BEYOND ILLUMINATION: AN INTERACTIVE SIMULATION FRAMEWORK FOR NON-VISUAL AND PERCEPTUAL ASPECTS OF DAYLIGHTING PERFORMANCE

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ABSTRACT

This paper presents a proof-of-concept for a goal-based simulation structure that could offer design support for daylighting performance aspects beyond conventional ones such as illumination, glare or solar gains. The framework uses a previously established visualization platform that simultaneously and interactively displays time-based daylighting performance alongside renderings, and relies on a goal-based approach. Two novel performance aspects are investigated in the present paper: health and delight. For the first aspect, drawing from the latest findings in photobiology in terms of effects on sleep, health and well-being, the goal is to integrate time-dependencies of non-visual responses to light into a dynamic light-response model for the non-visual system that can be part of a design process. For the second, the goal is to deepen our understanding of the perceptual qualities of daylight through a dynamic analysis of spatial contrast and its variability over time.

The two approaches discussed in this paper introduce a new framework for the Lightsolve simulation environment that includes a Radiance calculation engine combined with an interactive visualization platform for temporal and spatial ‘distribution’ of performance.

INTRODUCTION

Architects are increasingly using digital tools during the design process, particularly as they approach complex problems such as designing for successful daylighting performance. Building simulation models for daylighting have traditionally been developed to either evaluate task performance through workplane illuminance calculation (Mardaljevic et al., 2009), energy impacts of daylight such as active electric lighting, heating or cooling needs to compensate for excessive or insufficient daylight (IEA, 2008), or its impact on comfort and in particular on glare-based sources of discomfort within the visual field (Wienold, 2009).

Yet daylighting is known to be a field where strictly defined numerical boundaries are not strictly enforced: there is a vast range of parameters and values that contribute to “good” daylighting design and which make absolute performance targets of questionable relevance. To assist architectural designers in searching for “better” solutions to support a more flexible, user-centered approach, an annual daylighting simulation method was developed in 2008 (Andersen et al., 2008), called Lightsolve, meant to be used in the early design process (Andersen et al., submitted) when façade and space details are still being defined. Lightsolve took a new perspective on daylighting analysis, focusing on the variation of daylight performance over the day and the year by combining temporal performance visualization with spatial renderings (Kleindienst & Andersen, 2012). This simulation method included an expert system to support a guided search process and differed from previous approaches (Paule et al., 2011; Ochoa & Capeluto, 2009) in that it allowed a comprehensive understanding of daylighting and offered user interactivity regarding design choices (Gagne et al., 2011). One of the underlying principles in how daylighting performance is evaluated in Lightsolve is to make the results specific to the user’s own performance objectives and to his or her chosen areas of interest within the considered design project. On the other hand, it combines a synthetic perspective of full-year data with a visual impression of what the space looks like over time.

These two foundations provided a powerful basis upon which to build when considering the inclusion of qualitative or physiological aspects also inherent to daylight performance, yet not as easily associated with absolute thresholds of “good” versus “bad”. The two new performance aspects investigated here as potential complementary drivers for design decisions relate on one hand to the non-visual effects of light and on the other hand to its perceptual qualities regarding contrast.

Foundations for non-visual effects

In addition to stimulating visual responses, light can induce non-visual responses both through its phase shifting effects on the circadian clock and through direct activating effects (Cajochen et al., 2000; Zeitzer et al., 2000). These effects are mediated primarily via a novel non-rod, non-cone photoreceptor, which is most sensitive to blue light and exhibits different sensitivity to the intensity, spectrum, duration/pattern, timing and history of exposure as compared to visual responses (Lockley, 2009). The discovery of this novel photoreceptor, the intrinsically photosensitive retinal ganglion cell (ipRGC), has led to consideration of the non-visual effects of light as an important element of healthy lighting design in addition to vision (Webb, 2006; Pechacek et al., 2008).

In a recent field study, the effects of exposure to blue-enriched white light during daytime work hours were investigated in comparison to white light (Viola et al., 2008). Blue-enriched white light improved subjective alertness, performance, mood, and sleep quality. This suggests that blue-enriched white light in real-world settings can have beneficial effects for people working normal office hours, which makes it an appealing alternative to enhance alertness. Another study, where subjects were exposed to two realistic office lighting conditions for two consecutive days, reported higher subjective alertness in the afternoon in response to prior bright daylighting condition (~1000lx) compared to typical artificial lighting condition (~180lx) (Münch et al., 2012).

Before application of these new findings, however, it is necessary first to understand the dynamic relationship between light and human non-visual responses. Modeling can be a useful tool not only to gain deeper understanding of complex systems but also to point out gaps of knowledge, suggest specifics experiments and serve as a tendentious module for studying practical implications of simulated human-responses. One challenging aspect is the fact that the non-visual system adapts its responses to changes in light intensity and spectral composition over a much longer timeframe than the visual system (Gooley et al., 2010; Chang et al., 2012).

