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Computer-Aided Design AND APPLICATIONS

Exhibition Space Layout Design via Medial Axis Transformation and Stochastic Optimization

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Abstract. The design of exhibition space is a challenging task, which is a multiple targets optimization problem. We introduce an automatic layout generation method for an exhibition hall or similar applications. The proposed method employs medial axis transfer results to divide the exhibition space into several subspaces. Each subspace is filled with appropriate exhibits according to their topological order as the initial condition. Based on the cost function for the exhibition scenario, a simulated annealing method is introduced to optimize the layout in different subspaces to generate a suitable layout. Multiple types of exhibition space were selected for experiments, and the generated results proved the effectiveness of the proposed method. According to design principles, user studies are conducted to compare the results from different methods. Compared with the existing methods, the proposed method has advantages in deployment efficiency and effectiveness, and it can be applied to various types of exhibition space.

Keywords: Computer aided design, Simulated annealing, Medial axis transfer, Layout of indoor scene, Layout of exhibition space
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1 INTRODUCTION

Exhibition space such as museums and art galleries are the most typical places for displaying historical artifacts and artworks. The layout of exhibition space plays a crucial role in the exhibition design, which includes several elements, such as the arrangement of exhibits, display forms, and space allocation. The layout directly affects the overall effect of the exhibition and the participation experience of the audience. Designing an exhibition hall is challenging, considering the exhibit layout, space division, and audience routine. Traditionally, the designer utilizes bubble diagrams to assist layout design. However, with only bubble diagrams provided, they simply utilized heuristic methods for layout design, which heavily depends on the designer's experience and intuition.

There is a lack of specialized research efforts dedicated to the automatic design of the exhibition layout in the field of CAD [29]. Most of the existing works are focus on residential or office scenes [12, 24]. The challenges of layout design for exhibition space can be concluded in the following two aspects. First, the allocation of wall space becomes even more crucial in the exhibition layout design, as illustrated in Figure 1(a). In most of the existing methods, the exhibition space is limited without making full use of the display space on the walls. When the available wall space is insufficient, how to create a new wall becomes another challenge.

Figure 1: Exhibition scene cannot be processed by previous methods. (a) Exhibition items cannot be placed if there is not enough wall. (b) Wall extension can solve the challenge. For complex outline, existing methods cannot generate the desired layout plan. (c) A messy layout based on indoor scene generation. (d) A desired layout plan.

Another challenge is that most existing methods can only produce layouts in regular spaces. Given the complex space environment, as depicted in Figure 1, existing methods struggle to identify windows or doors as they would in regular space. As a result, furniture is often placed along walls, leading to undesired layout, as depicted in Figure 1(c). To produce a layout plan similar to Figure 1(d), the space needs to be divided into different subspaces, adapting to the complex space. In summery, two key points for solving the layout design problem in exhibitions are space division and wall extension.

Aiming to enhance the efficiency of exhibition design and provide designers with preliminary exhibition plans to facilitate decision-making, we propose a novel method for the automated generation of exhibition layouts.

Given a space outline and exhibition requirements as input, our proposed method first divides the given exhibition space into subspaces and allocates suitable exhibits to them. The exhibition layout is further optimized by performing a simulated annealing algorithm, with the well-designed cost function as well as the principles in the design of the exhibition space. The contributions of this work are summarized as follows:

1) the first attempt to automatically generate layout designs specifically for exhibitions.
2) the utilization of both middle axis transfer (MAT) and a novel graphic representation for the bubble diagram to record all exhibit components and their relationships.
3) comparison experiments showing that the proposed method outperforms state-of-the-art methods, particularly for complex space planning.

2 RELATED WORK

Related works in architectural space planning, indoor scene layout design, and show design are reviewed for further discussion.

In the design of exhibition space, there are three types of visitors' route: series, radial and lobby [32]. The lobby style is typically used for short-term art or photography exhibitions. The radial style is employed for exhibitions influenced by the internal structure of the building. These are traditional styles for designing an exhibition. In modern architectural exhibition spaces, visitor routes are well-designed, and the series style is more common.

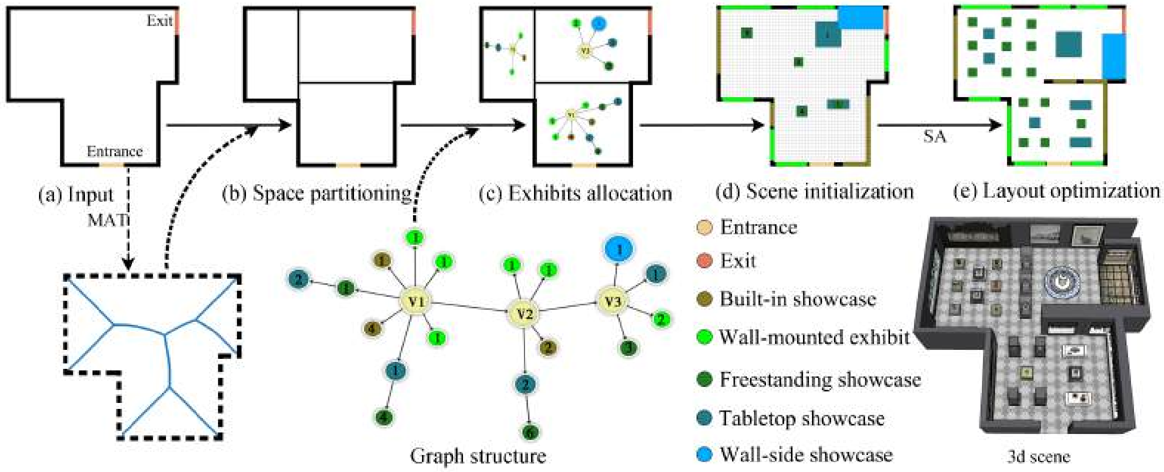


Figure 2: Processing pipeline of the proposed method. Given the requirement list and an outline as input. (a) The first step is to partition the space based on MAT. (b) The exhibits are then assigned to subspaces, and this information is recorded in a hierarchical graph structure. (c) Finally, a simulated annealing algorithm is used to optimize the layout(d).

