2024 IEEE Conference Virtual Reality and 3D User Interfaces (VR) | 979-8-3503-7402-5/24/$31.00 ©2024 IEEE | DOI: 10.1109/VR58804.2024.00050

Automatic Indoor Lighting Generation Driven by Human Activity Learned from Virtual Experience

Jingjing Liu*
Zhejiang University
Beijing Huairou Laborotory

Jianwen Lou†
Zhejiang University

✉Youyi Zheng‡
Zhejiang University

✉Kun Zhou§
Zhejiang University



Figure 1: Our approach learns the user's habitual behavior (e.g., reading while lying in bed) in an indoor scene from his/her immersive virtual experience (left). The learned behavioral data are applied to generate an optimized lighting solution (right).

Abstract

A good indoor lighting solution should fit with people's habitual activity and have a low energy cost. However, it's challenging to capture and model human activity in reality due to its high complexity, let alone incorporating it into lighting planning. As a result, indoor lighting designing still relies on professional's hands, which is laborious and inefficient. To solve this problem, we propose a novel framework for automatic indoor lighting generation driven by human activity learned from virtual experience. We first harnesses Virtual Reality to simulate and model the user's daily activities within an indoor scene, and then devises a robust objective function which encompasses multiple activity-driven cost terms for lighting layout optimization. With the objective function and the collected user behavioral data, such as trajectory and head pose, an optimization algorithm is applied to search for the optimal solution. Experiments under different indoor scenes demonstrate that the proposed method can generate lighting solutions that meet personalized behavioral needs in an energy-economic way, which are competitive against those designed by professionals.

Keywords: Human-centered Design, Virtual Reality, Interior Design, Remodeling.

1 Introduction

Research shows that people spend up to 18 hours indoor on average every day [12]. Ensuring optimal indoor lighting is thus essential for maintaining high living and working standards. In indoor lighting designing, human factors such as visual performance and visual comfort are at a central position, which has been delineated in lighting standards set by the International Commission on Illumination (CIE) [6]. Common standards include that the bedroom needs soft light to protect sleep, while the light in a study room should be sufficient to enable activities like reading and writing. However, such rules only apply to general scenarios and can hardly meet personalized demands. For example, some people prefer to work in the dining room rather than in the study, which could cause significant changes in the lighting layout of the corresponding functional area. Furthermore, additional factors, such as energy consumption and aesthetic considerations, exacerbate the complexity of the issue. As a result, designing indoor lighting properly is nontrivial, and it still relies on experienced professionals at present [7, 23], which is labor-intensive and time-consuming.

Recent studies resort to deep learning to achieve automatic generation of indoor lighting layout. The paradigm [5, 37] utilizes neural networks to model lighting's impact on key factors like space usage, aesthetics, and visual comfort. It achieves this by learning from numerous manually crafted lighting solutions and then optimizes an objective function based on lighting standards and predefined assumptions related to these factors. Despite their efficiency, existing methods neglect the effect of human activity when planning lighting, hence they yield solutions that are fixed to the indoor space layout and cannot fit with different occupants' needs. In reality, people move around the scene and interact with objects following their unique routines. This has posed a big challenge to capture and model human activities due to the intricacy of indoor scene and the variety of activity, thereby seriously obstructing the integration of human activity into lighting scheming algorithms. In comparison to recording real-life activities, capturing and modeling various activities in a virtual environment [27, 28] proves to be more feasible. Virtual Reality (VR) technology offers a cost-effective and controlled method for simulating real-world environments and immersive user-environment interactions. This capability facilitates efficient human data collection, paving a promising pathway to integrate human activity into lighting layout generation.

In this paper, we leverage virtual reality to simulate and model a person's daily activities within an indoor scene, and devise a robust objective function to optimize lighting layout with the collected behavioral data. Specifically, we build up high-fidelity virtual indoor scenes and let the user to immersively interact with the virtual scene using an HMD and a corresponding gamepad. The user's core

*e-mail: 12221107@zju.edu.cn
†e-mail: jianwen.lou@zju.edu.cn
‡corresponding author, e-mail: youyizheng@zju.edu.cn
§corresponding author, e-mail: kunzhou@zju.edu.cn

979-8-3503-7402-5/24/$31.00 ©2024 IEEE
DOI 10.1109/VR58804.2024.00050

Authorized licensed use limited to: Zhejiang University. Downloaded on November 06,2026 at 06:13:36 UTC from IEEE Xplore. Restrictions apply.

behavioral data including moving trajectory, gaze and head pose are simultaneously recorded. These data are then utilized to construct multiple novel human-centered cost terms to measure the degree of alignment between the received illumination intensity and the recommended one when the user is doing an activity, if lamps are placed on the user's moving pathway, and the energy consumption, etc. Additional cost terms on illumination smoothness over the space and lighting layout symmetry are further developed to strengthen the objective function. Finally, we apply an optimization algorithm to search for the optimal layout from a roughly-initialized state. We have evaluated the proposed method under different indoor scenes and validated its results with a rigorous user study.

The major contributions of this work are summarized as follows:

- We propose a novel framework for automatic indoor lighting generation driven by human activity data learned from immersive virtual experience.
- We devise a novel objective function for lighting optimization, which incorporates constraints on several crucial factors including human activity, energy consumption, illumination's spatial smoothness, and lighting layout symmetry.
- We conduct qualitative and quantitative experiments on multiple scenarios to validate the effectiveness of the proposed approach. The results show that our approach is able to generate comfortable and energy-saving lighting solutions.

2 Related Work

We provide a succinct overview of the aspects of personalized interior design and lighting evaluation. Additionally, we review previous works in human behavior modeling, which are highly related to our problem [15, 22, 36, 48].

2.1 Personalized Interior Design

There are many elements to consider in interior design, including furniture layout [32], materials [8], style [17] and so on, which affect the user's perception and experience. Different people have different preferences, so the same design may be evaluated differently by different users. In order to satisfy users' personalized needs, designers carry out user-centered design [25]. Some traditional methods are time-consuming in practice, include questionnaires [33], face-to-face interviews [2] and focus groups [1].

In recent years, deep learning has begun to be applied in various industries, including the design field. Xin et al. proposed an industrial furniture layout dataset that combines the individual needs of the owners, in which each furniture automatic layout sample corresponds to the individual needs of the owners [11]. Taking an empty floor plan and personalized needs as input, some jobs apply neural networks to automatically select furniture and automatically lay out furniture in indoor scenes to meet personalized needs [26, 47]. In addition, there are some studies on capturing users' personal habits and optimizing furniture layout [28] and object layout [29] through VR devices, which take into account the human consumption caused by user habits caused by layout. N. Vitsas [43] proposed a method to optimize furniture arrangement by combining lighting targets with functional constraints. Among other design elements, Yu et al. propose a method for texture assignment and colorization of virtual scenes based on user mood [38].

In the previous personalized interior design, little attention was paid to lighting, which is also an important part of interior design. Different from the previous personalized interior design, we propose a framework to optimize the indoor light source layout based on the user's personal habits, which makes the user feel comfortable.

2.2 Lighting Standards Assessment

Good lighting can not only illuminate a space, but also effectively prevent fatigue and accidents. In the field of interior design, there are many effective methods for evaluating indoor lighting effects [10, 41]. Some approaches suggest following standard practical guidelines in interior layout design [23, 42]. Others use indicators such as illuminance, brightness and color rendering to measure the effectiveness of lighting design. Illuminance measures the amount of light falling on a surface, while luminance measures the amount of light reflected from the surface [16]. Color rendering measures the ability of a light source to accurately render colors in its environment [19]. The combination of these metrics can provide a comprehensive assessment of lighting layouts and help designers identify areas for improvement, but these are not intuitive to the non-specialist.

