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INDOOR SPACE LAYOUT DESIGN BASED ON DIFFERENTIAL EVOLUTION ALGORITHM

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Abstract. To enhance the interactivity of spatial design, this study proposes an indoor spatial layout design method based on differential evolution algorithm, which combines backtracking strategy and reverse learning strategy to improve the interactive differential evolution algorithm. The experimental data demonstrated that the proposed method for indoor space layout design achieved an average user satisfaction of 81.7%, which increased by 16.8% compared with traditional interactive genetic algorithms. In addition, the improved human-computer interaction interface scored higher than 0.8 in terms of usability, reliability, customizability, and interactive feedback. This means that the improved interface can better meet user needs and provide a better user experience. This study shows that the indoor space layout design method ground on differential evolution algorithm and the improved human-computer interaction interface can significantly improve user satisfaction and user experience. This has brought more efficient and convenient solutions to the field of spatial design.

Key words: Differential Evolution Algorithm; Interior Design; Spatial Layout; Backtracking Strategy; Reverse Learning Methods

1. Introduction. With the acceleration of urbanization, the demand for indoor space layout design is becoming increasingly important. Reasonable indoor space layout design can not only improve space utilization, but also improve quality of life and work efficiency [1]. However, traditional design methods cannot meet the needs for personalization and efficiency, due to the complexity and diversity of indoor space layout design issues [2]. Modern indoor space layout design methods rely on computer technology and data analysis to design more objectively and scientifically [3]. By collecting and analyzing a large amount of data, designers can understand people's living habits, work needs, and space utilization, thus making reasonable and efficient designs. Computer technology can also simulate and predict the effects of different design schemes, helping designers make decisions [4]. The pursuit of personalization is constantly increasing, hoping to express their individuality and taste in indoor spaces. Modern design methods can be customized according to individual needs and preferences to meet personalized pursuits. Differential Evolution Algorithm (DEA), as a global optimization algorithm, has achieved significant results in many fields, with strong search capability and adaptability. Nevertheless, there is currently relatively little research on the application of DEA in indoor space layout design [5]. At present, traditional indoor space layout design methods are unable to meet the increasing personalized needs. Although modern design methods can provide more objective and scientific design, they lack a profound understanding of diverse needs. Therefore, it is necessary to design a technology that combines traditional and modern design methods to meet growing needs. Therefore, this study aims to explore indoor space layout design methods on the ground of DEA, providing a new solution to solve indoor space layout design problems. The study consists of four parts. The first is a review of relevant research. The second is designs the indoor Spatial Layout (SL) method. The third part is the application analysis of indoor space layout design on the ground of DEA. The fourth part is a summary of the entire study.

2. Related works. Spatial location layout refers to how to arrange and organize the positions and layout of various elements in the design and planning of buildings, indoor or outdoor spaces. Stephan et al. proposed a mixed integer program ground on orthogonal parking for parking lot space design, which maximized the number of parking spaces to effectively utilize urban space attributed to parking. Experimental data showed that the effectiveness of this method reached 77% [6]. The Boysen research team proposed a dynamic programming

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algorithm based on Multi-Objective (MO) optimization for the layout design of moving walkways, optimizing the position of two-way walkways. The results showed that the optimization efficiency of this method reached 85% [7]. Wang et al. used MO optimization methods to obtain a set of solutions for industrial park layout design. An extended risk map method was used for describing the risk distribution. The outcomes showcased that the effectiveness of this method was superior to that of non-dominated sorting genetic algorithm [8]. Related research proposed an improved search genetic algorithm for the layout design of multi-deck cabins in ship cabins. This algorithm considered the layout optimization of ship's multi-layer residential compartments as a combination optimization problem with multiple performance constraints. The energy method was combined to determine the deck layers of each compartment. The experiment showcased that this method was useful [9]. Fathy et al. proposed a simplified facade lighting design process for museum layout design. The current solar performance evaluation was used as an overall spatial indicator and considered spatial distribution relationships [10]. This study indicated that sustained solar autonomy and annual sunshine were the indicators that best meet the standards.

The DEA simulates the biological evolution process, searching for the optimal solution through continuous iteration and mutation. Lin et al. proposed a hybrid optimization algorithm for ship pipeline layout. A ship pipeline vector encoding method based on existing encoding methods and ship pipeline characteristics was proposed [11]. Then, the proposed vector encoding was used to implement the discrete mixed differential evolution and cuckoo search algorithms. The results indicated that the hybrid optimization algorithm could obtain optimization schemes with fewer elbows and more remaining area. Related research proposed an accelerated MO DEA for the layout of offshore power systems. The analytical wave tail model of the converter was used to optimize the device layout [12]. The experiment showcased that the optimized power system layout could increase the output energy by 37%. Pan et al. proposed a MO DEA on the ground of competition mechanism. The competition mechanism of shift density estimation strategy was used to design new mutation operations [13]. The dataset experiment showcased that this method was more excellent than six state-of-the-art MO optimization algorithms. DEA was used to optimize and identify the parameters of multi-layer T-S fuzzy models. Then it combined with adaptive fuzzy sliding surfaces to ensure the asymptotic stability of closed-loop systems. The simulation showcased that the performance indicators of this method were superior to both inverse fuzzy controllers and conventional adaptive fuzzy controllers [14]. A research team proposed a parameter optimization method for a swinging buoy type wave energy converter. The DEA and linear potential flow theory were used to analyze the impact of buoy volume on optimal power capture. The results indicated that this method improved the energy of the wave energy conversion system [15].

