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# CAD Ceramic Texture Synthesis Method Based on Convolutional Neural Networks

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**Abstract.** Ceramic texture design is an essential key mechanism in current design and production plans. Traditional texture processing methods have certain limitations in design innovation. Therefore, this article uses neural networks to optimize the design of ceramic textures by recommending solutions. This paper evaluates the ceramic texture information on different nodes by designing and synthesizing textures using recursive neural networks. Through the application of computer graphics design assistance systems, it has been found that systematic methods for ceramic textures have certain differences in processing time. Therefore, in the time calculation system of computers, the optimization performance of ceramic nodes has a high accuracy, reaching 15%. In addition, in the process of ceramic CAD production, the results of this article not only have strong functionality in the productivity of CNN (Convolutional Neural Networks) ceramic synthesis but also play a certain reference role in the ceramic industry.

**Keywords:** Deep Learning; CAD; Ceramics; Texture Synthesis
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## 1 INTRODUCTION

Ceramics is one of the most excellent traditional practices in China. Ancient ceramic products, as art pieces, have been extensively tested and summarized by craftsmen to enhance the aesthetic appeal of ceramic products. Solving the ceramic formula problem, which involves selecting ingredient ratios based on raw materials and target formulas to minimize chemical composition errors, is essentially a typical optimization problem. Alidoost et al. [1] summarized the impact of several important parameters in particle swarm optimization algorithms on algorithm performance and addressed the tendency of particle swarm optimization algorithms to fall into local optima. By introducing global range values, a new adaptive inertia weight strategy is designed to adaptively change the inertia weight of each particle in the particle population. When the fitness value of a particle is closer to the global range value, it can be determined that the particle needs to expand its search range more.


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When the fitness value of a particle is closer to the global optimal value, it can be determined that the particle needs to explore its neighbouring areas more. In the later stage of the algorithm, a smaller c and a larger cz are used to accelerate its flight towards the global optimal solution position, effectively balancing the global and local search performance of the particle population. In modern industry, ceramic products, as excellent non-metallic functional materials, are widely used in various fields such as architecture, aerospace, automotive industry, and military industry. Unlike ancient ceramic formulations that relied on ceramic raw material ratios, modern ceramic formulations are chemical formulations composed of chemical compositions. In the past, mathematical methods such as linear programming, gradient descent, and Newton's method were often used to solve optimization problems. By combining predicted THM and specific texture elements, they successfully reconstructed complex textures on ceramic surfaces, including their unique visual and tactile characteristics. However, in the process of ceramic texture design and production, traditional methods are often limited by the complexity of manual skills and the occasional design inspiration, which restricts the development of ceramic art to some extent.

In the ceramic manufacturing industry, quality control is a key link in ensuring product quality and meeting consumer expectations. Machine vision technology can achieve reliable, fast, and all-weather analysis of ceramic textures, providing manufacturers with precise quality control measures. The data accessible to these devices will be used to identify and report texture defects, such as uneven, blurry, or missing parts, while revealing the potential causes of defects. With the continuous innovation of technology, machine vision, as a cutting-edge technology, is gradually playing an important role in the field of ceramic texture expansion analysis. Benbarad et al. [2] captured texture images of ceramic surfaces and conducted detailed analysis by deploying visual devices. Burghardt et al. [3] regarded the combinatorial optimization problem in ceramic firing as a multidimensional knapsack problem and established a corresponding mathematical model for ceramic firing combinatorial optimization. Analyzed the problems in the behavior mechanism of wolf packs during predation and proposed an improved wolf pack algorithm based on an adaptive position update mechanism. Simulation tests on a set of standard test functions show that the proposed adaptive wolf pack algorithm has better convergence speed and optimization performance compared to other heuristic algorithms. By introducing incentive functions to construct dynamic walking and running stride sizes, the collective behaviour of wolf packs during predation has adaptive position-updating behaviour. It is beneficial for the wolf pack population to better explore solutions in a wide problem space, thereby improving the optimization ability and speed of the wolf pack algorithm. Verify the feasibility and effectiveness of the algorithm proposed in this article through two selected sets of ceramic product test cases. Compared to traditional wolf pack algorithms and the other two optimization algorithms, the improved wolf pack algorithm has significant advantages in solving accuracy and algorithm robustness. Conduct testing through three sets of simulation test cases. The experimental results show that compared to other heuristic algorithms, the binary adaptive wolf pack algorithm proposed in this paper can better explore the solution space. Not easily trapped in local optimal regions, it has better global optimization ability compared to other heuristic search algorithms.