Nowadays, some commercial software has emerged to simulate and visualize lighting layouts, such as DiaLux [31], SketchUp [9], and LucidShape. Guerry et al. [18] used DiaLux to optimize the luminous environment. PG Ellis [13] designed an energy design plugin for SketchUp. These applications leverage computer-generated models to simulate lighting conditions and visually represent the lighting layout. Designers can efficiently experiment with different lighting scenarios, assessing both suitable layouts and energy consumption [24, 30]. However, these evaluation methods still measure the lighting layout from the perspective of designers, without taking into account the evaluation of the lighting by the people who use the space in the scene activities in real. Considering people's feelings in the environment, some assessments incorporate ergonomic indicators, such as the Unified Glare Rating (UGR) [3], which quantifies discomfort caused by glare in the lighting environment.

In this paper, we design a loss function to evaluate interior design lighting layout, including indoor lighting evaluation criteria, energy consumption evaluation and human experience evaluation. This lighting evaluation aims to provide users with a personalized and adaptive lighting environment, presenting a promising avenue for future research in lighting assessment.

2.3 Human Behavior Modeling

According to the user's behavior sequence over a period of time, user portraits can be described, which is very helpful for improving many estimated effects. User behavior can be obtained through many aspects, such as system collection, video detection, etc. In the early days, some people regarded user historical behaviors as an unordered collection and then established a behavior pool. Someone proposed to flexibly capture the connection between global and local behaviors based on the Attention mechanism [14, 49]. Others propose to regard user behavior as a sequence with time attributes and use networks such as RNN and LSTN to extract behaviors [20, 44]. Accurate user behavior modeling can assist the model to better understand the key links of users.

With the development of virtual reality, virtual devices can accurately collect user operation data to model human behavior. Given the immersive nature of virtual reality, some studies use virtual devices (such as HTC Vive) to immerse people in the virtual environment and then collect data to model user behavior [28, 45]. Based on behavioral data that is close to reality, users' operating habits can be corrected in a targeted manner, such as driving, surgery [4], etc. In addition, Peck et al. studied the redirection problem of walking trajectories, allowing users to roam better in the scene [35, 40]. These methods have consolidated and verified the effectiveness of modeling user behavior in virtual reality.

In this paper, we propose to use an HMD and a corresponding gamepad to capture and model users' interactive behaviors, which is then employed for optimizing indoor lighting layouts. Our approach ensures that the resulting lighting layout is better aligned with the user's personalized requirements, addressing both energy consumption control and user experience.

Authorized licensed use limited to: Zhejiang University. Downloaded on November 06,2026 at 06:13:36 UTC from IEEE Xplore. Restrictions apply.

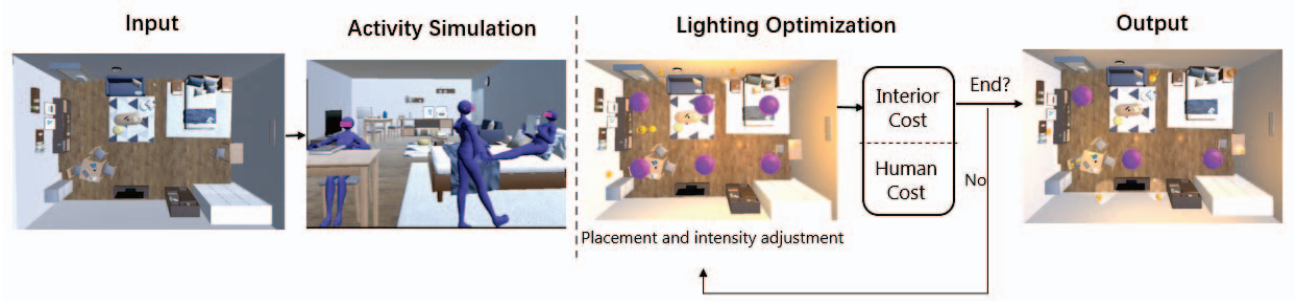


Figure 2: Overview. Given an indoor space layout (Input), the users wear HMD and hold the corresponding gamepad to complete some daily tasks in the virtual scene, just as they do in real life. Their moving trajectory, gaze and head pose are recorded during virtual experiencing (Activity Simulation). The collected behavioral data are utilized to construct novel cost terms to guide an optimization process (Lighting Optimization), which iteratively updates the light's position, intensity and direction to achieve a comfortable and energy-efficient lighting solution (Output).

3 Overview

Given an initial scene, our approach aims to find an optimal lighting configuration $L*$ that conforms to user habits while saving energy. The user habits refer to the activities that users frequently do in the scene, such as interactive objects, interactive locations, orientation of head posture, trajectory, and so on. Energy refers to the consumption of light energy provided for user activities. Lamps are available in various types and in varying numbers. However, the upper limit of the number of different lamps is directly related to the type and area of the furniture. For example, there is at most one bedside lamp on a bedside table. We specified the maximum number of various lights according to the type and area of furniture in the scene. The specific calculation process can be found in the supplementary materials.

Assuming that there are M pieces of furniture in the initial scene and the maximum number of placeable lights is N, where each light belongs to a piece of furniture in the scene. A complete indoor lighting layout is denoted as L, which includes the position (x_i, y_i, z_i), the direction o_i, and the intensity value of each light I_i. Therefore, $L = \{l_i | l_i = (x_i, y_i, z_i, o_i, I_i)\}$, where $i \in \{1, 2, \cdots, N\}$. To achieve our goal, our framework consists of two stages: activity simulation and lighting layout optimization, which is shown in Fig 2.

Activity Simulation. With an Oculus helmet and a gamepad, the user is immersed in a virtual scene with even and uniform lighting. Users control directions and select some actions through the gamepad to perform daily activities. We collect activity data in the virtual environment to model user behavior, which is then used to optimize interior lighting layouts. We will discuss the details in Section 5.

Lighting Layout Optimization. Lighting is divided into general lighting and local lighting. General lights provide overall illumination of the room, while local lights illuminate specific activity areas, which are described in Section 4. Based on the initialization of indoor lighting, we regard indoor lighting layout as an optimization process. A cost function is designed in the optimizer to generate a personalized lighting layout solution suitable for the user. Lighting standards, user behavior and energy consumption are combined to assess the quality of indoor lighting layouts. We will discuss the details in Section 6.

4 Light Types

There are various types of lamps in indoor scene. However, they are divided into seven categories functionally: floor lamps, ceiling lamps, pendant lamps, bedside lamps, cabinet lamps, table lamps, and wall lamps. As shown in Fig.3, we built a lighting library for indoor lighting design.

The light of indoor lighting is divided into general light and local light in effect. Among them, the general light ensures the overall brightness of the environment, which is provided by ceiling lights; the local light illuminates the specific area of each activity, which is provided by other types of lights.



Figure 3: Lights used in this work. (a) Floor lamp. (b) Ceiling lamp. (c) Pendant lamp. (d) Bedside lamp. (e) Cabinet lamp. (f) Table lamp. (g) Wall lamp.

4.1 General Light

General light mainly makes the overall uniform lighting in the space. Each space has a different recommended illuminance level according to different regional functions [34]. Taking the average recommended illumination value of the entire space as the standard, the number of ceiling lamps is calculated by the following formula.

$$N_{ceil} = \frac{I_{rec}}{I_{ceil}} \times S. \tag{1}$$

where N_{ceil} is the number of ceiling lamps, I_{rec} is the recommended illuminance value and I_{ceil} is the illumination value provided by the ceiling lamp, which is the same as the illumination of a general ceiling lamp in the real environment. S is the area of scene.

During initial placement, ceiling lights are placed at equal intervals in the room. In the optimization of lighting layout, the position change of local lights will also affect the position of ceiling lamps, especially pendant lamps. They are all mounted on the ceiling. If the ceiling lamp is too close to the pendant lamp, somewhere in the room will become too bright and strong shadows will be cast around the pendant lamp. Therefore, when the position of the ceiling lamp is too close to the position of the pendant lamp, we will

Authorized licensed use limited to: Zhejiang University. Downloaded on November 06,2026 at 06:13:36 UTC from IEEE Xplore. Restrictions apply.

