3D Digital Technology and Modeling for Material Design of Ceramic Manufacturing Industry

Rui Zhang[1] and Yue Zhang[2]

[1]College of Fine Arts and Art Design, LuoYang Normal University, Luoyang, Henan 471934, China, zhangrui@lynu.edu.cn
[2]College of Fine Arts and Art Design, LuoYang Normal University, Luoyang, Henan 471934, China, zhangyue@lynu.edu.cn

Corresponding author: Rui Zhang, zhangrui@lynu.edu.cn

Abstract. Computer aided design (CAD) technology has been widely used in the field of product design because it can accurately and truly show the plane design drawings in the form of 3D images. Compared with other products, ceramic products have their own characteristics in modeling, so there are special requirements for 3D modeling of ceramic works of art. This article mainly expounds the application of CAD and artificial intelligence (AI) technology in ceramic material art, and optimizes ceramic 3D modeling by combining with deep belief network (DBN), so as to improve design efficiency, reduce design cycle, save resources and reduce production cost, and realize design innovation of ceramic material products. The simulation shows that the error of this algorithm is only 0.207, and the modeling accuracy is above 95%. The application of CAD and AI technology makes the production mode of ceramics diversified. The ceramic products to be produced can be presented by computer 3D digital technology first, and then the ceramic production can be carried out after the customers confirm it, which changes the disadvantage that the traditional ceramic samples have to be produced before the customers can confirm it.

Keywords: Artificial Intelligence; Computer Aided Design; Ceramic Products; Three-Dimensional Modeling
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1 INTRODUCTION

With the high growth of computer hardware technology and the maturity of three-dimensional modeling technology, computers have become an effective driving force to promote the growth of art. With the continuous growth of AI, the traditional method of drawing product modeling with two-dimensional painting and manual modeling has been replaced by various 3D modeling software of CAD. Nanostructured zirconia-based ceramics and composites in dentistry are widely used in the field of Oral medicine. Their advantages include good biocompatibility, corrosion resistance, high strength and wear resistance. Arena et al. [1] conducted a matching analysis of tooth oxidation structure in accordance with material development status. Research has shown that there are some improvements in both optical and mechanical low-temperature resistance reduction of zirconia based nanoceramics. Due to its high strength and wear resistance, it can effectively simulate the mechanical properties of teeth while avoiding the drawbacks of traditional metal materials such as corrosion and allergies. As a part of industrial design, ceramic design is difficult to meet the needs of modern ceramic product design by traditional manual design methods, and the combination of ceramic design and computer has become an inevitable development. Functional gradient porous nanoceramic composites are materials with excellent properties, and their preparation process involves multiple steps and challenges. Barbaros et al. [2] applied an improved method for the production of composite ceramics using nano gradient materials. Through the analysis of the adjustable physical and mechanical properties of Graphene improvement. It constructs analysis of different material production elements. Select raw materials suitable for the preparation of functionally graded porous nanoceramic composites, such as ceramic powders, binders, additives, etc. Depositing a layer of nano coating on the surface of porous ceramic matrix to achieve functional gradient design. This can be achieved by using techniques such as chemical vapor deposition (CVD) or Physical vapor deposition (PVD). By combining nano coatings with porous ceramic substrates, functional gradient porous nano ceramic composites were prepared. This can be achieved by hot pressing sintering, Thermal spraying, electroplating and other technologies. CAD software gives modeling design a more intuitive and convenient design method. CAD software converts two-dimensional drawings into three-dimensional models, then endows materials and arranges scenes, and finally obtains product design renderings through rendering. Two-dimensional images contain abundant data information, and it has the advantages of high modeling efficiency and realistic effect to reconstruct 3D models and render them. It is of great significance to establish digital model from physical objects in the design of ceramics. First, cultural relics or some excellent works can be copied. Secondly, by using the digital model of the existing products, the new design scheme is obtained by combining and deforming in the modeling software. Because CAD technology can accurately and truly show the shape of products, it has been widely used in the field of ceramic material design. CAD technology mainly uses computer vision and other related sciences to reconstruct the high-precision 3D contour of the target object. Chen et al. [3] analyzed and compared the technical parameters and performance of 3D printed ceramics. It is necessary to design and prepare ceramic precursors suitable for 3D printing. The ceramic precursor should be printable and able to be converted into ceramic material after printing. Usually, ceramic precursors can be photosensitive, thermosensitive, or chemically sensitive, depending on the printing equipment and the required ceramic materials. Use 3D printing technology, such as photocuring, thermal curing, or chemical curing, to print ceramic precursors into the desired complex shapes. The accuracy and details of printing can depend on the resolution and capability of the printing device. Convert the printed ceramic precursor into ceramic material. This can be achieved through heat treatment, chemical treatment, or other appropriate methods. During this process, the printable part of the ceramic precursor should fully react to form the required ceramic material.

CAD/CAM technology is often applied in the ceramic mold manufacturing industry, which can effectively shorten the manufacturing cycle, save time, reduce production costs, and reduce the burden on staff, improving the production efficiency of ceramic molds. When using CAD/CAM technology in ceramic molds, it is necessary to follow the corresponding software process. Dal et al. [4] analyzed and studied the crystallization effects of different computer-assisted surface photocuring of ceramics during calcination. After comparing the wear of different oxidized transparent films, it prolongs the lifespan of feldspar ceramics in different oxidized crystals. Three-dimensional design software is not only a kind of operating software, but also a manifestation of Chinese art in the application field of modeling design, which inevitably shines in ceramic modeling design. The addition of CAD technology has brought great convenience and leap to the design of modern ceramic products in terms of product conception, structural analysis and model making. CAD software converts two-dimensional drawings into three-dimensional models, then endows materials and arranges scenes, and finally obtains product design renderings through rendering. In this process, three-dimensional modeling is a very important link. 3D modeling is to reconstruct the 3D model of the real object by using the plane image, which requires finding the corresponding relationship between the two-dimensional image elements and the 3D image elements, and then analyzing and calculating the spatial position and size of the real object in reality, and then reconstructing the 3D model of the measured object. Because of the huge number of 3D models, it will take a lot of time to identify 3D models only by hand. In this article, based on DBN to identify the image characteristics of ceramic products, the contour of ceramic products is tracked and extracted by image channel decomposition method, and the CAD modeling of ceramic works of art is realized. So as to improve the design efficiency, reduce the design cycle, save resources and reduce the production cost, and realize the design innovation of ceramic products.

