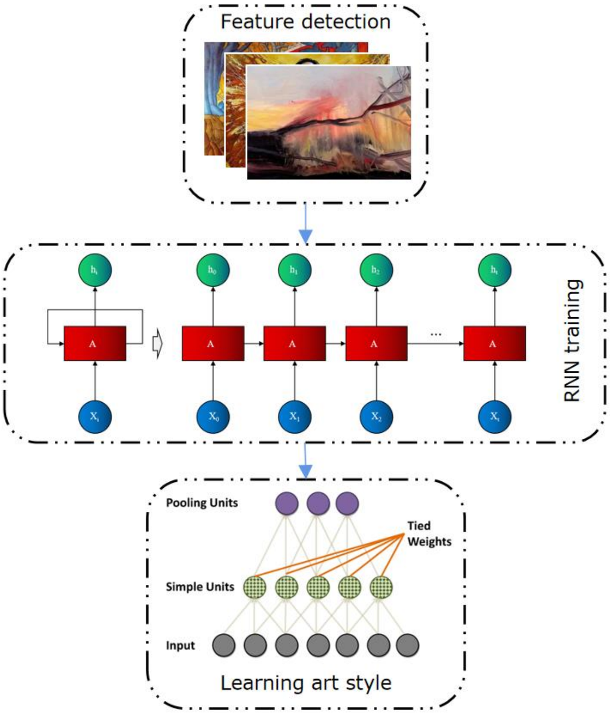


Figure 2: Architecture for automatic extraction of painting design elements.

In the automatic extraction method of painting design elements based on RNN, it is necessary to identify and extract key elements in the artwork.

$$A(x,y,\sigma)=B(x,y)\otimes C(x,y,\sigma) \tag{5}$$

Where ∂ is the scale space factor?

$$D(x,y,\sigma)=(C(x,y,n\sigma)-C(x,y,\sigma))\otimes B(x,y) \tag{6}$$

By employing an optimization technique, the estimation of the positional coordinates of spatial points X is achieved. Furthermore, through the utilization of the criterion that aims to minimize pertaining to geometric error is formulated.

$$C=d(m,\hat{m})^2+d(m',\hat{m}')^2, \quad \hat{m}'^T F\hat{m}=0 \tag{7}$$

The following steps were used in the study to extract painting design elements:

⊖ Data preprocessing: Firstly, it is necessary to preprocess the collected paintings, including image enhancement size adjustment. Then, use computer vision technology to preliminarily identify and annotate the elements in the painting works.

⊜ Feature extraction: Next, extract effective features from the preprocessed artwork to enable RNN to learn and recognize better and extract representative feature vectors from the artwork.

⊛ RNN modelling and learning: After obtaining feature vectors, use RNN to model and learn these vectors. Input the feature vectors into the RNN in chronological order, and then train and optimize the parameters of the RNN to learn the inherent laws and correlations of painting design elements.

④ Element extraction and reconstruction: After RNN learning is completed, use its output to automatically extract and reconstruct design elements in painting works. Identify key design elements from the output of RNN by setting thresholds or clustering methods and use these elements for design and editing.

4 CAD RECONSTRUCTION METHODS

CAD reconstruction refers to the process of editing and modifying extracted drawing design elements in CAD software to generate new design solutions.

(1) The basic principles and techniques of CAD reconstruction

The basic principle of CAD reconstruction is to transform the extracted drawing design elements into vector graphics in CAD software and then use the editing tools of CAD software for modification and reconstruction. CAD software usually supports various vector graphics formats, such as DWG, DXF, etc., and can import extracted drawing design elements into CAD software for editing and modification. In CAD software, various editing tools can be used to edit and modify imported graphics to generate new design schemes.

$$f(P(R,G,B)) = \begin{cases} 1 & R \in [R_{\min}, R_{\max}] \,\&\, G \in [G_{\min}, G_{\max}] \,\&\, B \in [B_{\min}, B_{\max}] \\ 0 & otherwise \end{cases} \tag{8}$$

$$E_i = \frac{1}{N} \sum_{j=1}^{N} p_{ij} \tag{9}$$

$$\sigma_i = \left(\frac{1}{N} \sum_{j=1}^{N} (p_{ij} - E_{ij})^2\right)^{\frac{1}{2}} \tag{10}$$

$$t_i = \left(\frac{1}{N} \sum_{j=1}^{N} (p_{ij} - E_{ij})^3\right)^{\frac{1}{3}} \tag{11}$$

When converting drawing design elements into CAD vector graphics, it is necessary to control the accuracy of the conversion to ensure consistency between the converted graphics and the original design elements. In CAD software, layer management tools are used to hierarchically manage different design elements. In the process of CAD reconstruction, parametric design tools are used to parameterize and modify design elements.

