Ceramic Process Optimization and Automation Design Based on CAD and Reinforcement Learning

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Abstract. As modern science and technology progress swiftly and market competition intensifies, conventional ceramic manufacturing techniques encounter numerous challenges. By introducing the overview of computer-aided design (CAD) technology and the basic principle of reinforcement learning (RL), this article analyzes the combination of them in the ceramic industry and puts forward a ceramic process optimization method based on CAD and RL. This method accurately extracts the design features and process features of ceramic products and combines the RL algorithm to automatically explore and optimize process parameters, thus realizing efficient optimization and automatic design of ceramic processes. As a key link in connection design and optimization, the importance of feature detection of ceramic products has been fully reflected in this study. The research results show that this method can significantly improve the quality and production efficiency of ceramic products and provide a new direction for the innovation, development, transformation, and upgrading of the ceramic industry. By combining the accurate modelling of CAD technology with the intelligent optimization of RL, the ceramic industry is expected to realize the automation and intelligence of the whole process of design, manufacturing, and optimization, and further enhance the market competitiveness.

Keywords: CAD; Reinforcement Learning; Ceramic Products; Process Optimization;
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1 INTRODUCTION

As a treasure of human civilization, ceramics have been loved by people all over the world for their unique artistic charm and practical value since ancient times. From ancient porcelain to modern industrial ceramics, its manufacturing technology has experienced a long development and evolution.

As modern science and technology rapidly evolve and market competition grows increasingly fierce, traditional ceramic manufacturing techniques encounter numerous obstacles, including low efficiency, elevated costs, and inadequate design innovation. Artificial neural networks (ANNs) have become a key tool in many fields. Especially in computer-aided design (CAD) and computer-aided process planning (CAPP), the application of ANN has brought revolutionary changes to the ceramic industry. Andriani et al. [1] reviewed the application of artificial neural network technology in computer-aided ceramic process planning. Ceramics, as an important engineering material, have a wide range of applications, ranging from daily necessities to high-end technological products. Ceramic process planning involves numerous complex factors, such as material properties, forming processes, sintering processes, etc. ANN can predict the physical and chemical properties of ceramic raw materials, such as density, hardness, thermal stability, etc., based on their composition and preparation process. This provides strong support for selecting suitable raw materials and optimizing preparation processes. By training the relationship between historical process parameters and ceramic properties, ANN can predict ceramic properties under different process parameters and provide guidance for optimizing process parameters. To address these issues, the ceramic industry must promptly integrate cutting-edge technologies and methodologies to refine production processes and facilitate automated design. CAD technology, a versatile design tool, has gained widespread adoption in various fields, including architecture, machinery, and electronics. The ceramic industry, as a combination of traditional and modern manufacturing technologies, is facing increasingly fierce market competition and constantly changing customer demands. Optimizing production planning and control is the key to enhancing the competitiveness of ceramic enterprises, ensuring product quality and delivery time. In recent years, with the rapid development of artificial intelligence technology, especially the outstanding performance of reinforcement learning (RL) in the fields of decision-making and control, its application in ceramic process optimization production planning and control has gradually received attention. Esteso et al. [2] explored the application and potential impact of reinforcement learning in ceramic process optimization production planning and control. In ceramic technology, reinforcement learning algorithms can be applied to optimize production plans. For example, using reinforcement learning algorithms to learn the production order and batch size between different products to minimize production time and cost. In addition, reinforcement learning can also consider uncertain factors such as equipment failures and unstable raw material supply, improving the robustness and adaptability of production plans. In the realm of ceramic design, CAD technology offers designers enhanced precision in creating three-dimensional models of ceramic products, thereby boosting design efficiency. Additionally, CAD facilitates the parameterization of design data, simplifying subsequent process optimization and automating design tasks. Nevertheless, the current application of CAD technology in ceramic design remains in its infancy, with significant untapped potential and value.

RL interacts with the environment through agents and learns the mapping strategy from state to action to maximize the cumulative reward. This method has made remarkable achievements in games, robot control, natural language processing and other fields. The application of computer-aided design (CAD) in the process design of molecular ceramic products is becoming increasingly widespread. However, in practical operation, the uncertainty of material properties often brings difficulties to the design process. To address this issue, Frutiger et al. [3] proposed an optimization strategy based on Monte Carlo simulation, aimed at improving the accuracy and efficiency of process design for molecular ceramic products. Molecular ceramic products have unique physical and chemical properties, which pose many challenges in their process design. Among them, the uncertainty of material properties is a particularly prominent issue. These uncertainties may arise from factors such as errors in the material preparation process, accuracy limitations of measuring equipment, and the non-uniformity of the material itself. In the process design of molecular ceramic products, Monte Carlo simulation can be used to simulate the uncertainty of material properties and evaluate the impact of these uncertainties on process design. During process optimization, RL can autonomously experiment and refine process parameters, ultimately leading to enhancements in both product quality and production efficiency. The implementation of RL in optimizing ceramic processes is anticipated to usher in transformative advancements for the ceramic industry. The application of advanced technologies such as computer-aided design (CAD) and reinforcement learning in ceramic process optimization and automation design is becoming increasingly widespread. The application of these technologies not only improves the production efficiency of ceramic products but also promotes innovation and development in the ceramic industry. CAD, as an efficient design tool, is widely used in the optimization and automation design of ceramic processes. Designers can use CAD software for 3D modelling, structural analysis, and optimized design of ceramic products. Through precise size control and material selection, CAD technology can ensure that ceramic products achieve the best process results while meeting design requirements. CAD can also be combined with CNC machining equipment to achieve automated production of ceramic products [4].

