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A Markov Decision Process Workflow for Automating Interior Design

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ABSTRACT

We present a novel workflow based on artificial intelligence (AI) techniques to automate interior design processes. We discuss the essential steps for creating an intelligent agent that can automatically perceive the design environment (perception) and produce design ideas (action). In the first step, we use photographs or video images to model three-dimensional coordinates and exact positions of surface points on objects inside the interior space. We then convert the collected spatial data to a set or cloud of points. To fully model the interior space, we create either a triangulated surface or a mesh from the points and then transform it into a detailed building information model (BIM). Last, we apply texture data to either the 3D surface/mesh or the building information model. In the second step, we develop a sequential decision-making model based on Markov decision process for the intelligent agent to make design decisions in the BIM environment. We apply the proposed workflow to a case study with 512 possible design options, conduct experiments with 20 participants where design decisions are made based on AI insights, and perform statistical analysis on the experiment results. Our findings show the proposed workflow is capable of improving participants' satisfaction by only searching through on average 5.1% of all possible design options. Also, across all performance measures, design decisions proposed by the AI system outperform designs made randomly.

1. Introduction

3D digital modeling tools are commonly used by architects and interior designers to make a 3D architectural visualization of their building and interior designs. New architectural innovations can be achieved through the utilization of the latest computer-aided design techniques and methods. Although these digital applications delivered new capabilities to automate the design process, they are not smart enough yet to perceive the design environment (e.g., room layout in interior design) and make design changes to maximize client satisfaction (as the ultimate goal). Artificial Intelligence (AI) could be a critical factor in the future of interior design and architecture because an AI system can provide better (or similar) outputs with less time and minimal manual interference. As the interior design of buildings incorporates a wide range of possible solutions, a combination of AI and a multi-criteria decision-making model can assist designers in generating and filtering appropriate alternatives (Hosseini et al., 2020). Additionally, the AI processing technologies obtain reliable design evaluation results in a quantitative analysis method that ultimately improves the utilization value of interior design solutions (Zhang, 2020).

Human-controlled design, regulated design, static construction, and observable and dynamic construction are four general categories of AI environments (Karan et al., 2020). This study focuses only on the human-controlled design environments, and does not address other environments. The study constitutes the first phase of a broader research plan that aims to create an AI system that can perceive the design environment (perception) and produce design ideas (action). For interior design and architecture AI, the development of such systems is envisaged to consist of two main stages: 1) visualization of the design environment into internal representations (e.g., geometry and color), and 2) changing the environment (e.g., making design changes). The objective is not to develop an AI agent as it is beyond the scope of this study; however, the proposed perception

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and action ways are developed in such a way that they can be modified and enhanced in the future into an AI system.

AI algorithms are capable of handling large amounts of data and they have proved to be highly valuable computational tools for extracting information from too large or complex datasets. As data and information are the essence of building information modeling (BIM), the integration of AI and BIM is a promising means of making more efficient design decisions (Che, 2020). In general, AI systems use sensors to get information from their environment (perception) and mathematical models to make design decisions (action). The sensors include those analogous to human perception such as a camera (eye) and a microphone (ear) or some that humans do not have such as infrared and sonar. 3D reconstruction of the true size (absolute scale) space is necessary for an intelligent agent to interact with its design environment. Recent AI systems employ relatively large numbers of sensors to collect spatial data and convert it to as-built geometry of built environment scenes. A large number of sensors increases the cost of maintenance and the likelihood of failure among some of the sensors and also requires computationally intensive data processing. To overcome this challenge, this study proposes a general method for automatically computing the absolute scale and generating 3D geometry of the interior environment from monocular (using a single camera) video without the use of additional sensors (stage 1).

Interior design is perceived as a sequential decision-making process made of a sequence of decision steps in an extended interaction with the design environment. After modeling the real-world indoor 3d scenes, we formulate the interior design problem as a sequence of independent decisions. The decisions are a finite set of actions, and the objective is to maximize a long-run measure of client satisfaction. We formulate the problem of selecting the optimal design as a Markov decision process (MDP); the design involves an alternating sequence of decisions such that design evolves from stage to stage. The quality or client evaluation of each design is independent of its predecessors, and the conditional probability of the next design depends only on the present design (stage 2). MDP is a mathematical framework that has been used for studying optimization problems for decades (Bellman, 1957). Nonetheless, the intention of this study is not to develop extensions to MDP, but rather to expand its application to the architecture and interior design domains. Despite the similar characteristics between interior design decision problems and MDP (e.g., being sequential, partly random and partly under the control of a decision maker), no previous research applied MDP to solve architecture and interior design decision problems. The results reported in the present study contribute to the advancement of the current MDP application in interior design decision-making.

When fully developed, the proposed AI system will be a machine that is capable of understanding its environment and replicates cognitive functions of interior designers to make design decisions. Understanding the environment is done through image and video sensory data. Once the 3D geometry of the interior environment is constructed, the AI system transforms them into machine-readable format (internal context). BIM makes it possible for the AI system to take an iterative approach to design and enhance the interior environment. The constructed data can be transformed into quantitative form (e.g., assigning grayscale values to an image) using libraries of components and BIM products right from the start. Last, the AI system agent makes decisions based on its perceived environment in a way to maximize client satisfaction (as the ultimate goal). AI techniques and algorithms play a significant role in taking actions to achieve such predefined goals. Choosing an appropriate AI technique depends largely on how much we know about the environment and the problem at hand. After extensive review of these techniques, MDP is chosen as the modeling formalism to quantitatively analyze the decisions in a formal and rigorous fashion.

In the next section, we present visualization techniques for the presentation of architecture and interior design concepts in light of the existing literature. Then, we describe the sequential decision-making approach followed by an application of the environment perception/design decision action.

2. 3D Visualization of Interior Spaces

2.1 Background

Interior design is a creative task that demands substantial design knowledge to balance several criteria including space, path distance, illumination, and object relations. It also requires technical expertise and effort in using complex 3D design interfaces and software packages. Currently, there are numerous software packages and online programs for interior design in the market. These packages, while with different levels of sophistication and quality, usually offer advanced design tools and features (e.g. automatic dimensioning, color blender, sample plans, and automatic cost estimator) and a rich Object Library with thousands of 3D models of pieces of furniture, fireplaces, doors, windows, cabinets, moldings, and textures. One common goal of these software packages is to assist a beginner or professional designer in visualizing design ideas effectively before implementing them. For example, they allow the user to pick and edit objects from its library and then add them to the designed space. Their drag and drop feature is reported as handy and of great assistance to the user. However, small progress has been achieved in the automation of the interior design process as a key feature of these software packages. Table 1 summarizes some of the existing automated features in major interior design software packages.

