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Research on the method of automatic matching of indoor design style based on AI technology

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Abstract The era of 'Intelligence +' has quietly arrived, and advanced science and technology such as AI technology and machine learning have begun to penetrate into the construction industry, bringing new design concepts. In this paper, based on building information modelling and machine learning, an automatic matching method for indoor building style layout is designed. Morphological parameters are extracted according to the designed indoor architectural form, and the mapping relationship between spatial form and architectural style is established based on the GAN model. An orthogonal model is used to model the generated architectural style image, and the spatial relationship of the indoor building, as the premise of the GAN model for style matching. It is found that traditional indoor style layout matching takes about 10 minutes, while the automated matching method proposed in this paper takes only 18.5 seconds, which greatly improves the matching efficiency. Even under different constraints, the method is still effective in matching interior architectural design solutions that simultaneously meet the contour constraints, as well as the style constraints.

Index Terms building information, interior architecture, interior style layout, orthogonal modelling, contour constraints

I. Introduction

The traditional interior design process is more complex and inefficient, which not only requires tedious calculations, but also multiple modifications and adjustments. With the advent of the information age, the rapid development of computer information interaction technology, people's pace of life continues to accelerate, the interior design has also put forward higher requirements, the personalised demand for interior design style is particularly obvious [1], [2].

From the current market development trend, interior design style will be developed to personalisation, artificial intelligence technology will be further developed. People's demand for interior design style is first to meet the need for comfort and practicality, then to meet the need for personalisation and art, and also to meet the need for a sense of science and technology and a sense of the future [3]-[5]. Artificial intelligence (AI) technology in the field of space and scene design has received more attention, and can better assist designers to complete the interior design style matching [6], [7]. The mainstream interior design product styles in the market generate specific demand-oriented scenes or spatial 2D scene graphs by providing inputs to the model to guide it to generate specific outputs of text or commands [8]-[10]. These products well reduce the threshold and cost of obtaining spatial scene renderings or conceptual renderings, and each has its own advantages in terms of functionality [11], [12]. Compared with the traditional image generation process, the application of AI technology has significantly reduced the technical complexity and operational threshold, and often demonstrates unique advantages with creative visual expression [13]-[15]. Contemporary designers should capture the trend of the artificial intelligence era, make reasonable use of AI technology in design work, and thus provide more possibilities for their own design content [16]-[18].

The innovation of this paper is to use AI, machine learning and other advanced technologies to build an automated matching method for interior architectural design styles to quickly match interior style design solutions for users. Taking the morphological prototypes of interior buildings as the skeleton, the automated layout matching method for interior styles under given constraints is established. Calculate the mapping relationship from the input of architectural parameters to the output of architectural spatial layout, reduce the matching time of the system and establish the optimisation objective. Based on the Rhino platform, the generator and discriminator models in the generative adversarial network are used to adjust the architectural parameters, and the discriminator is made to complete the style matching effectively by minimising the generation error. Finally, the orthogonal model is used to model the generated architectural style images.

II. Method

Generative design refers to the use of AI, machine learning algorithms and other technologies to integrate architectural generative design strategies into the process of performance optimisation to form a richer architectural spatial effect. For the problem of automated generation of architectural spatial layout, this section is developed from two aspects of automated matching of indoor architectural styles and generative design algorithms, respectively.

II. A. Automated matching of interior architectural styles

II. A. 1) Modelling of morphological prototype features

The feature model of morphological prototype is to take the morphological prototype component features, as the basic construction unit to define the morphological prototype model, and describe the morphological prototype as an organic collection of features.

The feature model of morphological prototype for indoor architecture is shown in Figure 1, and the feature model is divided into a three-layer structure, including component layer, feature layer and geometric layer. The component layer expresses the basic composition of the morphological prototype, the feature layer expresses the various features constituting each component and the basic operations of the features, and the geometry layer expresses the geometric modelling information of the features. Among them, the feature layer also expresses the relationships between features.