Micro textured surfaces are a technique that regulates material surface properties through microstructure, and in the control of ceramic wettability, micro textured surfaces have important application value. For the control of ceramic wettability, design goals may include reducing the wettability of ceramic surfaces, improving the wettability of ceramic surfaces, and achieving directional flow of liquids. In order to conduct artificial intelligence assisted design, it is necessary to collect data on the relationship between the microstructure and wettability of ceramic surfaces. These data may include the morphology, texture parameters, and wettability measurement results of the ceramic surface. Díaz et al. [5] explored and analyzed the model construction of ceramic materials in biomedical fields. Powerful engineering tools have been created through the prediction and biological exploration of neural networks. The collected data needs to be preprocessed, including Data cleansing, normalization, feature extraction, etc. The preprocessed data can be used to train and validate artificial intelligence models. The growth of computer graphics and image technology and its wide application in the field of product design have greatly improved the efficiency and quality of product design, and reduced the production cost increase and production design and development cycle. Taking computer three-dimensional modeling as the design method of ceramic product modeling also opens up a new space for ceramic product creation, brings brand-new design concepts and thinking, injects new high-tech vitality into traditional ceramic art, and also brings opportunities for those enterprises that produce ceramic products to improve their market competitiveness. Compared with other products, ceramic products have their own characteristics in modeling, so there are special requirements for 3D modeling of ceramic products. Many non-contact methods need to rely on the continuous movement of the imaging system to obtain multiple images of real objects, and then build 3D models of objects. This will not only increase the complexity of the hardware system, but also require high rigidity of the measured object, and the need to process multiple pictures will increase the complexity of image processing, which can not guarantee the real-time reconstruction of the system. In this regard, this article has made the following innovations:

(1) Based on DBN, the image characteristics of ceramic products are analyzed, and the contour of ceramic products is tracked and extracted by image channel decomposition method.

(2) This technology has high computational efficiency in image analysis of ceramic product CAD modeling, and has high applicability for most 3D modeling problems.

(3) According to the real image of ceramic products, the real representation of ceramic products is realized by CAD three-dimensional modeling.

The first section of the article is the introduction, which introduces the research background and requirements of CAD modeling of ceramic materials, and puts forward the application of AI algorithm to ceramic materials design. In the second and third sections, the basic theory of ceramic CAD modeling is introduced, and the optimization of 3D modeling of ceramic products is realized by combining DBN. In the fourth section, the effectiveness of this method is verified by simulation experiments. The fifth section is a summary of the whole paper, which summarizes the contributions and shortcomings of this article and puts forward the future improvement direction.

2 RELATED WORK

The current additive manufacturing technology focuses on the construction of pattern models for ceramic honeycomb structures. Its cross validation of machine learning has been validated through many training stages of lattice structure. Doodi et al. [6] improved the lattice structure performance of novel hybrid bio inspired 3D printing using artificial neural networks. Through artificial neural networks, structural and design optimization can be carried out based on the composition and performance requirements of ceramic materials. Ceramic 3D printing is a complex manufacturing process that involves multiple process steps, including printing path planning, layer thickness control, material extrusion control, and so on. By using artificial neural networks, these process steps can be intelligently controlled and optimized, thereby improving manufacturing efficiency and product quality. Through artificial neural networks, training and learning can be combined with ceramic lattice structure data and performance data to predict the impact of lattice structure on ceramic performance. By predicting the results, the performance of ceramic lattice structures can be further optimized to meet specific application requirements. Fang et al. [7] conducted a characteristic analysis of carbon fiber materials, which analyzed the thermoplastic image reconstruction of structural imaging. Reconstruction of regional images using filtered reflection. It analyzed and recognized the image feature detection of the training set. By using hyperspectral CT technology, detailed structural and chemical composition information of polymer materials can be obtained. Combining this information with artificial neural networks can more accurately identify the types, properties, and defects of 3D printed polymer materials, improving recognition accuracy. The reconstruction algorithm based on hyperspectral CT technology and artificial neural network has broad application prospects in 3D printed polymer recognition. By combining these technologies, polymer materials can be identified more accurately and reliably, providing more useful information for material research, production, and application.

Farook et al. [8] conducted a convolutional difference analysis of dental ceramics based on a three-dimensional convolutional network. By comparing and analyzing the workflow of Computer-aided design. It constructs a spatial volume overlap function for repairing teeth. Computer-aided design (CAD) for the synthesis and verification of digital partial ceramic crowns is a design method of crowns based on computer technology, which can help dentists quickly and accurately synthesize and verify ceramic crowns. Firstly, obtain the geometric shape and size data of teeth through oral scanning or X-ray film. Using CAD software, design and adjust the shape, size, and color of ceramic crowns based on dental data and patient needs. Generate a digital model of ceramic crowns through calculation and optimization using CAD software. Convert the digital model into a 3D printing file and print the ceramic crown using a 3D printer. Verify and correct the 3D printed ceramic crown to ensure it meets the patient's needs and actual situation. Currently, ceramics based on artificial intelligence for mechanical performance correlation structures and large-scale datasets have broad application prospects. Artificial intelligence and machine learning in the design of ceramic mechanical materials have received increasing attention in recent years. Guo et al. [9] demonstrated that machine learning algorithms can be used to train the model. Common machine learning algorithms include regression analysis, decision tree, Random forest, neural network, etc. These algorithms can learn from preprocessed data and attempt to predict the performance of ceramic mechanical materials. After the training is completed, the model needs to be evaluated to determine its accuracy and generalization ability. Usually, techniques such as cross validation are used to evaluate the performance of the model and adjustments are made based on the evaluation results. The trained model can be applied to practical ceramic mechanical material design. The application of artificial intelligence and machine learning in the design of ceramic mechanical materials can improve the efficiency and accuracy of design, while also helping to optimize material performance. Hu et al. [10] conducted a digital ceramic investment analysis for 3D printing materials. It constructs an emerging comprehensive mathematical ceramic 3D printing method. The extrusion-based 3D printing technology of ceramic slurry is a 3D printing technology based on the principle of extrusion molding. This technology utilizes the flowability of ceramic slurry to extrude a certain shape of material from a certain caliber extrusion nozzle through extrusion, forming ceramic parts layer by layer like toothpaste. By describing different mathematical theories of drying. It constructs a mathematical comprehensive drying power system controlled by non-numerical factors. This technology is usually achieved using melt deposition manufacturing with nozzle heating and slurry direct writing technology with solvent addition.