Very few studies can be found that use this new knowledge to investigate which design factors can increase the non-visual potential of architectural spaces. The authors were the first to propose modelling frameworks that would address this question (Pechacek et al., 2008; Gochenour & Andersen, 2009; Andersen et al., 2012) but all of them were static in the sense that the slower adaptation of the non-visual system was not taken into account, nor were spectral sensitivity shifts and desensitization effects after prolonged exposure included. The objective here is to incorporate a mathematical model that the authors are currently developing to predict direct non-visual responses to light stimuli including time- and spectral-dependent shifts in sensitivity (Amundadottir et al., 2013*a*), in a way it can inform daylighting design through a goal-based simulation workflow such as proposed by Lightsolve.

Foundations for perceptual effects

The perception of daylight within architectural space is an important aspect of visual performance and impacts the ways in which that space is experienced. Contrast draws our attention toward spatial complexity and highlights areas of material transition, while the dynamic nature of sunlight generates varied luminous effects over time. The visual effects of daylight are subjectively perceived and evaluated by each occupant, making it very difficult to enforce them as design factors even though they ultimately drive many design decisions. The perceived qualitative aspects of daylight in a varying indoor space are underserved by the metrics currently available to designers: architecture must 'perform' in both qualitative and quantitative criteria, so we must work to re-establish the role of emotional and perceptual indicators in our language about performance.

While some metrics have emerged to try and quantify 'light quality' through identifying a relationship between brightness, contrast and occupant preference (Cetegen et al., 2008; Wymelenberg & Inanaci, 2009; Parpairi et al., 2002), they are generally based on occupant surveys of existing scenes or static digital images of an interior space taken at key incremental moments. Although occupant surveys were once the primary method of data collection, digital photographs have become a useful alternative for practical purposes (Cetegen et al., 2008). Since the advent of HDR imaging, we are now able to produce digital photographs and renderings with a broader range of luminance data that more accurately capture a scene from an occupant's point-of-view (Newsham et al., 2005). Two dimensions that are widely accepted to impact the field-of-view are average luminance and luminance diversity (Cetegen et al., 2008). The former has been directly associated with perceived lightness and the latter with visual interest. Those metrics that take advantage of HDR digital images aim to correlate factors such as view size, average luminance, or luminance diversity with an occupant's perception of pleasantness, excitement, and spaciousness of the view as established by surveys (Cetegen et al., 2008; Newsham et al., 2005). The studies that focus on average luminance are generally associated with perceived lightness, while luminance diversity (typically min/max ratios) is often associated with visual interest. Other studies have used genetic algorithms to predict occupant preferences toward average luminance and uniformity within a specific program environment, such as an office environment (Newsham et al., 2005). Although these findings are somewhat consistent in pointing out that occupants seem to prefer bright, non-uniformly lit environments with some luminance diversity (Parpairi et al., 2002; Wymelenberg & Inanici, 2009), none of these studies address the question of dynamic variability of daylight as it is impacted by seasonal and daily variations in strength, climate, and solar orientation. Outside of the Luminance Difference Index (Parpairi et al., 2002), there is also a lack of metrics that can distinguish between compositional variations in contrast across our-field-of-view, unlike the human brain which is capable of discerning such effects by mere observation. The dynamic nature of sunlight creates a visceral connection between the occupant and his/her surrounding environment and spatial contrast and variability are fundamental to the experiential impacts of architecture; yet architects still have to rely on intuition and experience to evaluate their dynamic effects against their intended programmatic use. What we propose is a set of metrics that would integrate the dynamic aspects of perceived daylight as tangible guiding factors for design. Such a method could help designers in contextualizing relative strength as well as temporal stability of contrast within an architectural space.

METHODOLOGY

What we propose in this paper is a preliminary workflow to integrate non-visual and perceptual aspects of daylighting performance into an interactive tool specifically developed for early stage, full year, climate-based daylighting design support.

Revised structure of the Lightsolve platform

The application of these concepts into a simulation framework required a new embodiment for Lightsolve to be developed. Its overall principle (cf. Andersen et al., 2008) – and the general layout of the user interface (new prototype shown in Figure 1), with goal-based temporal maps displayed alongside interactive renderings (Andersen et al., submitted), were maintained. Such temporal maps – with days of the year on the x-axis and time of day on the y-axis – exhibit how closely user-defined goals are fulfilled over the year using a triangular color scale (Fig. 3b, cf. Kleindienst & Andersen, 2012).

The fundamental changes compared to the original embodiment of Lightsolve relate to the new ray-tracing engines used and a completely new software and display structure. The main goal was to make the tool much more responsive and reliable.