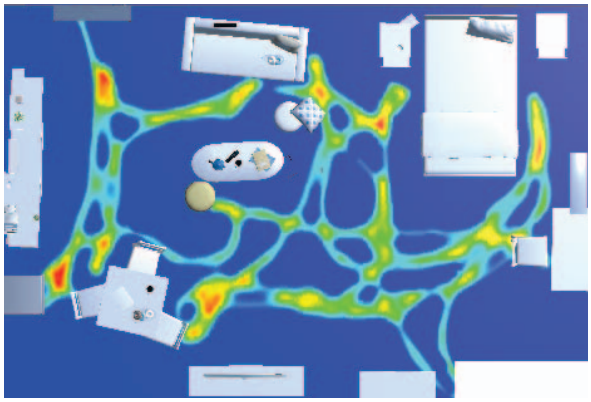


Figure 4: An example of the user's moving trajectory. We use heatmap to visualize the time the user spend on a location. The redder the color, the longer the user interacts with the scene on that point.



Figure 5: The position distribution when the user interacts with scene components. The redder the color, the bigger the probability of the user is doing an activity in that area.

move the ceiling light. If the pendant lamp is moved further away from the ceiling lamp, the ceiling lamp will be restored. During the optimization process, the ceiling lamp is moved along the ceiling and is removed when the intensity is 0.

4.2 Local Light

Local lights provide illumination for the spatial areas of specific activity, which are weaker than general lights. Through observation, it can be found that in indoor scenes, furniture and local lights usually appear in pairs. Each type of lamp has a maximum number on the corresponding furniture, which can be found in the supplementary material.. During initial placement, each type of lamp is randomly placed on the corresponding furniture, but cannot exceed its maximum value. During the optimization process, the lights can only move along the furniture to which they belong. When the light intensity drops to 0, it is removed from the scene.

5 Immersive Virtual Experience

With the popularity of consumer virtual reality, more and more people are using VR equipment in games, life, and even work, and have gradually mastered the method of controller control. Therefore, we use an HMD and the matching gamepad to experience it in the virtual environment. The HMD provides users with an immersive experience perspective, while the gamepad controls direction and selects actions.

In this section, we discuss how to learn activity habits that affect indoor lighting from user simulated experiences in virtual environments. We take an indoor bachelor apartment as an example to illustrate our approach in detail. More results of other scenes are shown in Sec. 7.4. It's crucial to emphasize that lighting conditions within the scene significantly impact user activities (for more details, refer to the supplementary document). Variations in lighting lead to deviations in user behavior data. To maintain consistency in human activity during both data collection and lighting optimization, we implement global illumination with uniform brightness and disable the shadow effect during activity simulation. These measures ensure that human activity is predominantly influenced by furniture layouts.

5.1 Activity Simulation

In the daily activities, we define 15 commonly object categories and establish a model library in the virtual environment, including computer, mouse, book, pen, notebook, teacup, pot, rag, broom, laptop, bowl, fruit, and mobile phone. We invited the participants to select objects for daily activities according to their preferences from the model library and place them in the initial interior scene with our assistance. The participants then wear the Oculus and hold the gamepad to simulate the daily routines in the virtual scene.

It should be noted that in the initial process, the body proportions of the characters in the scene would be set according to the measured body proportions of the participants. We record the height of Oculus h_0 when the user is standing in the natural state and the height of Oculus h_1 when sitting on a chair, which are regarded as fixed eye heights. In this way, the user's perspective switching from standing to sitting in the virtual world will be more natural.

Similar to the control method of mobile games, participants control the walking status and direction through the left button on the handle, and select actions through the right button. Specifically, the selection of actions is triggered when the participant is stationary, which advances according to the character's state. Participants select objects on the furniture in front of them and then select an actionable action based on the object. If it is a movable object such as a book, cup, etc., it is first picked up and put down, and then the next action is, such as moving, or reading for the book, drinking water for the cup, etc. If it is an immovable object such as a bed or chair, the actions are lying down, sitting down, standing up, etc.

The experience time is divided into two stages, day and night. Each time is 10-15 minutes. Choose the stage to experience based on the habits of the participants. For example, when he is at home during the day but not at night, he only experiences the daytime once. If he is home all day, he will experience it twice.

5.2 Habit Extraction

During activity simulation, the user's operations are mapped to the activities of the agent in the virtual environment, which are recorded with the help of HMD and gamepad. We attempt to extract personal behavior habits from activities, denoted as H, including path, interaction, and head pose.

Trajectory. We record the location sequence of the agent in the virtual scene as the trajectory of the user, which is refreshed every 20 seconds. On the one hand, the trajectory can reflect the path of the character in the scene. On the other hand, the position sequence can also represent the time the user stays at each location in the scene. Specifically, we define the waist of the agent as a key point to mark the agent's position. The trajectory of user is written as $P = \{p_1, p_2 \cdots\}$, where p_t is the set of 3D coordinate of the waist at time t. Figure 4 shows an example of a user's trajectory in the scene, represented by a heatmap. The redder the color, the longer the user stays.

Interaction. The sequence of where and what activities the user performed is represented as the user's interaction, which reveals the

Authorized licensed use limited to: Zhejiang University. Downloaded on November 06,2026 at 06:13:36 UTC from IEEE Xplore. Restrictions apply.

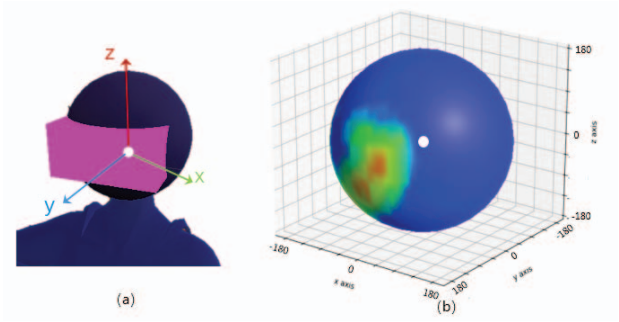


Figure 6: An example of head pose distribution when the user reads book on the sofa. (a) is a schematic diagram of the user's head rotation. (b) is a heatmap to visualize the head posture. The white dot represents the center point of the head. The redder the color, the more likely it is that the head posture will turn to that point.

distribution of each activity in the scene. The triggering of activities can be recorded through the operation of the gamepad. For each type of activity, we record the user's location when it occurred. The locations recorded for different activities are different. For example, the position of the agent's hands when writing is recorded, and the position of the head while sleeping is recorded. These are the main photosensitive locations during activity. For each type of activity, a heatmap is obtained as shown in Fig 5. The redder the color, the more frequently the user interacts with it.

Head Pose. The eyes are the direct channel for human beings to perceive light, and the posture of the head determines the direction of human perception of light. Different people turn their heads at different angles during activities. The Oculus captures the user's head pose. We stipulate that the vertical upward direction is the positive direction, and the head rotation direction recorded every 20s is F_i. The rotation direction data is then clustered around each furniture object, such as tables, sofas, etc. It is written as $F_i = \{\theta_1, \theta_2, \cdots\}$, where $i \in \{1, 2, \cdots, M\}$. Fig 6 visualizes the distribution of head poses for a user interacting at a desk. Oculus provides a visual frame rate of 70 fps with a tracking error of less than 1 degree. We calibrated the headphones before each test.

6 Lighting Layout Optimization

After setting an initial lighting layout in the virtual scene, we treat the lighting layout problem of the scene as an optimization problem similar to the furniture layout. Combined with the user's behavioral habits in the virtual scene, we use optimization algorithms to explore personalized lighting layout solutions in the space that conform to the user's behavior. In this section, the definition of the cost function and the process of optimization on the lighting layout are discussed in detail.

6.1 Costs

To obtain a lighting environment that is comfortable for users and saves energy consumption, we attempt to optimize the lighting layout denoted as L by analyzing the trajectory, interaction and head pose of the user denoted as H in the scene. We define a cost function that considers human constraints and interior constraints as follows:

$$C_{\text{total}}(H,L) = \omega_{\text{h}} C_{\text{h}}(H,L) + \omega_{\text{in}} C_{\text{in}}(L). \tag{2}$$

$C_{\text{h}}(H,L)$ is the human cost associated with personal habitual behavior, which is to penalize those lighting layouts that are not conducive to personal habitual behavior or increase energy consumption. $C_{\text{in}}(L)$ is the interior cost associated with the spacial layout design, in order to make the lighting in the scene more harmonious in the whole space. The ω coefficients determine the relative weighting of each item; in practice, we set $\omega_{\text{h}} = 0.5$ and $\omega_{\text{s}} = 0.5$.

