Indoor Landscape Design and Environmental Adaptability Analysis Based on Improved Fuzzy Control

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***Abstract*—With the increasing demand for automation and intelligence in indoor landscape design, exploring efficient and precise control strategies has become particularly important. Robot-assisted technology and A* algorithm are utilized for indoor environment localization and mapping. Then, type-2 fuzzy adaptive fuzzy control is applied for indoor landscape automatic design. An improved genetic algorithm is utilized for environmental analysis to enhance the adaptability of indoor landscape design to the environment. In the results, the robot adopting this algorithm was significantly better than ordinary robots in path planning optimization, with a fitting accuracy of over 95%. The type-2 fuzzy control model had a maximum speed of 0.75m/s and an overshoot of only 7.1% for balancing robots, resulting in a faster recovery speed and smaller overshoot. The proposed method performed the best in terms of functionality, aesthetics, technicality, accessibility, and user satisfaction for landscape design effectiveness and environmental adaptability. The research improves indoor landscape design's automation. Meanwhile, the combination of fuzzy control and genetic algorithms enhances the design accuracy and environmental adaptability. This provides a new technological path for indoor landscape design.**

Keywords—Fuzzy control; indoor landscape design; environment; adaptability analysis; robot assisted

I. Introduction

Indoor Landscape Design (ILD), as an important component of the built environment, is crucial for improving spatial quality and meeting functional requirements. However, when faced with the growing demand for personalization and diversity, traditional ILD shows significant limitations in terms of efficiency, accuracy, and adaptability. How to achieve efficient, precise, and environmentally adaptable design has become an urgent problem to be solved, especially in complex and ever-changing indoor environments [1]. As technology advances, automation and intelligence become new trends in design. Intelligent design not only improves design efficiency but also provides more accurate and personalized design solutions through data analysis and simulation [2-3]. Fuzzy Control (FC), as a control strategy that can handle uncertainty and fuzzy information, has shown its unique advantages in multiple fields. FC can effectively process fuzzy, inaccurate, or incomplete information by simulating human decision-making processes, thereby achieving optimized control in complex systems. Therefore, how to combine FC with ILD to improve the automation level and environmental adaptability of design has become a topic worthy of research [4-5]. To address this issue, this study proposes an improved FC-based ILD and environmental adaptability analysis method. This method combines robotics technology, A* algorithm, Range Type-2 Fuzzy Logic Control Mechanism (RT2FLCM), and Improved Genetic Algorithm (IGA). It aims to achieve automation and precision of ILD while improving environmental adaptability.

The innovation of the research lies in the application of fuzzy control theory to interior landscape design, and through the combination of robot-assisted technology and A* algorithm, the accurate location and mapping of indoor environment are realized. In addition, the study adopts type-2 fuzzy adaptive fuzzy control for interior landscape automatic design. The application of this method makes the design process more accurate and personalized. The contribution of the research is reflected in environmental analysis through improved genetic algorithms, which are capable of simulating natural selection and genetic mechanisms for global search and optimization. The application of this algorithm improves the accuracy and environmental adaptability of the design. By combining advanced control theory, algorithm and robot technology, a new analysis method of interior landscape design and environmental adaptability is proposed in this study, which provides a new technical path for the field of interior landscape design and has important theoretical and practical significance.

The article is divided into six sections. Section I is the introduction, through the background and research status of interior landscape design leads to the research theme. Section II is a literature review, which discusses and analyzes the research status of fuzzy control algorithm and interior landscape design at home and abroad. In Section III, robot assisted technology and A* algorithm are used for interior landscape positioning and environment mapping, and RT2FLCM is used for interior landscape automatic design. In Section IV, the effectiveness of the algorithm is verified by experiments. Section V is discussion, which discusses and analyzes the research results and compares them with other studies. Section VI summarizes the research results.

II. Related Work

When exploring the potential application of fuzzy logic in ecosystem service assessment, Biber et al. developed a biodiversity-based fuzzy logic evaluation system. This evaluation system was applied to three different forest management scenarios. A simulation study was conducted for up to 100 years. These results confirmed the effectiveness of fuzzy logic as an evaluation tool [6]. Colak et al. proposed an active power factor correction method based on FC theory to address the growing demand for reliable and efficient power systems. Fuzzy logic controllers provided a highly adaptable and flexible solution by addressing the inherent uncertainty in power systems. In comparison with traditional control methods, the FC-based method had significant advantages in accuracy, robustness, and response time [7]. Hussein et al. proposed a fuzzy logic-based model for evaluating the spatial spaciousness. The proposed fuzzy model could accurately reflect input variables' influence on spatial spaciousness [8]. Khafajeh et al. started designing and developing an FC system for hydroponic greenhouses. Through optimization of the FC system, the average temperature during the day and night decreased from 34.25℃ and 23.22℃ to 31.17℃ and 21.96℃, respectively [9].

For intelligent drone control, Al Gizi A J H utilized a remote FC vehicle-mounted sonar tracking and detection device mounted to collect data for preventive maintenance of high-voltage power lines. Combining deep neural networks and FC achieved more efficient power line maintenance work [10]. Kasruddin et al. proposed a novel hybrid strategy combining spiral dynamic algorithm and other methods for flexible robotic arm systems' wheel hub angle tracking. This strategy not only accelerated convergence speed but also improved the solution accuracy. The optimized controller accurately tracked the expected response [11]. Incekara developed a fuzzy logic-based design method for primary school ergonomics classroom furniture. These results confirmed this fuzzy mathematical model's effectiveness [12]. Obinna proposed an intelligent spectrum allocation method to address the rapid increase in IoT devices and limited spectrum resources. This method utilized fuzzy logic to handle uncertainty and imprecise data. The method based on fuzzy logic effectively balanced channel availability and interference level, significantly improving service quality satisfaction [13].