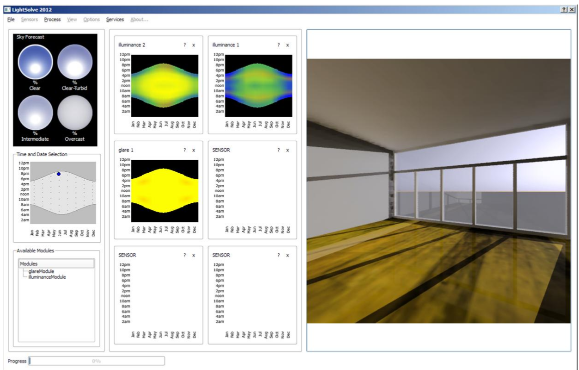

Figure 1 New Prototype for Lightsolve User interface

Thus, a specific selection of tools and libraries was selected for this new structure to rely upon:

- C++ as programming language using GCC (GNU Compiler Collection) for Mac OSX or MinGW (Minimalist GNU) for Windows systems

- Radiance as the best-validated daylighting simulation engine

- Nvidia Optix Application Acceleration Engine as a real-time ray-tracing tool for ensuring high responsiveness and interactivity in the 3D rendering (Nasman et al., 2011)

The functionalities of the application are based on modules and are designed to allow both local and remote development. These independent modules are detached from the core application to allow high flexibility in the development and later integration of new modules in the future. Two types of modular units can be distinguished: LightSolve Modules which are processing units with illuminance values as input, and LightSolve Services which are processing units with more complex inputs (Expert System, etc.). Only the latter can access and change whole scenes (mesh, position and point of view), start lighting simulation computing or reprocess modules. The Raytracing Engine and the Lighting Simulation Engine are also independent and detached from the core to allow future component replacements. Unlike LightSolve Services or Modules, the Raytracing and Lighting Simulation Engines are unique objects with precise goals and specific interfaces (see Fig. 2).

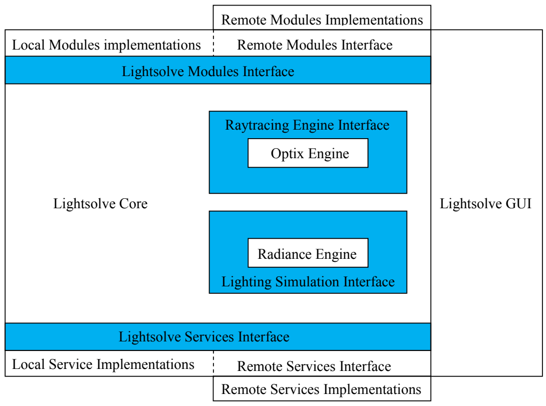

Figure 2 Lightsolve structure

General Lightsolve workflow

The Lightsolve interface and visualization framework offers a very powerful support to reveal multi-faceted performance thanks to its time-based focus combined with a simultaneous visualization of renderings.

In this new embodiment for Lightsolve, two analysis outcomes are proposed, illustrated in Fig 3 for the same West-facing room as in Fig. 1, located at 41 degrees North (latitude):

- the straightforward visualization of performance using an *absolute scale*, which displays the respective metric's average value over the area of interest (illuminance over workplane like in Fig 3a, or average DGP, etc., or unconventional performance such as derived from non-visual or perceptual effects expressed by the metrics described below)

- the less straightforward visualization of performance using a *goal-based scale* like in Fig 3b, which represents how closely prescribed goals are met.

For both the absolute and goal-based scales, two representations appear side-by-side on the Lightsolve interface to fully reveal annual, seasonal and daily performance over both time and space: a time-varied representation in the form of a temporal map (left) over which a cursor (cross in Fig 3 left) can be moved to select a given moment over the year; and a rendering (right) associated to that specific moment, where the spatial distribution of the respective metric's values (here, illuminance) can be visualized in false-color on the user-defined sensors (areas of interest). Weather conditions are accounted for thanks to the climate-based time segmentation method described in Kleindienst et al. (2008) and renderings can be associated to either the dominant sky type for that period (clear, clear-turbid, intermediate or overcast, cf. Kleindienst et al. 2008) or to one chosen by the user (clear sky in Fig. 3 e.g.)

Fig. 3a is quite easy to interpret: considering a sensor plane covering almost the entire space at workplane height (Fig. 3a, right) and given the West-orientation of the space, average illuminance over the sensor area (left) will be higher in the afternoon all year long but even more so in the winter (unless the local climate has particularly cloudy winters). As far as spatial illuminance distribution is concerned for the selected moment under clear sky, illuminance will of course be highest on the sun spots (> 2500 lx) and closest to the window, and lowest in the back corners (< 500 lux). Both temporal (climate-based maps) and spatial data (false-colors on renderings) are based on the same color scale, provided on the left.

To complement this information and interpret simulation outcomes in terms of how closely prescribed goals are met, an additional step is necessary, that translates absolute, time-based performance into a goal-based scale (Fig. 3b) using the triangular color scale introduced in Kleindienst & Andersen (2012). In this example, the targeted desired illuminance levels on the measurement area were between 800 and 1200lx and the extreme acceptable values were 500 and 2000lx. The obtained goal-based representation over a full year indicates that the objective is generally reached (dominating yellow), except during afternoons during the summer period, where objectives are not met because of simultaneously too high and too low illuminance values (depicted in purple).