The problem of automated interior design and layout generation has been addressed by academics and researchers using a variety of methods, either fully automated or semi-automated, that can be classified into three main categories: 1) optimization methods, 2) data-driven methods, and 3) procedural methods. Optimization methods are based on the assumption that there is an objective function that represents the quality and appropriateness of the design. Through an iterative process, the initial design is being revised, resulting in the optimal design. On the other hand, data-

Table 1. Examples of Automation Techniques in the Practice of Interior Design

Software	Automated features
Live Home 3D Pro	Offers the functionally automated building of a 3D model of the house while the user draws only 2D plan; After the plan is created in 2D, the user can switch to 3D mode and see the house in 3D view at once
Total 3D Home Design Deluxe	Its SmartRoom Blocks feature creates complete rooms automatically
Virtual Architect Ultimate Home Design	Offers bathroom and kitchen wizards that guide the user through the process of designing these rooms
Home Designer Interiors / Chief Architect Interiors	Has a feature that pre-arranges furniture groupings. Objects placed in 2D plan view are automatically created in 3D, real-time
TurboFloorPlan Home & Landscape Pro	Automatically adds plants or objects along a straight path with a user-defined spacing

driven (or example-based) methods use information from existing and/or user-created layouts in order to generate new acceptable arrangements of objects. Finally, procedural tools are based on a set of rules and constraints that assists a designer in generating acceptable design alternatives. Table 2 lists and briefly explains major works related to interior design visualization. Despite the significant contributions, these studies typically require designers to provide as-built data and geometric properties of surrounding objects. Today the technology has matured to a stage where it is possible to perform as-built documentation in a relatively short time.

A number of studies also addressed material selection as a key step in the interior design process. O'Donovan et al. (2011) used online datasets to examine new and existing theories of human color preferences and develop new color selection tools. Chen et al. (2015) modeled the problem of material suggestion as a combinatorial optimization subjected to local material rules and global aesthetic rules and developed a decorator system that automatically generates material suggestions for 3D indoor scenes. Given the existing furniture color and room shape and type, Chen et al. (2016) trained a Bayesian network using a real interior design dataset in order to automatically assign a harmonious color to the rest of furniture and room. Chang et al. (2017) developed an interactive text to 3D scene generation system that allows a user to design and iteratively refine 3D scenes using natural language. Finally, Kán and Kaufmann (2017) used a genetic algorithm to optimize the material assignment to attain harmonious color configuration and consistent material types. Professionals working in the architecture and interior design industry must use CAD or BIM to develop 3D visualization, however, equipment cost (both software and hardware) is still a constraint.

While effective, the existing interior design aided software packages and approaches have a significant issue: The entire process is not fully automated, and the focus has been on automating certain aspects of the process. This research is an attempt to address this major issue by proposing a novel approach capable of automating the entire process. After this discussion of the previous research efforts and current computer programs and commercial automation/visualization software, we will discuss how as-built geometric information is achieved based on monocular video without the use of additional sensors and how reconstructed 3D surfaced/models are perceived by an intelligent agent, as a solution to the limited capabilities outlined above.

2.2 Visual Data Collection

Video data is considered the primary source of information for this study. Visual observation of scenes and furniture elements is an essential aspect of interior design procedures. Due to advancements in digital and computational technologies, recording and processing video files are becoming common practices within the architecture, engineering, and construction (AEC) industry. 3D reconstruction of scenes using computer vision algorithms is a well-established area of research and practice (Brilakis et al., 2011). Depending on the number of applied sensors, 3D reconstruction algorithms could be divided into three major categories (Rashidi and Karan, 2018): 1) using a single camera or monocular video/photogrammetry, 2) using a set of stereo cameras or binocular video/photogrammetry, and 3) using multiple cameras or camera rig.

In this study, in order to present the most realistic and practical scenario, we select the monocular videogrammetry as the data collection method. Compared to capturing and processing images, working with video files provide at least two advantages: 1) The sequential nature of video frames is an advantage over randomly taken images and will significantly improve the quality of results and minimize the chance of failure in computer vision algorithms. 2) It is easier for the user to push a bottom and record videos instead of taking thousands of images. The entire indoor scene is videotaped from various views and using a smartphone or off-the-shelf cameras. The recorded video file is then fed into a computer vision pipeline, described in the next section, to generate a dense point cloud.

It is also necessary to mention that it is possible to deploy other data collection methods such as mounting cameras on unmanned aerial vehicle (UAV) systems or using autonomous robots depending on the expected level of automation as well as specific project needs. Although these automated methods have been used in many domains (e.g., flood modeling, transport management, archeology, and forestry management and planning), their application is recently being studied by AEC experts, and thus they are not used in the present study.

Table 2. Major Studies on Automated Interior Design

Study	Methodology	Description / Features
Sanchez et al. (2003)	Optimization	A general-purpose constraint-based approach It allows objects to have any orientations.
Akazawa et al. (2005)	Procedural	A framework for automatically and randomly generating 3D scenes considering the semantic constraints.
Germer and Schwarz (2009)	Procedural	An agent-based approach to generate furniture layouts for rooms near the viewer as exploring a building in real time
Tutenel et al. (2009)	Procedural	A rule-based approach to generate suitable layouts for both building floor plans and room layout. It enables the user to specify objects to be placed as instances of classes.
Merrell et al. (2011)	Optimization	An interactive furniture layout system that assists designers by suggesting furniture arrangement according to interior design guidelines (both functional and visual criteria) Resulted in a considerable improvement in the quality of furniture arrangements.
Yu et al. (2011)	Optimization	A framework for the automatic synthesis of furniture layouts It first extracts hierarchical, spatial, and pairwise relationships for various existing furniture objects and then optimizes furniture arrangement considering ergonomic factors using simulated annealing.
Fisher et al. (2012)	Data driven	An example-based synthesis system that generates a variety of plausible arrangements from a few user-provided examples by learning and incorporating design information from a database of 3D object arrangements. It does not need a user for specifying the set of furniture objects to be arranged and marking important object relationships.
Yeh et al. (2012)	Optimization	A Markov chain Monte Carlo algorithm that does not need the users to specify the number of objects beforehand. It overcomes the problem of synthesizing open world layouts.
Chojnacki (2012)	Procedural	A custom procedural mechanism and utilized a scoring function, instead of an objective function. It generates a small number of top rated but diversified recommendations for a designer.
Nam and Lee (2012)	Optimization	A constraint-based genetic algorithm to solve the multi-objective problem of interior space arrangement of mid-sized superyachts. It provides efficient layouts for the designer to choose from according to their design concept.
Xie et al. (2013)	Data driven	A reshuffle-based method for generating diverse and functionally plausible layouts from a very small set of input layouts
Akase and Okada (2013)	Optimization	An automatic optimization method based on interactive evolutionary computation It employs prior information stored in a semantic database and the user preference.
Guerrero et al. (2015)	Data driven	A probabilistic model that learns object layouts in 2D polygonal scenes from a few user-provided examples. It allows to generate complex layouts with a high number of objects with minimum user interaction.
Fisher et al. (2015)	Data driven	An activity-centric method for generating a variety of layouts that support the same activities of the captured real environments. It identifies objects and their functionalities in the real environment and then determines semantically plausible layouts of virtual objects retrieved from a shape database constrained by the observed scene geometry.
Lin and Ke (2015)	Data driven	A virtual reality based recommender system that suggests new prototype drawings to a consigner according to his interests and requirements by retrieving them from a historical interior design drawings database.
Zhao et al. (2016)	Data driven	An example-based method to generate scenes with complex relations. It presents relationship templates as descriptors of complex relations between objects.
Ma et al. (2016)	Data driven	An action-centric method for generating 3D indoor scenes based on human poses, object categories, and spatial configurations learned from annotated photos.
Fu et al. (2017)	Data driven	A system for automatically suggesting indoor objects and proper layouts by leveraging from activity-associated object relation graphs. It uses a database of 2D floor plans to obtain object relations and offer layout examples.
Kán and Kaufmann (2017)	Optimization	A novel method based on a genetic algorithm that automatically generates interior design for a given room by selecting and positioning furniture objects in an iterative optimization process. It performs the material assignment to attain harmonious color configuration and consistent material types.

