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ENVIRONMENTAL LANDSCAPE ART DESIGN BASED ON VISUAL NEURAL NETWORK MODEL IN RURAL CONSTRUCTION

Abstract: As the resources of social development continue to tilt to the countryside, the speed of rural construction continues to accelerate. In recent years, because of the higher quality of lifestyles, the demand of rural environment landscape art has gradually increased. In order to assist rural construction and improve the artistic quality of its environmental landscape, this paper proposes an environmental landscape art design method based on a visual neural network model. Firstly, the Swin Transformer text encoder is used to characterise the landscape art demand in rural construction. Then, the text feature vector of landscape art demand is input into the GAN model to generate the image content of rural construction. Finally, to better evaluate the landscape art level of the above methods in this paper, we propose an evaluating method for the landscape designing tasks. We conduct the experiments and achieve the FID value of 15.23, which can demonstrate that our method can effectively carry out an environmental landscape design for rural construction and simplify the process of rural construction. The landscape design evaluation method can evaluate the environmental landscape design accurately by the accuracy of over 80 %, and further improve and optimise the acceptance link of rural construction.

Keywords: rural construction, design of environmental landscape, neural network, evaluating method

Introduction

With the advancement of Chinese society, rural development has garnered increasing attention. When undertaking rural construction, it is crucial to consider both economic factors and the environmental aesthetics of the countryside. Consequently, the incorporation of environmental landscape art design in rural construction has become a pivotal task [1-3]. In order to enhance the realisation of environmental landscape art design in rural construction, the visual neural network model (VNN) is frequently employed as a methodology. This approach enables the extraction of distinctive features from numerous images, which are then utilised in the design process to capture the essence of the environmental landscape. Furthermore, the VNN model can also be utilised for the identification of environmental landscape elements in rural construction, facilitating a deeper understanding of the characteristics specific to the environmental landscape in rural areas, and ultimately facilitating the implementation of environmental landscape art design [4].

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The visual neural network model can be used to carry out environmental landscape art design in rural construction, to improve the beauty and attraction of rural areas. Its application scenarios and methods include [5]: 1. Building facade and interior design. Using neural network models for building facades and interior design, including colour, shape, material, etc. 2. Road and block design. The NN model is adopted to analyse the environmental of roads and blocks, such as traffic, greening, building density, etc. 3. Design of parks and recreational areas. Use neural network models to analyse the environmental features of parks and recreational areas, such as terrain, vegetation, water bodies, etc. 4. Rural landscape art design. The neural network model is used for rural landscape art design, such as landscape sculpture, landscape wall painting, landscape lighting, etc. In short, the use of visual neural network models can provide more beautiful and humanised environmental landscape art design for rural construction, thereby improving the quality of life of rural residents and attracting foreign populations.

With the continuous in-depth research of vision-language models, environmental landscape design gradually began to become visual and modelling. AI can be well used to help rural landscape design. It can be used to analyse terrain data, identify elements and features that need to be considered, and generate perfect landscape design images. By using deep learning technology, AI can identify images in landscape design, including trees, grass, water, etc., and convert these images into 3D models, so that a clearer understanding of rural landscape design can be obtained.

Therefore, this paper proposes an environmental landscape art design method based on a visual neural network model to support rural construction. Main contributions are as follows:

1. We characterise the landscape art demand in rural construction by embedding Attention mechanism to refine construction text.
2. We propose a GAN-based (Generative Adversarial Network) model to generate real designing images for rural construction text and propose a rural construction quality assessment method to support construction.
3. Our generation method and quality assessment method achieve the best performance while comparing with other competitive methods.

Related works

Research on Text-to-image generation methods

Image generation is a basic researching direction in graphics. Its task is to synthesise the expected image through a generative model. How to generate high-resolution and high-quality images is a problem that puzzles researchers in the field of computer graphics. Recently, by the continuous update of hardware devices as well as the enhancement of computing power, the generative model upon the VNN model, Generative Adversarial Network [6], is also developing rapidly.