Ceramics, as an ancient and important material, has always been a goal pursued by the manufacturing industry to improve its process strength. Lao et al. [5] explored how to use machine learning-based algorithms to construct directed optimization to enhance the strength of ceramic processes. The improvement of ceramic process strength is of great significance for improving product quality, extending service life, and expanding application fields. However, the strength of ceramic materials is influenced by various factors, such as material composition, preparation process, microstructure, etc. The relationships between these factors are complex and difficult to accurately control using traditional methods. Therefore, it is necessary to use machine learning algorithms to construct directed optimization models to address this challenge. It will apply the constructed machine learning-based ceramic process strength optimization model to practical production, and perform directional optimization on ceramic materials. By adjusting the material composition and preparation process parameters, the ceramic process strength can be improved. Practical applications have shown that this method can significantly improve the strength of ceramic products, reduce production costs, and enhance market competitiveness. Piezoelectric nanocomposite ceramic materials have broad application prospects in fields such as sensors, actuators, energy conversion, and storage due to their unique piezoelectric effect and excellent physical properties. Traditional material design methods often rely on trial and error methods and empirical knowledge, resulting in low efficiency and high cost. With the rapid development of computer science and artificial intelligence, high-throughput phase field simulation and machine learning methods have provided new avenues for optimizing piezoelectric nanocomposite ceramic materials. Li et al. [6] explored how to combine high-throughput phase field simulation and machine learning techniques to optimize the performance and design of piezoelectric nanocomposite ceramic materials. High throughput phase field simulation is a computational method based on physical models that can simulate the microstructure and properties of materials. Through high-throughput phase field simulation, the effects of different compositions, structures, and process parameters on the properties of piezoelectric nanocomposite ceramic materials can be systematically studied. Ceramic Reinforced High-Temperature Alloys (CRHTAs) combine the high hardness, wear resistance, and high-temperature stability of ceramic materials with the toughness and machinability of metal materials. Therefore, it has broad application prospects in fields such as aerospace, energy conversion, and automotive manufacturing. However, the design and optimization process of CRHTAs involves multiple complex physical and chemical processes, and traditional design methods often struggle to achieve optimal performance optimization. In recent years, with the development of machine learning technology, its application in the field of material design has gradually received attention. Liu et al. [7] explored how to use machine learning to assist in the design of high-performance optimized reinforced ceramic high-temperature alloys. By adjusting the type, morphology, size, and distribution of ceramic reinforcement phases, the microstructure of CRHTAs can be optimized to improve their properties. Machine learning can assist in analyzing the impact of microstructure on performance, providing guidance for microstructure design.

These research results cover many aspects of ceramic process optimization, including CAD technology application, RL algorithm application, intelligent control technology, etc., which provide useful literature for ceramic industry process optimization and automatic design. But at present, there is relatively little research on the application of CAD technology and RL in ceramic process optimization and automatic design. Therefore, this article aims to explore and study ceramic process optimization and automatic design methods based on CAD and RL, in order to provide new ideas for the development of the ceramic industry. Specifically, this study includes the following innovations:

(1) This article integrates CAD technology with the RL algorithm for the optimization and automated design of ceramic production techniques. This cross-disciplinary approach blends the precision of engineering design with the learning capabilities of artificial intelligence, paving the way for ceramic technology innovation.

(2) Traditionally, ceramic design heavily relied on manual labour and the artist's intuition. However, this article incorporates CAD technology to facilitate the parameterization of ceramic design. This advancement not only enhances design accuracy and consistency but also lays the foundation for subsequent automated optimization.

(3) The algorithm engages in interactive learning between the agent and the production environment, enabling it to autonomously explore and refine crucial process parameters in ceramic manufacturing. This, in turn, elevates product quality and streamlines production efficiency.

Initially, this article outlines the fundamental principles of CAD technology and RL, emphasizing their potential in ceramic process optimization. Subsequently, it delves into the optimization techniques of ceramic design based on CAD and the implementation strategies of RL in ceramic production optimization. An automated design system is then established, facilitating the seamless translation and optimization of CAD models into process parameters. Ultimately, the article validates the superiority of the proposed methodology through experimental analysis and discussion of the results.

The research of this article is expected to promote the wide application of CAD technology and RL in the ceramic industry, improve the design level and production efficiency of ceramic products, reduce production costs and enhance market competitiveness. Furthermore, we also hope that this research can provide useful literature for other related fields.

2 THEORETICAL BASIS AND RELATED TECHNOLOGIES

With the advancement of technology, machine learning algorithms have been widely applied in multiple fields, including the optimization of ceramic processes. Ceramics, as an ancient and important material, has always been a goal pursued by the manufacturing industry to improve its process strength. Malviya and Desai [8] explored how to use machine learning-based algorithms to construct directed optimization to enhance the strength of ceramic processes. The improvement of ceramic process strength is of great significance for improving product quality, extending service life, and expanding application fields. However, the strength of ceramic materials is influenced by various factors, such as material composition, preparation process, microstructure, etc. The relationships between these factors are complex and difficult to accurately control using traditional methods. It will apply the constructed machine learning-based ceramic process strength optimization model to practical production, and perform directional optimization on ceramic materials. By adjusting the material composition and preparation process parameters, the ceramic process strength can be improved. Practical applications have shown that this method can significantly improve the strength of ceramic products, reduce production costs, and enhance market competitiveness. The error problem in the CAM process limits the further improvement of its accuracy. To address this issue, machine learning technology has been introduced into error compensation in CAM to improve manufacturing accuracy and product quality. Omari and Ismail [9] analyzed the machine learning error compensation in ceramic additive manufacturing. In the ceramic additive manufacturing process, errors mainly come from multiple aspects such as material properties, equipment accuracy, environmental conditions, and manufacturing processes. These errors can lead to deviations in the size, shape, and performance of the final product from the expected design, thereby affecting the quality and performance of the product. Machine learning can model and analyze errors in the manufacturing process. By training historical data, machine learning models can learn the distribution patterns and influencing factors of errors, thereby establishing error prediction models.