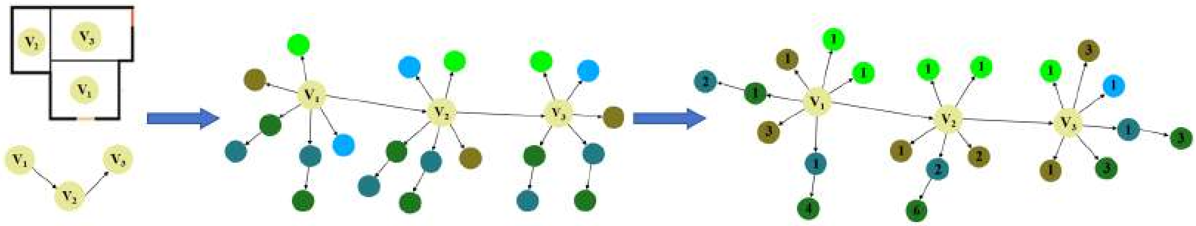


Figure 3: The process of constructing the hierarchical diagram structure, the space is divided to get the sub-space nodes V_1, V_2, V_3 of the hierarchical diagram, and branches containing various layout elements are created on each sub-node. The designer adjusts the nodes according to the demand and fills in the actual number of items needed to get the final hierarchical graph structure.

2.1 Scene Layout Design

The scene layout problem is a research hotspot in the field of computer graphics. It has been extensively studied in the fields of very large-scale integration circuit (VLSI) design, graphic design [26, 30], indoor scene design, building plan design, etc. Scene layout design can be divided into large-scale scene layout design and small-scale scene layout design according to scale. Large scale scene layouts mainly refer to urban layout design [18, 17], village layout design, etc. Such design should consider many intervention factors, such as terrain characteristics, road network, pedestrian density, lighting, etc., which have a low degree of automation. Moreover, this type of layout has low accuracy and spatial limitations, making it suitable for scenarios with low functional requirements for layout objects. The layout of medium and small-sized scenes mainly refers to the layout design of shopping malls [8], building space plan [28], indoor scene layout, etc. Simulated annealing, particle swarm optimization [6] and genetic algorithm [1] are generally used to solve the above problems. simulated annealing proven effectiveness in solving complex optimization problems that are similar in nature to exhibition space layout design challenges. This method is particularly adept at avoiding local optima and finding near-optimal solutions in a large search space, which is crucial for our application where multiple objectives and constraints are involved. With the emergence of large 3D scene datasets, such as SUNCG [21], machine learning based methods [16] have become possible. However, these method have one common major limitation, the generated results are fully based on existing datasets, which is difficult to adapt to various applications, such as the design of exhibition space.

In exhibition space layout design, graph theory provides a powerful tool to understand and optimize the spatial structure, Eades et al. [7] discusses in detail the application of graph theory to spatial topology in their study, especially in the drawing of graphs and layout optimization. Their approach transforms the complex spatial layout problem into a graph layout problem, emphasizing the cross ratio of the layout, i.e., minimizing the crossing of edges in the layout of the graph, which helps to improve the clarity of the exhibition space and the viewer's navigational experience. Battista et al. [4] delves into the problem of graph layout, providing a series of algorithms and techniques that can help designers to efficiently represent in the exhibition space and process spatial elements and their interrelationships.

2.2 Architectural Space Planning

Constraint based architectural spatial planning methods are widely used. The constraints are set for different categories, locations, and boundaries, then an optimization solution will be employed to obtain a target layout. For example, the hierarchical architecture based on the mixed integer quadratic programming (MIQP) [25] can generate a space planning diagram from coarse to fine. Another solution is to consider the adjacency relationship and size constraints of partitioned spaces [20], using graph theory and optimization techniques to construct a planning result. General optimization method for mixed constraint programming [9] converted the space into regular grids, and combines the spatial partitioning function to merge the grids to generate the planning result. Other studies also investigate the implicit design principles from existing layouts [13]. The above methods are guided by the careful set constraints among subspaces. The functional relationship of each space in the exhibition space is parallel, and there is no strict requirement for the number and size of each space, making it difficult to use effective constraint methods to complete space division.

2.3 Indoor Scene Layout Design

Currently, works in the field of indoor scene layout are focusing on residential space design, which can be divided into two categories: one is constraint-based methods, such as extracting the hierarchical and spatial relationships of various furniture objects [27], summarizing a series of constraints and encoding them into cost functions, and optimizing them through simulated annealing method. Berseth et al. [5] proposed IDOME, an interactive system for optimizing layouts in computer-aided design. Merrell et al. [11] proposed an interactive furniture layout system, which incorporated the layout guide as an item into the density function, and employed the hardware accelerated Monte Carlo sampler to quickly sample the density function to generate the layout. Bao et al. [3] used a set of strict constraints and coarse constraints to formulate constrained optimization for the representation of desired building layout. However, such methods can degrade in too many constraints and cannot generate a desired result in effective time.

Another category is machine learning-based methods, such as Wang et al. [23] proposed the first convolutional neural network-based system for synthesizing indoor scenes from scratch. Wang et al. [22] proposed PlanIT, which uses a deep graph convolutional generative model based on message passing graph convolution and image-based convolutional network modules to implement indoor scene synthesis tasks in two stages: planning stage and instantiation stage. Ritchie et al. [19] introduced a separate neural network module to predict the category, position, direction, and size of objects, iteratively inserting them into the scene to complete the synthesis of indoor scenes. These methods can only handle the challenge of placing a small group of furniture in simple room outlines. In summary, these works still remain in the manual design stage, and there is a lack of exploration in computer-aided tools for layout design of exhibition. In addition, the lack of datasets for exhibit layout makes it difficult to apply deep learning methods to the showroom layout task at this time. Compared to residential space design, the data for exhibit layout is more complex.

3 METHOD OVERVIEW

3.1 Pipeline of the Method

The framework of the proposed method consists of the following components, as depicted in Figure 2, with the outline of the exhibition space and a list of requirements; the proposed method generates a layout by following the steps of partition, initialization, and optimization. The right side of Figure 2 shows the final result. First, a parametric representation of the exhibit-related components is introduced, including exhibit items and subspaces. To maintain the relationship among exhibits and subspaces, a hierarchical graph structure is also used to provide exhibition requirements. Then, MAT is introduced to finish the space division from the outline of the exhibition space. After the space division, a uniform distribution and sequential placement strategy is introduced to determine the expansion items of each subspace and initialize the scene. Based on the cost function and constraints for the exhibition space, a simulated annealing method is employed to optimize the layout. To better arrange exhibition items along the wall, a wall extension strategy is also included. Finally, a desired layout which satisfied all user requirements and constraints can be generated.