In 2014, Goodfellow et al. [7] propose the GAN firstly, which is an unsupervised learning method. The basic idea is derived from game theory. In recent years, the studies and application of GAN have been great successful, which has become a popular topic of the depth image generation. However, GAN also has lacks, such as instable training, disappearing gradient and collapse mode. In 2017, NVIDIA researchers proposed StyleGAN [8], which trains Gans in a progressive augmentation approach, where new layers are gradually added starting from low resolution, thus adding finer details as the training phases. The way speeds up the training and increases the stability of the training, which enables the production of images of unprecedented quality. In 2019, NVIDIA introduced GauGAN2 [9], a new AI art generative adversarial network that combines segmentation mapping, image inpainting, and text-to-image generation, enabling it to create realistic art based on text and hand-drawn drawings. GauGAN2 can generate accurate landscape maps from text, and generate more variety and higher-quality images.

Evaluation methods of environmental landscape design

Aiming at the problem of landscape design effect evaluation, research institutions at home and abroad have been carried out for studies, which means that many researchers propose are many landscape designing evaluation methods. We can believe that the analytic hierarchy process [10], which is determined by landscape designing evaluation indicators and achieves evaluating results, is the most representative. Therefore, we can regard this method as the linearation modelling method simply. However, we should regard the landscape designing evaluation as a nonlinear mapping, which leads to a relatively large deviation of landscape design effect evaluation and low practical application value. As we know, the artificial neural network, such as RBF, BP, extreme learning machine network, etc., is the most representative quantitative analysis method. Artificial NN access the strong modelling ability of nonlinear, and landscape designing evaluation results are obtained. Due to the complexity of landscape designing evaluation, the single analytic hierarchy process and NN have their problems and can’t fully and accurately captioning the landscape designing, so the landscape designing evaluation methods achieve great challenges [11].

Research design

Rural environment landscape design is the use of local natural and human resources, fully reflecting the local characteristics and cultural connotations. Therefore, according to the VNN model, this paper further plans a completely rural environment landscape art design system. The system is designed to consider the topography and hydrological environment, cultural characteristics, site function, and natural ecology.

The rural environment is diverse, and considering the characteristics of topography and hydrological environment can be better integrated into the natural environment. In the design, terrain and landform, such as mountains, rivers and slopes, can be used for landscape construction to increase the plasticity of the site. In addition, the design needs to consider the function and use of the site, such as public leisure Spaces, recreation areas, courtyards, plazas, etc. The design should be in line with the actual use and needs of the site, while also preserving enough space for people to enjoy leisure and activities. The landscape design of rural environment needs to pay attention to integrating into the natural ecology and avoid destroying the natural environment and ecological balance. Models based on visual neural networks can help designers better understand site characteristics, such as 3D modelling, virtual reality technology, and data analysis.

Landscape design scheme of rural environment based on the text-generated images

Considering that the traditional recurrent neural network has a poor effect on long-distance sentence processing, and it cannot capture the semantic information in the left and right directions at the same time. In order to accurately extract the rural environment landscape design text, we use the improved Swin-Transformer as the information encoder.

Through the depth coding of the text content, the idea of rural environment landscape design is expressed in the way of features, the interrelationship between rural landscape content is fully mined, the fluency of landscape content is coordinated, and the calculation speed has a great advantage. Thanks to the self-attention mechanism, the context semantics can be better captured and problems such as long-distance dependence can be solved. Besides, the framework of the method is improved, and the attention alignment method is used to focus on some important word vectors, weaken the influence of irrelevant words, and generate reasoning vectors with stronger semantics. At the end of the model, an interaction layer is added to share semantic information between sentence pairs, to form a more semantically rich word vector, which is finally input to the latter layer for processing.

Each improved Swi-Transformer module consists of two consecutive multi-head self-attention modules. Each module includes Layer Normalisation (*LN*), multi-head self-attention mechanism, residual connection, and Multi-Layer Perceptron (*MLP*). The calculation process is as follows:

$$\hat{x}_i = MSA\big(LN(x_{i-1})\big) + x_{i+1} \tag{1}$$

$$x_i = MLP\big(LN(\hat{x}_i)\big) + \hat{x}_i \tag{2}$$

$$\hat{x}_{i+1} = MSA\big(LN(x_i)\big) + x_i \tag{3}$$

$$x_{i+1} = MLP\big(LN(\hat{x}_{i+1})\big) + \hat{x}_{i+1} \tag{4}$$

Therefore, the attention of multi-head can be calculated as follows:

$$At(Q,K,V) = S_{of}\left(\frac{QK^T}{\sqrt{D}} + B\right)V \tag{5}$$

where At represents attention mechanism, S_{of} - loss function calculation, $Q, K, V \in R^{S^2 \times D}$ refer to Query, Key, Value matrix, S^2 refers to the number of image grids in a window, D is the number of feature dimensions of the sequence. $B \in R^{S^2 \times S^2}$ means the corresponding encoding matrix, whose value is obtained in the bias matrix $R^{(2S-1)\times(2S+1)}$.