(2) A parameterized representation method for extracted painting design elements

In order to achieve CAD-based reconstruction of painting design elements, this study will digitize and parameterize the extracted design elements.

⊖ Digital representation: Transforming extracted design elements into digital images or digital vector graphics for easy editing and modification in CAD software.

⊜ Parameterized representation: Using parametric design tools to parameterize the extracted design elements. The commonly used parametric representation methods include feature-based parametric modelling, constraint-based parametric design, etc.

When implementing digital representation, attention should be paid to the conversion between different data formats to ensure data consistency. It is also necessary to set parameters reasonably and optimize them to ensure the accuracy of the representation results.

(3) The Implementation Process and Example Display of CAD Refactoring

After digitizing and parameterizing the extracted painting design elements, CAD software is used for reconstruction. First, import the design elements represented digitally into CAD software. Then, use layer management tools to layer and manage different design elements. Next, use parametric design tools to model and modify the imported design elements. Finally, export the reconstructed design scheme into CAD vector graphics or other formats for easy application and display.

5 EXPERIMENTAL VERIFICATION AND PERFORMANCE EVALUATION

5.1 Test Platform

For automatic extraction of painting design elements and CAD reconstruction, this study designed a system testing phase. The main purpose of the testing phase is to compare and analyze the performance differences between different methods in handling automatic extraction of painting design elements and CAD reconstruction tasks. The testing platform was designed and simulated using a common PC, and its operating environment is shown in Table 1.

Structure	Content	Parameter
Software part	Operating system	Windows 11
	Development tools	OpenCV
Hardware part	Processor	Intel Core series
	Internal storage	16 GB
	Hard disc	512 GB

Table 1: Test platform operating environment.

Build a system testing platform using the above software and hardware, install the pre-improvement and system designed in this article on the testing platform, and perform element matching tests on the selected flat images to obtain test results.

To verify the feasibility of the RNN-based automatic extraction method for painting design elements, the following experiments were conducted in this section:

⊖ Dataset construction: A large quantity of painting works was collected as training data in the study, and preprocessing and annotation work was carried out. Meanwhile, a test dataset was also constructed to assess the performance of the model.

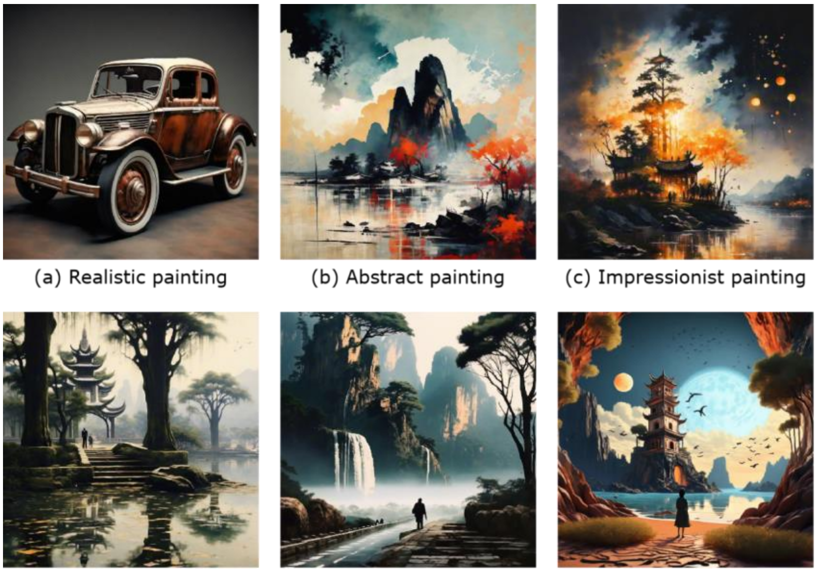
⊜ We trained and fine-tuned the RNN model using a designated training dataset, adjusting its parameters and architecture to enhance its performance and stability. Additionally, we employed techniques like regularization and batch normalization to mitigate overfitting and enhance the model's ability to generalize.

⊛ Element extraction and reconstruction experiment: After the model training was completed, we tested and assessed its ability to automatically extract and reconstruct painting design elements using a test dataset.

5.2 Result Analysis

The experiment mainly revolves around realistic painting, abstract painting, Impressionist painting, Symbolist painting, Expressionist painting, and Surrealist painting styles of painting art images in order to extract design elements from these different styles of painting works. Examples of material images for each style are shown in Figure 3.

Figure 4 shows that there are certain differences in the success rate of extracting painting design elements using different methods. The success rate of extracting design elements in the method proposed in this article is over 90%, which is significantly improved compared to other methods.



(a) Realistic painting (b) Abstract painting (c) Impressionist painting

(d) Symbolism painting (e) Expressionism painting (f) Surrealism painting

Figure 3: Different styles of works of art.