Building structures based on ceramic materials have excellent mechanical properties. Jiao and Alavi [11] analyzed intelligent mechanical building structures using mechanical superconducting materials. Through artificial intelligence, the design and optimization of ceramic machinery Metamaterial can be realized. For example, ceramic machinery Metamaterial can be designed and optimized according to the requirements of material composition, structure, performance, etc. to meet specific application requirements. The manufacturing of ceramic machinery Metamaterial involves many technological steps, including preparation process, structural molding, performance testing, etc. By using artificial intelligence, these process steps can be optimized to improve manufacturing efficiency and finished product quality. Artificial intelligence can combine the structure and performance data of ceramic machinery Metamaterial to achieve performance prediction and optimization. By establishing a machine learning model, the performance of materials can be predicted based on their composition and structure, further optimizing their performance. Ceramic 3D printing is an advanced manufacturing technology, in which artificial neural networks (ANNs) can play a role in multiple aspects. Ceramic 3D printing involves multiple process steps, including printing path planning, layer thickness control, material extrusion control, and so on. By using artificial neural networks, these process steps can be optimized to improve printing quality and efficiency. Ceramic 3D printing requires the use of different types of ceramic materials. Mahmood et al. [12] conducted parametric material part design analysis for 3D engineering printing. By optimizing the neural network model for 3D printing using traditional machine learning engineering modes, the need for developing and solving physical models is eliminated. Artificial neural network is a computer model that simulates the connection of human brain neurons. It can learn the relationship between input and output. In the new 3D printed non-uniform ceramic reflection array antenna, artificial neural networks can be used to predict and optimize the performance of ceramic reflection array antennas. By training a neural network, it is possible to learn the input geometric parameters and material properties, thereby generating a ceramic reflection array antenna design with optimal performance in a short period of time.

Mahouti et al. [13] optimized the ceramic reflection array of alumina using high-performance full wave sensors and 3D printing technology. An accurate ceramic tracking model was created by structural measurement of pre-set parameters and frequencies. In the manufacturing process of ceramic reflective array antennas, artificial neural networks can be used to predict and control the growth process of ceramic materials. By training neural networks, the growth mechanism of ceramic materials and the relationship between process parameters can be learned, thereby achieving precise manufacturing of non-uniform ceramic reflection array antennas. Verma et al. [14] conducted biomaterial analysis of composite materials. It further obtains the development rights of bioceramic compliant materials by 3D printing natural materials. Advanced processing of 3D printed ceramic composite materials using artificial intelligence can achieve optimization and control of ceramic composite materials. By using artificial intelligence, the design and optimization of ceramic composite materials can be achieved. For example, the structural design and performance prediction of ceramic composite materials can be carried out based on the requirements of material composition, structure, and performance. The 3D printing of ceramic composite materials involves multiple process steps, including printing path planning, layer thickness control, material extrusion control, and so on. By using artificial intelligence, these process steps can be optimized to improve printing quality and efficiency. The performance of ceramic composite materials is influenced by various factors, such as matrix materials, reinforcing phase materials, preparation processes, etc. By using artificial intelligence, these factors can be optimized and controlled to achieve optimal performance. Yamazaki et al. [15] conducted a planar orientation analysis of the layered structure of crystal oxides. IGZO is an oxide semiconductor material with high Electron mobility and good transparency, so it is widely used to manufacture high-resolution, high response speed liquid crystal displays and organic LED display. In artificial intelligence technology based on crystal IGZO ceramics, thin film transistors (TFTs) are usually used to prepare IGZO crystals, which are then used as active components in integrated circuits. These active components can achieve various functions such as amplification, filtering, and switching of input signals, which are widely used in fields such as image processing, video display, communication systems, and so on. Zhang et al. [16] selected raw materials suitable for preparing complex ceramic structures with fine characteristics, such as ceramic powders, binders, additives, etc. These materials should meet certain physical and chemical properties for subsequent processing and preparation. During the preparation process, it is necessary to control key parameters such as density, porosity, and structural stability of the green body. Depositing a layer of nano coating on the surface of ceramic bodies to achieve functional gradient design. This can be achieved by using techniques such as chemical vapor deposition (CVD) or Physical vapor deposition (PVD). During the coating process, it is necessary to control the thickness, uniformity, and stability of the coating.