In summary, many researchers have conducted extensive design and research on layout design and DEA, but the applicability of these methods and systems still needs to be improved. Therefore, an indoor SL design method ground on DEA is proposed, aiming to enhance the interactivity and user experience of SL design.

3. Design of Indoor Space Layout Method. Indoor SL refers to how to arrange and organize the positions of various functional areas, furniture placement, and decorations in indoor design, to achieve comfortable, practical, and aesthetic effects [16]. This study combines backtracking strategy and reverse learning method to propose an indoor space layout design method ground on DEA, thereby achieving optimized indoor space layout and improving design efficiency. Meanwhile, a two-stage indoor layout method is proposed to meet diverse needs, which divides the positioning of functional space positions and the generation of wall constraints in the surrounding area into two stages. Finally, the study adopts a reverse learning strategy to accelerate the convergence speed of the algorithm and achieve better experimental results.

3.1. Indoor spatial layout constraints. The layout design of indoor space is to arrange the placement of furniture and decorations reasonably on the ground of the size, shape, and functional requirements of the space, to achieve aesthetic, comfortable, and practical effects [17]. This study summarizes four main constraints through investigation and sample analysis, with geometric constraint *Geometry* shown in equation (3.1).

$$Geometry \rightarrow \{Fun, Dec, Pla, Spa\} \tag{3.1}$$

In equation (3.1), the room function is Fun. Decoration and placement are Dec and Pla respectively. The physical space size is Spa. Different functional rooms have different requirements depending on their purpose,

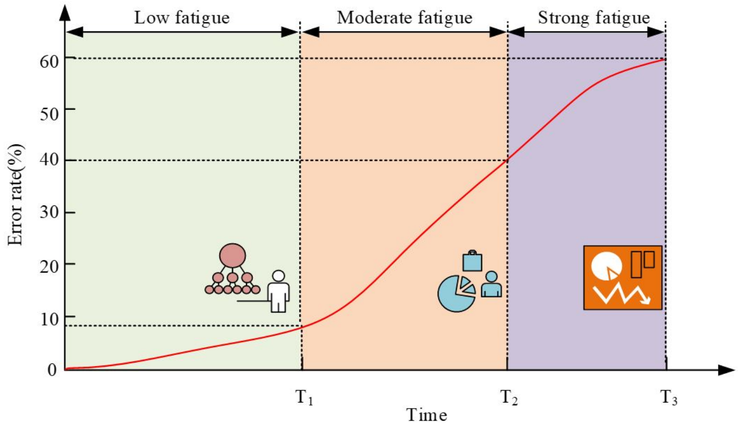

Fig. 3.1: Schematic diagram of user fatigue level

such as the master bedroom and the secondary bedroom. The special functional room constraint $Spef$ is shown in equation (3.2).

$$Spef \rightarrow \{Lig, Toi, Air\} \tag{3.2}$$

In equation (3.2), the lighting of the special functional room is Lig. The bathroom and other ventilation conditions are Toi and Air, respectively. The spatial topology constraint Top is shown in equation (3.3).

$$Top \rightarrow \{Rel, Lim\} \tag{3.3}$$

In equation (3.3), the adjacency relationship of spatial objects is Rel. The space constraint is Lim. A rough layout, such as the bathroom adjacent to the kitchen, and the bedroom close to the door, can affect the functionality and living experience of the room. The feng shui factor constrain $Geomantic$ is shown in equation (3.4).

$$Geomantic \rightarrow \{Con, Env, Sea\} \tag{3.4}$$

In equation (3.4), the geographical condition is Con. The environmental factor is Env, and factors such as climate are Sea. A high-quality feng shui layout can leverage the functionality of rooms and furniture, providing a comfortable living space, and also having an indescribable impact on academic, career, and fortune. In traditional MO weighting methods, each objective function is weighted and summarized into a single objective value to solve a single objective optimization problem, for obtaining the optimal solution. The MO genetic algorithm can generate a set of preference free Pareto optimal solutions for decision-makers to choose ground on their preferences. However, selecting the appropriate solution from numerous feasible solutions increases the decision-making burden and reduces the effectiveness. To address these issues, Interactive Genetic Algorithm (IGA) replaces complex fitness functions with subjective choices by users. The evolutionary algorithm is used to gradually search for individuals that meet user requirements in complex environments, seeking better solutions. However, methods on the ground of the genetic algorithm and manual scoring may lead to user fatigue, which can affect usage persistence and result accuracy after multiple iterations [17, 18]. The study analyzes the accuracy of fatigue level assessment through comparative testing. The schematic diagram of user fatigue is shown in Figure 3.1.