Most of the raw materials for ceramic product production come from natural mineral rocks, which have a wide variety and obvious regional distribution. In the process of ceramic product production, the most important thing is the design of ceramic formulas. Ceramic formula design refers to selecting the required production raw materials and determining the percentage content ratio of various raw materials based on the existing ceramic formula. This formula design method, which highly relies on the professional experience and knowledge of practitioners and has uncertainty, is not conducive to the modernization and intelligent development needs of the modern ceramic industry. Ceramic formula refers to the analysis of the chemical composition and percentage ratio of existing ceramic products based on their raw materials and glazes. After considering various factors such as cost, profit, and production difficulty, the final design method is obtained. In the past, ceramic formula design mainly relied on countless professionals, guided by professional theories, to produce and analyze the chemical composition and physical properties of test products through a large number of experiments. Therefore, it is necessary to adopt more systematic and intelligent


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methods to optimize formula design [4]. Machine vision inspection, as a non-contact detection technology, has the advantages of high efficiency and repeatability, and is increasingly being valued by people. Hanssen [5] designed a complete surface defect detection system for functional ceramic chips based on machine vision technology to meet the surface defect detection requirements. A functional ceramic chip defect detection algorithm based on edge features and morphological information was proposed to address the diverse and complex surface defect types of functional ceramic chips, achieving a detection accuracy of 89.2%. It mainly includes a ceramic chip image acquisition and control unit with lower computer functions, upper computer management software, etc. The lower computer image acquisition unit obtains surface image data of functional ceramic chips and transmits the data to the upper computer software system. As the electrolyte of high-temperature solid oxide fuel cells, the quality of functional ceramic chips directly affects the energy conversion efficiency and service life of fuel cells. However, the production and preparation process of functional ceramic chips is complex and prone to surface defects such as cracks, pores, scratches, and defects. The upper computer management software is responsible for data storage and management, executing surface defect detection algorithms, and conducting statistical analysis and visual feedback on defect detection results. The results showed that the average detection accuracy (mAP) of the model reached 92.5%, which can meet the requirements of production enterprises for screening surface defects of functional ceramic chips.

The quality of stereo matching algorithms in binocular stereo vision technology directly affects the positioning accuracy of targets in three-dimensional space. In response to the problem of poor matching accuracy in depth discontinuous areas on images, Jamal et al. [6] proposed a local stereo-matching algorithm based on SLIC superpixel segmentation. The algorithm calculates the initial disparity map through cost filtering and obtains the initial plane parameter map through SLIC superpixel segmentation and disparity plane fitting. The proposed local stereo matching algorithm and improved SGBM stereo matching algorithm are used to calculate the three-dimensional positioning error of ceramics. The average error of the improved SGBM algorithm tested under Middlebury was 0.9. Research and improvement were conducted on the SGBM semi-global stereo matching algorithm, and an SGBM semi-global stereo matching algorithm combined with the Census algorithm was proposed. Then, the iterative propagation and random search ideas in the PatchMatch algorithm are utilized to further improve the matching accuracy of disparity. The proposed algorithm has an average error of approximately 0.7 under the Middlebury test chart. Based on the calibration results, achieve stereo correction of daily ceramics and apply the BM stereo matching algorithm separately. The stereo matching algorithm was applied to the three-dimensional positioning problem of ceramics, and a hardware platform for binocular stereo vision was built to calibrate the binocular camera using the Zhang calibration method. The results indicate that the proposed stereo-matching algorithm can effectively achieve three-dimensional localization of ceramic feature points. In terms of texture expansion, we found that the addition of kaolin significantly reduces the shrinkage rate of ceramics. In fact, through mixed design experiments, we found that montmorillonite can be incorporated into industrial ceramic products up to 45wt% while maintaining high mechanical resistance. However, when combined with kaolin and illite, the interaction between them can produce a synergistic effect, further improving the texture structure and mechanical properties of ceramics. This research carries profound theoretical importance and offers expansive application possibilities. The fusion of DL algorithms and CAD technology introduces an innovative approach to ceramic texture design, fostering a deeper amalgamation of ceramic art and contemporary science and technology. This integration promises to enhance designers' productivity, diminish design expenditures, and expand the array of ceramic product styles, catering to the market's ever-growing and diverse demands.

(1) This article presents a ceramic texture synthesis method which combines the DL algorithm with CAD technology.

(2) This method combines the learning ability of DL and the editability of CAD technology, which brings new possibilities for ceramic texture design.


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(3) Through the DL algorithm, this article realizes automatic feature extraction from a large number of ceramic texture samples and generates new ceramic textures with artistic beauty.

In the following chapter, we delve into the principles of the DL algorithm, elucidating its application in CAD ceramic texture synthesis. We validate the feasibility and efficacy of this approach through rigorous experiments. Additionally, we explore the practical implications of this method in the ceramic industry, discussing how it can enhance designers' efficiency. Ultimately, we aspire for this research to offer fresh perspectives in ceramic texture design, thereby fostering continuous growth in ceramic art.