2.3 Video to Point Cloud

Converting captured videos to informative Point Cloud Data (PCD) is the next step of the proposed workflow. To achieve this goal, we devise and implement a core videogrammetric pipeline. The pipeline is based on a Patch-based Multi-View Stereo algorithm (PMVS) proposed by Furukawa and Ponce (2010) as the core processing unit (see Fig. 1).

In order to meet the specific requirements of interior design processes and also improve the quality of the generated PCD, we add the following three components to this core component. While we provide a brief description of the added components below, further information regarding this pipeline can be found

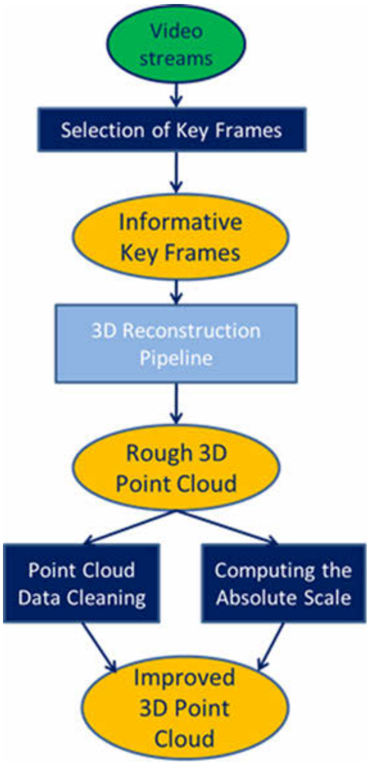

Fig. 1. An Overview of the Implemented Videogrammetric Pipeline for Converting Video Files into PCD

at Nistér et al. (2004), Furukawa and Ponce (2010) and Rashidi et al. (2011).

2.3.1 Optimized Selection of Key Video Frames

Video files captured from indoor environments include blurry, redundant, and less informative frames. For efficient processing purposes, it is necessary to select a number of informative, key frames diligently. To handle this task, we implement the robust key frame selection algorithm proposed by Rashidi et al. (2013). This algorithm considers several factors for selecting optimal frames for processing: Sufficient overlap, avoiding degeneracy cases, and removing low-quality cases.

2.3.2 PCD Cleaning and Refining

It is well known that PCD generated by processing images and videos are not as high quality as laser scanning PCD (Dai et al., 2012). There might be outliers, holes, gaps on surfaces, and poorly reconstructed areas. For tackling this issue, post-processing techniques are often implemented to improve the quality of the generated PCD and prepare them for further processing and extracting necessary information. In this research, we implement the PCD cleaning algorithm proposed by Rashidi and Brilakis (2016). This algorithm includes three major components: removing outliers, filling gaps and holes, and balancing the density of PCD at various locations. Further information is available at Rashidi and Brilakis (2016).

2.3.3 Automated Calculation of Absolute Scale of Generated PCD

Another significant issue about using the concept of monocular videogrammetry is that the generated PCD is up to unknown scale and it is not possible to directly extract dimensions and distances. This is a significant obstacle for implementing videogrammteric techniques for AEC applications where dimensions and geometry are major factors. Many solutions have been presented to tackle the issue including the use of stereo cameras (instead of monocular camera settings). Placing predefined calibration objects with known dimensions is another effective method which has been devised in this study. We implement this idea previously explored by Rashidi et al. (2014). Based on this idea, letter size papers would be placed in indoor scenes. Letter size papers are common objects that can be found in various indoor settings (including offices and houses). Their dimensions are predefined, and it is possible to scale up the entire scene by using robust image processing and computer vision algorithms to detect the papers in videos and PCD (Rashidi et al., 2014). It is worth mentioning that in order to make the detection algorithm functional, the piece of papers should be placed on darker surfaces (see the middle and right parts of Fig. 2). For further information regarding auto calculation of the absolute scale of the indoor scenes, refer to Rashidi et al. (2014).

Several factors can play important roles in quality and accuracy of generated PCD. These factors include lighting conditions, camera resolutions and lens distortions. Compared to larger size and outdoor infrastructure scenes, application of videogrammetry for interior design is less challenging since the lighting condition is under control and also the impacts of lens distortions are not significant due to smaller size of objects in the scene.

2.4 Point Cloud to Surface/Building Information Models

This study contributes to and advances the architecture and interior design literature by integrating automated methods for supporting design decisions. Enhancing the interior of a building includes three phases: first, measuring and capturing the geometry of interior spaces, second, modeling the space, and third, making design decisions. Many architects and interior designers now rely on PCD as a common ground for the acquisition of the as-is state of existing buildings. Video- or photogrammetry scanning allows interior designers to visualize and document the current

Fig. 2. Placing Letter Size Sheets of Paper for Calculating the Absolute Scale of the Scene

space (first phase). Both methods produce point clouds. As discussed in the previous sections, videogrammetry can be used to achieve this goal since it permits to collect information about object geometry in the form of point clouds and provide a large amount of data in a convenient and fast way. The next step is to create a 3D surface or building model from the PCD. BIM allows interior designers to manage the design as multiple options as multiple design alternatives can be studied within a single model (second phase). To automate the modeling process, PCD and relevant images from the field should be compiled to create 3D building information models. Last, mathematical formulations such as MDP can be used to automate the decision-making process. Surface models only describe the external aspects of an object and essentially describe the surface boundaries of the object. Interior designers use surface modeling for creating the external aesthetics of a design.

In contrast, building information models use mathematical principles to create 3D solid objects including the interior details of the object. It is worth noting that the PCD only provides information about the external aspects of objects and does not provide semantic information such as the materials or object properties. The following steps are recommended to create a 3D surface or building information model from the PCD:

2.4.1 Transfer of the PCD into the BIM System

Currently, many BIM systems are capable of importing and displaying large point clouds. Few of them also provide point snapping that would allow us to use the PCD as a 3D modeling reference. For example, “Scan Terrain” application creates Autodesk® Revit® Toposurface models from a laser scanned point cloud or “XYZ to Floor” application takes PCD and creates structural floor BIM elements.