By combining nano coatings with ceramic bodies, ceramic composite materials with complex structures are prepared. This can be achieved by hot pressing sintering, Thermal spraying, electroplating and other technologies. During the preparation process, it is necessary to control the sintering temperature and time to ensure that the structure and performance of the composite material meet the expected requirements. With the continuous and rapid development of Big data computer technology, the current development in ceramic materials and polymers has been unprecedented. Big data and machine learning have created new opportunities in ceramic materials research. By utilizing machine learning algorithms, it is possible to predict the properties of ceramic materials, such as mechanical properties, thermal properties, electrical properties, etc. These predictions can help researchers better understand the characteristics of materials and provide guidance for material design and optimization. Zhou et al. [17] found that machine learning algorithms can be used to optimize the design of ceramic materials. For example, through genetic algorithm, Particle swarm optimization algorithm and so on, we can find the best composition and structure to achieve the best performance. By analyzing a large amount of data, useful information and patterns can be extracted to better understand the essence of ceramic materials. For example, by analyzing a large amount of data on the composition, structure, and performance of ceramic materials, the patterns and trends of material design can be discovered. Machine learning has important application value in ceramic material design, which can help researchers design and optimize ceramic materials faster and more accurately, while improving production efficiency and quality control level.

3 CAD MODELING OF CERAMIC PRODUCTS

The 3D model is mainly composed of grids and textures. The grids are composed of many point clouds, which are usually triangular, quadrilateral or simple convex-edged. The textures include not only the uneven grooves on the surface of the object, but also the color patterns on the smooth surface of the object. Because of the different light reflection characteristics between the object and the background, the occlusion contour line will be formed when imaging, which provides a restriction on the geometric shape of the object. The object must be located in the cone formed by the viewpoint and the occlusion contour. If orthogonal projection is used, the cone degenerates into a cylinder. When viewed from different positions, multiple viewing cones will be formed, and objects must be located in the common intersection of these viewing cones. The secondary object elements in 3D modeling include points, lines, surfaces, edges, etc. The establishment of 3D models is usually completed by editing the secondary object elements in 2D or 3D. This has something in common with the point, line, surface and body of the morphological elements of ceramic works of art. In CAD, modeling can be done by any modeling method, but there are some differences according to the ability of tools and personal habits. At present, there are many kinds of 3D software applied in the field of CAD, and some large-scale CAD software provide users with various modeling methods, such as basic modeling and polygon modeling. The whole creation process is a concrete process from coarse to fine and from sparse to dense, which has a good sense of operation.

Using modern CAD technology to model ceramic art, designers communicate fully with clients, and use 3D digital modeling software to model ceramic art; Then use model rendering software to render ceramic artworks. The curvature estimation algorithm of Quadric fitting can improve the region growing method and apply it to mesh segmentation with arbitrary structure. This paper analyzes the generalized image-based modeling technology from the perspective of computer graphics. There are various algorithms for image contour extraction, including threshold segmentation, thinning processing, edge detection, vector contour graph generation, etc. Contours include straight line segment contours and curved segment contours. The parameterization of the contour of a straight line segment is relatively simple, while the contour of a curve needs to be represented by parameters such as curvature, radius of curvature, and center of curvature, as shown in Figure 1.

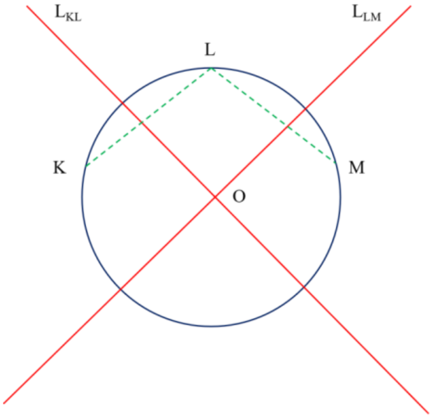

Figure 1: Curve chart.

Using three points to determine the radius of curvature of the curve, the principle is: take three points on the curve:

$$\begin{cases} K=(x_K, y_K) \\ L=(x_L, y_L) \\ M=(x_M, y_M) \end{cases} \tag{1}$$

The curve is a part of the circle, and the method of finding the radius of the circle with three points is used to find the radius of curvature of the curve on the circle. First calculate the mid-perpendicular equation L_{KL} for the K and L points, and the mid-perpendicular equation L_{LM} for the L and M points. According to L_{KL} and the straight line equation L_{LM}, the center and curvature radius of the circle where the curve is located can be determined. The intersection of L_{KL} and the equation L_{LM} is the center (a_c, b_c), and the distance between the center and any point is the radius r_c, as shown in the following formula:

$$a_c = -\frac{d_{KL} - d_{LM}}{k_{KL} - k_{LM}} \tag{2}$$

$$b_c = k_{KL} a_c + d_{KL} \tag{3}$$

$$r_c = \sqrt{(x_k - a_c)^2 + (y_k - b_c)^2} \tag{4}$$

In the process of establishing the model, the perfection of details can truly and effectively show the effect of the product. In shape reconstruction, for each captured image, the outline of ceramic artwork is segmented according to the brightness difference and tone difference of foreground and background; If necessary, the contour image can be corrected manually.

4 OPTIMIZATION OF CAD MODELING OF CERAMIC PRODUCTS BASED ON DBN

In the process of traditional ceramic design and manufacture, it is often necessary to wait until the product is sampled, and after the defects are found, it must be modified from the sub-type, which leads to the extension of the design cycle. In today's increasingly fierce market competition, this problem must be solved in order to shorten the development cycle, improve product quality and launch new products faster and better. Three-dimensional modeling is to establish a three-dimensional model according to the geometric shape of real objects. From the perspective of computer graphics, this process is three-dimensional geometric modeling. The high efficiency and low energy consumption of CAD greatly shortens the product design cycle, promotes the breakthrough and innovation of ceramic product design in modeling, and gives designers more room to play and devote more time and energy to product design. The new modeling language brought by computer urges people to explore and create more ideal forms and better integrate science and art. The influence of CAD on ceramic product design is not limited to this, but more importantly, it brings more new possibilities and attempts for the innovation and growth of ceramic product design.

