ABSTRACT

Human-centered daylighting design and operation aim to ensure visual comfort, support perceptual delight (visual preferences), and deliver health benefits (non-visual effects) by accounting for the underlying biological mechanisms and the correlations between psycho-physiological responses and environmental factors. Energy considerations are secondary in human-centered daylighting operation; with proper window and shading selections during the design stage, energy efficiency can be largely optimized in advance. With emerging techniques and devices, this Thesis aims to explore new opportunities to address research gaps across multiple aspects of human-centered daylighting. Using modeling and experimental methods, the work spans from the selection of realistic window and roller shade properties to the investigation of computational methods for assessing visual discomfort, the exploration of non-intrusive luminance monitoring using small low-cost sensors and deep learning, and the validation of non-invasive daylighting preference evaluation. This work is the first to demonstrate that daylight preferences can be learned non-invasively by employing the full potential of HDRI and deep learning techniques.

First, this Thesis proposes a simulation-based optimization workflow (integrating EnergyPlus with a genetic algorithm) to select optimal window properties which can be mapped to existing products. A tree-type optimization design space is built upon an existing glass library to dynamically constrain the correlations of glazing properties and to ensure that optimal solutions correspond to real products. Optimizations are performed to select glazing and window system solar-optical properties that minimize site energy use in south zones (with and without interior shades) or north zones of a typical medium-size office across different US climates. The results yield climate-specific recommendations for selecting energy-efficient window products.

Second, this Thesis presents a measurement-aided modeling workflow for selecting roller shade properties that can significantly reduce the risk of glare, using limited BSDF data. The workflow integrates detailed daylight modeling (Radiance 5-Phase Method (5PM)) and light transmission models through roller shades (Radiance aBSDF with PE), a revised analytical transmission model using limited BSDF data, and a process for refining upper bounds of recommended properties. Radiance 5PM is selected to estimate annual visual discomfort frequency because its results are in a good agreement with the ground-truth ray-tracing tool rpict.

The annual visual discomfort frequency, computed from hourly image-based daylight glare probability (DGP) analysis through the year, is parameterized by shade properties listed by manufacturers (openness factor and total visible transmittance). Recommended upper bounds of shade properties are graphically presented in openness-transmittance 2-D charts, for different locations, orientations and view directions, for dark, medium and light-colored shades in each case.

The final part of this Thesis establishes a basis for future studies to assess the effect of visual environment on human perception using non-intrusive measurements. It provides a theoretical justification to support the feasibility of using a non-intrusive camera to learn personal daylight preferences using deep learning, and validates this feasibility through experiments with human subjects. The justification is provided by demonstrating that luminance information is consistent and transferable between occupants' field of view (FOV) and non-intrusive viewpoints. A Conditional Generative Adversarial Network (CGAN), pix2pix is used to predict FOV luminance maps based on images captured by a wall- or monitor-mounted camera. The results show that the predicted FOV images closely match the measured ones in terms of luminance errors and structural similarity. Then, experiments with human subjects were conducted in an open-plan office. The method of pairwise comparative preference learning is applied to minimize biases in subjective assessments; subjects compared consecutive visual conditions in pairs and indicated their visual preferences. Meanwhile, ten small and calibrated High Dynamic Range Image (HDRI) cameras captured luminance maps from both the FOV of each subject and non-intrusive viewpoints (on Monitor, Ceiling, and Desk) under various sky conditions. Convolutional Neural Network (CNN) models were trained to predict which of the two visual conditions an occupant would more likely prefer by comparing these two conditions using luminance similarity index maps (which quantify differences between two consecutive luminance maps in terms of magnitude and direction changes). The CNN models trained on the luminance information collected from the FOV, Monitor-mounted, and Ceiling-mounted camera demonstrated consistent accuracy across all subjects. The results support that non-intrusive cameras can effectively replace intrusive measurements for visual preference learning, marking a significant milestone towards practical human-centered daylighting control.