Non-Intrusive Luminance Mapping via High Dynamic Range Imaging and 3-D Reconstruction

Michael Kim\textsuperscript{1,2}, Athanasios Tzempelikos\textsuperscript{1,2}

\textsuperscript{1} Lyles School of Civil Engineering, Purdue University, 550 Stadium Mall Dr., West Lafayette, IN 47907 USA
\textsuperscript{2} Center for High Performance Buildings, Ray W. Herrick Laboratories, Purdue University, 140 Martin Jischke Dr., West Lafayette, IN 47907, USA
tzempel@purdue.edu

Abstract. Continuous luminance monitoring is challenging because high-dynamic-range cameras are expensive, they need programming, and are intrusive when placed near the occupants’ field-of-view. A new semi-automated and non-intrusive framework is presented for monitoring occupant-perceived luminance using a low-cost camera sensor and Structure-from-Motion (SfM)-Multiview Stereo (MVS) photogrammetry pipeline. Using a short video and a few photos from the occupant position, the 3D space geometry is automatically reconstructed. Retrieved 3D context enables the back-projection of the camera-captured luminance distribution into 3D spaces that are in turn re-projected to occupant-FOVs. The framework was tested and validated in a testbed office. The re-projected luminance field showed with good agreement with luminance measured at the occupant position. The new method can be used for non-intrusive luminance monitoring integrated with daylighting control applications.

1. Introduction

Daylighting in buildings has a significant impact on occupants, including non-visual effects [1]. These effects have been investigated through human physiological and biological functions, human performance, health and behavioral studies [2–5] to achieve systematic, performance-based lighting design and operation in buildings [2,6]. As indicators of visual perception, luminance-based metrics have a higher correlation to the human perception of brightness [7] compared to illuminance and can capture the spatial composition of luminous environment within the human FOV [6]. This trend was enhanced by the advent of High Dynamic Range Imaging (HDRI), a technique that allows retrieval of luminance maps by merging camera photographs with bracketed exposures [8]. This technique allows us to capture accurate per-pixel luminance distribution within human-FOV by combining a wide-angle fisheye lens with the camera, and has been validated and established by several research groups [9–15].

The HDRI technique has been used to associate luminance-based metrics with various effects on building occupants including visual comfort and preference. Despite the obvious potential of luminance-based sensing, and daylighting control in buildings, however, there is an apparent gap between the accumulated knowledge from human-centric lighting studies and their practical building applications. This is due to two major reasons: (i) low-cost, programmable HDRI sensors only became available recently; and (ii) measuring luminance distribution within the occupant FOV requires placing the camera adjacent to the occupant, which is distracting and impractical. Placing the sensors at alternative, less-obtrusive positions has been recently investigated in a few studies, e.g. on the ceiling or elsewhere in the occupant vicinity [13,14,16–19]. Recent efforts successfully attempted to model the occupant-
perceived luminance distribution as a function of the camera-measured values using regression models [16], however this requires some manual commissioning; in addition, the camera-to-occupant FOV conversion can be compromised without knowing the 3D context of the interior space.

In this regard, the main objective of this study is to propose a novel, semi-automated framework for monitoring of luminance distribution within occupant-FOV, which leverages a non-intrusive HDRI sensor and Structure-from-Motion (SfM) - Multiview Stereo (MVS) photogrammetry pipeline. The 3D model reconstructed from the photogrammetry pipeline enables the back-projection of the luminance distribution captured by the HDRI sensor into 3D room surfaces which are in turn re-projected into occupant-FOVs with the head poses estimated. The only commissioning effort required is to capture a short video of the room and take low-dynamic range (LDR) photographs from the occupant-head position using consumer-grade camera devices, such as smartphones (Figure 1). Since the framework does not require labor-intensive commissioning or expensive, measuring devices, it has the potential of wide application in buildings for monitoring of luminous conditions, lighting and window controls.