2.4.2 Surface Model Segmentation

Most of the building elements are primitive objects; For example, walls, floors, ceilings, and roofs can be modeled as geometric shapes and planes or pipes, and round columns can be modeled as cylinders. Algorithms such as RANSAC (Fischler and Bolles, 1981) enable us to set a distance threshold and classify PCD into multiple homogenous regions.

2.4.3 Object Assignment and Relationships Definition

Up to this point, the geometry of elements are extracted from PCD. If the ultimate goal is to create an as-is BIM, then the following and final step is to assign semantic information to the extracted elements. The process of object recognition becomes a significantly time-consuming task. Over the past years, many researchers in the fields of computer vision and remote sensing have been striving to develop a comprehensive method with either full automation or semi-automation to reduce the need for human intervention.

In this study, we are interested in furniture and interior partition recognition in an indoor environment. We analyze the whole PCD to locate object instances and recognize them by matching a geometric model of the object into the PCD. The entire process is not fully automated because it requires modeling of everything in the PCD. Thus, manual interaction is necessary; otherwise, interference objects (or partial data) would hinder the recognition of the object in which occlusions are encountered or incorrectly interpreted. Besides, we use standard sizes for wall thicknesses (whenever possible) and assume that architectural elements such as columns and walls lie on a grid and they have right angles. Once the spatial relationships between elements are established, the BIM is then used as the reference and guide for organizing the interior design process.

For developing an intelligent interior designer, we need to enable the AI system to visualize and change the design environment. The key advantage of the proposed video to PCD method is the speed and ease of creating a 3D interior model. This advantage coupled with the visualization capability of BIM provides an AI with the ability to capture and change the design as multiple options such as material selection and furniture layout within a single model. The use of mathematical modeling in AI decision-making is discussed further in the next section.

3. Sequential Decision Making for the Intelligent Interior Designer

An AI system is an intelligent agent that interacts with its environment and changes the environment by doing something. This interaction is primarily based on a perception-decision-action cycle. Perception is the process of gathering information from the environment and transforming them into internal context. The environment itself can be complete, if we have enough information to anticipate decisions’ effect (e.g., chess) or incomplete, fully observable, if we have access to all required information about the environment, or partially observable, and deterministic, if the outcomes can be determined based on a specific state, or stochastic. The design environment in the interior design and architecture domain is complete as we can define the environment in such a way that the agent understands the laws that govern the design environment’s properties (e.g., curtains must be hung from the ceiling). It is also fully observable because image recognition and videogrammetry operate in fully observable contexts. The design environment is stochastic (not perfectly predictable) as the next stages are partly influenced by the client’s feedback and partly influenced by the regulations, standards, and guidelines.

AI systems can perceive the surrounding environment through sensors and cameras. We use the video to point cloud to surface/building information models described in the previous section for deriving perceptions. After having a perception of the design environment, the next question is how to frame decisions. In architectural and interior design, the designer listens to the clients’ needs, requirements, and constraints and provides them with various design solutions. Feedback from the clients will be used as performance measures and to further improve the design. We formulate actions (or decision problems) as a sequence of independent decisions; we view decisions as a sequence of design options which are observed and evaluated by the client at consecutive time intervals called epochs. The essence of the sequential interior design process is that decisions made at each epoch can have both immediate and long-term effects. The best decision to make depends on future situations and how the client will interpret them.

Sequential decision making under uncertainty has gained significant attention in the AI literature. Various algorithms and formal models can facilitate this sequential decision-making. For an intensive review of algorithms for sequential decision making the reader can refer to Littman (1996). Although formal models differ with regard to the level of detail of designs and the level of fidelity of analyses the designs are subjected to, they have the following elements in common; agent, environment, objective, and plan. An intelligent agent is a system responsible for interacting with the environment and making decisions. In this study, the agent is the interior designer. The environment changes from state to state in response to decisions made by the agent. We assume that the environment is the interaction between the client and the design. In addition to the agent and the environment, we need to determine the objective of the agent's decisions. In most cases, the objective is to maximize a reward function. In this study, we define the reward function as the client's satisfaction that can be measured via survey or direct feedback. Last, the agent needs a plan to carry out a sequence of decisions (or actions). When the structure of the environment is not completely known in advance, conditional planning (policy) is a way to deal with uncertainty. These elements are further described in the next section to formulate a sequential decision-making problem.

3.1 Mathematical Model to Formalize Interior Design Decision Problems

The architecture and interior design process is similar to a Markov decision process, one of the most important and widely used models of sequential decision making in AI. The similarity of the two is that the decision outcomes in both of them are partly random (i.e., same decision for different people can result in different outcomes) and partly under the control of a decision maker. They assume that the conditional probability of the next state depends only on the present state and independent of the history of the process. A state is one of the possible quality values or satisfaction rates that the design option can have.

In this study, we model the interior design process as a Markov chain with 6 states designated 1 = poor, 2 = fair, 3 = satisfactory, 4 = good, 5 = very good, and 6 = excellent. Each design option is observed (or assessed) by the client at consecutive time intervals called epochs. If at epoch n the design is observed by the client at received rating value of i (state i), then $X_n = i$. For example, X_3 = good means that the design option is at epoch 3 and the client rates the design good (i.e., state = good). Note that the client has already observed other design options at epoch 0, epoch 1, and epoch 2. The intelligent agent selects a decision from a set of possible decision alternatives designated 1, 2, …, K.

All decision sets used in this study are assumed to have a finite number of alternatives, so that K is a finite integer. The objective of an agent's decisions is to maximize the reward. In the present model, we define the reward, R, as the difference between successive states:

$$R = X_{n+1} - X_n . \tag{1}$$

For achieving the maximum reward, the intelligent agent needs a policy to determine the optimal decision at every epoch. In order to determine the optimal decision, we need to know the current state at epoch n and find conditional probability that the design will be in state j at epoch $n + 1$ when decision k is made. The state of each design option is determined at every epoch by asking the client (or experiment participant) to rate his or her degree of satisfaction on a Likert scale from 1 (poor) to 6 (excellent). The probability that the design will be in state j at epoch $n + 1$ when decision k is made, given that it is in state i at epoch n, is estimated as follows:

$$P(j|i,k) = \frac{\Sigma\mathcal{N}(X_n = i|K = k) \cap \Sigma\mathcal{N}(X_{n+1} = j|X_n = i)}{\Sigma\mathcal{N}(X_n = i|K = k)} , \tag{2}$$

where $\Sigma\mathcal{N}(X_n = i|K = k) \cap \Sigma\mathcal{N}(X_{n+1} = j|X_n = i) =$ total number of j states when decision k is made at previous epoch with state = i, and $\Sigma\mathcal{N}(X_n = i|K = k) =$ total number of times that decision k is made at an epoch with state = i.

