

Experiential Lighting

Development and Validation of Perception-based Lighting Controls

BY

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Submitted to the Program in Media Arts and Sciences,
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Abstract

Lighting, and its emergence as a digital and networked medium, represents an ideal platform for conducting research on both sensor and human-derived methods of control. Notably, solid-state lighting makes possible the control of the intensity, spatial, and color attributes of lighting in real-time. This technology provides an excellent opportunity to conduct new experiments designed to study how we perceive, judge, and subsequently control illumination.

For example, given the near-infinite variation of possible lighting attributes, how might one design an intuitive control system? Moreover, how can one reconcile the objective nature of sensor-based controls with the subjective impressions of humans? How might this approach guide the design of lighting controls and ultimately guide the design of lighting itself? These questions are asked with the benefit of hindsight. Simple control schemes using sliders, knobs, dials, and motion sensors currently in use fail to anticipate human understanding of the controls and the possible effects that changes in illumination will have upon us.

In this work, the problem of how humans interact with this new lighting medium is cast as a human-computer interaction. I describe the design and validation of a natural interface for lighting by abstracting the manifold lighting parameters into a simpler set of controls. Conceptually, this “simpler set” is predicated on the theory that we are capable of discerning the similarities and differences between lighting arrangements (scenes).

I hypothesize that this natural ordering (a metric space in a latent multidimensional basis) can be quantitatively extracted and analyzed. First, in a series of controlled experiments, I show how one can derive this mapping and I demonstrate, using empirical evidence, how future sensor networks will eventually emulate our subjective impressions of lighting. Second, using data obtained in a user-study, I quantitatively derive performance estimates of my proposed lighting user-interface, and statistically contrast these performance results with those obtained using a traditional interface comprised of sliders and buttons. I demonstrate that my approach enables the user to attain their illumination goals while substantially reducing task-time and fatigue.

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Chapter 5 and Chapter 6 of this thesis detail results obtained using our state-of-the-art lighting testbed at the Media Lab. The design, installation, and operation of this test-bed was the result of many hours of work from colleagues and friends. Susanne Seiting and the excellent staff at Philips Color-Kinetics donated all the lighting equipment, controls, and data-communication hardware. In addition to the countless hours invested by Susanne, I relied heavily on the engineering expertise of PCK's in house staff of engineers and lighting designers who all helped make this project a reality.

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Contents

Abstract	3
List of Figures	11
List of Tables	13
1 Introduction	15
1.1 What is Experiential Lighting?	16
1.2 Motivation and Opportunity	17
1.3 Motivating Example	18
1.4 Subsets and Sensors: Duality in Lighting User-Interfaces	20
1.5 Thesis Outline	22
1.6 Hypotheses	23
2 Related Work	25
2.1 Overview	26
2.2 Higher-Order Perception of Lighting	26
2.3 Pervasive Computing and Lighting Control	29
2.4 Beyond Lighting: Incorporating Preference and Opinion in Design and Control	30
3 A New Framework For Lighting Control	33
3.1 Perception, Interaction, and Control: A Framework	34
3.2 Invariants and Affordances as Mechanisms to Define Interaction	34
3.3 Processing the Perceptual Structure of Multidimensional Stimuli	35
3.4 Reality-based Interfaces	37
3.5 Measurement and Mathematical Modeling	38
4 Human Subjects Test I: A Control Prototype in a Virtual Model	39
4.1 Introduction	40
4.2 Experiment Setup	40
4.3 Results	45
4.4 Discussion	53

4.5	Summary	53
5	Human Subjects Test II: Physical Space	55
5.1	Introduction	56
5.2	Experimental Setup	56
5.3	Results	63
5.4	Discussion	75
5.5	Summary	76
6	Human Subjects Test III: Performance Testing	79
6.1	Introduction	80
6.2	Experimental Setup	80
6.3	Results	86
6.4	Discussion	90
6.5	Limitations and Future Work	91
6.6	Summary	91
7	Conclusions	93
7.1	Feasibility	94
7.2	Justifiable Effort	94
7.3	Relevance	95
7.4	Outlook	96
A	Pilot Study of Lighting Controller Preferences	99
A.1	Purpose	99
A.2	Method	100
A.3	Results	100
A.4	Discussion	101
B	Description of Lighting Scales	103
B.1	Survey Items in Human Subjects Test I	103
C	MDS Modeling Error	105
C.1	Background	105
C.2	Discussion of Model Fitting Procedure	106
C.3	Fitted Results	106
D	Fitted Splines for 2-Axis Controller	107
D.1	Control Surfaces	107
D.2	Control Surface Contour Plots	107
E	Raw Datasets for Analysis	111
F	IRB Approval Forms	113
	Bibliography	117

List of Figures

1.1	Lutron Grafik Eye Lighting Control System.	17
1.2	Lighting presets and measurement of room attributes.	19
1.3	Representation of orthogonal lighting attributes in two dimensions (axes).	20
1.4	Lighting presets are a subset of all possible luminous conditions.	21
1.5	Sensor-based control of illumination and actuation.	21
1.6	Sensor-based methods select and identify presets of lighting conditions.	22
1.7	Lighting control in dual form.	22
3.1	A framework for lighting control.	34
3.2	Examples of separable and integral stimuli.	36
3.3	The dimensionality of perception and corresponding user-interfaces.	37
3.4	A work-flow for creating an orthogonal basis for controlling lighting.	38
4.1	Plan view of CGI-based “boardroom” designed in the Unity.	41
4.2	Six CGI-based lighting scenes.	42
4.3	Interpolation of the axes and the lighting control values.	45
4.4	Parallel analysis and determination of the number of components.	46
4.5	Visualization of first two principal components obtained in the CGI study.	48
4.6	Mean scores by scene of the four eigenvalues of the luminous conditions.	50
4.7	Visualization of three possible lighting control surfaces.	51
4.8	Prototype user-interface to adjust luminous conditions in Unity.	52
4.9	Illustration of the final lighting control prototype in Unity.	52
5.1	Illustrations of the lighting laboratory at the MIT Media Lab.	56
5.2	Plan of physical environment to evaluate the perception of lighting.	57
5.3	Collected spectra of the luminous conditions at two color temperatures.	58
5.4	Photographs of the eight lighting scenes in the physical space.	59
5.5	Illustration of method to measure brightness of luminous conditions.	60
5.6	Visualization of objective (sensor-based) model using the eight scenes.	67
5.7	A completed survey of the impressions of similarity.	68
5.8	Stem plot and 3D visualization of the MDS experiment (human-based model).	70
5.9	The two perceptual dimensions extracted in the physical experiment.	71
5.10	Parameterization of the control surface (Wallwash:red channel).	75

LIST OF FIGURES

5.11	Parameterization of the control surface (Wallwash:blue channel).	76
6.1	Illustration of the software used to measure performance data.	81
6.2	The “axes” user-interface tested in the performance experiment.	82
6.3	A visualization of room appearance and the axes set-points.	83
6.4	The linear-slider interface used in the performance experiment.	84
6.5	Measured difference in task-time using both user-interfaces.	88
C.1	Error of MDS fitting procedure on the perceptual data.	106
D.1	The interpolated surfaces comprising the “axes” user-interface.	108
D.2	Contour plots of the interpolated control surfaces.	109

List of Tables

4.1	Observer brightness (cd/m ²) for the CGI-based lighting-scenes.	42
4.2	Rotated component loadings derived from subjective impressions.	47
4.3	Analysis of variance (ANOVA) results in the CGI study.	49
5.1	Photometric and power characteristics of the eight evaluated lighting scenes.	58
5.2	Component loadings derived in the objective (sensor-based) model.	65
5.3	Mean component scores (objective model).	65
5.4	Dissimilarity matrix derived from human responses.	68
5.5	Scene coordinates of three models of luminous appearance.	72
5.6	Multiple regression results using the 3D-MDS configuration.	73
5.7	Multiple regression results using the 2D-MDS configuration	74
6.1	Description of task instructions.	85
6.2	Description of exit questionnaire.	86
6.3	Summary statistics of lighting control performance data.	87
6.4	Analysis of variance (ANOVA) results of user-performance study.	87
6.5	Summary of exit survey results.	89
A.1	Lighting tasks in preference pilot study.	100
A.2	Results of preference pilot study.	101
A.3	Summary of preferred set-up time.	101
B.1	Semantic differential scales used in Chapter 4.	104

Introduction

The work detailed in this thesis describes and tests a theory of how and why a better user-interface for lighting control exists. In this work, a series of experiments will demonstrate that human impressions of lighting are efficient representations of luminous conditions and constitute the basis for an entirely new method of lighting control. The instantiation of such a user-interface is derived using a quantitative and analysis-driven approach. The resulting interface is a compact representation of the appearance of luminous conditions. Outwardly, the resulting user-interface is simple to use and extremely efficient compared to existing methods of lighting control.

Using empirical evidence, this thesis also argues for the generality and automation of this technique by demonstrating the fundamental relationship between a subjective model (human) and an objective model (sensor) of the luminous conditions.

Accordingly, the first part of this thesis concentrates on the background and theory required to experiment, analyze, and understand how such an interface is possible and why it is useful. The second part of this work details three experiments in which a prototype is quantitatively designed using the underlying experimental data. This approach to the design and control of lighting is then tested against a common method of lighting control.

1.1 What is Experiential Lighting?

The study of human factors in lighting focuses on four primary areas. Generally, these are: the physical properties of the electromagnetic spectrum (radiometry), the photons' neurophysical effects in humans (photometry and colorimetry), lighting and health, and the psychological effects "seeing" and "experiencing" (visual perception). Broadly, lighting control involves aspects of all four of these fields. It represents an indirect link or "communication interface" between the human and the (computer-actuated) lighting.

The motivation for this research is predicated on the observation that our control methods for lighting lag behind the capabilities of our lighting technology. Nowhere is this more apparent than in the design and control of solid-state lighting.

The research proposed here addresses the specific problem of multivariate lighting control. By multivariate, I am implying the simultaneous control of several physical parameters: radiant energy, wavelength, and location (in space). Such lighting systems contain a panoply of individual parameters to control, each of which range several orders of magnitude. An honest question is whether we actually need such complexity and further, how might we organize such a system for human use?

