Data Mining-based Optimized Pattern Design and Color Scheme in Planar CAD

Fang Chen[1] and Gongsheng Zang[2]

[1]School of Art, University of Sanya, Sanya 572022, Hainan, China,
fangchen@sanyau.edu.cn
[2]School of Information & Intelligence Engineering, University of Sanya, Sanya 572022, Hainan, China,
gongshengzang@sanyau.edu.cn

Corresponding author: Fang Chen, fangchen@sanyau.edu.cn

Abstract. As technology progresses and market demand diversifies, there has been an escalation in the expectations pertaining to pattern design and color schemes within computer-aided design (CAD) systems. Through the analysis and research of existing data mining (DM) techniques, this article proposes an improved threshold segmentation method for planar design images. This method can extract key features from images more accurately, providing a foundation for subsequent pattern design and color-matching optimization. In terms of algorithm performance, the algorithm proposed in this article has shown significant advantages in computational efficiency, accuracy, and recall. This method improves the accuracy and robustness of segmentation and makes the segmentation results more in line with human visual perception. Through the display and analysis of experimental results, it can be seen that our method has achieved superior performance in image threshold segmentation tasks. In evaluating graphic design works, users have given good feedback on the works' aesthetics, functionality, and innovation. These results fully demonstrate the superiority of this method in aesthetic expression, practicality, and creative conception, providing strong evidence for the creative ability and professional level of designers.

Keywords: Data Mining; CAD; Pattern Design; Color Schemes
DOI: https://doi.org/10.14733/cadaps.2024.S19.148-163

1 INTRODUCTION

In the digital age, CAD has become an indispensable tool in many industries, especially in the field of graphic design. As technology continues to evolve and market demands become more diverse, the standards for pattern design and color schemes within CAD systems are increasingly elevated. Planar CAD (computer-aided design) software provides designers with powerful tools, enabling them to carry out design work more efficiently. However, how to optimize the performance of these tools and further improve the quality and efficiency of design is an important issue currently faced. The introduction of data mining technology provides new ideas for solving this problem. Fan and Li [1] explored how data mining can optimize computer graphics processing in planar CAD, thereby playing a greater role in visual communication design. Computer graphics processing technology has brought revolutionary changes to visual communication design. Designers can use these technologies to create richer and more realistic visual effects, thereby better-conveying information. Data mining techniques can help designers build predictive models to predict the impact of different parameters and settings on graphic processing performance. By training models, designers can predict future design trends and styles based on historical data, thereby better-grasping market and user needs. DM, a methodology aimed at extracting valuable insights and knowledge from vast datasets, has gained widespread adoption across various domains in recent times. The application of computer-aided design (CAD) in the field of art and design is becoming increasingly widespread. Especially in terms of improving art aesthetics, CAD technology combined with data mining algorithms provides artists and designers with a new way of creation and improvement. He and Sun [2] discussed how to use data mining to optimize the application of planar CAD in computer-aided art aesthetic enhancement. Data mining techniques can extract patterns and features of beauty through in-depth analysis of a large number of art and design works. These patterns and characteristics can serve as a reference for artists and designers to enhance their aesthetic level. It utilizes data mining techniques to conduct in-depth analysis of preprocessed data, extract features related to art aesthetics, and construct classification or clustering models. These models can be used to predict future aesthetic trends or evaluate the aesthetic value of works. Based on the analysis results of data mining, artists and designers can adjust and improve their works in a targeted manner during the creative process, thereby improving the aesthetic level of their works. Meanwhile, it can utilize model predictions and market feedback information for continuous optimization and improvement. Specifically, in the realm of graphic design, DM techniques can facilitate the analysis of numerous design samples, revealing underlying patterns such as associations between design components, user preferences, and prevalent design trends. This article aims to investigate the potential of DM technology in optimizing pattern design and color schemes within planar CAD environments.

Traditional pattern design and color matching methods mostly rely on the designer's personal experience and intuitive judgment, which makes it difficult to ensure that the best design scheme can be obtained every time. With the advancement of technology and the arrival of the digital age, computer-aided design (CAD) is playing an increasingly important role in the clothing industry. Especially in the field of clothing styling design, CAD technology provides designers with unlimited innovation space. Hu [3] discussed the design and implementation of a component-based aesthetic clothing modeling CAD system. Based on the design concept of components, this CAD system is constructed in a modular manner, with each module representing an independent component. These components include basic components (such as neckline, sleeves, hem, etc.) and aesthetic components (such as patterns, colors, textures, etc.). By combining and adjusting these components, designers can quickly create aesthetically pleasing clothing designs. Based on data mining technology, the system can automatically evaluate the aesthetic value of clothing styling and provide optimization suggestions. Designers can make adjustments based on the feedback provided by the system, thereby improving the aesthetic level of the design. Through 3D rendering technology, the system supports a virtual fitting function, allowing designers and consumers to preview clothing effects in real time. At the same time, the system also provides various display methods, such as dynamic display and interactive display, to comprehensively showcase the aesthetic charm of clothing. Computer-aided design (CAD) is playing an increasingly important role in the clothing industry. Especially for pattern design and color schemes, CAD technology provides designers with unlimited creative space. In the fields of knitted and woven fabrics, the application of CAD has significantly improved production efficiency and design quality. Knitted and woven fabrics are the two main types of fabrics in the clothing industry. Knitted fabrics have good elasticity and are suitable for making close-fitting clothing and sportswear. The structure of woven fabrics is more stable and is often used for making formal attire and outerwear. These two types of fabrics have their own unique patterns and color schemes in computer-aided design. For knitted fabrics, due to their unique structure, pattern design needs to consider the elasticity and texture of the fabric. Through

CAD software, Indrie et al. [4] created dynamic knitted patterns, simulated the texture and stretchability of the fabric, and accurately evaluated and optimized the design before actual production. In terms of color scheme, the color selection of knitted fabrics is usually more diverse and lively, which can demonstrate a unique sense of fashion.