## 2 LITERATURE REVIEW

Marian and Tremmel [7] mainly studied the application of the PSO algorithm in solving ceramic formulation problems. In response to the drawbacks of slow convergence speed and susceptibility to local extremum in the later stage of search in particle swarm optimization algorithm. Introduced the basic principle, birth, and development process of particle swarm optimization algorithm. And elaborated on several important parameters in particle swarm optimization algorithm: inertia weight w, learning factor c1 c, and Performance impact in algorithm optimization. The adaptive inertia weight and nonlinear asynchronous learning factor particle swarm optimization algorithm (APSO) were proposed. It can be determined that this particle needs to explore its neighboring areas more. When the fitness value of the particle is closer to the global range value, it can be determined that this particle needs to expand its search range more. This algorithm adaptively changes the inertia weight of each particle in the particle population by introducing a global range value as the fitness value of the particles approaches the global optimal value. Considering that in the early stages of the algorithm, the particle population needs to pay more attention to self-awareness, and in the later stages of the algorithm, more attention needs to be paid to group cognition. In addition, for the improvement of learning factors, the standard particle swarm optimization algorithm uses a fixed and equal learning factor c1 c2. The proposed APSO algorithm was tested using standard test functions, and the test results showed significant performance improvements in optimization accuracy, convergence speed, and stability. CZ gradually increases with the evolution process, thereby enhancing the algorithm's global search ability in the early stage and the convergence speed in the later stage. The linear weighting method is used to address the issues of multiple optimization objectives and great difficulty in optimizing ceramic formulas. Combined with the critical method to assign weight values to the main chemical components in the ceramic formula, the multi-objective problem is transformed into a single objective problem and solved using the APSO algorithm [8]. The complexity and diversity of ceramic textures make manual detection and evaluation difficult and time-consuming. Fortunately, deep learning techniques, especially in image analysis and object recognition applications, have provided new possibilities for the automatic detection of ceramic texture defects. However, the scarcity of ceramic texture defect datasets makes it difficult to directly use deep learning models for defect recognition. The global average pooling rule reduces the number of parameters by calculating the global average of feature maps, while retaining spatial information, further improving the performance of the model. Through testing on the ceramic texture defect dataset, we found that TL MobileNet achieved a prediction accuracy of 97.69%. Significantly superior to other transfer learning models and traditional neural network methods. The application of style transfer technology in deep learning originally focused on visual images, which fuse the styles of two images through activation and feature statistics. Shahrin and Wyse [9] explored the potential of applying this technology to the audio field, particularly in combination with ceramic texture extension analysis. After research, it was found that the traditional CNN architecture based on 2D representation and convolution performs well in processing visual images. The experiment revealed an interesting finding: despite this mismatch, the audio "style" defined by the Gram matrix is more in line with the timbre characteristics. The texture of ceramics is an important component of their artistic expression, which shares similarities with the timbre and rhythm structure of audio. By combining ceramic texture extension analysis, these texture synthesis methods can not only be applied to music production and audio art but also provide new sources of inspiration for ceramic


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designers. These networks have a natural advantage in processing one-dimensional signals, such as audio, and can generate results that are more in line with the intuitive concept of audio texture. Although one is a static visual presentation and the other is a dynamic sound expression, they have potential similarities in style and content processing. In addition, these technologies can also be extended to fields such as infinite texture, multi-texture, and parameter control of receptive fields, further enriching the expression methods and means of ceramic art.

Shi et al. [10] studied the combinatorial optimization allocation problem of ceramics during firing in kilns, treating it as a multidimensional knapsack problem and using a binary wolf pack algorithm for the optimization solution. Three sets of cases were tested and compared with classical heuristic algorithms and two improved binary optimization algorithms, respectively, to compare the solution results under different data scales. Using a reverse population strategy to initialize the population size, replacing a fixed walk size with a walk size that varies with the number of iterations, reduces search time, and is beneficial for mining potential solutions and enhancing the detection ability of the algorithm. The test results show that the improved binary wolf pack algorithm has better optimization performance and higher accuracy in solving large-scale problems. Introducing an incentive function to construct a summoning step size improves the accuracy of the solution and further enhances the overall optimization performance of the wolf pack algorithm. BAWPA is less affected by dimensionality and the number of items in classic test cases of knapsack problems, and the algorithm overall shows good convergence and stability, which is of great significance for improving enterprise production profits.

Machinable ceramics have been applied in more and more fields in recent years due to their many excellent characteristics. Roughness is an important characteristic for measuring the surface quality of workpiece machining, which directly affects the performance of the workpiece and is an important factor for evaluating the cutting quality of the workpiece [11]. Cutting temperature is an important characteristic that characterizes the cutting state during the cutting process. Due to the poor thermal conductivity of machinable ceramics, the cutting temperature of machinable ceramics is the main cause of thermal gradient and thermal stress between the workpiece and the tool, leading to tool breakage and local workpiece fragmentation. Therefore, the selection of machining parameters for ceramic turning has become a worthwhile research topic. The reasonable selection of cutting process parameters is a decisive factor in achieving high machining quality and efficiency in turning machining. Therefore, reasonable parameters should be selected during the machining process to minimize cutting temperature and roughness as much as possible while ensuring machining efficiency [12]. At present, research on machinable ceramics cannot meet the requirements of numerical simulation of cutting temperature and roughness in multi-objective optimization processes.