The input to the hierarchy diagram depends on the result of spatial partitioning. As shown in Figure 3, after the spatial partitioning yields sub-space nodes, the initial hierarchical diagram structure is constructed. Subsequently, branches incorporating various layout elements are created on each sub-node, with the nodes on the branches not containing the number of exhibits. Finally, after the initial hierarchical diagram is generated, the designer adjusts the nodes according to requirements and fills in the actual number of exhibits needed, resulting in the final hierarchical diagram structure.

3.2 Parametric Representation

As depicted in Figure 4, the hierarchical graph layout is used to represent exhibits and relations among them. The exhibition layout is defined as $G_L = \{V, E\}$, where $V = \{V_i\}$ represents the set of subspaces, the initial state $V = \{V_0\}$ is the outline. The edge $E = \{e_i\}$ between V_i represents the connectivity of subspaces. Subordinate node of V_i is the exhibit $S = \{s_i\}$, which records the basic information of each exhibit in the requirements list, including basic information of the exhibit and user requirements.

Subspace representation. Figure 5(a) shows the details of each subspace, which is recorded as $V_i = \{P, W, S\}$. Here, $P = \{p_i\}$ represents the set of nodes, $W = \{w_i\}$ comprises the wall information for the subspace, and $S = \{s_i\}$ represents the exhibits within the subspace.

Exhibits representation. Figure 5(b) shows basic information about exhibits, which is recorded as $S = \{s_i\}$. Each exhibit item $s_i = \{c, \theta, w, h, t, r\}$ includes the location, angle, horizontal length, vertical length, type, and a label r that captures any additional user requirements. As depicted in Figure 5(c), the layout of specific exhibits is not universal, so different types of showcases are used instead of exhibits. They are classified as built-in showcases, freestanding showcases, wall-side showcases, wall-mounted exhibits, and

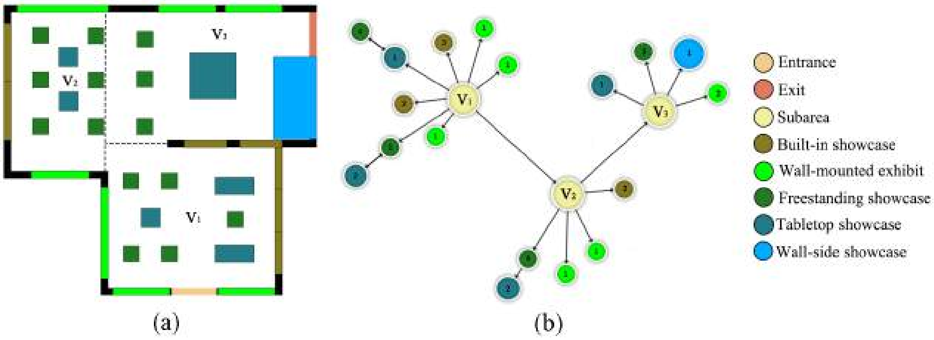


Figure 4: Hierarchical graph structure. $G_L = \{V, E\}$. (a) Exhibition layout. (b) graph structure description. V_i is subspace nodes,the child nodes of V_i are the exhibition items s_i placed within it.A branch represents a group, and the number represents the member count in the group.

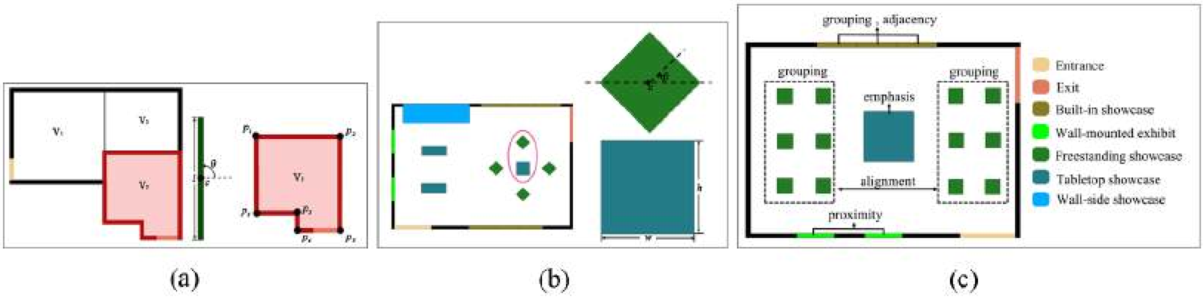


Figure 5: Parameter representation of components for exhibition. (a) subspace representation, each subspace $V_i = \{P, W, S\}$. (b) Exhibit items representation, $s_i = \{c, \theta, w, h, t, r\}$. (c) Exhibition items type and user requirement.

tabletop showcases, according to commonly used showcase types. The layout generation must meet the user requirements, which include emphasis, alignment, adjacency, proximity and grouping.

4 METHOD DESCRIPTION

4.1 Space Partitioning

MAT is a compact shape representation consisting of a series of inner tangent circle centers. It has been used in the field of 3D shape segmentation [10]. An algorithm [31] is introduced to calculate the MAT of the given outline to help with the partitioning process, as depicted in Figure 6.

MAT based partitioning. As depicted in Figure 6(a), ternary structures were extracted from the MAT. Such structures consist of at least three segments. Two of them are having monotonly increasing radius(m_1,m_2), and the other one is having constant radius(m_3). The segments m_1 and m_2 originate from adjacent endpoints of the input outline, converging at a single point, while m_3 is a segment originating from this convergence point. Along the m_3 segment, all recorded radii of the inner tangent circles fall within the specified threshold. The point p on the input outline closest to m_3 is identified, and then moved the line segment formed by the endpoints of m_1 and m_2 to p. Thus the space is divided into subspaces. This process is executed iteratively until the partition result remains unchanged or ternary structures are removed.