In view of this, the focus of current research is on finding a new method that can intelligently and automatically optimize pattern design and color matching. Planar CAD (computer-aided design) and pattern-making are playing an increasingly important role in the clothing industry. Especially with the combination of 3D printing technology, clothing design has entered a new era. Kang and Kim [5] explored how to use data mining techniques to optimize planar CAD patterns and 3D-printed clothing production. It uses data mining techniques to conduct in-depth analysis of historical design data and extract the most popular pattern elements, such as flowers, geometric shapes, etc. These elements can serve as important sources of design inspiration. By analyzing trend data, data mining techniques can predict pattern trends for a period of time in the future. Designers can plan and prepare their designs in advance based on these predicted results. By analyzing historical printing data, key parameters that affect printing quality and efficiency can be identified, such as printing speed and layer height. By optimizing these parameters, printing efficiency can be improved, and the waste rate can be reduced. In the synthesis of art graphic layouts, the application of vector wireframe adversarial networks provides designers with a powerful tool for generating highly artistic and innovative graphic layouts. Li et al. [6] explored how to use vector wireframe adversarial networks to synthesize art graphic layouts and evaluated and optimized the generated layouts using pattern analysis and machine intelligence techniques. It trains a vector wireframe adversarial network to transform one style of graphic layout into another, thereby achieving flexible style transformation and creative design. By utilizing vector wireframe adversarial networks, aesthetically valuable graphic layouts can be automatically generated based on design requirements and goals, providing inspiration and choices for designers. By optimizing the objective function of adversarial networks, the details and features of the generated graphic layout can be adjusted to improve the quality and diversity of the layout. By training machine learning models, it is possible to automatically recognize and classify the style, features, and themes of generated graphic layouts. This helps designers understand the characteristics and applicable scenarios of different styles. Based on machine learning algorithms, the generated graphic layout can be evaluated and optimized. It uses the collected data to train a vector wireframe adversarial network, enabling it to generate graphic layouts with specific styles from random noise. Optimize the quality and diversity of generated layouts by adjusting network structure and parameters.

Pattern design is the core of graphic design, with complexity and creativity coexisting. Data mining technology provides strong support for designers, making it possible to extract useful information from a large amount of historical design data. Using cluster analysis, Liu and Yang [7] quickly found patterns with similar styles or elements, thus inspiring new design inspiration. Association rule mining can help designers understand which elements often appear together and guide them to make effective combinations in design. The color scheme plays a crucial role in the overall effect of the design. The application of data mining technology in this area is mainly reflected in in-depth analysis and optimization of color matching. By analyzing historical color-matching data, designers can find the most popular or eye-catching color combinations. In addition, some advanced algorithms can also predict which color scheme will perform better in different backgrounds or contexts, thereby helping designers make wiser choices. Ma et al. [8] utilized deep generative models such as GANs and variational autoencoders to generate dashboard visualizations with similar styles and layouts from existing images or sketches. This method can help designers quickly create multiple design solutions and find the best visual presentation through iteration and optimization. Deep learning can also be used to apply one design style to another, thereby achieving personalized dashboard visualization. Through transfer learning and style transformation techniques, the works of well-known designers or popular design styles can be applied to dashboard visualization, creating unique and attractive visual effects. Deep learning can help improve the interpretability of dashboard visualization data. By generating highly interpretable visual features, users can better understand data and insights. For example, using a generative model to encode data and then using a decoder to reconstruct these encodings into a visual representation can reveal patterns and relationships in the data. Evaluate and provide feedback on the generated dashboard visualization. This may involve methods such as user surveys, professional reviews, or performance metrics to determine whether the generated visual effects are effective and attractive. Therefore, the improved image threshold segmentation method proposed in this article aims to solve this problem. This method combines image processing and DM technology, which can automatically segment and extract features of the image, thus improving the design efficiency. Different color schemes can convey different emotions and atmospheres and have a decisive influence on the overall effect of design works. By applying DM technology to optimize pattern design and color-matching schemes, we can expect more creative, user-friendly, and competitive works to appear in the future graphic design field. Moreover, it also provides a new perspective and tool for designers so that they can be liberated from complicated design tasks and focus more on the pursuit of innovation and art.

Highlight points:

(1) By deeply digging and analyzing the user's behavior data and preference patterns in the design process, this article constructs a dynamically updated user data model, which provides strong support for personalized design.

(2) Based on big data analysis and color psychology theory, this article develops a recommendation system that can automatically generate and optimize color schemes, which improves the scientificity and aesthetics of color matching.

(3) This article not only pays attention to the innovation of a single technology but also integrates a variety of intelligent technologies (such as DM and deep learning) into the plane CAD system, which significantly improves the overall performance and intelligence level of the system.

In the next chapter, this article will introduce in detail the specific implementation process, experimental verification results, and practical application effects of the improved image threshold segmentation method. Moreover, it will also discuss how to combine this method with other DM technologies to build a complete graphic CAD pattern design and color-matching optimization system. I believe that the research in this article can inject new vitality into the development of graphic design.

2 RELATED WORK

Pattern design and color scheme design are two key components in graphic design which have a significant impact on the overall visual effect and user experience. With the development of deep learning technology, more and more researchers are paying attention to how to use deep learning models to optimize and automate these design processes. Murugesan et al. [9] explored the visualization and interactive comparison of deep learning model performance in pattern design and color scheme design. By training deep learning models, creative and aesthetically pleasing patterns can be automatically generated based on user needs and style requirements. This model can learn the inherent laws and patterns of pattern generation, improving the diversity and quality of generated patterns. Deep learning models can also be used to optimize and improve existing patterns. By training the model, fine adjustments can be made to the details and features of the pattern based on user feedback and performance evaluation results, improving the aesthetics and attractiveness of the pattern. By training deep learning models, color schemes with coordination and aesthetics can be automatically generated based on theme or style requirements. This model can learn the inherent laws and patterns of color matching, improving the quality and diversity of color schemes. Deep learning models can also be used to optimize and improve existing color schemes. By training the model, the color and proportion of the color scheme can be adjusted based on user feedback and performance evaluation results, improving the coordination and aesthetics of the color scheme. Wing design plays a crucial role in aircraft performance. Geometric aesthetics plays a crucial role in wing design, and pattern mining optimized through data mining techniques can further optimize wing design. Su et al. [10] aim to explore how to optimize pattern mining in geometric aesthetics processing using data mining techniques, using the CAD wing dataset as an example. It uses data mining techniques to conduct in-depth analysis on the CAD wing dataset, extracting features related to geometric aesthetics, such as line fluency, proportion coordination, etc. These features can reflect the aesthetic characteristics of wings, providing inspiration and reference for designers. Based on the extracted features, data mining techniques can construct an aesthetic evaluation model to evaluate the geometric aesthetics of wing design quantitatively. By comparing the aesthetic evaluation results of different design schemes, designers can choose and optimize design schemes more scientifically. Based on the analysis results of data mining, designers can make targeted adjustments and optimizations to the design scheme in wing design, improving its aesthetic level. At the same time, continuous improvement and optimization are carried out using model predictions and market feedback information. The application of machine learning in the visualization of art graphic color-matching design data provides a new way for designers and artists to explore and express creativity. Wang et al. [11] explored how to apply the advancement of machine learning to the visualization of color-matching design data in art graphics. It utilizes machine learning algorithms to automatically generate coordinated and aesthetically pleasing color combinations based on a given color theme or style. This technology can help designers quickly explore different color schemes and improve design efficiency. By analyzing historical data and trends, machine learning models can predict future color trends. This helps designers understand the market and consumer preferences, providing valuable reference information for design decisions. Machine learning techniques can also be used to analyze the emotions expressed by colors. By training models to identify the emotions represented by different colors, designers can choose appropriate color schemes based on specific themes or target audiences. Machine learning-based algorithms can optimize and improve existing color schemes. By analyzing the patterns and aesthetic standards of color matching, machine learning models can provide adjustment suggestions to make color schemes more attractive and expressive.