Again, the instantaneous 3D rendering corresponding to the time selected on the time-based representation allows refining the analysis of the results. In this example, the purple spots are clearly explained by the false-color rendering (Fig. 3b, right), with locations too dark (in blue) and others too bright (in red). More specifically, the sensor areas which receive direct sun rays are above the goal (red when higher than 2000lx and in a variable orange when between 1200 and 2000lx). Parts which are nearer the left wall are either in blue (illuminances lower than 500lx) or variable green (illuminances between 500 and 800lx).

The resulting "double combination" of absolute vs. goal-based and time-based vs. spatial visualization makes the performance analysis particularly interactive and – as previous studies have shown for the goal-based scale (Andersen et al., submitted) – intuitive to the user.

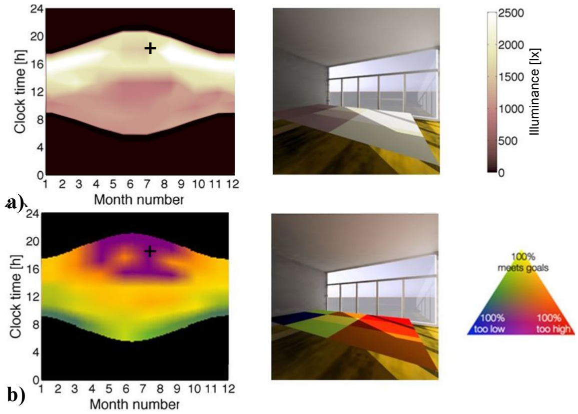

Figure 3 Time-based illuminance analysis (left) with associated rendering at given moment (right and cursor) on an absolute (a) and goal-based scale (b)

Incorporating non-visual aspects

At this point in time, there does not appear to be sufficient information on non-visual responses to light to produce a detailed mathematical model that would work in real-world settings. Despite knowledge gaps in photobiology literature, experimental findings still offer the means to advance and validate novel design support tools to assess how architectural spaces might affect human health and wellbeing. Here, we propose a dynamic model of the non-visual light-response relationship that combines two temporal integration modules and a nonlinear response function, and whose outcomes can be effectively formatted within the context provided by Lightsolve, i.e. as goal-based, time-driven performance maps. Its foundations are summarized below and are further described in (Amundadottir et al., 2013*a*).

To extract mathematical relationships from observed non-visual effects in the photobiology literature, we will focus on the five essential characteristics of light exposure summarized in Fig. 4a. There is a nonlinear relationship between the intensity of light and its effects on the non-visual system (Cajochen et al., 2000; Zeitzer et al., 2000). The nonlinearity is saturating that is as light intensity increases, eventually a point is reached where adding more light does not increase the response. In addition to this, the ipRGCs, which appear to be the primary mediators of non-visual responses to light, allow the integration of light exposure over long periods of illumination compared to rods and cones but the mechanism underlying the sluggish response is unknown (Berson et al., 2002). Experimental findings have demonstrated a nonlinear duration–response relationship to light exposure (Chang et al., 2012), while light exposure does not need to be continuous to affect the system (Gronfier et al., 2004).

To include the identified nonlinear intensity- and duration-response relationship, we propose a block-structured model for simulating the direct non-visual responses to light. Such models can be represented by interconnections of linear filters and nonlinear terms, as illustrated in Fig. 4b. The light stimulus $l(t)$ – time samples of light exposure derived from lighting calculations e.g. – is passed through a linear filter $L_1(t)$ that averages the light exposure pattern over current and past time samples, giving the output $u(t)$. Then $u(t)$ is transformed by a nonlinear function $N(u)$ describing the intensity-response to the light stimulus. To account for timing of light exposure and prior photic history, this term must be converted into a dynamic function as demonstrated in Fig. 4c-d: during daytime or after long-term exposure in bright lighting conditions, the dynamic range of the system increases (Fig. 4c) but during nighttime or after spending long time in darkness, the dynamic range of the system decreases (Fig. 4d). The output $v(t)$ is finally passed through a second filter $L_2(t)$ to integrate duration-response. The two linear filters thus reflect the temporal processing between the light stimulus and the output response. The inputs to the model are discrete time samples of light intensity and spectrum, obtained from lighting simulation or empirical spectral measurements. The model outputs are time-sampled relative non-visual responses, that we will use as proxy for healthy non-visual light-exposure in the same way we previously used subjective alertness (Pechacek et al., 2008; Gochenour & Andersen, 2009; Andersen et al., 2012). The model outputs will be used to evaluate direct non-visual responses to light with, we hope, significantly higher accuracy than existing static models. Ultimately, we envision that the model can also be incorporated into comprehensive circadian process models (Jewett & Kronauer, 1999).

