www.cad-journal.net
Computer-Aided Design AND APPLICATIONS

Generation Method of Visual Communication Design Elements Based on Recurrent Neural Network

Shuaisen He[1] and Juan Lu[2]

[1,2] Department of Creative Design, DongGuan City University, Dongguan 523000, China, heshuaisen@dgcu.edu.cn, [2]lujuan@dgcu.edu.cn

Corresponding author: Shuaisen He, heshuaisen@dgcu.edu.cn

Abstract. This article constructs a sequence data processing capability for visual element design by generating element models of neural networks. This method has a relatively significant ability in data processing for custom visual key features of recursive neural networks and in extracting visual communication of element key features. By accurately capturing the basic functions of visual communication, it constructed a neural network element model for visual recursive optimization. In the process of computer-style transfer image generation, its model has a unique visual element design advantage in optimizing the clarity of visual transfer images. The study selected visual communication elements based on different design styles to design clear image experiments. Based on the extraction of aesthetic knowledge, a model of creative design elements for the design style was constructed. By constructing and extracting stylized design element models, a new innovative aesthetic construction has been carried out. In the process of optimizing design style, this model incorporates highly sensitive image visual elements in visual communication design. This has promoted the creative design elements of visual communication.

Keywords: Recurrent Neural Network; visual communication Design; Design Element Generation; Computer-Aided; Image Resolution
DOI: https://doi.org/10.14733/cadaps.2025.S1.149-163

1 INTRODUCTION

With the continuous innovation of science and technology, digital media art is constantly developing, the communication media of visual communication design is constantly advancing, and images have also entered the field of popularization. In the era of new digital media, it is a brand new era of digitalization and visual impact that we feel. Breaking through the shackles of art and the transformation of ideological concepts, it has undergone new changes and upgrades in the development of modern and postmodern art, thereby also driving the development and interpretation of traditional art. And extend to the exploration of design forms and information dissemination methods in practice, striving to open up new forms of information dissemination through the integration of image and visual communication research and exploration, enriching the audience's experience and deep perception. From traditional visual communication with text and images to today's dynamic, multimedia, and rich visual sensory image-based visual communication and media art, breaking the monotonous form of communication brings audiences a new feeling and rich experience, which is breathtaking under the continuous changes and updates in the current media of visual communication, the integration and innovation of semiotics such as image art and dynamic visual communication. Increase the dissemination of visual effects and interaction with information, break through a single visual experience, optimize the experience and communication media of visual communication to people, and promote innovation in visual communication design [1].

In the development of modern and postmodern art, visual art is an extremely important component, evolving from photography, film, recording, and video to the visual communication elements combined with new media art today. Taking the visual design of the opening ceremony of the Beijing Winter Olympics as an analysis case, this study explores the application of digital images in the form of GIFs in visual communication design. Explore the psychological perception of the audience, the ways of disseminating rich information, and the factors that stimulate the sensory experience of the human body, and deeply reflect on the impact and innovation of images on visual communication in the new media era. The integration of images in visual communication has driven new developments in visual communication media, innovated new forms, broken traditional static display methods, and made communication more informationized and entertaining. They help algorithms better understand user needs and aesthetic preferences, thereby generating design works that better meet the requirements [2].

In the design of cultural and creative products, color is not only an important component of visual presentation but also an important bridge for conveying brand concepts, cultural values, and emotional connections. In colour design, Deng et al. considered how to combine colours with other design elements such as graphics and text to achieve the best communication effect. By utilizing colour contrast and hierarchical changes, highlight the key information and graphic elements of the product. Determine the main colour and auxiliary colour tones to ensure visual consistency and coherence of the product. In the analysis of colour visual aesthetics, quantitative analysis methods were used to further derive calculation formulas for aesthetic principles such as colour harmony, balance, and symmetry [3]. Thereby guiding the direction of algorithm evolution. These formulas not only provide quantitative guidance for designers but also help ensure the visual beauty and harmony of colour schemes. In the optimization process of colour schemes, we always consider the interaction between these elements to ensure that the final colour scheme is not only harmonious in colour. It can also coordinate with the overall design style, thereby maximizing the communication of design intent and emotions. At the intersection of literature and art, we explore various methods of creating unique artistic patterns. Among them, the orbital trap method, as a unique design strategy, brings infinite possibilities to the field of visual communication design. Gdawiec and Adewinbi [4] extend the parameters in S iteration from a single scalar to multi-dimensional vectors, making the design process more flexible and versatile and able to produce richer and more diverse visual effects. The change in this measurement method has brought new perspectives and dimensions to the generation of patterns, making their presentation more diverse and unique. It will delve into a variant of the orbital trap method and propose a series of innovative modifications to generate unique patterns with wallpaper symmetry. The iterative process of the orbit trap method has been optimized. The Picard iteration used in the original method has been replaced with the more complex S-iteration in fixed point theory.