We introduce an example here in order to explain the estimation of the abovementioned conditional probabilities better. Assume that a client observes a given interior design option and gives a fair rating value to it. The intelligent agent selects decision $k = 9$ to change the wallpaper of interior partitions. The client observes and assesses the modified design option again. Let's assume that this situation (i.e., current state = fair, decision made = 9) occurs eight times for different interior layouts, three times the modified design option receives poor, one time fair, and four times good. The conditional probabilities for this example are estimated as follows:

$$P(poor|fair, k = 9) = \tfrac{3}{8} = 0.375, \quad P(fair|fair, k = 9) = \tfrac{1}{8} = 0.125$$
$$P(satisfactory|fair, k = 9) = \tfrac{0}{8} = 0, \quad P(good|fair, k = 9) = \tfrac{4}{8} = 0.5$$
$$P(very\ good|fair, k = 9) = \tfrac{0}{8} = 0, \quad P(excellent|fair, k = 9) = \tfrac{0}{8} = 0$$

While the reward, R, is defined as the difference between successive states, due to stochastic variations of state transitions and clients' ratings, expected rewards are needed to determine the optimal decision at every epoch. The expected reward, $E(R)$ is a weighted reward of the possible values that R can take and calculated as follows:

$$E(R) = \sum P(j|i,k) \times R_{ij} , \tag{3}$$

where R_{ij} is the difference between the rating value of state j at epoch $n + 1$ and the rating value of state i at epoch n. Continuing in the previous example, the expected reward for decision k is calculated as follows:

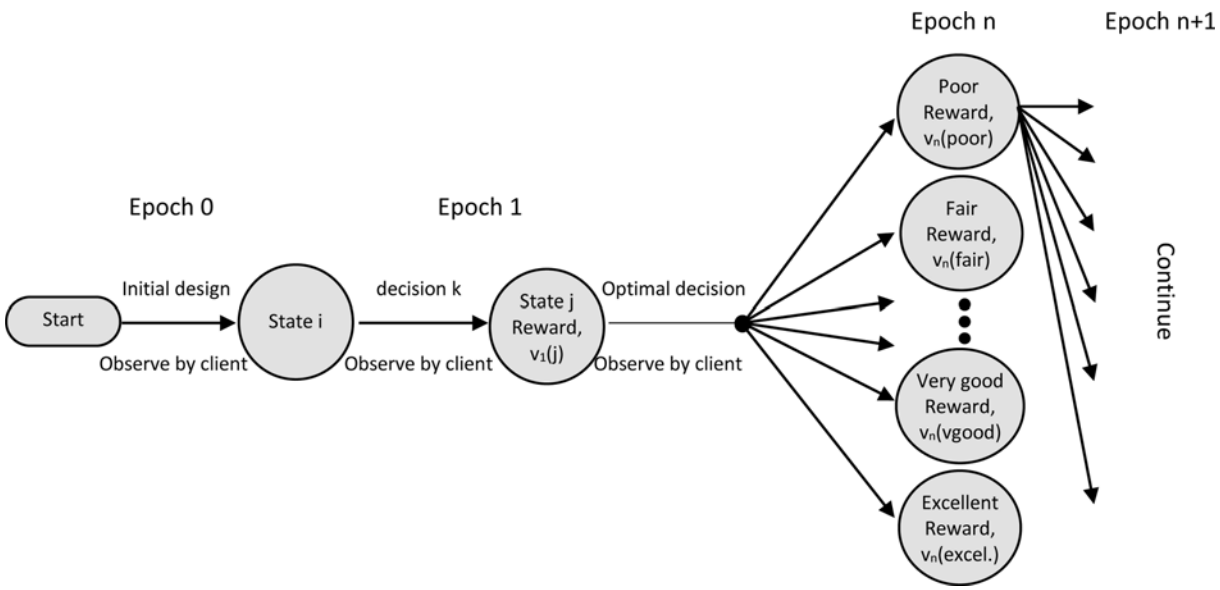

Fig. 3. Tree Diagram of Value Iteration for the Proposed MDP

$$E(R|K=9) = 0.375\times(1-2)+0.125\times(2-2)+0\times(3-2)+0.5\times(4-2)+0\times(5-2)+0\times(6-2)=0.125.$$

By comparing the expected reward for various decisions, the optimal decision can be identified. One way to identify the optimal decision is to use exhaustive enumeration that involves listing every possible decision, computing the expected reward for each decision, and selecting the decision with the highest expected reward. However, this approach is computationally expensive and only feasible for small problems. For a very simple problem with 6 states and 10 decisions, we would have to compute expected rewards for 10^6 or 1 million different decisions. Note that the number of possible policies is equal to the product of the number of decisions permitted in every state. To overcome this drawback, this study adopts an algorithm called value iteration (Bellman, 1957) that has a lower computational burden.

3.2 Optimal Decisions with respect to a Given Criterion

MDPs provide us a mathematical framework for modeling architecture and interior design decision making. In this optimization problem, the objective is to find the best solution from all feasible solutions that maximizes the reward. The problem is formulated as an MDP and can be solved by reinforcement learning or dynamic programming. Although both approaches share the same Markov property principles, the key difference between is that the dynamic programming assumes the environment model (e.g., transition probabilities and the expected reward) is known. The value iteration method is among the most widely used dynamic programming algorithms for solving MDPs. Assume that an interior designer chooses a finite designing horizon equal to N time periods. When the design is in state i at epoch n, the optimal decision for the designer is to select the alternative which will maximize the expected total reward earned during the next $T-n$ periods. The Bellman equation is adopted in this study to compute the expected value of state i at epoch $n+1$, $V_{n+1}(i)$:

$$V_{n+1}(i) = max\left\{R(i)+\sum_{j}^{N}P(j|i,k)\times V_n(j)\right\}, \tag{4}$$

where $R(i)$ is the expected reward in State i, $P(j|i,k)$ is the transition probability from state i at epoch n to state j at epoch $n+1$ when decision k is made, N is the total number of states, and $V_n(j)$ is the value of state j at epoch n.

The value iteration method is used to rank all decisions according to their expected value in every design attempt, in which the optimal decision yields the maximum expected value, $v(n)$. When the first-ranked decision is previously selected, the next decision with the highest expected value is chosen. In the absence of transition probabilities (e.g., at epoch 0), all decisions have the same expected value and thus the intelligent designer makes a random decision instead of an optimal decision. This procedure continues until all decisions are selected or the client is satisfied with the design. Fig. 3 is a tree diagram of the proposed mathematical model in sequential decision-making form for the six-state MDP.

4. Application of the Method: A Case Study

The application of the video to point-cloud to BIM to an intelligent designer can best be demonstrated through a generic example, decorating a baby room. In this study, we select a baby's room to reconstruct. The first step is to record a video of the indoor environment. The goal is to reconstruct a functional model of the room and all objects there on video recordings only. For this purpose, we use consistent lighting and good contrast, avoid using specialty lenses, keep the camera steady, and record video images with several concentric circles at various heights. We turn the video into keyframes and remove all low-quality cases. We avoid degeneracy cases and select key video frames with sufficient overlap using the approach suggested by Rashidi et al. (2013). We then turn the selected video frames into a point cloud. Before reconstructing 3D models, we remove outliers, fill gaps and holes, and balance the density of the point cloud at various locations. It is worth noting that we place predefined calibration objects with known dimensions in the room to scale up the entire scene. The following table summarizes information regarding the generated PCD:

Finally, we convert the PCD into a data-rich 3D BIM for turning the indoor scene into downstream interior design processes. We also extract texture maps from the video images and project those on object surfaces. Thus, the model contains both the geometric and radiometric components with photorealistic surfaces. Fig. 4 shows three data outputs for the case study; video frame, point cloud, and 3D BIM.