Based on DBN, this article puts forward a modeling design method of ceramic CAD. Firstly, the calibration disk is placed on the turntable, and a number of different rotation angles are taken to take pictures, thus determining the rotation axis of the turntable, and establishing the object coordinate system and the camera projection matrix at the initial position. Then, put the ceramic artwork on the turntable and take pictures at different positions. Finally, these images are input into the computer for processing, and the steps of contour extraction, volume intersection, feature matching, energy modeling and texture mapping are completed to obtain the 3D model of ceramic products. In the unsupervised pre-training stage, although the weight matrix obtained through training can reflect the structural information of the data to a certain extent, it has not achieved the optimal result. In order to obtain more accurate classification or regression parameters, BP algorithm should be used to fine-tune the DBN parameters. This process is a process of global training. The DBN model at this stage is regarded as a BP neural network, and the parameters obtained after unsupervised pre-training are used as the initialization parameters of the network, and then effective training is carried out with the help of traditional BP neural network training methods. The DBN structure of ceramic product feature recognition is shown in Figure 2.
Realize 3D model segmentation by modeling the spatial correlation between warehouses in the 3D model. The structure of the DBN model consists of multiple RBMs stacked in order and combined by distinguishing classification layers. The purpose of sequential stacking with multiple basic RBMs is to extract the features of input sample data layer by layer, while classification layers with discriminant functions are usually achieved through softmax functions. The main function of this function is to map the features extracted by RBM in the pre training stage to the corresponding labels, in preparation for parameter adjustment of DBN.

DBN is a neural network composed of multi-layer RBM, which can be regarded as both a generative model and a discriminant model. Its construction idea is to use unsupervised greedy layer-by-layer method to pre-train and obtain weights. Neurons are conditionally independent, and the neurons in the explicit layer and the hidden layer are not interconnected, only the neurons in the interlayer have symmetrical connecting lines. The advantage of this is that given the values of all explicit units, what value each hidden unit takes is irrelevant. Give a real-time prediction when every new data comes, instead of waiting for all the data to end before starting to estimate. When the data set is large, the data set is divided into many small data sets, and the small data sets are taken in turn, or the data can be regarded as a stream. Online learning has the characteristics of fast calculation process and low memory consumption.

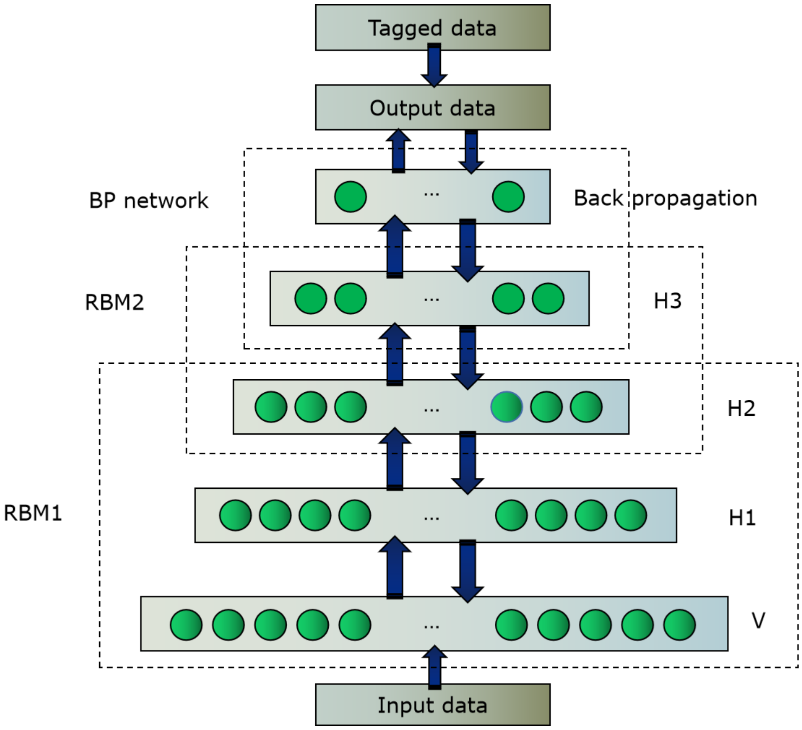

Figure 2: DBN structure of ceramic product feature recognition.

The advantage of DBN model training method is that it sets the initial value of the network in a range that is most likely to achieve global optimization through unsupervised pre-training process, and finally obtains the optimal solution of the network through supervised fine-tuning process, thus accelerating the convergence speed. Let X_i^k represent the sum of inputs of k layer neurons i, Y_i^k is the output, and the weights of $k-1$ layer neurons j to k layer neurons i are W_{ij}, then there is the following functional relationship:

$$Y_i^k = f\left(X_i^k\right) \tag{5}$$

$$X_i^k = \sum_{j=1}^{n+1} W_{ij} Y_j^{k-1} \tag{6}$$

Generally, f A is an asymmetric Sigmoid function:

$$f\left(x_i^k\right) = \frac{1}{1+\exp\left(-X_i^k\right)} \tag{7}$$

If the output layer is the m layer, the actual output of the i neuron in the output layer is Y_i^m. Let the corresponding ceramic feature be Y_i, and define the error function e as:

$$e = \frac{1}{2}\sum_i \left(Y_i^m - Y_i\right)^2 \tag{8}$$

The multi-layer and step-by-step structure of DBN determines that the initialization of DBN can be carried out layer by layer. By training the lowest RBM model, the trained hidden variables are used as the input of the second RBM, and the training of DBN is gradually completed. When the distribution of observed variables is normal, the RBM model in layer-by-layer training can obtain the global optimal solution, but the final solution is not the global optimal solution of DBN, but the initial solution of DBN. There are many difficulties in calculating the global optimal solution of DBN. Using unsupervised initialization process, all layers in DBN reflect some data characteristics, which is a reproduction form of observed data. Because there is a big gap between the output of DBN and the label data due to unsupervised learning, the parameters in the network are supervised learning by using the label data. The operation process of DBN is shown in Figure 3.