From the human's perspective, the variation of these physical parameters manifest sensations and carry the perception of brightness, color, and pattern. It is tenable that we might be able to design a simpler and a more natural system by attempting to understand how we judge and perceive lighting. Such an endeavor not only advises the future design of lighting controls (and improves their usability), but suggests how we might design sensor-enabled environments to emulate this behavior, or more radically, provide an optimal configuration of the lighting attributes that maximize affect (e.g., for museums, showrooms). Such an approach can also be extended to reconcile multiple individuals whose lighting goals may differ.

Crucially, it represents the first steps towards emulating our behavior and relationship with lighting, by attempting to statistically and empirically explore the precepts of our judgment of lighting. Although I have highlighted some examples, I also believe that this approach may be influential in further studies of context and lighting control.

My central thesis is that we may derive and construct a natural interface for lighting control by emphasizing a holistic approach; that luminous conditions should be judged as a whole, and not by their constituent parts. In the words of Buxton (1986), I am also advocating that "we must learn to match human physiology, skills, and expectations with our systems' physical ergonomics, control structures, and functional organization." What can be said of gestures and human-computer interaction can also be said of humans and lighting. The luminous minutia emphasized by present lighting controls are (possibly) unnecessary if we observe how humans naturally interpret lighting conditions. The plan, of course, is to test this hypothesis.

I argue that a successful lighting interface is one that is ultimately organized by the principals of how we judge and determine the differences between illuminants. It is then hypothesized that an empirically determined geometry that reflects these judgments represents a natural interface for controlling illumination and one that is significantly more appropriate for human control.



Figure 1.1: Example lighting interface to control preset “zones” of lighting found in MIT Building E14 (Image credit: Brian Mayton, MIT)

1.2 Motivation and Opportunity

Present-day lighting control solutions typically afford users a linear one to one mapping to adjust the brightness of a single luminaire, or even the room. Modern illumination, comprised of networked, and color adjustable solid-state lighting presents a challenge to existing user-interfaces. For example, perceptual color spaces such as CIE 1931 and CIE 1964 (Wyszecki et al., 1968) effectively represent color well, but ignore a critical factor in specific lighting installations: the designer and inhabitants are also concerned with the spatial characteristics of the room (e.g, wallwashing versus direct overhead lighting) in addition to intensity and color. How might these attributes be reconciled in a user interface?

On the other side of the spectrum, we often encounter the lack of personal control in office settings is borne out of the concern that personalized lighting is wasteful, and that occupants will simply select excessive amounts of illumination without regard. This has been demonstrated to be incorrect, and even shown that occupants prefer some level of lighting control (Veitch and Newsham, 2000).

Where things go horribly wrong is when building dwellers are confronted with excessive and burdensome controls. These interfaces consist of too many poorly labeled and undecipherable choices for adjustment of the lighting (Figure 1.1). These interfaces very general –which, in many cases is a great thing– for it allows an expert an unlimited palate to specify the lighting presets. It also incorrectly assumes (a) the average user has the patience to use such control and (b) a linear configuration control is the most intuitive mapping. It is difficult to use. Why?

A short discourse will help address this question. A simple explanation was offered in 1956 and has come to be known as Miller’s law (Miller, 1956). In this short treatise,

Miller describes, from an information-theoretic approach (Shannon, 1948), that the average person's information channel capacity is roughly 2 to 3 bits of information, which, Miller points out, corresponds to roughly our ability to distinguish between four to eight objects using our short term memory. Explaining poor design and user-interface was not an objective of Miller's. These theories would later evolve from Gibson's theories of perception (Gibson, 1971, 1977), and were ultimately made popular by the writings of Donald Norman (Norman, 1988, 1992, 1993). Norman's work lays the foundation and approach to user-centered design. To paraphrase Norman's work, I refer to psychologist Ian Gordon who states, "the essence of Norman's position is that humans naturally do some things well, others badly. Bad design fails to recognize this fact (Gordon, 2004)."

Regarding the controls in Figure 1.1, it is obvious why this design leads to so much frustration. Why must we perpetuate this mapping? Why should we emulate a control strategy for lighting (Holmes, 1884) that was designed to control simple incandescent technology (Edison, 1880) nearly 125 years old? These questions motivate the thoughts and ideas explored in this work.

One more point is in order – it has been recently suggested that as a lighting technologies become more efficient, we tend to use more lighting. This is an example of a positive feedback. This is analogous to widening a highway, and within a few months, observing that, rather than a reduction of congestion, the highway is now congested with even more cars. The theory behind our appetite for photons is due to Tsao et al. (2010).

In light of this evidence, one might readily contend that management and control of lighting – specifically the user-interface and control-strategy – is a key area of research. Thus, a reasonable goal in the design of the user-interface is a solution that not only allows a user to specify what they want, but to do so efficiently and without burden to the user.

1.3 Motivating Example

Consider three simple lighting presets consisting of eight sliders which control the flux of some arbitrary lighting arrangement in room. Let us assume that we can measure two simple attributes in the room, table brightness and wall brightness. Further assume that we collect these measurements using either an objective set of measurements (e.g., collected using a sensor) or a subjective set of measures (e.g., collected using human impressions).

This idea (Figure 1.2) presents a linear configuration of sliders (three scenes total) and the corresponding measurements of two attributes, table brightness and wall brightness. For each of these attributes, we now have measures about the relative distance between the three lighting presets.

If we further assume that one can center these data (i.e., the mean is zero) and, that these two attributes are independent from each other (either by experiment design, or through some algorithmic processing), we can then represent the two metric distances simultaneously (Figure 1.3). In this new configuration, we now have a metric space consisting of the underlying scenes represented by coordinates on these two axes.

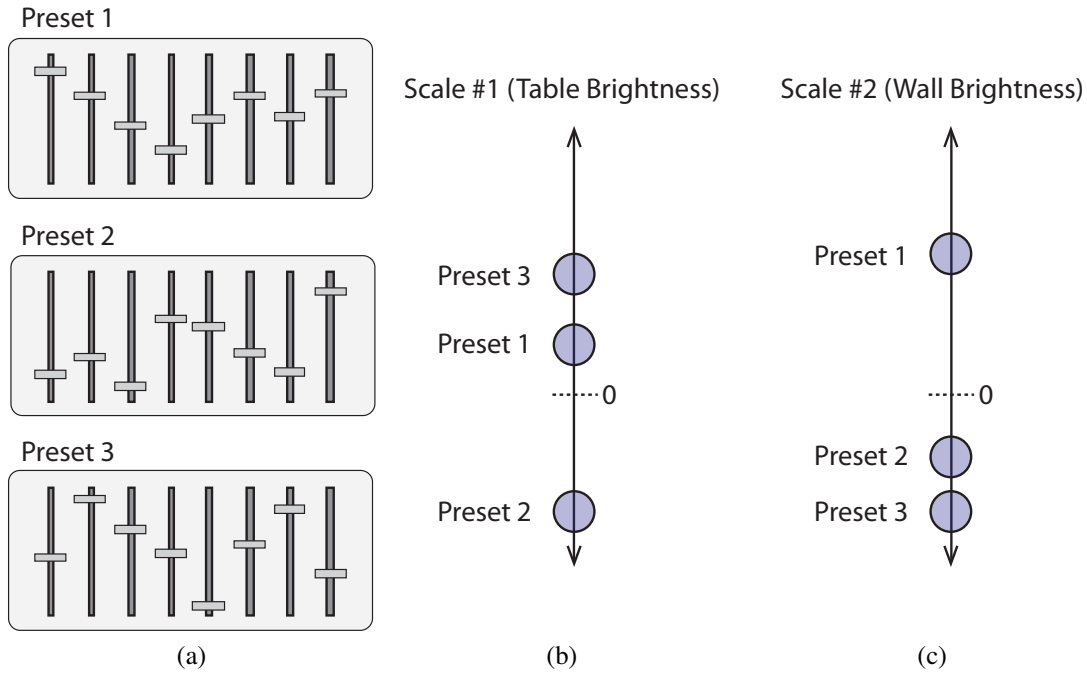


Figure 1.2: The initial problem setup. In (a) three presets of lighting arrangements. In (b) and (c), we have hypothetically measured two orthogonal attributes in the space, table brightness and wall brightness.

Let us further assume in this example, that we can derive a mapping which relates Ω , the metric space the scenes and Γ , the state space of the luminaire setpoints. In other words, our measurement function implies $f : \Gamma \rightarrow \Omega$. This supposition subtly implies that Ω is some lower-dimensional projection of a multidimensional (non)linear manifold Γ .

In Figure 1.3b, suppose we now wish to estimate the state-space Γ within the shaded region bounded by Ω . This goal is analogous to a interpolation in Ω . Specifically, we seek to estimate \hat{f}^{-1} , the inverse mapping which implies $\Omega \rightarrow \Gamma$. Practically, this implies that there exist a continuum of lighting presets bounded by these presets.

In this work Ω is assumed to be a latent and unobserved variable. In the motivating example, it was suggested that Ω can be measured without noise and is completely recoverable. This is likely not the case. Through a set experimental procedures, we analytically derive an estimate of Ω from both objective and subjective measurements. We then estimate \hat{f}^{-1} from Γ and Ω . This mapping allows a user to control and adjust the lighting in a compressed state space Ω and perceive the effects of indirectly adjusting Γ .

