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Design of an Intelligent Algorithm for Rural Antique Ceramic Bottom Pattern

Ru Zhang, Zhenhua Guo, Yangfan Xu

Mechanical and Electrical Engineering College, Jingdezhen ceramic Institute, Jingdezhen 333000, China

Abstract: The style of ancient ceramics has always been one of the most important factors affecting the sales of antique ceramic products. Although it has certain rules, due to the complexity of current product design and the limitations of designers in the design process, intelligent algorithms are needed to assist in design. In response to the diversity of intelligent design solutions for antique ceramic products, this paper proposes a research method for antique ceramic product design based on AGCGAN. Combining with the universal links in the process of intelligent product design, a generative adversarial network is used to learn the rules of excellent product design samples, and the generator generation scheme is obtained. Then, through the constructed design scheme filter, the generation scheme is filtered according to the requirements, and a design scheme generation system with certain reference value is constructed.

Keywords: Artificial Intelligence; Bottom Text; Rural Culture; Ceramic Design; Intelligent Generation.

1. Introduction

In recent years, deep learning, as a branch of machine learning, has achieved unprecedented development and application. In 2016, Afagou achieved remarkable results in the Go industry, demonstrating the potential of deep learning applications in pattern recognition and artificial intelligence[1].

Traditionally, the identification of ancient ceramics has been carried out through manual visual inspection and physical and chemical identification methods, which are either time-consuming or inaccurate, making it difficult to meet the needs of professional workers and the general public. From the current scale of economic development, the traditional market for ancient ceramics is rapidly developing, while the new technology market that applies modern science and technology to the study of ancient ceramics is hesitating. This does not meet the needs of modern ancient ceramic technology market development and is not in line with the overall trend of domestic economic development. At present, there have been a large number of samples of ancient ceramics from the Ming and Qing dynasties in the ancient ceramic market [2-3]. This naturally enables Ming and Qing ancient ceramics to meet the basic requirements of artificial intelligence for datasets. Therefore, using deep learning theory to conduct application research on Ming and Qing ancient ceramic art will be very feasible, and these studies and practical applications are also the focus of this study.

At present, the generation of the base object of antique ceramics (as shown in Figure 1) can be achieved using Generative Adversarial Networks (GAN), which is a powerful deep learning model composed of two neural networks: a generator and a discriminator. The background and significance of GAN lies in its ability to generate realistic and fake data, which is of great significance for fields such as image generation, audio synthesis, and natural language processing. The background of GAN can be traced back to 2014, first proposed by Ian Goodfellow et al. Since then, GAN has become a research hotspot in the field of deep learning and has made breakthrough progress in many applications. The core idea of GAN is to continuously improve the generator's ability to generate realistic data by playing games with the discriminator, while making the discriminator more accurate in distinguishing between real data and generated data [4-5].

Figure 1. Example of Chinese Ancient Green Flower Pattern (a) Bottom Style of Da Ming Xuande Banana Bowl (b) Da Ming Chenghua Blue and White Wing Dragon Bowl

2. Methodology

2.1. Basic Content of GcGan Principle

In computer vision, supervised learning of CNN is widely favored and has been widely applied. However, the unsupervised learning of CNN has received less attention. DEEP CONVOLUTIONAL GENERALIZE ADVERSARIAL WORKS (DCGAN) can connect supervised and unsupervised learning together. It is divided into CNN type networks of generator G (supervised) and discriminator D (unsupervised) connected together (as shown in Figure 2) (generator in the article is abbreviated as G, discriminator is abbreviated as D). After G collects and trains image data, D conducts unsupervised training and effectively restores G's images. GCGAN adds a set of convolutional constraints to the existing GAN network and can stably learn configurations. The core of GcGAN's idea is the Geometry consistency constraint, which means that the result obtained by inputting an image into a function after geometric transformation should have no difference or very little difference from the result obtained by inputting it into the function and then performing the same geometric transformation on the result[6-7].

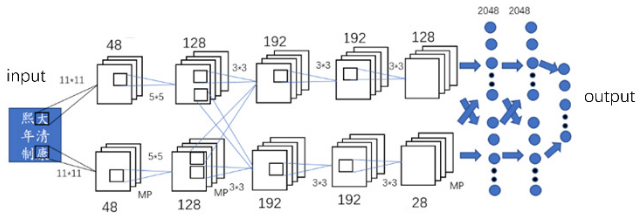

Figure 2. Basic Convolutional Network Structure of Generators

The main improvements of the GCGAN network include better performance in image classification tasks compared to other unsupervised networks. G can distinguish the generated targets based on the filters trained by the GAN network, and D can perform any operation on the semantic quality of the generated sample images[8].