As users invest more time and iterations, they quickly feel fatigued, leading to a significant decrease in the accuracy of evaluation scores. Therefore, in interactive algorithms, user fatigue is a key factor affecting the accuracy of the final solution. When fatigue cannot be avoided, one of the directions for algorithm improvement is how to accelerate algorithm convergence to find satisfactory solutions before users enter moderate and severe fatigue.

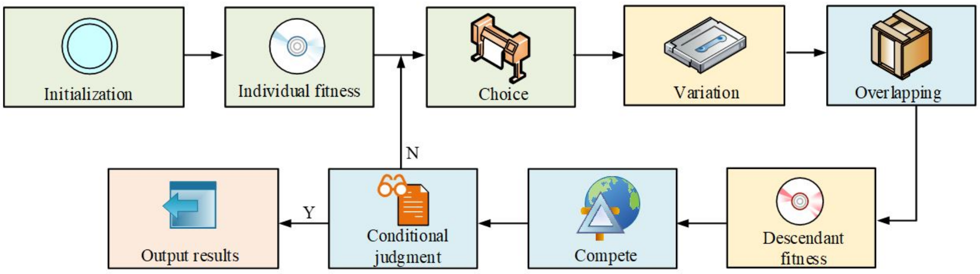

Fig. 3.2: IDE algorithm steps

3.2. Indoor Space Layout Method Based on DEA. Interactive Differential Evolution Algorithm (IDE) is an optimization algorithm compared to IGA. IDE adopts a selection operation to replace the scoring mechanism, where users only need to choose a more satisfactory individual in two individuals without the need for complex comparative scoring processes. This simplified operation method decreases the operation complexity and alleviates fatigue during the operation process [19]. In recent years, IDEs have been widely used in fields such as image retrieval, image enhancement, and image filtering. The IDE algorithm steps are shown in Figure 3.2

The steps of interactive DEA include crossover operation, evaluation of fitness, competition operation, termination condition judgment, result output, and iteration and other relevant steps. The algorithm initialization is shown in equation (3.5).

$$x_{j,i,0} = x_i^{\min} + (x_i^{\max} - x_i^{\min}) \times rand \tag{3.5}$$

In equation (3.5), the i-th gene of the chromosome for the j-th individual in the initial population serves as $x_{j,i,0}$. The lower bound of the i-th component serves as $x_i^{\min}$, and the higher bound of the i-th component serves as $x_i^{\max}$. The uniformly distributed random number is $rand$, with a value range of [0,1]. The mutation operation involves different mutation operators (MOP). The DE/rand/1 MOP is showcased in equation (3.6).

$$V_{j,i} = X_{r1,t} + F_j \times (X_{r2,t} - X_{r3,t}) \tag{3.6}$$

In equation (3.6), the j-th individual of the population in the t-th iteration is $X_{j,t}$. The corresponding mutation factor is $V_{j,t}$. The mutually exclusive positive numbers randomly selected from the array are $r1$, $r2$, and $r3$, respectively, and the scaling factor of the j-th individual is F_j. The DE/test/1 MOP is shown in equation (3.7).

$$V_{j,t} = F_j \times (X_{r1,t} - X_{r2,t}) + X_{best,t} \tag{3.7}$$

In equation (3.7), the optimal individual in the t generation is $X_{best,t}$. The DE/current to best/1 MOP is shown in equation (**??**).

$$V_{j,t} = X_{j,t} + F_j \times (X_{r1,t} - X_{r2,t}) + F_j \times (X_{best,t} - X_{j,t}) \tag{3.8}$$

In equation (3.8), the characteristic of the DE/current to best/1 MOP is to combine the information of the current individual and the optimal individual. The information of the best individual is introduced, which can accelerate the convergence speed of the algorithm. The DE/current to pbest/1 MOP is shown in equation (3.9).

$$V_{j,t} = X_{j,t} + F_j \times (X_{r1,t} - X_{r2,t}) + F_j \times (X_{pbest,t} - X_{j,t}) \tag{3.9}$$

In equation (3.9), the randomly chosen individual among the top ranked $p\%$ individuals is $X_{pbest,t}$. The advantage of the DE/current to pbest/1 MOP over other MOP is that it uses the information of the optimal individuals in the population. In the crossover operation, the crossover operator is shown in equation (3.10).

$$U_{j,i,t} = \begin{cases} V_{j,i,t}, \; if \; rand < CR \; and \; i = i_{rand} \\ X_{j,i,t}, \quad\quad\quad\quad\quad otherwise \end{cases} \tag{3.10}$$

In equation (3.10), during the t-th iteration, the i-th component of the experimental vector for the j-th individual is $U_{j,i,t}$. The crossover rate for the j-th individual is CR, and the random number is i_{rand}. In the selection operation, the selection operator is shown in equation (3.11).