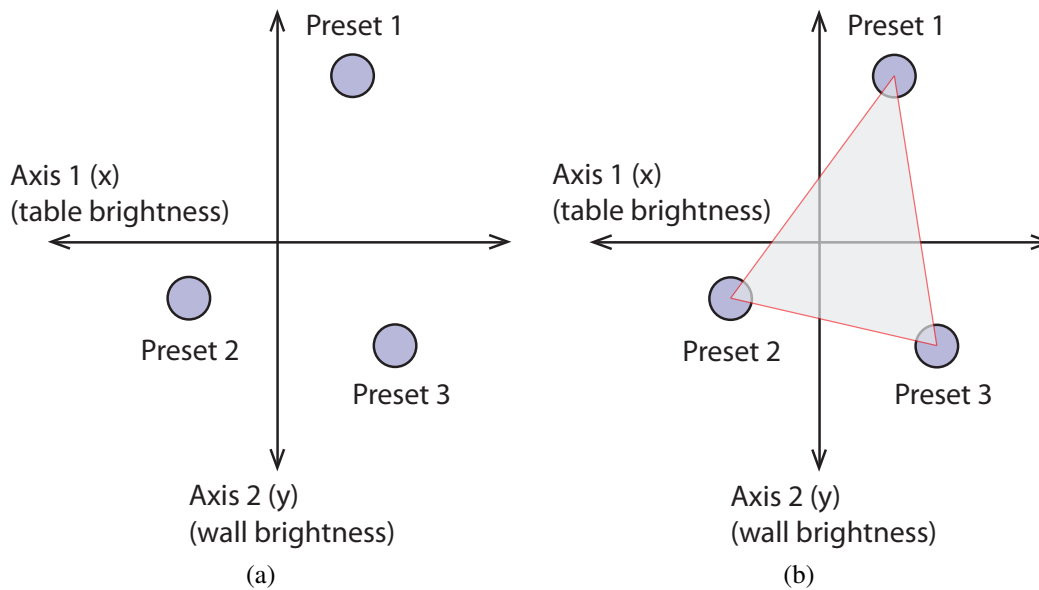


Figure 1.3: A two-axis representation of two attributes of a hypothetical space.

1.4 Subsets and Sensors: Duality in Lighting User-Interfaces

Consider a discrete slider of 8 bits of resolution used to control the intensity of a single luminaire. In this example there are 255 possible states of brightness (assume the brightness matches the logarithmic function of the eye). In a system consisting of 8 luminaires and 8 sliders, there are approximately 17 quintillion states (17 billion billion). Intuitively, we know that a large portion of these states are not preferred by many users, and this leads to the notion of a typical set of lighting configurations (Figure 1.4). A lighting design expert essentially finds a set of lighting configurations that are elements of the set of all states. Given some unknown utility function of lighting design, $f(D)$, the expert compresses the set \mathcal{A} into a typical set \mathcal{B} whose cardinality $|\mathcal{B}| < |\mathcal{A}|$.

There exist other –automatic ways– of identifying these subsets, but require explicit definitions of $f(D)$, such as the minimization of power consumption. For example, consider scenario in Figure 1.5, where the user can place a wireless illuminance at an arbitrary position in the room. In prior work, we¹ demonstrated how a simple linear program can automatically adjust the lighting in a room (Aldrich, 2010; Zhao, 2010; Aldrich et al., 2010; Lee et al., 2011; Mayton et al., 2013) using sensor-nodes and wearable sensor-bracelets. The key insight was that the controllable lighting was modulated such that the sensor-node could easily identify the corresponding contributions of light at a point incident to the surface. Dimming was controlled via buttons (Figure 1.5b) which set the constraints of the linear program.

Other mapping functions exist, such as pointing (Mayton et al., 2013) and learning

¹The Responsive Environments Group at the MIT Media Lab.

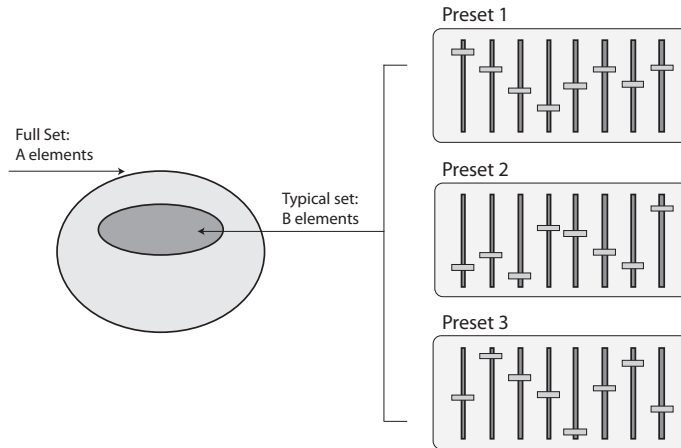


Figure 1.4: Presets are a random variable drawn from a set of “preferred” luminous conditions.

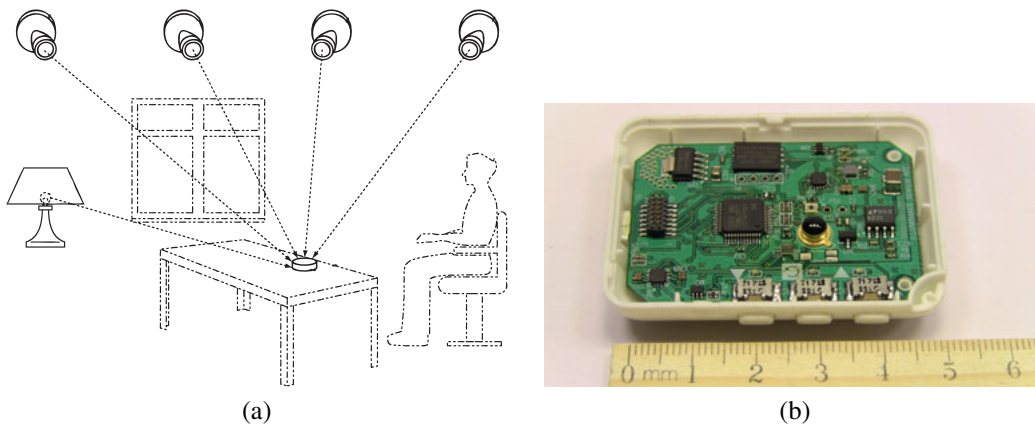


Figure 1.5: In (a), a hypothetical use-case with controllable and background illumination. In (b), the prototype sensor node to measure intensity, color, and control the lighting.

patterns of movement in lattice-type networks of motion-sensors (Aldrich et al., 2013). All of these systems are perceived as simple and easier to use because, either through the direct measurement of illuminance or motion, or by allowing the user to gesture, the resulting set of lighting states \mathcal{B} is smaller than full set of states \mathcal{A} .

In this thesis, the set $\mathcal{B} \in \mathcal{A}$, is chosen apriori, without the aid or intervention of a sensor network, since the primary goal is understanding how to design a lighting user-interface which allows the user the ability to interpolate over the states in \mathcal{B} . However, given some lighting design/control strategy $f(D)$, it is possible to automatically acquire \mathcal{B} (Figure 1.6).

Moreover, this thesis argues that the available user-interface to adjust and manipulate the luminous conditions is inefficient and demonstrates the effectiveness of a user-interface analytically inferred by our impressions of lighting in a space. In this work, the relationship between the slider states, Γ and the orthogonal basis Ω is measured and computed. In other words, these representations are duals (Figure 1.7). The approach

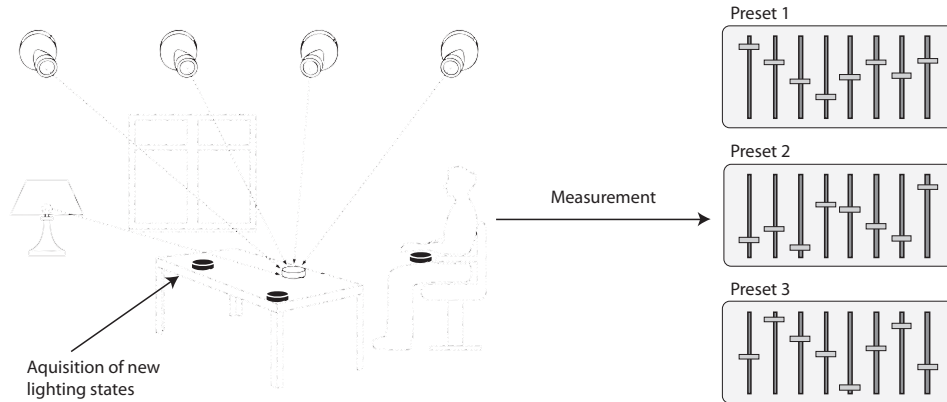


Figure 1.6: Acquisition of new lighting presets using a sensor-network. The sensor-node infers the contribution from the lighting in various positions in the room. Given some simple control strategy (e.g., a linear program). The user can quickly configure a series of preset lighting conditions. (The number of luminaires and corresponding slider interface in this figure are simply illustrative of the technique.)

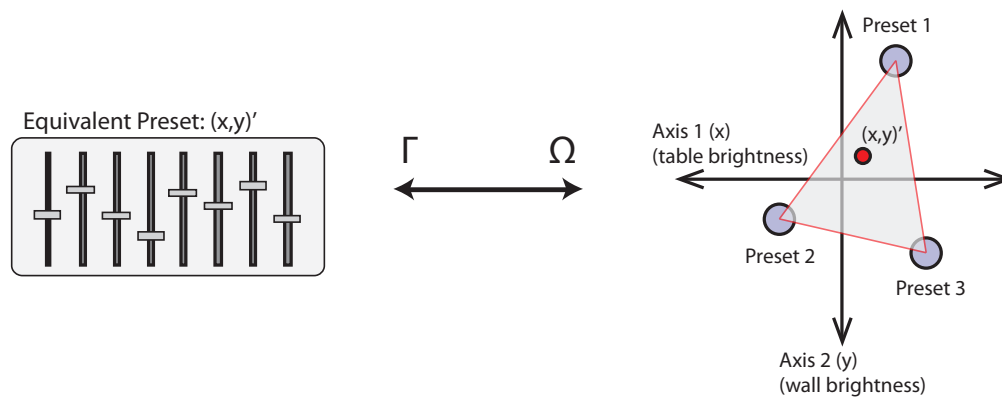


Figure 1.7: The relationship between the slider state Γ and subjective state Ω .

and methods in this thesis allow one to build a user-interface that can map any arbitrary configuration of states onto the simpler basis. For example, one might automatically acquire Γ through the use of a sensor network and project these data onto Ω . Furthermore, as a user-interface, one might configure the lighting globally according to Ω and then fine-tune the system by small adjustments in Γ .

