www.cad-journal.net
Computer-Aided Design AND APPLICATIONS

Application of Data Mining in Computer Aided Art Design and Algorithm Optimization

Zhu Liu[1] and Boyuan Cui[2]

[1]School of Music, Henan Polytechnic, Zhengzhou, Henan 450046, China, 14008@hnzj.edu.cn
[2]School of Electronics and Internet of Things, Henan Polytechnic, Zhengzhou, Henan 450046, China, 37042@hnzj.edu.cn

Corresponding author: Zhu Liu, 14008@hnzj.edu.cn

Abstract. Art and design is a process full of creativity and inspiration, but traditional computer-aided art and design (CAAD) systems often lack effective support for designer creativity and inspiration. Graphics processing algorithms are one of the core technologies in CAAD. Data mining (DM) technology can extract common and individual features in design by mining and analyzing a large amount of design data. This article aims to explore optimization methods for graphics processing algorithms in CAAD, especially the application of DM technology. By introducing the principles and methods of DM, this article proposes an innovative graphic processing algorithm optimization scheme. This method utilizes the principles of data-driven and model optimization to analyze and optimize the performance of graphic processing algorithms through techniques such as association rule mining, clustering analysis, and classification prediction. The results show that DM technology can improve the performance and effectiveness of graphics processing algorithms, providing strong support for the development of CAAD.

Keywords: Data Mining; Computer Aided Art Design; Graphics Processing
DOI: https://doi.org/10.14733/cadaps.2024.S19.17-32

1 INTRODUCTION

As information technology advances rapidly, DM technology stands out as a crucial tool for extracting invaluable insights from the immense sea of data. CAAD, as a product of the combination of traditional art and modern science and technology, constantly absorbs various advanced technologies in its development process to improve the quality of design. As an important means of diagnosis and treatment, graphic imaging, combined with data mining and machine learning technologies, has brought revolutionary changes to the field. Agnihotri et al. [1] explored the role of data mining and machine learning techniques in graphic imaging. Data mining refers to the process of extracting useful information from a large amount of data. In graphic imaging, data mining techniques can help us extract valuable information from massive images, providing strong support for doctors' diagnosis and treatment. In graphic imaging, machine learning techniques can help us automatically analyze and process images, improving diagnostic accuracy and efficiency. Data mining and machine learning technologies are expected to play a greater role in graphic imaging. For example, with the popularization and application of high-resolution imaging technology, we need more efficient and accurate algorithms to process these massive images. The application of digital image technology in the field of art is becoming increasingly widespread. Fiber art, as a representative of the combination of traditional craftsmanship and modern design, is constantly innovating and transforming its creative methods. Carmen [2] explored how to combine information literacy with pattern design through digital imaging technology, injecting new vitality into fiber art. In pattern design, information literacy is mainly reflected in the interpretation, analysis, and re-creation of images. By processing digital images, we can delve deeper into the information in the images and transform it into creative and aesthetically pleasing pattern designs. In fiber art creation, digital images can be obtained through photography, scanning, and other methods. Through image processing software, basic operations such as cropping, adjusting brightness, contrast, etc., can be performed on digital images to meet the needs of fiber art creation. By utilizing digital image technology, we can design various patterns as needed. For example, using drawing tools in software, abstract or concrete patterns can be drawn. By using filters, color adjustments, and other operations, patterns with special effects can be generated. In addition, algorithms can be used to generate unique patterns, providing more possibilities for fiber art creation. Moreover, algorithm optimization, as an important means to improve the performance of computer systems, has been seeking more efficient and intelligent methods. In this context, the application of DM technology in CAAD and algorithm optimization is particularly important and forward-looking. In the field of CAAD, designers usually need to deal with a lot of data, including images, colors, shapes, textures, and so on. However, traditional design methods often rely on the designer's personal experience and intuition. Not only does this hinder design efficiency, but it also has an impact on design innovation to a certain degree. Chinese ink painting is an important component of Chinese culture; its unique artistic style and expressive techniques provide rich materials for digital art. Chung and Huang [3] explored how to use boundary-enhanced generative adversarial networks (GANs) to interactively transform Chinese ink paintings into real-life images. Chinese ink painting is known for its concise lines, elegant colors, and profound artistic conception. However, traditional ink painting often faces some challenges in the process of digital transformation, such as the loss of detailed information, the restoration of color and texture, etc. Therefore, it is particularly important to develop a method that can preserve the essence of ink painting and convert it into real-life images. In the task of converting Chinese ink painting into real images, the characteristics of GAN can be utilized to learn the style and features of ink painting through training generators. In order to better preserve the boundary information and details of ink paintings, a technique called boundary enhancement can be used to provide the edge information of ink paintings as additional input to the generator. In this way, the generator can pay more attention to the preservation of boundary information and the presentation of realism when generating images. The advent of DM technology has ushered in groundbreaking transformations within CAAD. By leveraging DM technology in CAAD, designers can not only streamline the processing and analysis of vast datasets during the design phase, extracting invaluable insights but also unearth potential patterns and trends hidden within historical design data. This, in turn, equips designers with robust decision-making support. Generative Adversarial Networks (GANs) have become a powerful tool for generating highly realistic handwritten text. However, existing GAN models still face some challenges when imitating handwritten text, such as the diversity and readability of generated text. To address these issues, Gan et al. [4] proposed a new GAN model called HiGAN+, which combines entanglement representation and generative adversarial networks, aiming to improve the accuracy and diversity of handwriting imitation. The task of the generator is to generate realistic handwritten text images based on input random noise and entangled feature vectors. To achieve this goal, we adopt a Conditional Convolutional Neural Network (CNN) as the architecture of the generator. During the training process, we use adversarial training methods to optimize the parameters of the generator so that the generated images can deceive the discriminator. The task of the discriminator is to determine whether the input handwritten text image is real or generated. In HiGAN+, we use CNN to construct discriminators. Unlike traditional GANs, we pass entangled feature vectors as part of the input to the discriminator. This enables the discriminator to distinguish between real and generated images using the features learned from entanglement representation.