Xu et al. [12] explored how to optimize hand-drawn sketch processing in planar CAD using deep learning and data mining techniques. Deep learning techniques, especially Convolutional Neural Networks (CNNs), have shown great potential in hand-drawn sketch processing. By training deep neural networks, they can automatically recognize and extract key features from hand-drawn sketches, thereby improving the automation and intelligence level of design. By utilizing deep learning techniques, it is possible to automatically recognize information such as the style, lines, and shape of hand-drawn sketches. By training deep neural networks, hand-drawn sketches can be classified, annotated, and organized, providing basic data for subsequent design processing. A deep learning-based generative model can automatically generate new sketches with similar styles based on existing hand-drawn sketches. This technology can provide designers with more creative inspiration and improve the diversity and efficiency of design. Data mining can also be used to collect and analyze user feedback on hand-drawn sketches. By analyzing user behavior, preferences, and evaluations, the functionality and attractiveness of sketches can be understood, leading to improvements and optimizations in design. Deep learning, as a powerful machine learning technology, has gradually penetrated into CAD/CAE systems, providing a new perspective and method for design, evaluation, and optimization. Yoo et al. [13] explored how to integrate deep learning techniques into CAD/CAE systems, particularly in the generation, design, and evaluation of art patterns, as well as the application of structure and multidisciplinary optimization. By utilizing deep learning techniques, it is possible to learn rules and patterns for pattern generation from a large amount of data and automatically generate aesthetically pleasing patterns. By training deep neural networks, the system can learn the features and aesthetic standards of various patterns and generate new patterns based on these standards. In CAD/CAE systems, deep learning can be combined with geometric modeling techniques to generate models with specific aesthetic features automatically. This technology can greatly shorten the design cycle, improve design efficiency, and enable designers to focus more on innovation and optimization. Through deep learning techniques, it can automatically generate aesthetically pleasing patterns, evaluate the aesthetic quality of patterns, and perform structural and multidisciplinary optimization. This will greatly improve the efficiency and quality of design and promote the development and application of CAD/CAE technology.

The synthesis of artistic sketches has become a highly focused research field. In order to achieve better automation and intelligence in sketch synthesis, neural probabilistic graphical models are widely used in this field. Zhang et al. [14] explored how to use data mining techniques to optimize neural probabilistic graphic models for synthesizing art sketches in planar CAD. It utilizes neural probability graphical models to automatically generate aesthetically valuable sketches based on a given theme or style. This model can learn the inherent laws and patterns of sketch generation, improving its diversity and quality. By training and adjusting the neural probability graph model, the generated sketches can be optimized and improved based on user feedback and performance evaluation results. This helps to improve the coordination and attractiveness of sketches, meeting the needs and expectations of users. The neural probability graphical model can also be used to achieve the transformation of sketch styles. By training the model, one style of sketch can be transformed into another style, thereby expanding the application scope and representation of sketch synthesis. Data mining techniques can help extract the features required for neural probability graph models. These features can include the shape, lines, colors, and other attributes of the sketch, as well as their relationships and patterns. Effective feature extraction can improve the training efficiency and accuracy of the model. Facial photo sketch synthesis technology has become an important application field. However, this technology faces many challenges, among which color matching is a key issue. Zhu et al. [15] explored how to use data mining techniques to optimize the color-matching framework for facial photo sketch synthesis in planar CAD. It utilizes data mining techniques to analyze colors in facial photos and sketches, extracting key color features. By comparing and matching these features, the best color scheme can be found, making the synthesis results more natural and coordinated. Collect a large amount of facial photos and sketch data, and perform preprocessing work such as image format conversion, color space conversion, etc. Ensure the accuracy and consistency of data, providing a foundation for subsequent data mining. It utilizes image processing techniques to extract color features from facial photos and sketches. These features can include color distribution, saturation, brightness, etc. The extracted features should be representative and comparable for subsequent data analysis. Based on the results of data mining, optimize the color-matching framework for facial photo sketch synthesis. This includes adjusting color combinations, improving color schemes, and enhancing color coordination. The optimized color framework should better meet user needs and market trends.

3 AN IMPROVED THRESHOLD SEGMENTATION METHOD FOR GRAPHIC DESIGN IMAGES

3.1 Principle of Improved Image Threshold Segmentation Method

Data mining (DM) is a widely utilized process in numerous fields, involving the extraction of concealed yet valuable information and knowledge from substantial volumes of imperfect, noisy, ambiguous, and unpredictable data. In the process of DM, data preprocessing is a key step. Because the original data are often missing, abnormal, and inconsistent, direct analysis may affect the accuracy and reliability of the results. Therefore, data cleaning, data transformation, data reduction, and other technologies are widely used in the data preprocessing stage to improve the quality and availability of data. As a visual communication method, graphic design aims to convey specific information and emotions through the combination and arrangement of elements such as graphics, text, and color. However, with the intensification of market competition and the diversification of user needs, graphic design is facing more and more challenges. The utilization of DM technology in graphic design offers designers a fresh approach. Through the aggregation and examination of a substantial amount of design samples, user feedback, and market data, DM technology aids designers in deriving insights such as association rules among design components, user preference patterns, and prevalent design trends.

