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Application of Museum Spatial Layout Optimization Based on Genetic Algorithm in Multimedia CAD Platform

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Abstract. This article aims to improve the museum's space utilization and audience satisfaction by optimizing the museum's space layout based on GA. In order to achieve this goal, this article first designs the coding mode, fitness function, and genetic operation of GA to ensure that the algorithm can effectively search for the specific layout requirements of museums. Then, the spatial model of the museum is built by using the multimedia CAD (Computer Aided Design) platform, and the designed GA (Genetic Algorithm) is integrated into it for the simulation experiment. The simulation outcomes indicate that the museum space layout optimization approach utilizing GA (Genetic Algorithm) can significantly enhance space utilization and viewer contentment across various scales and complexities. When juxtaposed with the PSO (Particle Swarm Optimization) and SAA (Simulated Annealing Algorithm), this method exhibits superior accuracy and efficiency. It offers innovative solutions and techniques for addressing museum layout challenges, thereby carrying substantial theoretical and practical significance.

Keywords: Genetic Algorithm; Museums; Spatial Layout Optimization; Multimedia; Computer-Aided Design
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1 INTRODUCTION

With the progress of society and the development of science and technology, as an important place to display human cultural heritage and artistic achievements, the spatial layout of museums is of great significance to enhance the visitors' visiting experience, protect exhibits, and realize the educational and research functions of museums. Traditional 3D reconstruction methods often rely on a large number of manual operations, which are inefficient and prone to errors. To address this issue, Arce et al. [1] proposed an automatic 3D reconstruction method for spatial layout structures based on optimized view planning algorithms. The optimization view planning algorithm is a technique that calculates and analyzes spatial information from different perspectives to obtain the optimal view combination. In 3D reconstruction, by optimizing the view planning algorithm, the optimal shooting position and angle can be automatically selected to obtain the most comprehensive and accurate spatial information. By optimizing the view planning algorithm to process and analyze these images, the optimal image combination is automatically selected. Next, use 3D reconstruction algorithms to model these images in 3D and generate a 3D model of the spatial layout structure. Finally, the 3D model is presented through visualization technology for designers and engineers to analyze and modify. However, the traditional spatial layout methods of museums often rely on artificial experience and subjective judgment, and it is difficult to achieve the optimal effect. With the advancement of technology, the application of interactive design and CAD visualization technology has provided new solutions to this problem. Berseth et al. [2] explored how to use interactive design and CAD visualization technology to achieve interactive architectural spatial layout optimization design with multiple solutions. Interactive design allows designers to adjust parameters and variables in real-time during the design process, and observe the design effects under different parameter combinations. By building interactive design platforms or tools, designers can easily try different spatial layout schemes and receive immediate feedback. This real-time interaction greatly accelerates the design iteration process, allowing designers to explore more solutions in a short period. Through CAD software, designers can present design proposals in the form of 3D models, making the spatial layout more intuitive and visible.

In recent years, the development of CAD technology has provided a new solution for the spatial layout of museums. The traditional process of architectural spatial layout design often relies on the experience and intuition of designers, which is not only time-consuming and labor-intensive but also difficult to ensure the optimality of the design. The emergence of an automatic generation system for optimizing architectural spatial layout provides a solution to this problem. By extracting information such as size, shape, and proportion from the drawings, the system can automatically construct a three-dimensional building model and optimize the spatial layout based on this. During the optimization process, the system will iterate and simulate the spatial layout multiple times based on preset rules and constraints, such as structural safety, functional requirements, lighting, and ventilation. Byun and Sohn [3] selected the optimal layout scheme by comparing the effects of different layout schemes, thereby achieving efficient utilization of architectural space. Against this background, this study combines GA with a multimedia CAD platform, aiming at exploring a more scientific and efficient optimization method of museum spatial layout and providing new ideas and technical support for museum design and management. In the optimization design of architectural spatial layouts, traditional design methods are often limited by centralized data management and collaborative modes, resulting in opaque information, cumbersome design processes, and limited optimization effects. However, with the integrated application of BIM (Building Information Modeling) and blockchain technology, decentralized architectural spatial layout optimization design is becoming a new trend. Dounas et al. [4] discussed the importance, advantages, and application prospects of decentralized architectural spatial layout optimization design under the integration of BIM and blockchain. Through BIM technology, designers can establish precise building information models and digitize the various elements of building space. This allows designers to observe and analyze spatial layouts more intuitively, identify potential problems, and optimize them. At the same time, BIM technology can also achieve information sharing and collaborative work, allowing multiple participants to participate in the design process together, improving the efficiency and quality of design. A deep neural network is a computational model that simulates the structure and function of human brain neural networks. Through training and learning a large amount of data, it can automatically extract feature information from images. In terms of extracting wireframes for architectural spatial layouts, deep neural networks learn from a large number of architectural images and construct corresponding spatial layout models. Compared with traditional image processing methods, deep neural networks have higher accuracy and flexibility. Traditional image processing methods often rely on fixed algorithms and rules, making it difficult to cope with complex and ever-changing architectural spatial layouts. Deep neural networks can adaptively adjust and optimize recognition algorithms based on the specific content of the image, thereby achieving accurate extraction of different architectural spatial layouts [5].

