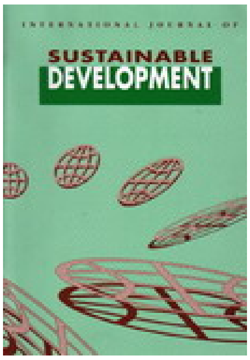

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An interior design method based on the coupling of I-GWO and self-updating neural network under the background of green interaction

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An interior design method based on the coupling of I-GWO and self-updating neural network under the background of green interaction

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Abstract: In the context of verdant interplay, interior design is progressively compelled to appraise the equilibrium between ecological sustainability and user experientiality. To this end, this manuscript postulates a novel interior design algorithm rooted in the interaction grey wolf algorithm (I-GWO) conjoined with a self-updating neural network. Initially, a tailored I-GWO is harnessed to fine-tune the interior design proposal, wherein the design quandary is transformed into an optimisation conundrum, thereby deploying the I-GWO to navigate the realm of optimal solutions. Subsequently, a bespoke self-updating neural network is architected, amalgamating convolutional neural networks (CNN) and long-short-term memory (LSTM), thereby refining the design blueprint even further. This contrived neural network evinces the innate capacity to autonomously assimilate and update weights and biases. The nomenclature and precepts of interior design are thereby assimilated through the synergy of the I-GWO and self-updating neural network. Finally, empirical attestations evince the algorithm's meritorious aptitude in optimising interior design schemes while adeptly incorporating considerations of environmental sustainability. The outcomes evince a noteworthy 42.5% enhancement in temporal efficiency when compared to extant state-of-the-art algorithms. Furthermore, the proposed method attains the zenith in convergence efficacy when juxtaposed with six other state-of-the-art algorithms.

Keywords: long-short-term memory; LSTM; optimisation; interior design; green interaction; neural network.

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Biographical notes: Shasha Luo obtained her Bachelor's in Literature from the Shanghai Normal University in 2007 and Master's in Engineering from the Nanjing University in 2017. Since 2013, she has been a professional teacher and the Director of the Teaching and Research Department at the School of Creative Design at Shanghai Vocational College of Business and Foreign Languages. Her main research directions are interior design, landscape design, soft decoration design, etc. and also published more than ten papers, including three core papers and one monograph. She guided some students to participate in domestic and international art and design competitions and achieve good results multiple times. She also won numerous awards in the Shanghai Teacher Lecture Competition and won the first prize for teaching and research achievements in the National Key Project of the 14th Five Year Plan of the Ministry of Education.

1 Introduction

Green interaction refers to a design concept with environmental protection and sustainable development as the core concept. It aims to provide a more lively and engaging user experience by using a green palette and interactive elements. Moreover, it emphasises the harmonious symbiotic relationship between man and nature, advocates the use of environmentally friendly and renewable materials and energy, and reduces the negative impact on the environment (Fuchs et al., 2020). In this context, the development of interior design algorithms also faces new challenges and opportunities.

Interior design is a discipline that specialises in the study of interior space layout, colour, materials, lighting, etc. with the aim of creating an interior environment with aesthetics, practicality and comfort. Interior design usually includes the following aspects: space planning, colour matching, material selection, lighting design. In order to design an interior space with high quality, practicality and aesthetics, all elements must be optimised, so interior design can be regarded as an optimisation process (Kim and Lee, 2020; Can et al., 2023).

In order to get better interior design results, some algorithm-based interior design methods have emerged in recent years. These methods help interior designers quickly generate high-quality design proposals. For example, interior design methods based on optimisation algorithms such as genetic algorithms, neural networks, and simulated annealing can generate optimal design schemes by searching for optimal solutions. In addition, interior design methods based on rules and constraints can automatically generate interior spaces that meet design requirements by defining rules and constraints. In addition to the above methods, there are some interior design methods based on machine learning and deep learning (Meisrimler et al., 2021). These methods use a large amount of interior design data and deep learning algorithms to learn design rules and style features, thereby generating interior spaces that meet design requirements. For example, the interior design method based on generative adversarial network (GAN) can generate an interior space that meets the design requirements by means of generative confrontation (Kasap and Kasap, 2021).

Although the existing methods have achieved certain results and applications, there are still problems such as long design time, low design efficiency, limited design process, unsatisfactory design results, and single design style. Therefore, existing methods lack the flexibility and variety needed to meet the complex dynamic needs of interior design (Tan et al., 2018).