Wei et al. [13] aimed to establish an orthogonal model of cutting temperature and roughness, with cutting temperature, roughness, and cutting efficiency as objectives, to optimize the spindle speed, feed rate, and cutting depth on a multi-day scale. Establish single-factor models for cutting temperature and roughness separately, and further establish orthogonal models for cutting temperature and roughness based on the common characteristics of the single-factor models. Using a mutated artificial fish swarm algorithm to optimize the BP neural network, based on existing experiments, for single-factor prediction of cutting temperature and roughness. The final experimental verification results indicate that the prediction is reliable. Design and conduct single factor and orthogonal turning experiments on machinable ceramics, collect and process cutting temperature and roughness. By utilizing low-temperature simulated annealing to optimize the mutation fish swarm algorithm, the SA-IAFSA algorithm was obtained. Based on prediction and experimental results, the SA-IAFSA algorithm is used to solve the problem. Specifically, through laser engraving technology, we have successfully created two unique textures on these ceramic surfaces: micro pits and microgrooves. The experimental results reveal an interesting phenomenon: the influence of surface texture on tribological properties is not constant, but is influenced by multiple factors such as material and texture type. However, the situation is different when C/SiC rubs against Si æ $N_4$ friction plates with micro pits. During the entire friction process, the formation and


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detachment of wear debris occur frequently, resulting in poor tribological performance. This result may be attributed to the excellent performance of $ZrO_2$ material itself and the effective improvement of friction interface by micro indentation texture.

Traditional ceramic texture recognition technology is difficult to comprehensively and stereoscopically capture and present the unique texture of ceramic art. Wei and Ko [14] proposed a study on ceramic texture segmentation and synthesis based on deep-learning convolutional neural networks. This algorithm can accurately simulate the lustre, texture, and hierarchy of ceramic textures, making the generated ceramic texture images more realistic and three-dimensional. Through this analysis, it successfully obtained key image information of ceramic textures, providing rich materials for subsequent texture synthesis. With the help of semantic image segmentation techniques in deep learning, the segmentation methods of ceramic texture images are deeply analyzed to capture and analyze the complexity and uniqueness of ceramic textures. In terms of ceramic texture rendering, a specialized ceramic texture rendering algorithm is proposed that utilizes convolutional neural networks and combines the characteristics of ceramic textures. More importantly, our algorithm can accurately restore the hierarchy and direction of ceramic textures, making the generated texture images closer to real ceramic artworks. The experimental results show that compared with traditional ceramic texture recognition and synthesis methods, our method can generate more specific and flexible ceramic texture images while exhibiting stronger stereoscopic and realistic effects. To better integrate online teaching resources in the new educational environment and build a computer graphics and image-assisted art teaching platform with digital content innovation as the core, Zhang and Rui [15] have paid special attention to the research and teaching of ceramic textures. It explores how to use modern computer design methods, especially in the analysis of ceramic textures, computer graphics, and image-assisted art design, to establish a comprehensive and efficient computer-aided design platform system. In the interdisciplinary field of computer graphics and image-assisted art design, the extended analysis of ceramic textures has brought new vitality and depth to this field. This study not only helps to promote the teaching concepts of digital computer graphics and image-assisted art design but also provides new teaching methods and training modes for ceramic texture design. Specifically, through digital means, we can establish a sensory interactive teaching method that enables students to intuitively understand the application of spatial morphology theory in ceramic texture design. Based on summarizing the general design methods of artistic products, combined with the characteristics and applications of ceramic textures. Using the modular decomposition method, the ceramic texture art design process is implemented on a computer. Meanwhile, by utilizing digital design experience methods, students will be able to explore the creativity and beauty of ceramic textures more deeply, thereby cultivating their modelling ability and aesthetic judgment.

## 3 SYNTHETIC METHOD OF CAD CERAMIC TEXTURE

As a cherished aspect of traditional Chinese art, ceramics embody rich cultural significance through their distinctive textures and shapes, showcasing the remarkable craftsmanship of artisans. Ceramic texture design, a pivotal aspect of this art form, has long captivated ceramists and academics alike.

In the field of DL, CNN has been proven to have excellent performance in image processing tasks. Therefore, CNN is chosen as the basic model, and it is modified and optimized appropriately to meet the needs of ceramic texture synthesis. The network comprises multiple convolution layers, pooling layers, and fully connected layers. The convolution layer extracts local input image features, whereas the pooling layer downsizes data and minimizes computational load. Meanwhile, the fully connected layer integrates these extracted features to output the final texture image. To enhance the model's generative capabilities, GAN principles are incorporated. GAN is made up of a generator and a discriminator: the former creates new texture images, and the latter assesses their authenticity.

