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Spatial-temporal event-driven modeling for occupant behavior studies using immersive virtual environments

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ABSTRACT

It is widely accepted that the prediction of building energy performance is strongly related to the occupancy parameters. Currently, existing buildings and laboratories are the main sources for collecting occupancy related data. However, using such data for predicting the energy consumption of future buildings can create a considerable amount of uncertainties. Recent studies show that Immersive Virtual Environments (IVEs) have the potential to generate design and context sensitive occupant-related data. However, extended observations (longitudinal data covering relevant spatial and temporal events) which are necessary for developing quantitative predictive models are impractical using conventional IVEs. To that end, the authors propose a Spatial-Temporal Event-Driven (STED) modeling approach to enable IVEs for longitudinal studies. Using a single occupant office as case study, two sets of occupancy and lighting data, from IVEs and a comparable physical environment (*in-situ*), were collected. The occupancy/lighting data was organized in form of state transitions at six events (*i.e.*, arrival in the morning, leaving for and returning from a short leave, leaving for and returning from a long leave, and leaving at the end of a day). It was hypothesized that the probabilities of the occupancy/lighting state transitions in a given event across the two experimental environments (*i.e.* IVE *vs. in-situ*) are not statistically different. Results revealed similar patterns at four of the six events ($\alpha = 0.05$), except at the short leave events. Thereby, STED modeling enabled the potential viability of IVEs for extended observations and generating data to support predictive models. Clearly, more basic research is needed to make data collection using IVEs more effective including a better understanding of virtual cue design and participant's physiological and psychological conditions at the time of experiments.

1. Background

Recent studies suggest that occupant behavior has a significant impact on building energy consumption [1] and has caused high performance buildings to fail in meeting their design expectations [2]. Meanwhile, work productivity, human health, and building energy efficiency are intertwined and heavily dependent on occupant comfort (*e.g.*, [3,4]). Thus, a better understanding of human and building interactions in different settings is critical to building design and operations. Currently, mainstream studies on occupant behaviors have been mainly conducted *in-situ* using actual buildings [5]. While such studies are important to the operations of existing buildings, results of those studies are often difficult to generalize and apply to other buildings or new designs [6]. This is one of the reasons that after decades of building performance research, performance gaps still exist [7]. In buildings where automated systems are used occupants' interactions with such automated systems (*e.g.* technology–user interactions, program design, and data analysis) are critical for the successful implementation of full automated systems [8,9]. Therefore, human-building interactions are a topic that will not be exempted from future research. Let alone to say that passive building designs are also gaining popularity [10,11].

The authors suggest a new approach, the application of immersive virtual environments (IVEs) for generating and examining occupant-related data during the preconstruction phases of a building project. IVE's are rich multisensory computer simulations that can afford the feeling of being mentally immersed or present in the simulations, *i.e.*,—a virtual world [12].The level of immersion in Virtual Reality (VR) is dependent upon the graphic frame rate, overall extent of tracking, tracking latency, quality of the images, the field of view, the visual quality of the rendered scene, dynamics, and the range of the sensory modalities accommodated [13,14]. VR experiences can be classified into 1) fully immersive or first-order immersive systems that

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have a lot in common with our everyday experiences (*e.g.* head-mounted displays). Lower order VR systems are 2) semi-immersive (*e.g.* projection-based displays), and 3) non-immersive (*e.g.* desktop stereoscopic displays) complied with fewer immersion capabilities, however, they still offer some levels of presence [15,16]. The advantage of using IVEs for data collection is its ability to retain the control of an experimental environment, and its flexibility in designing experimental contexts. "IVE's attraction lies in the tendency for individuals to react in virtual reality as they would in the real-life situation." [17]. They have been effectively utilized to testing situations that are too risky to be examined in reality, such as emergency evacuation in tunnels [18] [19] or hotels [20]. Furthermore, IVE applications have made an exceptionally useful contribution to cases with non-existing testing platform or experiences that cannot be easily replicated in *in-situ*; for instance, building design review and analysis [21,22], the review of full scale physical mock-ups of hospital patient rooms [23,24], and architectural design [25–27]. Above all, IVE applications to occupant energy–use behavior studies are emerging [27] [28–33]. These studies have demonstrated the outstanding capabilities of IVEs to model: 1) building components such as rooms, spaces, windows, lights, or blinds, as well as their properties such as space layout and luminance levels; 2) states of a building component such as blinds close or open and lights on or off; 3) indoor environments specific to the purpose of a study, such as addressing visual, acoustic, and thermal comfort factors; and 4) interactions with building components such as operations of lights or blinds.