Genetic algorithm is an optimisation algorithm based on genetics and evolution theory, which is used to find the optimal solution or better solution in a large-scale search space (Ibrahimb et al., 2021). It was proposed by American computer scientist John Holland in 1975. Characteristics of genetic algorithms include parallelism, adaptability, robustness, and non-locality. Its idea comes from the natural selection and genetic mechanism in biology. In the genetic algorithm, the solution to the problem is expressed as a chromosome, and the natural selection and genetic mechanism are simulated through genetic operations (crossover, mutation, etc.), and new solutions are continuously generated, and the pros and cons of each individual are evaluated through the fitness function. Then determine the next generation of outstanding individuals. At present, genetic algorithm has been widely used in various fields, such as machine learning, data mining, control system, optimisation problems, etc.

Self-updating neural network is an unsupervised learning neural network model, also known as self-organising feature map (SOM). It was proposed by Teuvo Kohonen, a professor at the Helsinki University of Technology in Finland in 1980. Self-updating neural network can map high-dimensional input data to low-dimensional space by performing cluster analysis on input data, and preserve the topological relationship between input data during the mapping process (Sydor et al., 2021). It can be used in data compression, feature extraction, data visualisation and other fields. The learning process of the self-updating neural network is an iterative process, and each iteration will perform a cluster analysis on the input data until the network converges. In each iteration, the self-updating neural network selects an optimal neuron as the winning neuron, and then updates its weight and the weights of neighbouring neurons so that similar input data is mapped to neighbouring neurons (Ahmad et al., 2020). It has a simple structure, high computational efficiency, and is robust to noise and outliers.

Based on this motivation, in the context of green interaction, this paper designs a new interior design algorithm by combining genetic algorithm and self-updating neural network. The main innovations of this paper include a newly designed intelligent optimisation algorithm, which can find the optimal design results more quickly. In addition, this paper innovatively combines LSTM and CNN to achieve better convergence accuracy and convergence speed. In sum, the main contributions of this paper are as follows:

1. We analysed the existing interior design methods and found that the existing methods did not consider the interrelationships of the input elements due to the large number of parameters, resulting in low time efficiency and accuracy of the existing algorithms.
2. This paper designs an interior design method based on interaction grey wolf algorithm (I-GWO), CNN and LSTM. It can automatically optimise the parameters of interior design, and adjust and optimise the interior design effect in real time.
3. This paper verifies the effectiveness of the algorithm through experiments and explore its application prospects in practical interior design. Experiments results suggest that the proposed method has higher time efficiency (higher than 42.5%), and better visual results. This paper will provide new ideas and methods for automation and intelligence in the field of interior design.

2 Related works

Interior design is a complex issue involving many fields, and needs to take into account many factors such as space layout, functionality, and aesthetics. In recent years, many interior design methods have been proposed (Park and Kim, 2019). These methods can be divided into VR-based methods, deep learning-based methods, and intelligent optimisation-based methods (Alawad, 2021).

2.1 VR-based methods

The initial interior design method is based on VR, which achieves promising results. In detail, Fernandez and Brooker (2021) establish a virtual reality-based interior design display system. The system uses virtual reality technology to help designers better display and demonstrate design solutions, thereby providing a more intuitive and immersive design experience. The study also explores the impact of the system on the designer's design efficiency and design quality through experiments.

However, the existing method is too expensive, therefore, Gokturk and Ozturk (2021) proposed an interior design system based on virtual reality. The system can realise the real-time demonstration and modification of the interior design scheme. Users can use augmented reality to view and modify interior design proposals in real-world scenarios to better understand and optimise designs. Furthermore, Xue and He (2023) explore the application of virtual reality technology in interior architecture education, aiming to improve students' design skills and design thinking. The study adopts a teaching method based on virtual reality, and through the establishment of a virtual interior architectural scene display, simulating the real design process, so that students can better understand the design requirements and design schemes.

At the same time, Farran (2021) explore the application of virtual reality technology in interior architecture education, aiming to improve students' design skills and design thinking. The study adopts a teaching method based on virtual reality, and through the establishment of a virtual interior architectural scene display, simulating the real design process, so that students can better understand the design requirements and design schemes. This method establishes a decoration design system based on virtual reality technology, which can realise real interior decoration display and design operation. Designers can display, adjust and modify interior design through the system, so as to achieve a full range of design experience.

2.2 Deep learning-based methods

Stafford et al. (2023) proposed a method for generating interior design schemes based on generative adversarial networks (GAN). The method mainly consists of two parts: generator and discriminator. The generator uses a deep convolutional neural network (DCNN) to generate images that match a specific interior design style, and the discriminator uses a convolutional neural network to evaluate the difference between the image generated by the generator and the real image.