Han et al. [5] quickly generated design drafts based on these suggestions and further optimized and adjusted them. The system provides real-time feedback during the design process, helping designers identify and correct design issues in a timely manner. This not only improves design efficiency but also promotes innovation and development in the field of design. In brand image design projects, the system can intelligently analyze the characteristics of the brand image and the preferences of the target audience, providing design suggestions that are in line with the brand tone. Designers can quickly generate design solutions based on these suggestions and continuously optimize and adjust them through real-time feedback from the system. In visual communication design, elements such as shape, colour, layout, and texture collectively constitute the overall effect of the design. The attention mechanism allows the model to dynamically adjust the weights between different views based on the unique views of each shape class during the prediction process, thereby more accurately capturing key elements and details of the design. Targeting diverse types of plastic parts, through in-depth analysis of the feature classification scheme of plastic parts, combined with 3D feature modelling and parameterization technology, Hu [6] has built a comprehensive 3D feature library for injection moulded products. In the research of engineering drawing design based on solid models, 3D CAD technology not only leads the trend of technological innovation but also brings new possibilities for visual communication design. This non-geometric information plays a crucial role in visual communication design, enriching design expression and making products more vivid and personalized. In order to further expand the application of visual communication design in engineering drawings, we propose an innovative method for establishing an "object orthographic projection digital model". This method not only showcases the physical model itself but also presents its orthogonal view through a virtual projection surface. In the process of constructing this feature library, not only the geometric shape of the parts was considered, but also the entity extension database technology was used to enable the features to carry non-geometric information, such as material properties, colours, textures, etc. From the perspective of visual communication design, this "object projection digital model" has multiple advantages. By introducing virtual projection surfaces, designers can more conveniently generate and compare views from different perspectives, improving design efficiency. This digital model not only provides higher realism and intuitiveness but also allows designers to interpret and present orthographic views in engineering drawings more accurately through digital means.

In the field of data analysis, especially when dealing with high-dimensional data containing interaction effects, classical statistical learning techniques often encounter the challenge of feature selection. Just like feature selection in statistical learning, visual communication design also requires selecting the most critical and informative parts from numerous design elements. When designers face a large number of design elements such as colour, shape, layout, and texture, they also need a method to effectively select and combine these elements to create designs that are both attractive and have clear information transmission. The dimensionality reduction-based interactive high-dimensional feature selection algorithm (RHDSI) proposed by Jain and Xu [7] provides us with a new perspective. Rough feature selection can be seen as the designer's screening and experimentation of design elements during the initial conceptual stage. In the context of visual communication design, The three steps of RHDSI can be analogized as different stages of design. If design elements are viewed as data features, RHDSI's dimensionality reduction techniques can help us simplify the design space, allowing designers to see more clearly which design elements and their interactions have the greatest impact on the overall design. This problem also exists in the process of visual communication design, especially when the mutual influence between design elements becomes complex and difficult to predict. Jarossová and Gordanová [8] explore and analyze in depth the use of folk patterns in Slovak food and beverage packaging design, as well as how these elements are influenced by various factors. These patterns also enhance the overall beauty of the product through artistic processing, bringing consumers a better visual experience. Visual communication design plays a crucial role in product packaging, establishing emotional connections with consumers through elements such as colour, shape, image, and text, conveying brand value and product information. From the perspective of visual communication design, the application of these folk patterns in packaging has multiple meanings.

During the design process, designers must take into account not just technological feasibility but also design aesthetics, communicated information, and audience psychology. This study aims to delve into RNN-based methods for generating visual communication design elements, ultimately aiming to enhance design efficiency. By constructing the design element generation model based on RNN, and training and optimizing it, the aesthetic and creative design elements can be automatically generated to provide inspiration and reference for designers. This research not only has theoretical value but also has broad application prospects. In the practical application of visual communication design, such as advertising design, packaging design and brand image design, the design element generation method based on RNN is expected to greatly improve the design efficiency and provide designers with richer and more personalized design elements.

This study also pays attention to the creative performance of design elements generated by RNN. In traditional visual communication design, designers often rely on their own experience to create. The design element generation method based on RNN can automatically extract and simulate the rules in design by learning a large number of design works, so as to generate creative design elements. Of course, we should also be soberly aware that although the application prospect of RNN in visual communication design is broad, there are still many challenges and problems. For example, how can a large number of design works be collected and processed to build a high-quality data set? How do you design a reasonable model architecture to capture the complex relationship between design elements? How do we evaluate and optimize the quality and creativity of generated design elements?

Highlights:

(1) Artificial intelligence technologies such as deep learning provide new possibilities for visual communication design, especially the advantages of RNN in processing sequence data.

(2) Because many elements in visual communication design have sequential characteristics, RNN technology is expected to provide designers with new design ideas.

(3) Visual communication design is not only a technical issue but also involves artistry. The research focuses on how to integrate RNN technology with the artistry of design.

Initially, this article clarifies the significance of visual communication design, prevalent obstacles, and fresh opportunities presented by RNN technology in the introduction section. Subsequently, the article delves into the pertinent theoretical and technical backgrounds, constructs an RNN-based model for generating visual communication design elements, and assesses its efficacy through rigorous experimentation. Furthermore, the article innovatively scrutinizes the design elements produced by RNN. Lastly, it delves into the challenges, future outlook, and conclusions pertaining to this approach.