To sum up, the application of fuzzy control is still in its infancy, especially in robot-assisted design and environmental adaptability analysis. A comprehensive method of interior landscape design and environment adaptability analysis is proposed by combining robot assistance technology, A* algorithm, type-2 fuzzy adaptive fuzzy control and improved genetic algorithm. This approach excelled in automation and precision, especially when dealing with uncertainty and complexity in the design process, showing superior performance over existing solutions. Compared with other studies, such as the fuzzy logic evaluation system based on biodiversity developed by Biber et al., the research method transforms the theory into practice through actual robot operation and automated design process, and improves the practical operability of the design. Compared with the active power factor correction method based on fuzzy control theory proposed by Colak et al., the application field of the research is more focused on interior landscape design, more targeted, and more in-depth in environmental adaptability analysis.

III. Methods and Materials

Firstly, the study utilizes robot assisted technology and A* algorithm for indoor landscape localization and environmental mapping. This helps robots to accurately draw and measure in complex indoor spaces. Then, RT2FLCM is utilized for automatic indoor landscape design. Finally, IGA is utilized for indoor environment analysis.

A. *Robot Indoor Environment Mapping Based on A* Algorithm*

In the automatic ILD, robot technology is adopted to assist in indoor spaces' construction and layout. The RB08 robot, as a compact and highly maneuverable multifunctional robot, is very suitable for complex operations in indoor environments. This robot has six degrees of freedom. Three degrees of freedom are specifically used for terminal positioning, while the rest are utilized to ensure precise positioning of the terminal [14-15]. SolidWorks software is utilized to construct robot's various joints. These joints are then imported into 3D Max to achieve coordinate transformation and relationship establishment between joints. Through this method, passive control between each joint can be achieved. This can precisely control the robot's movements, ensuring the automation and precision of ILD. By combining robotics technology and 3D modeling tools, ILD can not only improve efficiency, but also achieve more complex and refined designs. Fig. 1 shows the robotic arm's coordinate system in landscape design.

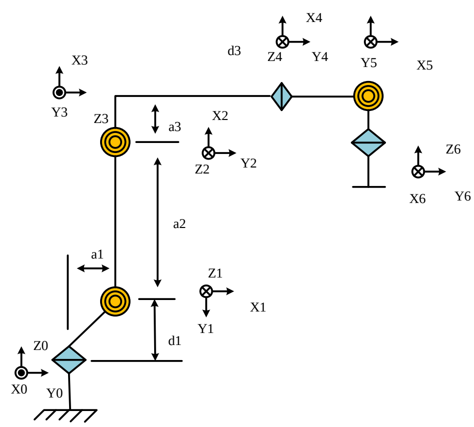


Fig. 1. Robot arm's coordinate system.

In Fig. 1, the D-H matrix is utilized to import the D-H parameter information into the connecting rod transformation matrix. The transformation matrices of each connecting rod are obtained, represented by Eq. (1).

$$A_i^{i-1} = A_{rot}(z_{i-1}, \theta_i) A_{tran}(z_{i-1}, d_i) A_{tran}(x_{i-1}, \alpha_i) A_{rot}(x_{i-1}, \alpha_i) \quad (1)$$

In Eq. (1), A_i^{i-1} refers to each connecting rod's transformation matrix. θ_i refers to the joint rotation angle. d_i refers to the joint displacement. α_i refers to the connecting rod's torsion angle. Based on two adjacent coordinate systems, using a homogeneous transformation matrix, the transformation matrix A_m^0 between the final attachment coordinate system and the base system of the m-freedom serial manipulator is obtained, represented by Eq.

(2).

$$A_m^0 = A_1^0 A_2^1 \cdots A_{m-1}^{m-2} A_m^{m-1} \tag{2}$$

In Eq. (2), A_m^0 represents the base system's transformation matrix. Any point's posture on the robotic arm's end connector can be described using the basic coordinate system, represented by Eq. (3).

$$p^0 = A_1^0 A_2^1 \cdots A_{m-1}^{m-2} A_m^{m-1} p^m \tag{3}$$

In Eq. (3), p represents any point's posture on the robotic arm's end connector. By multiplying the six joints' connection transformation matrices order, the terminal transformation matrix A_6^0 corresponding to the base coordinate system can be obtained, represented by Eq. (4).

$$A_6^0 = \begin{pmatrix} m_x & o_x & a_x & p_x \\ m_y & o_y & a_y & p_y \\ m_z & o_z & a_z & p_z \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{4}$$

On this basis, a reverse kinematics method is proposed and transformed into reverse kinematics to calculate the corresponding joint parameters. The reverse calculation of motion is represented by Eq. (5).

$$\theta = [\theta_1 \theta_2 ... \theta_{m-1} \theta_m] = IKP(A_m^0) \tag{5}$$

In Eq. (5), IKP represents reverse motion. The indoor drawing path optimization of robots utilizes the A* algorithm, which is a widely utilized search algorithm in path planning. The A* algorithm excels at finding the shortest path from the starting point to the endpoint in complex graphical structures. The A* algorithm's core lies in its clever combination of heuristic functions and cost functions. Heuristic functions are utilized to predict the possible cost from the current node to the target node. The cost function evaluates the actual cost from the starting point to the current node [16-17]. Fig. 2 shows the A* algorithm.