In actual sculpture creation, artists can use computer-aided design to carry out preliminary design and conceptualization. By establishing digital models, artists can better grasp the structure of forms and the relationship between space, making them more adept in practical production. In addition, computer-aided design can also be used to create three-dimensional renderings and animations of sculptures, helping artists better present the artistic effects of their works. Computer-assisted design not only provides more precise tools for sculpture creation but also stimulates artists' innovative thinking. Through digital technology, Guo and Wang [5] attempted various forms and spatial combinations, breaking through traditional limitations and exploring more unique and avant-garde techniques for sculptural, graphic art spatial expression. This innovative way of expression expands the boundaries of sculpture art and attracts more audience attention and participation. Chinese painting is a unique art form, and its color application and coloring techniques have a crucial impact on the painting's overall style and artistic conception. In recent years, with the continuous development of deep learning technology, more and more researchers have begun to attempt to use machine learning methods for the automatic coloring of Chinese paintings. The task of the generator is to generate fake data that is as similar as real data as possible, while the task of the discriminator is to distinguish between real data and fake data generated by the generator. Through the adversarial training of these two, the generator can gradually improve the authenticity of its generated data. In the local color simulation method of landscape painting, He [6] uses GAN to control and adjust the local colors of landscape painting. Specifically, local color features are first extracted from a large number of landscape paintings, and then GAN is used to generate local colors similar to these features, thereby achieving local color simulation of landscape paintings.

In the traditional art environment design process, designers need to spend a lot of time and effort on hand drawing and model making. And computer-aided clustering design software can quickly generate design schemes, greatly improving the efficiency of design. Jin and Yang [7] use computer-aided clustering design software to enable designers to control elements such as proportions, colors, and materials in their designs more accurately, thereby creating more realistic and vivid design effects. Computer-assisted clustering design software supports multiple people to design and edit online simultaneously, which helps promote team collaboration and improve the quality and efficiency of design. The computer-aided clustering design software provides a rich library of materials, including various shapes, textures, and colors. These materials can help students quickly complete design proposals and improve design efficiency and quality. Through virtual reality technology, students can engage in practical operations of art environment design in a virtual environment and experience the skills and methods of design more realistically. This will help improve students' practical abilities and creativity. The above research has made remarkable progress in CAAD and algorithm optimization, but there are still some limitations. First of all, some research studies are too focused on specific fields or technologies and lack comprehensive consideration of the overall design process and user needs. Secondly, some studies have made achievements in algorithm optimization and innovation, but they may face challenges such as scalability, universality, and user acceptance in practical applications. This study explores the use of DM in CAAD, including the following innovations:

(1) Aiming at the graphics processing algorithm in CAAD, this article proposes an intelligent optimization strategy based on DM. These strategies automatically identify performance bottlenecks by analyzing the historical execution data of the algorithm and putting forward targeted optimization suggestions.

(2) To ascertain the tangible benefits of DM in CAAD, this article conducts a comprehensive set of experimental investigations, providing a meticulous comparison of design performance pre and post-optimization.

Subsequently, the upcoming chapters will commence with an overview of the fundamental principles and prevalent methodologies associated with DM technology. This will be followed by a detailed exposition of the application contexts and tailored implementation techniques of DM within the CAAD domain. Furthermore, the article delves into the utilization of DM technology for refining graphics processing algorithms, proposing a refined framework centered around DM and substantiating its efficacy and predominance through rigorous experimentation. Finally, this article will summarize and prospect the full text and point out the direction of future research.

2 RELATED WORK

Generative Adversarial Networks (GANs) have become an important tool in the field of image generation and transformation. In the field of art education, utilizing GAN for learning and analyzing pencil drawing has enormous potential and value. Jin et al. [8] explored how to construct a GAN-based art education pencil drawing learning system based on large-scale image datasets and analyzed its learning process. It collected a large-scale dataset of pencil drawing images. These data can come from various sources, such as artist works, online galleries, art education resources, etc. The task of the generator is to learn the intrinsic distribution of data and generate new images. The task of the discriminator is to determine whether the input image is real and provide the corresponding probability value. The pencil drawing learning system uses Convolutional Neural Networks (CNN) as the basic architecture of the generator and discriminator. During the training process, the generator and discriminator will undergo adversarial training. The generator attempts to generate more realistic pencil drawing images to deceive the discriminator, while the discriminator strives to improve its discriminative ability to distinguish between real images and generated images. Through this adversarial training, the generator can ultimately generate high-quality pencil drawing images. Computer-aided design provides artists and designers with a new way of creating. Through software, they can easily modify, refine, and implement their creativity. This technology not only improves the efficiency of creation but also opens the door to infinite possibilities for artists. At this stage, artists should fully unleash their imagination and come up with ideas without any limitations. CAD technology can help artists quickly convert ideas into visual graphics, thereby better understanding and refining creativity. After initial creativity, CAD technology can help artists accurately implement these ideas. Through parameterized design, artists can easily adjust various aspects of the design to achieve optimal results. After completing the design, artists can evaluate the feasibility and innovation of the design through various analysis tools in CAD software. These tools can help artists identify potential issues in their designs and provide suggestions for improvement [9].

Generative Adversarial Networks (GANs), as a deep learning model, have demonstrated strong capabilities in image generation and transformation. In interactive drawing tools, neural stroke engines provide artists and users with a richer and more diverse creative experience by learning potential style spaces. Shugrina et al. [10] explored the application of association rule mining and clustering analysis in neural stroke engines to explore their potential style space further. The neural stroke engine is an interactive drawing tool based on deep learning technology. It utilizes the GAN model to learn the intrinsic distribution of image data through training generators and discriminators, thereby generating images with similar styles and features. In the neural stroke engine, the generator adopts a Convolutional Neural Network (CNN) architecture, while the discriminator also adopts a CNN architecture. By continuously optimizing and adjusting the parameters of the generator and discriminator, neural stroke engines can gradually improve the authenticity and diversity of generated images. In the field of artistic creation, artificial intelligence technology has also brought us new ways of creation. A collaborative creation drawing system based on generative adversarial networks is a typical example, which utilizes the characteristics of generative adversarial networks (GANs) to achieve intelligent multi-user collaborative creation. Generative Adversarial Network (GAN) is a deep learning model consisting of two parts: a generator and a discriminator. The task of the generator is to learn the distribution of real data and generate new data, while the task of the discriminator is to determine whether the input data is real. By continuously optimizing and adjusting the parameters of the generator and discriminator, GAN can gradually improve the authenticity and diversity of the generated data. In collaborative drawing systems, the application of GAN is mainly reflected in two aspects: firstly, utilizing GAN to generate diverse painting styles and content, providing rich materials for collaborative creation; The second is to use GAN to evaluate and optimize painting works, improving their quality and artistic value [11].