2 RELATED WORK

Kumari et al. [9] explored novel applications of viscous approximation iterative methods, which were originally used to solve fixed point problems and find the zeros of the maximum monotonic operator. In the context of visual communication design, these complex fractal images are not only visual expressions of mathematical models but also unique, dynamic, and deep design elements. In the brand visual recognition system, these fractal images can serve as unique patterns or logos, showcasing the brand's personality and uniqueness. Digital advertising can be accurately created based on the characteristics of the product itself, attracting target audiences in diverse forms. In digital advertising, text layout not only requires clarity and readability but also needs to be coordinated with graphics and colours to create a harmonious visual effect. In digital advertising, reasonable colour matching and application can quickly attract the audience's attention and convey the emotions and atmosphere that the advertisement aims to express [10]. In this article, the contemporary art computer-aided design (CAD) teaching model is not only the construction of a technical framework but also a platform for in-depth exploration and application of visual communication design elements. ASP. NET is a powerful web development technology that provides rich controls and tools for building dynamic and interactive web applications. Liu and Yang [11] utilize ASP. The controls and features of NET can create pages with rich interactivity, such as dynamic images, animation effects, responsive layouts, etc., all of which can enhance the learning experience. In the CAD teaching mode, modular design means breaking down different design skills, theories, software operations, etc., into independent modules, and students can choose to learn according to their interests and needs. The design of each module should consider its visual appeal, such as using clear titles, colour contrasts, images, and icons to convey the theme and content of the module.

Modular design itself is a key concept of visual communication design, emphasizing the decomposition of complex design tasks into smaller and more manageable parts.

With the wave of digitization sweeping across various design fields, we have observed that the product design field still heavily relies on traditional simulation tools for conceptual visual representation, even in the context of widespread and reasonably priced immersive 3D technologies such as virtual reality (VR). Lorusso et al. [12] not only focus on the surface of technological growth but also pay attention to the gap between it and visual expression in design practice. In the early stages of product design, conceptual visual representation is a key bridge for designers to communicate with stakeholders. On the basis of analyzing existing technologies, the study classified and evaluated new methods for product concept representation using immersive technology. In addition to focusing on geometric representations (such as parameterization or polygons) and interaction methods, we also pay special attention to the application of visual communication design elements in them. Visual communication design is not only about conveying information but also a carrier of emotions, culture, and brand. We found a clear disconnect between the implemented modelling paradigm and the interaction methods. Although many VR systems provide highly realistic 3D environments, there is still room for improvement in terms of spatial loyalty, ergonomics, and quantitative evaluation. Although this two-dimensional representation is classic, it often appears inadequate in conveying the three-dimensional form, spatial relationships, and user interaction experience of the product. Meng and Huang [13] focused on interactive advertising and explored in depth the application and importance of visual communication design elements in interactive advertising in the context of new media. In the era of new media, interactive advertising is no longer just a tool for conveying information but also an important means of establishing emotional connections with consumers and creating unique brand experiences. Based on the needs of the advertising industry, they listed the problems of interactive advertising in the new media environment, such as lack of innovation and poor user experience. Visual communication design elements, such as colour, graphics, images, layout, fonts, etc., play a crucial role in interactive advertising. Especially how visual communication design elements play a role in this field. Through unique colour combinations and graphic designs, eye-catching visual effects can be created to attract the attention of consumers. By analyzing the application of visual communication design elements in these cases, it can be seen that successful interactive advertisements can visually attract consumers while providing a rich interactive experience. They can not only attract consumer attention but also quickly and accurately convey advertising information through visual language while enhancing the infectivity and persuasiveness of advertising. The case not only demonstrates the important role of visual communication design in interactive advertising but also provides useful insights for the future development of interactive advertising.

The graphic flat design captures the public's attention with concise and concise graphic symbols, clear information hierarchy, and bold colours, and is favoured by designers. This not only reflects people's aesthetic changes but also a shift in the design thinking and language of contemporary designers. The flat design of graphics is highly praised and favoured by designers, which naturally has its advantages, but it does not mean that it is suitable for application in all designs. From interface design to logo design and packaging design, graphic flat design has emerged in various design fields. Summarize the principles that graphic flat design should follow in the field of visual communication from three aspects: functional principles, visual language principles, and audience emotional needs. In order to better integrate graphic flat design into graphic design works and seek the perfect integration of function and form beauty, this article will deeply explore the origin, development process, and style characteristics of graphic flat design style [14]. For example, designers can adjust fractal parameters in real-time and immediately see changes in the effect, greatly improving the flexibility and creativity of the design. This technology not only improves computing speed but also enables applications in real-time interaction and large-scale generation scenarios [15]. As the cornerstone of generating fractal images, the Mandelbrot set's algorithm iteration not only optimizes computation but also visually demonstrates the infinite charm of fractal art. The influence of image processing in the software industry continues to grow, and with the advancement of technology, its application in IT and industrial environments is becoming increasingly widespread. From the perspective of visual communication design, fractal images have extremely high aesthetic value. Their unique forms and colours enable designers to create visual works that are both technological and artistic. The software implementation developed in this article not only optimizes the generation of fractal images but also provides rich testing packages and tools, allowing designers to apply fractal images to practical projects [16] easily.

3 VISUAL COMMUNICATION DESIGN ELEMENT GENERATION BASED ON RNN

3.1 Data Preprocessing

To account for the vast diversity inherent in visual communication design, this study amassed an extensive collection of design works encompassing various industries, styles, and themes. This approach guaranteed the dataset's comprehensiveness and ability to represent the field accurately. These data include posters, advertisements, brochures, and other design works, covering text, graphics, colours, and other design elements. The key to data preprocessing is to transform the design works into a format that the model can understand. In this study, the collected design works are processed by image processing and feature extraction and then converted into sequence data suitable for RNN model input. Divide each design work into several small pieces, and each small piece contains certain design elements and information. Then, the features of each block, such as colour, shape, texture, etc., are extracted and encoded into vector form. Finally, a sequence composed of multiple feature vectors is obtained as the input of the RNN model.