Generally, interior design is the process of enhancing all aspects of the interior space, including arrangement, color, furniture, texture, and spatial relationships. An interior designer selects furniture, arranges the room, and chooses paint colors to create an aesthetically pleasing baby's room (pleasing visual environment for parents and children). To approach the problem as faced in reality, we categorize the design decisions adopted in this study into four dimensions: carpet texture, furniture arrangement, wall paint/wallpaper (texture), and window blinds. As illustrated in Fig. 5, we further divide each category into more specific subcategories. This interior design project has 4 decision variables which results in 512 ($4 \times 8 \times 4 \times 4$) possible design solutions. Creating and presenting all solutions is not feasible due to time and resource constraints. This is one reason why this study adopts the value iteration method (Bellman equation) to find and present optimal decisions, not all possible solutions.

In order to measure the effectiveness of the proposed AI system, we conduct the experiments with 20 different participants comparing different design options and evaluating the quality of the design solution based on their preference by giving it a score. Each experiment begins with the as-is BIM at epoch 0. The design code for the as-is BIM is C1-W-A1-WW (refer to Fig. 5 for code details). The participant views the rendered image of the design solution and then evaluates the state or quality based on his/her

Table 3. Summary of Information regarding the Generated PCD

PCD Information	
Length of video	06:37 minutes
Total number of frames (based on a 30fps setting)	11,466
Total number of extracted keyframes	2061
Number of generated points in raw PCD	743,298
Number of generated points after removing the outliers	607,321
Average density of PCD on surfaces	22.5 points per square inch
Average dimensional accuracy of PCD	>98%

preference by giving it a score; one of the possible values of 1 = poor, 2 = fair, 3 = satisfactory, 4 = good, 5 = very good, and 6 = excellent. The evaluation score at each epoch is used to calculate the MDP-transition probabilities for obtaining the best possible design. Table 4 summarizes pertinent information about the MDP and the interior design case study. In the absence of past data, random decisions are made to change and improve the initial design. Otherwise, the expected total reward is calculated for all decisions, and the alternative that will maximize the reward in every state is selected as the optimal decision. The objective is to make decision k to maximize the expected total reward. The AI system selects one of the several decisions, k, at each epoch, to see which decision improves the design (or makes it worse). The decisions are ranked in order of the expected reward, and the design with the highest rank that has not been presented to the client is chosen.

Although this case study project is admittedly simplistic, it provides valuable insights into the sequential structure of the decision-making process and the AI training process. For example, in Experiment 3, it takes 14 epochs to train the AI to learn about the client's preferences. However, even after that, there are cases where the AI has no optimal option, and the design decisions are made randomly. This could happen in the absence of transition probabilities or when the optimal decision(s) has or have been presented already. As more data become available in the present application, more improvements are seen

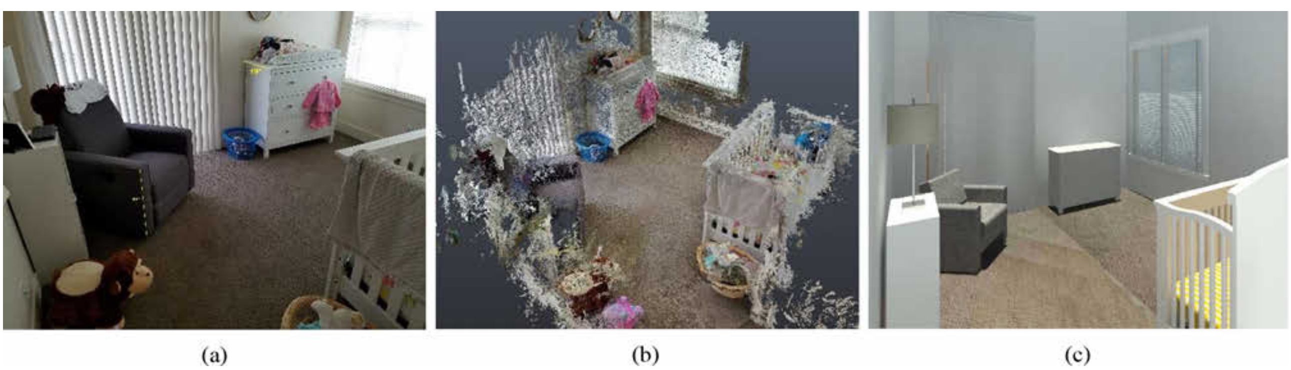

Fig. 4. Process for Converting the Scene into BIM for the Case Study: (a) Video Frame, (b) Point Cloud, (c) BIM