GA, grounded in the principles of biological evolution, is a robust search optimization algorithm. It mimics natural selection and genetic processes like reproduction, mutation, competition, and selection to pinpoint the most viable solution within a given solution space. This algorithm stands out for its exceptional global search capabilities, resistance to local optima traps, and versatility across diverse problem sets, making it a popular choice in various domains. The core tenets of GA involve three key steps: encoding, evaluating fitness, and genetic manipulations. Initially, potential solutions are encoded into strings, forming an initial population. Subsequently, each individual's fitness is assessed using a dedicated function, favoring those with higher fitness for reproduction. Lastly, genetic operations give rise to a new population, and this cycle continues until a termination condition is fulfilled.

When tackling intricate combinatorial optimization challenges, such as optimizing museum spatial layouts, GA proves particularly adept. Its ability to recast these problems as chromosome solution space searches via encoding techniques simplifies the solution process. Furthermore, by simulating natural selection and genetic mechanisms, GA swiftly homes in on globally optimal or near-optimal solutions. Its robustness and adaptability allow it to tackle large-scale, high-dimensional problems and adjust its search strategy dynamically. The practical integration of GA with museum layout optimization involves crafting suitable encoding methods, fitness functions, and genetic operations, offering significant theoretical and practical value. The main content of this study is the realization and application of the GA-based museum spatial layout optimization method on a multimedia CAD platform. First of all, this article will deeply study the basic theory and operation flow of GA, and design the appropriate coding method, fitness function, and genetic operation in combination with the specific problems of museum spatial layout. Then, this article will develop a museum spatial layout optimization system based on a multimedia CAD platform to realize seamless integration of GA and CAD platforms. Ultimately, simulation experiments confirm the efficacy and superiority of the proposed methodology.

In this article, several innovations are introduced in the application of the algorithm, the design of the fitness function, the integration of the multimedia CAD platform, and the evaluation and comparison of algorithm performance. These innovations offer a fresh perspective and solution for advancing research and practical applications in museum spatial layout optimization. Specifically, the innovations encompass the following aspects:

(1) The article pioneers the application of GA in optimizing museum spatial layouts. Unlike traditional methods that rely heavily on manual expertise or basic rules, the GA-based approach proposed here enables automatic and efficient layout optimization, significantly enhancing both the efficiency and quality of the layout process.

(2) In crafting the fitness function, the article takes into account multiple factors, including space utilization, visitor satisfaction, exhibit preservation requirements, and operational costs. This comprehensive approach leads to the creation of a multi-objective fitness function that makes the optimization process more nuanced and aligned with the museum's actual needs.

(3) The article breaks new ground by integrating GA with a multimedia CAD platform, facilitating visual simulation and optimization of museum spatial layouts. This integration allows designers to visualize the layout effects, promptly adjust optimization strategies, and enhance the interactivity and convenience of the design process.

(4) Beyond merely verifying the algorithm's effectiveness through simulation experiments, the article also compares it with PSO and SAA. Through a combination of qualitative and quantitative analyses, the article provides a comprehensive assessment of the algorithm's performance advantages, offering a novel approach and methodology for tackling museum spatial layout optimization challenges.

The structure of this article is organized as follows:

Section I: Presents an overview of the research background, its significance, the theoretical underpinnings, methodologies employed, and the structural outline of GA.

Section II: Provides a concise summation of the current research landscape and outlines the focal points addressed in this article.

Section III: Delves into the intricacies of optimizing museum spatial layouts and formulates the corresponding mathematical framework.

Section IV: Introduces the capabilities and distinct features of the multimedia CAD platform, emphasizing its utilization in museum spatial arrangements.

Section V: Details the design and execution of a museum spatial layout optimization approach rooted in GA.

Section VI: Validates and assesses the efficacy of the proposed methodology through rigorous simulation experiments.

Section VII: Offers a concise recap of the research accomplishments and contributions, while also providing an outlook on potential future research avenues.

2 RELATED WORK

Han et al. [6] used deep learning techniques to conduct an in-depth analysis of the completed model, thereby achieving optimization of building spatial layout. By extracting information such as lines, shapes, and proportions from CAD drawings, deep learning models can construct three-dimensional building models and identify various elements and components within the model. This enables us to have a more comprehensive understanding of the structure and spatial layout of the building, providing basic data for subsequent optimization analysis. Secondly, deep learning techniques can intelligently analyze and optimize architectural spaces. Based on a large amount of training data and learning experience, deep learning models can automatically evaluate the rationality, aesthetics, and functionality of building spaces. The rise of augmented reality (AR) and virtual reality (VR) technologies provides new solutions for layout optimization between ships and offshore structures. Especially when these technologies are combined with 3D CAD data extraction and conversion, designers can explore and optimize design solutions in unprecedented ways. Han et al. [7] explored how to apply augmented/virtual reality technology to 3D CAD data extraction and conversion for layout optimization between ships and offshore structures. 3D CAD software can create detailed 3D models that accurately reflect the shape, size, and construction of ships and offshore structures. However, traditional CAD data extraction and transformation methods are often limited to 2D views or static 3D displays, making it difficult to present spatial layout and dynamic interaction visually. The introduction of augmented/virtual reality technology provides designers with a new way to extract, transform, and present 3D CAD data. The multifunctional landscape spatial layout design provides important theoretical support and practical guidance. Lavorel et al. [8] combined a multifunctional landscape spatial layout design template to explore the application and practice of landscape ecology. In terms of spatial division, designers need to comprehensively consider natural factors such as terrain, climate, vegetation, and the influence of human activities to divide the landscape space into different functional areas. Functional positioning determines the dominant and auxiliary functions of each region based on its characteristics and needs in order to meet the needs of different users. Ecological connectivity is an indispensable part of multifunctional landscape spatial layout design. By constructing ecological corridors and setting ecological nodes, we can strengthen the ecological connections between various functional areas. Promote species migration and energy flow, and maintain the stability and diversity of ecosystems.