In terms of pattern design, DM technology can help analyze the correlation and matching rules between different pattern elements. By learning and analyzing a large number of design samples, the DM algorithm can automatically extract information such as which pattern elements often appear together and which matching methods are more popular. These pieces of information can provide inspiration and reference for designers, helping them design patterns that are more in line with user preferences and market demands. In terms of color schemes, through DM technology, a large number of color schemes and user feedback data can be analyzed to extract effective color-matching rules and patterns. These rules and patterns can provide designers with scientific and objective color-matching suggestions, helping them design more harmonious and beautiful color combinations. In graphic design, image segmentation directly affects subsequent feature extraction, pattern recognition, and color scheme selection. Although traditional image threshold segmentation methods are simple and easy to implement, they often have poor results when dealing with complex backgrounds and detailed images and are prone to over-segmentation or under-segmentation. Therefore, this article proposes an improved threshold segmentation method for planar design images, aiming to improve the accuracy and robustness of segmentation and provide a more reliable foundation for subsequent design optimization work. The process of multi-scale decomposition of graphic design images is shown in Figure 1.

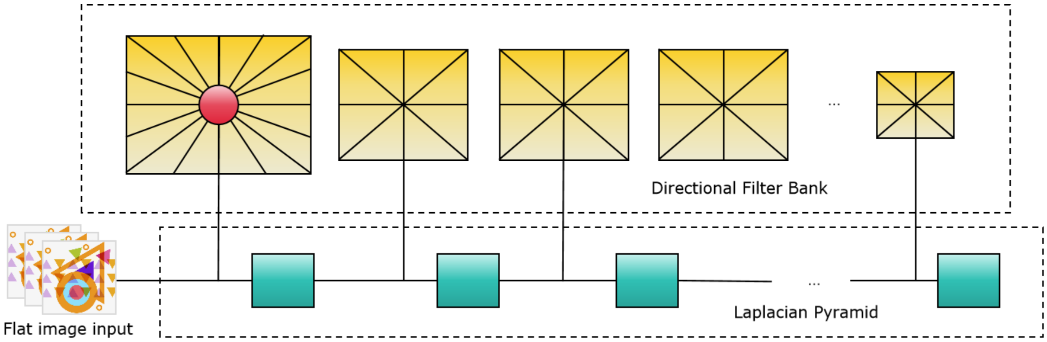

Figure 1: Multi-scale decomposition process of graphic design image.

In order to overcome the sensitivity of global thresholds to lighting and noise, this article adopts a local adaptive threshold segmentation method. This method divides the image into several sub-regions and dynamically calculates thresholds based on the grayscale distribution characteristics of each sub-region. This can not only better adapt to changes in lighting and noise but also retain more detailed information. Edge is one of the most important features in an image, which contains rich shape and structural information. In order to improve the accuracy of segmentation, this article introduces edge detection and enhancement techniques on the basis of local adaptive threshold segmentation. After obtaining several sub-regions through preliminary segmentation, this article further uses region merging and optimization techniques to optimize the segmentation results. This method combines the similarity and connectivity between adjacent sub-regions to obtain more complete and accurate segmentation results. The process of generating fractal art graphics is shown in Figure 2. Firstly, select a point x, y on the complex plane, then choose a special effects processing scheme, and then perform Newton iteration and coloring to generate fractal art graphics.

Utilizing the graphic structure outlined in the sample plan, the node vector, initially assigned at random, undergoes an update process to generate the comprehensive plan vector. Following this, the parameters of the neural network, which include the plan vector, are optimized via backpropagation to predict the plan's score. In this context, M it represents the total number of r radius subgraphs present within an image. The subgraph vector is subsequently revised by applying the subsequent formula:

$$x_i^{t+1} = x_i^t + \sum_{j \in N_i} x_{ij}^t \tag{1}$$

In this context, x_i it represents the i subgraph vector, while x_j it denotes the subgraph vector encompassing all of its neighboring elements.

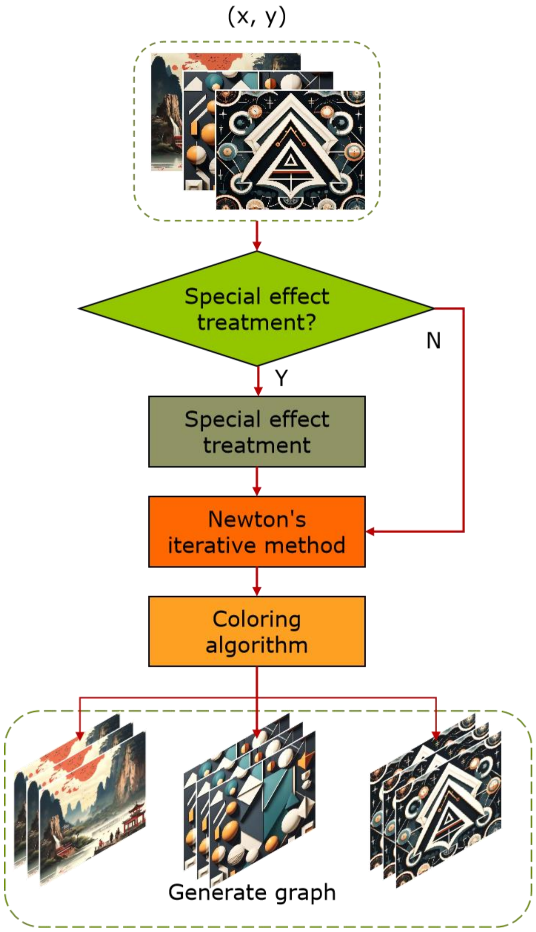

Figure 2: Process of generating fractal art graphics.