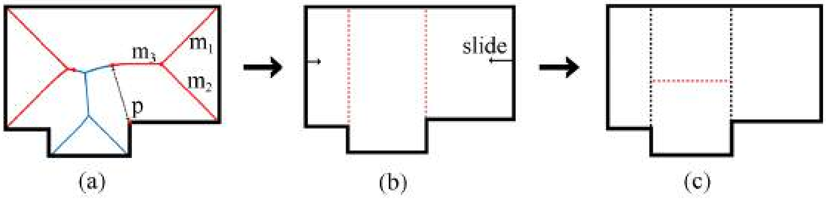


Figure 6: The steps of MAT based space division.(a) Ternary structure extraction,red segments are tenery structures, point p is the selected minimum distance reference point (b) Scan line algorithm to generate walls, move the wall segments identified by m_1,m_2 to point p (c) Area adjustment, overlong space will be divided into two blocks from the middle.

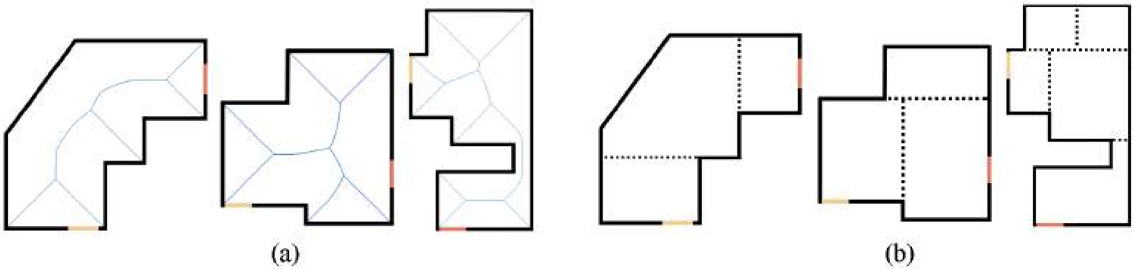


Figure 7: Division results for different outlines.(a)MAT of outline. (b) Partition results

Space adjustment. After partition, all separated subspaces needs to be filtered based on shapes. Certain subspaces which are excessively large or narrow require adjustment. Subspaces with a side length exceeding maximum threshold are divided by drawing a perpendicular line from the midpoint, as depicted in Figure 6(b). Subspaces having a side length less than the minimum threshold are merged with their adjacent space along the respective side. Figure 7 shows the spatial planning results based on the medial axis, which can divide the exhibition space into various suitable subspaces. Based on the partitioning results, fill G_L in the order from entry to exit.

4.2 Layout Initialization

Graph generation. Subspace contours and subspace nodes (e.g., v1,v2 in Fig 2) are obtained by spatially dividing the complete layout scheme, and we establish some mappings of subspace contours to subspace nodes. On the one hand, the designer can specify all the elements in the graph. On the other hand, the subspace contours obtained after space division can be searched from empirical data to approximate the subspace nodes, which can be used to form a hierarchical graph structure.

Exhibits allocation. Since the space is divided and all items to be exhibited are prepared. Each subspace V_i needs to be filled with s_i to finish the allocation. First, the wall-dependent showcases (S_1) are allocated, which include built-in showcases, wall-side showcases, and wall-mounted exhibits. Then, come to the wall-independent exhibits (S_2). Detailed steps for allocating S_1 is described in Algorithm 1, where $A(\cdot)$ is the space operator and $L(\cdot)$ is the required wall length operator, A_r and L_r are the total space of the input outline and the length of the input outline, respectively. Allocation of S_2 follows the same strategy.

Position initialization for exhibits. The initialization of positions for each exhibit relies on the relationship among exhibits and subspaces, which is maintained in G_L. As depicted in Figure 2(d), the subspaces are first transformed into uniform square grids. The length of each grid is set to 1, which is the minimum moving step

Algorithm 1: Exhibits allocation

Input: Unassigned layout, G_L; Wall-dependent showcases, S_1.
Output: Allocated layout, G_L^*.

begin
  $List_V$ = topologicalSort(G_L), $Uti_{space} = \sum_{s \in S_1} \frac{A(s)}{A_r}$, $Uti_{wall} = \sum_{s \in S_1} \frac{L(s)}{L_r}$
  Find utilization upper and lower bounds
  $[Uti_{space} - \kappa_1, Uti_{space} + \kappa_1]$, $[Uti_{wall} - \kappa_2, Uti_{wall} + \kappa_2]$
  for V_i *in* $List_V$ **do**
    if *All edges of* V_i *are longer than the minimum threshold* **then**
      for s *in* S_1 **do**
        Pre-allocate s and its associates to V_i
        Update the two utilization rates of V_i
        if *either rate is above the upper bound* **then**
          Skip s and restore parameters
        else
          Confirm to allocate s
        end if
        if *Acceptable wall utilization* **then**
          Break
        end if
      end for
    end if
  end for
end

for the optimization of exhibits. Exhibits in S_1 are placed randomly on the walls, where the exhibits in S_2 are placed at the points of the grid. It is ensured that their orientation is consistent with the grid, and a group of exhibits share the same center point.

4.3 Cost Function for Optimization

After initialization, it is necessary to find an efficient exhibition layout $G_L^* = argmin \sum_{V_i \in V} E_r(S)$, where E_r represents the weighted sum of the underlying cost functions. The optimal exhibition layout solution can be determined by minimizing this cost function. The objective of this section is to create a layout efficiently. We refer to anthropometrics and exhibition design specifications [15] to design each constraint in order to optimize the layout of the exhibition.

Non-overlap constraint. It is important to avoid overlap between any two exhibits by applying the non-overlap constraint, which is assessed by calculating the overlapping area. The cost function of the non-overlap constraint is defined as

$$E_o = \sum_{s_i, s_j \in S} \varphi\left(\varepsilon - 2\varepsilon\sigma\left(A\left(s_i \cap s_j\right)\right)\right), \varphi(x) = \frac{1}{x + \sqrt{x^2 + \tau^2}} \tag{1}$$

where ε is a constant valued at 1.5, and $\sigma(x)$ is the Sigmoid function. τ is a step increment taken as 0.05.