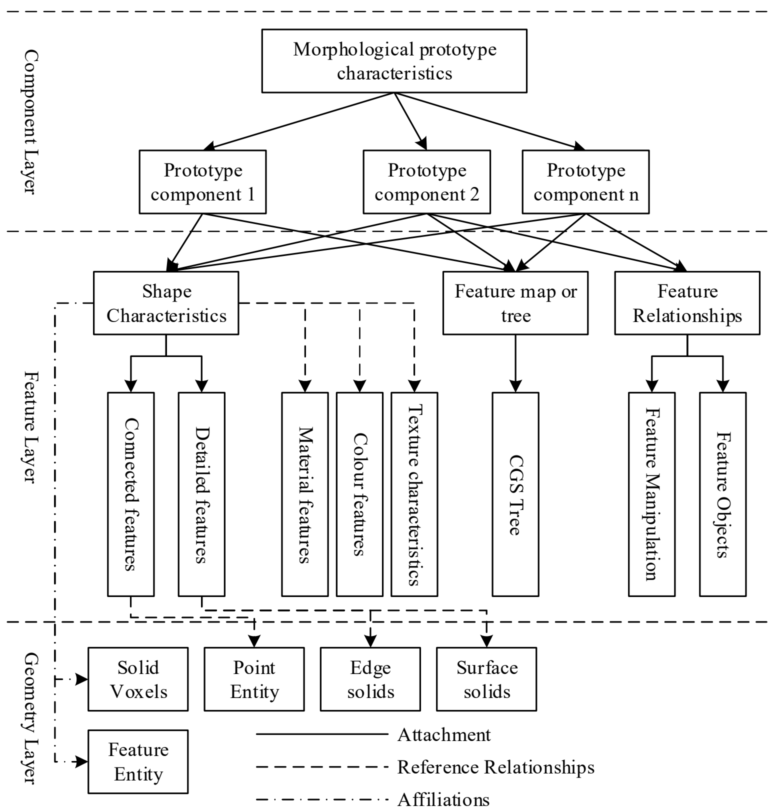


Figure 1: Morphological prototype feature model

Morphological prototype modelling with the application of morphological component features is essentially a description of the features, which is processed by AI technology to abstract the morphological prototype information into an organic collection of morphological component features, so that the morphological component features are used as the basic unit for the definition and modelling of morphological prototypes. In this way, the morphological prototype feature model not only supports the interior architectural design parameters required for the morphological design activity, but also contains the style information of the interior architecture and expresses the design intention of the interior architectural style.

II. A. 2) Style semantic factors

According to the basic principle of perceptual engineering, each indoor architectural style semantics is taken as a cognitive dimension, which constitutes the perceptual cognitive space of indoor architectural style imagery, so as to express and test the user's perceptions of indoor architectural styles. In this paper, factor analysis is used to reduce the number of dimensions of cognitive space, simplify the structure of cognitive space, and achieve the categorisation of style semantics.

The mathematical model for factor analysis of style semantics of indoor architecture is as follows:

(1) Let $X=\left(X_1,\cdots,X_p\right)$ be a p-dimensional random vector consisting of p sensible words with a covariance array of Σ, and diagonalise its orthogonal array U, with the diagonalised elements all being $\sum$ the characteristic roots. The elements of U are denoted by e_i and written as $U=\left(e_i\right)=\left(e_1,\cdots,e_p\right)$, where e_i is the vector of $p\times 1$ and the corresponding eigenroot of $\sum$ is denoted by $\lambda_1,\lambda_2\cdots,\lambda_p\geq 0$, then Σ can be decomposed as:

$$\sum=\sum_{i=1}^{p}\lambda_i e_i e_i{}' \tag{1}$$

Let $Y=U'X$, then:

$$Var(Y)=Var\left(U'X\right)=U'\Sigma U=\begin{bmatrix}\lambda_1 & & 0\\ & \ddots & \\ 0 & & \lambda_p\end{bmatrix} \tag{2}$$

That is, from the covariance array $\sum$ of X one can find a linear transformation U' of X such that the components of $Y=U'X$ are uncorrelated, i.e., correlations between the original sense words are eliminated. By linear transformation style semantic vector X and its common factor vector F can be expressed as:

$$\underset{(p\times 1)}{X}=\underset{(p\times m)(m\times 1)}{A}+\underset{(p\times 1)}{\varepsilon} \tag{3}$$

This equation is called the perceptual factor analysis model, where A is the factor loading matrix and ε is the residual matrix. The A in the above equation is the initial factor loading matrix, because the meaning of each factor is not obvious, it also needs to be rotated. That is, each factor is polarised so that each variable has a larger loading on only one common factor, in order to simplify the factor structure. Finally, the top m largest principal factors are selected according to the given threshold θ, i.e., the information of the selected principal factors satisfies the proportion of the overall information:

$$\sum_{j=1}^{m}\lambda_i\Big/\sum_{i=1}^{p}\lambda_i\geq\theta \tag{4}$$

II. A. 3) Matching interior architectural styles

Due to the complex mapping relationship between the interior architectural style variables and the morphological design variables, in order to automate the matching of interior architectural styles, a design object (design model) is introduced as an intermediate variable for matching (a mediating variable, acting as a 'link'). The process of matching interior architectural style constraints and contour constraints to morphological designs can then be described as the problem of determining the set of intersections of a given design model d with S and T.

For defined subsets $R^S\subseteq D\times S$ and $R^T\subseteq D\times T$, $\times$ denotes the Cartesian product, and these R^S and R^T are the specific sets of properties of s_i and t_i to which a given d is applied. Conversely, the elements in D are arrays satisfying S and T, which leads to the following assessment of the individual propositions for the case of R^S, which form the specification of the morphological design system that examines the stylistic constraints of the product:

(1) For a given $d\in D$, there exists no $s\in S$ such that $(d,s)\in R^s$, then S is incomplete.

(2) For a given $d\in D$, there exists a unique $s\in S$ such that $(d,s)\in R^S$, then S is unique.

(3) For a given $d\in D$, there exists more than one $s\in S$ such that $(d,s)\in R^s$, then S is indeterminate.

(4) For a given $s\in S$, there exists no $d\in D$ such that $(d,s)\in R^s$, then S is too rich or D is too deficient.

(5) For a given $s\in S$, there exists a unique $d\in D$ such that $(d,s)\in R^S$, then S is definite.