3.2 Model Construction

In the traditional neural network architecture, layers are fully connected, but the nodes in each layer are independent of each other. This structure limits the scope of its processing problems, especially the time-dependent data. In contrast, RNN shows a strong ability to process time series data. In RNN, the output at a certain moment depends not only on the input at that moment but also on the output at the previous moment. This unique sequential memory mechanism makes RNN shine in natural language processing and other tasks involving sequential data. In the model-building stage, the long-term and short-term memory network (LSTM) is selected as the infrastructure of RNN. LSTM can effectively capture the long-term dependence in sequence data and alleviate the problem of gradient disappearance, which is very suitable for dealing with design element sequences with complex time series relations. The RNN model in this article is composed of several LSTM layers, so as to understand the internal structure and relationship of design elements deeply. The input of the model is the preprocessed feature vector sequence, and the output is the generated design element sequence. At each time step, the model predicts the next design element according to the current input and the previous hidden state. The basic model of RNN and its expanded structure can be seen in Figure 1.

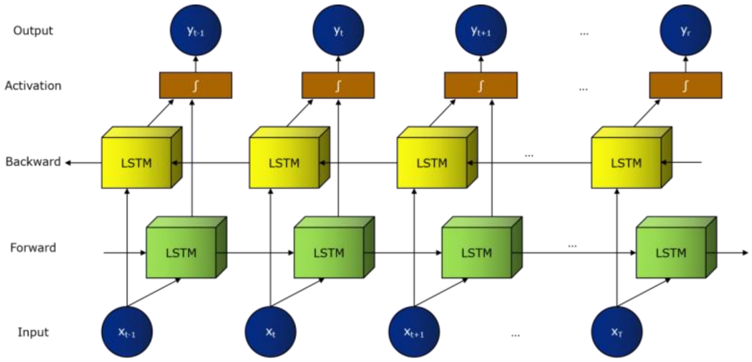


Figure 1: RNN structure.

In order to enhance the model's perception of visual communication design principles, an attention mechanism is introduced into the model. The attention mechanism allows the model to give different attention to different parts when dealing with sequence data. In the process of generating design elements, important design elements or features will be given higher weight. In addition, design rules and aesthetic knowledge are integrated into the model. By coding this prior knowledge into the form of constraints or loss functions, the model is guided to follow certain design principles and aesthetic standards when generating design elements.

RNN generates an output at every time step, featuring a cyclic connection within its hidden unit. Alternatively, the circular connection links the output of the preceding time step to the hidden unit of the present time step. Consistently, each time step is associated with a single output. The equation for network forward propagation is expressed as:

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

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

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

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

The weight matrix U,W and offset vector b relate to the input connections of the hidden unit, whereas the weight matrix V and offset vector c pertain to the connections between consecutive time steps within the hidden unit. In the depicted figure, the hidden unit h serves as an intermediary, disentangling the past from the future, thereby enabling variables with significant time intervals to indirectly shape the network's output by influencing h.

The input signal $I(X,t)$ undergoes comparison with various N distribution models, and subsequently, the most suitable model undergoes updating. Provided that:

$$\left|I_j(X,t) - \mu_{ij}(X,t)\right| < \tau D_{ij}(X,t) \tag{5}$$

If $I(X,t)$ aligns with model p_i, where τ denotes a universal threshold, i signifies i's initial distribution pattern, and the subscript j identifies a specific element within the (s,r,g) dimension.

$$d_i(X,t) = \sum_{j=s,r,g} \frac{\left|I_j(X,t) - \mu_{ij}(X,t)\right| D_{ij}(X,t)}{h_{ij}(X,t)} \tag{6}$$

To update the matching p_i, apply the formula below:

$$\mu_{ij}(X,t+1) = (1-\alpha)\mu_{ij}(X,t) \alpha I(X,t) \tag{7}$$

$$D_{ij}(X,t+1) = \min\left\{\left[(1-\beta) D_{ij}^2(X,t) + \beta \left\| I(X,t) - \mu_{ij}(X,t) \right\|_2\right]^{1/2}, D_{\max}\right\} \tag{8}$$

In this context, $\alpha \in (0,1)$ represents the mean update factor, dictating the speed of mean adjustment. $\beta \in (0,1)$, on the other hand, is the variance update factor controls the rate of variance modification. Additionally, $D_{\max}$ stands for the estimated maximum variance value across all models, serving as a universal ceiling for variance.

Based on the visual communication image with successfully adjusted basic parameters, the pixel nodes of the visual communication image are accurately mapped to the anti-sitter space by further using the Gaussian function. This mapping process not only realizes the transformation of image information from plane to hyperbolic space but also significantly enhances the degree and accuracy of node mapping with the help of improving the intensity mapping function. Furthermore, in order to eliminate the halo effect caused by the poor mapping effect of nodes at the junction of anti-sitter space, this study specially optimizes the mapping algorithm to ensure the clarity of the image in the process of spatial transformation.

Anti-sitter space and visual communication image mapping pixel nodes jointly construct an innovative non-visual imaging system model. This model not only combines the geometric characteristics of hyperbolic space but also fully considers the unique attributes of visually conveyed images.