6.1.1 Human Cost

In the human cost, we mainly consider the interation area of human behavior, the trajectory and the head pose of user in human interaction. In terms of energy use, we also estimated the energy consumption of lighting in the scene when human interact. It is defined as follows:

$$C_{\text{h}}(H,L) = \omega_{\text{ac}} C_{\text{ac}}(H,L) + \omega_{\text{m}} C_{\text{m}}(H,L) + \omega_{\text{e}} C_{\text{e}}(H,L), \tag{3}$$

where $\text{C}_{\text{ac}}(H,L)$ is the activity cost, $\text{C}_{\text{m}}(H,L)$ is the move cost and $\text{C}_{\text{e}}(H,L)$ is the energy cost. The ω coefficients determine the relative weighting of each item; in practice, we set $\omega_{\text{ac}} = 0.3$, $\omega_{\text{m}} = 0.3$ and $\omega_{\text{e}} = 0.4$.

Activity. Inappropriate lighting affects the user's mood and even activity efficiency. Lighting studies show that different activities have different recommended illuminance values [21]. Since the eyes are the direct receptors for light, the angle of the head posture and the light source will directly determine the intensity of light received by the user. To simplify the problem, we assume here that the direction of light intensity is mainly determined by the main light source, which is the nearest light. Under identical lighting conditions, users experience the most comfortable light intensity when their line of sight is perpendicular to the main light source. Gazing directly at the main light source may dazzle the user, while turning away reduces the received light intensity. Therefore, the user's head posture habits influence the position and intensity of the main light source during an activity. This local light serves as illumination for the activity. For each activity, we initially sample the user's potential activity location based on the activity probability map (Fig 5). We then predict the user's head angle during the activity using the activity's head angle probability map. The duration of each activity during the experience acts as its weight. Specifically, the activity cost is defined as follows:

$$C_{\text{ac}}(H,L) = \frac{1}{X} \sum_{x} \frac{t_x}{T} \frac{|I_{rec_x} - I_i(1 - |\phi(o_i, h_i)|)|}{I_{max}}, \tag{4}$$

where I_{rec_x} the recommended specific illumination value when doing activity x. i is the sampled coordinate of the location where the activity occurs, and I_i is the intensity value at i , including both local and global light. h_i is the predicted head pose and o_i is the vector from the position of nearest local light where the activity occurs to i. $\phi(o_i, h_i)$ is the cosine value of the angle between o_i and h_i. I_{max} is the maximum value in the entire I_{rec_x}. t_x represents the length of time that activity x occurs during the experience. T is the total time of user interaction. X is the total number of activities.

Move. Different types of lamps are placed on different planes. Improper placement of lights affects user interaction in the scene. If the lights on the ground are placed on the path that users often walk, it will affect the user's movement trajectory. If the desktop lights are placed where users often interact, users will be forced to change their habits. We penalize lights placed on user interactive behaviors based on the heatmap of interactions and trajectory on each plane as extracted in Section 4.2. The move cost is defined as:

$$C_{\text{m}}(H,L) = \frac{1}{N} \sum_{i} \mathbb{H}_{p_i}, \tag{5}$$

where i are local light i and p_i is the position of the light i projected onto the plane of corresponding furniture. $\mathbb{H}_{p_i}$ is the value of the position of lamp i on the furniture on the interactive heat map. Normalize the corresponding values of the heat map to 0-1. The redder the color, the larger $\mathbb{H}_{p_i}$ is. N is the number of the local lights in the scene.

Energy. The distribution of user activities directly affects the power consumption in the scene. The lighting layout in real life should

Authorized licensed use limited to: Zhejiang University. Downloaded on November 06,2026 at 06:13:36 UTC from IEEE Xplore. Restrictions apply.

not only make users' activities comfortable, but also reduce lighting energy consumption as much as possible and control living costs. Different activity distributions in the same lighting layout will cause differences in energy consumption. It is assumed that general lights are turned on and off uniformly to ensure the brightness of the room, and when the user moves in the corresponding area, the local lights of the furniture are turned on, just like an intelligent sensing system. The energy cost is defined as:

$$C_{\mathrm{e}}(H,L) = \frac{1}{N}\sum_{i}\frac{t_i}{T}I_i + \lambda I_g, \tag{6}$$

where I_i is the light intensity of local light i and I_g is the light intensity of general light. t_i is the total duration of activities occurring around light i. T is the total time of user interaction. N is the number of the local lights in the scene. λ is the coefficient of general lighting. We assume that the lights are generally turned on at night and not during the day. That is, when the user is only active during the day, *lambda* is 0, and when the user is only active at night, λ is 1. When he is at home all day, λ is equal to 0.5.

6.1.2 Interior Cost

In the interior cost, we consider the average illumination provided by the lighting and the symmetry of the lamp group. It is defined as follows:

$$C_{\mathrm{in}}(L) = \omega_{\mathrm{a}}C_{\mathrm{a}}(L) + \omega_{\mathrm{s}}C_{\mathrm{s}}(L), \tag{7}$$

where $\mathrm{C_a}(L)$ is the illumination cost. $\mathrm{C_s}(L)$ is the symmetry cost. The ω coefficients determine the relative weighting of each item; in practice, we set $\omega_{\mathrm{a}} = 0.5$ and $\omega_{\mathrm{s}} = 0.5$.

Illumination. The large difference between light and dark in the scene makes people visually uncomfortable. Uniform lighting is very important to the overall feel of a scene. First, we determine the sampling points uniformly in the scene, and then calculate the light intensity they receive. Here, we use the variance of the illumination intensity at each point in the scene to measure whether the illumination in the scene is uniform. The illumination cost is defined as follows:

$$C_{\mathrm{a}}(L) = \frac{1}{Q}\sum_{j}(I_j - \bar{I})^2, \tag{8}$$

where I_j is the illuminance value at the sampling point j. $\bar{I}$ is the average illuminance value of the whole sampling points. Q is the total number of sampling points.

Symmetry. Some furniture in the room usually appears in pairs and rarely exists alone, such as tables and chairs. The division of furniture groups can be manually defined based on real life or found using the connection strength calculation suggested by Xu et al. [46]. The lamps are arranged symmetrically in the furniture group so that the light can evenly cover each piece of furniture. Specifically, after obtaining the center point of the furniture group, we combine the lamps on the ceiling to which the furniture group belongs and calculate their center points. The goal is to have the center point of the furniture group and the center point of the light fixture coincide in horizontal dimensions. The symmetry cost is defined as:

$$C_{\mathrm{s}}(L) = \frac{1}{M}\sum_{i} d(f_i, l_i), \tag{9}$$

where f_i is the center coordinate of the furniture group where furniture i is located. l_i is the center coordinate of the lighting group corresponding to the furniture group where furniture i is located. Both of them are projected horizontal 2D coordinates without height information. $d(f_i, l_i)$ is the distance between f_i and l_i, etc. M is the number of furniture.

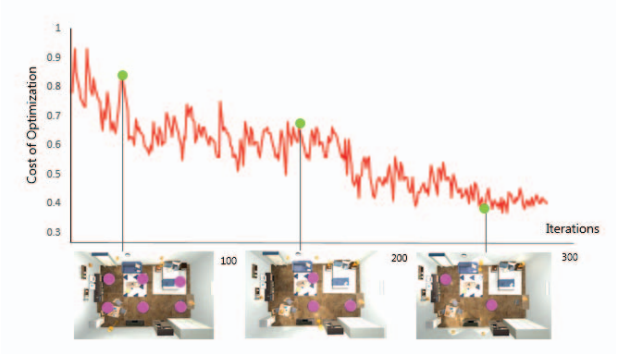


Figure 7: An example of the optimization process. The red curve shows the cost change during the optimization, while the green circle exhibits the lighting layout generated on the specific optimization point.