In Fig. 2, the initial point is included in the OPEN list and the points in this table are checked. If the OPEN list is empty, the search is terminated and the path is reported as non-existent. If the OPEN list is not empty, the node n with the lowest $F(n)$ value is selected. Node n is removed from the OPEN list and added to the Completed list. Applying this algorithm to ILD can assist robots in precise drawing and measurement in complex indoor spaces. Designers can obtain higher quality spatial data, providing a solid foundation for creative design.

B. Indoor Landscape Design Based on Fuzzy Control

A step-by-step design method is adopted for a balancing robot's straight system. Firstly, a set of fuzzy logic adjusters is developed to address the characteristics and motion features of the balancing robot. Furthermore, by utilizing the membership functions of fuzzy sets, a preliminary architecture of an advanced fuzzy logic control system is constructed. Finally, detailed adjustments and optimizations are made to the overall equipment parameters to improve control effectiveness [18-19]. FC's core process is fuzzification, which is achieved by defining fuzzy sets and their membership functions. Within the determined input range U, usually within the interval of [0, 1], the fuzzy generator utilizes a specific mapping function to convert the exact value into a fuzzy value, represented by Eq. (6).

$$U \to [0,1], u \to \mu_A(u) \tag{6}$$

In Eq. (6), μ_A represents the uncertainty set A's membership function value. A fuzzer's core function is to convert the precise input data captured by the control mechanism into a set of uncertainties. Meanwhile, the membership function values are utilized to measure each component's membership strength. The strategy proposed by Zadeh for processing discrete information has been widely adopted. It expresses the fuzziness of input data through membership functions, enabling the control system to more effectively handle uncertainty and fuzziness, represented by Eq. (7).

$$A = \frac{A(u_1)}{u_1} + \frac{A(u_2)}{u_2} + \cdots + \frac{A(u_n)}{u_n} \tag{7}$$

In Eq. (7), u_n represents an element. $A(u_n)$ means membership degree. Type-2 fuzzy sets are extensions of Type-1 fuzzy sets that introduce additional dimensions to represent uncertainty. Assuming x is an element defined on a certain domain, its membership degree in a type-1 fuzzy set is represented as u. Therefore, the type-2 fuzzy set further refines x's membership degree by introducing an additional membership function, represented by Eq. (8).

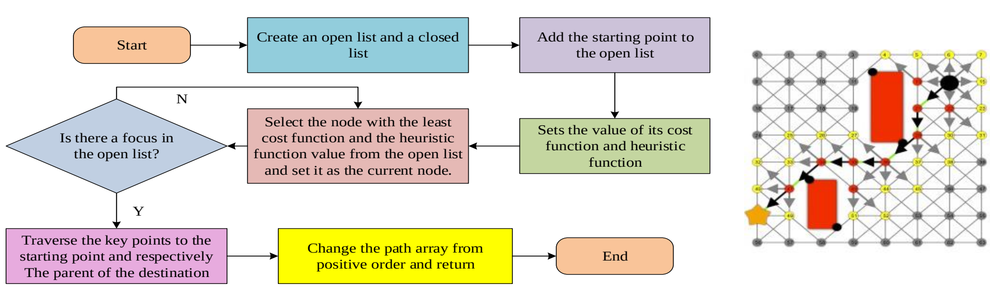


Fig. 2. Process of A* algorithm.

$$\tilde{A} = \left\{((x,u), u_{\tilde{A}}(x,u) \mid \forall x \in X, \forall u \in J_x \subseteq [0,1]\right\} \tag{8}$$

In Eq. (8), J_x represents the primary membership degree of x. $u_{\tilde{A}}$ means the sub-membership degree. Type-2 fuzzy set is an extension of Type-1 fuzzy set, which represents the uncertainty of membership degree by adding a dimension. The membership degree range of each type-1 fuzzy set is also from 0 to 1. However, when they combine, they form a more complex structure. This structure can express higher levels of uncertainty, thus forming a type-2 fuzzy membership function. In the advanced fuzzy sets, the Uncertainty Scope (US) is utilized to represent the set of all principal membership functions within the domain [20]. US provides a method for quantifying and visualizing the uncertainty of fuzzy sets. US covers all possible membership values, allowing for more accurate description and analysis of the characteristics of fuzzy sets. US is represented by Eq. (9).

$$FOU(\tilde{A}) = \bigcup_{x \in X} J_x \tag{9}$$

In Eq. (9), $\bigcup$ means the union of all principal membership functions. The uncertainty domain can also be represented in a coordinate system in Fig. 3.

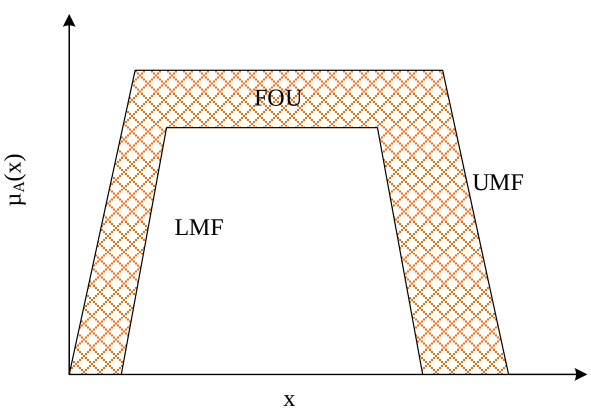


Fig. 3. Type-2 fuzzy set uncertainty field.