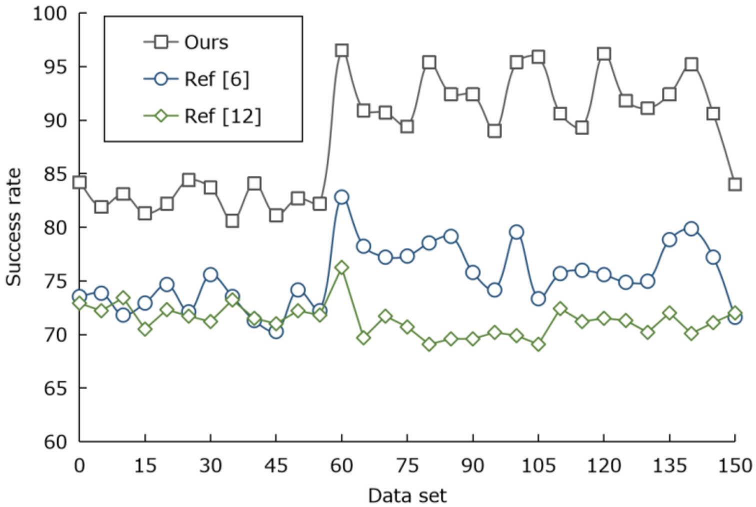


Figure 4: The success rate of design element extraction.

The method proposed in this article adopts operations such as image enhancement and size adjustment in the data preprocessing stage, which improves the quality and consistency of the data. This enables the model to better learn the inherent laws and correlations of painting design elements during training. The automatic extraction model of painting design elements based on RNN has a memory function, which can capture temporal dependencies in sequence data. Throughout the model training, we employed techniques like regularization and batch normalization to avoid overfitting and enhance the model's generalization capacity. To bolster the test's reliability, we established and reconfigured six sample groups. The outcomes of this reconstruction are presented in Table 2.

Sample serial number	*Size/(mm×mm)*	*Resolution /dpi*	*Vein*	*Colour matching*
1	60×60	280	Smooth	Deeper
2	120×120	350	Smooth	Deeper
3	160×160	380	Smooth	Deeper
4	220×220	275	Deep texture	Normal
5	280×280	264	Deep texture	Normal
6	360×360	288	Deep texture	Normal

Table 2: Sample reconstruction results.

According to the results in Figures 5 and 6, our method achieves better reconstruction accuracy and user satisfaction in the 3D reconstruction task of drawing images compared to the feature extraction methods proposed in references [6] and [12].

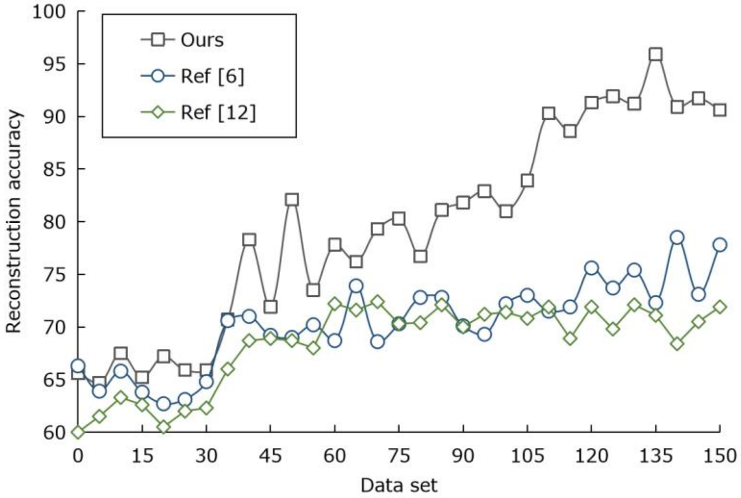


Figure 5: Comparison of reconstruction accuracy.

The purpose of this article is to mitigate the occurrence of overfitting by introducing a regularization term into the loss function, which imposes a penalty for model complexity. By comparing the image matching results before and after the improvement, it can be clearly seen that the improved method has significantly improved the matching accuracy.

The user satisfaction with the method proposed in this article is generally high, which also verifies the superiority of the method in terms of reconstruction quality and visual effects. The improvement in user satisfaction may be due to the more realistic and detailed 3D models reconstructed by the method proposed in this article, which can better restore the original style and intention of the artwork, thus bringing a better visual experience to users. This article made detailed adjustments during the model training and optimization process, improving the stability of the model by setting appropriate parameters and structures providing assurance for achieving good reconstruction accuracy and user satisfaction.

In this article, we incorporate a regularization term into the loss function to impose a penalty for the intricacy of the model, effectively diminishing the likelihood of overfitting. There are six sets of images in the test sample of this article, excluding two sets of images with distortion issues in preprocessing and only matching the remaining four sets of images. Figure 7 shows the matching results after and before the improvement.