1.5 Thesis Outline

The rest of the thesis is organized as follows. In Chapter 2, I present related work on subjective measurements of lighting and objective-mappings using sensor networks. In Chapter 3, I discuss the ontology behind this work and present a framework that addresses the goals of the motivating example. I then present the results of three experiments, which contrast the various ways of observing these latent dimensions, and

discuss the performance of lighting control user-interfaces that utilize these mappings.

Chapter 4 describes how I developed a prototype lighting user-interface using subjective responses collected using immersive 3D computer graphics. Chapter 5 studies how these impressions can be collected and mapped in the physical space, using real lighting conditions. Chapter 5 also describes and quantifies the fundamental connection between a subjective mapping of lighting scenes and an objective mapping, a crucial step in moving towards a general methodology. In Chapter 6, I present the performance results of using the subjective mapping derived in in the previous chapter. This chapter contrasts the performance of my proposed lighting control user-interface with a traditional approach of lighting control. Additionally in Appendix A, I present a preliminary analysis of user-interface preferences as a follow-up study to the experiment discussed in Chapter 6.

Chapter 7 summarizes the results of this thesis.

1.6 Hypotheses

The research presented in this thesis is based on the assumption that is *useful* and *possible* to develop a lighting user-interface that simplifies the number of parameters to control in solid-state lighting systems. This conviction is founded on the following hypothesis which will be discussed in the concluding Chapter 7.

Feasibility Subjective impressions of lighting can be measured and used in the design of lighting control. The evaluation of these impressions indicates people base their decisions on criteria that are complimentary, but independent of perceived brightness and color.

Justifiable Effort There exists an identifiable relationship between the objective (sensor-based) and the subjective (human-based) models of lighting-scene appearance. Establishing this relationship implies that sensor-networks may automatically build and infer the lighting control user-interface without requiring human assistance.

Relevance The user-experience is better than (traditional) direct-control mappings of luminous intensity. This can be measured in a user study by analyzing task-time, and other human-factors.

Related Work

This thesis builds on the rich tradition of psychophysical lighting research and extends this work into the area of controls and actuation. An overview of human factors and lighting is presented, focusing on perception of lighting. Next, a short survey of recent sensor-based lighting research is presented. Contrasting these two fields is important; to what extent might a sensor network model and mimic the perceptual space as described in the lighting literature? Recent work in fields unrelated to lighting have investigated the actuation, control, and design by incorporating subjectivity into their modeling procedure. The future of user-centered design will incorporate both subjective and objective data parsimoniously.

2.1 Overview

The work in this thesis builds on the rich tradition of psychophysical lighting research and extends this work into the area of controls and actuation. Prior research in lighting is concerned with identifying the dimensions that subjects perceive the lighting in a space. This thesis shows that these techniques are extremely relevant for the design of control systems.

To contrast the traditional goals of lighting research, I summarize the field of sensor-based lighting control – where the goal is often controlling “intensity” and minimizing power. These represent objective measures used to control lighting. Are the subjective measures plausible? Do the objective measures reflect human intent? This Chapter presents evidence from both sides.

2.2 Higher-Order Perception of Lighting

An excellent summary of both the lower-order and higher-order effects of lighting in humans is given by Boyce (2003). Boyce explains (and these are generally accepted principles) that perception is affected by stimulus but not the stimulus alone. First, perception depends on the state of the adaptation of the visual system. Second, the stimulus for perception in the real world is rarely a single item, seen in isolation, but a complex structure in which objects are seen against different backgrounds. Third, perception is guided by our present knowledge and past experience of the luminous environment which determine the assumptions we make about objects and the ways they are usually lit.

Ultimately, the basis for the existence and measurement of these dimensions may be suggested by Kaplan and Kaplan (1982); Kaplan (1987) whose work focused on the role of cognitive processes in environmental appraisals. In this specific cognitive model, appraisal occurs across four dimensions: coherence, legibility, mystery, and complexity. The model emphasizes information-processing: brightness certainly allows us to obtain more information. Mystery and complexity may arise by varying the spatial and size attributes of the space.¹

2.2.1 Lighting, Perception, And The Energy Crisis of the 1970s

In the late 1950s, Osgood found that meaning in language is perceived along three dimensions: *evaluative* (good-bad), *potency* (heavy-light), and *activity* (fast-slow) (Osgood, 1957). Osgood’s experiments utilized a multivariate method of analysis known as factor analysis (see Hair et al., 2009) to attempt to identify a causal relationship between words and their meaning. Nearly 40 years ago, researchers began to apply these methods to lighting – their goal was clear: find satisfying and pleasing rooms that cut energy costs.

¹Figurative “goodness” is described by the Gestalt theorists, for an example of “goodness” and its link to information theory see pp. 45-51 of Gordon (2004).

One of the first researchers to adopt these psychometric methods was John Flynn. He reflects on the underlying goals of the work.

As we look back on the development of electric lighting in 20th century American building, we see the year 1973 as a prominent and significant turning point. Prior to 1973, American practices were based on an assumption of plentiful and inexpensive electric energy; and this in turn led to a widespread attitude that electric light was inexpensive and readily available. . .the post-1973 period has therefore produced many questions regarding the value of lighting.” (Flynn, 1977)

Nearly all the works summarized below account for brightness, or a dimension on which people evaluate a visual environment. Another appears to be something with variety, meaning the non-uniformity in the light distribution away from the work surface. After that, there is basically no agreement. The relevant historical papers are Flynn et al. (1973); Hawkes et al. (1979). The work was extended to pictures Hendrick et al. (1977) and to nonuniform scenes Flynn (1977).

One of the broader ideas that emerged from this period of research was that it appeared that preferences and way that we interpreted lighting appeared to be similar – that it was shared. In the wake of such metaphorical analysis, researchers began to challenge the broad acceptance of the *semantic differential scale* in favor of scaling methods of paired-comparison data (Rea, 1982; Tiller, 1990; Tiller and Rea, 1990; Houser and Tiller, 2003).²

2.2.2 The Post-Flynn Era

Indeed, a comparison of recent dimensional modeling of lighting perception backs off from the heady optimism and near metaphorical descriptions of lighting. Nearly thirty years later, similar exploratory experiments were carried out by Veitch et al. (1996), who generally found similar dimensions, and discussed a third deemed, “complexity.” Loe et al. (2000) described work conducted in a physical space and indicated scales that are described as “visual lightness” and “visual interest.” Quite recently, the proliferation of solid-state lighting has led some researchers to conduct similar studies related to its naturalness and colorfulness (Dangol et al., 2013) and a factor analysis of how we may perceive dynamic lighting installations (Wang et al., 2013).

Multivariate modeling continues to happen in various guises. Rather than discuss perception, some proponents of correlation-based methods describe lighting in terms of atmosphere. Atmosphere is defined as the experience of the surrounding in relation to ourselves, through the perception of external elements and internal sensations. An atmosphere does not necessarily give rise to a particular feeling, it only has the potency of changing people’s affective state (Vogels, 2008).

Vogel’s thesis is that traditional methodologies to measure mood and emotion cannot be used and proposes the use of derived scales to measure the human’s response. Rather

²For an excellent response and defense of the semantic differential, and the difficulties is assessment of lighting, see DK Tiller’s comments on the work of Houser and Tiller (2003) at the end of the paper.

than apply a factor analysis (requires large sample sizes), the author performs ANOVA on the principal components of the response data, assuming normality (of ordinal data). Such an analysis tests where the centroids or points on the orthogonal basis are different than one another. Within the lighting community, the treatment of ordinal scale as ratio scale appears common. This technique is also reflected in Wang et al. (2013) and Dangol et al. (2013).

2.2.3 Lighting, Interaction, and Our Insatiable Appetite of Photons

The work under in this section is an amalgam: it's part lighting research, part pervasive computing (see Sec .2.3 for a focused Ubicomp review). In the nascent stages of solid-state lighting Bergh et al. (2001) and Schubert and Kim (2005) both opined the future and flexibility of solid-state lighting. Today, lamp efficacies are nearly suited for traditional lighting applications (Haitz and Tsao, 2011). Indeed, a recent analysis suggests that as we improve the efficiency of lighting, we tend to consume more lighting (Tsao et al., 2010). This is counterintuitive; one would expect efficient technologies to save money. If one puts any stock in this analysis, then one might conclude, based the control opportunities for lighting and the growing need to manage all this light, that control and interaction will be the next key area of lighting research.

In what will become a landmark paper in this burgeoning area³, Newsham et al. (2004) describe a series of experiments where subjects rated their preferred lighting scenes (on a computer). The computer scenes allowed for adjustment of the surface illuminance of the various facets of the scene (ceiling, desk, side partitions, etc.). Through the aid of a genetic algorithm, it was shown that subject's arrived at their preferred lighting conditions simply by rating what was preferred and what was not. Furthermore, there was similarity between these preferences across people. A factor analysis revealed that the underlying causes of ratings on both the grey scale computer simulation as well as the physical office setup were similar. Finally, these subjective ratings of brightness, uniformity, and attractiveness were found to be significantly related to the luminance in the images. Villa and Labayrade (2013) recently described a multi-objective approach to balancing perceived brightness and "coziness" in an office setting (using ray-traced computer images). Again, the authors employ a genetic algorithm to find Pareto-optimal solutions of multiple objective functions. The biggest drawback in the two approaches described here is that genetic algorithms are not suitable for run-time performance (e.g., their application in lighting controls is doubtful). In Villa and Labayrade (2013), the independent variables are regularly spaced, for example the setpoints of the luminous conditions and the dependent variables are preference or energy. In this work, bi-linear interpolation makes sense, as the independent variables form a grid of points. In this thesis, since the main focus is to build a user-interface, the independent variables are ordinated lighting scenes (which are irregularly spaced) and the dependent variables are the luminous set-points.

³Despite being published nearly 10 years ago, at the time of writing, this paper is cited by only 11 authors. Alas, the fields of pervasive and ubiquitous computing have not converged on this field.