Paired D++GAN (also known as Double Diverse GAN) has become a highly anticipated method aimed at addressing the challenges faced by GANs in generating images and texts, as well as improving the quality and diversity of generation. Vo and Sugimoto [12] introduced the basic principles, applications, and future development directions of paired D++GAN. Paired D++GAN can be used to generate images with specific styles or structures. By adjusting the parameters of the generator, users can obtain images with different styles, colors, and textures. This ability has broad application prospects in fields such as artistic creation, virtual reality, and game development. Paired D++GAN can also be used to generate text data with semantic similarity. By learning from a large amount of text data, paired D++GANs can generate articles or sentences that are similar in theme and structure to a given text. Paired D++GAN can be used to generate realistic virtual scenes and characters. By combining image generation and text generation techniques, paired D++GANs can help create a richer and more diverse virtual world, providing more creativity and possibilities for virtual reality and game development. Wang and Qin [13] used CAD software to design art connecting rod molds, greatly improving the accuracy and precision of the design. Through precise 3D modeling and simulation analysis, defects in the design can be identified and corrected in a timely manner, reducing modifications and adjustments in the later manufacturing process. CAM technology can directly convert CAD design data into manufacturing instructions, achieving fast and accurate machining. This can not only improve manufacturing efficiency but also reduce manual intervention, reduce human errors, and improve product quality. The application of CAD/CAM technology can greatly reduce the repeated trial and repair work in traditional design and manufacturing processes, thereby reducing production costs. Meanwhile, optimizing the design scheme can also reduce material costs and energy consumption. Using CAD software for 3D modeling of art connecting rod molds, precise control of the mold's structure, dimensions, and accuracy. Evaluate the mechanical and thermal properties of the mold through simulation analysis to ensure the reliability and stability of the design. Import CAD design data into CAM software for machining path planning and CNC programming. By optimizing CAM software, precise machining instructions are generated to achieve efficient machining of art connecting rod molds.

Due to its rich and diverse culture and vast market, multimedia information processing technology has broad prospects for regional development and application. At the same time, the rise of artificial intelligence technology has brought revolutionary changes to the fields of art, design, and education, especially in the teaching environment of universities. Xu and Jiang [14] discussed the development of multimedia graphic information processing and how universities can use artificial intelligence for innovation in art design and teaching. In terms of art and design, artificial intelligence technology can help designers better carry out creative designs and improve design efficiency. For example, using machine learning techniques to learn a large number of design works can help designers gain inspiration and predict fashion trends. Meanwhile, artificial intelligence technology can also provide designers with precise target positioning and decision support through the analysis of user feedback, market data, etc. Illustrated sketches are a creative and expressive form of visual expression widely used in fields such as design, art, and entertainment. However, manually creating high-quality illustration sketches requires a high level of professional skills and time investment. Therefore, automatic or semi-automatic illustration sketch-making methods are of great significance. Generative adversarial networks provide a new solution to this problem, but existing methods still have shortcomings in terms of generating image authenticity and detail richness. Yeom et al. [15] proposed an attention-based generative adversarial network. This network introduces attention mechanisms in the generator and discriminator to improve attention to image details and the quality of generation. The attention mechanism is a powerful technique that enables models to focus on key areas in the input. By combining GAN and attention mechanism, we aim to generate more realistic and detailed illustration sketches. With the rapid development of computer vision and deep learning technology, adversarial networks (GANs) have achieved significant results in image generation and coloring. However, existing GAN models still face some challenges in coloring animated sketches, such as unnatural color transitions and insufficient expressive power of details. To address these issues, Zhang et al. [16] proposed a Cycle Consistent Adversarial Network (CycleGAN) aimed at providing high-quality coloring for animated sketches. The basic idea of GAN is to generate real images through competition between a generator and a discriminator. The task of the generator is to generate an image based on the input random noise, while the task of the discriminator is to determine whether the generated image is real. However, traditional GAN models often overlook the cyclic consistency between sketches and shading results when dealing with animation sketch coloring problems. To address this issue, CycleGAN introduces a cyclic consistency loss function, which enables the generated images better to match the style and features of the original sketch.

3 CAAD FOUNDATION

3.1 Basic Concepts of CAAD

DM denotes the extraction of concealed and potentially advantageous information and knowledge from substantial volumes of incomplete, noisy, ambiguous, and random data that are unknown beforehand. This technology integrates knowledge and advancements from diverse domains, encompassing databases, statistics, machine learning, pattern recognition, and artificial intelligence. Its objective is to cull insights that facilitate decision-making from vast datasets. As a technique tailored for extracting valuable data from extensive repositories, DM has recently garnered increasing adoption across various sectors. The dawn of the big data era has further accentuated the significance of DM technology.

The basic principle of DM can be summarized as:

⊖ Data Preparation: This initial phase of DM encompasses procedures like data cleansing, integration, selection, and transformation. Data cleansing primarily focuses on eliminating noise and outliers to maintain data coherence. Integration amalgamates data from disparate sources, creating a cohesive dataset. Selection filters out data pertinent to the mining objectives from the raw corpus. Transformation, meanwhile, standardizes and discretizes the data.

⊜ DM Process: Once the data is meticulously prepared, a range of DM algorithms can be deployed for processing and analysis. These algorithms primarily encompass classification, clustering, association rule extraction, sequence pattern identification, and anomaly detection, among others.

⊛ Pattern evaluation: Not all mined patterns are valuable, and valuable patterns need to be screened through pattern evaluation.

④ Knowledge representation: Finally, represent the valuable information and knowledge mined in an easily understandable way.

CAAD, an abbreviation for Computer-Aided Art Design, denotes the utilization of computer systems alongside associated software tools in the realm of artistic design. This fusion of artistic, design, and technological elements presents designers with innovative methods and mediums for creation. CAAD effectively converts a designer's creativity and concepts into a digital format, leveraging computer technology for modeling, rendering, artistic enhancements, and simulations and culminating in the visual representation of the design.

3.2 The Development Course of CAAD

The origins of CAAD can be traced back to the 1960s. This was a time when computer technology was in its infancy, and individuals began exploring its potential in assisting with design and drafting tasks. As computer technology continued to advance, CAAD underwent several stages of growth and transformation.