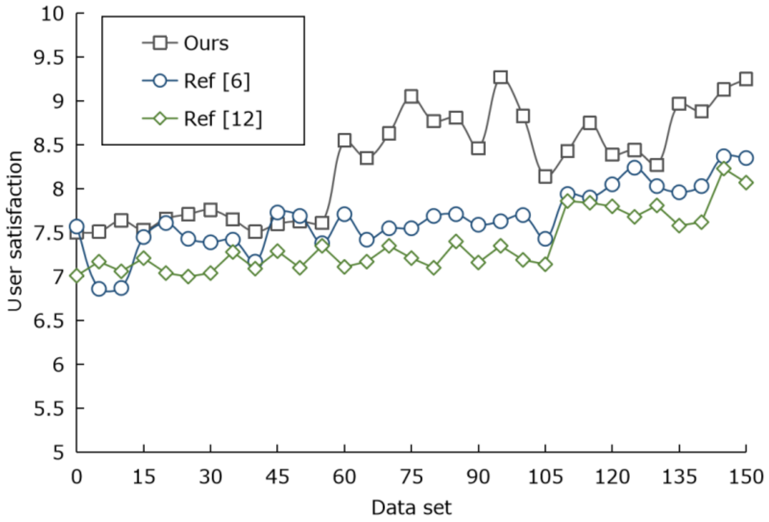


Figure 6: Comparison of user satisfaction.

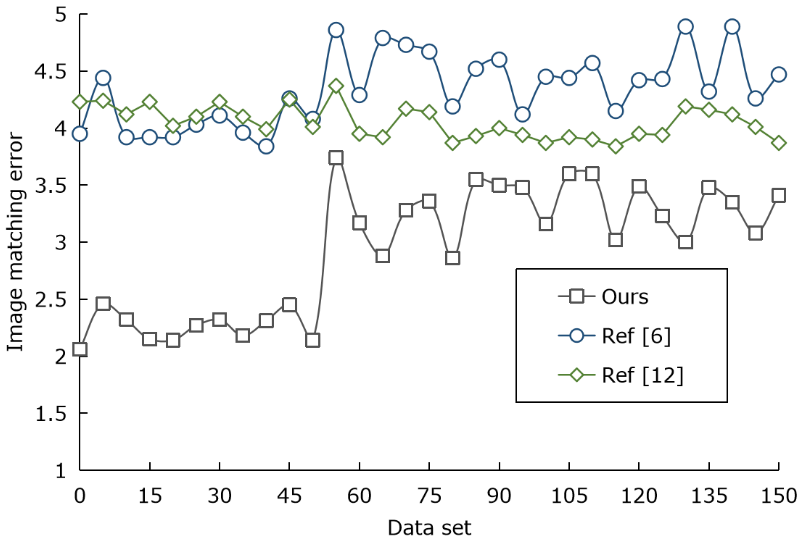


Figure 7: Image matching error rate.

According to the matching results in Figure 7, the pre-improved image matching error rate is between 9% and 10%, while the improved matching error rate is between 3% and 5%. This indicates that the improved method significantly reduces the error rate of image matching and improves the accuracy of matching. The minimum error rate before improvement was 9%, while the maximum error rate after improvement was 4.5%. Even in the worst-case scenario, the improved method still has a lower error rate than the lowest before improvement, further verifying the effectiveness of the improved method. The reduction in matching error rate is mainly attributed to the punitive effect of regularization terms on model complexity. By constraining the model parameters, the regularization term prevents overfitting of the model on the training data, allowing the model to better generalize to the test data and improve the accuracy of matching.

6 CONCLUSION

In the field of painting and design, artists put effort into hand drawing or design work. Computer vision is the field of studying how to enable computers to obtain high-level semantic information from images or videos. The incorporation and utilization of deep learning techniques have led to remarkable breakthroughs in tasks such as image identification, object detection, and image generation. This article examines the practical application of computer vision and neural networks in the domains of painting and design. Furthermore, it introduces an automated extraction and CAD reconstruction method for painting and design elements that is based on RNN. The pre-improvement image matching error rate is between 9% and 10%, while the improved matching error rate is between 3% and 5%. This indicates that the improved method significantly reduces the error rate of image matching. The minimum error rate before improvement was 9%, while the maximum error rate after improvement was 4.5%, further verifying the effectiveness of the improvement method.

The current research mainly focuses on extracting features from a single painting image and performing 3D reconstruction. However, paintings usually contain rich semantic information and artistic style, which may not be fully captured through single-modal data. Therefore, future research can consider integrating multimodal data to gain a more comprehensive understanding of the intention and style of painting works.

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