6.2 Optimization

To avoid falling into local optima, our approach applies a Simulated Annealing algorithm to search a good light layout. Based on the designed cost function, we explore the number, position, direction and intensity of lamps with a certain sampling strategy during the optimization process, and finally obtain a good lighting arrangement.

6.2.1 Lighting Adjustment

In the simulated annealing algorithm, new solutions are generated by adjusting the lights in the scene. Specifically, we define three operations to generate solutions: position movement, direction movement and light intensity adjustment. Light k is selected and the sampling process performs these three actions alternately.

Position. The movement of the position is to modify the position of the light according its type. There are two steps for the movement of each type of lamp: First, we determine the furniture that the lamp belongs to and obtain the size of the furniture (f_x, f_y, f_z). Then two variables $(\Delta m, \Delta n)$ are generated through Gaussian distribution, which is used to determine the updated position of the light.

Assuming that the position of light i are (x_i, y_i, z_i), each light should update its positions according to the following rules. Ceiling lamps and pendant lamps always belong to the ceiling, and floor lamps are always on the ground. Their z-coordinates remain the same. The updated positions of them are $(x_i + \Delta m, y_i + \Delta n, z_i)$. Table lamps and bedside lamps are placed on the tabletop in the scene. Their z value is the height of the selected furniture in the scene. The updated positions of them are $(x_i + \Delta m, y_i + \Delta n, f_z)$. Wall lights and cabinet lights are placed on the wall. Assume that the walls in the scene are regular. For the vertical walls, their x-coordinates are consistent with the wall surface and the updated position is $(f_x, y_i + \Delta m, z_i + \Delta n)$; for the horizontal walls, their y-coordinates are consistent with the wall surface and the updated position is $(x_i + \Delta m, f_y, z_i + \Delta n)$.

Orientation. The movement of the orientation is to modify the direction of the lamp. The sampler generates a new orientation o_i based on the current orientation o_i'. For the selected lamp i, the rotation change Δo is generated by a Gaussian distribution. Then update the direction of the light by setting its rotation value to $(o_i + \Delta o)$.

Intensity. The adjustment of the intensity is to adjust the illumination of the light.The sampler generates variable values ΔI based on a Gaussian distribution, and the intensity of the light is $(I_i + \Delta I)$.

6.2.2 Solution Constraints

To speed up the optimization, we constrain the solution by three conditions:

Authorized licensed use limited to: Zhejiang University. Downloaded on November 06,2026 at 06:13:36 UTC from IEEE Xplore. Restrictions apply.

Range Constraints. The location of each light should be limited to its assigned furniture area. When the updated position of the light is outside the bounds of the region, a new position should be sampled. For example, when the desk lamp is moved outside the desktop or the height of the wall lamp exceeds the height of the wall, the movement strategy should be regenerated.

Collision Constraints. In the solution, attention should also be paid to preventing collisions between the lamp and other objects. Collisions can be easily detected between objects in the virtual engine. During the sampling process, we need to perform collision detection on each lamp in the scene. If the lamp collides with objects or other lamps in the scene, the position and direction of the lamp are resampled.

Illumination Constraints. To imitate real lighting, we specify some parameter ranges for the lights. The intensity of the general light in the scene is set to 0-10, and the intensity of the local light is set to 0-5.

6.2.3 Sampling

Given an initial configuration of a light L_0, our approach explores the solution space by iterating in two steps. First, we adjust the lights in the scene as described above, which is from $L^i \rightarrow L^*$. Then new solutions are accepted by Metropolis criterion with a certain probability, which avoids falling into local minima. Specifically, the acceptance rule of Metropolis-Hastings can be calculated by the following formula:

$$\alpha(L^i, L^*) = \min\left\{\frac{p(L^*)}{p(L^i)}, 1\right\}, \tag{10}$$

$p(\cdot)$ is computed by the defined cost:

$$p(\cdot) = \frac{1}{Z}\exp\frac{-C_{\text{total}(\cdot)}}{T}, \tag{11}$$

where $C_{\text{total}(\cdot)}$ is defined in Section 6.1. T is the temperature of the annealing process. Just like physical cooling, T is first set to a large value, then gradually decreases during the optimization process, and finally returns to a very small value close to 0. By default, we empirically set T to 1.0 and decrease it by 0.05 every 10 iterations until it reaches zero. Z is a constant for normalization. We terminate the optimization if the absolute change in the total cost value is less than 5% over the past 20 iterations. In our experiments, a full optimization takes about $200 \sim 300$ iterations.

7 Experiments

7.1 Implementation

We implemented our approach using C# and Unity 2020 and ran the optimization approach on a PC equipped with 32GB of RAM, a Nvidia Titan X graphics card with 12GB of memory, and a 2.60GHz Intel i7- 5820K processor. Participants experienced a virtual space of about 50-60 square meters, where they control the character's direction through Oculus and select actions with the gamepad.

7.2 Qualitative Experiment

To evaluate the lighting arrangement generated by our approach, we compared our approach with other approaches:

Our Approach: The lighting arrangements were optimized by our approach, which is based on personal activities.

Professional Approach: The lighting arrangements were manually organized by a professional designer who had about 3 years experiences in interior design, which is based on his own experience.

Customized Approach: The lighting arrangements were manually arranged by the user according to their own preference, which is operated with the help of us.

Participants. We invited 24 participants who did not know the purpose of experiment to join in the experiment, including 13 males and 11 females whose aged ranged from 16 to 48. 11 participants mentioned that they were only home at night, 5 participants were only home during the day, and the remaining 8 participants were usually home all day. In addition, 7 participants had experience designing the interior layout of their own homes. All participants reported normal or corrected-to-normal vision with no color-blindness, and have experience in using VR devices. It is worth noting that they all often play games, especially action games, to ensure smooth control of agents.

During the experiment, all participants were randomly divided into three groups of 8. They were randomly assigned to experience three single-person apartments, including three traditional square apartments with areas of 50, 60, and 80 square meters, respectively. The quantity of furniture in each scene remains constant, while the layouts differ.

Metrics. We define three metrics to investigate the comparison:

(1)*Harmony*: it refers to the harmony of light perceived by the user visually, which is used to evaluate whether the light is uniform.

(2)*Comfort*: it refers to the user's comfort level of local lighting when doing activities, which is used to evaluate whether the local lighting suits the individual.

(3)*Overall*, it refers to the comprehensive indicators of indoor lighting, which is used to evaluate the overall feeling of the user on the lighting arrangement.

The score range of each metric is from 0 to 10. Before users score, Prior to scoring, each participant were introduced the meaning of each metric and then scored the lighting arrangement produced by each approach. It is noted that the order of the three experienced arrangements was randomized to mitigate the influence of participants' subjective awareness.

Procedure. Participants do activities in the virtual environment through Oculus and gamepad.To make them more familiar with the use of the equipment, each participant will conduct a 5-minute warm-up before the formal experience. The warm-up procedure is carried out under the guidance of us. During this process, participants are introduced to the functions they will use during the experience, including controlling the direction and selecting actions.

During the formal experience, in order to avoid dizziness, participants were invited to experience the scene twice, for 15 minutes each time. Oculus controls direction and gamepad selects activity. Our approach is then applied to synthesis lighting arrangement combined with the personal behaviours. To avoid the impact of lighting on user behavior, users experience each approach according to their operations in the activity simulation.

Results and Analysis. 24 participants took part in the comparison experiments. They were divided into three groups, and each group was assigned to an initial single indoor home scene randomly. Fig. 8 shows the rating results on the three approaches. The blue, orange and green boxes depict the rating on the Our, Professional, and Customized approach, respectively. We compare the results generated from the three approaches by the mean and standard deviation of the users' ratings. We also carried out ANOVA tests on the scores to analyze the significance. Fig 8 shows the average scores and standard deviation of the harmony, comfort and overall.