(6) For a given $s\in S$, there exists more than one $d\in D$ such that $(d,s)\in R^S$, then S is non-deterministic.

R^S is a set of morphological design variables satisfying a one-to-one mapping $F^S: S \to D$, and assuming that there exists R^T a set of style variables satisfying a full-projective function (not necessarily a uniprojective function) $F^T: T \to D$, the mapping $f: T \to S$, i.e., the mapping from the style variables to the morphological design variables, can be defined as:

$$f(t_1, \cdots, t_n) = (F^S)^{-1} \circ F^T(t_1, \cdots t_n) \tag{5}$$

Its mapping matching process is shown in Fig. 2.

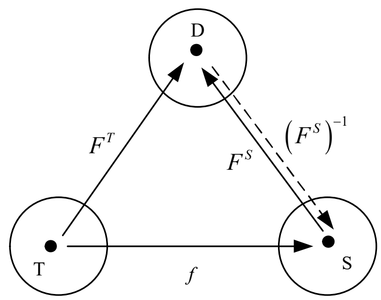


Figure 2: Style mapping matching procedure

For ease of expression, a point in T is written as a n-tuple $(t_1, \cdots, t_n)$, and t_i is understood to represent a value, not just a type and numeric value. Similarly, a point in S is written as a $(s_l, \cdots, s_m)$ form. In general, given f, each morphological design variable s_i defined as $f(t_1, \cdots, t_n) = (s_1, \cdots, s_m)$ is a function of all style variables. Thus, equation (5) can be written as:

$$f(t_1, \cdots, t_n) = \{f_1(t_1, \cdots, t_n), \cdots, f_m(t_1, \cdots, t_n)\} \tag{6}$$

From the formulation defined by mapping f, the following nine constraints are made for the automated matching process of interior building forms:

(1) Each point in S space is associated with one of the design models identified in D.

(2) Each point in T is associated with one model identified in D.

(3) Each design model in D has an associated point identified in S.

(4) Some design models in D may not have an association point with T.

(5) If the two design models are different in D, they have different points of association in S.

(6) If the two design models are different in D, their points of association in T may be absent, absent, or present at the same time, and the same or different.

(7) Each point in T maps to a point in S using f.

(8) Two points in T may map the same point in S.

(9) There are points in S that cannot be the result of the mapping in T.

II. B. Generating Design Models for Interior Building Layouts

II. B. 1) Parametric Modelling

The building information model in this study is based on the Rhino platform, which adopts a 3D modelling method with NURBS technology as the core [19]. Rhino is a powerful 3D modelling software, which is widely used in the fields of 3D animation production, industrial design, and architectural design. It is one of the most advanced 3D design software in the field of architecture, and has building design extension plug-ins such as Grasshopper and Building Information Modelling (Rhino BIM).

NURBS is an excellent method for representing curved surfaces and is widely used in the field of computer graphics. It has the ability to create arbitrary surface shapes and effectively control the smoothness of surfaces. By controlling three types of parameters - vertices, weights and node vectors - NURBS is able to tune the mesh faces to generate parametric models [20]. This method is very flexible and provides good control when creating surface shapes.

Generative Adversarial Networks (GANs), are trained using a competitive relationship between a generator model and a discriminator model. During training, one of them is fixed while the network parameters of the other are updated, and then alternate fixing and updating steps are performed until a converged state is reached. Suppose that at the beginning of training, generator G is fixed and the optimisation objective of the discriminator model at this point is:

$$\max V(D,G) = E_{x\sim Padw(x)}[\log D(x)] + E_{z\sim Pz(z)}[\log(1-D(G(z)))]^2 \tag{7}$$

In the discriminator model, when the input is a real image sample, the output of the discriminator should be close to 1, indicating that the discrimination result is real. And when the input is a generated image sample, the output of the discriminator should be 0. The loss is calculated by comparing the error between the discriminator's determination result and the real situation, and backpropagation is performed to adjust the network parameters. Next, the generator model G is optimised with Eq:

$$\min V(D,G) = E_{z\sim Pz(z)}[\log(1-D(G(z)))]^3 \tag{8}$$

The goal is to make the generated 'fake' image as close as possible to the real image, and the optimisation is achieved by adjusting the network parameters.

The training process of the generative adversarial network is shown in Figure 3. When updating the generator model, the goal is to make the generated image sample $G(z)$ closer to the real image. According to the feedback of the discriminator to adjust its own parameters, by minimising the generation error, so that it is difficult for the discriminator to distinguish between the real and generated images, that is, the discriminator's probability of discrimination output is close to 0.5.