In order to analyze this non-view imaging system model more deeply, we introduce an improved defogging algorithm. This algorithm can effectively analyze and extract the key information in the model, and then obtain the coarse refractive index of the image based on visual communication. The acquisition of this refractive index not only helps us to understand the performance of the image in the anti-sitter space but also provides important data support for the subsequent image optimization and application. In this process, the Gaussian function plays a key role. Its expression is as follows:

$$R^{filter} = \Delta K + \sum_{d\in\Omega} \left| g_0 + g_d \right|^2 \tag{9}$$

Where ΔK represents the Gaussian constant, g_0 represents the pixel node mapping rate of the visual communication image, and g_d represents the pixel node mapping error of the visual communication image. The function expression of the anti-sitter space is as follows:

$$H = \sum_{x\in\Omega} \left\| g\ x\ - t \right\| + \mu_m \tag{10}$$

This formula $g\ x$ denotes the anti-sitter constant, t signifies the weight assigned to the anti-sitter space, and μ_m embodies the accommodation rate of the anti-sitter space specifically for the pixel nodes within the visual communication image. The refined intensity mapping function is expressed as follows:

$$G_{pd} = \frac{n \cdot m}{\Omega\ s} \tag{11}$$

Where n represents the improved intensity mapping constant, m represents the node mapping enhancement coefficient, and $\Omega\ s$ represents the elimination rate of the halo effect. The function expression of the improved defogging algorithm is as follows:

$$A = \frac{v - \sin\theta}{k_\Omega\ 0} \tag{12}$$

The formula $k_\Omega\ 0$ represents the defogging improvement constant, $\sin\theta$ the computational complexity of the non-visual imaging system model, and v the acquisition error of the coarse transmission refractive index of the visual communication image.

The coarse refractive index of the visual communication image is input into the programming code of a 3.6GHz Intel Xeon CPU in the image defogging processing module, and the defogging processing of the visual communication image is realized by combining it with the MATLAB 2019 auxiliary program.

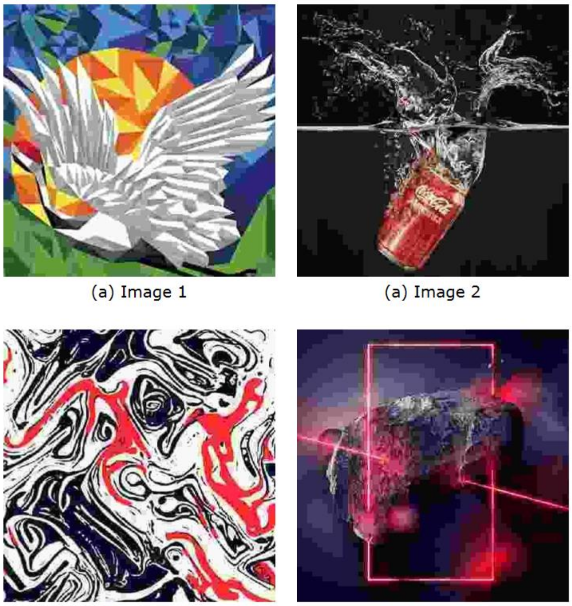
4 EXPERIMENTS AND RESULTS

Table 1 outlines the hardware and software setup utilized in the experiment. This setup incorporates high-performance CPU and GPU to expedite the training and inference stages of deep learning. The operating system chosen is Ubuntu 20.04 LTS, renowned for its stability and widespread adoption. TensorFlow, a robust open-source framework, is picked as the deep learning backbone due to its adaptability across various deep learning scenarios. Python, a prevalent language in data science and machine learning, serves as the programming language. Additionally, the OpenCV library aids in image processing and analysis, while Keras facilitates the construction and training of the RNN model.

Category	*Model/version*
CPU	Intel Core i9-10900K
GPU	NVIDIA GeForce RTX 3080
Internal storage	32GB DDR4
Save	1TB SSD
Operating system	Ubuntu 20.04 LTS
Deep learning framework	TensorFlow 2.4.1
Programming language	Python 3.8
Image	OpenCV 4.5.1
RNN library	Keras 2.4.3 (based on TensorFlow)

Table 1: Experimental environment.

In order to verify the effectiveness of the element generation model of visual communication design based on RNN, a series of experiments were designed. Firstly, four visual communication images with vague design elements are selected as the experimental objects, as shown in Figure 2.



(a) Image 1 (a) Image 2

(a) Image 3 (a) Image 4

Figure 2: Four visually conveyed images with blurred design elements.

Next, the RNN generation model proposed in this article, the method in reference [10] and the method in reference [14] are used to process these four images respectively. In order to show the processing effect intuitively, the processed images are shown in Figure 3, Figure 4 and Figure 5 respectively.

Figure 3 shows the visual communication image processed by our RNN generation model. Whether in bright or dim lighting conditions, the design elements of the image become clearer and more vivid. RNN model successfully restored the fuzzy design elements in the original image, and generated new and creative design elements, making the whole image more beautiful and attractive.