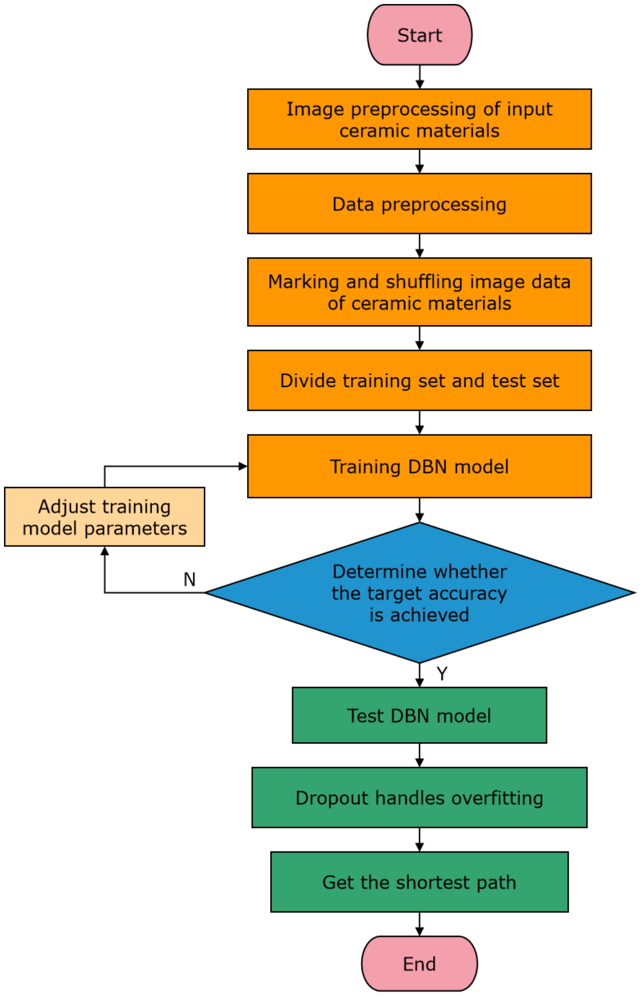

Figure 3: Operation process of DBN.

Based on the conditional correlation between random variables, this article reduces the computational complexity of joint distribution, accelerates the calculation speed of boundary distribution in joint distribution, and extends it to ceramic product design. Let the probability distribution of random variable set $X=\{X_1,X_2,\ldots,X_n\}$ be $P(X_1,X_2,\ldots,X_n)$. If all variables are taken as $\{0,1\}$, $2^n - 1$ parameters are needed to determine the joint distribution. Through Bayesian formula, the joint distribution can be written as:

$$\begin{aligned} P(X_1, X_2, \ldots, X_n) &= P(X_1)P(X_2|X_1)\ldots P(X_n|X_1, X_2, \ldots, X_{n-1}0) \\ &= \prod_{i=1}^{n} P(X_i|X_1, X_2, \ldots, X_{i-1}) \end{aligned} \tag{9}$$

For $\forall X_i \in X$, if there is $\pi(X_i) \subseteq \{X_1, X_2, \ldots, X_{i-1}\}$, the X_i assimilation $\{X_1, X_2, \ldots, X_{i-1}\}/\pi(X_i)$ condition is independent at a given $\pi(X_i)$, and the above formula can be changed to:

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i|\pi(X_i)) \tag{10}$$

Input the training samples into RBM, get the number of nodes, weights and offsets of hidden layers according to the reconstruction error, and initialize the first hidden layer and the second hidden layer in DBN with the obtained weights and offsets. According to the network recognition rate, the number of required RBMs and the number of nodes of each RBM are determined, the weights and offsets of each layer are obtained by training, and the parameters are updated by reverse fine-tuning until the network converges.

5 RESULT ANALYSIS AND DISCUSSION

After the design of a work is completed, the designer can not only grasp the specific size of the object, but also easily analyze the visual feeling of the picture from different angles. This systematic process design not only saves working time, but also designs a ceramic art work more scientifically. After the training, the network stores the eigenvalues of the training samples in each parameter value. When test samples are input into the trained network, image classification and recognition are carried out through eigenvalue matching. In order to verify the feasibility and accuracy of the method and scheme in this article, a 3D modeling system of structured light is constructed and many experiments are carried out. Firstly, the obtained curve coordinates, curvature centers and radii are smoothed and fitted as a whole, and the fitted results are taken as the final actual parameters of the contour. Table 1 shows the internal parameters of the camera.

	Internal parameter matrix	*Distortion parameter*
Left camera	$\begin{bmatrix} 1108.3 & 2 & 479.2 \\ 0 & 1207.8 & 325.7 \\ 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} -0.11776 & -0.26548 & -0.00035 \\ & 0.00035 & 0 \end{bmatrix}$
Right camera	$\begin{bmatrix} 1212.7 & 2 & 408.2 \\ 0 & 1231.4 & 394.2 \\ 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} -0.17010 & -0.062.7 & -0.00279 \\ & 0.00007 & 0 \end{bmatrix}$

Table 1: Internal parameters of the camera.

For the variables in the lowest observation layer, the samples obtained by bottom-up sampling and top-down sampling are the posterior distribution of the model. In the learning of DBN, the contrast bifurcation algorithm is extended, and the posterior distribution of the model is generated through a series of sampling. After unsupervised learning, DBN learned a set of initialized network parameters, which can continuously abstract the data, but there is a deviation between the initial sampling results and the reality. The whole process of subdividing the model should start from the big picture, and then make the details after determining the big proportional relationship. In the design of ceramic materials, the intuitive and simple operation mode of subdivision modeling makes designers design handier. Figure 4 shows the training results of this algorithm.