$$X_{j,t+1} = \begin{cases} U_{j,t}, if \; f(U_{j,t}) < f(X_{j,t}) \\ X_{j,t}, \quad\quad\quad otherwise \end{cases} \tag{3.11}$$

In equation (3.11), by selecting operators, genetic algorithms can optimize generation by generation, enabling individuals in the population to gradually tend towards better solutions. Although the DE algorithm is a global optimization algorithm, it may be hard for helping individuals break away the best solution in certain situations. To overcome this problem, the study adopts a backtracking strategy to improve the IDE. The IDE Backtracking Optimization (IDE-BO) algorithm first determines whether an individual has fallen into a local optimum, and then observes the slow update of individual data to determine. When an individual is considered stagnant, a new selection operator on the ground of backtracking strategy will be adopted. During each iteration, individuals who fail in competition are stored in a spatial warehouse. If an individual falls into a local optimum, continuous vectors are extracted from the storage space and randomly selected to survive to the next generation. When the individual still fails to leave the local optimum, the vector is further extracted from the storage space and a random vector is selected to survive to the next generation. It replaces the parent vector with discarded experimental vectors, which are not inherited by the next generation. Individuals evolved on the ground of these vectors are more inclined to aid in escaping local optima. The target feature vector and the most satisfactory target individual for the user are shown in equation (3.12).

$$\begin{cases} X = \{X_1, X_2, \ldots, X_n\} \\ O = \{o_1, o_2, \ldots, o_D\} \end{cases} \tag{3.12}$$

In equation (3.12), the target feature vector is X, which is the Euclidean distance between evolutionary individuals. The most satisfactory individual for users is O. The distance calculation between evolutionary individuals is showcased in equation (3.12).

$$f(x) = \sqrt{\sum_{i=0}^{n} (x_i - o_i)^2} \tag{3.13}$$

In equation (3.13), the distance between evolutionary individuals is $f(x)$. The i-th evolutionary individual is x_i, and the i-th target individual is o_i. The iterative process of improving the IDE algorithm with a backtracking strategy is shown in Figure 3.3.

3.3. The Application of Reverse Learning Strategy in IDE-BO Algorithm. In the actual market, the fixed number of rooms and the indoor layout design within a fixed area cannot meet the diverse needs of users [20]. Therefore, this study proposes a two-stage indoor layout method. The two-stage indoor layout method is an evolutionary method ground on interactive evolutionary algorithms, which eliminates a large number of rule constraints in the generation stage of indoor space and simulates the thinking mode of professional designers. This method is divided into two stages. The first is to locate the functional space position, and then is to generate wall constraints for the surrounding area. In the stage of positioning the functional space, the principle of prioritizing the positioning of the living room is adopted. Then, the positions of other functional areas are randomly generated by adjacent relationships with the living room or areas. In generating wall constraints, a constraint satisfaction based method is adopted, using the boundaries of the room extending outward from the origin as constraints for other rooms. On the ground of the principle of sequential design, each room is numbered according to its spatial location. Its size and shape are determined in sequence. The constraints

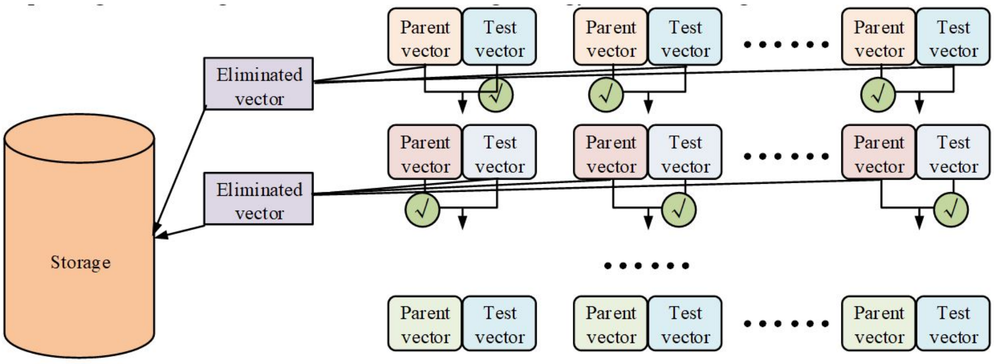

Fig. 3.3: The iterative process of improved IDE based on backtracking strategy

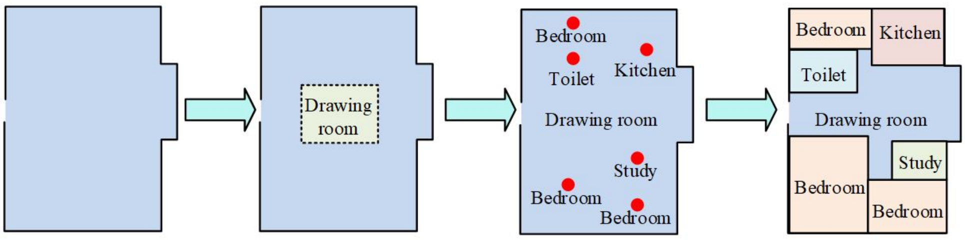

Fig. 3.4: The design process of the two-stage indoor layout method

generated earlier are then passed into the subsequent methods to provide constraints for determining the walls of subsequent rooms. The design process of the two-stage indoor layout method is shown in Figure 3.4