Although these capabilities are critical to modeling occupant energy behaviors, IVEs have not been used to develop quantitative predictive models yet. Typically, creating such models requires sufficient information about the variable of interest to enable establishing and examining the patterns in the data [34], which can only be achieved through extended observations (longitudinal data) or repeated measures. While acquiring longitudinal data is not a problem in *in-situ* studies or using surveys, it represents a significant challenge to IVE applications. In an IVE experiment, researchers typically cannot continuously put participants in IVEs for > 20 to 30 min or request the same participant to participate in many experiments. Thus, collecting longitudinal data using conventional IVE designs is impractical. To better address this limitation of IVEs, the authors propose a Spatial-Temporal Event-Driven (STED) modeling approach, which selects and models a series of critical events and thus condenses a long period of observations such as days or seasons into a considerably shorter time such as a couple of hours. In other words, continuous observations are broken down into numerous measurable experimental units, which represent benchmarks subjected to the planned interventions of an experiment. If successful, this approach will enable longitudinal data collection in IVEs, which is critical to support a larger range of applications including predictive modeling than existing applications of IVEs in building design.

2. The spatial-temporal event-driven (STED) model

2.1. Conceptual framework

Longitudinal studies supposedly contain a balanced coverage of observations based on the needs of research. Using a conceptual framework, this study was able to design a systematic method to generate sufficient data that will be useful for ensuring IVEs in extended observations. To begin with, the authors adopted four basic elements related to occupants and building energy performance, to describe the conceptual framework of a STED model, *i.e.*, "*State*", "*Context*", "*Event*", and "*Human* (*H*)-*Building*(*B*) *Interaction*." In this study, *State* (s_i, s_{i+1}, …, s_{i+n}) is defined as the collective status of operations in different building spaces at a certain point of time, especially the conditions of building systems and components that are operable by human beings and have energy efficiency consequences. An example of the state of a building can be the light-use condition of an entire building at 8:00 am on a normal working day. *Contexts* are situational factors that are associated with and describe the state of a building, but not necessarily a part of it. For example, a contextual factor can be the season for describing the light-use state of a building at 8:00 am, because the daylight condition in the winter can be significantly different from the summer at the same time point. *Event* (e_1, e_2, …, e_k) is an occurrence that triggers the change of a state or sets the foundation for future events to change a state. Thus, there are state changing events and non-state changing events. Finally, *H—B Interaction* refers to a particular type of occupant actions to mitigate a thermal, visual, indoor air quality, or acoustic discomfort of an occupant such as turning on artificial lighting at 8:00 am by an occupant, which is associated with a state change event.

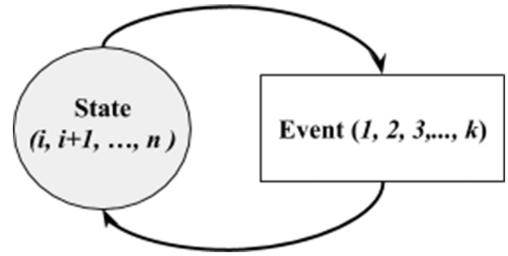

Fig. 1. State-event model.

At a higher level, states and events are interconnected, forming a constant loop between them (see Fig. 1). *State i* is the initial status of a given set of spaces at a specific time point along the time span of a study. *State i* will change to *state i + 1* upon the occurrence of an event. This structure allows researchers to connect space conditions and time, which is critical to designing experiments for longitudinal data collection in built environments.

Fig. 2 displays a more extensive model of the state-event diagram that incorporate "*occupant need*", and "*H—B interaction*" into the state-event model. Occupant needs are defined as human motivation under the context preceding the occurrence of an event, and consequently trigger H—B interactions. In fact, the occurrence of an event can impact occupant's overall comfort and generate a desire for H—B interactions, which leads a state change. Thus, a state transition, the change in the collective status of a building and its component will take place. Window-opening, shade control, lighting control, thermostat control, electric equipment usage, and space occupancy status are among the most common H—B interactions people perform to maintain or pursue their general comfort indoors.

2.2. Theoretical framework

Since state transitions are a key parameter to measure the impact of occupant behavior, this study uses a transition matrix to estimate all possible transitions from one state (s_i) to the following state (s_{i+1}). According to Fig. 2, the connection between two consecutive states is tightly related to possible events (e_k) in between. Consequently, the likelihood of state transitions is essential dependent on paired transitions, *i.e.*, from s_i to e_k and then from e_k to s_{i+1}. Therefore, two conditional probabilities are used to describe a state transition from s_i to s_{i+1}, the probability of the occurrence of an event given an initial state, $p(e_k|s_i)$, and the probability of an event leading to a succeeding state, $p(s_{i+1}|e_k)$. Hence, the probability of the occurrence of a state (s_{i+1}) given a certain initial state (s_i) is estimated by two conditional probabilities, $p(e_k|s_i)$ and $p(s_{i+1}|e_k)$, which is calculated by $p(s_{i+1}|s_i) = p(e_k|s_i) * p(s_{i+1}|e_k)$.

The probability, $p(e_k|s_i)$, is calculated as follows. The number of occurrence of event k (ne_k) at state i (s_i), is expressed as ne_ks_i and used to construct a probability matrix M. For instance, the number of event 2 at the occurrence of state 0 is ne_2s_0.