The proposed model has the potential to capture the non-visual effects of time-varying light exposure, but it has not yet been validated for 2-3 log illuminance units due to lack of experimental data. However, the model is not limited to one type of intensity-response function, which allows for more flexibility as knowledge accumulates. Moreover, additional effects need to be accounted for, which requires more sophisticated models. First, it has been shown that under dim light conditions and at the start of light exposure, cones (green-light sensitive) contribute at least equally to non-visual responses whereas at higher intensities, ipRGCs (blue-light sensitive) predominate (Gooley et al., 2010). Second, timing of light exposure and prior photic history seems to strongly influence the dynamic intensity-response range (the range of light intensities to which the non-visual system responds to before reaching the saturation point). Incorporating these additional effects into a single model is further discussed in Amundadottir et al. (2013*a*).

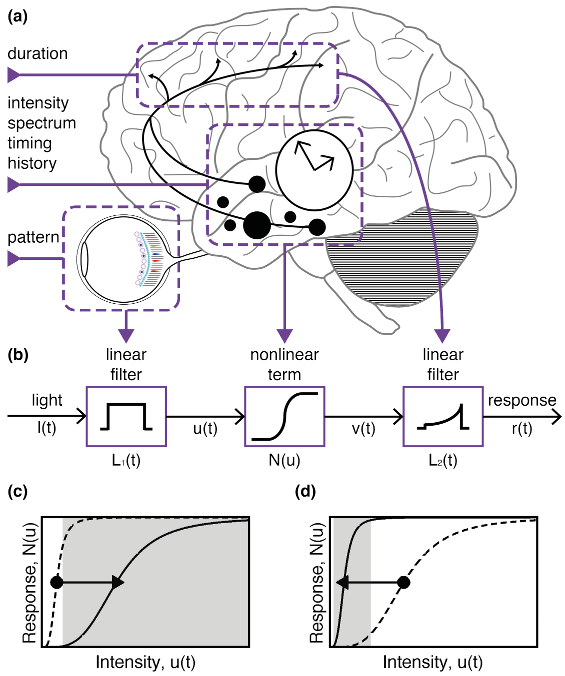

Figure 4 (a) The 5 characteristics of light exposure. (b) Diagram of the light-response model structure and its linkage. This type of functional model is referred to as linear-nonlinear-linear (LNL) model. (c-d) Time-varying intensity-response functions for the non-visual system during nighttime (c) and daytime (d).

Linking the model to a lighting simulation process is important, because the ultimate goal is to develop a new type of lighting design support. A parallel publication (Amundadottir et al., 2013*b*) focuses specifically how this type of support can be applied in an actual design exercise. In the interest of providing the designer with an informative visual representation, an additional user-defined input is required that would be specific to the desired design performance. By evaluating the response output against such user-defined goals, a format can be provided to the designer illustrating whether a given goal is met or not.

As an example of a preliminary format where goal-fulfilment in this human-centered context could be visualized, a simple room was modelled with a window facing West (space shown in Figs 1 and 3). Daylight exposure (vertical illuminance) for someone who would stand in the middle of the room and stare at the window all year long is provided in Fig. 5a, based on Radiance calculations and on Daysim's daylight coefficient method. Fig. 5b shows the estimated non-visual response once our model is applied and where one can clearly observe the effect of our non-visual system's sluggishness (response delayed compared to exposure).

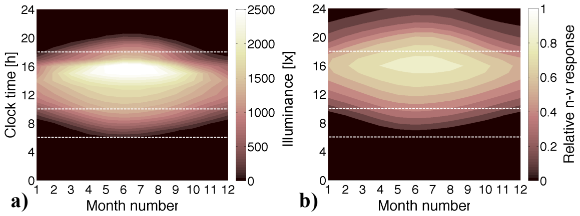

Figure 5 Illuminance (a) vs. relative n-v response as predicted by our proposed light-response model (b)

To adopt a goal-based perspective, since the non-visual system adapts to changes in light intensity and spectral composition over a much longer time period than the visual system, we cannot apply instantaneous performance criteria. If a non-visual response is categorized as "bad" after evaluating Fig. 5b's results against prescribed goals, it is far from trivial to trace the response back to a specific period of time over the day when light exposure was too low or too high (Fig. 5a). The main difficulty in tracing back the cause is that there exists not only one but infinite number of light patterns that may induce the same non-visual effects. In order to achieve this, we would need a search algorithm that will look for a set of light patterns that best fit the performance criteria, the development of which is beyond the scope of the present paper. Conceptually, such an approach would lead to outcomes that may look like the one displayed in Fig. 6a. The figure shows periods of time when light exposure should be avoided where it could have negative influences on circadian rhythms (red-orange) and when more light could have beneficial effects in terms of alertness and productivity (blue-green). The horizontal lines in Figs 5 and 6a mark three time periods. A goal-based performance criterion is assigned to each period to account for timing of light exposure relating to the circadian clock.