During the transfer of graphic design styles, three images are simultaneously inputted into the network: a content image, a style image, and an image with added white noise. To determine the content loss function, the content image and the white noise image are independently processed through a Convolutional Neural Network (CNN). Subsequently, the distance function between the outputs of the fourth layer is calculated using two norms, serving as the basis for the loss function.

$$L_{content}\ \vec{p},\vec{x},l\ = \frac{1}{2}\sum\nolimits_{i,j} F^{l}_{i,j}\ {}^{2} \tag{2}$$

In this context, $\vec{x}$ it represents the image with white noise intended for generation, $\vec{p}$ denotes the content image, l refers to each individual convolution layer, and F^l, p^l is a matrix consisting of M ----sized response outcomes from the l layer. F Signifies the final image to be generated while p representing the response result derived from the content image.

Standard CNN processing typically results in a significant reduction of the original image's resolution. However, dilated convolution (also known as hole convolution) enables the attainment of a large receptive field at any depth within the convolutional network without augmenting the number of parameters or computational load. The formula for the dilated convolution of a one-dimensional signal is as follows lows:

$$y_{[i]} = \sum_{k=1}^{K} x_{[i+r*k]} w_{[k]} \tag{3}$$

In this context, $x_{[i]}$ it represents the one-dimensional input signal, $w_{[k]}$ denotes the filter, r indicates the sampling step size of the input signal, k refers to the length, and $y_{[i]}$ signifies the ultimate multi-space convolution output result.

For the classification of design images, the Softmax function serves as the classifier. The formula for calculation is as follows shows:

$$Design\ image_p = \frac{1}{1+\exp\ -h_{FC3}} \tag{4}$$

In this scenario, $Design\ image_p$ it stands for the probability output associated with the design image while h_{FC3} designates the output generated by the preceding fully connected layer $FC3$. Leveraging the probability output of the design image, one can precisely acquire the specific design image pertaining to the input sample picture.

In the deep confidence network, the complete interconnection between interlayer neurons is modified to a partial connection. Additionally, the lower segment of the model incorporates a BP neural network with a bottom-to-top directional flow. The ultimate output value obtained is as follows:

$$O_i = f\ net_i\ = \frac{1}{1+e^{-\ net_i}} \tag{5}$$

The output generated by the i-th neuron within this layer is denoted as O_i, whereas the weighted summation of its inputs is represented by net_i.

In practical applications, the relationships between data are often complex and nonlinear. Traditional DM algorithms often have poor performance in handling such data. Deep learning technology can effectively capture complex relationships in data and improve the adaptability of algorithms through nonlinear activation functions and multi-layer network structures. Deep learning techniques can be combined with reinforcement learning and other methods to enable DM algorithms to make autonomous decisions based on historical experience and environmental feedback. This decision-making ability enables algorithms to adjust strategies in real time when facing dynamic and changing data environments in order to achieve the optimal DM effect. Through deep learning techniques, more complex prediction models can be constructed, which can more accurately capture potential patterns and trends in the data. This is crucial for tasks such as classification, regression, and clustering in DM, which can significantly improve the accuracy of predictions. This article uses deep learning methods to improve and enhance the DM algorithm, aiming to enhance the algorithm's autonomous decision-making and adaptability. Figure 3 shows a schematic diagram of a deep-learning vector model.

By introducing deep learning techniques, the DM algorithm can be effectively improved and optimized, enhancing its autonomous decision-making ability and adaptability. This not only helps extract more valuable information from massive data but also opens up broader prospects for the application of DM technology in various fields.

3.2 Experimental Verification and Result Analysis

In Figure 4, a comparison was made between the performance of the algorithm presented in this article, the fuzzy clustering (FCM) algorithm, and the particle swarm optimization (PSO) algorithm, focusing on computational time. The experimental findings unequivocally demonstrate that the algorithm introduced in this paper offers a notable enhancement in computational efficiency when compared to both FCM and PSO.

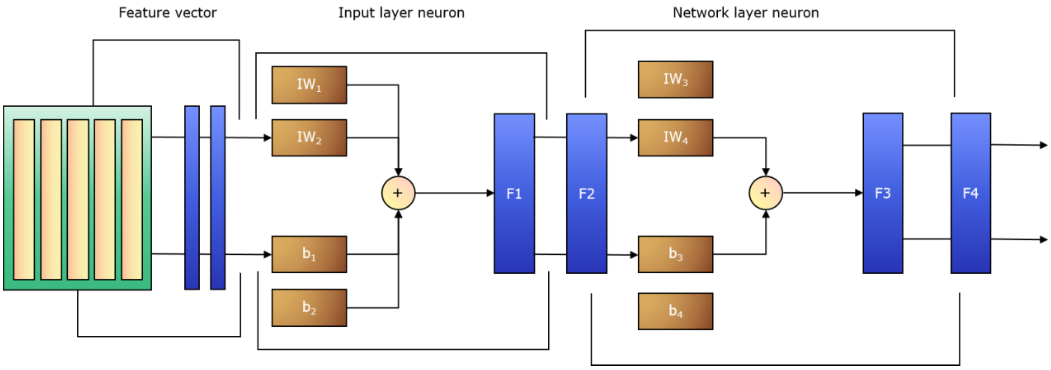

Figure 3: Deep learning vector model.

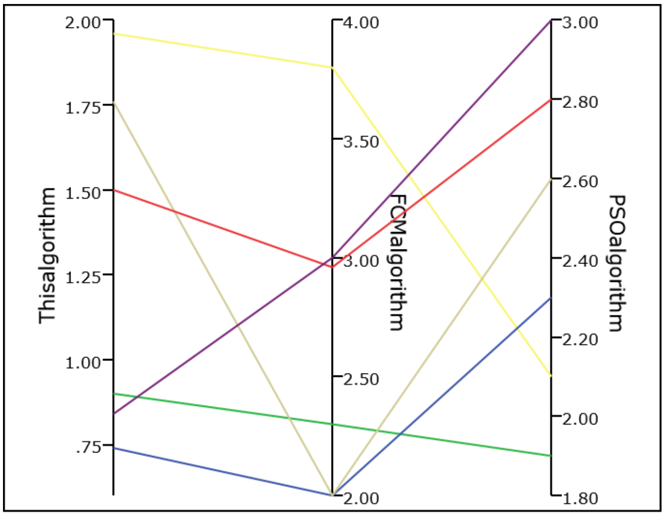

Figure 4: Calculation time comparison of three algorithms.