The formula for calculating LeakyReLU is as follows:


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$$f(x) = \begin{cases} x, x \geq 0 \\ x / a, x < 0, a > 1 \end{cases} \tag{1}$$

The super parameters are then adjusted in the direction that minimizes $L(y,\hat{y})$. This study employs cross entropy to determine the loss value, with the loss function for each batch of training samples represented as follows:

$$L\left(y_j, \overset{\wedge}{y}_j\right) = -\overset{\wedge}{y}_j \log_2 y_j - (1-\hat{y}_j)\log_2(1-y_j) \tag{2}$$

Here, $\hat{y}_j$ denotes the genuine theoretical value for the $j$ batch of samples, whereas $y_j$ signifies the model's actual output value. The model's overall loss value is computed as the mean loss value across all batch samples, expressed as follows:

$$\arccos(N_{new} \cdot N_{ini}) \leq \varepsilon L\left(y, \overset{\wedge}{y}_j\right) = -\frac{1}{N}\sum_{j=1}^{N}\left[\overset{\wedge}{y}_j \log_2 y_j + (1-\hat{y}_j)\log_2(1-y_j)\right] \tag{3}$$

BatchNormalization is a method designed to accelerate the convergence of the model. Its core idea is to normalize the input of each network layer, ensuring that it follows a standard normal distribution characterized by a mean of 0 and a variance of 1. Additionally, scaling and migration factors are incorporated to introduce nonlinearity into the transformation process, thereby mitigating the risk of gradient vanishing during training. Notably, the scaling and offset parameters are adjustable through training. In essence, BatchNormalization subjects the output of a unit to the following manipulations:

$$y = \frac{x^k - E\left[x^k\right]}{\sqrt{Var\left[x^k\right]}} * \alpha + \beta \tag{4}$$

In the formula, $x^k$ denotes the output value generated by the $k$ layer unit. $E\left[x^k\right]$ and $Var\left[x^k\right]$ correspond to the mathematical expectation and variance $x^k$, respectively. $\alpha, \beta$ signifies the scaling and offset parameters applied.

Texture is different from ordinary images, as it may be embedded in the image, but not all images necessarily exhibit texture characteristics. Therefore, texture images can be considered as a special category of images. The two prominent characteristics of texture images are their locality and stability, which are also the main differences between them and ordinary images. The so-called locality of texture refers to the value of any pixel in the texture, which is only influenced by other pixels in its neighboring area and is independent of other parts of the image. The smoothness of texture is reflected in the visual similarity between any part of the texture being observed. Taking Figure 1 as an example, (a) shows a regular image, and (b) is a texture image. When observing these two images with a fixed-size rectangular box and moving the box to examine different areas of the image, it is evident that (a) there is a significant difference in the content of the two black rectangular boxes in the image, while (b) the content of the two boxes in the image shows a general similarity. In addition, any pixel value within the black rectangular box in Figure 1 (b) can be inferred from the pixel values within its adjacent area, independent of other pixels outside the box. This observation further confirms the locality and stability characteristics of texture images.

As depicted in Figure 2, during the ceramic texture synthesis process, a cutting-edge spiral search approach is employed to locate a matching texture for the texture block undergoing synthesis. This method initiates at the spot where the synthesized texture block precedes the one being synthesized in the sample image and proceeds by searching in a spiral manner. This spiral search commences at the position of the already synthesized texture block, initially scouting its immediate surroundings and progressively widening the search in a spiral path.


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(a) (b)

**Figure 1**: Comparison diagram of texture and ordinary image.

The advantage of this method is that it can locate the texture that matches the texture block to be synthesized more quickly. This spiral search strategy also has good flexibility and expansibility. It can be adjusted and optimized according to different needs and scenes to adapt to various complex texture synthesis tasks.

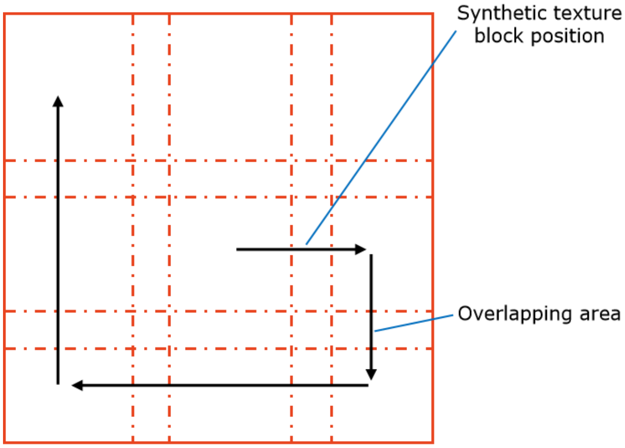


**Figure 2**: Spiral search matching block.

Because the encoder and discriminator have common weights throughout, except for the final layer, integration is feasible. The shared network segment is signified by $H$. As a result, the encoder's mathematical representation can be stated as:

$$\mu = f_1 \;\; H \;\; X \tag{5}$$

$$\log \sigma^2 = f_2 \;\; H \;\; X \tag{6}$$

The discriminator $D$ can be expressed as:

$$D = f_3 \;\; H \;\; X \tag{7}$$

$f$ represents distinct mappings for the network's final layer.