This model can predict potential errors in future manufacturing processes and provide data support for error compensation.

With the continuous development of technology, advanced technologies such as computer-aided design (CAD) and reinforcement learning are increasingly being applied in ceramic process optimization and automation design. The application of these technologies not only improves the production efficiency of ceramic products but also promotes innovation and development in the ceramic industry. Saucedo et al. [10] analyzed fault recognition and diagnosis methods for metal, hybrid, and ceramic bearings based on deep feature learning. CAD, as an efficient design tool, is widely used in the optimization and automation design of ceramic processes. Designers can use CAD software for 3D modelling, structural analysis, and optimized design of ceramic products. Through precise size control and material selection, CAD technology can ensure that ceramic products achieve the best process results while meeting design requirements. Reinforcement learning is an advanced machine learning technique that continuously learns and optimizes decision strategies through the interaction between intelligent agents and the environment, in order to achieve optimal task completion results. Reinforcement learning technology can be applied to intelligent control and optimization of production processes in ceramic process optimization and automation design. Ceramic Additive Manufacturing (CAM) is an advanced manufacturing technology that can manufacture ceramic components with complex shapes and high performance without relying on traditional molds or mechanical processing. Among them, Powder Bed Fusion (PBF) is a widely used technology in ceramic additive manufacturing, which builds three-dimensional solids by selectively fusing ceramic powder layer by layer. However, the process of powder bed fusion involves multiple complex physical and chemical processes, such as powder layer spreading, laser energy absorption, thermal conduction and diffusion, making process control extremely challenging. Sing et al. [11] provided a new solution for controlling the powder bed fusion process in ceramic additive manufacturing by analyzing machine learning techniques. The defects that may occur during the manufacturing process of ceramic additives (such as cracks, pores, lack of fusion, etc.) seriously affect the quality and reliability of the product. Machine learning can utilize image processing techniques to extract and classify features from image data during the manufacturing process, achieving automatic prediction and recognition of defects. This can not only improve production efficiency but also provide strong support for quality control and process improvement. The ceramic industry, as an important field that combines traditional and modern manufacturing technologies, has a complex manufacturing process and extremely high process requirements. With the continuous development of artificial intelligence technology, especially the successful application of reinforcement learning (RL) in the fields of decision-making and control, computer-aided ceramic Process Planning (CCPP) plays an increasingly important role in ceramic manufacturing systems. Soori and Asmael [12] conducted a classified discussion on the research and application of reinforcement learning in ceramic process planning. By using reinforcement learning algorithms, a predictive model for the ceramic process is constructed, and through interaction with the environment, model parameters are continuously optimized to achieve precise control of the ceramic process. This includes multi-dimensional optimization such as temperature, pressure, and time to improve the quality and production efficiency of ceramic products. Train an intelligent system that can automatically determine ceramic process parameters through reinforcement learning algorithms. This system can adjust process parameters in real time based on the characteristics of ceramic materials, production needs, and other factors, achieving intelligence and automation in ceramic manufacturing.

Ceramic tiles are widely used materials in the construction industry, and their surface quality directly affects the aesthetics and service life of products. However, during the production process, various defects may appear on the surface of ceramic tiles, such as cracks, stains, deformations, etc. Traditional defect detection methods mainly rely on manual visual inspection, which is not only inefficient but also susceptible to subjective factors. Stephen et al. [13] provided a new solution for the automatic detection of surface defects in ceramic tiles using convolutional neural networks. It collected a large amount of surface image data of ceramic tiles, including normal and images with various defects. After training and evaluation, the model can be deployed to production environments for practical applications. In practical applications, image data of ceramic tile surfaces can be obtained through devices such as cameras or scanners, and then trained models can be used for automatic defect detection. This will greatly improve detection efficiency and reduce labour costs. With the development of machine learning technology, machine learning classification methods based on ultrasound signals provide a new approach to the detection of microdamage in piezoelectric ceramics. Tripathi et al. [14] explored how to use machine learning of ultrasound signals to classify microdamage in piezoelectric ceramics. Ultrasonic signals are widely used in the field of non-destructive testing due to their sensitivity to internal defects in materials. In piezoelectric ceramics, the presence of microdamage can alter the acoustic properties of the material, leading to phenomena such as scattering, reflection, or transmission of ultrasonic signals during propagation. By collecting and analyzing these ultrasound signals, feature information related to microdamage can be extracted, such as signal amplitude, phase, frequency, etc. Machine learning is a technique that learns and extracts useful information from data. In the classification of microdamage in piezoelectric ceramics, machine learning can identify different types of microdamage by training models. The ceramic industry manufacturing industry is a highly complex field with extremely strict process requirements. With the digital transformation and intelligent upgrading of the manufacturing industry, the application of Statistical Process Control (SPC) in the ceramic industry is becoming increasingly widespread. Reinforcement Learning (RL), as an advanced machine learning method, provides a new perspective and solution for statistical process control in the ceramic manufacturing industry. Viharos and Jakarta [15] discussed the application of reinforcement learning in statistical process control in the ceramic manufacturing industry and related measurement techniques. Reinforcement learning is a machine learning method that learns the optimal decision strategy through interaction with the environment. In the ceramic manufacturing industry, reinforcement learning can be combined with statistical process control to achieve real-time monitoring and intelligent adjustment of the production process. By collecting various data during the production process, reinforcement learning algorithms can learn the optimal process parameters and operational strategies, thereby achieving precise control of the production process.