Considering that the previous method requires a large amount of training data. Fedorovskaya et al. (2021) proposed an interior design style recognition method based on deep learning, which aims to automatically identify the style of interior design by computer and provide a new intelligent solution for interior design. Authors propose two main aspects: feature extraction and classifier design. At the same time, Imamguluyev et al. (2022) proposed an interactive interior design method based on deep reinforcement learning, which aims to generate novel and personalised design schemes that meet the needs of interior design through the interaction between computers and designers.

Meanwhile, in terms of colour feature extraction, Darwish and Midani (2023) proposed an automatic colour matching method based on deep learning, which aims to automatically generate a colour scheme that meets the needs of interior design by computer, and provide a new intelligent solution for interior design. The method mainly includes two parts: colour feature extraction and colour scheme generation. The researchers employed a CNN to extract colour features in interior design pictures. In terms of colour scheme generation, the researchers used GANs to generate colour schemes that fit specific interior design styles. Furthermore, for generating interior design proposals, Wu (2022) proposed a deep learning method based on autoencoders and StyleGAN f they learn from existing interior design data using autoencoders and generate new interior design proposals using StyleGAN. The method can generate high-quality interior design proposals while preserving the characteristics of the original data.

2.3 Intelligent optimisation-based methods

Intelligent optimisation is the popular methods for multi-objective tasks. Fallatah (2020) first mainly introduces a multi-objective optimisation method for interior design based on particle swarm optimisation and genetic algorithm. This method first transforms the interior design problem into a multi-objective optimisation problem, including multiple design goals such as comfort, aesthetics, and functionality. For better time efficiency the particle swarm optimisation algorithm is used to speed up the search process.

For better time efficiency the particle swarm optimisation algorithm is used to speed up the search process. Pratiwi et al. (2021) translates sustainable building design issues into multiple design goals, including energy efficiency, interior comfort, environmental friendliness, and more. Then, a hybrid multi-objective optimisation method, including particle swarm optimisation algorithm and genetic algorithm, is used to optimise the design variables and obtain a set of optimal design schemes.

Recently, a new hybrid artificial bee colony algorithm was used and compared with standard artificial bee colony algorithm. In Manavis et al. (2021), first transforms the lighting design problem into an optimisation problem, with the optimisation goals of improving lighting quality, energy saving and cost-effectiveness. For example, the scale and diversity of the data set are insufficient, the interpretability of the model is poor, the degree of personalisation is limited, the fusion of multimodal information is difficult, and the interpretability and operability are insufficient. Then, genetic algorithm-based methods to find the optimal lighting design. In the hybrid artificial bee colony algorithm, the author combines the standard artificial bee colony algorithm with a local search strategy to speed up the search process and improve the convergence of the algorithm.

Although some progress has been made in these works, there are still some deficiencies (Habbak, 2021). Therefore, this paper designs a new interior design algorithm combining I-GWO and self-updating neural network (based on CNN and LSTM). In order to achieve better interior design effect. At the same time, the author also introduces an adaptive weight strategy to balance the weights among different optimisation objectives, thus avoiding the limitation of single-objective optimisation.

3 Method

This section illustrates the proposed interior design method based on I-GWO and self-updating neural network. Specifically, Subsection 3.1 shows the newly designed I-GWO based on traditional GWO. Subsection 3.2 shows the designed updating neural network based on CNN and LSTM. Then, Subsection 3.3 shows the framework of the combined interior design method.

3.1 I-GWO algorithm module

GWO algorithm simulates the action of grey wolves (Chp, 2020; Guevara et al., 2022). It is a heuristic optimisation algorithm that can be used for global optimisation problems, especially continuous optimisation problems. Furthermore, its advantage includes fast convergence, simple implementation, wide applicability, strong robustness. However, The convergence speed of the GWO algorithm is usually faster, but when the solution space is large or the function has multiple local optimal solutions, its convergence speed may be affected. Therefore, this section designs an interactive GWO algorithm based on the traditional GWO algorithm, shown as Figure 1.

Grey wolves are pack animals, and there is an extremely strict hierarchy in this group. Wolves are divided into four levels, namely α wolves, β wolves, δ wolves, and ω wolves. α wolf is the head wolf in the wolf pack, responsible for directing the actions of the wolf pack, and other wolves must obey its command (Hussein, 2020); β wolf is the subordinate wolf second only to α wolf, it is dominated by α wolf and is responsible for some decisions or other actions, strengthen the dominance of α wolves, and feed back to α. When α dies, β wolf has the first succession position and becomes the new α. The δ wolf is another subordinate wolf whose status is lower than β, and needs to be commanded by α wolf and β wolf at the same time, but can also command ω wolf. The ω wolf is the sentinel in the wolf pack, and its main duty is to maintain the territory of the wolf pack and take care of the weak and injured wolves in the wolf pack; the prey can only be eaten after the above three wolves are full (Deng, 2021). Although ω is very weak and has no status in the wolf pack, if the ω wolf is lost, it will lead to infighting among the wolves. Therefore, wolves of each level are in the pack have an important position.