In Fig. 3, the boundary of the type-2 fuzzy set is determined by both the Upper Membership Function (UMF) and the Lower Membership Function (LMF). UMF reveals the highest possible membership degree that a set can achieve within the domain of discourse. LMF reveals the lowest membership degree. These two functions' difference forms an interval. This interval's shaded area represents the uncertainty domain, which refers to all possible membership degree of this set within these two boundaries. A system based on RT2FLCM is developed, which integrates the advantages of interval type-2 fuzzy sets to enhance adaptability and control effectiveness in uncertain and complex situations. Fig. 4 shows the structure of RT2FLCM.

In Fig. 4, RT2FLCM inherits the basic structure of type-1 FC, including three main steps: fuzzification, inference, and defuzzification. However, RT2FLCM introduces an additional component, a type reducer, after processing the rule base, which is utilized to convert type-2 fuzzy sets into type-1 fuzzy sets or specific values for further processing. This step is crucial to ensure that the system can smoothly execute subsequent control tasks. Through this design, RT2FLCM can more effectively manage and reduce uncertainty, improving control systems' performance and reliability.

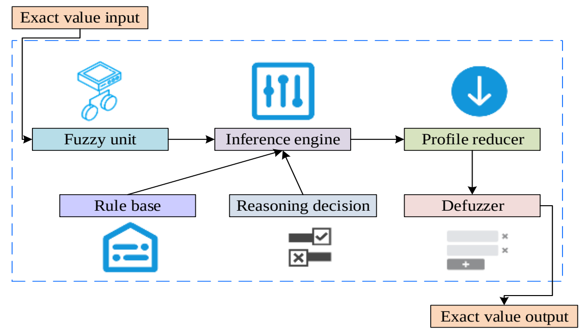


Fig. 4. The structure of RT2FLCM.

C. Indoor Environmental Analysis Based on Genetic Algorithm

For ILD and environmental analysis, an optimization technique that simulates natural selection and genetic mechanisms, namely GA, is utilized for environmental analysis and optimization. This method has significant parallel processing capabilities and global search advantages, enabling effective exploration in the parameter space in a probabilistic manner. It can automatically identify and guide the search process and dynamically adjust search strategies to adapt to constantly changing design requirements. Fig. 5 shows the GA.

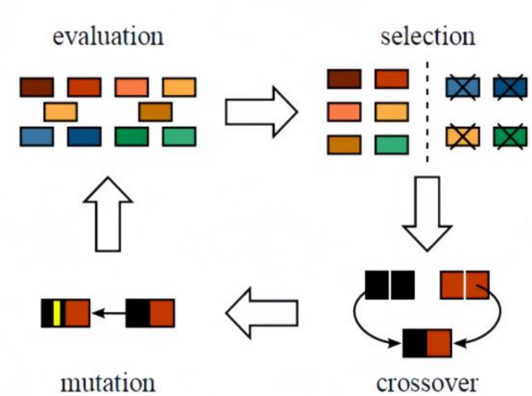


Fig. 5. Genetic algorithm flow chart.

In Fig. 5, the GA process includes encoding the initial population, using fitness values to measure the quality of chromosomes, and selecting individuals based on fitness values. Selection typically retains individuals with better fitness values. Crossover refers to gene exchange. Mutation refers to genetic modification. Adaptability is reflected in probability settings. When fitness begins to concentrate, the crossover and mutation probability increases to escape from local optima. When fitness is dispersed, reducing the crossover and mutation probability allows individuals to search for optimal solutions in their respective regions. The crossover probability is represented by Eq. (10).

$$P_c = \begin{cases} \dfrac{K_1(F' - F_{\min})}{F_{avg} - F_{\min}}, F' \le F_{avg} \\ K_2, F' > F_{avg} \end{cases} \tag{10}$$

In Eq. (10), P_c is the crossover probability. F is an individual's fitness utilized to perform mutation operations. F' means the smaller individual's fitness among two individuals that need to perform crossover operations. F_{avg} means the parental chromosome's mean fitness. $F_{\min}$ means the parent generation's minimum fitness. K is an adjustment parameter. The mutation probability is represented by Eq. (11).

$$P_m = \begin{cases} \dfrac{K_3(F - F_{\min})}{F_{avg} - F_{\min}}, F \le F_{avg} \\ K_4, F > F_{avg} \end{cases} \tag{11}$$

In Eq. (11), P_m is the crossover probability. When conducting ILD and indoor environment analysis, using GA alone requires multiple CFD simulations, which results in high computational costs. Neural networks are utilized as an alternative to CFD to reduce this cost, which are combined with GA to reduce the necessary computational workload. Fig. 6 shows the ILD process combining GA with neural networks and CFD.

In Fig. 6, during the initial stage of ILD, a neural network is utilized to predict the new design scheme's performance indicators. If these predicted results meet the expected design standards, CFD simulation is utilized to conduct the design scheme's in-depth analysis to obtain accurate CFD performance data. By combining neural networks and CFD, ILD can be more efficient and accurate, while providing designers with a powerful tool to achieve innovative and high-quality design results.

