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Inferring personalized visual satisfaction profiles in daylit offices from comparative preferences using a Bayesian approach

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ABSTRACT

This paper presents a new method for developing personalized visual satisfaction profiles in private daylit offices using Bayesian inference. Unlike previous studies based on action data, a set of experiments with human subjects and changing visual conditions were conducted to collect comparative preference data. The likelihood function was defined by linking comparative visual preference data with the visual satisfaction utility function using a probit model structure. A parametrized Gaussian bell function was adopted for the latent satisfaction utility model, based on our belief that each person has a specific set of neighboring visual conditions that are most preferred. Distinct visual preference profiles were inferred with a Bayesian approach using the experimental data. The inferred visual satisfaction utility functions and the model performance results reflect the ability of the models to discover different personalized visual satisfaction profiles. The method presented in this paper will serve as a paradigm for developing personalized preference models, for potential use in personalized controls, balancing human satisfaction with indoor environmental conditions and energy use considerations.

1. Introduction

Recent studies have focused on predicting visual discomfort in daylit spaces by evaluating and suggesting visual discomfort metrics, including daylight discomfort glare in perimeter offices with complex fenestration systems and variations in luminance patterns within the field of view [1–12]. In parallel, efficient shading controls have been developed to protect occupants from glare [13–22]. While preventing glare is essential, achieving general visual comfort conditions does not translate into satisfaction with the visual environment (or optimal visual conditions). Instead, learning individual preference profiles with respect to visual conditions, without just considering discomfort scenarios, could lead to optimized visual environments for these individuals. These environments could then be realized by implementing the learned personalized profiles in indoor environmental controls.

Therefore, efficient methods for learning personalized visual satisfaction/preference profiles are needed. This can be quite challenging in spaces with daylighting controls. Using simple variables to investigate lighting preferences, such as work plane illuminance, may not be sufficient, especially when occupants conduct vertical tasks (i.e., computer screens) and daylighting systems are dynamically controlled. Satisfaction with the visual environment is affected by objective (i.e., environmental variables) and subjective (i.e., personal preference or psychological) factors, as well as by other contextual factors such as the variability of exterior conditions, outside view [88,89], space function and layout, type of daylighting/electric lighting systems and control type [23–33]. The findings of [88,89] show that the nature of a window view is a factor affecting the sensation of visual discomfort –and therefore, certainly affects visual preferences overall. Also, more recent studies showed that perceived control, control access and user satisfaction with daylighting and electric lighting systems operation are inter-related and complex [34–38]; essentially, visual preferences need to be incorporated in the control system itself.

Adaptive controls, which take into account occupant preferences, are a potential solution to this problem. Indeed, modeling efforts have been made in this direction [39–43]; however, these models were developed based on occupant actions (or interactions with daylighting or electric lighting systems). Although monitoring these interactions and developing respective probabilistic models [37–50] are useful from an occupant behavior point of view (with applications in building simulation models), the cause of the action could be attributed to a variety of reasons (e.g., reducing discomfort, increasing only outside view, or

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even random effects, etc.). These causes are not necessarily related to achieving true satisfaction with overall visual conditions. Behavioral models may not be directly applicable for discovering personalized visual preference profiles, since human actions could be the combined results of several unknown factors [51–53]. As aptly stated by Lindelof and Morel [54], "*it makes sense for a controller to learn from the desired effects of the occupants' actions, not necessarily from the actions themselves*". In addition, only simple and easily measurable variables were considered in these approaches; in reality, occupant visual preferences may depend on multiple factors requiring information that can be difficult to collect in real buildings. Moreover, very few studies consider the diversity associated with occupant behavior [55–57].

Visual satisfaction and preference are two related but distinct concepts. In this study, visual satisfaction is defined as the magnitude (or level) of satisfaction with the perceived visual environment for an individual; while visual preference refers to a relative attitude towards two (or more than two) different visual conditions by comparing them. Using this definition, the visual satisfaction level could be modeled as a utility function $u(\boldsymbol{x})$, where $\boldsymbol{x}$ is a vector of variables describing the physical visual condition (state), and preference is a result of comparing the utility values corresponding to two (or more) conditions. The relationship between these two concepts is illustrated in Fig. 1.

Direct surveys using numerical scaled ratings is a commonly used method in occupant satisfaction research. User-friendly interfaces can be used as survey tools to extract some of the unknown information and rationale behind actions or dissatisfaction with visual conditions [23,38,58]. However, asking humans to rate with a scale has some built-in problems (i) scales could vary with different individuals and (ii) human evaluation is affected by drift, where the scale varies with time, and anchoring, where early experiences weigh higher [59,60]. Instead, studies have argued that relative preferences are often more accurate than absolute ratings [61,62]. Therefore, the satisfaction utility could be modeled as a latent function and inferred from comparative preferences (based on the satisfaction-preference relationship as shown in Fig. 1), following a Bayesian inference approach.