In addition to the grey wolves social hierarchy, their hunting mechanism is also very distinctive, and the GWO algorithm is a simulation of this process. Besides, the I-GWO algorithm is based on the Metcalfe (Markov) theory (Kim et al., 2017), that is, the current state is only related to the previous state and has nothing to do with the probability process theory of the earlier state. In the I-GWO algorithm, the position of each grey wolf is randomly updated, and the new position is regarded as the current state. Furthermore, in the I-GWO algorithm, each solution is regarded as a grey wolf. The optimisation problem is regarded as a prey. Moreover, it is solved by simulating the cooperative behaviour of grey wolves. It mainly includes three parts: surrounding the prey, chasing the prey, and attacking the prey. The specific behaviour is as follows:

Surrounding the prey is the first step in the activities of wolves. α wolves, β wolves, and δ wolves guide the pack of wolves to hunt. The formulas for grey wolves to defend their prey are shown in formulas (1) and (2).

$$\overrightarrow{X}(t+1) = \overrightarrow{X}_q(t+1) - \overrightarrow{A}M \tag{1}$$

$$\overrightarrow{M} = \left|\overrightarrow{N}x_q(t) - \overrightarrow{X}(t)\right| \tag{2}$$

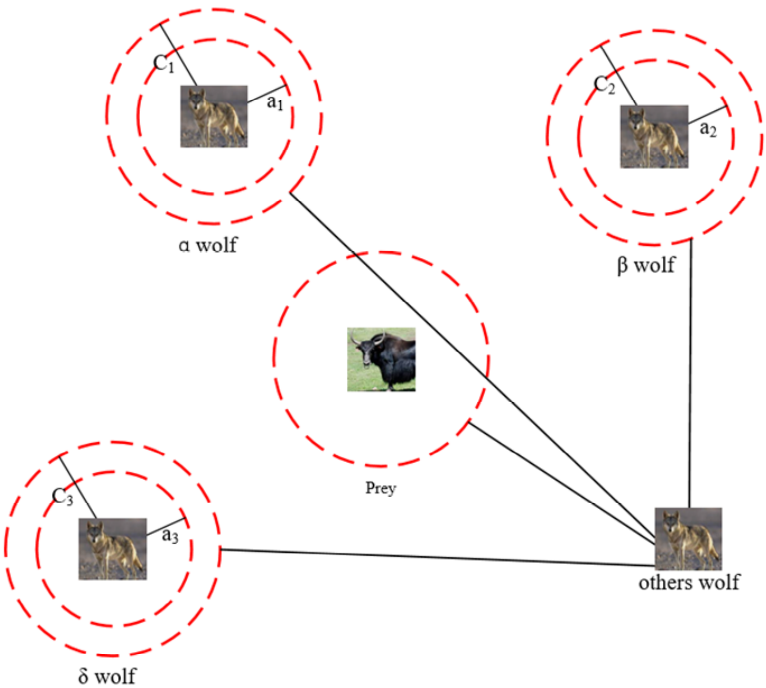
Among them, t is the number of algorithm iterations; $\overrightarrow{X}_q(t+1)$ and $\overrightarrow{X}(t+1)$ represent the coordinates of the wolf in iteration t and $t + 1$; $\overrightarrow{X}_q(t+1)$ is the coordinate of the prey in iteration t; $\overrightarrow{M}$ is the distance between the wolf and the target. And $\overrightarrow{A}$ and $\overrightarrow{N}$ are given by equations (3) and (4).

$$\vec{A} = 2\vec{a}\vec{r}_1 - \vec{a} \tag{3}$$

$$\vec{N} = 2\vec{r}_2 \tag{4}$$

$\vec{r}_1$ and $\vec{r}_2$ are random vectors, the value range is 0–1, and the value of $\vec{A}$ is determined by $\vec{a}$. $\vec{a}$ represents a convergent function that is linearly converged from 2 to 0 by the number of iterations.