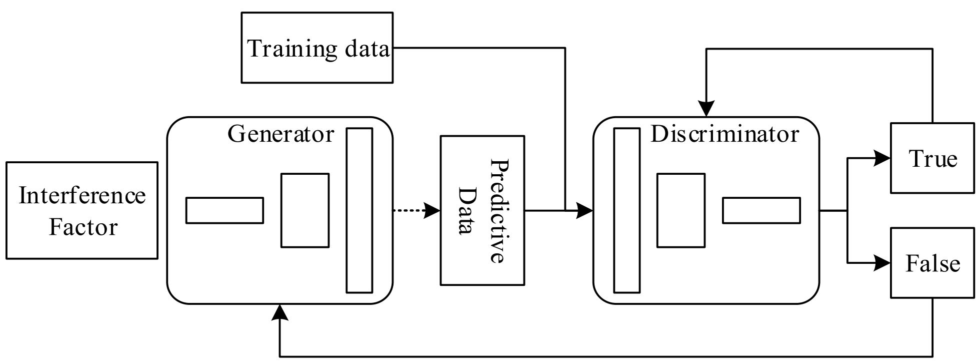


Figure 3: Adversarial generative network model structure

The application of adversarial generative network in this paper is mainly to use GAN model for image generation of indoor architecture.

Firstly, a representative and comprehensive input set (architectural style) and its corresponding output set are screened and introduced into the algorithm for learning and training at the same time, and after many iterations of the GAN model, the model of the adversarial generative network is generated. The model is not only able to predict the results of the original output set based on the input set of images through the model, but also can predict and generate the content of a brand-new output set based on the content of a similar input set, to achieve the purpose of indoor architectural layout generation.

II. B. 2) Modelling the spatial layout of buildings

When using machine learning methods for indoor architectural design, it is necessary to convert the architectural style images output from the GAN model from a geometric language to a coding language in order to describe the building form using computer language, so as to complete the optimised design of the physical properties of the building. According to the coding form adopted, it can be classified into two descriptive modes: continuous model and grid model, and according to the difference of the geometrical problem of building form, it can be classified into orthogonal model and non-orthogonal model respectively. In this paper, the orthogonal model is mainly used to model the generated architectural style images.

The orthogonal lattice grid model is suitable for regular rectangular plots and has the advantages of fast indexing and easy computation. The occupancy of building templates on the orthogonal grid is shown in Fig. 4. The integer planning algorithm based on the orthogonal grid model solves the feasible solutions under certain constraints, and fully explores the possibilities of the planar arrangement of the settlements under the constraints. Compared with other models, the orthogonal grid model is relatively simple, and the geometric problem can be transformed into the grid occupation problem for fast solution with high computational efficiency.

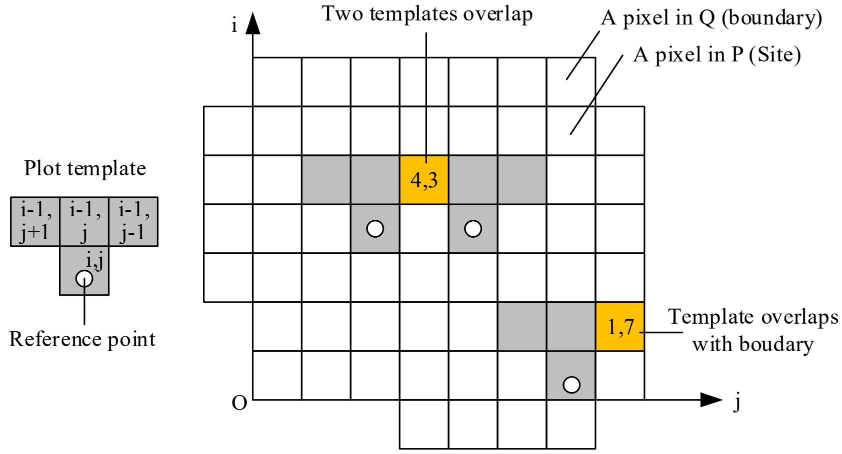


Figure 4: The occupation of building formwork in orthogonal grid

The orthogonal continuum model is applicable to the arrangement of rectangular or polygonal rooms whose edges are horizontal and vertical, and the model description is universal, so it is applicable to the generation of many types of building plans. The vertex coordinates and rectangular parameters of the rooms under the orthogonal continuum model are shown in Fig. 5, which describes the individual rooms by the coordinates of the rectangular origin and the parameters such as width, and relies on the two-dimensional coordinate computation to describe the connection relationship between the rooms, which extends the applicability of the mathematical planning method for solving the building planes to the two-dimensional orthogonal continuum model.

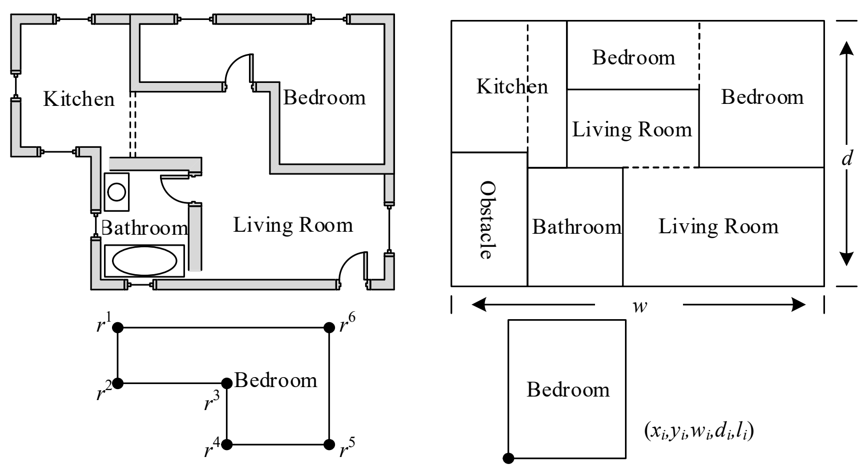


Figure 5: The vertex coordinates of the room are represented with rectangular parameters

II. B. 3) Interior Space Design Generation

Unlike the direct description of individual building volumes in terms of morphological parameters, the three-dimensional Rectangular Voronoi Diagram (RVD) is capable of describing the rows of building volumes and the plan layout within a square parcel in a more concise form of expression. The 2D RVD is the basis for the composition of the 3D RVD, therefore, this paper firstly describes the algorithm for the generation of the 2D RVD, and then extends it to the 3D space.