The loss function of GcGan is:

$$\mathcal{L}_{Gcgan} = \mathcal{L}_{gan}(x, y) + \lambda_1 \mathcal{L}_{gan}(x', y') + \lambda_2 \mathcal{L}_{geo}(x, y) \quad (1)$$

2.2. Collection of Bottom Glaze Samples for Ancient Ceramic Products

This paper focuses on target location and illustrates target location algorithm. According to received signal strength indication (RSSI), the distance between signal transmitter node and receiver node is measured, which is called signal intensity ranging. The transmitting power of the transmitting node is known, and the receiving power is calculated at the receiving node. The difference between the two is transmission power loss. Then, then from (1) the transmission loss is converted to the distance by using the theoretical or practical signal propagation model. This method can use the following gradient model to calculate the distance:

In terms of non-ranging algorithm, there are mainly DV-Hop algorithm, SPA algorithm, centroid algorithm and convex programming algorithm. Among them, the three-side measurement method is shown in Figure 3.

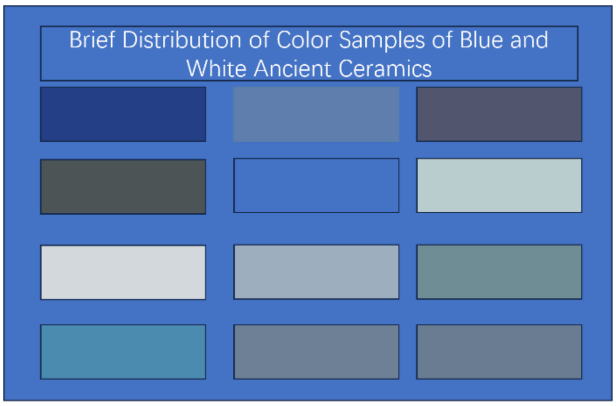

Figure 3. Multiple glaze color sample generation sample display

3. Results and Discussion

3.1. Improved AGcgan Overall Structure Design of the Intelligent Workshop Product

To make up for the shortcomings in current research in related fields, this article proposes a product glaze design method based on generative adversarial networks (as shown in Figure 4). The core research content includes two points: firstly, using generative adversarial networks to learn glaze design rules of ancient ceramic base glaze coding, constructing an innovative generation scheme for product glaze design method, and simplifying the process and steps of product glaze design; The second is based on convolutional neural networks, which drive product design to develop in different directions through differentiated consumer preferences, improving the problem of insufficient scheme diversification in current research on bottom glaze design and glaze scheme optimization generation.

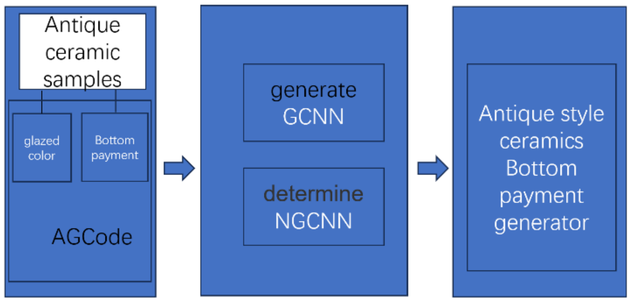

Figure 4. Schematic diagram of improving the network structure of ACGAN

Input the aforementioned sample set into the adversarial network model, and use the dimension of the 6-dimensional vector of the sample set as the input node number of the discriminator. Design and build a neural network model for the generator and discriminator, including the number of hidden layers, the number of neural nodes in each layer, and so on. The dataset is divided into training and testing sets, and an equal number of validation sets are randomly generated. Start training GAN. The probability of the generator generating samples being judged true by the discriminator is close to 0.5, and the probability of the training samples being judged true by the discriminator is also close to 0.5. Then use the generator to generate a 6-dimensional vector, which is the base glaze color design scheme. By inputting random noise, a glaze design scheme can be generated. Call the matplotlib library to directly generate glaze images to display the generated effect. Input 6-digit random noise to the input end of the generative adversarial network to generate a glaze design scheme. The results of the generated glaze scheme are shown in Figure 4. Due to the almost infinite number of iterations of the generative adversarial network, generally speaking, the more the number of iterations, the better the training effect of the model. Based on the model experience of handwritten digits and the performance of the generated glaze design scheme, 50 overall training epochs were selected as the number of training completed to achieve convergence. After that, the generator was continued to generate different structures and the comparison of the effects of using glaze design schemes can be seen (as shown in Table 1).

Table 1. Comparison between improved algorithms and original multiple algorithms

Number	Dcgan (ST)	Gcgan (ST)	AGcgan (ST)
1	58.8	60.8	67.5
2	59.7	62.3	65.6
3	56.8	63.2	68.5
4	57.3	62.8	65.4
5	52.8	61.3	63.5

4. Conclusion

This method ultimately achieved the generation of innovative color design schemes for antique ceramic products under modern, fashionable, and bright imagery, and obtained a generator that can generate diverse schemes (multi base styles). It can also further expand other image words as needed. This method can also be widely applied to the scheme design of other ceramic products. On this basis, this article also explores the general process framework of intelligent algorithm assisted design, improving some aspects of the framework (structure generation), and attempting to find a new approach in this aspect. This article has made some innovations and improvements in reducing the complexity of intelligent design and improving the diversity of solutions.

Acknowledgments

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