To better adapt to DEA, this study designs a new form of genetic coding. This encoding form adopts binary encoding ground on the character set [0,1] to represent functional region division and area parameters as chromosome bit strings. The coding form is designed on the ground of a two-dimensional coordinate axis, with the overall layout model located in the first quadrant. The smallest gene unit consists of two parts, X and Y, each in a 4-bit binary encoding form. It can represent all possible positions within the house model. The area type and number of rooms are independently composed of 3-bit and 4-bit binary codes, achieving code decoupling and merging. In the design, the positioning of the regional wall is based on a regular rectangle, which can be represented by the bottom left and top right coordinates on the coordinate axis. According to the process steps, the genetic coding of individual population consists of three parts, corresponding to determining the coordinates of the living room, determining the coordinates of the functional area, and generating the wall of the functional area. The new coding design eliminates hard constraints and introduces more randomness, which can adapt to the living needs of the vast majority of users in the market. The indoor layout design method has changed, no longer using fixed design methods, but determining the frame of the house and the number of rooms based on the number of people required for the residence. Users can choose the appropriate unit type according to their own needs. However, this method increases the complexity of evolutionary algorithms, resulting in an increase in the time required to generate the final satisfactory solution. In addition, users will enter a fatigue state after multiple iterations, and the evaluation error rate will also increase. To solve these problems, a reverse learning strategy can be utilized to accelerate the convergence speed and achieve better experimental results. Reverse points are the basic concept of reverse learning strategies. The one-dimensional reverse points are defined, as shown in equation (3.14).

$$\bar{x} = a + b - x \tag{3.14}$$

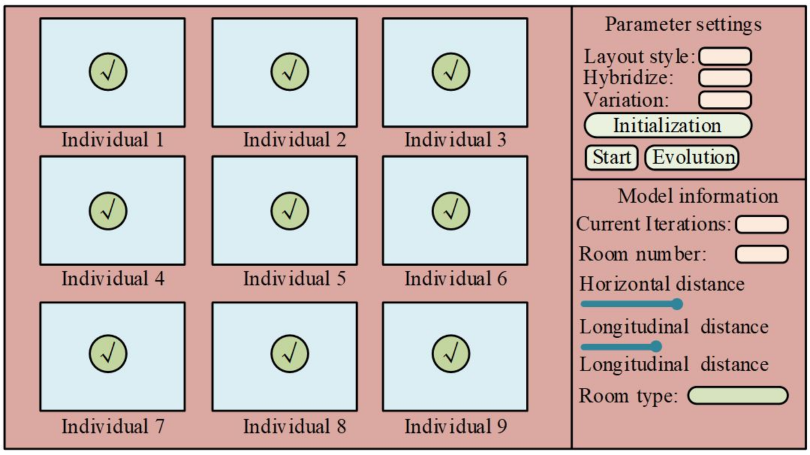

Fig. 3.5: Improved human-computer interaction interface design

In equation (3.14), the one-dimensional reverse point is $\bar{x}$, and the range of values for the real number x is [a, b]. The reverse point in N-dimensional space is shown in equation (3.15).

$$\begin{cases} \bar{X} = (\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_n) \\ \bar{x}_i = a_i + b_i - x_i \end{cases} \tag{3.15}$$

In equation (3.15), the reverse point in the N-dimensional space is $\bar{X}$, and its i-th coordinate is $\bar{x}_i$. Reverse optimization method is an optimization algorithm ground on the concept of reverse points, which iteratively finds the reverse points of the objective function for achieving the optimization goal. The reverse learning strategy in IDE algorithms is usually divided into two stages: the reverse strategy in population initialization and the evolutionary population jump. Among them, the fitness comparison is presented through the human-computer interaction interface. The user inputs the evaluation results. The initialization parameters include the original population and reverse original population, individual dimensions, and variable value ranges. After introducing the reverse learning strategy, new independent individuals are introduced in each iteration. The goal of user evaluation has also changed from two to three. In this study, the reverse learning strategy is applied to the population initialization and the end stage of the new species generation. The improved human-computer interaction page of indoor layout design adopts a selection mechanism, where users can evaluate the offspring or their reverse individuals in pairs and select the solution that suits their own preferences by checking the box. The improved human-computer interaction interface design is shown in Figure 3.5.

4. Application Analysis of Indoor Space Layout Design Based on DEA . This chapter is an application analysis of indoor space layout design ground on DEA. Different evaluation indicators and analysis methods are used in the experiment to evaluate the effectiveness of relevant methods. This is to validate the effectiveness and applicability of the research method.