Figure 1 The framework of I-GWO (see online version for colours)



After the siege is over, it is GWO's hunting action for the prey. This action is jointly determined by α wolf, β wolf, and δ wolf. The formula for updating GWO coordinates is shown in equations (5)–(11)

$$\vec{X}_1 = \vec{X}_\alpha(t) - \vec{A}_1\vec{M}_\alpha \tag{5}$$

$$\vec{X}_2 = \vec{X}_\beta(t) - \vec{A}_2\vec{M}_\beta \tag{6}$$

$$\vec{X}_3 = \vec{X}_\delta(t) - \vec{A}_3\vec{M}_\delta \tag{7}$$

$$\vec{D}_a = \left|\vec{N}_1\vec{X}_a(t) - \vec{X}(t)\right| \tag{8}$$

$$\vec{D}_\beta = \left|\vec{N}_1\vec{X}_\beta(t) - \vec{X}(t)\right| \tag{9}$$

$$\vec{D}_\delta = \left|\vec{N}_1\vec{X}_\delta(t) - \vec{X}(t)\right| \tag{10}$$

$$\vec{X}(t+1) = \frac{\left(\vec{X}_1 + \vec{X}_2 + \vec{X}_3\right)}{3} \tag{11}$$

Among them, $\vec{X}_\alpha(t), \vec{X}_\beta(t), \vec{X}_\delta(t)$ are the coordinates of α wolf, β wolf, and δ wolf GWO respectively, and $\vec{X}(t+1)$ represents the coordinates of the individual in the t^{th} iteration.

After the wolves complete the siege of the prey, it is the attack stage, during the attack process, the convergence factor expressed as $\vec{a}$ linearly decays from 2 to 0. It can be seen from formulas (3)–(5) that the value of $\vec{A}$ is between $\vec{a}$. When $\vec{A}$ = 1, it means that the wolves are attacking the target prey, if $\vec{A}$ > 1, it means that the wolves are searching for the next target, and GWO realises global optimisation. In formulas (3)–(11), t represents the current iteration round, and T represents the maximum iteration round.

3.2 Self-updating neural network module

In this section, a self-updating neural network module is designed based on CNN and LSTM to aggregate information from the output of I-GWO and learn the features required for interior design.

CNN is a multi-layer supervised learning network used to process neural networks similar to grid-structured data, including time series data and image data. The basic structure of CNN is shown in Figure 2, including input layer, convolutional layer, pooling layer, fully connected layer and output layer. Among them, the convolutional layer is the core component of the CNN that is different from other neural networks. This layer uses the filter parameters to perform convolution calculations on the input data to extract the most basic features. The filter parameters are randomly initialised, and then backpropagation is performed using the defined loss function to obtain the most suitable filter parameters for training to extract features. Taking the convolution of two-dimensional data as an example, the convolution operation formula is:

$$S(i, j) = (X * K)(i, j) = \sum_m \sum_n X(m, n)K(i-m, j-n) \tag{12}$$

Among them, * in the formula is convolution calculation. The pooling layer is used to calculate the static properties of a certain layer of the CNN. Its biggest role is to reduce the size of the model, improve the calculation speed, and at the same time improve the robustness of the extracted features and prevent overfitting. Our neural network designed based on LSTM and CNN can achieve better convergence results. Specifically, the dropout layer in CNN prevents overfitting during learning. At the same time, it can help LSTM to converge faster. Besides, the jump layer in LSTM can provide CNN with richer detailed features.

The units of the LSTM model are recurrently connected to each other, replacing the ordinary hidden layer in the general recurrent network. Its core is that there are three more switches, namely the forget gate, the input gate and the output gate. Here conventional artificial neurons are used to compute input features. Its value can be accumulated to the state if the input gate allows it. State cells have linear self-loops whose weights are controlled by forget gates. The output of the cell can be closed by the output gate. All gating units have nonlinearities, while input units can have arbitrary compressive nonlinearities. The status unit can also be used as an additional input to the gating unit. Moreover, the connection between LSTM and CNN is conducted by the last layer of the proposed LSTM. In particular, its fully connection layer has the same size as the first layer of CNN. Therefore, it enable the two network to connect.

Figure 2 The pipeline of CNN (see online version for colours)

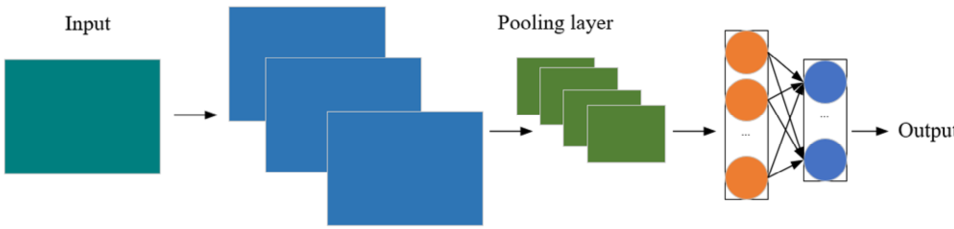
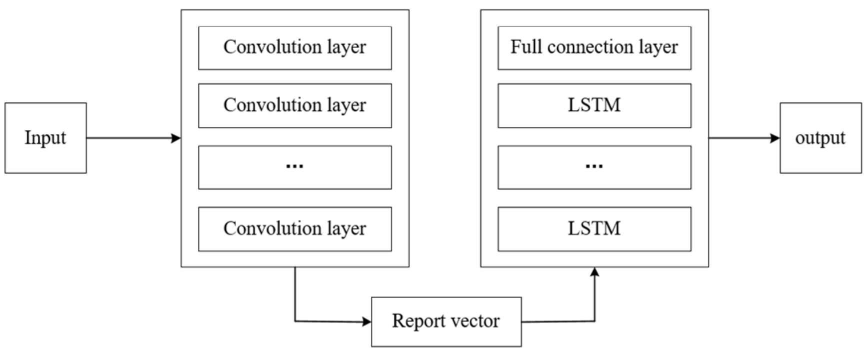