The FCM algorithm typically involves multiple iterations in computation to determine the optimal cluster center. Each iteration requires recalculating the membership of all data points to each cluster center, which results in a relatively long computation time. Especially when dealing with large-scale datasets, the computational burden of FCM will significantly increase. The PSO algorithm is an optimization method based on swarm intelligence, which simulates the foraging behavior of bird flocks to find the optimal solution to the problem. Although the PSO algorithm performs well in global search capability, during its iteration process, each particle needs to update its speed and position based on its own historical best position and the global best position of the population, which also leads to relatively long computation time. Compared with the above two algorithms, the algorithm proposed in this paper demonstrates significant advantages in computational efficiency. This algorithm adopts a more efficient data structure or algorithm logic, thereby reducing unnecessary computational steps. The algorithm utilizes the characteristics or prior knowledge of the problem to find satisfactory solutions in fewer iterations.

In order to comprehensively evaluate the performance of the algorithm proposed in this article, two assessment metrics, accuracy, and recall, were used in this section. The results are shown in Figures 5 and 6.

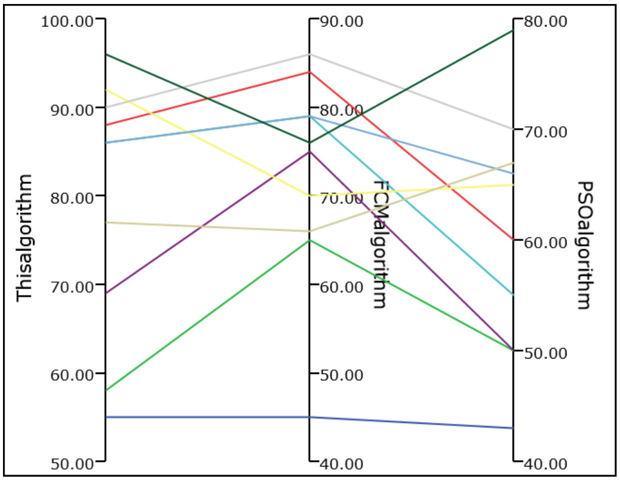

Figure 5: Comparison of accuracy of three algorithms.

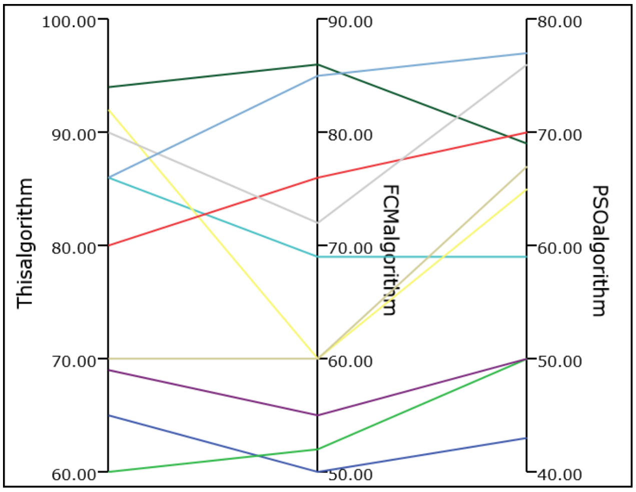

Figure 6: Comparison of recall rates of three algorithms.

The algorithm in this article is significantly better in accuracy than the FCM algorithm and PSO algorithm. This means that when processing the same dataset, this algorithm can more accurately identify and classify samples, thereby providing more reliable results in practical applications. The algorithm in this article also shows significant advantages in terms of recall rate. This means that this algorithm can not only accurately classify samples but also more comprehensively cover all real positive samples, thereby reducing the possibility of false positives in practical applications.

Figure 7 shows the results obtained from the threshold segmentation method proposed in this paper for the test image. Compared with traditional image threshold segmentation techniques, the uniqueness of this method lies in its integration of human visual characteristics and threshold calculation process, thereby achieving automatic extraction of target regions in the image.

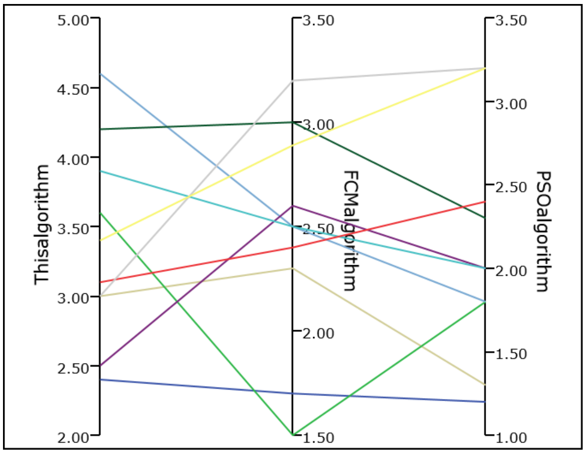

Figure 7: Image threshold segmentation results.

In the field of image processing, the characteristics of the human visual system (HVS) are often used to guide algorithm design to optimize the visual quality of images. The method used in this article obviously also adopts this strategy. By simulating human perception of visual attributes such as brightness, contrast, and color, this algorithm can more accurately identify key regions in images and perform effective threshold segmentation. The method in this article achieves automatic calculation and selection of thresholds by combining human visual characteristics. This means that the algorithm can adaptively adjust the threshold according to different image contents, thereby improving the robustness of segmentation.

The quality assessment of image segmentation aims to quantify the performance of different segmentation methods, usually including multiple indicators such as edge fit, regional consistency, and misclassification rate. These indicators comprehensively reflect the accuracy, clarity, and reliability of segmentation results. The comprehensive assessment results of segmentation quality for different threshold segmentation methods are compared in Figure 8.

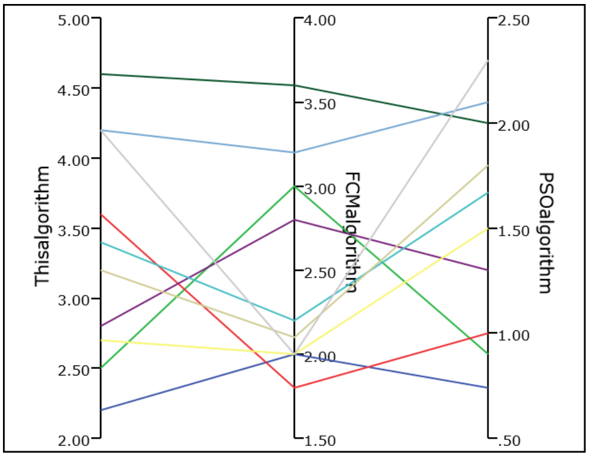

Figure 8: Comparison of segmentation quality of different threshold segmentation methods.