Initially, CAAD primarily depended on basic drawing software and tools. Designers would often create hand-drawn sketches, which they would then digitize using computers. However, with the evolution of computer graphics and the advent of 3D modeling technology, CAAD ushered in a new era of three-dimensional design. Nowadays, designers can leverage sophisticated 3D modeling software to produce highly detailed and realistic renderings of their creations.

3.3 The Core Technology of CAAD

CAAD involves multiple fields of technology, among which core technologies mainly include computer graphics, 3D modeling and rendering, art production and simulation, etc. Computer graphics studies the principles and techniques of computer-generated and manipulated graphics. Through computer graphics, designers can transform design ideas into digital graphics and perform various transformations and processing. 3D modeling and rendering involve the modeling of 3D objects, material mapping, lighting effects, and other processing. Art production and simulation technology have further expanded the application scope of CAAD. By utilizing art production techniques, designers can add dynamic effects to their designs, making them more vivid and interesting. Simulation technology can simulate and analyze designs, helping designers predict the effectiveness of their designs.

4 APPLICATION OF DM IN OPTIMIZATION OF GRAPHICS PROCESSING ALGORITHM

Traditional graphics processing algorithms often face performance bottlenecks and optimization challenges, which cannot meet the growing design demands. Therefore, applying DM technology to optimize graphics processing algorithms has become an innovative solution. The application principles of DM in graphic processing algorithm optimization mainly include data-driven and model optimization. Data-driven refers to the collection and analysis of a large amount of graphic processing data to uncover potential patterns and patterns in the data, thereby providing strong support for algorithm optimization. These data can include performance data during algorithm execution, image feature data, user feedback data, etc. By mining these data, performance bottlenecks, optimization space, and user needs of the algorithm can be discovered.

Before extracting artistic features, it is necessary first to clarify the purpose and requirements of the design, which determines the direction and focus of feature detection. After completing the feature analysis, it is necessary to organize and summarize the artistic features obtained from the analysis. This includes merging similar features, distinguishing different features, and forming a systematic feature system. The extracted artistic features do not exist in isolation but need to be applied to specific designs. The basic operation process of extracting artistic features is shown in Figure 1.

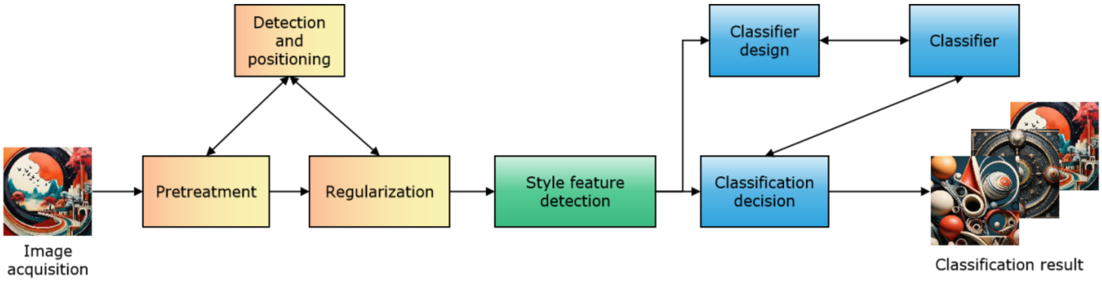

Figure 1: Operation flow.

Traditional graphics processing algorithms are often based on fixed mathematical models and algorithm flows, which are difficult to adapt to complex and changeable design requirements. The DM technology can find the shortcomings and improvement space in the model through the analysis and mining of the algorithm model and then put forward targeted optimization strategies. The operation flow of style migration of artistic graphics generation is shown in Figure 2.

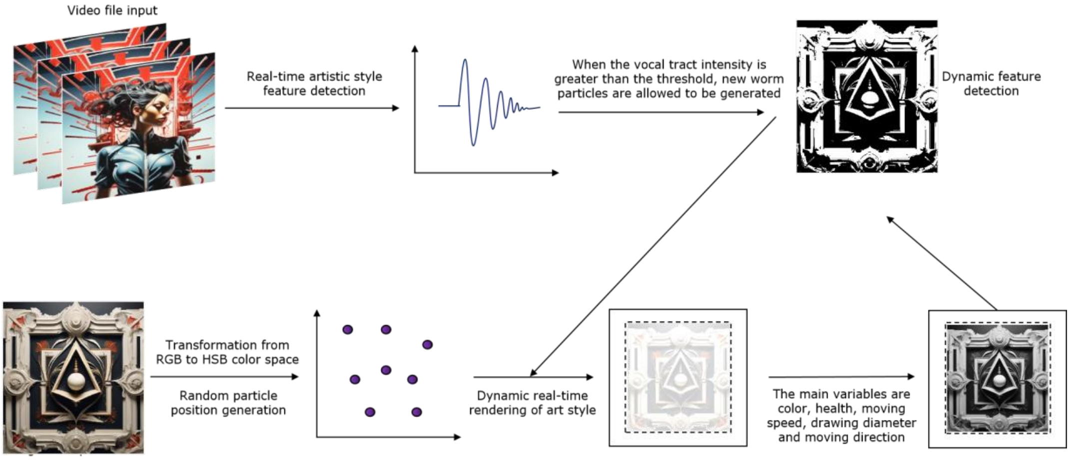

Figure 2: Style transfer process for artistic graphic generation.

In the stage of style transfer of artistic graphics generation, two images need to be prepared first: one is the content image, which provides the information of objects and scenes to be preserved. The other is a style image, which contributes to the artistic style that I hope to migrate. For the content image, the algorithm will extract its key feature information, such as the outline and texture of the object, to ensure that these contents can be preserved in the stage of style transfer. For the style image, the algorithm will capture its unique artistic style, including the use of color, the direction of brush strokes, and the overall visual effect. After extracting the content features and style features, the style migration algorithm begins to fuse these features together. To create a new image, it is essential to precisely align both content and style features. This ensures that the resulting image preserves the object details from the content image while seamlessly blending in the artistic essence of the style image. Figure 3 illustrates the fundamental principles behind feature detection.