Figure 3 The designed self-updating neural network

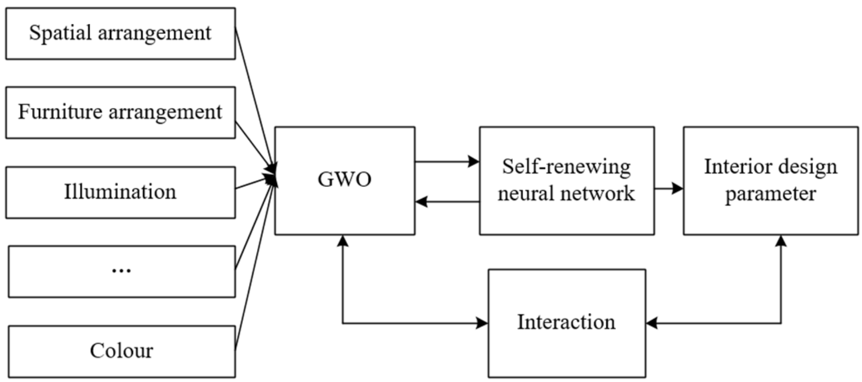


The self-updating neural network CNN-LSTM model we designed is a hybrid neural network model based on the encoder-decoder framework, and its basic structure is shown in Figure 3. In this model, the CNN is used as the encoder, and the effective representation is obtained directly from the original data through the use of the convolutional layer and the pooling layer through local connections and shared weights, and the local features of the data are automatically extracted, and establish a dense and complete feature vector; use the long-term short-term memory network as the decoder, and obtain the time characteristics of the data through the long-term short-term memory unit with long-term memory function.

3.3 Interior design method based on GWO and self-updating neural network

The framework of our proposed algorithm is shown in Figure 4. Firstly, we take the main parameters of the interior design as the input of the GWO algorithm. These parameters include: space layout, furniture placement, lighting, colour, material, functionality, humanisation, etc. The GWO algorithm takes the input parameters as a population, and optimises the interior design effect as the optimisation goal. After 100 iterations, the generated parameters are used as the input of the self-updating neural network. After that, the self-updating neural network learns features through the parameters input by GWO, and outputs the parameters of the final interior design scheme. In addition, the main role of the interaction module is to feed back the results obtained by the self-updating neural network to the GWO module. GWO can better generate optimised populations during optimisation. The feedback function shown in Figure 4 is mainly conducted by the interaction module. Once a result is outputted by the main module, it will be send to the interaction module. Its aim is to guide the better output of next generation.

Figure 4 The framework of the proposed interior design method



4 Results

To evaluate the effectiveness of our algorithm on the network, we conduct comparative experiments in this section. In detail, we first introduce the evaluation metrics in Subsection 4.1, then the training process is evaluated in Subsection 4.2. Finally, the main results is shown and analysed in Subsection 4.3.

4.1 Evaluation metrics and comparison methods

The comparative models include: interior design based on AutoCAD (CAD), interior design method based on VR, interior design method based on BIM design, interior design method based on intelligent optimisation (IO). The evaluation indicators of our experiment include the final effect of interior design, algorithm running time and questionnaire survey. The experimental environment is shown in Table 1.