In practical applications, images often have complex interference factors such as texture, illumination, and noise. These factors will have a great influence on the segmentation results. From the results of Figure 8, the proposed method can still maintain high segmentation quality when dealing with these complex situations, which shows that the proposed method has strong robustness and generalization ability.

4 OPTIMIZATION OF COLOR SCHEME BASED ON DM

4.1 Extraction of Color Matching Rules Based on DM

Color matching rules refer to the matching relationships and principles between different colors in design. These rules can be knowledge of harmony between colors, contrast, color psychology, and other aspects. Through DM technology, we can extract these potential color-matching rules from a large number of design samples and user feedback data. Firstly, we need to collect a large quantity of design samples, including design works with various styles, themes, and color combinations. These samples can come from designer portfolios, design websites, social media, and other channels. Moreover, it is needed to collect feedback data from users on these design samples, including preferences, emotional reactions, etc. Next, the DM algorithm can be used to process and analyze these data.

Firstly, it is necessary to clarify the objectives of optimizing the color scheme. This may involve achieving color harmony, contrast, emotional response, or specific design goals. Once the objective function is determined, the Newton iteration method can be used to find the color combination that minimizes or maximizes the function. The Newton iterative graph is a visually represented output generated by a computer, which performs iterative calculations on the complex plane using the mathematical framework of Newton's transformation. This transformation is formally defined as a method to determine the solutions of a given equation $F(z)=0$ within a complex domain. The associated dynamic system that facilitates this process is represented as:

$$\left\{C; f(z)=z-\frac{F(z)}{F'(z)}\right\} \tag{6}$$

$f(z)$ is called Newton's transformation of adjoint function $f(z)$.

According to this iterative formula, Newton's iterative graphics with novel shapes, complex structures, and exquisite structures can be obtained by computer drawing.

A common approach to addressing the nonlinear equation is to convert it into a linear form. Assuming x^J represents the equation's solution and x_0 approximates the initial value x^J, we can leverage Taylor's formula to express this relationship. By doing so, we can more easily manipulate and solve the equation.

$$f(x)=f(x_0)+f'(x_0)(x-x_0)+\frac{f''(x_0)}{2!}(x-x_0)^2+\cdots+\frac{f^{(n)}(x_0)}{n!}(x-x_0)^n+R_n(x) \tag{7}$$

Among them,

$$R_0(x)=\frac{f^{(n+1)}(\xi)}{(n+1)!}(x-x_0)^{n+1} \tag{8}$$

ξ here is a value between x, x_0.

4.2 Automatic Generation and Optimization Algorithm of Color Scheme

After extracting effective color-matching rules, these rules can be further utilized to generate and optimize color schemes automatically. This can help designers quickly generate color schemes that meet design requirements and user preferences; in color scheme generation, each color can be encoded as a gene, and the color scheme can be represented as a gene sequence. Then, the quality of each color scheme is evaluated by defining a fitness function, which can be defined based on design requirements and user preferences, such as color harmony, contrast, emotional response, etc. Next, use heuristic search algorithms to iteratively optimize the gene sequence until the optimal color scheme is found.

During image transmission and processing, images can be susceptible to both additive and multiplicative noise, which can alter pixel values. These noise-affected pixel values can be represented as follows:

$$F(x,y) = f(x,y) \cdot (1 + n(x,y)) + N(x,y) \tag{9}$$

Where: $n(x,y)$ represents multiplicative noise; $N(x,y)$ means additive noise.

The minimum distance between the central pixel and its surrounding area effectively reflects noisy pixels. The value of this distance represents the relationship between good pixels and noisy ones. Assuming that the maximum noise has minimal impact on surrounding good pixels, the Center-to-Boundary filter utilizes Newton's iterative formula to scan pixels from the center toward the edges and calculate the distances between them:

$$C_j = C_i - \frac{f(C_i)}{f'(C_i)} \tag{10}$$

Let C_i denote the central pixel and C_j denote any neighboring pixel. Supposing the central pixel holds a value of 1, the computation of the distance between the central pixel and its adjacent pixels is carried out using a 4-connectivity approach along with Newton's formula. Subsequently, all pixels undergo the same processing technique, ensuring that once a pixel has been processed, it is not subjected to further processing.

The DM-based color scheme optimization method can help designers extract effective color-matching rules and patterns from a large number of design samples and user feedback data, providing scientific and objective color-matching suggestions and guidance for designers. By using algorithms that automatically generate and optimize color schemes, it is possible to quickly generate color schemes that meet design requirements and user preferences. In color scheme optimization, the color scheme can be represented as a multidimensional vector, with each dimension representing the attributes of color. Then, define an objective function to evaluate the quality of the color scheme, which can be defined based on design requirements and user feedback. Next, use optimization algorithms to iteratively optimize multidimensional vectors until the optimal color scheme is found.

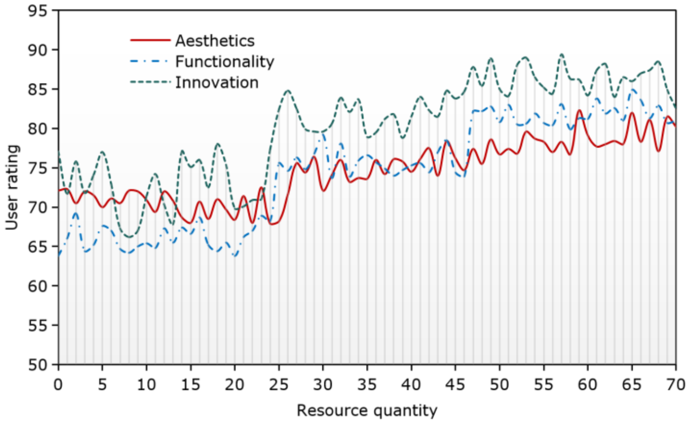

Figure 9: User subjective ratings of graphic design works.