4.1. Application Analysis of Indoor Space Layout Method Based on DEA . The experiment randomly generates 500 sample models. The indoor space layout design styles are divided into 6 types: modern, classical, rural, industrial, Nordic, and Mediterranean, labeled 1-6. Subsequently, the study selects 10 testers to evaluate the satisfaction and feasibility of interactive SL design methods. The evaluation results of the interactive SL design method are shown in Figure 4.1

In Figure 4.1, the evaluation results showed a satisfaction rate of 95% and a feasibility rate of 94%. This indicates that most testers have a positive attitude towards the interactive SL design method. It performs well in meeting their needs and feasibility. Interactive SL design methods may provide an intuitive interface and real-time feedback, enabling testers to better understand and explore different layout choices. This participation

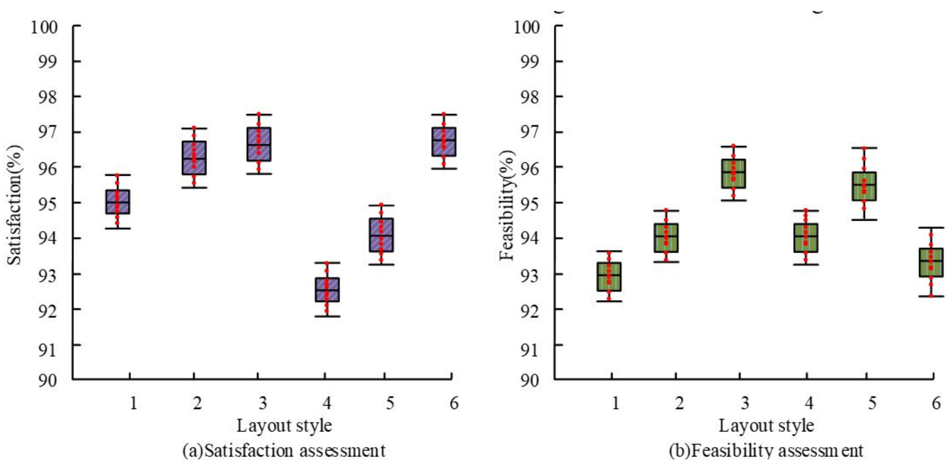

Fig. 4.1: Evaluation results of interactive spatial layout design methods

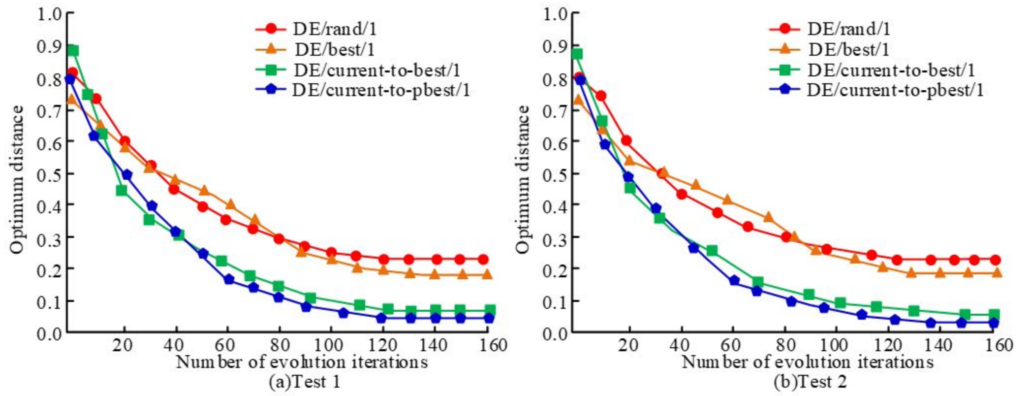

Fig. 4.2: Comparison results of different MOP

may increase the satisfaction of testers with the layout design process and increase their acceptance of the final design solution. This method provides effective tools and functions during the design process, enabling testers to conduct layout design in actual environments and ensuring the feasibility of the design scheme. The comparison results of various MOP in the IDE algorithm are shown in Figure 4.2.

Figure 4.2 showed that the two MOP, DE/current to pbest/1 and DE/current to best/1 had the most excellent performance because they possessed more excellent performance in terms of convergence. Next were DE/rand/1 and DE/test/1. This means that DE/current to pbest/1 and DE/current to best/1 MOP are more suitable for individual selection in IDE algorithms, which can more effectively help users make judgments in an extremely short time and reduce errors. To reduce the possible errors caused by selecting time sorting, this research chose DE/current to best/1 as the MOP, which is simpler and has equally excellent performance. The experiment uses the target vector as a reference to analyze the convergence of different algorithms when searching for target values. The convergence of different algorithms is shown in Figure 4.3.