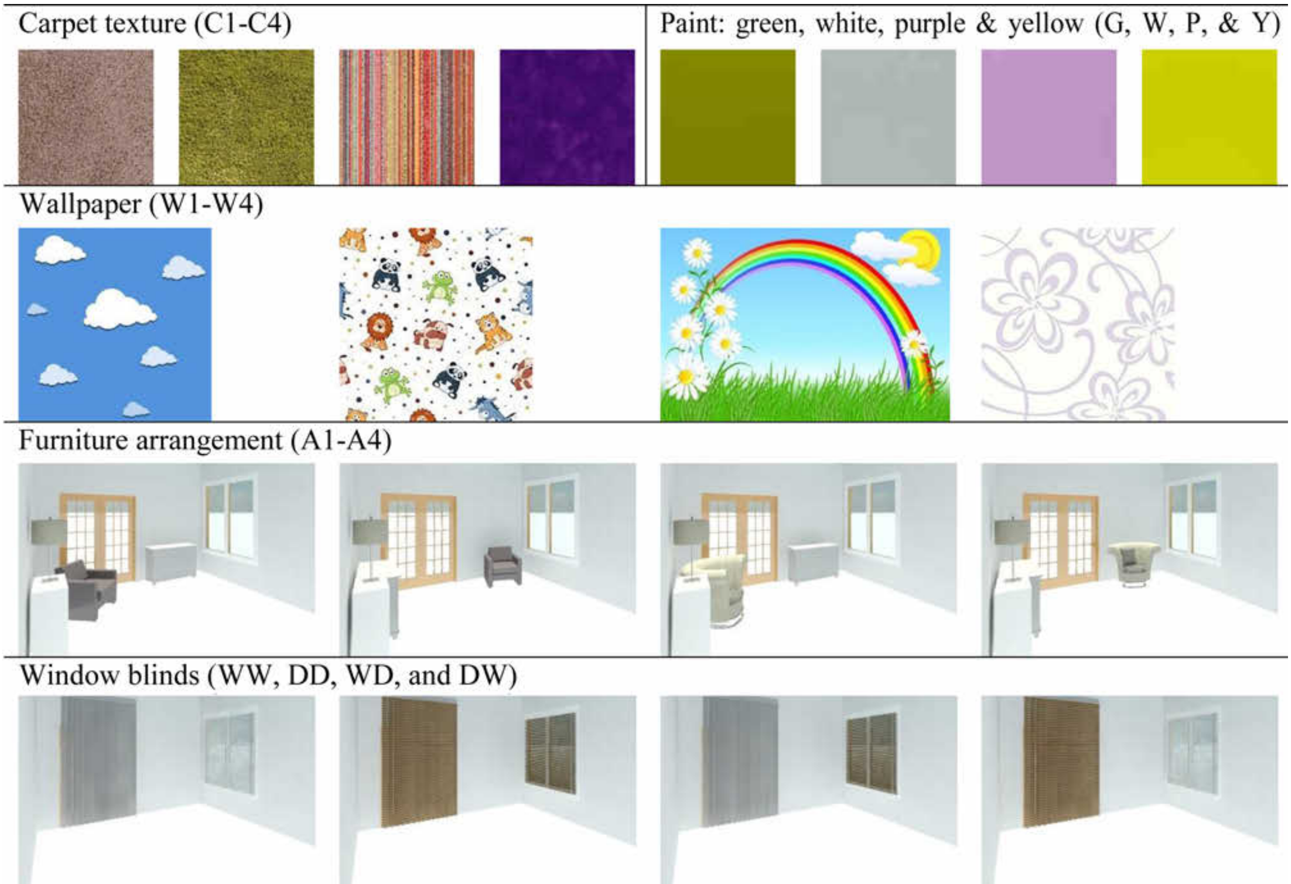

Fig. 5. Design Decisions for the Interior Design Case Study

in the evaluation scores. The procedure continues until the client is satisfied with the design (score = 6 or excellent). Fig. 6 shows the initial design (C1-W-A1-WW) at epoch 0 and best design (C3-W4-A3-DD) at epoch 26 for participant (experiment) 3.

In experiment 3, by comparing evaluation scores for optimally selected decisions to randomly selected decisions, optimal decisions can potentially improve the design; around 50% of the time the client gives better scores to designs changed based on optimal decisions, while this happened only 39% of the time for randomly selected decisions. In this experiment, the client never gives a lower score to designs changed based on optimal decisions; however, 43 percent of time the randomly selected designs results in a lower score. The average evaluation score for optimally selected designs is 3.75 (between satisfactory and good), 11% more than the average score of randomly selected designs with an average of 3.39.

The purpose of the experiments is to determine whether decisions made by the proposed AI system improve participants' satisfaction. To measure the overall performance of the proposed AI, we compare evaluation scores for design decisions proposed by the AI system with randomly made design decisions.

Table 5 presents the key performance measures of the design experiments. Across all measures, design decisions proposed by the AI system perform better than the random ones. First, on average, the design options proposed by the AI system results in a 1.01-point increase in the evaluation score while design options that are randomly made results in a 0.01 decrease in the evaluation score. Also, the average score of the optimal decisions is simply 0.7 point (= 3.9 - 3.2) higher than the random decisions.

The percentage of random (or optimal) improvements can be calculated by dividing the number of random (or optimal) improvements by the total number of random (or optimal) design decisions. Under this measure, the optimal decisions improve the score of the design decisions 75% of the time while the random decisions do this only 32% of the time. Another important measure of the AI performance is the number of epochs taken to reach the maximum score given by participants which can indirectly suggest the time required to satisfy the objectives and meet the client's expectations. On average, it takes 26 out of 512 possible epochs (5.1%) for the AI to meet participants' maximum evaluation score. It is expected that more epochs are needed to meet participants' maximum evaluation score as the design becomes more complex.

For each pair of random and optimal decisions, we conduct a t-test associated with a 95% significance level and present the results in Table 5. For instance, in case of the average score, the null hypothesis states "there is no difference in the average score when design decisions are randomly made or when they are

Table 4. Design Improvement Process Based on the AI System for a Participant in the Case Study

Epoch	Design code	Score	Exp. value	Decision (optimal or random)
0	C1-W-A1-WW	3 (satisfactory)	N/A	Random >> A4 (change arrangement to A4)
1	C1-W-A4-WW	4 (good)	4-3=+1	Random >> C4 (change carpet to C4)
2	C4-W-A4-WW	2 (fair)	2-4=-2	Random >> Y (change wall color to Y)
3	C4-Y-A4-WW	1 (poor)	1-2=-1	Random >> W1 (change wall color to W1)
4	C4-W1-A4-WW	3 (satisfactory)	3-1=+2	Random >> DW (change blinds to DW)
5	C4-W1-A4-DW	4 (good)	4-3=+1	Random >> P (change wall color to P)
6	C4-P-A4-DW	3 (satisfactory)	3-4=-1	Random >> C2 (change carpet to C2)
7	C2-P-A4-DW	4 (good)	4-3=+1	Random >> W (change carpet to W)
8	C2-W-A4-DW	4 (good)	4-4=0	Random >> C1 (change carpet to C1)
9	C1-W-A4-DW	3 (satisfactory)	3-4=-1	Random >> DD (change blinds to DD)
10	C1-W-A4-DD	4 (good)	4-3=+1	Random >> C2 (change carpet to C2)
11	C2-W-A4-DD	5 (very good)	5-4=+1	Random >> W4 (change carpet to W4)
12	C2-W4-A4-DD	4 (good)	4-5=-1	Random >> WD (change blinds to WD)
13	C2-W4-A4-WD	3 (satisfactory)	3-4=-1	Random >> DW (change blinds to DW)
14	C2-W4-A4-DW	4 (good)	4-3=+1	Random >> W3 (change carpet to W3)
15	C2-W3-A4-DW	3 (satisfactory)	3-4=-1	Random >> G (change carpet to G)
16	C2-G-A4-DW	3 (satisfactory)	3-3=0	Random >> A2 (change arrangement to A2)
17	C2-G-A2-DW	2 (fair)	2-3=-1	Random >> A3 (change arrangement to A3)
18	C2-G-A3-DW	3 (satisfactory)	3-2=+1	Random >> DD (change blinds to DD)
19	C2-G-A3-DD	4 (good)	4-3=+1	Random >> W2 (change carpet to W2)
20	C2-W2-A3-DD	3 (satisfactory)	3-4=-1	Random >> A4 (change arrangement to A4)
21	C2-W2-A4-DD	3 (satisfactory)	3-3=0	Random >> DW (change blinds to DW)
22	C2-W2-A4-DW	3 (satisfactory)	3-3=0	Random >> C3 (change carpet to C3)
23	C3-W2-A4-DW	3 (satisfactory)	3-3=0	Random >> DD (change blinds to DD)
24	C3-W2-A4-DD	5 (very good)	5-3=+2	Random >> A3 (change arrangement to A3)
25	C3-W2-A3-DD	4 (good)	4-5=-1	Random >> W4 (change carpet to W4)
26	C3-W4-A3-DD	6 (excellent)	6-4=+2	End

(a) (b)

Fig. 6. Design Improvement Process for a Participant in the Case Study: (a) Initial Design, (b) Best Design

proposed by the AI system". The significance (2-tailed) value for score improvement is 0.0053 meaning that there is a significant mean difference between the average score of the random design decisions and those proposed by the AI system. Since the average evaluation scores for the design options proposed by AI is greater than random options, we can conclude that participants are more satisfied with the decisions made by the intelligent designer.