The ceramic industry, as an important component of traditional manufacturing, involves multiple complex process steps in its production process, such as raw material preparation, molding, sintering, decoration, etc. With the intensification of market competition and the increasing demand for product quality from consumers, the optimization of the production process in the ceramic industry has become particularly important. In recent years, the development of machine learning technology has provided new means for optimizing the production process of the ceramic industry. Weichert et al. [16] reviewed the application and prospects of machine learning in the optimization of ceramic industry production processes. Raw materials are the foundation of ceramic products, and their quality directly affects the subsequent process and the performance of the final product. Forming is a crucial step in the ceramic production process, which directly determines the shape and structure of the product. Machine learning can optimize the forming process, and improve the dimensional accuracy and surface quality of products by analyzing the relationship between forming parameters and product performance, establishing predictive models. With the rapid development of renewable energy technology, the application of ceramic materials with high energy storage density in the field of energy storage is increasingly receiving attention. However, traditional material development processes are often time-consuming and costly, especially when searching for ceramic materials with high energy storage performance in low fields. Yuan et al. [17] explored how to use machine learning and experimental design methods to accelerate the search for matrix ceramic materials with high energy storage performance in low fields. Machine learning can analyze the relationship between material composition and structure, as well as their impact on material properties. By optimizing the composition and structure of materials, the energy storage performance of ceramic materials can be further improved. Experimental design can help researchers explore new ceramic materials. Through carefully designed experimental plans, the impact of different compositions and structures on material properties can be systematically studied, thereby discovering new materials with excellent performance.

3 OPTIMIZATION METHOD OF CERAMIC PROCESS

3.1 Optimization of Ceramic Design Based on CAD

CAD technology, a pivotal tool in contemporary design, has found widespread application across diverse industrial design and manufacturing processes. Leveraging the robust computing and processing powers of computers, CAD technology aids designers in executing efficient and precise design tasks. In the realm of ceramic design, CAD technology offers designers a more convenient and adaptable approach to their craft. Contrastingly, traditional ceramic design methods often rely on manual sketching and production techniques, which are not only time-consuming but also challenging in ensuring design accuracy and consistency. However, with CAD software, designers can effortlessly create and refine 3D models of ceramic products, enabling precise manipulation of design parameters. CAD technology also supports parameterization and standardization of design data, providing strong support for subsequent process optimization and automated design. By simulating and analyzing the design parameters such as structure, shape, and size of ceramic products, CAD technology can help designers identify potential design problems and optimize them. This optimization process can not only improve the design quality of ceramic products but also reduce production costs and improve production efficiency.

However, the application of CAD technology in ceramic design also has certain limitations. Firstly, the special properties of ceramic materials make their design process more complex and difficult. For example, the brittleness, shrinkage rate and other characteristics of ceramic materials need to be fully considered in the design process. Secondly, the operation and use of CAD software require a certain level of professional knowledge and skills, which puts higher demands on the quality and ability of designers.

RL is an important branch of machine learning. Its basic principle is to learn the mapping strategy from state to action through the interaction between agents and the environment, to maximize the cumulative reward. In the process of RL, the agent chooses an action to execute according to the current environmental state, then observes the reward and new state of environmental feedback, and updates its strategy according to this information. Through continuous trial and error and learning, agents can gradually find the optimal action strategy to complete specific tasks. The core of the RL algorithm is how to balance the relationship between exploration and utilization. Exploration means that agents try new actions and environmental states to gain more information and learning experience. Utilization means that the agent chooses the best action according to the existing knowledge and experience to maximize the reward. In ceramic process optimization, the RL algorithm can be applied to many aspects. Firstly, the design parameters and process parameters of ceramic products can be automatically explored and optimized by the RL algorithm. For example, a reward function can be set to maximize some performance indexes of ceramic products (such as strength, toughness, etc.), and then design parameters and process parameters can be automatically adjusted through the RL algorithm to achieve these goals. Secondly, the RL algorithm can also be applied to the automatic control of the ceramic production process. For example, the RL algorithm can be used to learn the optimal production control strategy to improve production efficiency and product quality.

CAD technology can provide RL with accurate and reliable design data for ceramic products. The three-dimensional model created by CAD software can contain rich geometric information and physical information, which can be used as input features of the RL algorithm for training and optimization. The RL algorithm, when paired with CAD models, can autonomously explore and refine ceramic production parameters. By establishing suitable reward functions, state spaces, action spaces, and other components, the algorithm can independently discern the optimal mix of production parameters, eliminating the need for prior expertise. This, in turn, elevates product quality and streamlines production efficiency. Conventionally, ceramic design processes heavily relied on the designer's expertise and instincts for decision-making, a method that was both time-consuming and unreliable in ensuring design optimization. However, by integrating CAD technology with RL, an automated design system can be devised to seamlessly translate and optimize ceramic designs. This system can generate compliant ceramic product models and fine-tune their production parameters based on design specifications and constraints, ultimately enhancing product quality and production efficiency.

The amalgamation of CAD technology and RL presents vast opportunities and potential in optimizing and automating ceramic production processes. This integration promises to enhance the efficiency, precision, and innovation of ceramic product design, while simultaneously boosting production quality and efficiency. Moreover, it provides robust technical backing for the sustainable advancement of the ceramic industry. Stereo registration is a commonly used 3D mosaic algorithm at present. Its central idea is to find the nearest point of the distance difference between point pairs in two groups of point clouds by using a search algorithm, to establish the error function of point pairs, and finally to minimize it. This method has strict requirements for selecting the initial position. Once the selected position is not good, the algorithm will easily fall into local optimization. The algorithm is to find the coordinate transformation relationship between two groups of point clouds, and then mosaic them according to their relative positions. In fact, we can get the coordinate transformation relationship between two groups of point clouds in advance, as shown in Figure 1.