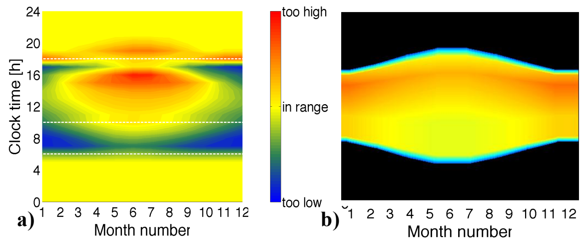

Figure 6 Conceptual maps for goal-based performance representation of a) n-v effects and b) contrast

Incorporating perceptual aspects

To celebrate the role of daylight as a fundamental element of dynamic visual interest, we need a new perspective about subjective preferences and design intent regarding contrast and variability. Towards this end, we propose to establish a methodology for comparing annual contrast and luminance variability in daylit architecture. Its implementation as a Lightsolve metric is discussed below, building upon initial results (Rockcastle & Andersen, 2012), and its conceptual interpretation from a goal-based perspective is introduced (work in progress).

Contrast and luminance variability of daylight are essential to the visual performance of architecture, yet architects have no means of comparing design options from a perceptual perspective, nor do they have support in manipulating parameters to achieve a desired intent. These limitations establish the need for a new class of metrics that can reveal the complexity and instability of daylit architecture. Based on the medium of photographs and rendered scenes, which architects use readily within the practice of design, we previously introduced a dual approach for perceptual daylight analysis in the form of complementary perceptual metrics (Rockcastle & Andersen, 2012).

To establish these metrics, we generated a linear taxonomy derived from global contemporary architecture examples, based on our intuitive perception of contrast and temporal variability within each selected space. Our prediction for luminance variability was determined through the composition of external fenestration within each space and the resulting sunlight patterns that we could expect to shift throughout the space, creating a dynamic composition of light and shadow. The more extreme cases of spatial contrast and luminance variability were located to the left side of the gradient, while the more uniform and stable examples where located to the right side of the gradient (Fig. 7a). From this analysis, we established that the composition of contrast within the image, and not the average luminance or standard deviation across the image, was what generated the impression of spatial contrast.

To test this method, we distilled each of the categories from the full linear taxonomy of existing spaces (Fig. 7a) down into a single representative digital model (10 in total, Fig. 7b) that expressed the associated gradient of contrast or variability on a more explicit level, with a luminous character similar to the existing examples' but with an abstracted level of detail. These simplified digital models were then used to produce a time-lapse series of renderings. To limit the number of produced images, the time segmentation method developed for Lightsolve was used as a reduced climate-based framework (Kleindienst et al., 2008), resulting in a time-series of 56 key moments from across the year.

We developed a quantitative method for measuring the compositional boundaries between light and dark pixels and used this as a basis for generating Spatial Contrast and Luminance Variability metrics, first as static instances then extended to cumulative (annual) representations (Rockcastle & Andersen, 2012).

Spatial Contrast estimates the spatial distribution of contrast across a selected view at a given moment; its annual dynamic variability can be represented using an *absolute-scale* temporal map in Lightsolve (Fig. 8a, left), which shows *when* that contrast will change throughout the day and year as a result of sunlight dynamics (all afternoons and mornings in the winter in this example). To complement this time-based

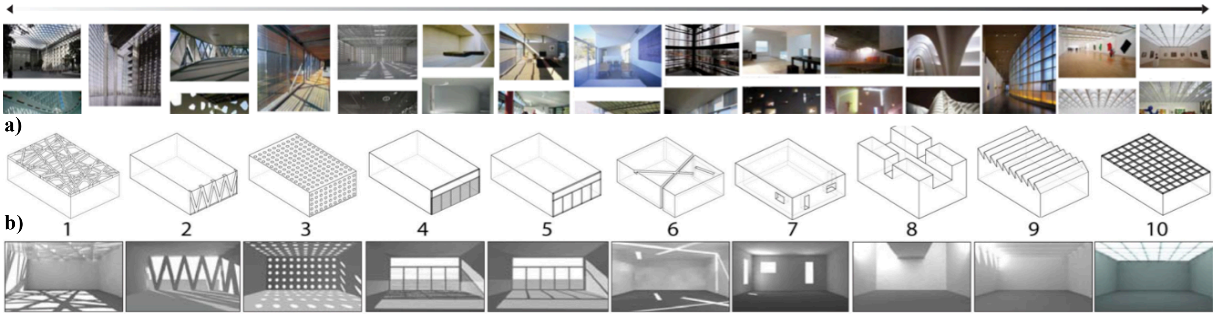

Figure 7 Taxonomy of contrast / variability gradients in a) architectural spaces and b) typological matrix

information, instantaneous false-color renderings of spatial contrast can be produced for every moment and displayed simultaneously in the Lightsolve interface to show *where* (i.e. in which portions of the view) most spatial contrast will be experienced. But we can also display *cumulative annual* contrast renderings (Fig. 8a, right) to evaluate spatial contrast when considering the *entire year* (highest on floor).