Within the rectangular field, S_x and S_y are divided as shown in Fig. 6, there exists a point set P, where points

$p=(x_p, y_p)$, $p \in P$. For point p, two sets are created, which classify the other points $p_i=(x_{pi}, y_{pi})$ into two categories S_x and S_y, with the division rule:

$$\begin{cases} |x_p - x_{pi}| > |y_p - y_{pi}| \Rightarrow p_i \in S_x \\ |x_p - x_{pi}| \le |y_p - y_{pi}| \Rightarrow p_i \in S_y \end{cases} \tag{9}$$

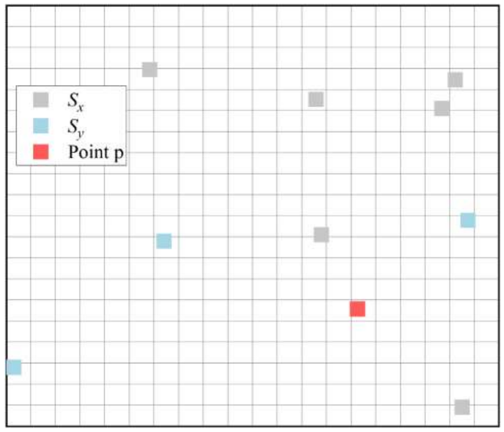


Figure 6: Division of S_x and S_y

The sideline is determined by the centre line of two points in that direction, or if there is no nearest point on that side, the boundary of the rectangular parcel on that side is taken as the sideline in that direction. The formula for determining the right-hand side line is:

$$\begin{cases} x_{right} = \frac{1}{2}\left(x_p + \min(x_{pi})\right) & \exists p_i \in S_x, x_{pi} > x_p \\ x_{right} = x_{site} & \forall p_i \in S_x, x_{pi} \le x_p \end{cases} \tag{10}$$

where x_{right} is the horizontal coordinate of the right edge, x_{site} is the horizontal coordinate of the right boundary of the rectangular field, and the other three directions can be determined in an analogous way.

Based on the above operations, the rectangle corresponding to point p can be determined in 2D space, and the entire RVD graph can be obtained by traversing the points in point set P. However, the edges of the image cannot be aligned and the planar dimensions are not modelled, so it is considered to be placed into a 2D orthogonal grid for modelling to align the rectangular edges, which also facilitates the subsequent calculations in the grid, and a 2D RVD with aligned edges of the indoor building is obtained as shown in Fig. 7.

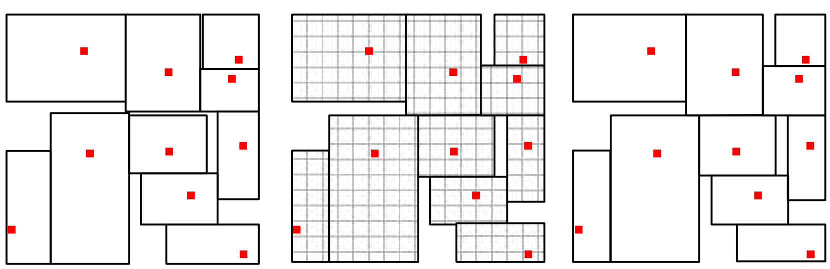


Figure 7: The 2D RVD graphics aligned with interior edge alignment

The 3D RVD has evolved somewhat from the 2D RVD, but is still considered as a planar unit. Within the 3D orthogonal grid, each point p is given a set Z of coordinates in the z-axis direction to determine the extent of its influence in the z-axis direction. For example, $Z=\{2,3,4\}$ represents that point p comes into play when RVD calculations are performed in the second, third and fourth layers of the grid, while point p can be simply ignored when calculations are performed in the remaining layers. For point p, the point set P is all points within the range of these three layers. Thus, the rectangular boundaries corresponding to point p in the x and y directions can be derived by the 2D RVD method described above. And in the z -axis direction, the boundary corresponding to point p is directly given by the boundary bounded by these three layers of the grid, yielding a three-dimensional RVD of the volume distribution as shown in Fig. 8. Similarly, the generated volumes can be further meshed in the x and y directions to obtain the edge-aligned 3D square volume combination as shown in Fig. 9.