As an important venue for showcasing and disseminating historical and cultural heritage, the spatial design and layout of museums are crucial for the audience's visiting experience. In recent years, with the development of digital technology, multimedia CAD analysis technology has gradually been applied to the spatial design of museums, providing strong support for the transformation from functional space to experiential space. Li et al. [9] used a museum in China as an example to explore the application of spatial syntax multimedia CAD analysis in museum spatial design. In the spatial design of museums, spatial syntax can help designers better understand and optimize spatial layout, and improve the visitor experience. Multimedia CAD analysis technology combines computer-aided design and multimedia technology to accurately model and visually analyze space, providing designers with more intuitive and comprehensive design tools.

With the rapid development of digital technology, architectural space design is gradually shifting from traditional manual drawing and model-making to a digital and algorithmic direction. Topological vision, as an emerging technology, Lin [10] developed architectural spaces using this application algorithm framework. Topology is a mathematical branch that studies the continuous changes in spatial shape and structure, while topological vision applies the principles of topology to the field of vision, analyzing and processing spatial forms through computer algorithms. Generate a topology structure that meets the design requirements by calculating the connection relationships, morphological changes, and spatial layout parameters of spatial elements. This algorithmic design method can greatly improve the accuracy and efficiency of design, reduce the repetitive labor of designers, and also explore more unprecedented spatial forms and layout methods. The concepts of digital twins and digital shadows are gradually entering the field of vision in the construction industry. Both, as key elements of digital transformation, are of great significance in promoting the paradigm shift of sustainable architectural spatial environment. Sepagozar [11] explores the differences between digital twins and digital shadows and analyzes their application and impact in sustainable architectural spatial environments. Digital twins can reflect the status of physical buildings in real-time, providing comprehensive data support for the design, construction, operation, and maintenance of buildings. Digital shadows refer to the collection of data generated during the use of buildings, including energy consumption, environmental parameters, usage behavior, and other related information. Digital shadows provide a decision-making basis for optimizing building performance and sustainable development through data analysis. In terms of sustainable architectural spatial environment, digital twins and digital shadows play different roles. Digital twins provide architects with more accurate design solutions through simulation and prediction.

Traditional urban spatial layout design methods often rely on the experience and intuition of designers, making it difficult to fully consider various complex factors, resulting in design results that may not be optimized enough. Stojanovski et al. [12] proposed a new solution for digital urban spatial layout design using genetic algorithms. Search for the optimal solution in the solution space by simulating natural selection and genetic mechanisms. In urban spatial layout design, we can encode urban spatial layout schemes as individuals of genetic algorithms, and through continuous evolution and iteration, find the optimal urban spatial layout scheme. The core of digital urban spatial layout design practice lies in establishing mathematical models and algorithms. The objective function can be a comprehensive evaluation of multiple indicators such as urban space utilization rate, traffic smoothness, environmental comfort, etc. The constraints include land use planning, building height restrictions, environmental protection requirements, etc. Digital archiving of the perception and experience of architectural space is of great significance in the field of architectural design and planning. Through computer-aided methods, Tai and Sung [13] effectively recorded and preserved people's perceptions and experiences in architectural spaces, providing valuable information for subsequent design optimization, historical research, and cultural inheritance. The traditional way of recording the perception and experience of architectural space often relies on text and images, which, although intuitive, is difficult to fully reflect people's true feelings in space. 3D scanning technology can accurately obtain geometric information about building space and generate high-precision 3D models. These models can not only be used for visual display but also provide data support for subsequent spatial analysis and optimization. Secondly, virtual reality technology can simulate people's perceptions and experiences in architectural spaces. By wearing virtual reality devices, people can freely explore the architectural space in a virtual environment, feeling the light, shadow, materials, and atmosphere inside. This approach can enable people to have a more intuitive understanding of the characteristics of architectural space, providing designers with richer design inspiration.

Tytarenko et al. [14] explored how to use digital tools for 3D modeling to optimize the layout of virtual building environments. Through 3D modeling, designers can present and modify building layouts in unprecedented ways to better meet practical needs. At the same time, 3D models can accurately reflect the spatial structure, materials, lighting, and other elements of the building, making the design results more realistic and credible. Using digital tools for various attempts and simulations can adjust parameters such as height, width, and length of buildings, and observe the impact of different layouts on space utilization. Change the material and color of the building and observe its impact on the overall visual effect. It is also possible to simulate different lighting conditions and observe the performance of buildings under different lighting conditions. Xin and Qiu [15] have utilized advanced image processing technology and neural network technology to achieve precise expression of ancient architectural decorative elements, providing strong support for the protection and inheritance of ancient architectural decorative art. Obtain original images of ancient architectural decorations through high-definition cameras or scanners. Then, image processing techniques are used to preprocess the image, including denoising, enhancing contrast, and other operations, in order to improve image quality. The system utilizes neural networks to extract features from images. Neural networks can automatically recognize and extract key features in images, such as lines, textures, colors, etc., through extensive learning and training. This feature information will serve as the basis for subsequent analysis and processing.