The application principles of DM in graphic processing algorithm optimization mainly include data-driven and model optimization. Data-driven refers to the collection and analysis of a large amount of graphic processing data, mining potential patterns and patterns in the data, and providing strong support for algorithm optimization. These data can include performance data during algorithm execution, image feature data, user feedback data, etc. By mining these data, performance bottlenecks, optimization space, and user needs of the algorithm can be identified, providing guidance for subsequent algorithm optimization. Model optimization refers to the use of DM technology to improve and optimize the mathematical model of graphics processing algorithms. Traditional graphics processing algorithms are often based on fixed mathematical models and algorithmic processes, making it difficult to adapt to complex and ever-changing design requirements. DM technology can analyze and mine algorithm models to identify shortcomings and areas for improvement and then propose targeted optimization strategies.

The fundamental concept behind the variational automatic encoder dictates the objective of the algorithm: to learn a complementary set of encoders and decoders, thereby achieving a bidirectional mapping between graph G and latent variable $z \in R^c$. The loss function is outlined as follows:

$$L(\varphi,\theta;G) = E_{q_\varphi(z|G)}\left[-\log p_\theta(G|z)\right] + KL\left[q_\varphi(z|G)\,\|\,p(z)\right] \tag{1}$$

Among the terms, the initial $E_{q_{\varphi}(z|G)}\left[-\log p_{\theta}(G|z)\right]$ represents the reconstruction loss. The maximum likelihood estimation of every graph observation is subsequently divided into:

$$-\log p(G|z) = -\lambda_A \log p(A|z) - \lambda_F \log p(F|z) \tag{2}$$

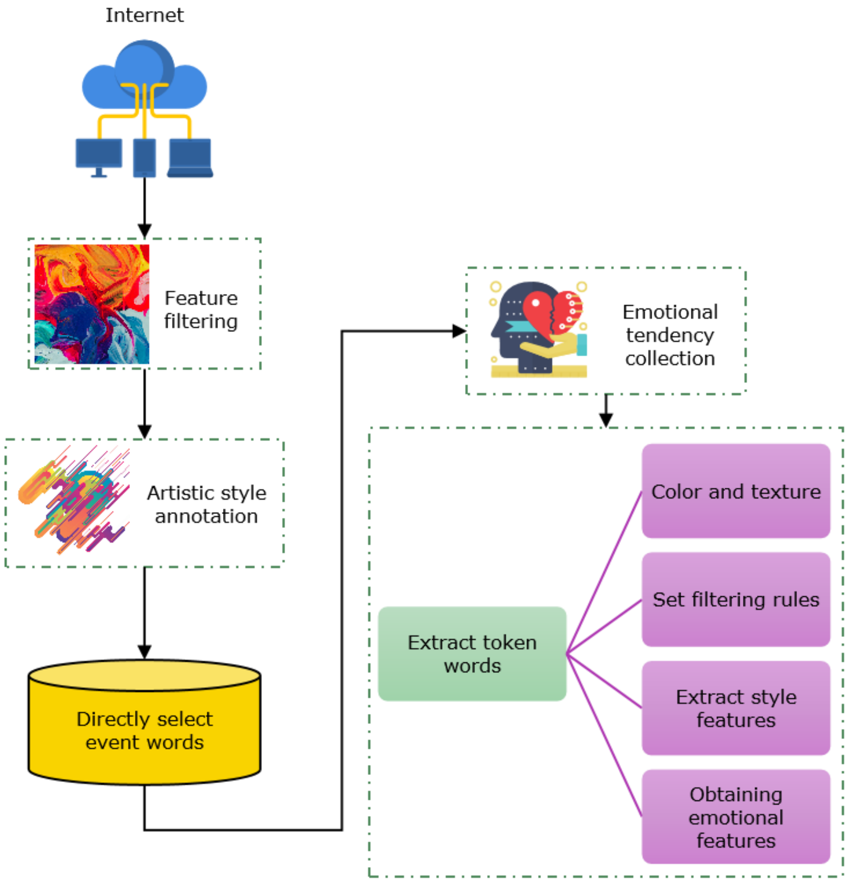

Figure 3: Principle of feature detection.

Due to the graph's adaptable configuration, the resulting dataset may not strictly adhere to the identical node sequence, leading to complications in computing the loss function. This study introduces evasion during the training procedure, guaranteeing accurate calculations of the loss function and ensuring smooth backpropagation of parameter gradients.

Assuming that the state vector sequence of the system is: $x_k, k \in N$, n_x is the dimension, and $x_k \in R^{n_x}$, which represents the state vector at time k:

$$x_k = f_k(x_{k-1}, u_{k-1}, v_{k-1}) \tag{3}$$

Observation equation:

$$y_k = h_k(x_k, w_k) \tag{4}$$

Where y_k is the observed value of the system state vector, f_k and h_k are known nonlinear functions, the prior distribution of the initial state x_0 is $p\ x_0$, u_{k-1} is the input term, and v_k ω_k are independent and identically distributed state noise and observation noise.

Let's assume that denotes the authentic artwork image, $x^{'}_{jui}$ identifies the surrounding pixels of any given pixel $c^{'}_{sg}$ within that image, $w^{'}_{wer}$ signifies the range of values for each image characteristic, and $b^{'}_{wep}$ is the overall pixel count of the image. Enhancement of the image occurs within the frequency domain as follows:

$$E^{'}_{qwu} = \frac{b^{'}_{wep} \times f^{"}\ x,y}{x^{'}_{jui} * c^{'}_{sg}} \times\ w^{'}_{wer} \oplus e^{'}_{gtu} \tag{5}$$

$e^{'}_{gtu}$ Denote the distribution pattern of the image's gray values. Assume that $\xi^{'}_{uio}$ signifies the frequency of each gray value's occurrence within the image, $O^{'}_{hjk}$ designates the image's gray level, x,y identifies any arbitrary point within the image, $x+a,y+b$ pinpoints a disturbance within the image, and $x+a,y+b\ ^{kl}$ corresponds to a related point between x,y and $x+a,y+b$. With these elements, we construct a fresh gray scale for the image.

$$b^{"}_{poi} = \frac{x+a,y+b\ ^{kl}}{x,y\ \times\ x+a,y+b} \oplus \frac{\xi^{'}_{uio}}{O^{'}_{hjk}} \tag{6}$$

Suppose that $\iota^{"}_{pol}$ stands for the image's first-order derivative function, $v^{'}_{wer}$ reflects the inherent characteristics of the image, and designates the amplitude-frequency response function. We can then outline the gray-scale features of the image as follows:

$$e^{'}_{yup} = \frac{d^{'}_{sgh} \pm \iota^{"}_{pol}}{v^{'}_{wer}} \mp d^{'}_{sgh} \tag{7}$$

Assuming that $\partial^{'}_{uip}$ denotes the variance resulting from the fusion of the original image block with its adjacent basic image blocks and $c^{'}_{wepp}$ signifies the percentage contribution of each image block within the entire image, we can derive the enhancement function aimed at increasing the gray contrast along the image edges.

$$r^{'}_{rti} = \frac{c^{'}_{wepp} \pm \partial^{"}_{uip}}{h^{'}_{tu}} \times f^{'}_{rty} \tag{8}$$

In this context, $h^{'}_{tu}$ it represents the mask operator while $f^{'}_{rty}$ designating the texture attribute associated with the low-frequency component.