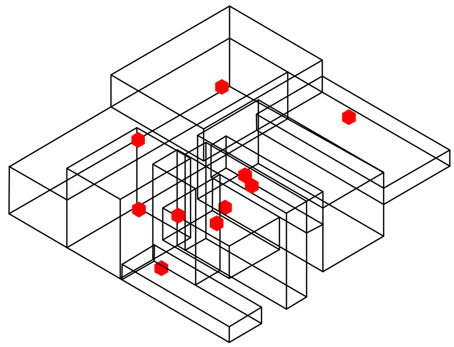


Figure 8: The 3D RVD point set P

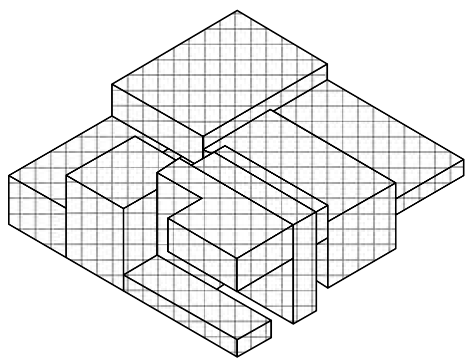


Figure 9: The 3D RVD Graphics

III. Results and discussion

This research is based on the method proposed in the previous section to develop a GAN model-based interior architecture auxiliary design system, which carries the dataset and the backend computation algorithm on the cloud server, deploys the dataset in the cloud, and uses the cloud server for computation, which enables a more lightweight client to achieve efficient and convenient auxiliary design functions. There are two main parts in the background of the system, the pre-processing and storage of scene space layout data, and the calculation of automated matching algorithms for indoor architectural styles.

III. A. Indoor scene modelling simulation

Modelling the indoor environment scene helps computational simulation and facilitates the matching of design styles using the indoor architectural assisted design system. In this paper, the indoor scene is first modelled on the Rhino platform, and on this basis, the simulation analysis and comparison of channel parameters are carried out for the empty room and the scene with objects in the room.

For the indoor scene 1 modelling effect is shown in Figure 10, scene 2 for $4\times5\times3$ m of the classic indoor space model, do not take into account in the wall accessory surface, in the ceiling uniformly distributed four LED light source, where the height of the work plane are horizontal desktop height h=1.00m.

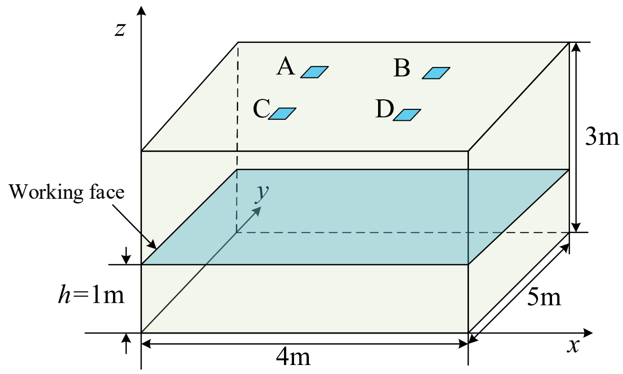
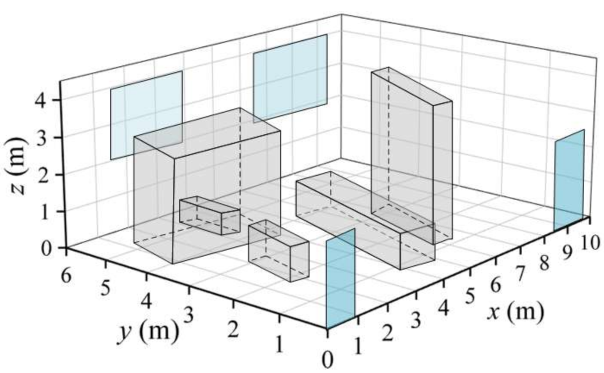
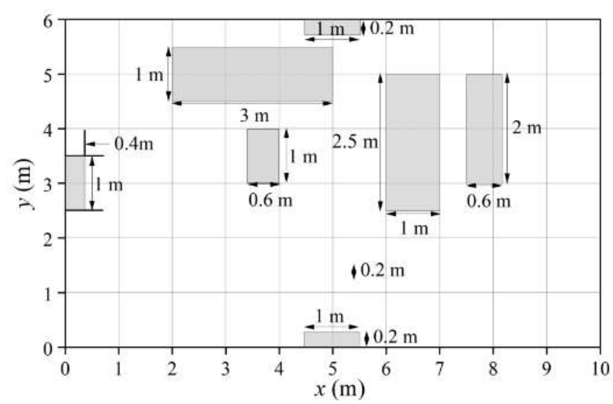