Boundary constraint. Proper placement of exhibits requires adherence to two basic conditions, wall-independent exhibits item should not exceed subspace boundaries, and exhibits placed against walls should not exceed wall or subspace boundaries. The boundary constraint is formulated using the same cost function as the non-overlap constraint, which represented as

$$E_b = \sum_{s \in S} \varphi \left(\varepsilon - 2\varepsilon\sigma \left(A^* \left(s \right) + \iota_1 \right) \right) \quad + \sum_{s \in S_1} \varphi \left(\varepsilon - 2\varepsilon\sigma \left(L^* \left(s \right) + \iota_2 \right) \right) \tag{2}$$

where $A^* \left(\cdot \right)$ is responsible for calculating the area of exhibits that exceed their designated subspace, and $L^* \left(\cdot \right)$ determines the length of items that extend beyond the walls upon which they rest. Furthermore, the penalty parameters ι_1 and ι_2 contribute to constraining the exhibits within their subspace. Larger values of ι_1 and ι_2 result in better constrained exhibits within their subspace.

Area constraint. Adequate open space should be preserved around the exhibits, to facilitate easy viewing and movement. Placing other exhibits in front of the wall-mounted exhibit should be avoided to prevent any obstruction of view. Additionally, it is recommended that irrelevant exhibits should not be placed next to each other. The ergonomic principle [2] stipulates that individuals require a horizontal view of 120°to achieve a comprehensive observation area. Furthermore, individuals require at least 0.93 square meters of room to move freely. Based on these principles, a square with a side length of 0.96m can be used instead of a human projection.

Area constraints are determined through the measurement of the overlapping areas between open area, and the area between any two exhibits and area between nonwall placed exhibits and the boundary of the area. The cost function for the space constraint is defined as

$$E_a = \sum_{m_i, m_j \in M_{S_2}} A \left(m_i \cap m_j \right) + \sum_{m_k \in M_{S_2}, m_l \in M_{S_1} \cup M_W} A \left(m_k \cap m_l \right) \tag{3}$$

where M_{S_2} represents the set of open spaces for objects not adjacent to walls, M_{S_1} denotes the set of open spaces for objects adjacent to walls, and M_W signifies the set of open spaces for wall segments.

Scale constraint. To prevent objects within the same group from being too far apart, it is necessary to control the aspect ratio of the enclosing box for the group. Additionally, to prevent certain exhibit from occupying too much exhibit space and restricting the space for others, the area of the enclosing box for the group must also be kept within a certain range. The cost function of the proportional constraint is denoted as

$$E_s = \sum_{b \in B_{S_2}} \varphi \left(1 - \frac{\vartheta_b}{\vartheta_{max}} \right) + \sum_{b \in B_{S_2}} \varphi \left(1 - \frac{\delta_b}{\delta_{max}} \right) \tag{4}$$

where B_S is the maximum enclosing box of the exhibit groups in the corresponding exhibit collection. ϑ_b is the aspect ratio of the group enclosing box, δ_b is the area ratio of the group enclosing box to its subspace, and ϑ_{max} and δ_{max} are the specified maximum thresholds. In the experiments, δ_{max} is set to 0.5, while different values of ϑ_{max} were used for different groups.

User requirements. Exhibit items with emphasis attributes are placed initially at the center of the subspace, and their perturbation range are restricted. Exhibit items with alignment and adjacency attributes are constrained using a set of linear equations. Specifically, the alignment attribute is achieved by controlling the same coordinate values within a single axis, and the adjacency attribute is achieved by constraining the spacing of exhibit pairs to within 0.1m.

For the proximity constraint, exhibits whose distance exceeds the threshold are subjected to a cost function defined as

$$E_p = \sum_{b_1, b_2 \in B_{S_1} \cup B_{S_2}} \gamma \left(e^{\mu (d^* - d)} - 1 \right) \tag{5}$$

where d^* represents the distance between exhibits, and d is the distance reference value. μ is the penalty parameter, with larger values of μ corresponding to stronger distance constraints on the exhibits. γ is a 0-1 parameter, where $\gamma = 1$ indicates that the exhibits are subjected to proximity constraint. d is set to 0.5m and μ to 1 in the experiments. The cost functions are weighted to form the resulting cost as follows:

$$E_r(S) = \omega_o E_o + \omega_b E_b + \omega_a E_a + \omega_s E_s + \omega_p E_p \tag{6}$$

where ω_o, ω_b, ω_a, ω_s and ω_p are the positive weights. We seek the minimum value of the cost function subject to linear equality constraints.

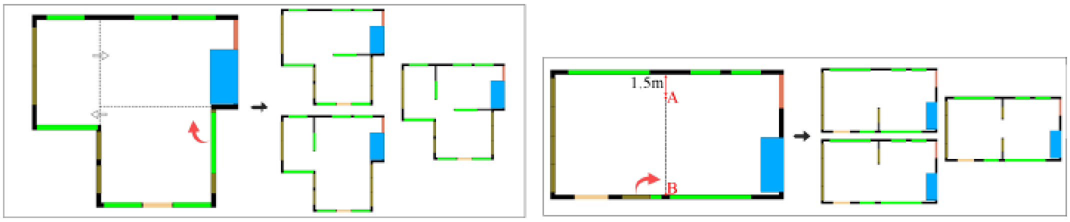
4.4 Proposed Moves

To find a better layout with less cost, the proposed method introduce a combination of local and global adjustment. Local adjustments focus on the translation and rotation of exhibits. Global adjustments focus on the exchanging of a group of exhibits. These moves are designed to explore possible changes in the arrangement.

Local adjustment. Local adjustments includes translation or rotation for an exhibit or a group of exhibits. Adjustments to a group of exhibits include moving the groups of collection S_1 along the wall direction and moving the groups in collection S_2 along the grid direction. For each exhibit in a group, it will be translated ot rotated, along with other exhibits that have a linear relationship constraint with it, to ensure that the relative position relationships of members within the group are maintained. In the experiment, the movement distance is set to at least one unit.

Global adjustment. To prevent the occurrence of local minima, the position and orientation are designed to be exchanged among groups within S_1 and S_2. In addition, there are also changes in the arrangement within the group. These swaps frequently bring about notable cost changes, thereby resulting in substantial modifications to the overall layout. In this process, if the wall is not enough to allocate exhibits. the wall generation step is used to generate new wall.

Wall generation. The result from space partitioning is used to generate a new wall segment. Walls are generated between adjacent subspaces, and the diversity of wall generation plans is enhanced through combinations. The simulated annealing algorithm is employed to select the optimal wall generation scheme. As depicted in Figure 8(a), if there is more than one edge in the subspace that can generate a wall, priority is given to the edge of the subspace that is not adjacent in topological order. If no wall exists on the selected edge, the remaining continuous available length of other wall segments in the subspace is being calculated. If the edge is the only pathway between adjacent space in the topological sequence, as depicted in Figure 8(b), a walking gap of 1.5m should be allocated. The final result removes the unused part of the generated wall segment.