$$L_{identity} \;\; G_1 \;\; = E_{x \sim p_{data} \;\; x} \left[ \left\| G_1 \;\; x \;\; - x \right\|_1 \right] \tag{8}$$


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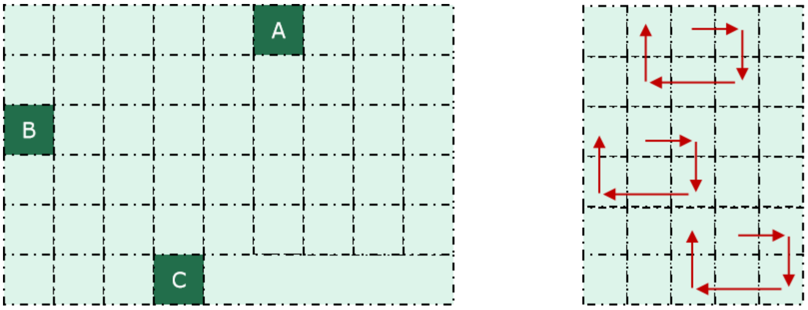
In this context, $x \sim p_{data}\ x$ signifies that the image was sourced from the domain $X$ for transformation while $G_1\ x$ denoting the falsified output created by the generator $G_1$.

The starting point for spiral search varies based on the specific location of the texture block to be synthesized in the output image. There are three scenarios to consider: Firstly, if the texture block to be synthesized is positioned in the first line of the output image (refer to block A in Figure 3), the search commences from the matching position in the sample image preceding block A, following a spiral path. Secondly, for blocks to be synthesized in the first column (illustrated by block B in Figure 3), the search begins at the location of the first block in the sample image's previous row relative to block B, also tracing a spiral path. Lastly, for blocks situated elsewhere (like block C in Figure 3), the search starts from the texture block's position in front of block C in the sample image, progressing in a spiral manner.




(a) Synthetic output image (b) Sample texture image

**Figure 3**: Schematic diagram of the starting block of spiral search.

To combine the texture generated by DL with CAD design, the following steps are adopted in the study: ⊖ Data preprocessing: First, a large number of ceramic texture samples are collected and preprocessed. This includes image size adjustment, color normalization, and other operations for subsequent model training. ⊜ Model training: training DL model with preprocessed data. ⊛ Texture generation: After the training is completed, a new ceramic texture image is generated by the generator. These images will have similar styles and characteristics to the training data, but at the same time, they will maintain enough diversity. ④ CAD integration: Import the generated texture image into CAD software. ⑤ Designer adjustment and optimization: Designers can further edit and improve the generated textures according to their own aesthetic and design needs.

During the synthesis of ceramic texture, GAN can be utilized to produce remarkably realistic images. Through the incorporation of a coding network $E$ and classification network $E$, we can manipulate the attributes of the generated samples by modifying the latent space. The loss function of the coding network can be mathematically expressed as:

$$L_E = \frac{1}{n}\sum_{i=1}^{n} \ y_i' - y_i \ ^2 \tag{9}$$

The style of ceramic texture is determined by the correlation coefficient of activation items across channels in a specific layer of CNN. The similarity between the output results of different CNN layers is gauged using the style matrix, known as the Gram matrix. Specifically, the Gram matrix $G_{ij}^l \in R^{N_l \times M_l}$, $G_{ij}^l$ signifies the product of the activation items outputted by the $i$ and $j$ convolution kernels in the $l$ layer of CNN. In other words, it represents the inner product of the feature maps generated by the $i$ and $j$ convolution kernels:

$$G_{ij}^l = \sum_k F_{ik}^l F_{jk}^l \text{。} \tag{10}$$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To infuse the style of style image $\vec{a}$ into content image $\vec{p}$, we need to align both the stylistic elements of style image $\vec{a}$ and the content features of content image $\vec{p}$, thereby generating a unique image $\vec{x}$. This process aims to minimize the loss of feature representation from a single CNN layer of the content image and the cumulative loss of feature representation from multiple layers of the style image:

$$L_{total}\left(\vec{p},\vec{a},\vec{x}\right)=\alpha\times L_{content}\left(\vec{p},\vec{x},l\right)+\beta\times L_{style}\left(\vec{a},\vec{x},l\right) \quad (11)$$

## 4 RESULT ANALYSIS AND DISCUSSION

When using the same algorithm to synthesize the same size output image, the time required for synthesis varies according to the sample size and texture randomness. In the statistical calculation, the time used by the algorithm in this article is compared with that used by Efros. Table 1 lists some related parameters of texture runtime.

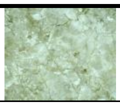
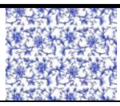
| *Texture type* |  |  |  |
|---|---|---|---|
| Sample size | 256×256 | 256×256 | 256×256 |
| RNN | 19.211 | 18.842 | 18.556 |
| CNN | 12.456 | 12.011 | 11.978 |

**Table 1**: Experimental results of algorithm synthesis.

The experiment is carried out on ceramic texture synthesis scenes with different numbers of photos and different numbers of nodes. This means that two variables, the number of images and the number of computing resources (that is, the number of nodes), are considered in the experiment. Figure 4 shows the performance comparison under different numbers of images and nodes.