Nearly 14 years after a landmark framework for tangible interaction (Ishii and Ullmer, 1997; Ullmer and Ishii, 2000), these powerful ideas of interaction have appeared in the lighting community. The first basic analysis of modern lighting control systems (Dugar and Donn, 2011) brought the vision and ideas of the general human-computer interaction (HCI) community into the lighting world. Their focus is specifically on tangible computing, but they propose a rather narrow framework. I would suggest future analysis of lighting controls focus adopt a *morphological analysis* of the control space (see the seminal HCI work by Card et al. 1991 and Mackinlay et al. 1990 for an example). Dugar et al. (2012) recently published a user-study based on their physical prototype of a lighting control tangible user interface (TUI). HCI purists may argue if it is actually a TUI, or an example of gesture-based interaction, however it is certainly a step in the right direction.

2.3 Pervasive Computing and Lighting Control

Within the last five years, there has been considerable progress by the pervasive computing community using sensor-networks to control illumination. An updated review will be included in the dissertation, but the work reviewed below gives sufficient breadth.

To date, occupancy-based controls represent the majority of automatic building lighting control systems. Early studies of stochastic modeling and lighting are reported in Newsham et al. (1995); Reinhart (2004); Singhvi et al. (2005). The work conducted at the turn of the millenium broadly reflects the underlying goals and principals of pervasive computing (Weiser, 1991; Abowd et al., 2002). In what follows, I present a small survey of the sensor networks and lighting. Crucially, one should notice how the pervasive and ubiquitous computing communities tend to marginalize the human in these cyberphysical systems.

Increasing research and commercial deployments of sensor networks have motivated the use of networks that monitor lighting conditions and the development of closed-loop lighting control. In these systems, illuminance-sensors are placed (generally in a fixed position) in the area of interest in order to detect the luminance surface and feedback the lighting information.

Dynamic and adaptive lighting enabled by environmental sensors offers additional energy savings. Early work by Crisp and Hunt in the 1970s focused on estimating internal illuminance from artificial and external light sources in order to reduce unnecessary lighting and excess energy expenditure (Crisp, 1977; Hunt and Crisp, 1978). This early work discussed the use of photosensors to monitor the natural daylight in the office place. With the availability of low-cost photosensors and an influx of low cost embedded devices, this simple form of intensity feedback was extended to networks of fixed color incandescent and fluorescent lights. Singhvi et al. (2005) designed and tested closed loop algorithms to maximize energy efficiency while meeting user lighting requirements in an incandescent lighting network. Park et al. (2007) developed a lighting system to create high quality stage lighting to satisfy user profiles. Wen and Agogino (2011) researched fuzzy decision making and Bayesian inference in lighting control networks. Machado and Mendes (2009) tested automatic light control using

neural networks, as did Mozer (1998) where light switches and thermostats in his house provided reinforcement for a neural network that incorporated motion sensors to build a user activity model to automatically control utilities.

Wen et al. (2006) researched fuzzy decision making and Bayesian inference in lighting control networks as well as designed a versatile plug-and-play wireless-networked sensing and actuation system and included a control method incorporating multiple management strategies to provide occupant-specific lighting (Wen and Agogino, 2011). Miki et al. (2007) studied the trade-offs between energy consumption and lighting preferences for multiple users using a linear program to calculate the optimal intensity settings in a lighting network. Similarly, Pan et al. (2008) used a linear program and considered the power consumption as the objective and the user-preference as constraints. Both algorithms require the knowledge of the positions of the occupants, which can be detected using RFID tags or other similar user localization systems.

Increased efficacy and performance of solid-state lighting has reinvigorated interest in intelligent dimming, color control, and networked lighting (Schubert and Kim, 2005). Caicedo et al. (2011) consider the problem of energy-efficient illumination control based on localized occupancy models. In this work, an occupant's trajectory is modeled as a Markov chain and tracked using ultrasound while a linear program controls the dimming level. Bhardwaj et al. (2010) use a predetermined illuminance setting and context (i.e., reading by a lamp) which can compensate for changing ambient light levels or the presence of additional LEDs.

2.4 Beyond Lighting: Incorporating Preference and Opinion in Design and Control

Although not directly related to lighting or lighting control, the short survey of works here share a similar philosophy with the work outlined in this proposal. The primary link is that all the works here suggest ways to incorporate some notion of perception, map it to some physical parameters, and then perform some actuation or decision using the subjective human criteria.

The design of objects, artifacts, and products certainly benefits from this type of approach (Hsiao and Chen, 1997; Achiche and Ahmed, 2008). The broad goals of these works seek relate the perceptual or emotional attributes of an object to its physical attributes. Using these perceived dimensions, one can proceed to design an optimal chair or virtual character – one that directly speaks to how we understand the artifact.

A similar approach can be taken with the design of virtual characters – for example, what makes them memorable to us? This requires modeling emotion, mood and personality, as well as social relationships. The frameworks for conducting such research are potentially beneficial for the design and incorporation of our subjective responses to lighting (see Kasap et al. 2009 for more detail).

Chaudhuri et al. (2013) present an approach for modeling and design of whimsical creatures and toys using computer graphics by mapping the semantic attributes of the individual components of these objects (e.g., the head, tails, body, feet) and show how

2.4. Beyond Lighting: Incorporating Preference and Opinion in Design and Control

the design of such objects is more enjoyable, faster, and intuitive when the user can design these attributes using scales (“actuators”) that reinforce the emotive and affective attributes of the character. This of course, has strong similarities to the design and control of a lighting system in which we vary the primary dimensions in which we perceive and judge the differences of lighting.

The nascent field of “visual stylometry” is concerned with the study of how computers can understand the authenticity of artwork (Graham et al., 2012). What is important here is that in order to study this problem, the authors have to describe the visual processing of an entirely perceived phenomenon – style – in a way that ordinary computers can understand. If one were to adopt a computational framework of human vision (e.g., Marr 1982) and study how spectrometry and computer vision can emulate lighting control based on our comparative judgments of scenes, these hybrid perception+computation studies of computers are of great considerable interest.

A New Framework For Lighting Control

The ontology governing this work is developed and presented in this chapter. The fundamental aspects of psychology and human-computer interaction relevant to the design and analysis of lighting control are presented.

3.1 Perception, Interaction, and Control: A Framework

Unlike the field of human-computer interaction, research in *lighting control* does not carry a rich tradition of toolkits, taxonomies, and performance studies. This is not a comment on the quality of lighting control research, but rather a statement about the organization of the field. Thus, to formalize a research endeavor in this space, I am proposing a layered-framework which spans the metaphysical and technical. In this approach, the layers proceed downwards, with each layer successively refining and reinforcing the entire framework.

The framework (see Figure 3.1) consists of four layers, with the highest layer comprising the metaphysics of the framework and lowest layer, the technical substrate.

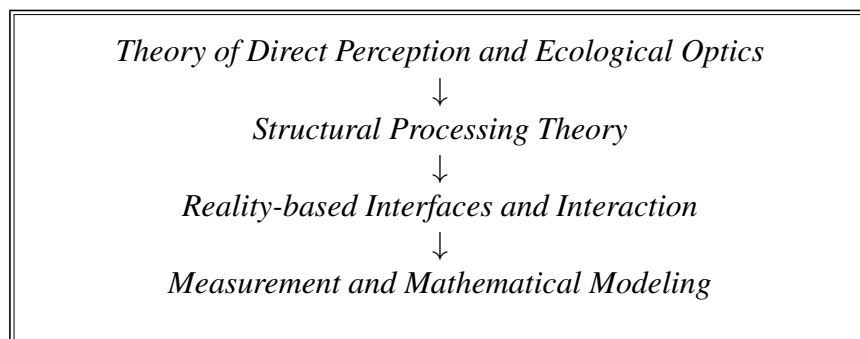


Figure 3.1: The proposed framework for conducting research on human interaction with lighting control.

3.2 Invariants and Affordances as Mechanisms to Define Interaction

The theory of direct perception and ecological optics (Gibson, 1986, 1977) are natural frameworks to approaching a study of our (indirect) interaction with lighting. To Gibson, the words “animal and environment” form an inseparable pair. Ecological optics is an approach to study an animal’s perceptual systems in its physical environment. Of course, artificial lighting is not the natural environment, but the transmission of photons is essentially the same.

To study our interaction and perception of lighting Gibson would advocate to “find out about the patterns of light that arrive at the eye from the environment and ask what potential information about the environment is contained in these patterns (Gordon, 2004).” Specifically, these patterns indicate the higher-order properties of an object. These properties are known as *invariants*. Artificial lighting, and the space in which we perceive it, contains invariant information. Furthermore, Gibson defines the concept of an affordance, which is the meanings that an environment has for an animal. In the words of Gibson (1971), “Affordances of things are what they furnish, for good or ill,

that is, what they *afford* the observer.” Affordances are simply the meanings that an environment has for an animal and it is these meanings that guide behavior. It is obvious that specific arrangements of lighting indicate affordances.

Most importantly, Gibson asserts that invariants and affordances, “these seemingly abstract properties of things and events” (Gordon, 2004), are there to be perceived *directly*. Thus, within such a theory, it is logical to conclude that the higher-order properties of lighting are there to be perceived directly from the patterns of stimulation arising from the objects and the room itself. Gibson’s theories provide us with an ontology – we can rationally argue that higher-order perceptions of lighting may exist.

At the highest level, I am asking a basic question: what is a suitable representation of the affordances of lighting as inferred by the patterns artificial illumination in the physical space? In other words, is the (learned) structure of meaning from a patterned set of stimuli a suitable representation for human interaction with a complex object? I am interested in ascertaining whether the organization and representation of lighting scenes (by their affordances) is adequate for the design and application of multivariate lighting control. Such an approach, at this point, transcends the interface in which we may realize such goals.

Having defined a metaphysical approach for studying lighting, we can turn our attention to a theory put forth by experimental psychology: the manner in which we perceive multiple attributes of an object. The insight born out of this theory gives us a firmer theoretical framework in which we can anticipate the effects of multivariate lighting control.

3.3 Processing the Perceptual Structure of Multidimensional Stimuli

Every object can be described by its attributes. For example, a lighting scene has brightness, saturation, hue, size, and location. It was found that the spatial structures that describe the perception of an object’s multidimensional attributes vary depending on the attributes under study (Attneave, 1950; Shepard, 1964).