For the harmony rating item, our approach got the highest score ($M = 7.21$, $SD = 0.96$), followed by Professional approach ($M = 7.16$, $SD = 1.06$) and Customized approach ($M = 6.21$, $SD = 0.99$). Our approach incorporates some calculation of interior uniformity, and the designer has professional interior design knowledge. The ratings of our approach is very close to the Professional approach in harmony, which demonstrates the effectiveness of the professional rules of design used in our approach. Users are mostly based on their own experiences in life, so our approach and the designer's approach score higher than the user's own approach.

Authorized licensed use limited to: Zhejiang University. Downloaded on November 06,2026 at 06:13:36 UTC from IEEE Xplore. Restrictions apply.

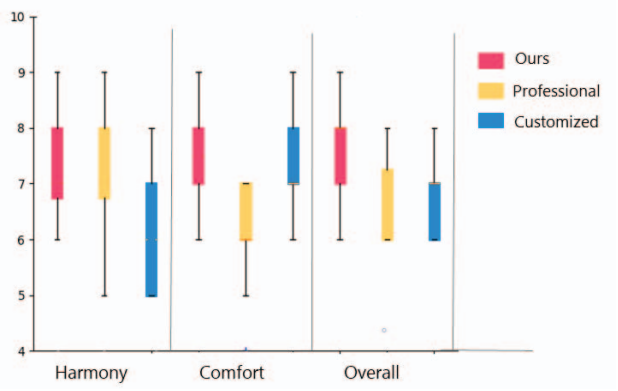


Figure 8: User ratings on the generated lighting solutions. The bottom and top edges of the colored box indicate the 25th and 75th percentile, respectively. The horizontal lines indicate the median rating. The whiskers indicate the most extreme data points.

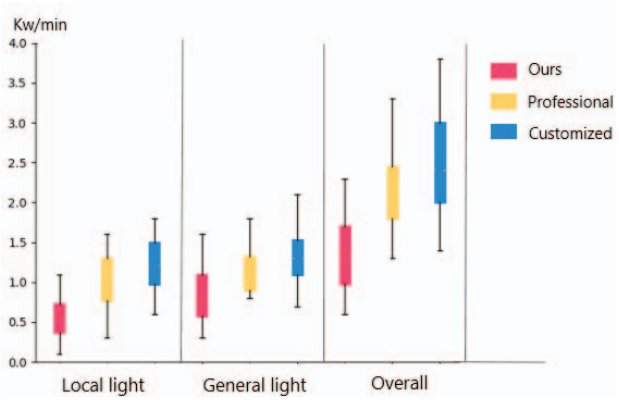


Figure 9: User ratings on the energy consumption of the generated lighting solutions. The bottom and top edges of the colored box indicate the 25th and 75th percentile, respectively. The horizontal lines indicate the median rating. The whiskers indicate the most extreme data points.

For the comfort rating term, our approach($M = 7.54$, $SD = 0.82$) and Customized approach($M = 7.46$, $SD = 0.64$) are better than the Professional approach($M = 6.08$, $SD = 0.81$). Professional designers extract users' personal habits and preferences by observing user interaction videos, and then arrange indoor lighting. However, some customary details may be ignored during extraction, such as the user's head orientation posture, the interaction point between specific objects, etc., which even the user himself does not necessarily pay attention to will only be revealed when acting. The results reflect that our approach has basically learned the user's behavior in a comprehensive way.

For the overall rating term, our approach ($M = 7.71$, $SD = 0.68$) is the best compared to Professional approach ($M = 7.12$, $SD = 0.73$) and Customized approach ($M = 6.75$, $SD = 0.66$). It proves that our approach not only learns the expertise of the design field, but also integrates the personal habits of the users. The similarity of Professional approach and Customized approach also represents that different from interior design, the importance of personal habit preference in lighting layout is more prominent.

There is a significant difference among three approaches for harmony($\chi^2 = 8.43$,$p < .05$,$df = 2$), comfort($\chi^2 = 27.17$,$p < .05$,$df = 2$) and overall($\chi^2 = 14.29$,$p < .05$,$df = 2$). We also did an ANOVA test on the harmony, comfort and the overall rating at the $\alpha = 0.05$ significance level. For harmony, the results showed statistically significant between Our and the Customized approach($F_{[1,23]} = 12.02$, $p < .05$). For comfort, the results showed statistically significant between Our and Professional approach($F_{[1,23]} = 36.93$, $p < .05$). For overall, our approach showed statistically significant with Professional approach ($F_{[1,23]} = 11.98$, $p < .05$) and Customized approach ($F_{[1,23]} = 21.61$, $p < .05$).

The results did not show statistically significant between Our and the Professional approach in harmony($F_{[1,23]} = 0.02$, $p = 0.88 > .05$). And our approach did not have statistically significant with Customized approach in comfort($F_{[1,23]} = 0.15$, $p = 0.70 > .05$). It illustrates that our approach effectively combines the strengths of Professional approach and Customized approach. Our approach not only reflects professional design knowledge through rule definition, but also takes into account the user's personal habits.

Interestingly, our approach takes longer to produce results for larger apartments, but users of larger apartments seem to report better results on our approach. In a scene with a larger area, the solution space to be explored will be correspondingly larger, and the user's habits will be more difficult to obtain, which can reflect the advantage of our method in learning user habits to a certain extent.

7.3 Quantitative Experiment

We quantitatively verify the effectiveness of our approach by calculating the scene lighting energy consumption for personal activity of each approach.

Participants. The 24 participants are the same as in Sec 7.2. They wore Oculus and gamepads and entered the corresponding scenes according to the previously divided groups to experience it again.

Procedure. Each participant was invited to play another round of the simulation in the original scenario. We estimate energy consumption in the light layouts generated by each of the three approaches, depending on the time period (e.g., day or night) and activity experienced by the participants. Local lights turn on when the user is active in the area and general lights turn on at night. The processing time for each approach was also calculated. For our approach, the processing time is the time spent from light placement to optimized generation; the time for the professional approach is the time spent by the designer communicating with the user and designing the plan, and the time for the customize approach is the process of the user completing the lighting arrangement in the virtual scene.

Results and Analysis. We conducted energy consumption assessments of user activities in our approach, professional approach and customized approach. The energy consumption of each approach is divided into two parts: general light and local light. Figure 10 shows the energy consumption results of the three approaches. Among the three approaches, our approach consumes less energy (local light: $M = 0.58$ kw/min, $SD = 0.27$ kw/min; general light: $M = 0.82$ kw/min, $SD = 0.32$ kw/min; total: $M = 0.92$ kw/min, $SD = 0.38$ kw/min;) than the professional approach (local light: $M = 1.2$ kw/min, $SD = 0.3$ kw/min; general light: $M = 1.32$ kw/min, $SD = 0.35$ kw/min; total: $M = 1.42$ kw/min, $SD = 0.39$ kw/min;), customized approach (local light: $M = 1$ kw/min, $SD = 0.35$ kw/min; general light: $M = 1.21$ kw/min, $SD = 0.29$ kw/min; total: $M = 1.31$ kw/min, $SD = 0.34$ kw/min;). Neither professional designers nor users can quantify energy consumption based on human behavior when arranging lighting. Therefore, professional and customized approach cannot save energy consumption in future life.

For the processing time of each approach, our approach and the professional approach used about the same time. Our approach took 4.2 minutes and the professional approach took 3.9 minutes. The customized approach spent the longest time, near 8 minutes. However, the professional approach relies heavily on the designer's experience in learning personal habits.

The quantitative results show that our method can learn the user's habitual behavior intelligently and generate the lighting arrangement

Authorized licensed use limited to: Zhejiang University. Downloaded on November 06,2026 at 06:13:36 UTC from IEEE Xplore. Restrictions apply.