After obtaining the text-encoded features, we used inverse convolution, spectral norm normalisation, batch normalisation and RELU activation function to form the rural environment landscape design image generation Network (IGN). Spectral norm normalisation and Lipschitz continuity constraint are added to the generative network to make the neural network more insensitive to input disturbances so that the train phase is great stable and the model is easier to converge.

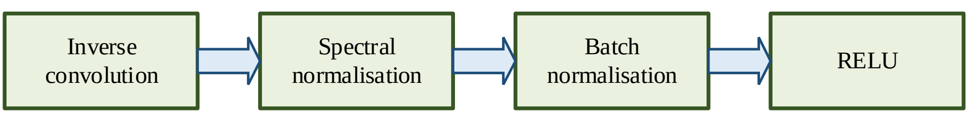

Fig. 1. IGN structure

The framework of the generating network model is present in Figure 1, and a four-layer inverse CNN is used for upsampling. Firstly, the 100-dimensional noise is used to be the input for generative network. The feature maps of (512,4,4) were obtained by the first IGN module, and then the feature maps of (256,8,8) were obtained by the second IGN module. After upsampling by the third IGN module, the feature maps of (128,16,16) are obtained, and they are sent to the self-attention module for calculation. Different from the original model that only uses convolution, the self-attention is adopted to calculate the correlation between each vector in the feature map to capture global information to obtain a larger receptive field to solve the problem of long-distance dependence. After that, the feature map is upsampled by an IGN module, and the obtained (64, 32, 32) feature map is calculated by self-attention again, and the feature map are kept with the same size by self-attention calculation. Finally, after another inverse convolution operation and Tanh activation function, a three-channel image of 64×64 pixels is output.

Quality evaluation methods of environmental landscape design drawings

To accurately assess the impact of landscape design, we have developed an enhanced landscape evaluation system. This evaluation system is built upon the principles of representativeness, testability, comparability, validity, and scientific rigor, as outlined in Table 1. These criteria are specifically tailored for assessing the rural environment and landscape.

In addition, we quantified the quality of landscape design drawings by establishing an environmental landscape design quality discrimination matrix, as shown in the following formula.

$$A = \begin{bmatrix} aa & \cdots & am \\ \vdots & \ddots & \vdots \\ ma & \cdots & mm \end{bmatrix} \tag{6}$$

Among them, *aa*, ..., *mm* represent the corresponding relative weight.

Using the aforementioned evaluation indices, we employed a BP neural network to assess the quality of rural environmental landscape design maps. The following steps were taken:

Sample Collection: We gathered landscape design evaluation samples and invited individuals to provide assessments regarding the impact of landscape design. These evaluations were then normalised using landscape design evaluation methods.

Determining BP Network Structure: The number of design evaluation indicators served as the basis for determining the nodes within the BP network. We identified the indicators that significantly influenced the evaluation and considered them as inputs to the BP network. This process also helped establish the optimal number of hidden nodes within the BP network, defining the network's topology framework.

Table 1

Quality evaluation index of rural environment landscape design

Economy	Project cost
	Maintenance fee
Artistry	Natural aesthetics
	Local culture
	Space design
Protectiveness	Landscape protection
	Local culture protection
	Space protection

Initialisation and Training: We initialised the associated factors of the BP network and inputted the landscape design evaluation samples. The accuracy of the design evaluation was used as the target to determine the optimal parameters. Through the training process, the BP network adapted to the samples, optimising its parameters accordingly.

Experiment and analysis

Dataset and implement details

We used the MSCOCO dataset as the carrier of our experiment (https://cocodataset.org/#download) and verified the effect of our evaluation system. The dataset consists of images of complex scenes, including people, animals, and common everyday objects. It contains more than 120,000 images, each labelled with a five-sentence description, divided into 82,783 images for training and 40,504 images for verification. We select samples related to rural construction from the dataset and extract their corresponding language descriptions for training.