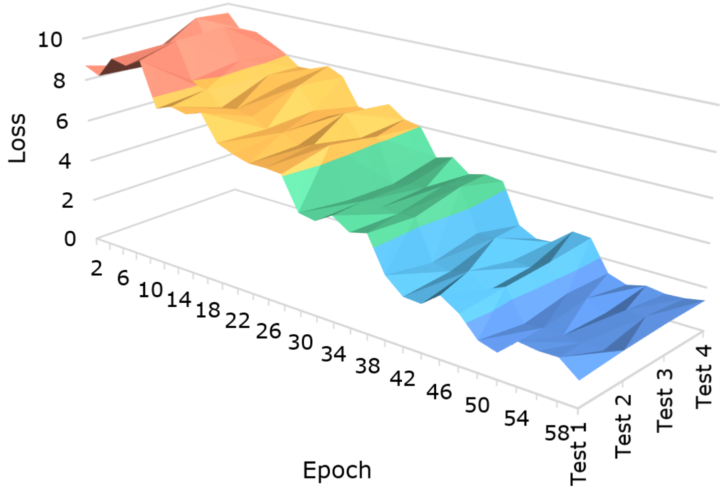

Figure 4: Training results of the algorithm.

Point cloud data obtained by comprehensive utilization of outer contour limitation and feature limitation. After data fitting, it is transformed into non-uniform spline description as modeling data; On the other hand, the mesh model described by VRML is directly output, further modified and improved in other modeling software, and the texture mapping of ceramic product surface is completed. The image data of ceramic products with different data distribution intervals are discretized, as shown in Figure 5.

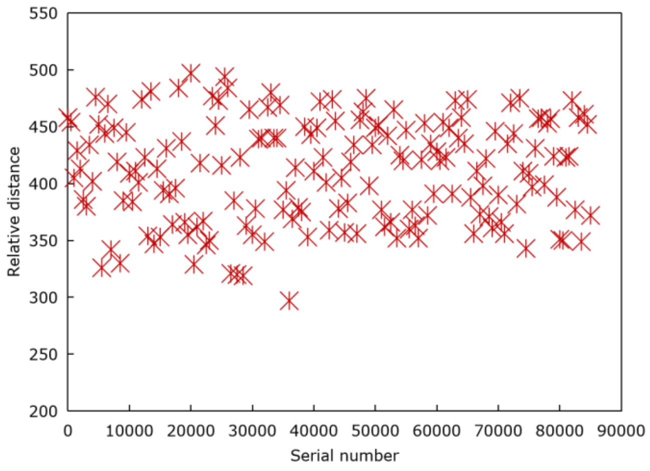

Figure 5: Interval discretization processing.

When performing Boolean operation, it is required that the objects involved in the operation must have an absolutely complete surface, no holes, overlapping surfaces or unmerged nodes to keep the normal direction consistent, and do not easily flip the normal of the object surface, otherwise unpredictable results will be produced. With the application of three-dimensional modeling technology, designers can quickly express the ideas of product modeling design, which provides a visual means to express and reflect designers' creativity. Designers construct models from the conception, randomly modify the parameters under the command or add deformation modifiers to the body, which can produce various effects that cannot be expected in reality or in traditional thinking methods.

The quality of model creation depends not only on whether it can show the general shape of the product, but also on its grasp of the details. Ceramic art has its own characteristics, and whether it can show its own characteristics is the key to the success of a model. Figure 6 shows the modeling error simulation of ceramic products based on the algorithm, and Figure 7 shows the modeling accuracy simulation of the algorithm.

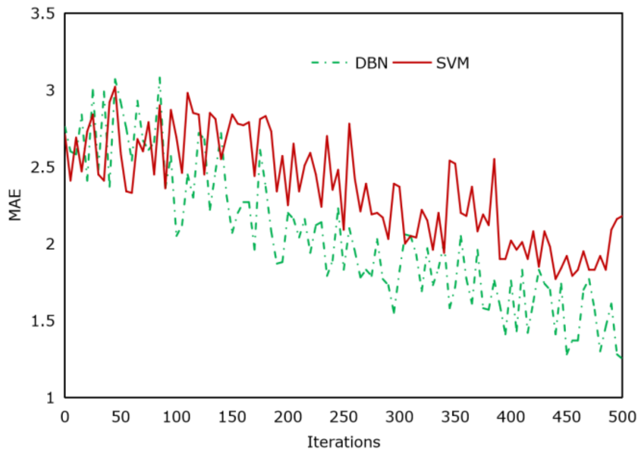

Figure 6: Modeling error test of algorithm.

Figure 7: Modeling accuracy test of the algorithm.

The simulation shows that the error of this algorithm is only 0.207, and the modeling accuracy is above 95%. In this study, according to the image of ceramic products, contour tracking and extraction, as well as contour parameters identification, the parameters of image modeling are obtained, and the 3D modeling of ceramics is realized by CAD technology. The model described by VRML, a VR language, can be directly used for remote display, or can be input into geometric modeling software such as AutoCAD for further processing. The application of CAD, 3D scanning, data reverse modeling and processing, rendering and other related modeling and processing technologies can provide customers with a variety of shapes and renderings of ceramic artworks for customers to choose from, making the early design process more convenient faster.

6 CONCLUSIONS

The growth of CAD technology accelerates the intelligent growth of ceramic manufacturing industry, provides a broader development space for ceramic art design, and accelerates the diversified growth of ceramic art design. The application and popularization of CAD in the design of ceramic materials is the general trend. This design method keeps advancing in the design of ceramic materials with multiple advantages, helping the traditional ceramic technology to complete the innovation. According to the real images of ceramic artworks, it is of great significance to realize the real reproduction of ceramic artworks through 3D modeling, which is of great significance to the network display of ceramic artworks and the digital protection of cultural relics. This article mainly expounds the application of CAD and AI algorithm in ceramic product design, and adopts DBN to optimize ceramic 3D modeling to realize the design innovation of ceramic artworks. DBN is a superposition of several RBMs, and its training mode can actually be regarded as the process of parameter initialization of BP neural network by RBM. In order to better interpret the characteristics of DBN and deepen RBM's understanding of the process of parameter initialization of BP neural network, this article has carried out simulation verification. The results show that the error of this algorithm is only 0.207, and the modeling accuracy is above 95%. This result proves that it is feasible to use this method to optimize ceramic CAD modeling. The research of this project focuses on model construction and algorithm evaluation, and there is no man-machine interaction, which leads to low test efficiency and needs to be further improved.