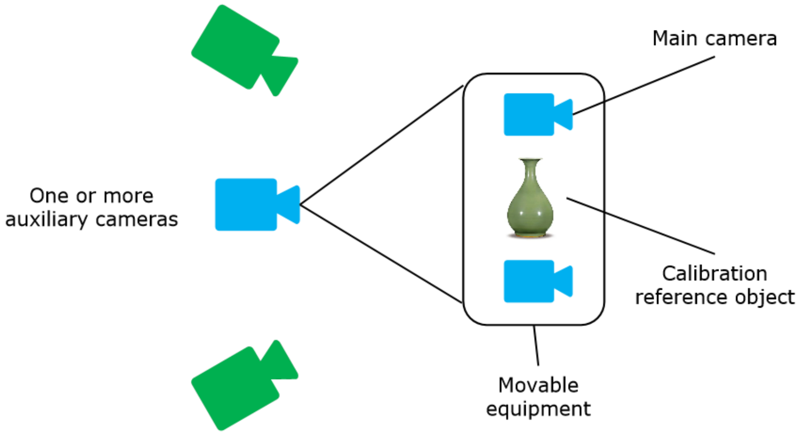

Figure 1: Schematic diagram of handheld device for assisting camera calibration.

When simulating the ceramic sintering process, we can ignore some physical effects that have little influence on the final product performance, and only pay attention to those key factors that play a decisive role in sintering quality and efficiency. By simplifying the physical model, the complexity and cost of calculation can be greatly reduced, and at the same time, enough accuracy can be ensured to meet the needs of process optimization. The flow chart of the model simplification algorithm is shown in Figure 2.

Considering the original ceramic image $f(x,y)$, let $g_{\min}, g_{\max}$ represent its grey value range. Subsequently, choose a suitable threshold denoted as T, and proceed accordingly.

$$g_{\min} \le T \le g_{\max} \tag{1}$$

The process of image segmentation utilizing a solitary threshold can be formulated as follows:

$$g(x,y) = \begin{cases} 1, & f(x,y) \ge T \\ 0, & f(x,y) < T \end{cases} \tag{2}$$

$g(x,y)$ is a binary image that allows for effortless separation of objects from the background through the process of binarization.

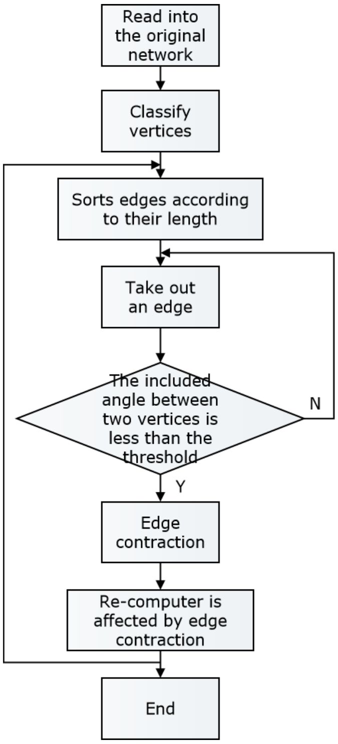

Figure 2: Algorithm flow chart.

The camera model mathematically represents the triple transformation process of point coordinates across four coordinate systems. For simplicity, homogeneous coordinates are employed in the derivation. By appending an algebraic component of 1 to $n+1$-dimensional points, the translation, rotation, and scaling of n-dimensional points can be concisely expressed in matrix notation. The camera model's mathematical formula is as follows:

$$u \cong \begin{bmatrix} f/dx & s & x_0 \\ & f/dy & y_0 \\ & & 1 \end{bmatrix} \begin{bmatrix} R_{3\times3} & T_{3\times1} \end{bmatrix} X_W = K\begin{bmatrix} R & T \end{bmatrix} X_W = PX_W \tag{3}$$

The matrix P, known as the projection matrix, comprises the internal parameter matrix K, the camera's rotation matrix R, and its translation matrix T. By utilizing the plane coordinate u of a corresponding point obtained through feature matching, the three-dimensional coordinate X_W can be computed. Notably, the camera's internal parameter matrix K solely depends on its internal structure and remains unaffected by the reconstruction process. This matrix can be accurately determined through camera calibration.

The incremental algorithm facilitates the reconstruction of a sparse point cloud, commencing with two view units to restore both the projection matrix of the two views and the three-dimensional point cloud. Subsequently, a solitary new view is progressively integrated, aligning with the world coordinate system of the existing views and expanding the imaging geometry structure. In an ideal scenario, the projection beams of each point converge at the camera's optical centre, while the beams from multiple cameras intersect at a spatial point. The objective function quantifies the aggregate projection error squared for all correspondingly named points.

$$\min \sum_{i,j} d\left(\hat{P}^i \hat{X}_j, x_j^i\right)^2 \tag{4}$$

The aforementioned formula demonstrates that the smallest possible sum of squared distances is achieved between the estimated re-projection point $\hat{P}^i \hat{X}_j$ and the actual projection point x_j^i. Herein, x_j^i signifies the projection coordinates of a point j on the i image.

3.2 Application of RL in Ceramic Process Optimization

Feature detection of ceramic products is one of the core links in this study, which aims to systematically identify and extract key design features and process features from complex ceramic design models or objects. These characteristics, such as geometric shape, size, surface texture and physical properties, such as density and hardness, form the basis of uniqueness and performance of ceramic products. Through high-precision feature detection method, we can transform these complex features into quantifiable data, which provides solid support for subsequent data analysis and optimization. RL algorithm relies on a deep understanding of the environment to make effective decision-making strategies. In ceramic process optimization, these extracted features provide key information about ceramic product performance and design constraints for the RL algorithm. By taking these features as input, the RL algorithm can automatically explore and optimize process parameters without manual intervention so as to maximize the quality and production efficiency of ceramic products. The feature detection process of ceramic products is shown in Figure 3.