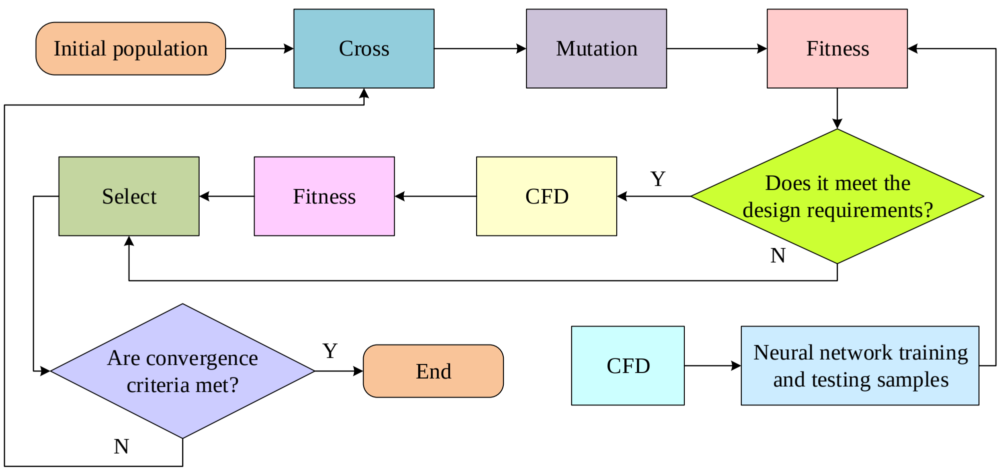


Fig. 6. Indoor landscape design process combining genetic algorithm with neural network and CFD.

IV. Results

Firstly, the robots and algorithmic performance based on A*+IPID+IGA was evaluated. The mean square error, sum of squared errors, and fitness curve of A*+IPID+IGA were analyzed. Then, simulation analysis was conducted on the type-2 FC model. Finally, the landscape design effects and environmental adaptability of different methods were compared and analyzed.

A. *Performance Evaluation of Robots and Algorithms based on A*+IPID+IGA*

Simulation experiments were conducted on robots based on A*+IPID+IGA using Matlab2018b. Figure 7 shows the mean square error, Sum of Squared Error (SSE), average fitness, and optimal fitness curves of A*+IPID+IGA.

In Fig. 7 (a), the average and minimum SSE of A*+IPID+IGA converged after only 6 iterations, and SSE remained stable at 0.19. In Fig. 7 (b), A*+IPID+IGA showed a faster iteration speed in the first 7 iterations. However, from the 8th to the 19th iteration, the iteration speed slowed down slightly. Finally, at the 20th iteration, the algorithm achieved convergence, indicating that the algorithm improved the convergence rate during the iteration. In Fig. 7(c), A*+IPID+IGA achieved convergence between average and optimal fitness in the first 20 iterations. This method showed a fast convergence rate at the beginning of the iteration and reached the convergence point at the 20th iteration, with the final convergence value stabilizing at 1.44. The path planning optimization accuracy for indoor landscape mapping and design of robots based on A*+IPID+IGA was analyzed. The study compared the real and planned trajectories of ordinary robots and robots based on A*+IPID+IGA in Fig. 8.

In Fig. 8 (a), the fitting accuracy of the robot's real and planned trajectories based on A*+IPID+IGA reached over 95%. In contrast, the fitting accuracy of ordinary robot path planning in Fig. 8 (b) was only about 67%. Therefore, robots based on A*+IPID+IGA had significant optimization improvements in path planning optimization compared to ordinary robots.

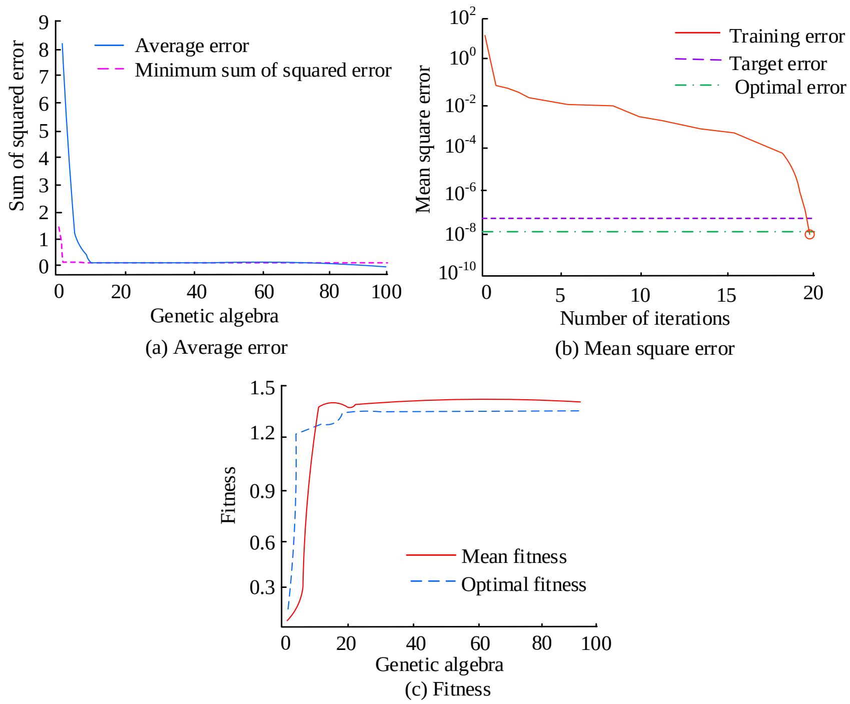


Fig. 7. Mean square error, SSE, and optimal fitness curve.