From the changes in the average convergence curve shown in Figure 3.3, there were no significant differences among the three algorithms (IGA, IDE, and IDE-BO) during the initial stage of the experiment. However, in the later stage, the IDE and IDE-BO algorithms showed better convergence performance, while the IGA showed slight shortcomings. Especially when the number of iterations reached 60, the IDE-BO algorithm showed

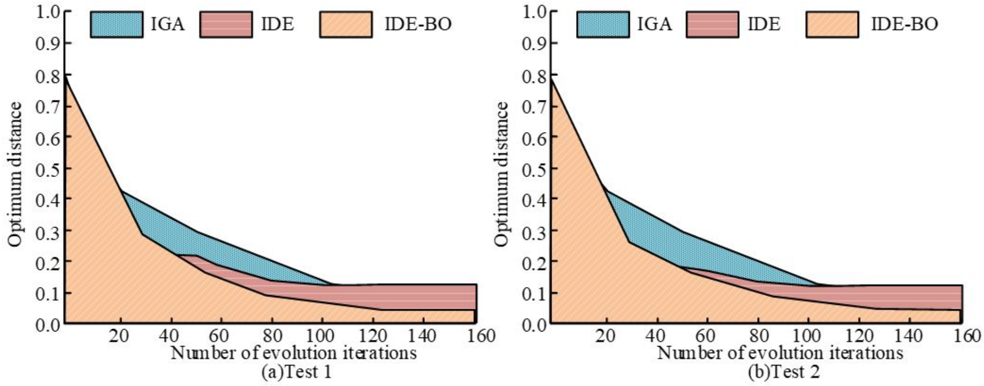

Fig. 4.3: Convergence of various algorithms

Table 4.1: The quantity of iterations required for reaching convergence

Test group number	IGA	IDE	IDE-BO	Maximum value	Minimum value
1	92	136	122	136	92
2	85	120	118	120	85
3	96	145	120	145	96
4	99	163	121	163	99
5	89	126	129	129	89
6	92	131	122	131	92
7	96	136	131	136	96
8	87	130	128	130	87
9	91	139	119	139	91
10	89	124	119	124	89
Average value	91.6	135	122.9	/	/

obvious advantages, with faster convergence speed and higher convergence accuracy. The optimal distances between IGA, IDE, and IDE-BO algorithms and the objective function were 0.09, 0.13, and 0.04, respectively. In real human-computer interaction environments, to avoid the impact of user fatigue on the results, the lowest quantity of iterations is usually set to 50. The iterations required for reaching convergence is shown in Table 4.1.

Table 4.1 showed that the IDE BO algorithm achieved convergence with an average of t=122.9 iterations in 10 simulation experiments. The IDE algorithm required approximately 135 iterations. Although the convergence speed of the IGA was significantly faster than IDE-BO, the IGA was trapped in local optima. To compare the relevant differences in IDE-BO and other competitors, Wilcoxon sign rank test is conducted. The significance is lower than 0.05, indicating that IDE-BO algorithm has a significant convergence advantage compared with IDE algorithm.

4.2. Analysis of the Application Effect of Reverse Learning Strategy in IDE Algorithm. To test practicality in practical applications, convergence testing is conducted and the impact of user subjective selection on convergence is investigated. In this experiment, 10 testers are selected to use the system and the highest quantity of iterations is set to 45 to investigate their satisfaction with the individual. In each iteration, the tester selects the most suitable individual in the group according to own preferences, with a score of 0 to 100. Then the average score is calculated from the 10 testers. A high score in both indicators indicates good convergence ability. If the final solution score reaches 75 or above, it can be considered that the system has generated the most satisfactory solution for the user. The user satisfaction test results of different methods are shown in Figure 4.4

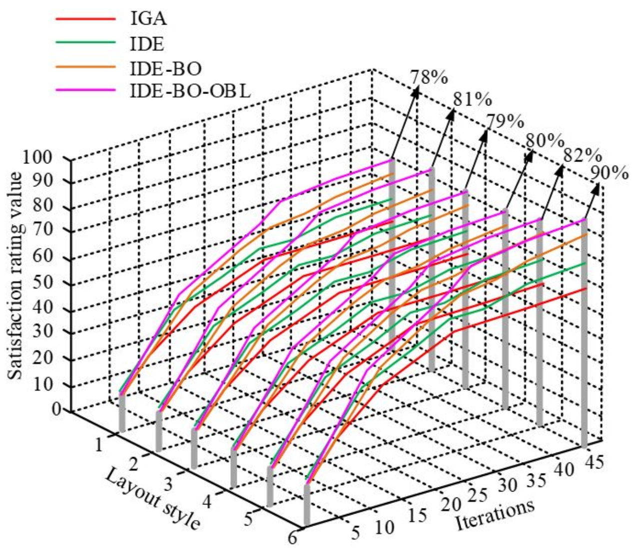

Fig. 4.4: User satisfaction test results of different methods

Table 4.2: Wilcoxon sign rank test results

Layout style	Algorithm	t=[1,10]	t=[11,30]	t=[31,40]	t=[1,40]
Modern	IGA	0.836	0.001	0.003	0.017
	IDE	0.468	0.092	0.003	0.111
	IDE-BO	0.397	0.330	0.003	0.256
Classical	IGA	0.581	0.002	0.004	0.015
	IDE	0.603	0.089	0.005	0.116
	IDE-BO	0.945	0.333	0.004	0.255
Rural	IGA	0.361	0.001	0.002	0.017
	IDE	0.902	0.084	0.004	0.111
	IDE-BO	0.788	0.323	0.006	0.212
Industrial	IGA	0.816	0.002	0.003	0.016
	IDE	0.665	0.089	0.002	0.112
	IDE-BO	0.679	0.346	0.001	0.245
Nordic	IGA	0.977	0.003	0.003	0.015
	IDE	0.646	0.078	0.002	0.156
	IDE-BO	0.975	0.379	0.004	0.215
Mediterranean	IGA	0.854	0.003	0.001	0.016
	IDE	0.768	0.089	0.002	0.136
	IDE-BO	0.664	0.336	0.004	0.189