3 ANALYSIS OF OPTIMIZATION OF SPATIAL LAYOUT OF MUSEUMS

3.1 The Importance and Challenges of Optimizing the Spatial Layout of Museums

As a gathering place of culture and art, the spatial layout of a museum not only directly affects the visitors' visiting experience but also relates to the protection of exhibits, the display effect, and the operational efficiency of the museum. A reasonable spatial layout can effectively guide the streamlining of the audience and improve satisfaction of the audience. Furthermore, it can also ensure that exhibits are displayed and protected in the best environment, thus prolonging the life of exhibits and reducing maintenance costs.

The optimization of museum spatial layout is a complex combinatorial optimization problem that faces many difficulties and challenges. For example, Table 1 shows the difficulties and challenges in optimizing the spatial layout of museums.

Difficulties and challenges	*Specific issues*
Multi-factor consideration	The spatial layout of the museum needs to comprehensively consider the size, weight, protection requirements, the streamlining of visitors' visit, the aesthetic effect of space, and other factors, that restrict and influence each other.
Multi-objective optimization	The optimization objectives of the museum spatial layout include maximizing audience satisfaction and minimizing operating costs, etc. There may be conflicts between these objectives, which need to be weighed and chosen.
Dynamic change factor	The optimization of museum space layout needs to consider dynamic factors such as the renewal of exhibits and the change of audience flow and requires the layout to be flexible and adjustable.

Table 1: Difficulties and challenges in optimizing the spatial layout of museums.

3.2 Mathematical Model for Optimizing the Spatial Layout of Museums

To efficiently tackle the optimization challenge of museum spatial layout, it is imperative to devise a suitable mathematical model. This model must precisely capture crucial elements like the museum's spatial configuration, exhibit attributes, and visitor behavior, translating them into quantifiable mathematical representations. Subsequently, by outlining the objective function and constraints, the mathematical framework for the optimization problem can be formulated. The objective function may encompass a weighted combination of individual or multiple metrics, including visitor satisfaction and space utilization, among others. Constraints reflect various constraints in the spatial layout of museums, such as the size limitation of exhibits and the connectivity requirements of space. By solving this mathematical model, we can get the optimal solution or approximate optimal solution of the spatial layout of museums.

4 MULTIMEDIA CAD PLATFORM

4.1 Multimedia CAD Platform Helps to Optimize the Spatial Layout of Museums

A Multimedia CAD platform is a CAD tool that integrates graphics processing, data analysis, simulation, and other functions. It can not only support traditional two-dimensional and three-dimensional graphic design but also integrate text, images, audio, video, and other media elements to provide designers with a more intuitive and comprehensive design experience. In the field of museum spatial layout optimization, multimedia CAD platform plays a vital role, which can help designers design, analyze, and optimize spatial layouts more efficiently. Multimedia CAD platform has rich functions and characteristics, which makes it a powerful tool for optimizing the spatial layout of museums. For example, Table 2 shows the functions and characteristics of multimedia CAD platforms in optimizing the spatial layout of museums.

Functions and characteristics	*Specific description*
Two-dimensional and three-dimensional graphic design	Support designers to easily create and modify the spatial layout scheme of museums through drawing tools, editing tools, and rendering tools.
Data analysis tool integration	Integrate spatial analysis, pedestrian flow analysis, and other data analysis tools to help designers scientifically assess and optimize the layout plan.
Simulation function	Simulate the operation of the museum in the virtual environment and accurately predict the actual effect of the layout scheme.
Openness and scalability	It has good openness and expansibility and can be integrated with other optimization algorithms (such as GA) to realize intelligent spatial layout optimization.

Table 2: Functions and characteristics of multimedia CAD platform in the optimization of museum space layout.

The Multimedia CAD platform plays a key role in the optimization of museum spatial layout, which supports designers in creating two-dimensional and three-dimensional layout schemes and uses data analysis tools for scientific assessment and optimization. In addition, the platform can also predict the actual effect of the layout scheme through simulation and support the integration with other optimization algorithms, such as GA, to realize intelligent spatial layout optimization.

4.2 Integration of Multimedia CAD Platform and GA

The amalgamation of multimedia CAD platforms with GA serves as a pivotal step toward the intelligent optimization of museum spatial layouts. By seamlessly integrating GA into the multimedia CAD platform, we leverage its exceptional global search capabilities and optimization prowess to scour and refine museum spatial layouts autonomously. Designers can seamlessly outline objective functions and constraints for layout challenges within the multimedia CAD platform, subsequently harnessing GA for tasks like encoding, fitness evaluation, and genetic manipulation of the layout schemes. Through iterative searches and refinements, we ultimately arrive at an optimal or near-optimal layout blueprint that aligns with design specifications. This integrated approach not only elevates the efficiency and quality of museum spatial layouts but also offers more scientific and holistic support for museum operations and management. The ensuing section delves into the nitty-gritty of GA's implementation process.