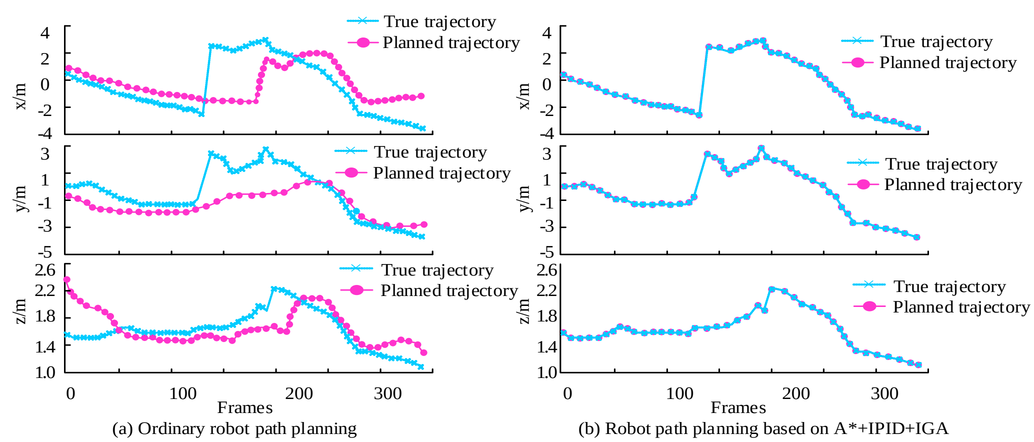
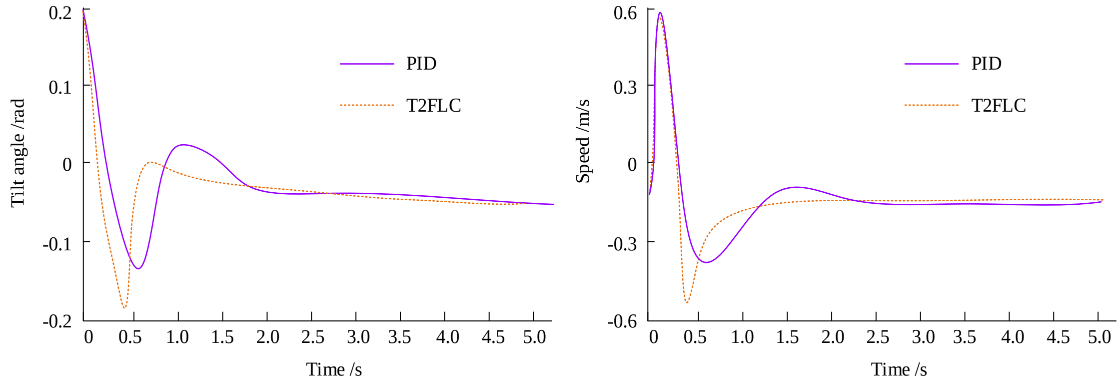


Fig. 8. Comparison of paths and trajectories of robots.

B. Simulation Analysis of Robot Type-2 Fuzzy Control

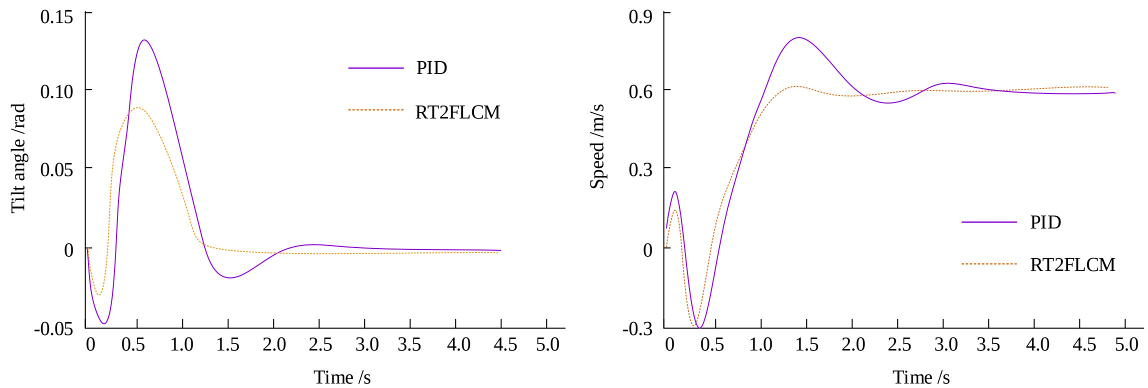
The research assumed that robot's intrinsic parameters were not only accurate and error-free, but also remained constant during operation. External interference factors were excluded. The initial tilt angle was set to 0.3 radians, with the target velocity set to zero, to evaluate the robot's ability to restore balance to a specific tilt angle. The experiment utilized the Simulink module of MATLAB, set the target speed to zero, and set the initial state array. The study compared the classical Proportional-Integral-Derivative (PID) regulation technique with the fusion function integrated RT2FLCM. Fig. 9 shows the robot's tilt angle and velocity changes.

In Fig. 9 (a) and Fig. 9(b), when initially tilted at 0.3 radians, the robot increased to a speed of nearly 0.6m/s in a short period of approximately 0.2s. As the speed of the robot increased, the tilt rapidly decreased and exceeded the equilibrium point, entering a reverse tilt state, indicating that the robot was starting to tilt backwards. Subsequently, the robot began to slow down its speed and gradually returned to equilibrium after experiencing two oscillations. When using traditional PID control, the robot's maximum tilt angle reached 0.16 radians. In contrast, when using the RT2FLCM strategy, although the tilt angle was slightly larger, RT2FLCM significantly improved the recovery speed. Specifically, the robot restored the tilt angle and velocity to zero in about 1.7s. This meant the robot reached a balanced and stationary state, while PID took about 2.5s. After evaluating the stability adjustment ability, further testing will be conducted on robot performance in rate adjustment. This robot was accelerated from a stationary state to a target speed of 0.7m/s while maintaining its initial state unchanged. Fig. 10 shows the changes in speed and tilt angle under two control modes.