(a) (b)

Figure 8: Wall generation strategy. (a) Selected the edge to generate a wall. The white arrows indicate the space order. (b) Wall generated with assigned exhibit.

5 EXPERIMENT

5.1 Experiment Setup

The combination of various input outlines and exhibits are collected and investigated to generate exhibition scenes. In the experiments, the configuration of the work station is, CPU Xeon W-2235 3.80 GHz, Memory 64GB, Display card GeForce RTX3060 12GB.

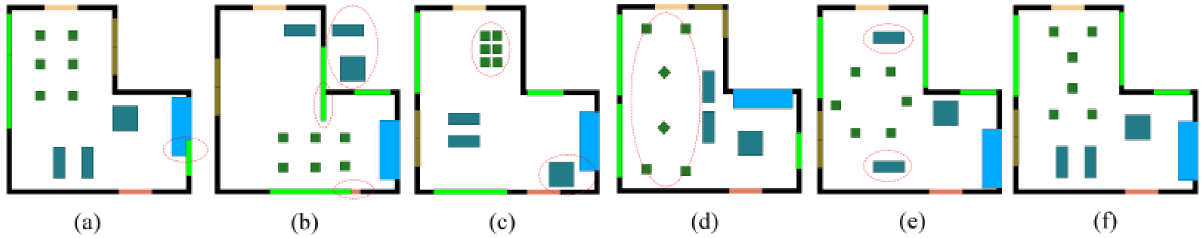


Figure 9: The importance of individual constraints in the cost function. (a) Overlap of exhibit items (b) Out of bounds (c) Screening between exhibit items (d) Excessive size (e) Excessive spacing (f) Suitable layout

In the experiment, the values of the parameters are: $\omega_o = \omega_b = \omega_a = 1.0$, $\omega_s = 10.0$ and $\omega_p = 0.5$. Each cost term is necessary, and the impact of omitting individual cost terms is demonstrated in Figure 9. In the simulated annealing algorithm, the initial temperature T is set to 1000°C, the declining rate α is 0.99, and the number of iterations is 1000. Details of the steps are shown in Algorithm 2.

Algorithm 2: Simulated Annealing

Input: Initialized layout G_L; Initial Temperature T; Minimum Temperature T_{min}; Declining rate α.
Output: Optimized layout, G_L^*.

begin
  $Score_0 = CompConstraint(G_L)$
  while T >T_{min} **do**
    $G_L = createNewLayout(G_L)$
    if *OutOfOutline*(G_L) **then**
      Restore to the previous state
    end if
    $Score_{new} = CompConstraint(G_L)$; $\beta = Score_{new} - Score_0$
    Rand = $getRand()$
    if β *>0 and exp(-* β */ T) >Rand* **then**
      Restore the previous state
    end if
    T = α·T; $Score_0 = Score_{new}$
  end while
  $G_L^* = addWall(G_L)$
end

The results of the proposed method are depicted in Figure 10, and the variation in cost for the first scene is shown in Figure 11. Figure 10(a) displays the layout results for identical user requirements and input outline. Figure 10(b) illustrates the results for identical user requirements but different input outlines. In contrast, Figure 10(c) demonstrates the results for the same input outline but varying user requirements. Different

Table 1: For each given example, the number of objects, the value of each constraint, the value of total constraints, and execution time are given. The third column shows the numbers of $\omega_o E_o$, $\omega_b E_b$, $\omega_a E_a$, $\omega_s E_s$, and $\omega_p E_p$.

Figure	Objects	Cost	$E_r(S)$	Time(s)
Fig. 2 (e)	36	0,26,56,14,0	96	42.35
Fig. 10 (a) upper	26	0,23,42,17,0	82	34.68
Fig. 10 (a) middle	26	0,20,38,22,0	80	32.45
Fig. 10 (a) lower	26	0,22,35,19,0	76	38.23
Fig. 10 (b) upper	50	0,72,44,28,37	181	96.53
Fig. 10 (b) middle	50	0,69,43,14,33	159	103.06
Fig. 10 (b) lower	50	0,46,52,49,27	174	115.89
Fig. 10 (c) upper	40	0,28,32,60,21	141	47.12
Fig. 10 (c) middle	47	0,43,37,21,49	150	76.08
Fig. 10 (c) lower	42	0,32,28,50,20	130	55.67
Fig. 12 (b) upper	40	0,40,32,21,33	126	54.42
Fig. 12 (b) middle	19	0,0,29,13,0	42	26.58
Fig. 12 (b) lower	65	0,66,46,59,55	226	144.64

layout arrangements were generated based on the combination of the requirement list and input outline, demonstrating its adaptivity. The performance of the proposed algorithm is shown in Table 1.

5.2 Comparison

As discussed before, there is few existing data set with well labeled tags for the generation of layout for exhibition space. So examples from real exhibitions are needed, some criteria are also need to be adopt for comparison. In order to better evaluate the proposed method with existing ones, both quantity evaluation and user study are introduced.

Participants. To evaluate the effectiveness of the proposed method, 12 volunteers specializing in architectural art were trained and divided into 3 groups. The requirement list is extracted from show in museums and each person is assigned with a layout task without interfering with each other. People in the same group were given the same input, and they finished the work for 12 exhibition layouts in 3 groups. For comparison, the cost function from Merrell [11] was introduced for evaluation. It starts by using the space division result from the proposed method for initialization and then applying a simulated annealing algorithm with parameters aligned to our experiments. The method of Zhang [28] is also implemented for comparison. First, a set of layout patterns is used to be applied to the exhibition layout. Then, the MH algorithm was adopted for iterative optimization. Zhang's method is adopt to generate new layouts for exhibition space, which involves adding or removing patterns, translating or rotating existing patterns, and modifying internal parameters within the patterns.