The theory of processing perceptual structure (Garner, 1974) suggests that the way a multidimensional stimulus is perceived and processed depends on the nature of its component dimensions; in some cases it is perceived and processed holistically and in other cases, in terms of its structural components. Further studies revealed that the attributes of visual objects combine perceptually to form a unitary whole (e.g., lightness and saturation of colors), while others remain distinct (e.g., size and rotation of shapes). These distinctions between multidimensional stimuli are known as *integral* and *separable*. If the underlying dimensions of test stimuli are integral, then classification is based on similarity; subjects tend to form “clusters” of integral stimuli sets in experiments. On the other hand, if the dimensions of the stimuli are separable, then discrimination is based on the dimensional structure. Moreover, mental models of how these differences are perceived have been proposed and experimentally verified. In Figure 3.2, separable attributes, such as the size and rotation of the squares in the figure are modeled as a

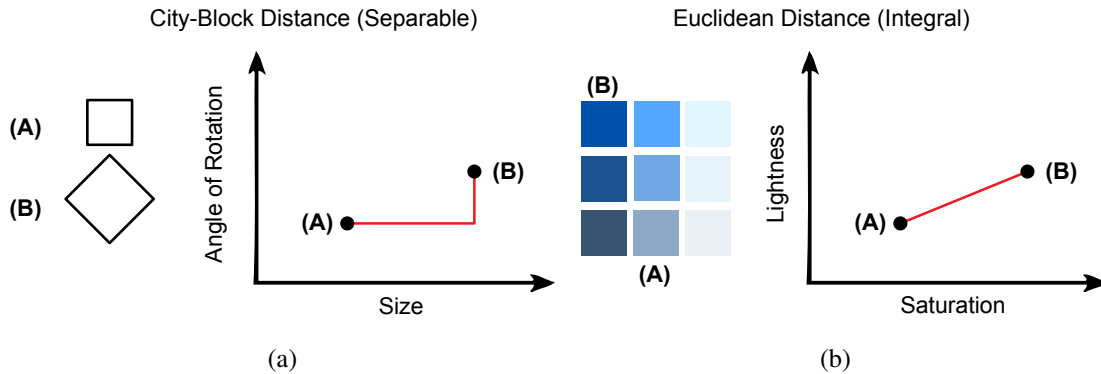


Figure 3.2: Examples of separable and integral attributes of objects.

city-block (Manhattan) distance metric (also the ℓ_1 -norm). Thus, in this example, the distance between both squares A and B is given as $\|A - B\|_1$. Likewise, the Euclidean norm (ℓ_2 -norm) best describes the perceived distance between integral attributes. Perception of various attributes of a room is likely to adhere to basic theory of integral stimuli.

Stimuli rich in similarity structure do not have a single attribute which dominates; with dimensional structure the attributes are directly perceived and cannot be ignored. Furthermore, stimuli can exist anywhere along the continuum of integral or separable.

This theory ultimately tempers the expectations for what we may reasonably expect to measure in the studies. The proposed lighting stimulus must be capable of being understood by the subjects, and have an empirical basis in support of the measurement.

Notably, structural processing theory was extended by Jacob et al. (1994) to include interaction. Jacob et al. found that the dimensionality and structure of the control must reflect the dimensionality and structure of the stimulus. These results were demonstrated using free-gesture to control simple attributes of objects displayed on a computer screen. When dimensionality of the task matched the dimensionality (affordance) of the user-interface, human performance is improved. For lighting, this means that our performance is ultimately governed by how well the interface reflects the integrality of the luminous conditions. I believe this important concept has been overlooked in much lighting practice. In Figure 3.3, I interpret Jacob et al. results and the corresponding user-interfaces. The point is that integral control, for example, like the sliders in Figure 3.3 is perceptually the wrong affordance for the adjustment of luminous conditions. On the other hand, the parametric control offered by the axes, assuming the perception of lighting consist of integral stimuli, is the proposed affordance to control and adjust lighting.

The effects of these user-interfaces are experimentally verified in (Chapter 6). Subsequently, Chapter 4 and Chapter 5 discuss experiments designed to find a suitable basis to simultaneously represent the perceived attributes of the luminous conditions of a room.

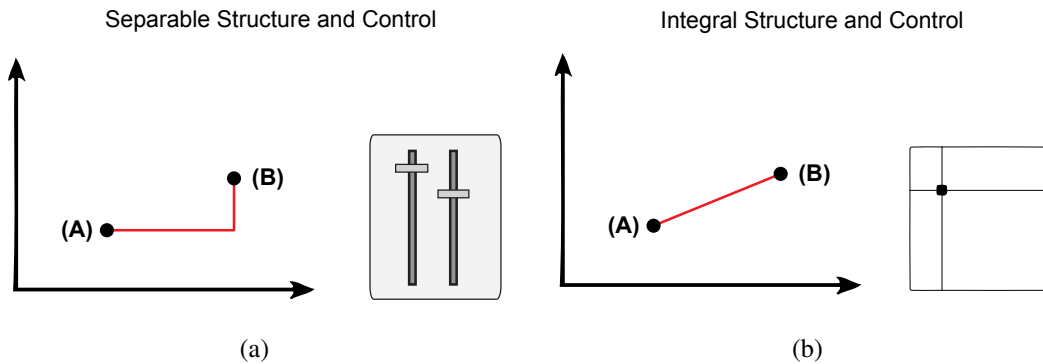


Figure 3.3: The dimensionality of perception and corresponding user-interfaces.

3.4 Reality-based Interfaces

Given our philosophical and experimental viewpoints of how humans may understand and process multivariate lighting, we now turn our attention to the interface for control. The goal is not to define the exact interface, but to introduce a viewpoint that organizes a large body of interaction styles.

Of importance is that any framework gracefully reconcile both the human and pervasive computing-inspired (e.g., sensor-based) interfaces in lighting. It is neither my goal to alienate the human from the sensor, nor the sensor from the human. I am simply stating that how we perceive lighting, the space, and the objects within this space should be taken into account.

Broadly, the notion of reality-based interaction attempts to identify the unifying concepts that tie together a large subset of emerging interaction styles. Some examples of reality-based interaction styles are:

Virtual, mixed and augmented reality, tangible interaction, ubiquitous and pervasive computing, handheld or mobile interaction, perceptual and affective computing as well as lightweight, tacit, or passive interaction.

(Jacob et al., 2008)

Conceptually, all these styles build on the users' (pre-existing) knowledge and experience of the everyday world (e.g., physics, their bodies, the surrounding environment, and other people). For lighting control, this implies that the interface should *directly* make use of our perceived affordances of lighting. This strengthens the relationship between the human and the photon – the interface symbolically represents the locus of the human, the environment, and the lighting.

In other words, it should follow that the appropriate design of the interface should expressly model the *integrality* and *separability* of the lighting stimulus. Succinctly, form follows function. The lighting interface should allow the user to express their goals and desires naturally – what better an input method and interaction than one that

seeks to identify the basis of the meaning of the illuminants and their subsequent digital representation?

3.5 Measurement and Mathematical Modeling

Traditionally, the tools for understanding and quantifying the human experience with lighting are adopted from a branch of psychology known as psychophysics. This experimental framework provides the tools to study lighting preferences. Questionnaires, rating scales, magnitude estimation techniques, and paired comparisons resemble common techniques to quantify the subjective aspects of lighting. The two most popular techniques being the semantic differential and multidimensional scaling (MDS) (see Hair et al. 2009). The use of the semantic differential technique implies that the experimenter knows (or seeks to measure) the relationship of a set variates that are causally linked to a set unobserved variables.

The use of MDS implies that the subject is free to use their own internal criteria to judge the difference between two objects. In the proposed work, the use of MDS as an experimental method for designing lighting control is evaluated. It is expected this technique is easier to generalize in actual practice.

In principle, either an individual or group can perform a series of paired comparisons which rate the similarity of pairs of lighting scenes (presented either simultaneously or sequentially). The scaling procedure performs an ordination of the data, the differences between the pairs are related to distance in some dimensional space. The basic concept and modeling workflow is given in Figure 3.4.

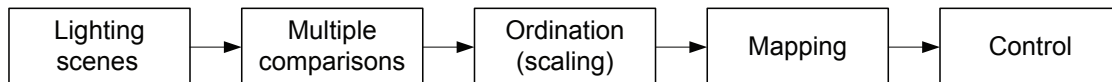


Figure 3.4: A sketch of the procedure.

Human Subjects Test I: A Control Prototype in a Virtual Model

This chapter is the first of three empirical chapters which describe evidence in support of the theory and framework described in the previous chapters. In this first experiment, subjective impressions of lighting are collected from participants who viewed luminous conditions in an immersive three-dimensional “virtual” board room on a computer monitor. The technique describes the use 29 scales and the subsequent dimensionality reduction to extract the principal components of lighting control. The statistical details of the analysis first presented and the first prototype user-interface is disclosed.

4.1 Introduction

A recent series of papers have presented results of using computer-graphics in conjunction with the evaluation of the subjective impressions lighting conditions (Newsham et al., 2010; Engelke et al., 2013; Villa and Labayrade, 2013; Murdoch and Stokkermans, 2014) Recently, the use such procedures was discussed as an opinion piece (Boyce, 2013). Entitled, “A Virtual Opportunity,” Boyce the describes the challenges of performing experiments involving humans and impressions of lighting. Notably, these experiments are expensive, difficult to scale, and typically recruit only a subset of the population. These are valid criticisms. However, the wide-spread applicability of accurate and visually compelling still-images of virtual models is becoming prevalent.

In this chapter, we detail the results of a pilot study designed to study the feasibility of creating a prototype lighting controller designed from human impressions of lighting. Our primary objective was not a photo-accurate rendering of the luminous conditions, but the measurements of these impressions in an immersive three-dimensional environment.

The experimental results presented in this chapter are motivated by the initial work of Flynn et al. (1973). In effect, this chapter first replicates the experiment of Flynn et al. and then extends the results into the realm of control and actuation.

4.2 Experiment Setup

The experiments were carried out in a dark, windowless office, at the MIT Media Lab. The physical measurements of the space in which participants viewed the scenes was approximately 4.2m \times 2.8m. The room height was 2.6m. The room temperature was maintained at 22 – 23°C via building HVAC.