We conduct the experiments on a device with i7-13700 CPU, RTX 4090 GPU and the system of Windows. Besides, the network model is implemented under the Tensorflow framework. The total number of rounds of the experiment is set to 2000. Then, we set the batch size to 36 and the initial learning rate to 0.001. Also, we apply the ADAM as the optimiser of the model, and the momentum is 0.9.

To evaluate the performance of our method we used the Frechet Inception Distance score (FID) as the evaluation index. This is done by calculating the distance between the generated image and the real image distribution, which is calculated using the following formula:

$$F = \|\mu_x - \mu_{\tilde{x}}\|^2 + Tr\left(v_x + v_{\tilde{x}} - 2\sqrt{v_x \cdot v_{\tilde{x}}}\right) \tag{7}$$

where $\mu_x, \mu_{\tilde{x}}, v_x, v_{\tilde{x}}$ represent the meanings of the real image, the generated image, the covariance matrix of the target image and the generated image, respectively. The smaller the FID, the closer the generated image is to the real image.

Results and discussion

We conduct the experiment of landscape design method in rural environment on MSCOCO dataset, and three evaluation levels of excellent, good and medium are set. Compared with four advanced technologies: StackGAN [12], AttnGAN [13], DMGAN [14] and MPRGAN [15], the results are presented in Table 2.

Table 2

Comparison with other methods [%]

Methods	**StackGAN**	**AttnGAN**	**DMGAN**	**MPRGAN**	**Ours**
FID	51.69	23.28	16.49	18.57	15.23
R	62.76	70.18	73.83	72.46	75.35

Our model achieves the best representation performance of rural environment landscape design map, and the FID reaches 15.23 %. Compared with StackGAN, the accuracy FID is reduced by about 36.46 %. Compared with AttnGAN, the accuracy FID is decreased by about 8.05 %. Compared with DMGAN, the accuracy FID is decreased by about 1.26 %. Compared with MPRGAN, the accuracy FID is decreased by about 3.34 %.

Therefore, from the quantitative analysis, the performance of our method is better than the performance of other methods and reaches the advanced level.

In addition, we show some generated landscape design renderings of rural environments, as shown in Figure 2. First, we use attention mechanism to quantify the design text of rural construction to get features. Then, these features are input into the image generation model based on GAN to obtain the most intuitive rural design diagram. It can be found that our method can generate the corresponding effect image according to the text scheme in rural construction, the image content is close to the text description, the targets in the image are complete, and the correspondence between the targets is complete.

Fig. 2. The results of our methods

We similarly tested the quality assessment method of environmental landscape design. We selected StackGAN, AttnGAN, DMGAN and MPRGAN as comparison methods. In the case of several methods using the same text to generate images, the target quality of the generated image is determined according to the performance of the above models, and the results are shown in Table 3.

Table 3

The difference of quality for generated image and expected results

Methods	StackGAN	AttnGAN	DMGAN	MPRGAN	Ours
Quality of generated image	3	2	2	2	1
Evaluate results	3	2	1	2	1

From Table 3, we can see that our evaluation method can accurately obtain quality scores of 3, 2, 2 and 1 respectively when evaluating the images generated by StackGAN, AttnGAN, MPRGAN and our method. However, there was a bias when evaluating the images generated by DMGAN. Considering the overall effect, the accuracy of our quality evaluation method can reach more than 80 %. The experimental results show that our rural environment landscape design quality assessment method can accurately evaluate the artistry and feasibility of the already generated design drawings. it can be found that our quality evaluation method can accurately identify the quality of each design drawing generation method and make a sharp comparison.

Conclusion

To help rural construction and meet the needs of rural environment landscape art design. This paper discusses the combination of visual neural network and environmental landscape design tasks, and proposes an environmental landscape art design method based on visual neural network model. Through the improved attention mechanism, we quantified the text of the rural art design scheme to dig out the key points in the design. Using the quantitative results, we proposed an image generation model based on GAN to get the visual image of rural art design. In addition, we propose a quality assessment method for rural design images to monitor the generation of design images. The experimental results show that our method can effectively provide visual environmental landscape design schemes for rural construction, and can intuitively reflect the rural construction process. In addition, our proposed landscape design quality assessment method can achieve accurate quality judgment, provide feedback for rural construction work, and further improve and optimise the acceptance link of rural construction. In future, we will explore to refine the generated image content of the village design to show more design detail and art.

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