5 OPTIMIZATION METHOD OF MUSEUM SPATIAL LAYOUT BASED ON GA

5.1 GA Coding Design

In the optimization of museum spatial layout based on GA, coding design is the first step, which transforms the museum spatial layout problem into a chromosome form that GA can handle. Commonly used coding methods include binary coding, integer coding, and real coding. Considering the complexity and flexibility of the spatial layout of museums, this article adopts an integer coding method. Integer coding assigns a unique integer number to each exhibit in the museum and then arranges these numbers according to the order of the exhibits to form a chromosome. The length of the chromosome is equal to the number of exhibits or display units. This coding method is simple intuitive, and easy to understand and realize. The formula is as follows:

$$\mathrm{Pheromone}_{i,j} = 1-\rho * \mathrm{Pheromone}_{i,j} + \rho * Q / d_{i,j} \tag{1}$$

This formula is used to update the pheromone concentration of ants between exhibits, where $\mathrm{Pheromone}_{i,j}$ is the pheromone concentration from exhibit i to exhibit j, ρ is the pheromone evaporation rate, Q is the pheromone intensity, and $d_{i,j}$ is the distance from exhibit i to exhibit j. The optimization of museum space layout based on GA is shown in Figure 1.

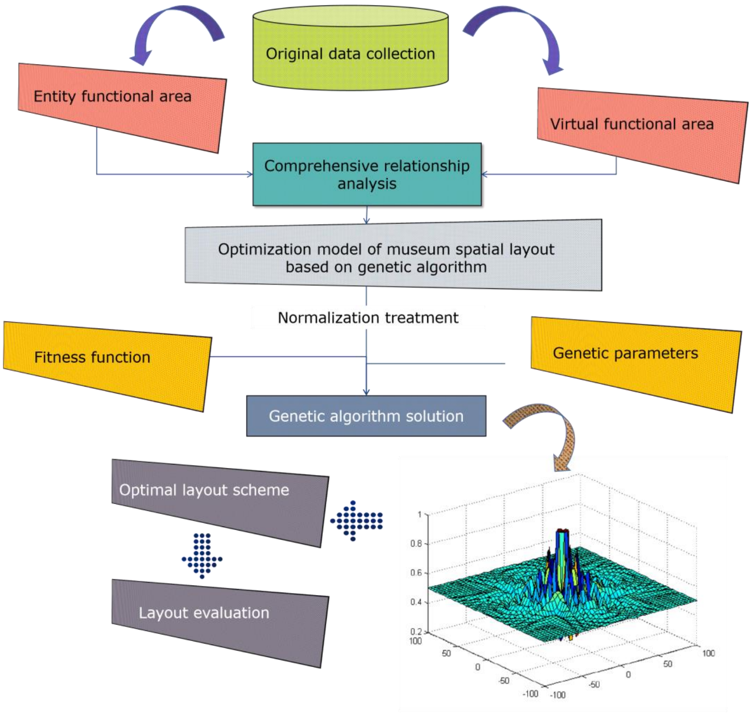

Figure 1: Optimization of museum spatial layout based on GA.

When solving the optimization problem of museum space layout, this article first discretizes the continuous space, and divides the grid in the variable area, taking the adjacent grid points as the possible path for ants. When all ants complete a cycle, this article will adjust the pheromone intensity on each path according to a specific formula. The calculation formula is as follows:

$$\tau_{i,j_1,j_2}\left(N_c+1\right)=\left(1-\rho\right)\cdot\tau_{i,j_1,j_2}\left(N_c\right)+\sum_{k=1}^{n}\Delta_{i,j_1,j_2}^{k} \tag{2}$$

Where n is the total number of ants; $\tau_{i,j_1,j_2}(N_c)$ and $\tau_{i,j_1,j_2}(N_c+1)$ are the pheromone concentration values after N_c and N_c+1 cycles, respectively; ρ is the degree of pheromone volatilization on the path. Δ_{i,j_1,j_2}^{k} is the pheromone left by the k and on the side $N_{new}(i, j_1, j_2)$ after one cycle.

5.2 Fitness Function Design

The fitness function is an important index used to assess the merits of individuals in GA. In the optimization of the museum's spatial layout, the fitness function should be able to reflect the quality of the layout scheme. In this article, the fitness function is designed from the following aspects:

(1) Audience satisfaction: Considering factors such as the audience's comfort and streamlined smoothness during the visit, the audience's satisfaction assessment on the layout scheme can be obtained through questionnaire survey, simulation, and so on.

(2) Space utilization ratio: Calculate the space utilization ratio of each area in the museum to avoid space waste and congestion.

(3) Exhibit protection requirements: Ensure that exhibits are fully protected and displayed in the layout plan to avoid mutual interference and damage.

(4) Operating costs: Consider the impact of the layout scheme on the museum's operating costs, such as energy consumption such as lighting and air conditioning, and maintenance costs.