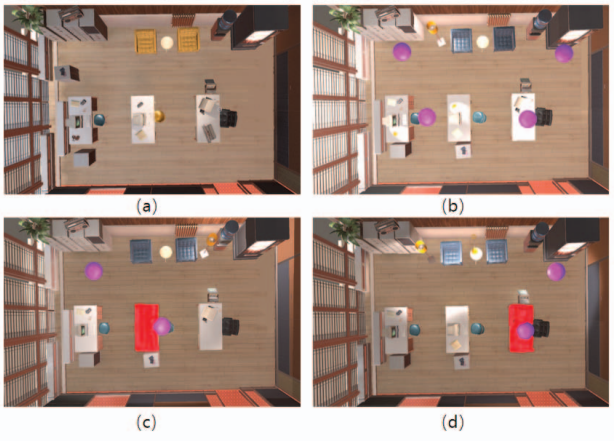


Figure 10: Office Lighting layouts generated under different settings. (a) is the given office scene, (b) is the lighting layout generated from the combination of two users' behavioral data, (c) and (d) are lighting layouts generated for the two different users, respectively.

effectively, which is suitable for the user.

7.4 Extended Experiment

To verify the generality of our approach, we experiment in a multi-person office, which is shown as Fig.10(a). Two people are invited to simulate activities separately in an office, where their workstations are fixed. Our approach is then used to generate the lighting arrangement of the office based on their behavior.

Fig. 10 shows the optimized results. Fig 10(b) shows the optimized lighting arrangement based on the activities of two people, while Fig 10(c) and 10(d) are based on the activities of individuals respectively. The workstation of user 1 is the red table in Fig 10(c). Her main job is to take files from the filing cabinet to her workstation area to read and write, mostly in the middle area of the desktop. She rarely went to the leisure area to get snacks except to drink water. It can be observed that a floor lamp is placed next to the water fountain. The workstation of user 2 is the red table in Fig 10(d). He is more like a manager than user 1. Specifically, his active area in the scene was mainly on the sofa in the reception area for meeting, and he almost never went to the filing cabinet. He also likes to move around the scene, so the overall brightness of the room results in better results than user 1. We invited user 1 and user 2 to experience and rate the two lighting layouts again. It is interesting that Fig 10(b) has achieved higher evaluation. The reason is the overall brightness of Fig 10(b) is better. Our approach considers the control of energy consumption, so the average indoor brightness is weaker in a lighting layout based on single-person activities.

Extensive results carried out show that our approach is still feasible when applied to multi-person activities, which is not limited to single-player scenarios. Furthermore, our approach will generate a more complete lighting layout of the scene when people with different roles are invited to experience.

8 Summary

In this paper, we propose a novel approach to optimize lighting arrangements in a scene driven by human activity. The user simulates daily routines through an HMD and a corresponding gamepad in a given indoor scene, from which learn personal habitual behavior. We initialize the lighting layout in a given scene, and then design a cost function to evaluate whether the lighting layout in the scene is reasonable and consistent with the user's personalized habits.

In practical applications, this algorithm can be seamlessly integrated with automated furniture layout algorithms, such as [28]. Following the completion of furniture arrangement, users can be invited to engage in simulated activities within the scene. By collecting user habits during these simulations, an optimization algorithm is then applied to adjust the lighting layout, generating a scheme that prioritizes user comfort and energy conservation. Furthermore, the versatility of the algorithm extends to utilizing 3D scanning reconstruction techniques, allowing for the direct scanning of existing environments. Subsequently, the lighting layout of the real environment can be optimized based on the collected data. Unlike real life, diverse time periods can be seamlessly experienced in a virtual environment. As VR becomes increasingly familiar, a variety of VR devices can efficiently gather personal behavior data. In our method, users employ Oculus and a gamepad to simulate interactions, akin to mobile games. Gaze, trajectory, and interactions are extracted from user activities for indoor lighting optimization, resulting in personalized lighting arrangements. Qualitative user studies affirm the effectiveness of our approach, while quantitative energy consumption evaluations demonstrate significant energy savings. Furthermore, our method adeptly extends to multi-person scenarios.

Limitations. While virtual reality offers users an immersive experience, the perception of light effects may still differ between virtual and real scenes. Traditional VR engines tend to simplify lighting and shading. By integrating our framework with advanced lighting engines such as DiaLux and KooLight, known for accurately simulating real lighting conditions, we anticipate a significant enhancement in immersive experiences.

In practice, lamp placement must account for the indoor circuit layout, considering the impact of other electrical appliances on circuit balance. Our approach, however, does not factor in the cost of indoor circuit layout. As 3D reconstruction advances, the ease of scanning and reconstructing actual circuit structures brings estimates of lighting arrangement costs and energy consumption closer to reality.

The lighting sources of indoor scenes include lamps and natural light. Besides weather, natural light is also affected by the surrounding environment. For example, when there are many high-rise buildings around, indoor light is greatly reduced. Due to computational power constraints, we did not take into account the effects of natural light. As computing power improves, the impact of natural light will be taken into account in indoor lighting.

Future Work. One possible extension is to consider more factors in the optimization cost, such as color, style, mood, etc. In future work, it would be interesting to extend the style of the lamp models in the model library and then make the style of other indoor furniture and lamps consistent in shape and texture. The color effect of light affects the visual experience of the scene and even the user's mood. There should be different style tags for different types of scenes. For example, the lights in a secret room are dim and scary, while the lights in an office are bright and energizing.

Another possible extension is to transfer the lighting arrangement of a user in a scene to an unknown scene, even a game scene. Wang et al. [39] proposed a method to transfer the furniture layout to a new scene. The transfer of users' behavioral habits will be of great value to the development of personalized design.

The impact of lighting on human activities is substantial. In this paper, we simplified the problem by creating a bright environment similar to the outdoors' during the user behavior collection phase to mitigate the influence of lighting. An intriguing avenue for further exploration involves studying the dynamic interplay between human behavior and evolving lighting conditions. Similar to smart lighting systems, adjusting smart switches based on user habits can drive innovation in the smart lighting industry.

Acknowledgments

This research is supported in part by the Management Center of the School of Software(Ningbo) at Zhejiang University under Grant No.Z24001.

Authorized licensed use limited to: Zhejiang University. Downloaded on November 06,2026 at 06:13:36 UTC from IEEE Xplore. Restrictions apply.

REFERENCES

[1] C. Abras, D. Maloney-Krichmar, J. Preece, et al. User-centered design. *Bainbridge, W. Encyclopedia of Human-Computer Interaction. Thousand Oaks: Sage Publications*, 37(4):445–456, 2004.

[2] Y. Afacan. Exploring the effectiveness of blended learning in interior design education. *Innovations in Education and Teaching International*, 53(5):508–518, 2016.

[3] Y. Akashi, R. Muramatsu, and S. Kanaya. Unified glare rating (ugr) and subjective appraisal of discomfort glare. *International Journal of Lighting Research and Technology*, 28(4):199–206, 1996.

[4] D. Andersen, V. Popescu, M. E. Cabrera, A. Shanghavi, B. Mullis, S. Marley, G. Gomez, and J. P. Wachs. An augmented reality-based approach for surgical telementoring in austere environments. *Military medicine*, 182(suppl_1):310–315, 2017.

[5] S. Borile, A. Pandharipande, D. Caicedo, L. Schenato, and A. Cenedese. A data-driven daylight estimation approach to lighting control. *IEEE Access*, 5:21461–21471, 2017.

[6] P. R. Boyce. *Human factors in lighting*. Crc press, 2003.

[7] U. Brandi. *Lighting design: principles, implementation, case studies*. De Gruyter, 2006.

[8] G. Brooker and S. Stone. *What is interior design?* Rotovision, 2010.

[9] A. Chopra. *Introduction to google sketchup*. John Wiley & Sons, 2012.

[10] D. T. Delaney, G. M. O'Hare, and A. G. Ruzzelli. Evaluation of energy-efficiency in lighting systems using sensor networks. In *Proceedings of the First ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings*, pp. 61–66, 2009.