If an attribute in the sample provides valuable information for classification, its information gain is higher. The attribute with the highest information gain value is the most discriminative within the set. The definition of an attribute A's information gain is as follows:

$$Gain\ \ A\ = I\ \ s_1, s_2, \ldots, s_m\ \ - E\ \ A \tag{9}$$

Where $I\ \ s_1, s_2, \ldots, s_m$ is determined by the entropy of the sample and is defined as:

$$I\left(s_1,s_2,\ldots,s_m\right)=-\sum_{i=1}^{m}P\left(C_i\right)\log_2 P\left(C_i\right) \tag{10}$$

Where $P\left(C_i\right)$ is the probability that any sample belongs to C_i; m represents the quantity of sample categories; s_i is the quantity of samples belonging to class C_i; s is the total sample data.

5 EXPERIMENTAL ANALYSIS AND DISCUSSION

The experiment was carried out on a high-performance computer equipped with sufficient computing resources and storage space. In this study, popular DM tools and graphics processing software libraries are used. In order to evaluate the optimization effect, we set up a control experiment. The traditional graphic processing algorithm is used in the control experiment, and DM technology is not used for optimization. By comparing the performance of the algorithm before and after optimization, the contribution of DM in the optimization of the graphics processing algorithm can be objectively evaluated. In the research, we choose the data sets of art design pictures with different artistic characteristics and set different parameter configurations according to the requirements of the algorithm. In order to verify the performance comparison before and after optimization, the feature calculation time is tested (Figure 4).

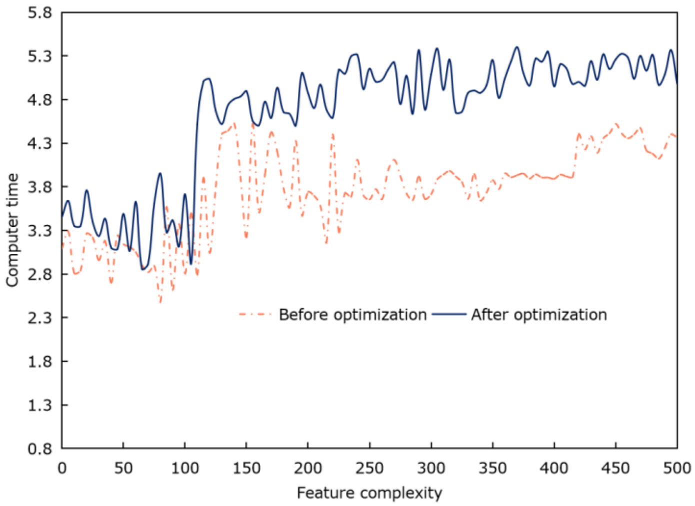

Figure 4: Calculation time comparison.

This shows that the calculation efficiency of the traditional algorithm and the improved algorithm is similar when dealing with relatively simple graphics problems. With the complexity of artistic graphics processing problems increasing, the running time of traditional algorithms increases obviously. Traditional algorithms need to perform more calculation steps and iterative processes when dealing with complex graphics, which leads to a significant increase in calculation time. By comparing the feature calculation time of the algorithm before and after optimization, it can be found that the improved algorithm has better performance in dealing with complex artistic graphics problems. This performance improvement may be due to the optimization strategy or calculation method adopted by the improved algorithm so that it can better cope with the calculation challenges of complex problems.

To comprehensively assess the effectiveness of the enhanced algorithm in artistic rendering, this section deliberately chooses a diverse range of artistic scenes, varying in complexity and unique features, for rigorous testing. These meticulously selected scenes encompass a wide array of artistic design elements, ranging from basic to intricate, with the intention of replicating various rendering demands commonly encountered in real-world applications. The rendering speed test results of the algorithm are vividly illustrated in Figure 5.

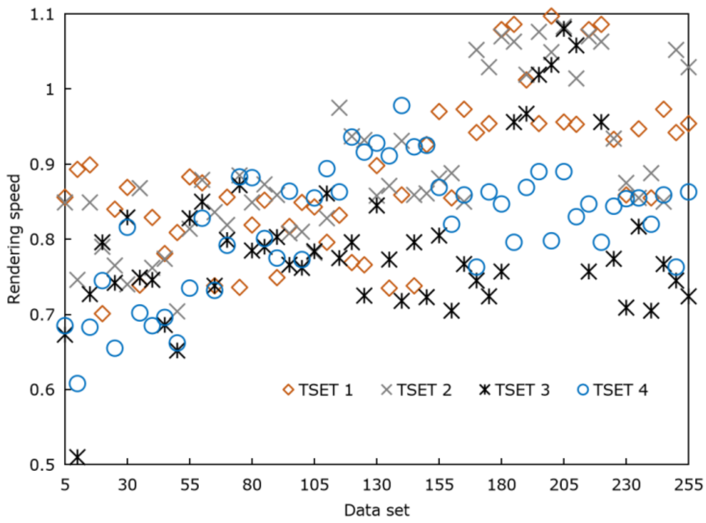

Figure 5: Rendering speed of algorithm.

This result is consistent in several scenes with different complexity, which shows that the improved algorithm has significant advantages in rendering efficiency. The improved algorithm is excellent in artistic rendering speed, especially suitable for dealing with complex scenes.

Figure 6 shows the classification accuracy, and the improved algorithm shows significant advantages in classification accuracy. This advantage is mainly due to the fact that the improved algorithm can extract the key features related to artistic style from the image more effectively.