Based on the above factors, a multi-objective fitness function can be constructed, and multiple objectives can be transformed into a comprehensive assessment index by the weighted summation method. It should be noted that when designing fitness functions, the dimension difference and weight distribution between different goals should be considered. Let the objective function be I:

$$F_c^{'}\left(I\right)=\left(1-w_c\right)F\left(J\right) \tag{3}$$

Among them, $F_c^{'}(I)$ is expressed as the objective function description of data individuals with low fitness; w_c is expressed as a positive penalty factor; $F(J)$ is expressed as the objective function. The crossover rate and variation rate are P_c P_m, respectively:

$$P_c=\begin{cases}\dfrac{k_1\left(f^{'}-f_{\min}\right)}{f_{avg}-f_{\min}} & f^{'}<f_{avg}\\ k_1 & f^{'}\geq f_{avg}\end{cases} \tag{4}$$

$$P_m=\begin{cases}\dfrac{k_2\left(f^{'}-f_{\min}\right)}{f_{avg}-f_{\min}} & f^{'}<f_{avg}\\ k_2 & f^{'}\geq f_{avg}\end{cases} \tag{5}$$

Where f_{avg} is the average fitness value; $f^{'}$ is the smaller fitness value in crossover individuals. Several filter genes with high adaptability in the parent are copied to the offspring, thus forming the genes of the offspring. Where GN is the total number of filter genes? The calculation formula for probability λ_i is as follows:

$$\lambda_i=\frac{q_i}{q_{\max}} \tag{6}$$

Among them:

$$q_{\max} = \max\ q_i\ , i = 1,2,\cdots,GN \tag{7}$$

Genetic operation is the core step in GA, including selection, crossover, and mutation. These operations simulate the processes of reproduction and mutation in natural selection and genetic mechanisms and are used to produce new individuals and retain excellent genes. The selection operation is to select the excellent individual from the current population as the parent according to the fitness value of the individual to produce the next generation population. Selection probability determines which individuals will participate in crossover and mutation operations and is calculated according to the fitness value of individuals:

$$P\ i\ = \frac{f\ x_i}{\sum_{\mathrm{j=1}}^{\mathrm{population}} f\ x_j} \tag{8}$$

Where $P\ i$ is the selection probability, $f\ x_i$ is the fitness value of the i individual, and the denominator is the sum of the fitness values of all individuals in the population. Crossover operation simulates the biological hybridization process and produces new individuals by exchanging some genes between parents. The formula is as follows:

$$x_{ij}^{'} = \begin{cases} x_{ij}, if\ r_1 < p_c \\ x_{ij}^{''}, otherwise \end{cases} \tag{9}$$

Among them, $x_{ij}^{'}$ is the gene at the j position of the i individual after crossover, r_1 is a real number randomly generated in the interval of [0,1], p_c is the crossover probability, and $x_{ij}^{''}$ is the gene at the j position of another parent individual. Mutation operation is to simulate the process of gene mutation in biology and introduce new genetic information by randomly changing the value of a gene on an individual chromosome. The formula is as follows:

$$x_{ij}^{''} = \begin{cases} x_{ij}, if\ r_2 > p_m \\ g_j + \lambda \cdot\ b_j - x_{ij}\ , otherwise \end{cases} \tag{10}$$

Among them, $x_{ij}^{''}$ is the gene at the j position of the i individual after mutation; r_2 is a real number randomly generated in the interval [0,1]; p_m is the mutation probability; λ is the coefficient of variation; g_j is the gene center of the j gene, and b_j is the gene boundary.

5.3 Algorithm Flow and Implementation

The operation flow of GA generally includes the following steps: (1) initializing the population; (2) calculating individual fitness; (3) selecting operation; (4) cross operation; (5) mutation operation; (6) judging whether the termination condition is met, if so, outputting the optimal solution, otherwise, returning to step (2). In this article, the algorithm flow of the museum spatial layout optimization method based on GA is as follows:

(1) Initial population: an initial population is generated according to the coding design method, and each individual represents a museum spatial layout scheme.

(2) Calculating the fitness value: calculating the fitness value of each individual according to the fitness function and evaluating the advantages and disadvantages of the layout scheme.

(3) Genetic operation: genetic operation is carried out on the population in the order of selection, crossover, and mutation to produce new individuals and populations. Repeat this step until the termination condition is met (the layout scheme that meets the requirements is found).

(4) Decoding and outputting: decoding the code of the optimal individual into the concrete form of the museum spatial layout scheme, and outputting the results for designers' reference and use.

6 SIMULATION EXPERIMENT AND ANALYSIS

To validate the efficacy of the GA-based optimization method for museum spatial layout, simulation experiments were conducted in this section. A diverse range of museum spatial layouts, encompassing varying scales, shapes, and exhibit types, were carefully chosen as experimental subjects. Then, according to the specific characteristics of each case, the corresponding experimental scheme is formulated, including coding mode, fitness function design, genetic operation design, and so on. In the process of the simulation experiment, firstly, the spatial model of the museum is created by using the multimedia CAD platform, and the exhibit information is imported into the model. Then the spatial layout optimization method based on GA is realized and applied to the optimization process of each case. In the process of optimization, the running time, iteration times, and optimal solution of the algorithm are recorded for subsequent analysis and comparison. Furthermore, this section also uses simulation software to simulate and assess the optimized layout scheme, so as to intuitively show the optimization effect. The layout simulation is shown in Figure 2.