4.2.1 The Virtual Lighting Room

A virtual, windowless board room was designed using the Unity game engine with surface area 12.5 m² (length=4.6 m, width 2.7 m). The room height was approximately 2.6 m. The initial concept was interpreted from Flynn et al. (1973). The room was furnished to resemble a board room, with a long rectangular table placed in the center of the room (approximately 2.2 m \times 0.90 m). The table height was roughly 0.70 m high. Ten office-type chairs were also present in the model. Decorative furnishing consisted of two paintings on the on a single wall in the room. The model also featured two laptop computers (turned on), a readable newspaper, and some office supplies. (Figure 4.1)

Notably, during the experiment, participants were free to move about the space, controlling their position and viewing angle using the mouse and keyboard.

4.2.2 Equipment

The experiment was carried out using a PC running the Unity lighting model. Participants viewed the lighting scenes on a 3D-capable monitor (Asus VG236H) and wore



Figure 4.1: Illustrations of virtual board room designed in Unity to evaluate lighting conditions (after Flynn et al., 1973).

active-shutter 3D glasses (Nvidia P854). Participants viewed the computer-model at distance of approximately half a meter. For each tested scene, we collected brightness measurements from four distinct locations in the model using a Konica Minolta LS110 luminance meter and adjusted for the effects of the 3D glasses.

4.2.3 Lighting Scenes

The experimental design of the lighting scenes followed Flynn et al. (1973). In the model, we specified 4 distinct luminaire types to replicate the six original lighting configurations. These four luminaire types were: downlighting, diffuse overhead, long wallwash, and short wallwash. Our replication of Flynn’s original six scenes tested in the experiment are shown in Figure 4.2.

At the time of the experiment, Unity did not allow for absolute specification of the lighting models, so the lighting scenes were designed using relative setpoints in the boardroom model. Then, we sampled the brightness from the monitor using the luminance meter at four distinct points for each of the six scenes. Using this process, we attempted to model the luminous conditions provided in the original Flynn study. The brightness measurements (from the viewpoint of the observer) are given in Table 4.1. As a rule of thumb, the measurements were found to be approximately 20 times brighter without the glasses.

4.2.4 Participants

Forty students and staff from the MIT campus (21 women and 19 men) ranging in age from 21 to 45 years old voluntarily participated in this experiment. All were assigned to the same experimental tasks. The study was conducted in a darkroom at the MIT Media Lab over a three-week period by Media Lab researchers.

4. HUMAN SUBJECTS TEST I: A CONTROL PROTOTYPE IN A VIRTUAL MODEL



Figure 4.2: The six lighting scenes evaluated in the study (after Flynn et al., 1973).

Table 4.1: The measured scene brightness for the six test conditions adjusted for the attenuation of the 3D glasses; measurements can be adjusted by multiplying each entry by a factor of 20.

Scene	Brightness (cd/m ²)			
	table midpoint	long-wall midpoint	short-wall midpoint	ceiling midpoint
1	1.3	0.3	0.2	0.3
2	2.6	5.0	7.4	2.4
3	2.7	2.4	2.5	9.1
4	2.4	0.5	5.9	0.6
5	10.7	11.8	10.0	11.2
6	5.2	7.1	6.5	5.4

4.2.5 Procedure

Altogether, forty subject rated each of the six lighting scenes using 29 bipolar scales. These scales were derived from (Flynn et al., 1973; Hawkes et al., 1979), but are not considered an exhaustive pool of rating criteria for lighting. Each bipolar pair was rated on a scale of -3 to 3, where zero was neutral. An example pair in the experiment could be “pleasant” and “unpleasant,” and a negative score indicated the participant’s attitude to the negative attribute; similarly a positive score, the positive attribute.

The experimenter reviewed the experiment instructions with the participant. All participants were told that the experiment was designed to measure their subjective judgment of computer-generated imagery. The participants were not made aware that the lighting would be varied across the six scenes. Then, participants were given a two minute period to walk around a demonstration-room to learn how to control their position and viewing angle using the mouse and keyboard. This time also allowed participants to adjust to the effects of the 3D glasses.

Participants could view each scene as long as necessary, and when ready, removed the glasses and reported their scores on a small portable computer running the survey software. This procedure was iterated until each participant completed all six scenes. Each experiment required approximately 30 minutes.

The order of the six lighting scenes were drawn at random. For each scene, the order in which scales appeared in the survey were also randomized.

4.2.6 Evaluation

The two primary goals of the experiment were the analysis of the subjective data regarding participants’ impressions of the room and, the prototype design of a lighting composed of the two major axes which measured the largest variation in their responses. Several assumptions are required to carry out the analysis and are stated below.

4.2.6.1 Dimensionality Reduction of Responses

In this exploratory analysis, it was anticipated that subject’s impressions as measured by the 29 scales were correlated. A principal component analysis was carried out to understand the major sources of the observers’ response variation. Altogether, each participant contributed 6×29 (174) data points. We now state our assumptions in this phase of the analysis.

The observations treated as independent. This assumption allows the researcher to study the responses using a simple two-way analysis (e.g., a 240×29 design) versus a three-way analysis of the data (e.g, a $6 \times 29 \times 40$ design). Alternative approaches for a three-way principal component analysis include multifactor-analysis (Abdi et al., 2013; Acar and Yener, 2009).

4.2.6.2 Assessment of Component Scores

There are several assumptions are required to perform this analysis with the primary disclaimer that the results are not confirmatory, but suggestive (the major caveat are that

the calculated F-scores, which are used to determine statistical significance are likely inflated in this analysis). This work guided the design of further experiments in this dissertation.

In the next phase of the analysis, the four principal component scores are first tested using a multivariate analysis of variance (MANOVA) to determine if at least one scene caused an effect. If an effect is found, one then tests each of the dimensions individually (ANOVA). The analysis determines if at least one scene had some effect on the group-means of the lighting scenes. For each principal component in which an effect was measured, we follow up the statistical test with a Tukey's Honestly Significantly Different (HSD) test to determine which lighting scenes are statistically different. We now review the assumptions behind this evaluation.

Performing an analysis of variance on the principal component scores has precedence in recent lighting literature (Vogels, 2008; Dangol et al., 2013; Wang et al., 2013), however the conclusions that can be drawn from the results are limited – one only gains insight as to which scenes vary amongst the components, but is left with no evidence as to which specific variable caused the effect.

The major assumption in this analysis is that the principal component scores are independent; this is clearly not the case in the actual experiment design, since each participant was tested six times during the experiment. However, since application of PCA assumes independence, the assumption of independence is carried forward in the ANOVA.

4.2.6.3 Design of the User-Interface

The final objective of the analysis is to estimate the mapping between a configuration of points, Ω (e.g., the principal components) and the corresponding setpoints of the luminaires Γ (e.g., their red, green, and blue control values). In other words we seek a solution of the form $f : \Omega \rightarrow \Gamma$ where f is the mapping between our configuration of the lighting scenes and their control values. The intent is the function f provides a mapping for control of the luminaire setpoints, such that the function provides a means to manipulate the state-space of Γ . Thus, this section describes the design of a lighting user-interface derived from either objective or subjective mappings of the lighting scenes. In particular, we focus on solutions where Ω is two-dimensional.

Using the first two components, appearance and intensity, we evaluated three distinct mapping strategies. Recall that 4 groups of luminaires were present in the study: downlighting, diffuse overhead, long wallwash, and the short wallwash. In the experiment, only relative intensity of these four fixtures were varied, therefore a subsequent control strategy required estimating four unique control surfaces. In this procedure, the dependent variable, the relative intensity setpoint of the luminaires, is a vector Z_i for $i = 1, 2, \dots, 4$ where i indexes the luminaire type. The dependent variable X describes the mean principal component score for each lighting scene. We estimate four distinct surfaces. Subsequent operation requires the user to specify an (x, y) pair, and the control system then sets the four luminaires to the corresponding intensity determined from the surface fitting procedure. An example control surface for a single luminaire fit using bilinear interpolation is presented in Figure 4.3.

Mapping Principal Component Scores to Lighting Parameters (Bilinear Interpolation)

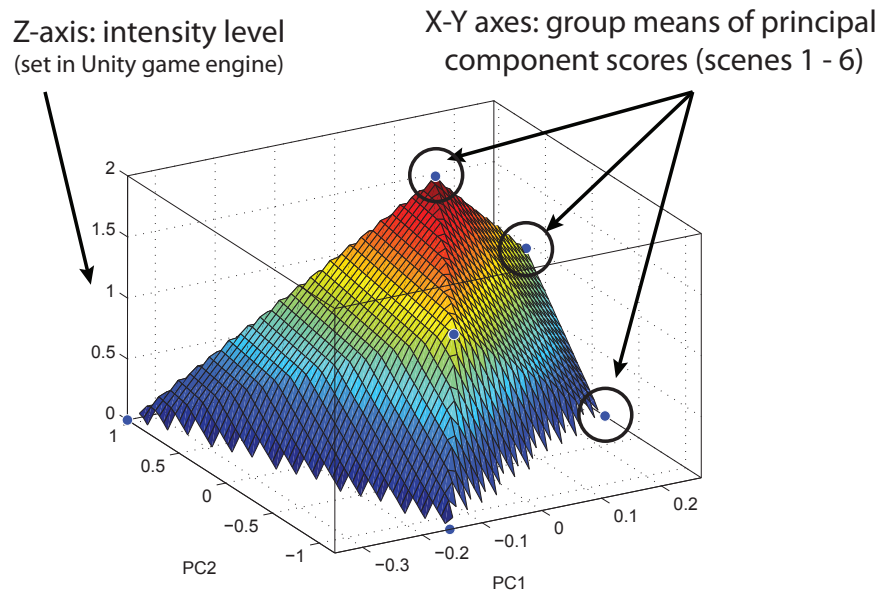


Figure 4.3: Example surface fitting procedure for luminaire (bilinear interpolation).

In this prototype, we evaluated a linear fit (fitting a plane through the intensity z -axis), a linear interpolant, and a spline interpolant. Each of these estimation procedures produces different experiences for the user, and makes different assumptions about the continuity of the fitted surface.

For example, a linear plane fit through the data minimizes the sum squared error of the intensity axes, however, in such a procedure, the original test conditions are unreachable (recall the plane is fit through the data themselves).