VR task and user study. The above three sets of generated results were randomly ordered and presented to another group of participants for a subjective evaluation experiment. The participants, totaling 20 individuals from diverse backgrounds, consisted of undergraduate and graduate students majoring in architecture,

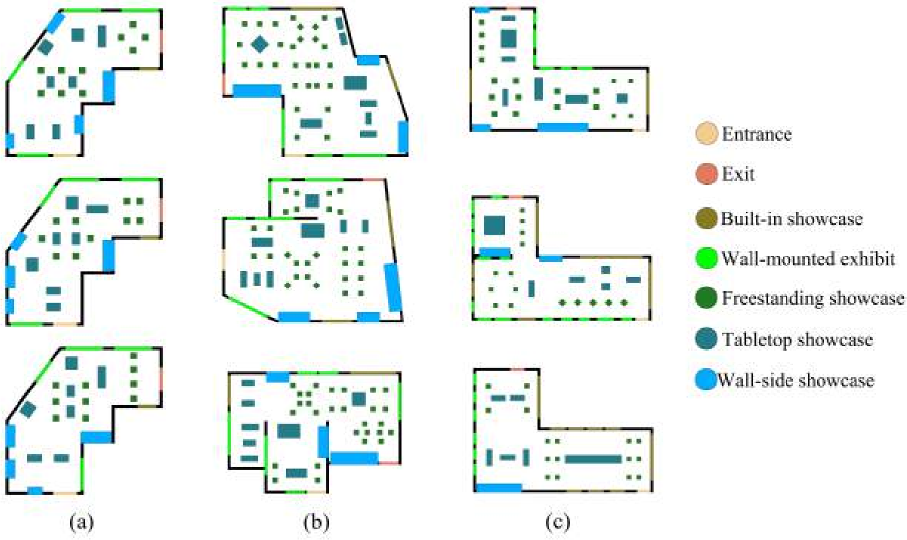


Figure 10: Various results from the proposed method. (a) Same input outline and requirement list. (b) Different input outline and same requirement list. (c) Same input outline and different requirement list.

computer science and others.

The experiment included two types of scenes: a museum scene and an art exhibition scene. As depicted in Figure 13, each scene had three layout schemes: a real layout, a layout generated by our method, and a layout generated by Merrell's method. 3D scenes are generated based on these three layouts and placed identical exhibits in the corresponding positions of the display cases to ensure consistency in the experiment.

All participants were asked to wear VR headsets and freely explore the generated scenes, using XR controllers to interact with the scenes, as depicted in Figure 14. After completing the exploration, participants removed the headsets and rated the scenes according to the following two aspects. Scene pass-ability (P.A.), evaluating the ease of movement and flow within the scene. Display case layout rationality(L.R.), assessing the logical and reasonable arrangement of the display cases, including whether the exhibits were orderly placed and the spacing between display cases was appropriate. The ratings were conducted using a 10-point Likert scale

Figure 11: The variation in cost for the top scene of Figure 10(a). The x-axis is the number of iterations, and the y-axis is the cost value.

Figure 12: Three exhibition layouts for comparison. Tags ① to ⑪ are six kinds of not desired results.① The viewing areas of exhibits are overlapping.② Unreasonable space occupation.③ An important exhibit is not placed in the right space. ④ Exhibits are placed in the too narrow space. ⑤, ⑧,⑩,⑪ The exhibits are overlapping. ⑥, ⑦ Exhibits in the same group are not parallel. ⑨ Exhibits blocked the walking space.

(from 0: extremely unreasonable to 10: very reasonable). To ensure the fairness of the ratings, participants were not informed of the scene generation method during the rating process.

After each rating session, participants rested for 30 seconds to avoid visual fatigue and psychological bias before proceeding to the next scene test. The entire experimental process was designed in a random order to prevent the order of ratings from influencing the results.

Participants can observe the reasonableness of the position of the exhibits during the tour. And they can adjust the position of unreasonable exhibits through the control of VR handle.

Evaluation metrics. The criteria $aesthetic$, $distance$ and $uniformity$ metrics were used to quantitatively evaluate real designs, artificial results, Merrell et al [11], Zhang [28] and results from the proposed method. The $aesthetic$ metric(Aest.), as referenced in [14], aims to reflect the alignment and combination effects among interface elements. This index is quantitatively calculated by counting the number of alignment points in both horizontal and vertical directions. Its mathematical expression is as follows:

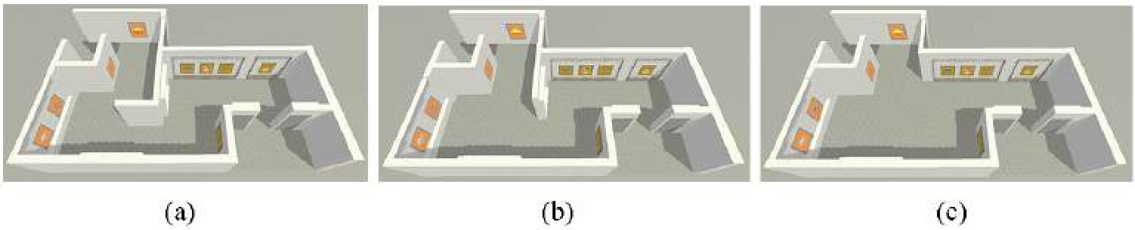


Figure 13: Layout result of art exhibition from three different methods.

Figure 14: Participants wearing virtual reality (VR) devices freely roam in a virtual scene, with the right side displaying the view seen by the users through the device.

$$T_a = \frac{3}{n_{vap} + n_{hap} + n} \tag{7}$$

where n_{vap} is the number of vertical alignment points, n_{hap} is the number of horizontal alignment points, and n is the number of layout objects.

The $distance$ metric(Dist.) measures the reasonableness of the spacing distance, is defined as

$$T_d = \sum_{a,b \in S} \varrho \left| l^* - l \right| \tag{8}$$

where l^* represents the distance between any two exhibits, l is the width needed for one person's movement, set at 1 meter [2]. ϱ is a binary variable, taking the value 1 when $l^* - l < 0$, and 0 otherwise.

The $uniformity$ metric(Unif.) is designed to measure the even distribution of interface elements within the overall layout. Ideally, each layout object should be evenly dispersed across various subspaces, avoiding situations where parts of the layout are excessively dense or sparse. The $uniformity$ metric is defined as

$$T_u = \frac{\sum_{v \in V} \left(|U^v_{area} - U_{area}| + |U^v_{wall} - U_{wall}| \right)}{N_V} \tag{9}$$

where N_V represents the number of subspaces, U^v_{area} is subspace area utilization,and U^v_{wall} is the subspace wall utilization. A smaller $uniformity$ metric value indicates a more uniform exhibit distribution.