In Figure 4.4, IDE-BO-OBL represents the IDB-BO algorithm incorporating a reverse learning strategy. This indicated that the IDE-BO-OBL algorithm had the highest user satisfaction, with an average satisfaction rate of 81.7%. It was 16.8% higher than the IGA. To further compare the relevant differences in IDE-BO-OBL and traditional evolutionary algorithms, the study conducts the Wilcoxon sign rank test. The relevant outcomes are showcased in Table 4.2.

Table 4.2 showed that the differences among the four algorithms were not significant at the beginning of the algorithm. However, in the middle to late stages, the advantages of the IDE-BO-OBL algorithm were clearly reflected. This indicates that the IDE-BO-OBL algorithm has significantly improved compared with IGA. To

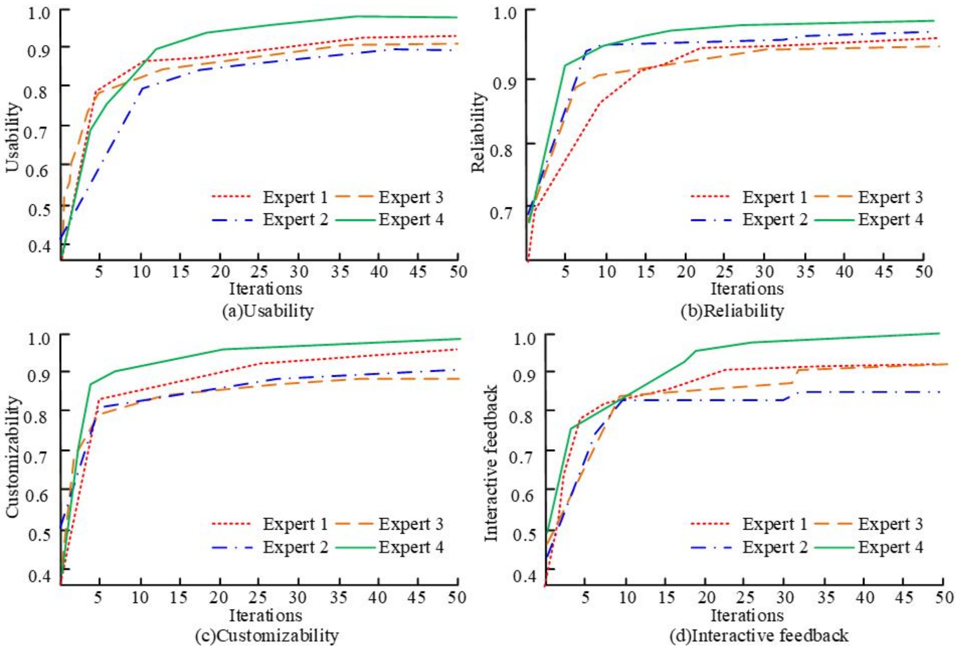

Fig. 4.5: Improved human-computer interaction interface evaluation results

evaluate the effectiveness of the improved human-computer interaction interface, four experts were selected in the experiment to evaluate its usability, reliability, customizability, and interaction feedback. The evaluation results of the improved human-computer interaction interface are shown in Figure 4.5.

Figure 4.5 demonstrated that the improved human-computer interaction interface had usability, reliability, customizability, and interaction feedback scores higher than 0.8. The improved human-computer interaction interface has significantly improved in multiple aspects, meeting the user needs and providing a better user experience.

5. Conclusion. In traditional IGAs, there may be some ineffective design solutions due to the limitations of the algorithm itself and the subjective preferences of the designer. To overcome these problems, this study focuses on indoor space layout design, and combines backtracking strategy and reverse learning strategy to optimize the interactive DEA. An improved human-computer interaction interface was proposed. Experimental data showed that the improved DEA achieved an average user satisfaction of 81.7% in indoor space layout design, which was 16.8% higher than the traditional IGA. In addition, the improved human-computer interaction interface scored higher than 0.8 in terms of usability, reliability, customizability, and interactive feedback, indicating that the improved method had a good user experience. The experiment showcased that the improved method achieved significant improvements in user satisfaction and human-computer interaction interface ratings, providing an efficient, reliable, and user-friendly solution for indoor space layout design. The limitation of this study is that it only considers the SL and does not involve other factors such as material selection and color matching. Future research can consider spatial factors such as material selection, color matching, and furniture layout to improve the comfort, aesthetics, and functionality of the space.

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