Figure 10: Modeling effect of indoor scene A

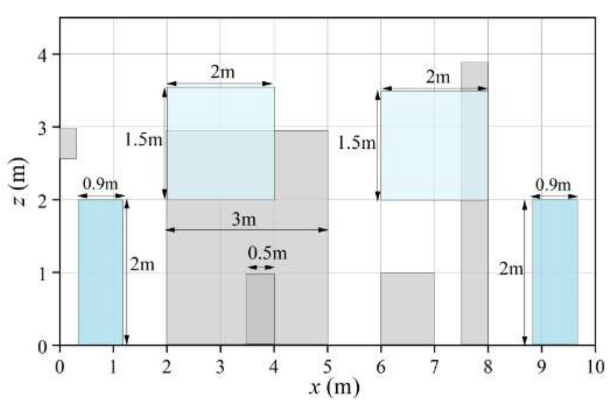
For the modelling of indoor scene 2 shown in Figure 11, scene 2 is a scene model of objects present in an indoor space of 10 × 6 × 4.6 m. There are five indoor objects, two wall appendages and two doors in this model. Fig. 11(a)~(c) shows the 3D view, top view, and main view, respectively. It is assumed that the indoor objects are made of the same material, which means that the reflection coefficients of the surfaces of the objects are the same, while the doors and the wall appendages are regarded as wall appendages with different reflection coefficients. The simulation process is limited to conventional construction design methods and common building materials, ignoring the experimental error due to material factors.



(a) Three-dimensional view



(b) Top view



(c) Main view

Figure 11: Indoor scene model (Scene 2)

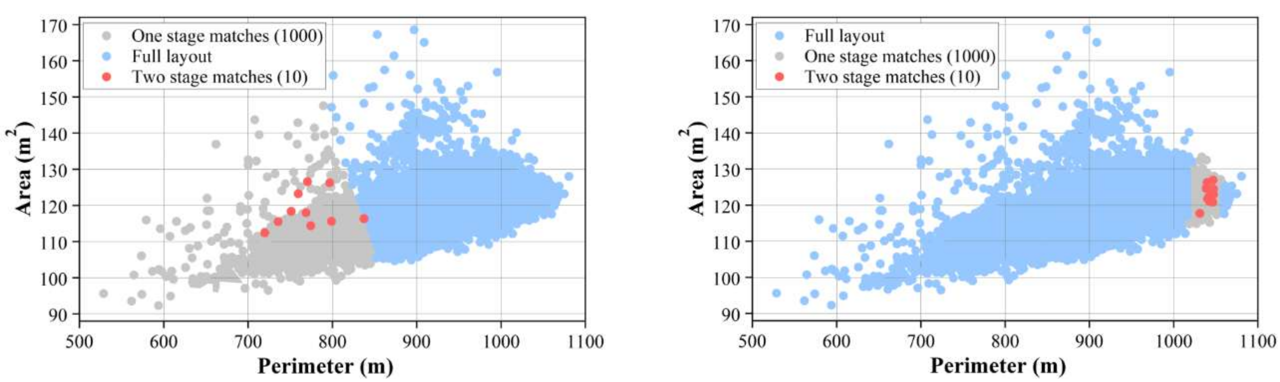
Good lighting in a building not only improves the quality of the building, but also reduces artificial lighting and saves energy. The experiment uses the DayLight Factor module of Rhino platform to calculate the daylighting coefficient, which is based on a grid with a grid subdivision of 0.5 m. The daylighting coefficient is calculated based on a fully cloudy sky environment, and the standard value of daylighting in the 'Building Lighting Design Standard GB50033-2013' is stipulated as follows. The indoor design illuminance value is set to 15000 lx , and the reference plane of civil buildings is taken to be 0.8m from the ground. Different interface materials are bound to affect the results of the lighting coefficient analysis, because this experimental study will be carried out several times to simulate the analysis, using the method of convergence to the optimum to find the relative optimal solution set, so due to the material factors of the lighting coefficient of the simulation of the calculation of the error is negligible.

Data processing and screening includes objective settings and subjective choices in the process of generating and optimising architectural design solutions, where screening rules are set objectively based on specifications and design experience. According to the formal appearance of the interior building, the architect selects alternatives subjectively based on aesthetics and design concepts. The experimental process only generates the interior building plan contour design scheme, the other three elevations can be used to pick up the interior building plan contour lines and adjust the local parameters by using the programmed GH program. In the actual design process, it is necessary to consider the relationship between the building and the city, the relationship with the surrounding environment, and at the same time, it is necessary to achieve the integrity of the building itself. Therefore, it is necessary to consider more factors to filter and compare the optimised data in the process of actual operation.

III. B. System testing

III. B. 1) Style Matching Test

Firstly, the style automation matching algorithm in the interior architectural assisted design system, is tested and evaluated. Figure 12 demonstrates the feature distribution of the style matching results for interior scenes 1 and 2 proposed in the previous modelling simulation, (a) and (b) for scene 1 and scene 2 respectively, with the first 1000 features close to the retrieval results highlighted in grey, and the first 10 optimal fine contour matching results highlighted in red. The area and perimeter vectors of the layout are computed as 2D shape features to show the feature distribution of the retrieval results performed on the dataset based on the 2D shape features of the dataset.



(a) Style matching results for interior scene 1 (b) Style matching results for interior scene 2

Figure 12: Interior building spatial layout map matching results feature distribution

Shape fitting of the constraint contours and the spatial layout of each interior building in the dataset is necessary to ensure the matching results. However, matching fitting for a large volume dataset takes a long time, and efficiency is very important for a style matching system. Therefore, in this paper, a two-stage automated matching algorithm is used to efficiently improve the matching efficiency while ensuring the retrieval quality, and the volume of retrieved data is compressed once based on shape features. The system was built on a server equipped with Intel Core i9-10900 CPU, 32GB RAM and RTX 3090Ti GPU configuration for the matching test, when the direct fitting matching, the indoor style layout matching time consumed about 10 minutes or so, while the two-stage matching method was used to consume about 18.5 seconds, which greatly improves the matching efficiency.