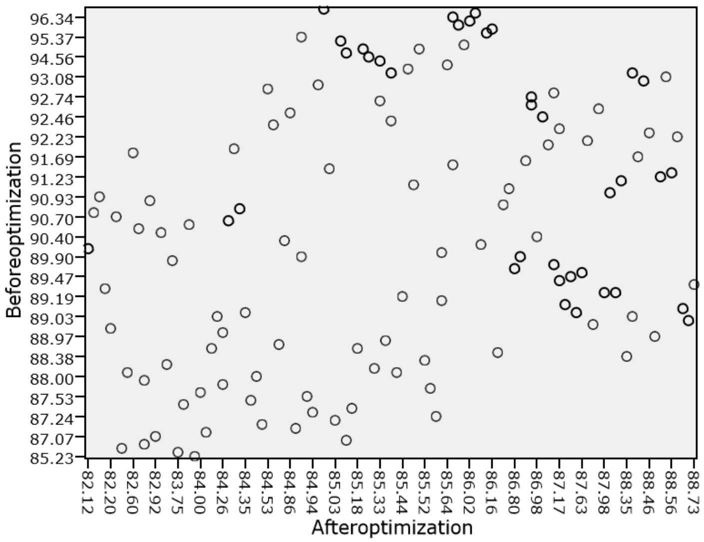

Figure 6: Accuracy of artistic style classification of different algorithms.

The key to artistic style classification is to extract features that can represent different artistic styles from images. By refining the feature detection approach or incorporating cutting-edge feature representation techniques, the enhanced algorithm can more precisely grasp the artistic style details embedded within the image. This outcome underscores the algorithm's proficiency in artistic feature identification and categorization, offering robust evidence for artistic style classification within the realm of CAAD.

From the presentation in Figure 7, we can clearly observe the image changes of the artistic style transfer algorithm in the iterative process. This process reflects how the algorithm gradually integrates the characteristics of content pictures and style pictures and finally generates new images with unique artistic styles. With the progress of iteration, the algorithm began to gradually transfer the characteristics of style pictures to the generated pictures. By the 100th iteration, the style of the generated pictures has changed significantly. At this point, the generated picture no longer only retains the characteristics of the content picture but also begins to blend into the unique elements of the style picture. This makes the generated picture visually present a completely different artistic effect from the content picture, and at the same time, has a great similarity with the style picture. When the iteration reaches the 1000th time, the algorithm generates an artistic figure with excellent visual performance. This graphic is still close to the original content picture in content, but it is very similar to the style picture in style. This means that the algorithm successfully migrates the artistic features of the style pictures to the generated pictures while retaining the core information of the content pictures.

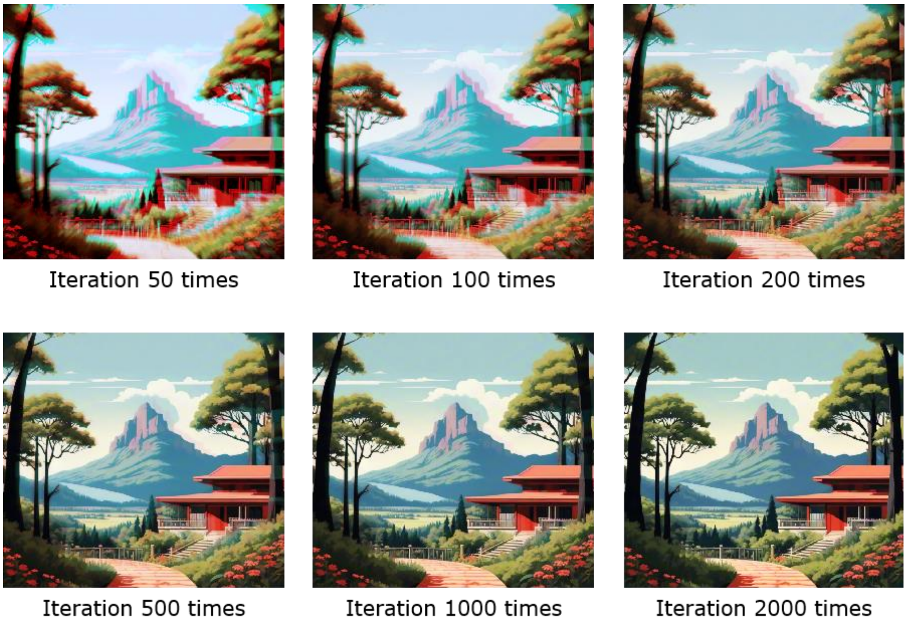

Figure 7: Generation diagram of different iterations.

The result of Figure 8 vividly reveals the key role of the weight ratio of content to style in the artistic style migration algorithm. By adjusting these two weights, we can control the tendency of the generated image in content and style so as to achieve different artistic effects. When the weight of the style image is large and the weight of the content image is relatively small, the generated image is very similar to the input style image in terms of color, texture, and other style characteristics. However, under this setting, the details of the generated image are seriously lost. When the weight of the style image is small, and the weight of the content image is large, the generated image retains more and more details. The content of the generated image under this setting is very close to the input content image, but it may only retain some or weak style features in style. It should be noted that there is no completely clear boundary between image content and style. In practical applications, the weight ratio can be finely processed according to the specific input images and application scenarios.

Figure 8: Weight generation diagram for different content and style.

From the perspective of rendering quality, the optimized algorithm presents a more delicate and realistic artistic effect. In contrast to Figure 9, the optimized image is more natural and exquisite in color transition, texture details, and light and shadow effects. This is because the optimization algorithm adopts more advanced rendering technology or more accurate parameter configuration in the rendering process, thus improving the accuracy and realism of rendering.