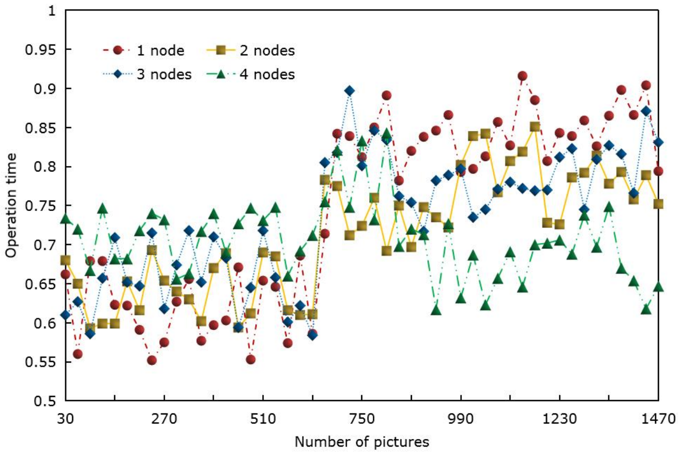



**Figure 4**: Image retrieval consumes time.

The results demonstrate that the multi-node approach excels in handling large volumes of images due to its ability to execute multiple tasks concurrently, thereby enhancing overall processing efficiency. For smaller image sets, the disparity between single-node and multi-node performance may not be evident. Nonetheless, as the number of images increases, the benefits of the multi-node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strategy become progressively apparent. Ceramic texture synthesis frequently entails extensive image manipulation and computations, such as texture extraction, matching, and fusion, which often demand substantial computing power. Hence, the multi-node approach proves highly beneficial in such contexts.

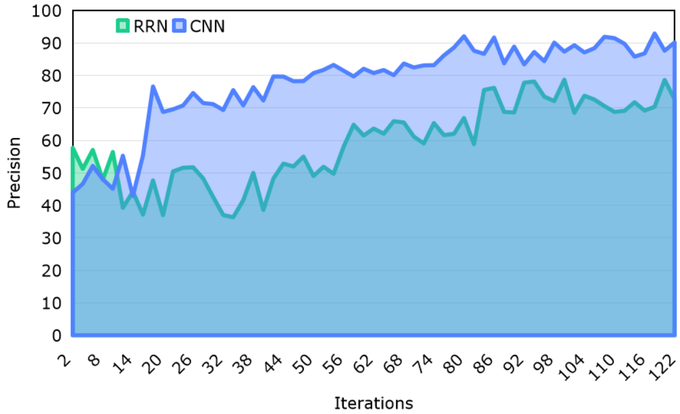


**Figure 5**: Accuracy results of different algorithms.

In Figure 5, we compared the performance of ceramic texture synthesis methods based on recurrent neural network (RNN) and convolutional neural network (CNN) in terms of accuracy. It can be observed from the graph that the CNN algorithm is significantly superior to the RNN algorithm in accuracy, with an advantage of over 15%. The hierarchical structure of CNN enables it to gradually extract features from images, ranging from low-level to high-level. This hierarchical processing method helps the model better understand and generate ceramic textures. At each level, CNN can capture different texture features and integrate them at higher levels to generate more accurate and natural texture effects. This result highlights the unique advantage of CNN in ceramic texture synthesis tasks. In the task of ceramic texture synthesis, CNN can capture the details and features of the texture more accurately, because its convolution and pooling operations can effectively extract the spatial information of the image. In contrast, RNN may not be able to extract these features so accurately when processing images, especially when processing complex texture patterns.

For application scenarios such as ceramic texture synthesis, the improvement of accuracy means that more realistic and natural texture patterns can be generated, thus improving the quality and market competitiveness of products. High-precision texture synthesis is also helpful in improving the consumer experience because more realistic textures often bring better visual enjoyment.

As shown in Figure 6, as the number of feature information pixels increases, the processing duration of various texture processing methods generally shows an upward trend. This phenomenon is in line with expectations, as the increase in the number of pixels directly leads to an increase in the dimensionality and complexity of the input data. A higher data dimension means an increase in the amount of information that the algorithm needs to process, which naturally leads to an increase in computational complexity and an extension of computation time.

It is worth noting that in Figure 6, the CNN model shows a significant advantage in processing time compared to the RNN model. This is mainly attributed to the unique way CNN processes image data. CNN can efficiently extract local features from images through convolution and pooling operations, and gradually integrate these features through a hierarchical structure to form a global representation. This processing method enables CNN to maintain relatively stable computational efficiency when processing high-pixel images, and compared to RNN's serial processing method, CNN's parallel computing ability makes it more advantageous in processing large-scale data.