Since it is difficult to measure the exact shape of a floor plan based on the area perimeter feature, for example, the points of the 1000 floor plans matched in the first stage of Case 2 in Fig. 10(b) have a large distribution difference, which verifies that the fine retrieval among the 1000 candidate layouts in the second stage matches the layout with the exact shape well. From the figure, we can see that the layouts represented by neighbouring feature points have similar boundaries, while the indoor layouts represented by points farther away have large differences in boundary shapes, which proves that the matching algorithm proposed in this paper can efficiently match indoor spatial style layouts with similar contours. Since shape features are mainly used to encode the shapes of floor plans rather than their interior spatial layouts. It can also be seen that even floor plans with similar boundaries may have different interior space layouts, which ensures that the interior design style matching results have a rich variety of interior divisions for a given boundary input.

III. B. 2) Constraint fitting test

In this section application tests based on the system's functionality will be demonstrated to validate the ability of the previously proposed style automation matching algorithm to assist in the design of interior architectural spaces.

Firstly, Fig. 13 demonstrates a series of results of the system for interior space layout matching under constraints. The figure shows the retrieval results under 3 different sets of input constraints, with the left side indicating the given input polygon constraint boundaries. In the middle, the system matches appropriate interior design solutions from the dataset based on the input contour similarity based on the GAN model. The design diagrams are arranged in descending order of similarity from left to right, which shows that all the interior style design solutions matched by the system have obvious contour similarity, and the automated matching algorithm is able to match similarly shaped styles. The right side shows the matching results under the joint influence of the input contour constraints and the number of subspaces constraints, and the number of constrained subspaces ranges from 4 to 6 subspaces from left to right, which shows that the method in this paper can effectively match interior architectural design solutions that meet the contour constraints, as well as the style constraints, at the same time.

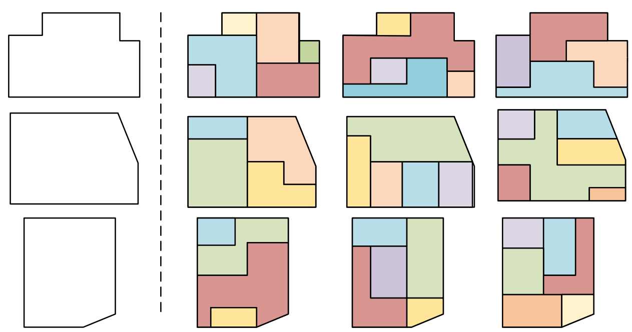


Figure 13: System matching result constraint fitting test diagram

Tests were performed to validate the results of both hard and soft fitting. Figure 14 shows six sets of interior architectural design solutions fitted with different contour constraints, with the input polygonal contours in the top left corner, the original layout plan in the bottom left corner, and the fitted generated results on the right side of each test set. Columns a and b show the synthetic results of hard boundary fitting for the design solutions obtained by system matching. From the test results, it can be seen that the hard fitting algorithm gives reasonable results for both straight line input contours and input contours in the presence of curves. As with the straight line constrained contour input, the surface boundary input has boundary pixel points for layout matching hard boundary fitting. Therefore, the fitting methods for straight-line contour inputs can also be used for surface boundary inputs. In addition, the results of the planar fitting of soft constraints are shown in column c. The semantic labelling of the outdoor scene is used to demonstrate the application of soft fitting, i.e., area planning and designing of two open space areas with a certain shape. From the test results, it can be seen that the soft-fitting approach crops the boundaries of the matched layout maps, which satisfies the hard spatial constraints of the open space and the existence of flexible planning creativity design.

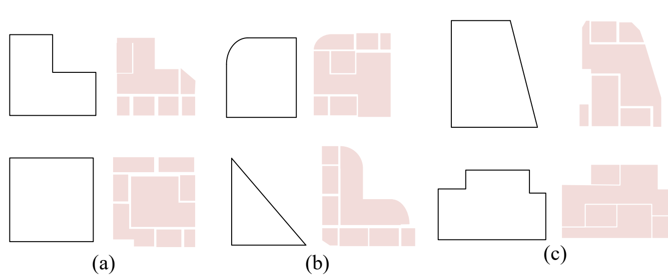


Figure 14: System hard fit and soft fit function test diagram

IV. Conclusion

Existing architectural style layout matching work is greatly limited by hard contour input conditions. In the architect's workflow, for large-scale spatial layout planning work, building shapes, plan boundaries and indoor space divisions are interacting with each other, which makes the diversity and creativity of the matching results of traditional methods limited. In this paper, we propose a GAN-modelled interior space style matching method and construct a large-scale dataset containing interior space style layouts based on this method. The dataset has different shapes of spatial contours, different internal divisions, and similar abstract shapes, which is more applicable to the automatic layout of scene space at different scales of indoor architecture, and ensures the diversity and creativity of design style matching under the constraints of softer generative conditions.

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