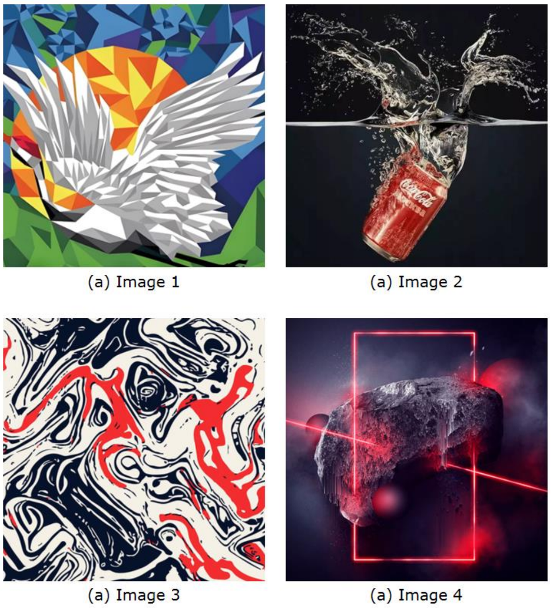


Figure 3: After RNN generation model processing.

Figure 4 shows the visual communication image processed by the method of reference [10]. Although this method improves the clarity of the image to a certain extent, it is relatively weak in the generation and optimization of design elements, and cannot be compared with our RNN model.

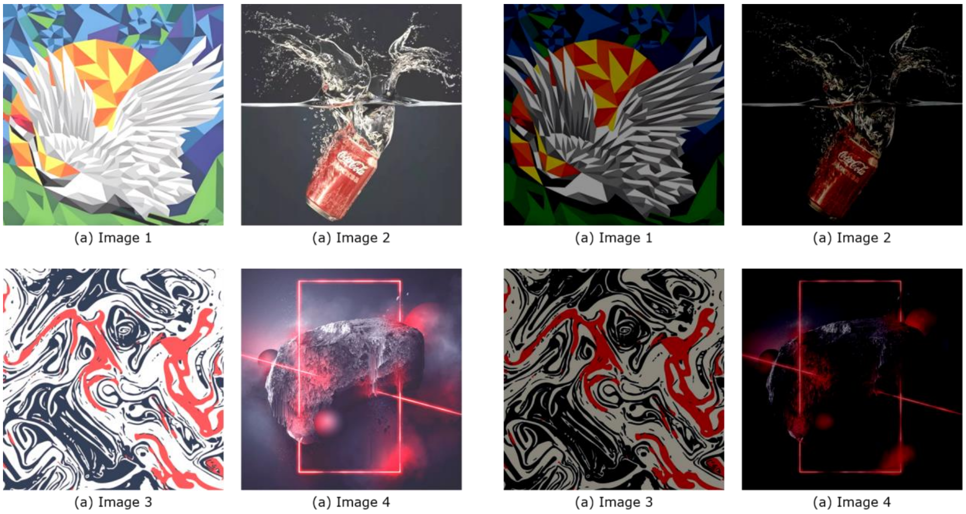


Figure 4: After processing by the method of reference [10].

Figure 5 shows the visual communication image processed by the method of reference [14]. This method has a certain effect on improving clarity, but it is also mediocre in the generation and optimization of design elements, which cannot be compared with the RNN model.

Figure 5: After processing by the method of reference [14].

By comparing and analyzing the processing effects in Figure 3, Figure 4, and Figure 5, it can be clearly seen that the RNN generation model can not only improve the image definition but also effectively optimize and generate design elements, making the processed image more aesthetic. This advantage benefits from the RNN model's in-depth understanding of the design element sequence and its powerful generating ability.

In the experiment, the responses of different types of images and visual communication design basis functions are tested, and the kurtosis distribution of the obtained coefficients is deeply explored (see Figure 6 for details). These basic functions of visual communication design are specially designed to capture and present the key features of various design elements. According to the expectation, when the test images are highly consistent with the design elements, the responses of these images and the corresponding basis functions will be more significant and consistent, and then the coefficient kurtosis will show a higher value.

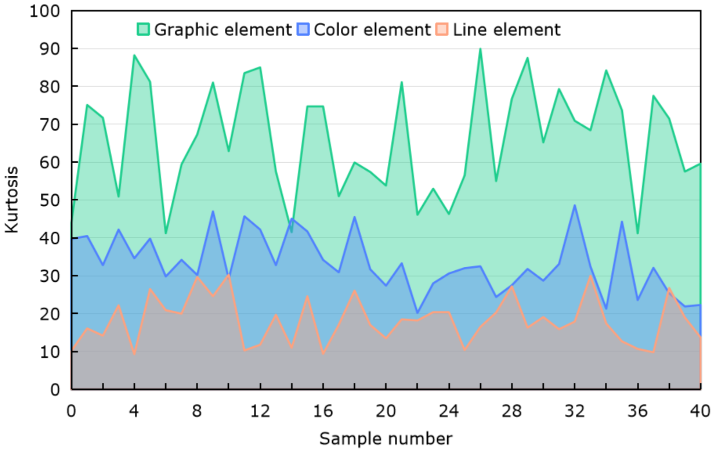


Figure 6: Kurtosis distribution diagram.