[11] X. Di, P. Yu, H. Zhu, L. Cai, Q. Sheng, C. Sun, and L. Ran. Structural plan of indoor scenes with personalized preferences. In *Computer Vision–ECCV 2020 Workshops: Glasgow, UK, August 23–28, 2020, Proceedings, Part IV 16*, pp. 455–468. Springer, 2020.

[12] B. L. Diffey. An overview analysis of the time people spend outdoors. *British Journal of Dermatology*, 164(4):848–854, 2011.

[13] P. G. Ellis, P. A. Torcellini, and D. B. Crawley. Energy design plugin: An energyplus plugin for sketchup. Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States), 2008.

[14] Y. Feng, F. Lv, W. Shen, M. Wang, F. Sun, Y. Zhu, and K. Yang. Deep session interest network for click-through rate prediction. *arXiv preprint arXiv:1905.06482*, 2019.

[15] Q. Fu, X. Chen, X. Wang, S. Wen, B. Zhou, and H. Fu. Adaptive synthesis of indoor scenes via activity-associated object relation graphs. *ACM TOG*, 36(6):201, 2017.

[16] R. Ganslandt and H. Hofmann. Handbook of lighting design. *ERCO GmbH*, 1992.

[17] C. Grimley and M. Love. *Color, space, and style: all the details interior designers need to know but can never find*. Rockport Publishers, 2007.

[18] E. Guerry, C. D. Gălăţanu, L. Canale, and G. Zissis. Optimizing the luminous environment using dialux software at "constantin and elena" elderly house–study case. *Procedia Manufacturing*, 32:466–473, 2019.

[19] K. Houser, M. Mossman, K. Smet, and L. Whitehead. Tutorial: color rendering and its applications in lighting. *Leukos*, 12(1-2):7–26, 2016.

[20] E. P. Ijjina and K. M. Chalavadi. Human action recognition in rgb-d videos using motion sequence information and deep learning. *Pattern Recognition*, 72:504–516, 2017.

[21] C. C. institution of building services engineers. *Code for interior lighting*. CIBSE, 1994.

[22] C. Jiang, S. Qi, Y. Zhu, S. Huang, J. Lin, L. F. Yu, D. Terzopoulos, and S. C. Zhu. Configurable 3d scene synthesis and 2d image rendering with per-pixel ground truth using stochastic grammars. *IJCV*, 126(9):920–941, 2018.

[23] M. Karlen, C. Spangler, and J. R. Benya. *Lighting design basics*. John Wiley & Sons, 2017.

[24] M.-T. Ke, C.-H. Yeh, and J.-T. Jian. Analysis of building energy consumption parameters and energy savings measurement and verification by applying equest software. *Energy and Buildings*, 61:100–107, 2013.

[25] J. Kramer, S. Noronha, and J. Vergo. A user-centered design approach to personalization. *Communications of the ACM*, 43(8):44–48, 2000.

[26] K. Leimer, P. Guerrero, T. Weiss, and P. Musialski. Layoutenhancer: Generating good indoor layouts from imperfect data. In *SIGGRAPH Asia 2022 Conference Papers*, pp. 1–8, 2022.

[27] C. Li, W. Liang, C. Quigley, Y. Zhao, and L. F. Yu. Earthquake safety training through virtual drills. *IEEE TVCG*, 23(4):1275, 2017.

[28] W. Liang, J. Liu, y. Lang, B. Ning, and L.-F. Yu. Functional workspace optimization via learning personal preferences from virtual experiences. *IEEE Transactions on Visualization and Computer Graphics*, 25(5):1836 – 1845, 2019.

[29] J. Liu, W. Liane, B. Ning, and T. Mao. Work surface arrangement optimization driven by human activity. In *2021 IEEE Virtual Reality and 3D User Interfaces (VR)*, pp. 270–278. IEEE, 2021.

[30] J. Lobão, T. Devezas, and J. Catalão. Energy efficiency of lighting installations: Software application and experimental validation. *Energy Reports*, 1:110–115, 2015.

[31] R. A. Mangkuto. Validation of dialux 4.12 and dialux evo 4.1 against the analytical test cases of cie 171: 2006. *Leukos*, 12(3):139–150, 2016.

[32] P. Merrell, E. Schkufza, Z. Li, M. Agrawala, and V. Koltun. Interactive furniture layout using interior design guidelines. In *ACM TOG*, vol. 30, p. 87, 2011.

[33] Y. Miwa and K. Hanyu. The effects of interior design on communication and impressions of a counselor in a counseling room. *Environment and behavior*, 38(4):484–502, 2006.

[34] PANASONIC.NET. The light required for each room. `https://panasonic.net/ecosolutions/lighting/technology/knowledge/03/`.

[35] T. C. Peck, H. Fuchs, and M. C. Whitton. Evaluation of reorientation techniques and distractors for walking in large virtual environments. *IEEE transactions on visualization and computer graphics*, 15(3):383–394, 2009.

[36] S. Qi, Y. Zhu, S. Huang, C. Jiang, and S. C. Zhu. Human-centric indoor scene synthesis using stochastic grammar. In *CVPR*, 2018.

[37] H. Ren, H. Fan, R. Wang, Y. Huo, R. Tang, L. Wang, and H. Bao. Data-driven digital lighting design for residential indoor spaces. *ACM Transactions on Graphics*, 42(3):1–18, 2023.

[38] M. Solah, H. Huang, J. Sheng, T. Feng, M. Pomplun, and L.-F. Yu. Mood-driven colorization of virtual indoor scenes. *IEEE Transactions on Visualization and Computer Graphics*, 28(5):2058–2068, 2022.

[39] S. Song, Y. Wang, W. Liang, and X. Li. Moving soon? rearranging furniture using mixed reality. pp. 798–799, 2022.

[40] R. R. Strauss, R. Ramanujan, A. Becker, and T. C. Peck. A steering algorithm for redirected walking using reinforcement learning. *IEEE transactions on visualization and computer graphics*, 26(5):1955–1963, 2020.

[41] G. G. Thiel, S. R. Ensslin, and L. Ensslin. Street lighting management and performance evaluation: opportunities and challenges. *Lex Localis*, 15(2):303, 2017.

[42] P. Tregenza and M. Wilson. *Daylighting: architecture and lighting design*. Routledge, 2013.

[43] N. Vitsas, G. Papaioannou, A. Gkaravelis, and A.-A. Vasilakis. Illumination-guided furniture layout optimization. In *Computer Graphics Forum*, vol. 39, pp. 291–301. Wiley Online Library, 2020.

[44] P. Wang, W. Li, P. Ogunbona, J. Wan, and S. Escalera. Rgb-d-based human motion recognition with deep learning: A survey. *Computer Vision and Image Understanding*, 171:118–139, 2018.

[45] B. Xie, H. Liu, R. Alghofaili, Y. Zhang, Y. Jiang, F. D. Lobo, C. Li, W. Li, H. Huang, M. Akdere, et al. A review on virtual reality skill training applications. *Frontiers in Virtual Reality*, 2:645153, 2021.

[46] K. Xu, R. Ma, H. Zhang, C. Zhu, A. Shamir, D. Cohen-Or, and H. Huang. Organizing heterogeneous scene collections through contextual focal points. *ACM Transactions on Graphics (TOG)*, 33(4):1–12, 2014.

[47] H. Yi, C.-H. P. Huang, S. Tripathi, L. Hering, J. Thies, and M. J. Black. Mime: Human-aware 3d scene generation. In *Proceedings of the IEEE/CVF CVPR*, pp. 12965–12976, 2023.

[48] L.-F. Yu, S. K. Yeung, C.-K. Tang, D. Terzopoulos, T. F. Chan, and S. Osher. Make it home: automatic optimization of furniture arrangement. In *ACM TOG*, 2011.

[49] G. Zhou, X. Zhu, C. Song, Y. Fan, H. Zhu, X. Ma, Y. Yan, J. Jin, H. Li, and K. Gai. Deep interest network for click-through rate prediction. In *Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining*, pp. 1059–1068, 2018.

Authorized licensed use limited to: Zhejiang University. Downloaded on November 06,2026 at 06:13:36 UTC from IEEE Xplore. Restrictions apply.