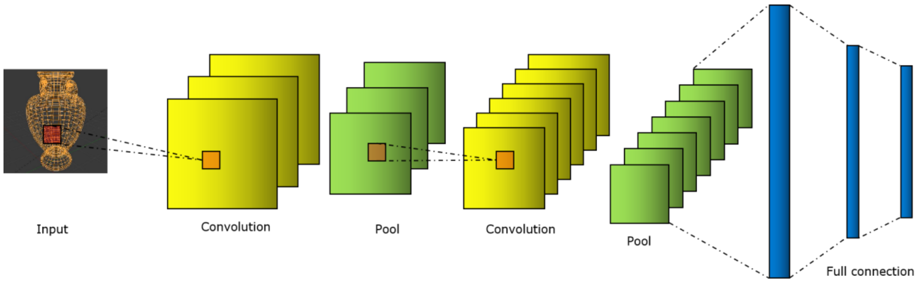

Figure 3: Feature detection of ceramic products.

Each convolution layer is interconnected with all subsequent convolution layers, enabling the l convolution layer to acquire feature information extracted from all preceding layers. Consequently, the input x_l for each layer can be represented as follows:

$$x_l = H_l\left[x_0, x_1, \cdots, x_{l-1}\right] \tag{5}$$

Where $\left[x_0, x_1, \cdots, x_{l-1}\right]$ represents the set of features extracted from layers 0 to l.

In this design, the look-up table method is employed, necessitating the storage of only half of the information of the unsaturated region of the tanh function. Function values for other parts can be computed using the aforementioned method. Furthermore, the two activation functions can undergo mutual transformation through translation and scaling within the coordinate system:

$$\sigma\ x\ = \tanh\left(\frac{x}{2}\right) + \frac{1}{2} \tag{6}$$

$$\tanh\ x\ = 2\sigma\ 2x\ - 1 \tag{7}$$

In addition to the nonlinear activation function, the model incorporates crucial operations such as matrix-vector multiplication and element-wise vector multiplication. This integration of multi-dimensional information facilitates the filtering of pertinent and extraneous data, thereby enhancing the linkage between entity words and their corresponding relations. This approach ultimately aims to bolster the acquisition of entity relations. At each time step t, the selection gate mechanism is utilized S,h_n,e_1,e_2 to produce the representation $h_t^{'}$ of individual selection gates, utilizing the following calculation formula:

$$S=\begin{bmatrix}\vec{h}_n\\ \bar{h}_1\end{bmatrix} \tag{8}$$

$$SGate_t=\sigma\ W_s h_t+U_s S+V_s e_1+V_s e_2+b \tag{9}$$

$$h_t^{'}=h_t\otimes SGate \tag{10}$$

In this context, W_s,U_s,V_s serves as the weight vector, b as the offset value, σ denotes the sigmoid activation function, and $\otimes$ represents array point multiplication. As a result, a fresh sentence representation sequence, $h_1^{'},h_2^{'},\cdots,h_n^{'}$, is acquired.

Within this structure, the initial step involves applying linear transformations to the input data and two sets of entity word vector data. Subsequently, these transformed values undergo nonlinear computation through the sigmoid activation function, yielding a nonlinear decision boundary that facilitates more accurate data fitting.

4 EXPERIMENT AND ANALYSIS

4.1 Experimental Setup

This study selected various types of ceramic products as experimental subjects to verify the universality and effectiveness of the proposed method. These ceramic products cover different shapes, sizes, and uses, including tea sets, tableware, decorations, etc. (see Figure 4). To ensure the reliability of the experimental results, we collected real data on these ceramic products from the market and preprocessed and standardized them. In terms of sample selection, a random sampling method is used to randomly select a certain number of samples from each product category as the training and testing sets. The training set is used to train the RL algorithm and optimize process parameters, while the test set is used to evaluate the performance and optimization effect of the algorithm. This sample selection strategy can ensure the objectivity and representativeness of the experimental results.

In order to simulate a real ceramic production environment, we have built an experimental platform that includes CAD design software, an RL algorithm library, and a ceramic production simulator. Among them, CAD design software is used to create and modify three-dimensional models of ceramic products; The RL algorithm library provides a variety of commonly used RL algorithms for selection; The ceramic production simulator simulates the production process of ceramic products based on the input process parameters and outputs the quality indicators of the products.

4.2 Experimental Process

During the experiment, a 3D model of the ceramic product was first created using CAD design software, and the geometric and physical information of the model was extracted as the basic data for subsequent processing. Then, input these data into the ceramic production simulator to simulate the ceramic production process under different process parameters, and record the corresponding product quality indicators. In order to facilitate the training and optimization of the RL algorithm, the collected data was preprocessed and standardized.

Figure 4: Example of ceramic products.

Preprocessing mainly includes steps such as data cleaning, denoising, and missing value filling to ensure the accuracy and integrity of the data; Standardization is the process of converting data to a unified scale, eliminating dimensional differences between different features. These processing steps are crucial for improving the performance and stability of the algorithm.

After completing data collection and processing, start training and optimizing the RL algorithm. We have selected the RL algorithm suitable for this problem and configured the corresponding parameters according to the experimental settings. Then, use the training set data to train the algorithm and find the optimal combination of process parameters through continuous trial and error and learning.

In order to verify the effectiveness and superiority of the proposed method, we compared and analyzed the experimental results with other benchmark methods. By comparing the experimental results, it was found that the ceramic process optimization method based on CAD and RL showed good performance in multiple indicators.

4.3 Result Comparison and Analysis

The feature matching of two viewpoints is constrained by the polar geometric relationship, which can be established through the basic matrix to establish coordinate relationships and assist in feature matching. Therefore, the key to the problem lies in how to select the optimal matching pair from the initial matching results that contain errors and errors, in order to accurately calculate the base matrix. Meanwhile, accurate point matching can also improve the accuracy of line matching. However, the computational efficiency of the feature number algorithm itself is relatively low, which is a problem that needs to be solved.