Luminance variability throughout a selected view calculates the absolute difference in pixel values between daily and seasonal instances. Similarly to contrast, we can generate instanteneous (from one time-step to the next) but also accumulative (annual) luminance variability (Fig. 8b, right) to highlight which areas experience the most frequent change over the year (here also floor and to some extent wall). The associated temporal map (Fig. 8b, left), shows when the most variability occurs through the day and year (afternoons, and throughout the day in the winter months).

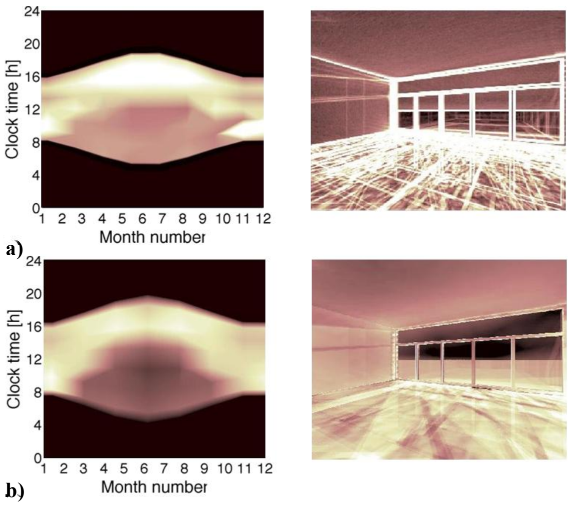

Figure 8 Perceptual contrast (a) and variability (b) over time (left) vs. space (right)

For perceptual daylight performance, the 'non-absoluteness' of performance takes its full meaning more than ever: there is no objectively "good" or "bad" performance (except in terms of norms or comfort requirements), what counts is the designer's intent. In the design support framework that Lightsolve offers, reference spaces, such as those shown in Fig. 7a, could thus serve as a "delight target" database (i.e. a set of freely-interpreted effects ranging from low to high contrast and/or variability) while their associated simplified models can serve as a support from which our metrics, used as indicators of performance, could be calculated and graphed. The theoretical example shown in Fig. 6b shows how we might represent the degree of annual spatial contrast in terms of goal-based targets established by the designer. Using the same west-facing space as an example – corresponding to typology 5 in Fig. 7b –, if the designer had in mind to achieve high contrast to stimulate visual interest but keep it within a certain threshold (closer to what a typology 4 would generate e.g.), Lightsolve would generate a goal-based temporal map conceptually similar to Fig. 6b: it would exhibit "too high" spatial contrast (compared to target goals) in the winter (especially afternoons) – leading to red or orange – and acceptable spatial contrast in the mornings and most of the summer days – leading to yellow. As an evolution from Fig. 8a, designers would then be able to initiate changes within their design model and test to see whether those changes meet their design goals.

As illustrated by this conceptual analysis, performance can be understood, even for somewhat subjective, intent-driven metrics expressing contrast or variability, by how closely a desired effect will be matched, i.e. how similar the metrics' values are between the desired effect (target, here associated with an image) and the considered one. Such an approach, which is currently under development, will ultimately allow objective comparisons between spaces while keeping the perceptual aspects of light intact: the designer will still be able to freely interpret light quality with his/her own sensitivity.

CONCLUSION

This paper presents the latest developments of a full-year, comprehensive daylighting support tool named Lightsolve, with a focus on its potential to show a combination of time-varied, spatial, absolute and goal-based performance interactively and highly visually. The results show the potential of such visualization formats to express annual daylighting performance even for highly unconventional metrics such as derived from non-visual effects or perceptual daylight, whose time-dependency represents the most essential aspect of performance. Goal-based color scales are particularly powerful in proposing a unified framework to describe performance in terms of how closely prescribed goals are met, and thus assessing how "successful" a design option is (especially in relative terms) from many perspectives.

Beyond their complementarity in supporting a unified daylighting performance framework, the two proposed models regarding non-visual effects and perceptual daylight embed highly innovative aspects by themselves. The light-response model represents a first attempt to functionally describe the underlying mechanism of direct nonvisual effects, which holds promise as new approach to support healthy lighting design once further research will have been conducted to refine and validate the proposed model (Amundadottir et al., 2013*a*,*b*). On the other hand, the proposed metrics for perceptual daylight are unique in enabling designers to contextualize the relative strength as well as the temporal stability of contrast within a given architectural space.