Result and discussion. Table 2 presents a comparison of the average metric values and the time cost for 3 groups. The result of the proposed method showed similarities to the real layout, and all metrics outperformed the artificial results. As depicted in Figure 12, three sets of layout results illustrate the advantages of the

Table 2: Comparison of average evaluation indicators, **bold** font indicates the best results

Type	Aest.↓	Dist.(m)↓	Unif.($\%$)↓	Time(s)↓
Real layout	0.043	**0.46**	22.30	–
Artificial	0.045	3.58	36.76	763.08
Merrell's [11]	0.061	6.74	32.46	104.82
Zhang's [28]	0.041	4.02	22.64	84.32
Ours	**0.038**	0.58	**17.64**	**75.21**

proposed method in a more intuitive way. Other methods tend to exhibit overlapping phenomena along walls in their layout.

Table 2 presents a comparison of the average metric values and the time cost for 3 groups. The result of the proposed method showed similarities to the real layout, and all metrics outperformed the artificial results. As depicted in Figure 12, three sets of layout results illustrate the advantages of the proposed method in a more intuitive way. Other methods tend to exhibit overlapping phenomena along walls in their layout.

Table 3: Comparison of scores given by participants

Type		Real layout	Merrell's [11]	Ours
Museum	P.A.	**8.2**	7.4	8.1
	L.R.	8.3	7.6	**8.4**
Art	P.A.	8.5	8.6	**8.7**
	L.R.	8.2	8.0	**8.4**

As shown in Table 3, the scores given by participants demonstrate that the results made it difficult for them to distinguish between real and generated result, thus validating the rationality of the proposed method. During the VR experiment, the time of each participant spent near four designated display cases are recorded, as well as the total exploration time for the space, as depicted in Table 4. It can be concluded that the layout generated from the proposed method can make visitors spend more time for these target exhibits. And it also means that the layout make visitors easily to locate the exhibits rather than disorientated in the space.

Table 4: Comparison of collected results from user study

Type		Real layout(s)	Ratio	Merrell's [11](s)	Ratio	Ours(s)	Ratio
Museum	Site1	32.6	9.4%	2.7	1.0%	20.7	6.9%
	Site2	28.0	8.0%	25.0	9.6%	24.2	8.3%
	Site3	18.2	5.2%	13.8	5.3%	26.0	8.8%
	Site4	48.6	14.0%	40.7	15.8%	51.1	17.6%
	Total time	347.2	36.7%	256.2	32.1%	290.3	**42.0%**
Art	Site1	23.4	8.8%	20.4	11.1%	19.4	8.1%
	Site2	31.2	11.7%	10.0	5.4%	26.9	11.3%
	Site3	33.0	12.3%	7.8	4.2%	21.3	8.9%
	Site4	19.3	7.2%	19.7	10.7%	33.3	14.0%
	Total time	266.8	40.0%	183.8	31.5%	238.4	**42.3%**

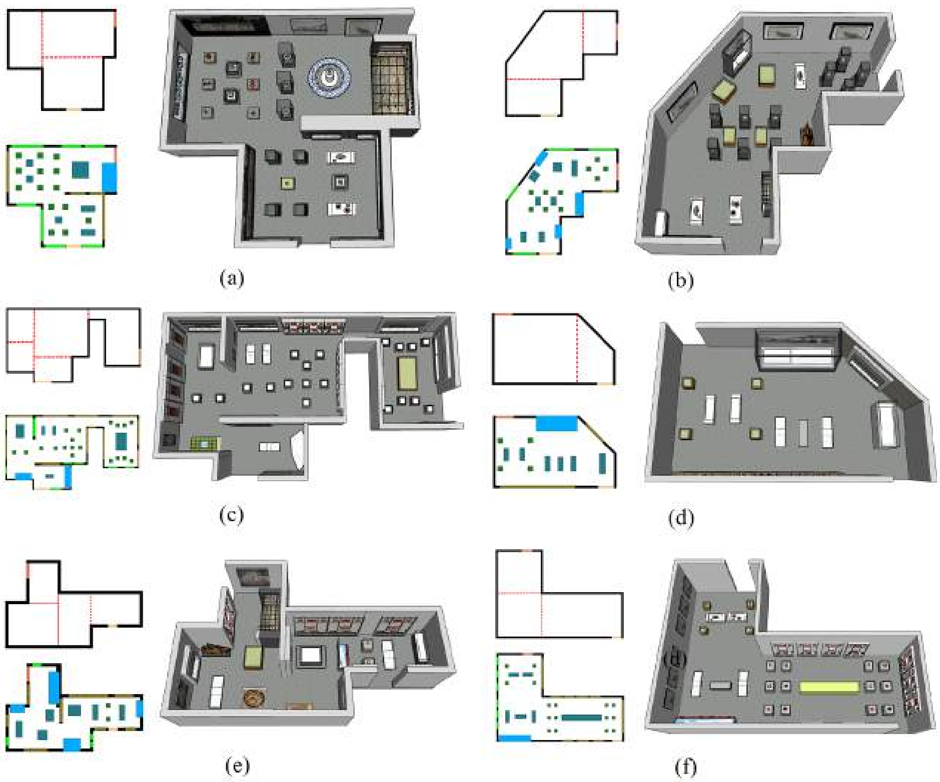


Figure 15: The proposed method generated layouts for six different exhibition spaces.

6 CONCLUSIONS

Quality exhibition is becoming more and more important in daily life. A well designed tool will help designers to verify and present their ideas. We propose a layout design method via MAT and stochastic optimization for exhibition space or similar applications. The proposed method employ results from MAT to divide the exhibition space into several separated subspaces. Each subspace is filled with suitable exhibition items based on the ratio of completeness as the initial status. Based on the energy function and linear constraints for the exhibition scene, simulated annealing method is introduced to optimize the layout. Multiple types of exhibition space were selected for experiments, and the generated results proved the effectiveness of the proposed method, as depicted in Figure 15. For different requirements, exhibition space can be divided into subspaces with various layout, which demonstrated the diversity of the proposed method. However, the proposed method has some limitations in that it requires many parameter settings at the input stage, and strong constraints such as alignment cannot be achieved. In the future, we will use our method to generate datasets and continue to explore exhibition layouts using deep learning algorithms.

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