(a) Tilt angle (b) Speed

Fig. 9. Tilt and velocity response curve.



(a) Tilt angle (b) Speed

Fig. 10. Velocity and tilt curves under two control modes.

In Fig. 10(a), PID had a maximum negative tilt angle of 0.08, while RT2FLCM had a maximum negative tilt angle of 0.04. PID had a maximum positive tilt angle of 0.2, while RT2FLCM had a maximum positive tilt angle of 0.14. In Fig. 10(b), PID's maximum speed reached 0.9m/s, with an overshoot of 28.6%. In contrast, the maximum speed under RT2FLCM control was 0.75m/s, with an overshoot of only 7.1%. Using PID caused two oscillations, while RT2FLCM only produced one oscillation. In terms of reaching the target speed, the type-2 FC was completed within 1.6s, while using a dual closed-loop PID required approximately 3s. During the overall speed adjustment process, RT2FLCM exhibited smoother and faster performance, with better control effects.

C. Analysis of Landscape Design Effects and Environmental Adaptability

A comparative analysis was conducted between the proposed ILD (Method 1), ILD based on GA (Method 2), ILD based on linear programming (Method 3), ILD based on deep learning (Method 4), and ILD based on building information model (Method 5). The comparative indicators were normalized. Table I shows the final ILD effect.

TABLE I. COMPARISON OF INDOOR LANDSCAPE DESIGN EFFECTS

Method index	Method 1	Method 2	Method 3	Method 4	Method 5
Functionality	0.93	0.71	0.63	0.77	0.83
Aesthetic	0.97	0.68	0.75	0.71	0.85
Technicality	0.94	0.75	0.69	0.82	0.91
Environmental quality	0.89	0.73	0.81	0.79	0.88
Aesthetic value	0.85	0.79	0.75	0.68	0.74
Accessibility	0.92	0.82	0.84	0.65	0.82
Social benefit	0.83	0.81	0.82	0.63	0.78
Innovativeness	0.91	0.88	0.73	0.74	0.86
User satisfaction	0.95	0.74	0.78	0.77	0.90

In Table I, Method 1 performed the best in terms of functionality, aesthetic, technicality, accessibility, and user satisfaction, with scores of 0.93, 0.97, 0.94, 0.92, and 0.95, respectively. Method 5 also performed well on most indicators, especially in terms of functionality and user satisfaction, with scores of 0.83 and 0.90, respectively. In contrast, Methods 2, 3, and 4 scored lower on some indicators, indicating that their performance in these areas needed improvement. Overall, Method 1 became the most popular and effective design method due to its comprehensive advantages. Table II shows the environmental adaptability of five methods.

TABLE II. ENVIRONMENTAL ADAPTABILITY OF THE FIVE METHODS

0	Method 1	Method 2	Method 3	Method 4	Method 5
Functional adaptability	0.95	0.77	0.67	0.67	0.83
Human body engineering	0.91	0.73	0.59	0.82	0.88
Thermal comfort	0.86	0.82	0.68	0.73	0.91
Acoustic adaptability	0.88	0.79	0.81	0.76	0.83
Light environment	0.94	0.61	0.73	0.68	0.85
Air quality	0.92	0.64	0.75	0.85	0.88
Materials and finishes	0.91	0.81	0.80	0.65	0.79
Spatial flexibility	0.86	0.69	0.69	0.74	0.73
Psychological comfort level	0.88	0.78	0.74	0.71	0.68

In Table II, Method 1 performed outstandingly in terms of functional adaptability, human body engineering, thermal comfort, light environment, and air quality, with scores of 0.95, 0.91, 0.86, 0.94, and 0.92, respectively. This demonstrated its outstanding performance in meeting human needs and environmental comfort.

V. DISCUSSION

Improved fuzzy control and genetic algorithm are applied in interior landscape design to improve the automation and accuracy of the design and enhance the environmental adaptability. In terms of functionality, the proposed method shows a high score of 0.93, which is in contrast to the results obtained by Moreno et al. [1] in applying fuzzy logic to the preventive protection and restoration monitoring of heritage buildings. While Moreno et al.'s study focused on evaluation and monitoring, this study applies fuzzy control to the design process itself, achieving a higher functional score. In terms of aesthetics, the score of the study is 0.97, which is compared with the study of Hussein et al. [8] using fuzzy logic to evaluate the spaciousness of architectural design studios, which mainly focuses on the physical properties of space, while this study comprehensively considers aesthetics and provides a more comprehensive design scheme. In terms of environmental adaptability, the interior landscape design method proposed in this study got a score of 0.86 in terms of thermal comfort, which was compared with the result of Khafajeh et al. [9] applying fuzzy logic in the hydroponic greenhouse control system, which mainly focused on the optimization of environmental control, while this study took environmental adaptability as a part of the design process. To achieve a more comfortable indoor environment. Through these comparisons, it can be seen that the proposed method has obvious advantages in automation design and environmental adaptability. The research not only improves the accuracy of the design, but also significantly improves the automation level and environmental adaptability of the design through the combination of fuzzy control and genetic algorithm.