Bayesian approaches for learning occupant preferences are particularly attractive due to their innate ability to explicitly model uncertainty in occupants' latent utility functions [63,64,87]. Furthermore, Bayesian approaches automatically incorporate epistemic uncertainty (uncertainty induced by the limited availability of data) in an intuitive and natural way [65]. These advantages allow for addressing decision-making problems in a principled manner: *combine existing knowledge (prior beliefs) with additional knowledge that is derived from new data at hand (likelihood function), resulting in our prior knowledge (beliefs) being updated to new knowledge (posterior beliefs)*. These posterior beliefs can then be used as priors in future analyses, providing learning chains in science [66]. The spread associated with the inferred posterior distribution quantifies the uncertainty associated with the sampling distribution. With these inherent advantages, we can develop flexible probabilistic models and investigate relationships between variables and models.

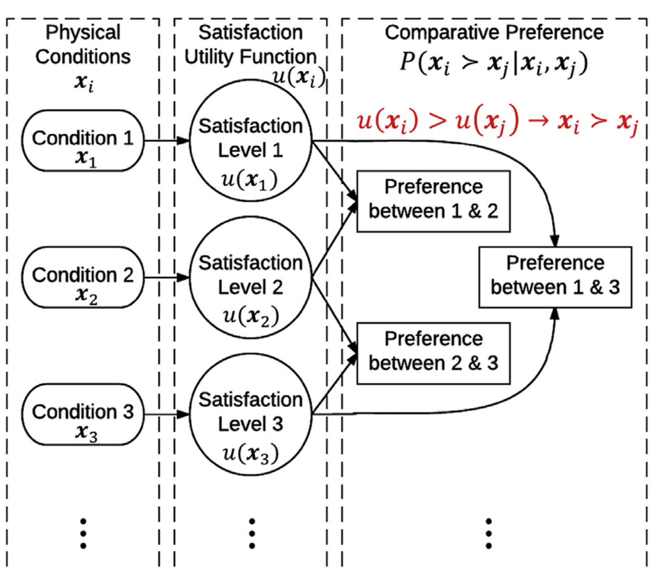

Fig. 1. Relationship between visual satisfaction and comparative visual preference.

Despite these benefits, so far, only three existing studies have tried to implement Bayesian inference-based models in this field. Lindelöf and Morel [54] applied a Bayesian formalism to infer the probability of occupants considering horizontal illuminance distributions as uncomfortable. This was the first study that used this approach, and the authors discuss the issues of including more variables, challenges related to implementation in adaptive controls, and balancing visual comfort and energy use. More recently, Sadeghi et al. [55] inferred behavioral probability models of human interactions with shading and lighting systems following a fully Bayesian approach, showing that, besides environmental variables, human attributes are significant predictors of human interactions. Although these studies presented innovative predictive methods, they are still based on interactions with shading and lighting systems or visual discomfort –instead of visual preferences. Most recently, Sadeghi et al. [67] developed a Bayesian classification and inference method to predict probability distributions of occupant visual preferences in perimeter offices using a data set from a large number of occupants. The model structure includes environmental variables (work plane illuminance, shading position and electric lighting ratio) as well as latent human characteristics and is able to determine the optimal number of clusters of occupants with similar visual preference characteristics. Moreover, personalized profiles of new occupants were derived using a mixture of the clustered probabilistic preference models.

This paper presents a new method for developing personalized visual satisfaction profiles in daylit offices using Bayesian inference. Comparative visual preference data were collected from experiments with human subjects under changing visual conditions in identical daylit private offices. Visual satisfaction utility functions were then inferred through a Bayesian approach, adopting a parametrized Gaussian bell function for the latent satisfaction utility models.

2. Methodology

The statement that one visual condition is preferred to another can be expressed as an inequality relation $u(\boldsymbol{q}) > u(\boldsymbol{r})$, where $\boldsymbol{q}$ and $\boldsymbol{r}$ are two vectors of variables defining these two visual conditions (states), and $u(\cdot)$ defines the underlying (hidden) satisfaction utility function [65]. This approach of defining a satisfaction utility function for preference learning is intuitive and easy to implement, but it is often very difficult to define a meaningful utility function [68]. One approach for creating the utility function is the algorithmic preference learning [69]. In our case, the preference learning process requires two parts: (i) acquiring comparative visual preference data from occupants and (ii) learning the response surface of the satisfaction utility function from the comparative preferences. For the first part, comparative visual preference data were obtained from specially designed experiments (section 2.1). The preference data were used to infer the visual satisfaction utility functions as posteriors through a Bayesian approach, and the inferred utility was sampled using a sequential Monte Carlo algorithm (section 2.2).

2.1. Comparative preference experiment

2.1.1. Experiment design and setup

Following the principles of preference learning, a set of experiments