REFERENCES

Amundadottir M, St Hilaire M, Lockley SW, Andersen M. 2013*a*. Modeling non-visual responses to light: unifying spectral sensitivity and temporal characteristics in a single model structure. *CIE Conf,* Paris

Amundadottir M, Lockley SW, Andersen M. 2013*b*. Simulation-based evaluation of non-visual responses to light: proof-of-concept study of healthcare re-design, *BS 2013*, Chambéry

Andersen M, et al. 2008. An intuitive daylighting performance analysis and optimization approach, *Building Research & Information* 36(6): 593–607

Andersen M, Gagne JML, Kleindienst S. (submitted). Interactive expert support for early stage full-year daylighting design: a user's perspective on Lightsolve, *Automation in Construction*

Andersen M, Mardaljevic J, and Lockley, S. W. 2012. A framework for predicting the non-visual effects of daylight - Part I: photobiology-based model. *Lighting Research & Technology* 44(1):37–53

Berson DM, Dunn FA, Takao M. 2002. Photo-transduction by Retinal Ganglion Cells That Set the Circadian Clock. *Science* 295:1070– 1073

Cajochen C et al. 2000. Dose-response relationship for light intensity and ocular and electroencephalographic correlates of human alertness. *Behavioral Brain Research* 115(1):75–83

Chang A-MM, et al. 2012. Human responses to bright light of different durations. *The Journal of physiology,* 590(13):3103–3112

Cetegen D, Veitch, JA, Newsham, GR, 2008. View Size and Office Illuminance Effects on Employee Satisfaction. Proc. *Balkan Light*, Ljubljana

Gagne JML, Andersen M, Norford LK. 2011. An Interactive Expert System for Daylighting Design Exploration, *Build & Env* 46(11)

Gochenour, S. J. and Andersen, M. 2009. Circadian Effects of Daylighting in a Residential Environment. In *Proc LuxEuropa 2009*, Istambul

Gooley JJ et al. 2010. Spectral Responses of the Human Circadian System Depend on the Irradiance and Duration of Exposure to Light. *Science Translational Medicine,* 2(31ra33)

Gronfier C et al. 2004. Efficacy of a single sequence of intermittent bright light pulses for de- laying circadian phase in humans. *Amer. J. Physiology – Endocrin. & Metabolism,* 287(1):E174–E181

IEA. 2008. Testing and Validation of Building Energy Simulation Tools, *International Energy Agency Technical Report SHC Task 34*

Jewett ME, Kronauerm RE. 1999. Interactive mathematical models of subjective alertness and cognitive throughput in humans. *Journal of biological rhythms,* 14(6):588–597

Kleindienst S, Bodart M, Andersen M. 2008. Graphical Representation of Climate-Based Daylight Performance to support architectural design, *Leukos* 5(1)

Kleindienst S., Andersen M. 2012. Comprehensive Annual Daylight Design through a Goal-Based Approach, *Build. Res. & Info.* 40(2): 154-173

Lockley SW. 2009. *Circadian Rhythms: Influence of Light in Humans,* 971–988. Acad. Press, Oxford

Mardaljevic J, Heschong L, Lee E. 2009. Daylight metrics and energy savings, *Lighting Research and Technology* 41(3): 261-283

Münch M et al. 2012. Effects of prior light exposure on early evening performance, subjective sleepiness, and hormonal secretion. *Behavioral neuroscience,* 126(1):196–203

Nasman JD, Cutler B. 2011. Evaluation of a tangible interface for architectural daylighting analysis, *i3D:207-ACM SIGGRAPH*

Newsham GR, Richardson C, Blanchet C, Veitch JA., 2005. Lighting Quality Research Using Rendered Images of Offices. *Light Res Techn* 37 (2): 93-115

Ochoa C., Capeluto I. 2009. Advice tool for early design stages of intelligent façades based on energy and visual comfort approach, *Energy & Buildings* 41(5)

Parpairi K et al. 2002. The Luminance Differences index: a new indicator of user preferences in daylit spaces, *Lighting Research & Technology* 34

Paule B., Flourentzou F., Pantet S., Boutillier J. 2011. DIAL+suite […], Proc. of *CISBAT*, Lausanne

Pechacek CS, Andersen M, Lockley SW. 2008. Preliminary Method for Prospective Analysis of the Circadian Efficacy of (Day)Light[...] *Leukos* 5(1)

Rockcastle S, Andersen M. 2012. Dynamic Annual Metrics for Contrast in Daylit Architecture, In *Proc. SimAUD 2012*, Orlando

Viola AU et al. 2008. Blue-enriched white light in the work- place improves self-reported alertness, performance and sleep quality. *Scandinavian J. of work, environment & health,* 34(4):297–306

Webb A. 2006. Considerations for lighting in the built environment: Non-visual effects of light. *Energy and Buildings,* 38(7):721–727

Wienold J. 2009. Dynamic daylight glare evaluation, In *Proc. of IBPSA 2009 Conference,* Glasgow, UK

Wymelenberg K, Inanici M. 2009. A Study of Luminance Distribution Patterns and Occupant Preference in Daylit Offices, *PLEA 2009,* Quebec City

Zeitzer JM, Dijk D-J, Kronauer RE, Brown EN, Czeisler CA. 2000. Sensitivity of the human circadian pacemaker to nocturnal light: melatonin phase resetting and suppression. *J Physiol* 526(3)