Rui Zhang, https://orcid.org/0009-0001-7135-8435
Yue Zhang, https://orcid.org/0009-0005-6107-9394

REFERENCES

[1] Arena, A.; Prete, F.; Rambaldi, E.; Bignozzi, M.-C.; Monaco, C.; Di Fiore, A.; Chevalier, J.: Nanostructured zirconia-based ceramics and composites in dentistry: A state-of-the-art review, Nanomaterials, 9(10), 2019, 1393. https://doi.org/10.3390/nano9101393
[2] Barbaros, I.; Yang, Y.; Safaei, B.; Yang, Z.; Qin, Z.; Asmael, M.: State-of-the-art review of fabrication, application, and mechanical properties of functionally graded porous nanocomposite materials, Nanotechnology Reviews, 11(1), 2022, 321-371. https://doi.org/10.1515/ntrev-2022-0017
[3] Chen, Z.; Sun, X.; Shang, Y.; Xiong, K.; Xu, Z.; Guo, R.; Zheng, C.: Dense ceramics with complex shape fabricated by 3D printing: A review, Journal of Advanced Ceramics, 10(2), 2021, 195-218. https://doi.org/10.1007/s40145-020-0444-z
[4] Dal, P.-A.-M.-D.-O.; Bottino, M.-A.; Anami, L.-C.; Werner, A.; Kleverlaan, C.-J.; Lo, G.-R.; Tribst, J.-P.-M.: Toothbrushing wear resistance of stained CAD/CAM ceramics, Coatings, 11(2), 2021, 224. https://doi.org/10.3390/coatings11020224
[5] Díaz, L.-A.; Franco, M.-F.; Hengsbach, S.; Rupp, F.; Thelen, R.; Bade, K.: Artificial intelligence aided design of microtextured surfaces: Application to controlling wettability, Nanomaterials, 10(11), 2020, 2287. https://doi.org/10.3390/nano10112287

[6] Doodi, R.; Gunji, B.-M.: Prediction and experimental validation approach to improve performance of novel hybrid bio-inspired 3D printed lattice structures using artificial neural networks, Scientific Reports, 13(1), 2023, 7763. https://doi.org/10.1038/s41598-023-33935-0
[7] Fang, Z.; Wang, R.; Wang, M.; Zhong, S.; Ding, L.; Chen, S.: Effect of reconstruction algorithm on the identification of 3D printing polymers based on hyperspectral CT technology combined with artificial neural network, Materials, 13(8), 2020, 1963. https://doi.org/10.3390/ma13081963
[8] Farook, T.-H.; Ahmed, S.; Jamayet, N.-B.; Rashid, F.; Barman, A.; Sidhu, P.; Daood, U.: Computer-aided design and 3-dimensional artificial/convolutional neural network for digital partial dental crown synthesis and validation, Scientific Reports, 13(1), 2023, 1561. https://doi.org/10.1038/s41598-023-28442-1
[9] Guo, K.; Yang, Z.; Yu, C.-H.; Buehler, M.-J.: Artificial intelligence and machine learning in design of mechanical materials, Materials Horizons, 8(4), 2021, 1153-1172. https://doi.org/10.1039/D0MH01451F
[10] Hu, F.; Mikolajczyk, T.; Pimenov, D.-Y.; Gupta, M.-K.: Extrusion-based 3D printing of ceramic pastes: Mathematical modeling and in situ shaping retention approach, Materials, 14(5), 2021, 1137. https://doi.org/10.3390/ma14051137
[11] Jiao, P.; Alavi, A.-H.: Artificial intelligence-enabled smart mechanical metamaterials: advent and future trends, International Materials Reviews, 66(6), 2021, 365-393. https://doi.org/10.1080/09506608.2020.1815394
[12] Mahmood, M.-A.; Visan, A.-I.; Ristoscu, C.; Mihailescu, I.-N.: Artificial neural network algorithms for 3D printing, Materials, 14(1), 2020, 163. https://doi.org/10.3390/ma14010163
[13] Mahouti, M.; Kuskonmaz, N.; Mahouti, P.; Belen, M.-A.; Palandoken, M.: Artificial neural network application for novel 3D printed nonuniform ceramic reflectarray antenna, International Journal of Numerical Modelling: Electronic Networks, Devices and Fields, 33(6), 2020, e2746. https://doi.org/10.1002/jnm.2746
[14] Verma, D.; Dong, Y.; Sharma, M.; Chaudhary, A.-K.: Advanced processing of 3D printed biocomposite materials using artificial intelligence, Materials and Manufacturing Processes, 37(5), 2022, 518-538. https://doi.org/10.1080/10426914.2021.1945090
[15] Yamazaki, S.; Ohshita, S.; Oota, M.; Baba, H.; Onuki, T.; Kunitake, H.; Kato, K.: Crystalline IGZO ceramics (crystalline oxide semiconductor)–based devices for artificial intelligence, International Journal of Ceramic Engineering & Science, 1(1), 2019, 6-20. https://doi.org/10.1002/ces2.10005
[16] Zhang, D.; Peng, E.; Borayek, R.; Ding, J.: Controllable ceramic green‐body configuration for complex ceramic architectures with fine features, Advanced Functional Materials, 29(12), 2019, 1807082. https://doi.org/10.1002/adfm.201807082
[17] Zhou, T.; Song, Z.; Sundmacher, K.: Big data creates new opportunities for materials research: a review on methods and applications of machine learning for materials design, Engineering, 5(6), 2019, 1017-1026. https://doi.org/10.1016/j.eng.2019.02.011