The horizontal axis in Figure 6 represents the number of samples, which refers to the number of samples of different types of images used in the test. Each sample is an image, which may contain different design elements such as graphic elements, colour elements, or line elements. The vertical axis represents kurtosis, a statistical measure that describes the distribution pattern of data. In a kurtosis distribution map, kurtosis values represent the sharpness or flatness of the data distribution. The higher the kurtosis value, the more concentrated the data distribution is. The kurtosis distribution curve of graphic elements shows the kurtosis distribution of coefficients obtained by the RNN model when testing graphic element images. When the RNN model can accurately identify and extract the core features of graphic elements, the kurtosis value will be relatively high, indicating that the model's response to these design elements is significant and consistent. The kurtosis distribution curve of colour elements reflects the kurtosis distribution of RNN models when testing colour element images. If the RNN model can understand and respond well to colour elements, the corresponding kurtosis values will also be higher. The kurtosis distribution curve of line elements shows the kurtosis distribution of RNN models when testing line element images. As an important component of visual communication design, the kurtosis of line elements also reflects the ability of RNN models to recognize line features.

To demonstrate the excellence of the RNN-driven visual communication design element generation approach, a comparative assessment was undertaken against the conventional design element generation method. The outcomes, exhibited in Figure 7 and Figure 8, were thus attained.

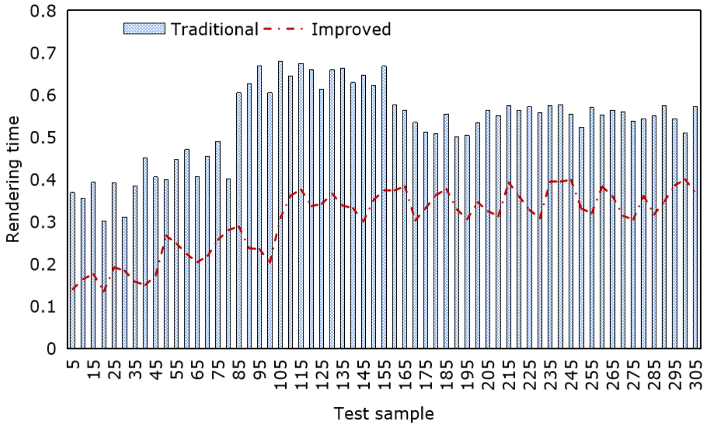


Figure 7: Rendering efficiency of different methods.

The horizontal axis in Figure 7 represents the number of samples, which refers to the number of image samples used to compare different design element generation methods. As the sample size increases, we can more comprehensively evaluate the performance of different methods in processing data of different scales. The vertical axis represents the rendering time, which is the time required to complete the generation and rendering of design elements. This time reflects the efficiency and speed of the design element generation method. A shorter rendering time means that the method is more efficient and can generate and display design elements faster. In Figure 7, different methods may be represented by different curves or markers. These curves or markers display the rendering time of each method when processing different numbers of samples. By comparing these curves, we can intuitively see that the optimized method performs better in rendering efficiency. The curve of the optimized method is located at a lower position, indicating that the method has a shorter rendering time and, therefore, has higher efficiency.

In Figure 8, the horizontal axis represents the number of samples, which is the number of design samples or images used to evaluate the performance of different design element generation methods. By increasing the sample size, we can gain a more comprehensive understanding of the performance of different methods in different design scenarios.

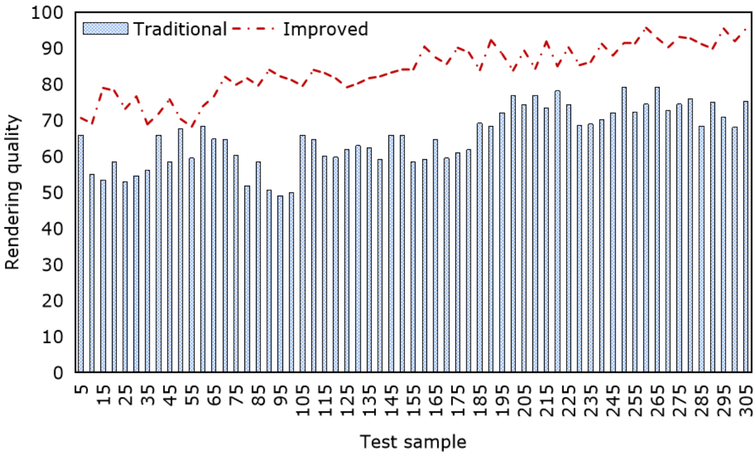


Figure 8: Rendering quality of different methods.

The vertical axis represents rendering quality and is used to quantitatively evaluate the visual effects and quality of design elements generated by different methods. The rendering quality may include multiple aspects, such as clarity, richness of details, color accuracy, overall aesthetics, etc. A higher rendering quality value indicates that the generated design elements are visually more attractive and better meet the aesthetic requirements of the designer. Different methods may be represented by different curves or markers. These curves or markers demonstrate the rendering quality of each method when dealing with different numbers of samples. By comparing these curves, it can be intuitively seen that the optimized method performs better in rendering quality. The comparison in Figure 8 shows that the RNN-based generation method significantly outperforms traditional design element generation methods in terms of rendering quality. This demonstrates the ability of RNN models to deeply understand and capture the complex relationships between design elements, thereby generating visually more attractive design elements. This method not only improves design efficiency but also promotes innovative development in the field of visual communication design.