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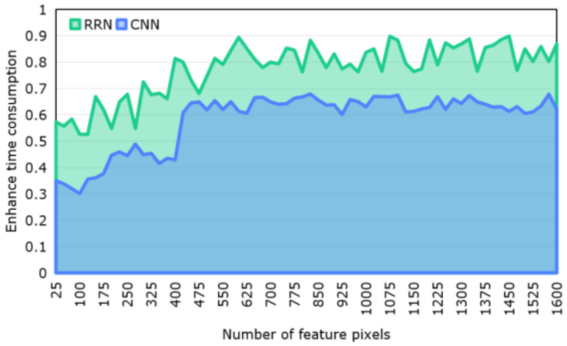


**Figure 6**: Texture processing using different methods is time-consuming.

The increase in the number of pixels of feature information means that the dimension and complexity of input data increase. This requires the model to do more calculations to extract features and generate textures, so the processing time will naturally increase. With the increase in the number of pixels, the CNN model has significant advantages over RNN in processing time. This is mainly because CNN and RNN have different calculation methods when processing image data.

CNN processes image data efficiently through convolution operation and can process different regions in the image in parallel, thus maintaining relatively high efficiency when processing a large number of pixels. Although RNN can also be accelerated by GPU, due to its inherent sequential processing characteristics, it is not as efficient as CNN in processing large-scale data.

In practical application, processing time is an important consideration. Especially in a design environment that needs real-time feedback or rapid iteration, CNN's high efficiency makes it a more suitable choice. Of course, RNN also has its unique advantages, such as its excellent performance in dealing with time-dependent data. However, in the task of ceramic texture synthesis, which pays more attention to image feature extraction and generation, CNN is superior.

Figure 7 shows the comparison results between the ceramic texture synthesis method proposed in this article and other methods or traditional CAD system functions. In CAD systems, high-quality texture is very important for product design and rendering, because it can simulate the appearance of the actual product more truly and help designers to better predict the effect of the final product.

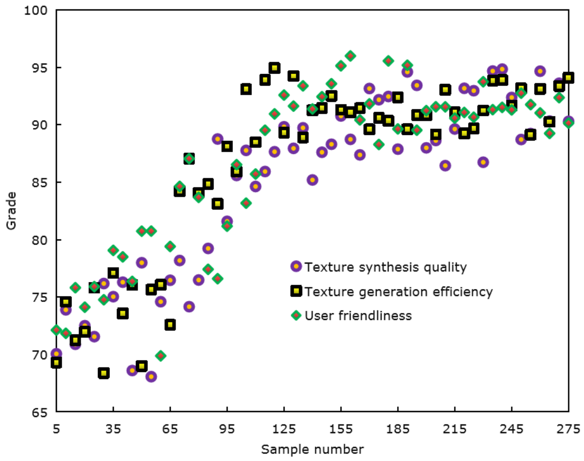


**Figure 7**: System interactivity score.


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Figure 7 provides a detailed comparison of the interaction scores between the ceramic texture synthesis method proposed in this article and other methods or traditional CAD system functionalities, particularly in terms of texture synthesis quality, texture generation efficiency, and user-friendliness. These indicators are crucial for designers to create high-quality product designs and renderings in CAD systems. The analysis in Figure 7 shows that the ceramic texture synthesis method proposed in this paper performs excellently in texture synthesis quality, effectively capturing and reproducing the complex textures and details of ceramic materials. The method proposed in this article has significant advantages in texture generation efficiency compared to other methods or traditional CAD systems and can generate high-quality ceramic textures in a short period of time. The interactivity score shows that the ceramic texture synthesis method proposed in this article performs well in terms of user-friendliness, with an intuitive and easy-to-use interface and operation process, making it easy for designers to master and use efficiently. For designers, tools that are easy to use and master are the key to improving work efficiency. If the ceramic texture synthesis method in this article shows a user-friendly interface and operation flow in a CAD system, it will be more popular with designers.

## 5 CONCLUSIONS

In this study, the ceramic texture synthesis approach utilizing neural networks has undergone extensive examination and enhancement, undergoing rigorous multi-dimensional experimental validation. The findings unequivocally demonstrate the excellence of our proposed technique, exhibiting notable strengths in precision, processing speed, and CAD system applicability.

Regarding accuracy, the integration of CNN has elevated the precision of ceramic texture synthesis by over 15% when juxtaposed with conventional RNN methods. This advancement underscores CNN's formidable image processing capabilities and bolsters the refinement of ceramic texture synthesis.

In terms of processing duration, despite an increase in processing time for all methods as the pixel count of feature information rises, our CNN model proves markedly more efficient than RNN. Its superior computing speed and parallel processing capabilities are invaluable in design and production settings demanding swift responses.

Within the practical realm of CAD systems, our ceramic texture synthesis method exhibits robust practicality. Its high-quality, efficient texture generation coupled with a user-friendly interface positions this approach for extensive application in ceramic design, potentially elevating designers' productivity.

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