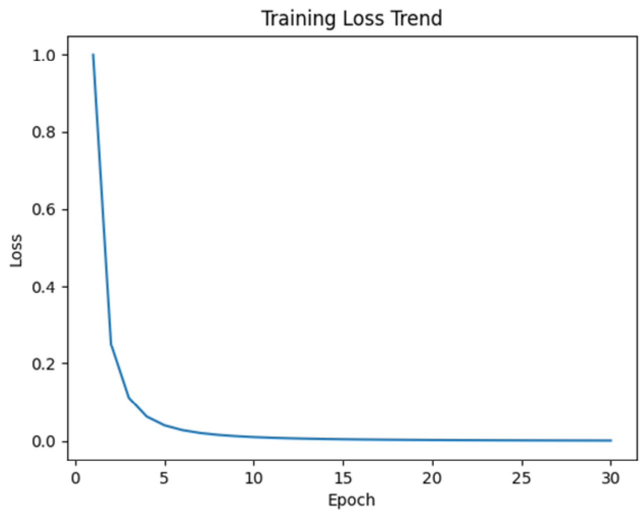
Table 1 Experiment setting

Serial number	*Tools*	*Parameters*
1	Operating system	Win10
2	Hardware platform	Intel Core 5, 1.99 GHz
3	Programming language	Python
4	Browser	Chrome

4.2 Training process

It can be seen from Figure 5 that in the training phase of the adaptive neural network, as the epoch gradually increases. The value of the loss function gradually decreases, indicating that the model is continuously optimised during the training process, and the error between the prediction result and the real value gradually decreases. The accuracy of the model gradually increases. In addition, when epoch > 10, the loss value is less than 0.1, and then decreases slowly, indicating that the convergence result of the adaptive neural network is good.

Figure 5 Training process (see online version for colours)



4.3 Result and analyses

We show the results of the proposed method and further analyses them in this section.

In Table 2, we first show the simulation results of the design parameters output by the algorithm in the figure, mainly including: cabinet, closes tool, staircase and whole composition. Experimental results prove that our method can well meet the design requirements. At the same time, the design results obtained by our algorithm have no artefacts and have a good interactive experience for users. Moreover, the generalisation of our designed model is guaranteed. Specifically, when the model is trained on indoor data, it can generate parameters for outdoor design, as shown in Table 3.

Table 2 Simulation results (see online version for colours)

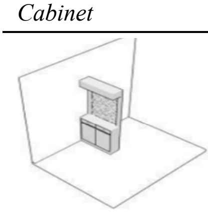
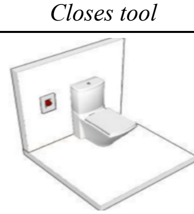
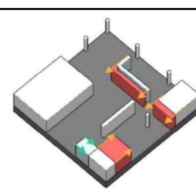
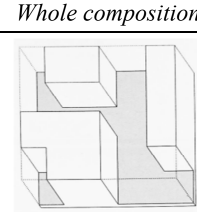
Cabinet	*Closes tool*	*Staircase*	*Whole composition*
			

Table 3 Time efficiency compared with exiting methods

Number of target parameters	*CAD*	*VR*	*BIM*	*IO*	*Ours*
1	7.424	8.204	8.646	7.424	2.104
5	9.433	8.021	7.314	8.534	3.021
10	10.324	8.036	8.314	8.942	3.659
15	14.321	9.524	9.314	9.244	4.152
20	18.532	12.504	15.336	8.434	5.034

As shown in Table 4, with the method proposed in this paper, as the number of layout design target parameters increases, the recommended time rises less; however, the traditional spatial layout design method has a larger increase in the recommended time with the increase in the number of recommendations. Among them, CAD has the largest increase. When the target parameter amount is 20, it reaches 18.532 s, which is three times that of the layout method proposed in this paper. The closest to the algorithm in this paper is the IO algorithm. Our algorithm offers several advantages over other existing algorithms. For instance, compared to this type of algorithm, our approach requires less historical data and is easier to implement in real-world environments. Table 3 provides evidence that our method significantly improves time efficiency by 42.5% compared to the second-best method, IO. This improvement results in a better user experience and increased design efficiency for designers.

Then, we conduct experiments to test the final solution and convergence result of the proposed I-GWO. Six different 3D models and six SOTA global optimisation algorithms including bacterial foraging optimisation algorithm (BWO), social spider algorithm (SSA), Humpback whale optimisation algorithm (HHO), modified enhanced Humpback whale optimisation algorithm (MEHHO), multi-objective antlion optimiser (MOA), and squirrel optimiser (SO) is used for comparison. The size of population is 50, and the termination condition is that iterations reach 70 times.