5 CONCLUSIONS

We propose an innovative RNN-based method for generating visual communication design elements to address the common issues of insufficient clarity and blurred design elements in visual communication images. It is worth mentioning that, The RNN model is not only good at restoring and highlighting the original design elements in images but also able to create novel and creative design elements based on design rules and aesthetic principles. After a series of rigorous experimental verification, this method has shown significant effects in improving image clarity and optimizing the generation of design elements. Regardless of different lighting conditions, RNN models can significantly improve the clarity and recognition of design elements in images. The research results indicate that compared to traditional image processing techniques, our RNN model exhibits significant advantages in processing visual communication images containing fuzzy design elements. During the experiment, we observed that when the test image highly matches the design elements, the response and corresponding basis functions of the image become stronger and more consistent, resulting in higher coefficient kurtosis values. In terms of generating design elements, we have customized basic functions for visual communication design to ensure that the model can accurately capture and display the core features of various design elements. This discovery further confirms the superior performance of the RNN model in generating visual communication design elements. Thanks to the support of computer-aided design, the RNN model has significantly improved the rendering speed, and the quality of the generated design elements is also better, which is more in line with the aesthetic criteria of visual communication design.

To sum up, the method of generating visual communication design elements based on RNN proposed in this study has shown remarkable advantages in improving image clarity, optimizing the generation of design elements, and identifying design styles. This innovative research result provides a brand-new and efficient design tool for visual communication designers, which is expected to play an important role in future design practice.

6 ACKNOWLEDGEMENT

Dongguan City University, Curriculum Ideological and Political Construction Reform Demonstration course "Illustration Design" (Item Number: 2023SFKC07).

Shuaisen He, https://orcid.org/0009-0009-6278-7789
Juan Lu, https://orcid.org/0009-0009-5590-2814

REFERENCES

[1] Bai, S.; Zhou, L.; Yan, M.; Ji, X.; Tao, X.: Image cryptosystem for visually meaningful encryption based on fractal graph generating, IETE Technical Review, 38(1), 2021, 130-141. https://doi.org/10.1080/02564602.2020.1799875
[2] Chao, H.: The fractal artistic design based on interactive genetic algorithm, Computer-Aided Design and Applications, 17(S2), 2020, 35-45. https://doi.org/10.14733/cadaps.2020.S2.35-45
[3] Deng, L.; Zhou, F.; Zhang, Z.: Interactive genetic color matching design of cultural and creative products considering color image and visual aesthetics, Heliyon, 8(9), 2022, 1. https://doi.org/10.1016/j.heliyon.2022.e10768
[4] Gdawiec, K.; Adewinbi, H.: Procedural generation of artistic patterns using a modified orbit trap method, Applied Sciences, 12(6), 2022, 2923. https://doi.org/10.3390/app12062923
[5] Han, Z.; Shang, M.; Liu, Z.: Seqviews2seqlabels: learning 3D global features via aggregating sequential views by RNN with attention, IEEE Transactions on Image Processing, 28(2), 2019, 658-672. https://doi.org/10.1109/TIP.2018.2868426
[6] Hu, L.: Application of AutoCAD's 3D modeling function in industrial modeling design, CAD and Applications,18(1), 2020, 33-42. https://doi.org/10.14733/cadaps.2021.S1.33-42
[7] Jain, R.; Xu, W.: RHDSI: a novel dimensionality reduction based algorithm on high dimensional feature selection with interactions, Information Sciences, 574(11), 2021, 590-605. https://doi.org/10.1016/j.ins.2021.06.096
[8] Jarossová, M.-A.; Gordanová, J.: Folk motifs as a new trend in foods and beverages packaging design, Studia Commercialia Bratislavensia, 12(41), 2019, 1. https://doi.org/10.2478/stcb-2019-0004
[9] Kumari, S.; Gdawiec, K.; Nandal, A.; Kumar, N.; Chugh, R.: An application of viscosity approximation type iterative method in the generation of Mandelbrot and Julia fractals, Aequationes mathematicae, 97(2), 2023, 257-278. https://doi.org/10.1007/s00010-022-00908-z
[10] Li, H.: Visual communication design of digital media in digital advertising, Journal of Contemporary Educational Research, 5(7), 2021, 36-39. https://doi.org/10.26689/jcer.v5i7.2312
[11] Liu, F.; Yang, K.: Exploration on the teaching mode of contemporary art computer-aided design centered on creativity, Computer-Aided Design and Applications, 19(S1), 2021, 105-116. https://doi.org/10.14733/cadaps.2022.S1.105-116
[12] Lorusso, M.; Rossoni, M.; Colombo, G.: Conceptual modeling in product design within virtual reality environments, Computer-Aided Design and Applications, 18(2), 2020, 383-398. https://doi.org/10.14733/cadaps.2021.383-398

[13] Meng, W.; Huang, L.: Study on design of interactive advertising in the environment of new media, Arts Studies and Criticism, 3(1), 2022, 93-97. https://doi.org/10.32629/asc.v3i1.711

[14] Nakamura, K.: Iterated inversion system: an algorithm for efficiently visualizing Kleinian groups and extending the possibilities of fractal art, Journal of Mathematics and the Arts, 15(2), 2021, 106-136. https://doi.org/10.1080/17513472.2021.1943998

[15] Popa, B.; Selișteanu, D.; Lorincz, A.-E.: Possibilities of use for fractal techniques as parameters of graphic analysis, Fractal and Fractional, 6(11), 2022, 686. https://doi.org/10.3390/fractalfract6110686

[16] Wang, Y.; Zhang, N.; Chen, D.; Vongphantuset, J.: Animation design using virtual reality modeling and fractal morphing technology, Fractals, 30(02), 2022, 2240100. https://doi.org/10.1142/S0218348X22401004