We use a bivariate correlation statistical technique to determine the existence of relationships between the rewards (or improvements) and decision epochs. Table 6 shows the Pearson's correlation test results for optimal or random decisions. Because the experiments end at different epochs and the number of randomly selected decisions is different from those for optimal decisions, the epochs are presented in percentage to better show the trend. The results demonstrate that a significantly positive correlation

Table 5. Comparison of Design Decisions Made Randomly and by the AI System

Measure	Average	SD	Max	Min	T-Test
Number of Design Decisions (Epochs)	26	9	44	12	-
Number of Random Decisions	22.5	7.2	37.0	11.0	1.0E-11
Number of Optimal Decisions	3.4	2.5	10.0	1.0	
Average Random Scores	3.2	0.5	4.4	2.2	5.4E-03
Average Optimal Scores	3.9	0.9	6.0	3.0	
Average Improvement by Random Decisions	-0.01	0.11	0.15	-0.26	1.2E-06
Average Improvement by Optimal Decisions	1.01	0.62	3.00	0.17	
Number of Random Improvements	7.1	2.1	10.0	3.0	6.6E-09
Number of Optimal Improvements	2.2	1.4	6.0	1.0	
Percentage of Random Improvements	32%	8%	43%	14%	4.7E-07
Percentage of Optimal Improvements	75%	25%	100%	33%	

Table 6. Pearson's Correlation Test between Sequence of Epochs and Rewards

	Random decisions	Optimal decisions
Pearson's correlation	0.057	0.459*
Sig. (2-tailed)	0.234	0.000
N	433	78

*Correlation is significant at the 0.01 level (2-tailed).

existed between the rewards resulting from optimal decisions and the percentage of the epochs completed (r = 0.459, p < 0.001). We can conclude that the client's satisfaction (that is measured in the reward) increases as the number of decision epochs increases. This outcome is not surprising because after each epoch more training data become available for the transition probabilities and thus the decisions become more precise. No significant correlation is observed for the random decisions, although the results show a weak positive correlation between the rewards resulting from random decisions and the percentage of the epochs completed (r = 0.057, p = 0.234). The continuous design improvement (in terms of evolution scores) for randomly and optimally selected decisions are presented in Fig. 7.

5. Conclusions

Improving interior design quality is still dependent on and limited to human capability. Currently, machines and algorithms are not capable yet to solve many complex, open-ended design problems. However, they can take an incredible amount of information and deal with more complex processes than human beings. This study is the first step of a broader, ambitious research project that aims to create an AI system that can perceive the design environment and produce design ideas. Automating interior design can provide significant benefits such as cost reduction, quality performance, higher productivity, and higher reliability. Interior design processes usually involve heuristic reasoning and require the management of interconnected quantitative and qualitative variables like constructability, aesthetics, safety, and cost. AI could be a critical factor in the future of interior design and architecture domain because an AI system can provide better (or similar) outputs with less time and minimal manual interference.

In this study, we apply AI techniques to automate interior

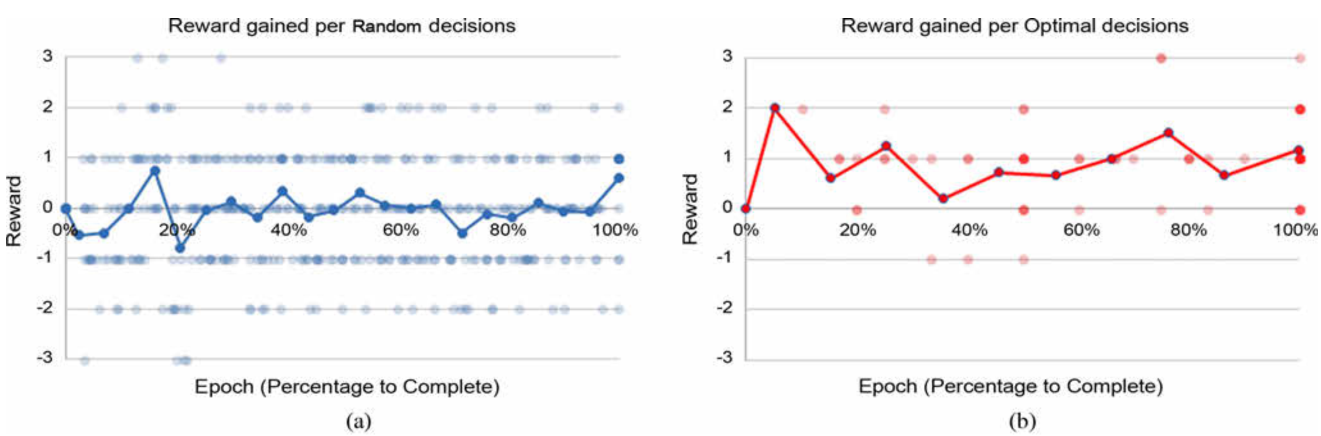

Fig. 7. Changes in the Evaluation Scores for the Case Study Experiments: (a) Rewards for Random Decisions, (b) Rewards for Optimal Decisions

design operations. Specifically, we propose a workflow for as-built documentation in a relatively short time. The most notable feature of using our proposed video-to-PCD method is to enhance service to clients with little or no knowledge about the modeling and documentation of as-built conditions for design and construction purposes while systematically reducing costs. We apply the Markov decision process for modeling the sequential process of design in which the client provides feedback to the intelligent designer until the design meets the needs and preferences of interior spaces' inhabitants. We use the proposed workflow in a case study and conduct experiments with 20 human participants as clients. The statistical analysis of the experiment results shows that the proposed workflow is effective in its objective: helping participants generate a design that maximizes their satisfaction in a reasonable time.

Training an AI interior designer can be challenging, especially in environments with subjective data and/or no direct way of collecting past data. Ideally, a simulation environment is used for training, and then the AI would make the decision or choose the path to follow to maximize the reward. In interior design and architecture, such data is either missing or very difficult to obtain. Future research might include automated ways of obtaining people's physical, emotional, and behavioral characteristics and preferences. Even then, the challenge is the subjectivity of each client's expectations and preferences. Technologies such as eye tracking, facial expressions, electrocardiogram, electroencephalogram, electromyogram, and galvanic skin response are promising as they can potentially enable us to understand potential applications of psychological measurement in the AI domain.

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