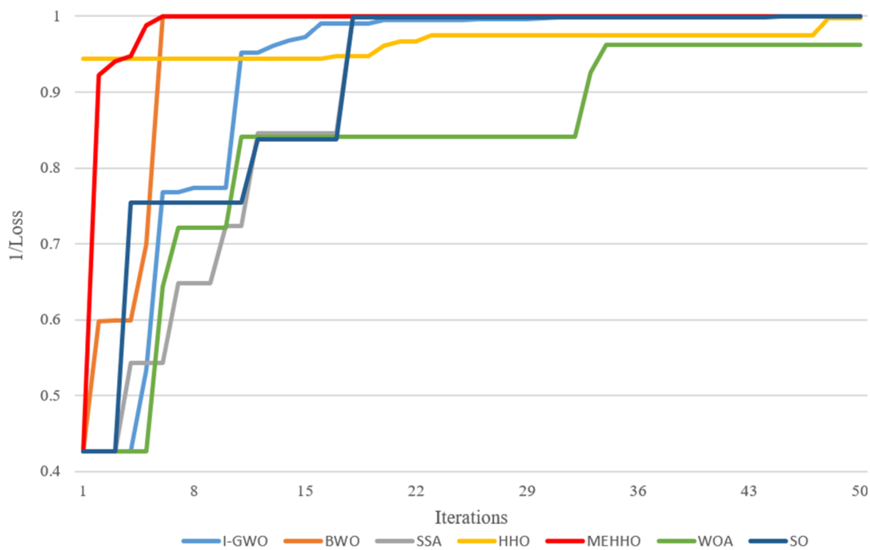
Table 4 Time efficiency and accuracy of the compared algorithms

	SSA	*HHO*	*MEHHO*	*MOA*	*SO*	*I-GWO*
Time(s)	0.314	0.412	0.462	0.531	0.412	0.135
Dis	0.013	0.032	0.134	0.154	0.094	0.005

We firstly evaluate the time efficiency and the distance from the ground truth (accuracy) with the selected six algorithms, shown in Table 4. Results suggest that for both time efficiency and accuracy of the proposed I-GWO achieves the best. Besides, for time efficiency, the second best is 0.314. I-GWO faster by about 0.179 second, which is a significant improvement. For accuracy, I-GWO achieve 0.005 distance between the ground truth, which surpass the existing methods.

To evaluate the convergence performance of I-GWO, we further conduct one certain algorithm five times, and select the convergence curve that closest to the bottom left axis for comparison, as shown in the Figure 6. The fastest convergence algorithm is SSA in the initial stage, which means iteration less than ten times, however, it always converges prematurely and cannot find the optimum. WOA can also find the same optimal result as ABWOA, but the convergence point of I-GWO is 10 which is smaller than that of WOA. BWO achieves the optimum with convergence point of 16 which is faster than I-GWO, however, I-GWO convergence faster than it in the initial stage, and can find the better solution.

Figure 6 The convergence result (see online version for colours)



4.4 Discussion

In sum, the interior design method proposed in this paper is based on the coupling of genetic algorithm and self-updating neural network, which effectively addresses the shortcomings of traditional methods and achieves a more refined goal. Notably, this method reduces the complexity of the design process by obtaining the corresponding spatial layout diagram. Compared with the traditional design method, this method offers several advantages, including a high degree of automation, good design effect, and significant time and cost savings. The automatic generation of design schemes, facilitated by the genetic algorithm and self-updating neural network optimisation, avoids the tedious manual design process. Moreover, the interior design scheme obtained has an excellent effect and meets people's aesthetic and use needs. This method has high practicality and application value, providing more convenient, efficient, and high-quality interior design services at a lower cost.

The interior design method based on genetic algorithm and self-renewing neural network has high practicality and application value overall. It can be applied to various types of interior design, providing people with more convenient, efficient, and high-quality interior design services. This method's ability to automatically generate design schemes and optimise interior design solutions using advanced algorithms significantly reduces the time and cost associated with traditional manual design methods. As a result, it offers a more accessible and affordable option for individuals or businesses seeking professional interior design services.

5 Conclusions

This paper presents a new approach for interior design optimisation using the I-GWO algorithm and a self-updating neural network based on CNN and LSTM. The proposed method takes into account various design factors and constraints, resulting in better quality design schemes. We evaluated our approach on a dataset containing multiple interior designs and found that it outperformed existing methods in both efficiency (improved by 42.5%) and effectiveness. Additionally, our intelligent algorithm showed that I-GWO achieved better convergence results. Overall, our algorithm enables intelligent design, optimises design schemes, and provides strong support for the advancement of the interior design field.

Although deep learning-based interior design methods have achieved impressive results in some aspects, there is still some potential room for improvement and research directions: future research can further optimise the deep learning model and improve the performance and generalisation ability of the model. This may include improving the model structure, introducing new training strategies, using larger and more diverse training data, etc. To improve user experience, future research can explore how to better interact with users and achieve a more intuitive and intelligent design process. For example, a new user interface can be developed to enable users to easily provide design requirements and feedback; or a more advanced recommendation system can be designed to recommend appropriate design solutions for users based on their historical behaviour and preferences.

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