To verify the effectiveness of the weighted processing algorithm, this study selected two ceramic images for experimentation. The initial matching obtained 3711 pairs of feature points, which were arranged in descending order of scale. Next, we calculated the average vertical distance from each group of points to the polar line and plotted the corresponding curve graph (as shown in Figure 5).

As the scale of feature points gradually increases, the volatility of the average distance between each group also increases accordingly. When the distance ratio continues to decrease, the confusion of feature points is effectively suppressed, and the average vertical distance from point to line is maintained at a low and stable level, making it very suitable as a consideration factor for weighted processing. The experimental results show that only the top 26% of the feature points in the comprehensive sorting can be used to calculate the basic matrix that meets the accuracy requirements.

Based on the above calculation process, we selected 10 sorted ceramic images for sparse 3D point cloud reconstruction, and finally successfully obtained the 3D coordinate information of 33125 points. For the error level of the analysis results, the reprojection RMSE of each view is detailed in Table 1.

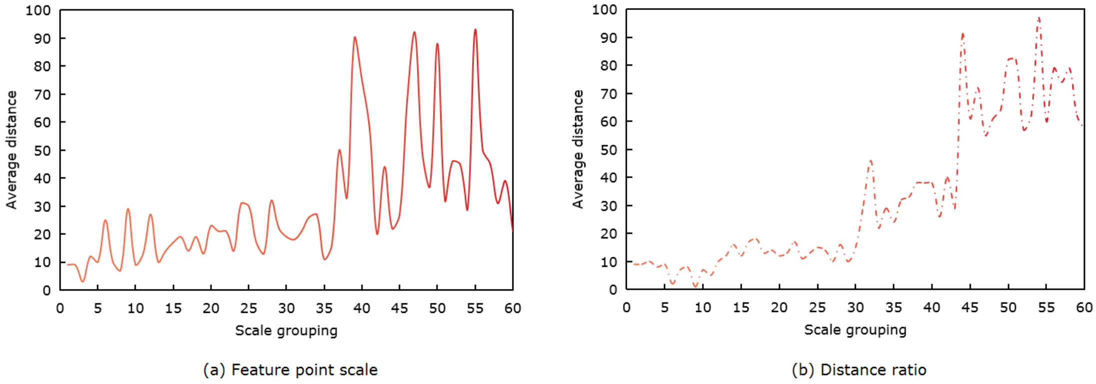

Figure 5: Relationship between geometry error and characteristic point scale and distance ratio.

View number	*RMSE*	*View number*	*RMSE*
1	0.4042	6	0.6221
2	0.4108	7	0.5487
3	0.4303	8	0.657
4	0.4222	9	0.5203
5	0.4245	10	0.5837

Table 1: Reproject RMSE for each view.

According to the data in Table 1, it can be found that the re-projection RMSE of 10 views is controlled within 1 pixel, which indicates that the reconstructed 3D point cloud has good accuracy in imaging structure. Furthermore, the display effect of the point cloud is highly consistent with the visual interpretation result of the image, which further verifies the accuracy of the reconstruction. This achievement has laid a solid foundation for the subsequent construction of dense point clouds and the introduction of straight-line features. Figure 6 shows the accuracy of the point cloud deep learning network in segmentation task training and the change curve of the loss function.

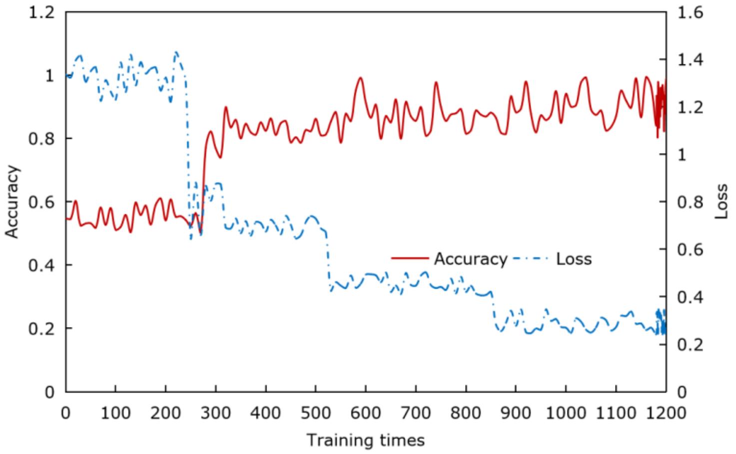

Figure 6: Curve of network training accuracy and loss function.

After sufficient training, the accuracy of the network gradually improves, while the loss function value also steadily decreases. After a certain number of training sessions, the network performance tends to stabilize, with an accuracy rate of about 95%, while the loss function value decreases to below 0.2. This indicates that the network has demonstrated good performance in scene segmentation tasks and has the potential to be applied to tasks such as segmentation and classification.

Literature [7] and [11] provide data on the average accuracy of different methods in ceramic design tasks and the modelling accuracy of each component. Table 2 shows the partial modelling results of three networks on the dataset, providing a basis for us to compare and analyze the performance of different methods.

Way	*Accuracy*	*Recall*	*F1*
Literature [7]	77.36	71.25	69.82
Literature [11]	81.21	76.39	72.18
This method	91.25	88.36	80.27

Table 2: Segmentation results.

From Table 2, it can be seen that compared with the literature [7] and [11], the method proposed in this article demonstrates higher accuracy in ceramic design tasks. Whether in the same or different scenes, this method can accurately segment the same type of object, and there is also a clear distinction between different objects.

In order to further investigate the influence of numerical range and accuracy on the inference calculation of the RL model, in addition to testing the accelerator designed in this study, we also tested the inference accuracy and numerical error of the RL model under different numerical formats during the validation process, as shown in Figures 7 and 8.