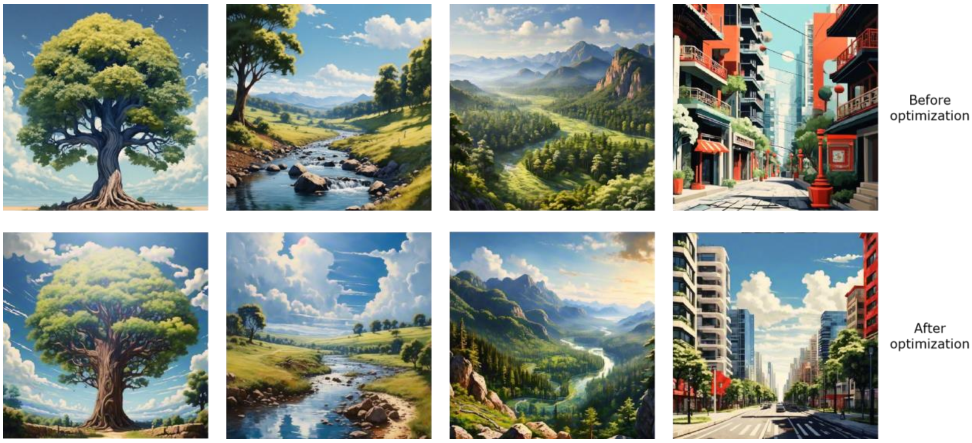

Figure 9: Comparison of rendering effects of artistic graphics before and after optimization.

6 CONCLUSION

As information technology advances rapidly, DM technology stands out as a crucial tool for extracting invaluable insights from the immense sea of data. In the field of CAAD, designers usually need to deal with a lot of data, including images, colors, shapes, textures, and so on. Traditional design methods often rely on the designer's personal experience and intuition. Not only does this hinder design efficiency, but it also somewhat impedes design innovation. The integration of DM technology in CAAD proves beneficial as it not only streamlines the processing and analysis of vast datasets during the design phase but also extracts insightful information for the design. Furthermore, it uncovers underlying patterns and trends in designs by tapping into historical design data. Focusing on the graphics processing algorithm within CAAD, this article introduces an intelligent optimization approach grounded in DM. These approaches proactively pinpoint performance bottlenecks through the analysis of the algorithm's historical execution data and offer tailored optimization recommendations. A comparison of the algorithm's feature calculation time before and after optimization reveals that the enhanced algorithm excels in tackling intricate artistic graphics challenges. By refining the feature detection technique or adopting more sophisticated feature representation methodologies, the revamped algorithm gains a keener ability to capture artistic style nuances within images. When it comes to rendering quality, the optimized algorithm delivers a more exquisite and lifelike artistic impact.

Zhu Liu, https://orcid.org/0009-0008-9949-1977
Boyuan Cui, https://orcid.org/0009-0000-4843-9758

REFERENCES

[1] Agnihotri, A.; Yadav, V.; Kaushik, V.-D.: Role of data mining and machine learning techniques in medical imaging, International Journal of Advanced Intelligence Paradigms, 15(3), 2020, 340-351. https://doi.org/10.1504/IJAIP.2020.105838

[2] Carmen, J.: Makerspaces: combining information literacy with pattern design for fiber art through digital images, Library Trends, 69(3), 2021, 585-611. https://doi.org/10.1353/lib.2021.0005

[3] Chung, C.-Y.; Huang, S.-H.: Interactively transforming Chinese ink paintings into realistic images using a border enhance generative adversarial network, Multimedia Tools and Applications, 82(8), 2023, 11663-11696. https://doi.org/10.1007/s11042-022-13684-4

[4] Gan, J.; Wang, W.; Leng, J.; Gao, X.: HiGAN+: Handwriting Imitation GAN with Disentangled Representations, ACM Transactions on Graphics (TOG), 42(1), 2022, 1-17. https://doi.org/10.1145/3550070

[5] Guo, S.; Wang, B.: Application of computer aided modeling design in the expression techniques of sculpture art space, Computer-Aided Design and Applications, 19(S3), 2021, 1-12. https://doi.org/10.14733/cadaps.2022.S3.1-12

[6] He, L.: Application of local color simulation method of landscape painting based on deep learning generative adversarial networks, International Journal of Pattern Recognition and Artificial Intelligence, 36(14), 2022, 2252026. https://doi.org/10.1142/S0218001422520267

[7] Jin, H.; Yang, J.: Using computer-aided design software in teaching environmental art design, Computer-Aided Design and Applications, 19(S1), 2021, 173-183. https://doi.org/10.14733/cadaps.2022.S1.173-183

[8] Jin, Y.; Li, P.; Wang, W.; Zhang, S.; Lin, D.; Yin, C.: GAN-based pencil drawing learning system for art education on large-scale image datasets with learning analytics, Interactive Learning Environments, 31(5), 2023, 2544-2561. https://doi.org/10.1080/10494820.2019.1636827

[9] Liu, F.; Yang, K.: Exploration on the teaching mode of contemporary art computer aided design centered on creativity, Computer-Aided Design and Applications, 19(S1), 2021, 105-116. https://doi.org/10.14733/cadaps.2022.S1.105-116

[10] Shugrina, M.; Li, C.-Y.; Fidler, S.: Neural brushstroke engine: learning a latent style space of interactive drawing tools, ACM Transactions on Graphics (TOG), 41(6), 2022, 1-18. https://doi.org/10.1145/3550454.3555472

[11] Sun, L.; Chen, P.; Xiang, W.; Chen, P.; Gao, W.-Y.; Zhang, K.-J.: SmartPaint: a co-creative drawing system based on generative adversarial networks, Frontiers of Information Technology & Electronic Engineering, 20(12), 2019, 1644-1656. https://doi.org/10.1631/FITEE.1900386

[12] Vo, D.-M.; Sugimoto, A.: Paired-D++ GAN for image manipulation with text, Machine Vision and Applications, 33(3), 2022, 45. https://doi.org/10.1007/s00138-022-01298-7

[13] Wang, S.; Qin, C.: Computer aided design and manufacturing of connecting rod mold, Computer-Aided Design and Applications, 18(S1), 2020, 65-74. https://doi.org/10.14733/cadaps.2021.S1.65-74

[14] Xu, B.; Jiang, J.: Exploitation for multimedia Asian information processing and artificial intelligence-based art design and teaching in colleges, ACM Transactions on Asian and Low-Resource Language Information Processing, 21(6), 2022, 1-18. https://doi.org/10.1145/3526219

[15] Yeom, J.; Yang, H.; Min, K.: An attention-based generative adversarial network for producing Illustrative Sketches, Mathematics, 9(21), 2021, 2791. https://doi.org/10.3390/math9212791

[16] Zhang, G.; Qu, M.; Jin, Y.; Song, Q.: Colorization for anime sketches with cycle-consistent adversarial network, International Journal of Performability Engineering, 15(3), 2019, 910. https://doi.org/10.23940/ijpe.19.03.p20.910918