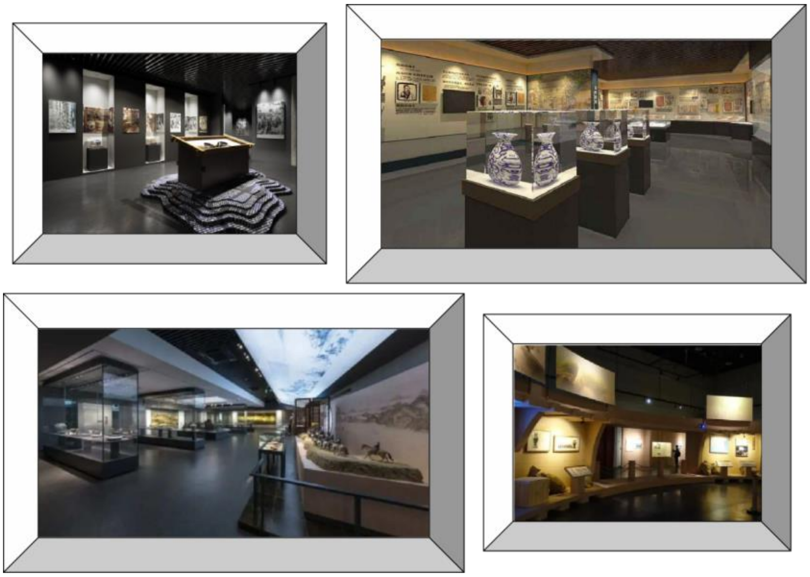

Figure 2: Simulation display of layout scheme.

Table 3 shows the protection effect of exhibits before and after optimization.

Exhibit number	*Protection effect score before optimization*	*Protection effect score after optimization*	*Lifting range*
Exhibit A	75	90	15%
Exhibit B	80	92	15%
Exhibit C	78	91	16.7%
Exhibit D	82	93	13.4%
Exhibit E	79	90	13.9%

Table 3: Comparison of exhibition protection effects before and after optimization.

Note: The score of protection effect is 100%, and the higher the score, the better the protection effect. The improvement range is the percentage of the score improvement after optimization compared with that before optimization.

According to the data in Table 3, it can be seen that the optimization method of museum spatial layout based on GA has a remarkable effect in improving the protection effect of exhibits. After optimization, the protection effect scores of all exhibits have been improved, with an average improvement rate of 14.8%. This shows that this method can effectively improve the spatial layout of museums, thus enhancing the protection effect of exhibits.

The comparison of space utilization before and after optimization is shown in Figure 3.

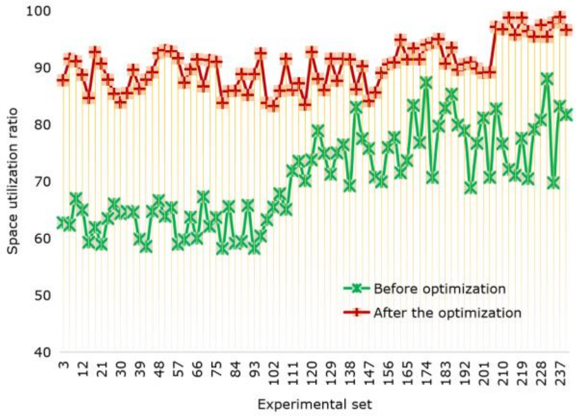

Figure 3: Comparison of space utilization ratio before and after optimization.

The comparison of audience satisfaction before and after optimization is shown in Figure 4 and Table 4.

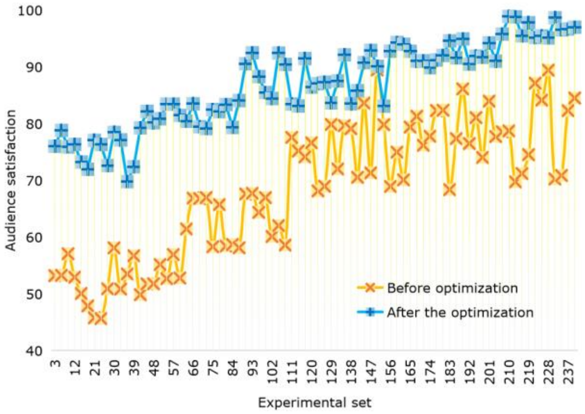

Figure 4: Comparison of audience satisfaction before and after optimization.

Assessment content	*Score before optimization*	*Score after optimization*	*Score improvement*
Rationality of exhibit layout	7.5	9.0	1.5
Convenience of visiting the	8.0	9.2	1.2

route			
Space comfort	7.8	9.1	1.3
Information indication clarity	8.2	9.3	1.1
Overall visit experience	8.5	9.5	1.0

Table 4: Assessment results of each index before and after optimization.