4.3 User Feedback Analysis

Figure 9 shows the subjective rating results of users for graphic design works. Users have given good assessments of the aesthetics, functionality, and innovation of graphic design works. It shows the subjective rating results of users for graphic design works, covering three key aspects: aesthetics, functionality, and innovation. Aesthetics is the first element that attracts users to graphic design works, which involve multiple aspects such as color matching, layout, and graphic design. From the rating results, users acknowledge the overall harmony and beauty of the visual presentation of the work. In terms of functionality, users also gave positive feedback. A high functional rating means that the work not only accurately conveys the designer's intention but also allows users to feel convenient and efficient during use. Innovation is a key factor for graphic design works to stand out in market competition. Innovative design work can often break conventions and bring users a brand-new visual and user experience. From the rating results, users appreciate the attempts and breakthroughs in the innovative expression of the work.

5 CONCLUSION

Through the analysis and research of existing DM technology, this article proposes an improved planar design image threshold segmentation method. In terms of algorithm performance, the algorithm proposed in this article has shown significant advantages in computational efficiency, accuracy, and recall. Compared with the Fuzzy Clustering (FCM) algorithm and Particle Swarm Optimization (PSO) algorithm, our algorithm significantly reduces computational time, which means that in practical applications, our algorithm can process data more quickly and provide results. In this article, we integrate human visual attributes with the threshold computation procedure to accomplish the automated extraction of desired regions within images. This method not only improves the accuracy and robustness of segmentation but also makes the segmentation results more in line with human visual perception. Through the display and analysis of experimental results, it can be seen that our method has achieved superior performance in image threshold segmentation tasks. In terms of evaluating graphic design works, users have given good feedback on the aesthetics, functionality, and innovation of the works. This fully demonstrates the superiority of this graphic design work in aesthetic expression, practicality, and creative conception.

These achievements not only enrich the theoretical connotation of relevant fields but also provide strong support and guidance for practical applications. In future work, we will continue to conduct in-depth research and explore more meaningful research directions and application scenarios.

6 ACKNOWLEDGEMENT

Project supported by the Education Department of Hainan Province, Research on Course Design of Innovation in Design of Traditional Sings for Art Design Majors under the New Media Environment, NO. Hnjy2021-95.

Fang Chen, https://orcid.org/0009-0001-4961-5239
Gongsheng Zang, https://orcid.org/0009-0005-7379-5435

REFERENCES

[1] Fan, M.; Li, Y.: The application of computer graphics processing in visual communication design, Journal of Intelligent & Fuzzy Systems, 39(4), 2020, 5183-5191. https://doi.org/10.3233/JIFS-189003

[2] He, C.; Sun, B.: Application of artificial intelligence technology in computer aided art teaching, Computer-Aided Design and Applications, 18(S4), 2021, 118-129. https://doi.org/10.14733/cadaps.2021.S4.118-129

[3] Hu, L.: Design and implementation of a component-based intelligent clothing style cad system, Computer-Aided Design and Applications, 18(S1), 2020, 22-32. https://doi.org/10.14733/cadaps.2021.S1.22-32

[4] Indrie, L.; Mutlu, M.-M.; Ork, N.: Computer aided design of knitted and woven fabrics and virtual garment simulation, Industria Textila, 70(6), 2019, 557-563. https://doi.org/10.35530/IT.070.06.1659

[5] Kang, M.; Kim, S.: Fabrication of 3D printed garments using flat patterns and motifs, International Journal of Clothing Science and Technology, 31(5), 2019, 653-662. https://doi.org/10.1108/IJCST-02-2019-0019

[6] Li, J.; Yang, J.; Hertzmann, A.; Zhang, J.; Xu, T.: Layoutgan: Synthesizing graphic layouts with vector-wireframe adversarial networks, IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(7), 2020, 2388-2399. https://doi.org/10.1109/TPAMI.2019.2963663

[7] 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

[8] Ma, R.; Mei, H.; Guan, H.; Huang, W.; Zhang, F.; Xin, C.; Chen, W.: Ladv: Deep learning assisted authoring of dashboard visualizations from images and sketches, IEEE Transactions on Visualization and Computer Graphics, 27(9), 2020, 3717-3732. https://doi.org/10.1109/TVCG.2020.2980227

[9] Murugesan, S.; Malik, S.; Du, F.; Koh, E.; Lai, T.-M.: Deepcompare: Visual and interactive comparison of deep learning model performance, IEEE Computer Graphics and Applications, 39(5), 2019, 47-59. https://doi.org/10.1109/MCG.2019.2919033

[10] Su, X.; Li, N.; Hu, Y.; Li, H.: AWSD: An aircraft wing dataset created by an automatic workflow for data mining in geometric processing, CMES-Computer Modeling in Engineering & Sciences, 136(3),2023, 2935-2956. https://doi.org/10.32604/cmes.2023.026083

[11] Wang, Q.; Chen, Z.; Wang, Y.; Qu, H.: A survey on ML4VIS: Applying machine learning advances to data visualization, IEEE Transactions on Visualization and Computer Graphics, 28(12), 2021, 5134-5153. https://doi.org/10.1109/TVCG.2021.3106142

[12] Xu, P.; Hospedales, T.-M.; Yin, Q.; Song, Y.-Z.; Xiang, T.; Wang, L.: Deep learning for free-hand sketch: A survey, IEEE Transactions on Pattern Analysis and Machine Intelligence, 45(1), 2022, 285-312. https://doi.org/10.1109/TPAMI.2022.3148853

[13] Yoo, S.; Lee, S.; Kim, S.; Hwang, K.-H.; Park, J.-H.; Kang, N.: Integrating deep learning into CAD/CAE system: generative design and evaluation of 3D conceptual wheel, Structural and Multidisciplinary Optimization, 64(4), 2021, 2725-2747. https://doi.org/10.1007/s00158-021-02953-9

[14] Zhang, M.; Wang, N.; Li, Y.; Gao, X.: Neural probabilistic graphical model for face sketch synthesis, IEEE Transactions on Neural Networks and Learning Systems, 31(7), 2019, 2623-2637. https://doi.org/10.1109/TNNLS.2019.2933590

[15] Zhu, M.; Li, J.; Wang, N.; Gao, X.: A deep collaborative framework for face photo–sketch synthesis, IEEE Transactions on Neural Networks and Learning Systems, 30(10), 2019, 3096-3108. https://doi.org/10.1109/TNNLS.2018.2890018