![Figure 1. Overview of the overall framework](image)

2. Methods
2.1. Devices and calibration
The HDRI sensor, a low-cost camera sensor integrated to a single board computer, runs on a UNIX-based operating system. The sensor is based on a CMOS image sensor with an 8-megapixel resolution and is fully programmable with Python language. Also, a fisheye lens with an aperture of f/1.8 and a focal length of 1.05 mm was attached to the camera to expand the field-of-view near 180 degrees. The details of the integrated HDRI sensing system and HDR imaging pipeline used in the study are elaborated in [20,21]. The HDRI sensor was photometrically and geometrically calibrated following the procedure introduced in [20], using the OpenCV-python library [22]. However, since the sensor is intended only for indoor (darker) measurements, a modified set of ten different shutter speeds ranging from 9μs to 799,980 microseconds was used for this study. Additionally, as a user-owned device for capturing video and images of the room, a common smartphone was used. The proposed framework assumes the installation of factory-calibrated HDRI sensor with known geometric and photometric parameters, while not requiring prior knowledge about the user-owned camera device for the enhanced scalability for real-building applications. However, to enhance the robustness of the photogrammetry, the geometric parameters of the device are recommended to be estimated. Thus, a very simple geometric calibration procedure for the user-owned device was included in the framework. We used a similar method to the HDRI sensor but instead of taking pictures of a calibration pattern (a flat checkerboard with a known square size), we chose to take a short video of it. By extracting the video frames that capture various views of the calibration pattern and using OpenCV-Python implementation of Zhang’s camera calibration algorithm [23], the camera parameters of the device can be estimated.
2.2. Data preparation
This framework only required the user to take two short videos and photographs (per occupant) with a user-owned camera device as presented in Figure 2. One of the two videos, Video A, is for the geometric calibration of the user-owned device. The video should capture the calibration pattern in various views for a robust estimation of the camera parameters (Figure 3a). The frames extracted from Video B (Figure 3b) will be used for the 3D reconstruction of the room via SfM-MVS photogrammetry. The quality of the reconstructed model through 3D photogrammetry largely relies on how the video is taken. In brief, it is advised to capture the images of the same object in as many view-angles as possible and to capture the same region of interest in smaller resolution for the robust model reconstruction. In addition to the manual collection, the HDRI sensor will automatically capture the room scene to estimate its camera-pose. The images put into the photogrammetry pipeline are rectified (i) to reduce computation during parameter refinement during the SfM; and ii) to use a COLMAP-compatible camera model (pin-hole projection). Thus, the camera parameters are updated to the rectified projection accordingly.

![Figure 2. Data preparation for SfM-MVS 3D reconstruction pipeline.](image)

2.3. SfM– MVS 3-D reconstruction pipeline
SfM-MVS is a workflow for the image-based 3D point cloud reconstruction of objects, with two sequentially connected algorithms: Structure-from-Motion (SfM) and Multiview-Stereo (MVS). SfM is the process of reconstructing 3D structure from its projections into a set of unstructured images taken from different viewpoints [24]. SfM automatically estimates and refines the camera parameters and poses. Since SfM reconstructs only the interesting points with distinct feature across multiple images, the resulting 3D point cloud is sparse. For more detailed 3D representation of the real scene, the sparse point cloud from SfM is subsequently densified through MVS algorithms. MVS uses the camera parameters and poses, estimated through SfM, to solve the stereo-correspondence problem in smaller subsets of images based on the photometric or geometric constraints. The advantages of the SfM-MVS pipeline are that the entire reconstruction can be fully automated and does not require expensive, scientific-grade sensors. In this paper, we used SfM-MVS pipeline combined with two open-source libraries, COLMAP [24] and OpenMVS [25]. The overall workflow of COLMAP-OpenMVS pipeline is presented as presented in Figure 4.