By analyzing the data presented in Figure 4 and Table 4, it becomes evident that the optimization of museum spatial layout utilizing GA has led to notable improvements in various aspects. These include the audience's perception of exhibit layout rationality, the ease of navigating through visiting routes, the spatial comfort offered, the clarity of informational instructions, and the overall visiting experience. Such improvements indicate that the optimized museum spatial layout is more aligned with the audience's needs and expectations, resulting in enhanced visitor satisfaction.
To provide further validation of the algorithm's performance advantages, this section compares the GA-based optimization method for museum spatial layout with two other approaches: PSO and SAA. A comparative analysis of solution accuracy is depicted in Figure 5. The comparison of operation efficiency is shown in Figure 6.

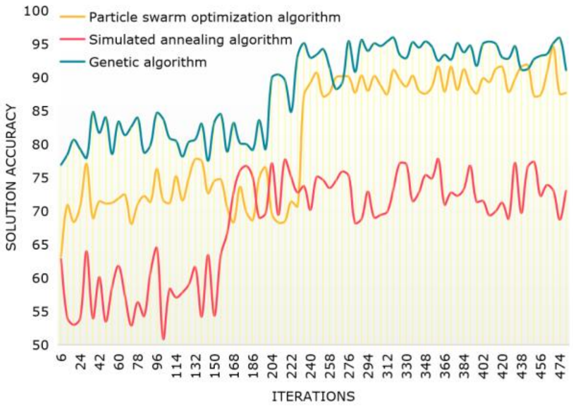

Figure 5: Comparison of solution accuracy.

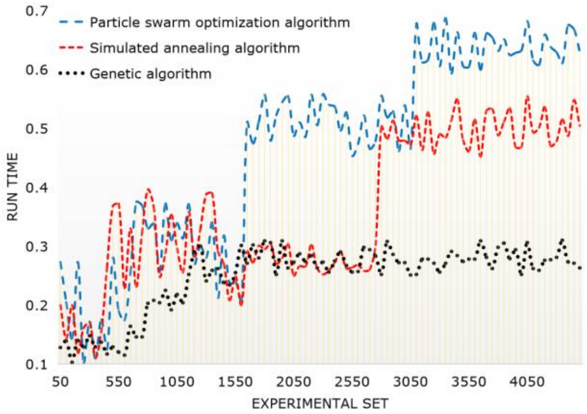

Figure 6: Comparison of operation efficiency.

Upon comparing the experimental data and outcomes, this article concludes that the proposed algorithm surpasses the other two methods in terms of solution accuracy and operational efficiency. This serves as compelling evidence for the algorithm's effectiveness and superiority in optimizing museum spatial layouts. Moreover, it introduces a novel approach to addressing the optimization challenges associated with museum spatial layouts.

Additionally, this section evaluates the algorithm's stability, as illustrated in Figure 7.

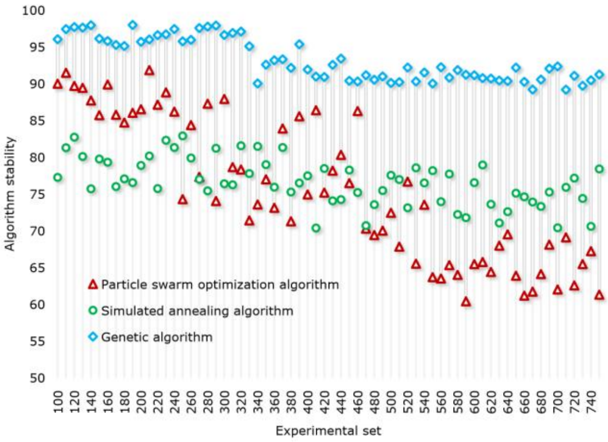

Figure 7: Stability of the algorithm.

The findings reveal that the algorithm exhibits impressive performance in terms of running time and iteration counts, consistently converging towards the optimal solution. This underscores the algorithm's practical feasibility and superiority.

The simulation experiment conducted in this section has yielded a substantial amount of experimental data and insights. Notably, the GA algorithm outperforms other methods across various metrics, particularly in solution accuracy and operational efficiency. This provides compelling evidence of the algorithm's efficacy in optimizing museum spatial layouts. Furthermore, the optimization method of museum space layout based on GA can effectively improve many indicators such as space utilization, audience satisfaction, and exhibit protection effect.

7 CONCLUSIONS

In this study, a solution based on GA is proposed to optimize the spatial layout of museums. Through an in-depth analysis of the characteristics and difficulties of museum spatial layout, this article designs a reasonable coding method, fitness function, and genetic operation, and realizes the effective solution of the algorithm. Furthermore, this article also uses the multimedia CAD platform to integrate and apply the algorithm, which improves the visualization and interactivity of the optimization process. Through rigorous simulation experiments and comparative analyses, the efficacy and superiority of the proposed algorithm have been established, offering a fresh perspective and approach to address the optimization challenges inherent in museum spatial layouts.

Looking ahead to future research endeavors and advancements in museum spatial layout optimization, the following recommendations emerge from this study: a stronger emphasis on integrating algorithms with practical application scenarios, taking into account the specific needs and constraints of museum spatial designs; fostering innovative research methodologies that embrace multidisciplinary perspectives, drawing insights from diverse fields of study; and a heightened focus on exploring the potential and implications of emerging technologies and methodologies, particularly the opportunities and challenges presented by artificial intelligence, big data, and other cutting-edge technologies in optimizing museum spatial layouts.

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