VI. CONCLUSION

A method for analyzing ILD and environmental adaptability based on improved FC is proposed. Its effectiveness is verified through experiments. In the results, A*+IPID+IGA showed good convergence performance during the iteration. The mean square error and SSE converged rapidly after 6 iterations and reached a stable state within 20 iterations. The average and optimal fitness also showed a rapid convergence trend. These results validated this algorithm’s effectiveness and reliability in solving optimization problems. For path planning optimization, robots based on A*+IPID+IGA showed higher fitting accuracy compared to ordinary robots, reaching over 95%. The ordinary robots’ fitting accuracy was only about 67%. These demonstrated the optimization capability of the improved algorithm in path planning. The ILD and environmental adaptability analysis method based on A*+IPID+IGA has demonstrated excellent performance in robot path planning, balance control, speed control, and landscape design effect evaluation. This method not only improves the automation and accuracy of design, but also significantly enhances environmental adaptability. However, there are still some shortcomings in the research. For example, it is assumed that robot’s internal parameters are constant without considering external interference factors. This may affect the control effect in practical applications. Future research can further explore the impact of parameter changes and external disturbances on system performance, as well as how to optimize algorithms to adapt to more complex real-world environments.

REFERENCES

[1] Moreno M, Prieto A J, Ortiz R. Preventive conservation and restoration monitoring of heritage buildings based on fuzzy logic. International Journal of Architectural Heritage, 2023, 17(7): 1153-1170.

[2] Çalışkan B. Spatial Suitability Scoring For Rail Transit Network Extension by Developing ‘Rail Transit Fuzzy Logic Model’ (RFLM) in Matlab Environment. International Review for Spatial Planning and Sustainable Development, 2024, 12(1): 222-241.

[3] Ting L, Khan M, Sharma A, Ansari M D. A secure framework for IoT-based smart climate agriculture system: Toward blockchain and edge computing. Journal of Intelligent Systems, 2022, 31(1): 221-236.

[4] Zhu Q, Kumar P M, Alazab M. Computer application in game map path-finding based on fuzzy logic dynamic hierarchical ant colony algorithm. International Journal of Fuzzy Systems, 2022, 24(5): 2513-2524.

[5] Àgueda A, Vacca P, Planas E, Pastor E. Evaluating wildfire vulnerability of Mediterranean dwellings using fuzzy logic applied to expert judgement. International journal of wildland fire, 2023, 32(6): 1011-1029.

[6] Biber P, Schwaiger F, Poschenrieder W, Pretzsch H. A fuzzy logic-based approach for evaluating forest ecosystem service provision and biodiversity applied to a case study landscape in Southern Germany. European Journal of Forest Research, 2021, 140(6): 1559-1586.

[7] Colak A M. Parameters Optimized with the Pattern Search Algorithm for Fuzzy Control Based Active Power Factor Correction. Electric Power Components and Systems, 2024, 52(7): 1115-1128.

[8] Hussein A Y, Mustafa F A. A quality learning environment: an assessment of spaciousness of architectural design studios of Iraqi Kurdistan region universities using fuzzy logic. Open House International, 2024, 49(1): 181-204.

[9] Khafajeh H, Banakar A, Minaei S, Delavar M. A hydroponic greenhouse fuzzy control system: design, development and optimization using the genetic algorithm. Spanish Journal of Agricultural Research, 2023, 21(1): e0201-e0201.

[10] Al Gizi A J H. UAV Flight Fuzzy Controller with Deep Learning Network Fault Checker of High-Voltage Lines. International Journal of

Intelligent Systems and Applications in Engineering, 2023, 11(2): 877-891.

[11] Kasruddin Nasir A N, Ahmad M A, Tokhi M O. Hybrid spiral-bacterial foraging algorithm for a fuzzy control design of a flexible manipulator. Journal of Low Frequency Noise, Vibration and Active Control, 2022, 41(1): 340-358.

[12] Incekara C O. Post-COVID-19 ergonomic school furniture design under fuzzy logic. Work, 2021, 69(4): 1197-1208.

[13] Obinna O R, Joseph E C. DYNAMIC SPECTRUM ALLOCATION IN COGNITIVE RADIO NETWORKS FOR IoT DEVICES USING FUZZY LOGIC. Advance Journal of Science, Engineering and Technology, 2024, 9(3): 1-14.

[14] Zhang Y, Chen J, Wang Q, Tan C, Li Y, Sun X, Li Y. Geographic information system models with fuzzy logic for susceptibility maps of debris flow using multiple types of parameters: a case study in Pinggu District of Beijing, China. Natural Hazards and Earth System Sciences, 2022, 22(7): 2239-2255.

[15] Gupta N, Lee S H. Trapezoidal interval type-2 fuzzy analytical hierarchy process technique for biophilic element/design selection in lodging industry. Journal of the Operational Research Society, 2023, 74(7): 1613-1627.

[16] Chiang T Y. Refurbishment criteria performance assessment methodologies based on a multiple-criteria approach. Journal of Housing and the Built Environment, 2021, 36(1): 263-282.

[17] Jiang Y, Fakhruldeen H, Pizzuto G. Autonomous biomimetic solid dispensing using a dual-arm robotic manipulator. Digital Discovery, 2023, 2(6): 1733-1744.

[18] Xiong Y, Pan L, Xiao M, Xiao H. Motion control and path optimization of intelligent AUV using fuzzy adaptive PID and improved genetic algorithm. Mathematical Biosciences and Engineering, 2023, 20(5): 9208-9245.

[19] Surendra H J, Deka P C. Municipal residential water consumption estimation techniques using traditional and soft computing approach: a review. Water Conservation Science and Engineering, 2022, 7(1): 77-85.

[20] Choudhuri S, Adeniye S, Sen A. Distribution Alignment Using Complement Entropy Objective and Adaptive Consensus-Based Label Refinement For Partial Domain Adaptation. Artificial Intelligence and Applications, 2023, 1(1): 43-51.