![Figure 3. Example video frames. (a) Video A (b) Video B](image)

2.4. Occupant view re-projection
The re-projection of the HDRI sensor-perceived luminance into the occupant-FOV follows the pipeline shown in Figure 5. Using the room mesh model and the HDRI sensor pose and camera parameters, the depth map of the room perceived by the HDRI sensor can be retrieved. By combining the depth map
with the luminance map from the sensor, an RGBD map can be created. The RGB channels of the map contain the per-pixel luminance values encoded in floating numbers while the remaining channel stores the per-pixel depth values. The RGBD map can be back-projected into 3D leveraging the HDRI camera parameters, which is in turn transformed into a new mesh model with a complete luminance map when re-projected. Now we can re-project the luminance-mapped mesh model into occupant-FOV, using the estimated head-pose and the user-defined camera parameters for the re-projection into 2D image (Figure 1). The depth map retrieval, RGBD creation, back-projection, and re-projection were conducted using Open3D-Python, an open-library for 3D geometry processing [26]. Since the current version of Open3D-Python only allows rectilinear camera projection, the luminance map was first projected with a pinhole projection and then remapped into a fisheye projection via a custom python script.

2.5. Experimental validation
To investigate the feasibility of the proposed framework, it was implemented in a private, testbed office. The details of the room and the sensor integration to the building management system is described in [21]. As shown in Figure 6a, two HDRI sensors are installed in the room: i) Sensor I for luminance monitoring, vertically attached to the wall behind the occupant position, looking 20 degrees downward [16] at 2 m above the floor; and ii) Sensor II for validation, installed at the occupant position (1.2m above the floor and is oriented to the task area). The camera FOVs of Sensor I and Sensor II are presented in Figure 6b-c. The window shade was 35% open during the measurement. For the validation, HDR luminance maps were taken by both sensors synchronously during sunny days in November – December 2020 with a 10-minute interval. Then the luminance maps from Sensor I re-projection were compared to the Sensor II measurements. Daylight Glare Probability (DGP) [27] was used as a comparison indicator, since it was recently found as the most robust among 22 glare predictors [28].

3. Results
A total of 77 measurements were collected for the purpose of validation. Overall, the luminance map re-projection shows a nice resemblance between the re-projection and the actual measurement (Figure 7). Also, the measured and predicted (re-projected) DGP showed a good agreement with RMSE of 0.01
These results show that the method is reliable and can predict reasonably the re-projected luminance in the occupant’s FOV using the non-invasive semi-automated framework.

Figure 6. Experimental setup. (a) Sensor installation (b) Sensor I view (c) Sensor II view

Figure 7. False-color luminance maps comparison.

Figure 8. DGP validation.

4. Conclusion
This study presents a new semi-automated framework for monitoring luminance within occupant-FOV using a low-cost, non-intrusive camera sensor and SfM-MVS 3-D reconstruction pipeline. The proposed framework allows accurate luminance monitoring without requiring manual commissioning and scientific-grade devices, thus it can be widely applied in various buildings. Future work includes further validation of the proposed method in various settings including more visual discomfort conditions and sensor positions to improve its robustness and further generalize results.

Acknowledgments
The authors would like to thank the Center for High Performance Buildings at Purdue University.