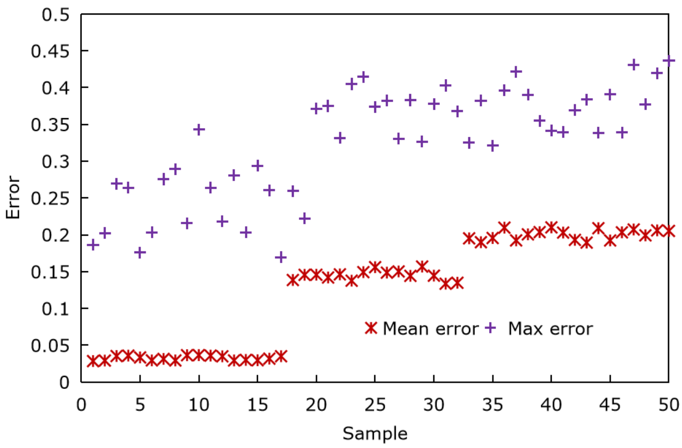

Figure 7: Network calculation errors under different numerical formats.

When reducing the range and accuracy of numerical values, the calculation error of the RL model will correspondingly increase, and the prediction accuracy will also decrease. However, by adopting specific numerical formats and optimization measures, the accelerator designed in this project can control the error within an acceptable range during inference operations, thereby ensuring the accuracy of inference. In addition, compared with the high-precision and large dynamic range implementation method, this design requires fewer hardware resources, achieving a reasonable balance between cost and performance.

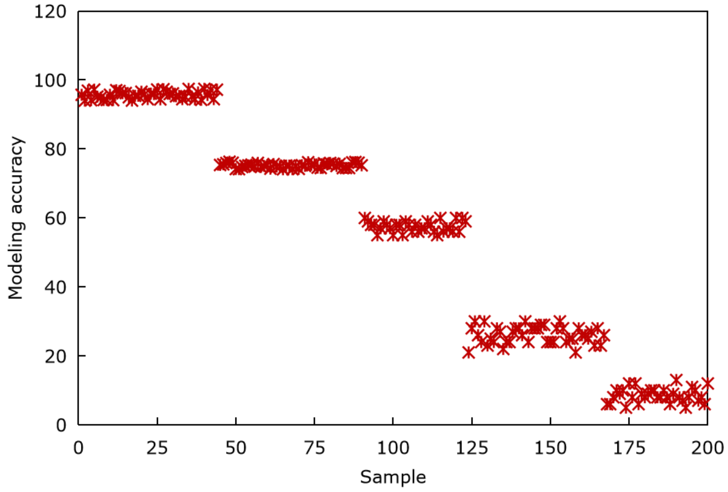

Figure 8: Inference accuracy under different numerical formats.

To verify the performance of the improved model in terms of training speed, we randomly selected 5 types from the database, totaling 4055 object objects, for testing. As shown in Table 3, the improved network has achieved significant improvement in training speed.

Way	*Time(min)*
Literature [7]	7.45
Literature [11]	6.72
This method	4.42

Table 3: Comparison of training speed.

In the tightly linked network, each layer can directly obtain the gradient of the loss function and the original input information, thus forming an implicit depth supervision mechanism. In contrast, the supervision information of traditional convolutional networks only comes from the upper layer, and with the increase of network depth, this supervision function will gradually weaken. In addition, another advantage of a dense link network is that it can effectively reduce the risk of over-fitting.

Next, the test is continued on the test machine, aiming at comparing the model coincidence rates of various methods for different types of objects. The related results will be shown in Figure 9, so as to analyze the performance differences of various methods more intuitively.

The improved model is superior to the original model in all kinds of modelling. Generally speaking, although the model proposed in this article is slightly inferior to the literature [7] in reconstruction effect, it is significantly superior in time efficiency, with a speed increase of more than 30%.

5 CONCLUSIONS

This study discusses ceramic process optimization and automatic design methods based on CAD and RL. By systematically introducing the basic principles of CAD technology and RL, their great application potential in the ceramic industry is revealed. In particular, as a key link in connection design and optimization, the importance of feature detection of ceramic products has been fully reflected in this study.

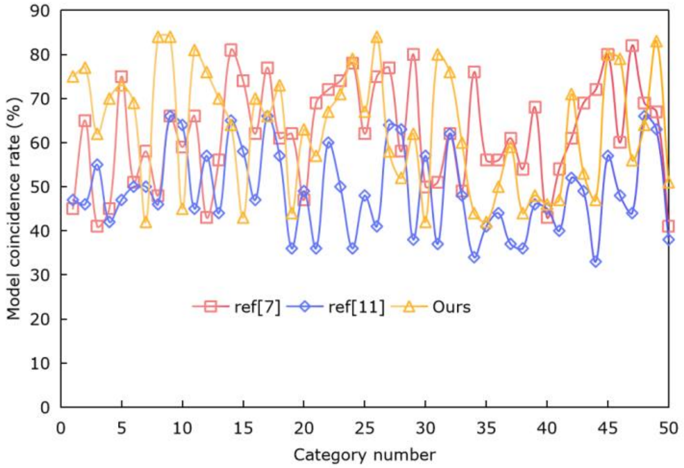

Figure 9: Coincidence rate between prediction model and real model.

By accurately identifying and extracting the key design features and process features of ceramic products, this study provides strong data support for the subsequent process optimization based on RL. After receiving these characteristic data, the RL algorithm can automatically explore and optimize process parameters, and significantly improve the quality and production efficiency of ceramic products. By combining the accurate modelling of CAD technology with the intelligent optimization of RL, the ceramic industry is expected to realize the automation and intelligence of the whole process of design, manufacturing and optimization, and further enhance the market competitiveness.

Although this article has made some achievements in ceramic process optimization and automatic design based on CAD and RL, there are still some limitations and challenges, such as the special properties of ceramic materials, the complexity of the production process and the optimization efficiency of RL algorithm, which need to be further studied and solved. These problems will be further discussed and solved in the follow-up research.

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