References
[1] Boyce P R 2014 Human factors in lighting, third edition
[2] Aries M B C, Aarts M P J and Van Hoof J 2015 Daylight and health: A review of the evidence and consequences for the built environment Light. Res. Technol. 47 6–27
[3] Borisuit A, Linhart F, Scartezzini J-L and Mü M Effects of realistic office daylighting and electric lighting conditions on visual comfort, alertness and mood
[4] Figueiro M G, Nagare R and Price L L A 2018 Non-visual effects of light: How to use light to promote circadian entrainment and elicit alertness Light. Res. Technol. 50 38–62
[5] Andersen M 2015 Unweaving the human response in daylighting design Build. Environ. 91 101–17
[6] Amundadottir M L, Rockcastle S, Sarey Khanie M and Andersen M 2017 A human-centric approach to assess daylight in buildings for non-visual health potential, visual interest and gaze behavior Build. Environ. 113 5–21
[7] Ware C 2013 Lightness, Brightness, Contrast, and Constancy Information Visualization pp 69–94
[8] Debevec P E and Malik J 1997 Recovering high dynamic range radiance maps from photographs Proceedings of the 24th Annual Conference on Computer Graphics and Interactive Techniques, SIGGRAPH 1997 vol 3965 pp 369–78
[9] Inanici M N 2006 Evaluation of high dynamic range photography as a luminance data acquisition system Light. Res. Technol. 38 123–36
[10] Pierson C, Cauwerts C, Bodart M and Wienold J 2019 Tutorial: Luminance Maps for Daylighting Studies from High Dynamic Range Photography LEUKOS - J. Illum. Eng. Soc. North Am.
[11] Suk J Y, Schiler M and Kensek K 2013 Investigation of Evalglare software, daylight glare probability and high dynamic range imaging for daylight glare analysis Light. Res. Technol. 45 450–63
[12] Wagdy A, Garcia-Hansen V, Isoardi G and Pham K 2019 A parametric method for remapping and calibrating fisheye images for glare analysis Buildings 9 1–24
[13] Adam G K, Kontaxis P A, Doulos L T, Madias E N D, Bouroussis C A and Topalis F V. 2019 Embedded microcontroller with a CCD camera as a digital lighting control system Electron. 8 33
[14] Motamed A, Deschamps L and Scartezzini J L 2017 On-site monitoring and subjective comfort assessment of a sun shadings and electric lighting controller based on novel High Dynamic Range vision sensors Energy Build. 149 58–72
[15] Cauwerts C and Piderit M B 2018 Application of high-dynamic range imaging techniques in architecture: A step toward high-quality daylit interiors? J. Imaging 4
[16] Krüsselbrink T W, Dangol R and van Loenen E J 2020 Feasibility of ceiling-based luminance distribution measurements Build. Environ. 172 106699
[17] Konis K 2014 Predicting visual comfort in side-lit open-plan core zones: Results of a field study pairing high dynamic range images with subjective responses Energy Build. 77 67–79
[18] Goovaerts C, Descamps F and Jacobs V A 2017 Shading control strategy to avoid visual discomfort by using a low-cost camera: A field study of two cases Build. Environ. 125 26–38
[19] Motamed A, Bueno B, Deschamps L, Kuhn T E and Scartezzini J L 2020 Self-commissioning glare-based control system for integrated venetian blind and electric lighting Build. Environ. 171 106642
[20] Kim M, Konstantzos I and Tzempelikos A 2019 A low-cost stereo-fisheye camera sensor for daylighting and glare control J. Phys. Conf. Ser. 1343
[21] Kim M, Konstantzos I and Tzempelikos A 2020 Real-time daylight glare control using a low-cost, window-mounted HDRi sensor Build. Environ. 177 106912
[22] OpenCV OpenCV Library
[23] Zhang Z 2000 A flexible new technique for camera calibration IEEE Trans. Pattern Anal. Mach. Intell.
[24] Schönberger J L and Frahm J M 2016 Structure-from-Motion Revisited Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition vol 2016-Decem pp 4104–13
[25] OpenMVS 2020 OpenMVS: open Multi-View Stereo reconstruction library GitHub Repos.
[26] Zhou Q-Y, Park J and Koltun V 2018 Open3D: A Modern Library for 3D Data Processing
[27] Wienold J and Christoffersen J 2006 Evaluation methods and development of a new glare prediction model for daylight environments with the use of CCD cameras Energy Build. 38 743–57
[28] Wienold J, Iwata T, M. S K, Ereell E, Kraftan Eran, Rodriguez R., Yamin Garreton J. A. T T, I. K, Christoffersen J., E. K T, C. P and M. A 2019 Cross-validation and robustness of daylight glare metrics Light. Res. Technol. 0 1–31