A linear interpolant is best suited for independent variables (e.g., the appearance and intensity components) that are regularly spaced (like a grid). Unfortunately, we cannot assume a priori that the resulting principal components of the lighting conditions will be a set of regular points.

Finally, a spline-based interpolant does not require regularly-spaced data and assumes the mapping $f : \Omega \rightarrow \Gamma$ that is everywhere continuous and differentiable.

4.3 Results

4.3.1 PCA Results

The 40 participants altogether evaluated altogether 6 lighting scenes on 29 questions. For each scale, the values range between -3 and $+3$, where the negative value is indicative of the “negative” side of the bipolar adjective and vice a versa for a positive score. A score of 0 represented neither positive nor negative, but a neutral response.

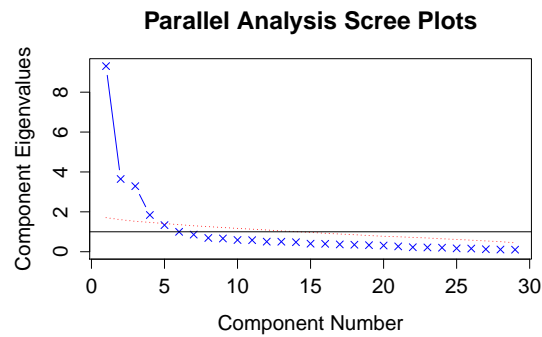


Figure 4.4: Plot of parallel analysis, 4 components were used in this analysis.

The component analysis was carried out using the PSYCH package in R (Revelle, 2014). The parallel analysis of the data revealed that four dimensions is a suitable fit (Figure 4.4). The data was centered and scaled. The 29 questions loading higher than ± 0.50 were then interpreted for each of the 4 components, identified as, appearance, intensity, clarity, and order (Table 4.2). Internal consistency reliabilities were good for the first two components (Cronbach's alpha ($\alpha > .8$)), but rather poor for the third and fourth components ($\alpha \leq .62$). Although the third and fourth components describe some variance in the data set (16% each), the reliability of these dimensions is not suitable.

4.3.2 A Two Dimensional Visualization

The lighting conditions can be described in two dimensions using their the appearance and intensity components. These form the lighting control axes which ordinate the six lighting scenes evaluated in the study (Figure 4.5). The reference coordinates (mean and standard deviation) of the four derived components per lighting scene are given in Table 4.3

4.3.3 Statistical Analysis of Lighting Scenes

MANOVA Results The results were examined using a simple one-way MANOVA to test for any effect of scene in the four component scales. We obtained a significant effect scene $F_{20,936} = 10.0, p < .0001$. The rest of the analysis proceeds as follows: for each of the four components (appearance, intensity, clarity, and order) perform a one-way ANOVA and for any significant result, follow-up with a post-hoc evaluation of which scenes were statistically different.

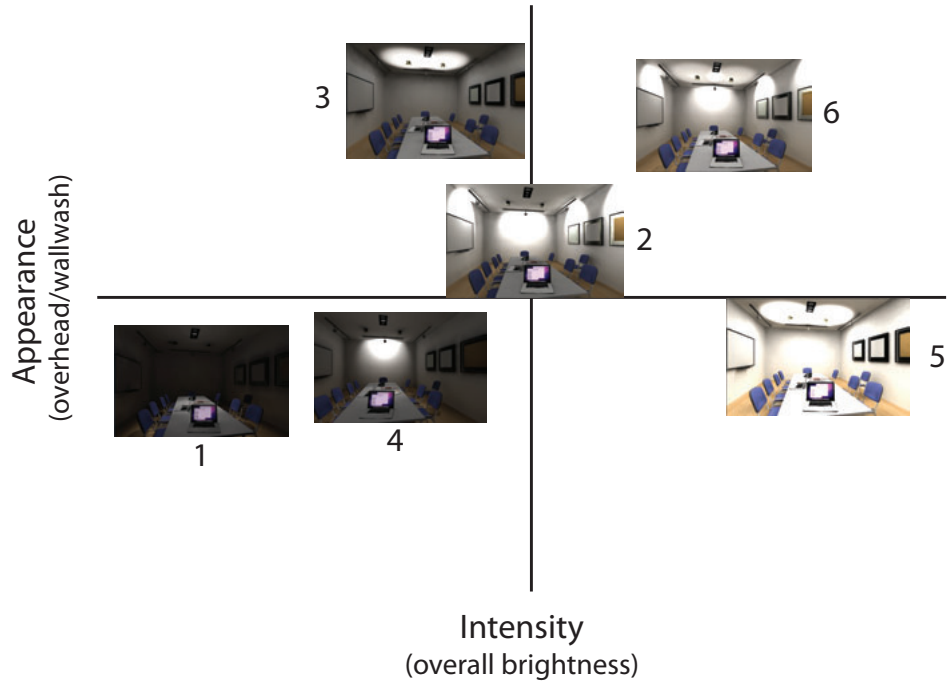
ANOVA Results The statistical analysis of the four derived components are reported in Table 4.3. For each significant ANOVA result, the test was followed up with Tukey's Honestly Significant Difference test with a the Holm correction of the p -value for multiple comparisons (15 comparisons for each component). Thus, if any of the average scores for each component were affected by the lighting, we could then investigate

Table 4.2: Rotated component loadings for 29 questions.

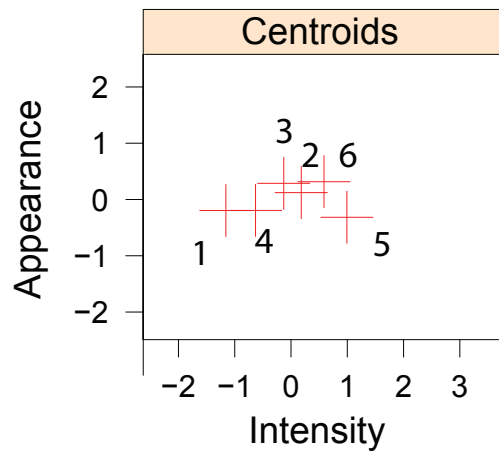
	Item (Adjective Pair)	(1) Appearance	(2) Intensity	(3) Clarity	(4) Order
1	pleasant/unpleasant	0.9	–	–	–
2	like/dislike	0.89	–	–	–
3	friendly/hostile	0.87	–	–	–
4	satisfying/frustrating	0.87	–	–	–
5	relaxed/tense	0.87	–	–	–
6	beautiful/ugly	0.86	–	–	–
7	harmony/discord	0.79	–	–	–
8	interesting/monotonous	0.73	–	–	–
9	rounded/angular	0.64	–	–	–
10	sociable/unsociable	0.64	–	–	–
11	spacious/cramped	0.51	–	–	–
12	bright/dim	–	0.84	–	–
13	public/private	–	0.72	–	–
14	faces clear/faces obscure	–	0.69	–	–
15	cheerful/somber	0.5	0.69	–	–
16	radiant/dull	–	0.67	–	–
17	quiet/noisy	–	-0.61	–	–
18	clear/hazy	–	0.54	–	–
19	distinct/vague	–	–	0.72	–
20	focused/unfocused	–	–	0.64	–
21	formal/informal	–	–	0.61	–
22	simple/complex	–	–	–	0.71
23	static/dynamic	–	–	–	0.63
24	uncluttered/cluttered	–	–	–	0.61
25	usual/unusual	–	–	–	0.57
26	horizontal/vertical	–	–	–	–
27	serious/playful	–	–	–	–
28	large/small	–	–	–	–
29	long/short	–	–	–	–
	% Variance Explained	44	24	16	16
	Cronbach's alpha	0.94	0.84	0.62	0.61

Note: Only loadings above a 0.5 criterion are shown

Centroid Locations of Principal Components with Reference Scenes



(a) Axes with reference scenes.



(b) Reference centroids

Figure 4.5: Graphical illustration of the axes (first two components, appearance and intensity) with the six reference scenes. In (a), the x -axis corresponds to the derived component, intensity and the y -axis corresponds to the component, appearance.

Table 4.3: Between groups variable, Scenes, and the main effect on appearance, intensity, clarity, and order.

Main effect	Scenes				Scenes	<i>M</i>	<i>SD</i>
	Wilks' Λ	F	<i>P</i> -value	η_p^2			
Multivariate	0.379	$F_{20,936} = 10.0$	< .0001				
Appearance	–	$F_{5,234} = 2.34$	< 0.05	0.05	1	-0.15	1.10
					2	0.04	0.95
					3	0.27	0.91
					4	-0.06	1.06
					5	-0.35	1.09
					6	0.26	0.79
Intensity	–	$F_{5,234} = 57.6$	< 0.01	0.55	1	-1.17	0.51
					2	0.25	0.89
					3	-0.14	0.62
					4	-0.64	0.66
					5	1.06	0.69
					6	0.64	0.69
Clarity	–	$F_{5,234} = 1.61$	= .16	0.03	1	-0.16	0.97
					2	0.17	1.03
					3	0.31	0.84
					4	-0.15	0.97
					5	-0.18	1.21
					6	0.02	0.98
Order	–	$F_{5,234} = 3.66$	< 0.05	0.07	1	0.26	1.17
					2	-0.13	0.86
					3	-0.40	0.90
					4	-0.19	0.85
					5	0.38	0.96
					6	0.09	1.09

which lighting conditions were different. One can judge these reported results by consulting Figure 4.6.

Overall, scenes caused the largest effect in the intensity component, followed by order and appearance (e.g., the intensity component measured the greatest differences in the scenes).

Appearance We measure an effect of scene in appearance ($F_{5,234} = 2.34$, $p < .05$, $\eta_p^2 = .05$), implying that the average scores of this component differed by varying the lighting conditions. Two weakly significant differences were found between lighting scenes 5 and 3 ($p < .10$) and scenes 6 and 5 ($p < .10$). No other comparisons were significantly different.

Intensity The different lighting scenes significantly effected the intensity scale ($F_{5,234} = 2.34$, $p < .05$, $\eta_p^2 = .55$). Overall, this scale was affected the most by changes in the lighting conditions. All fifteen comparisons were significantly different. In other words,

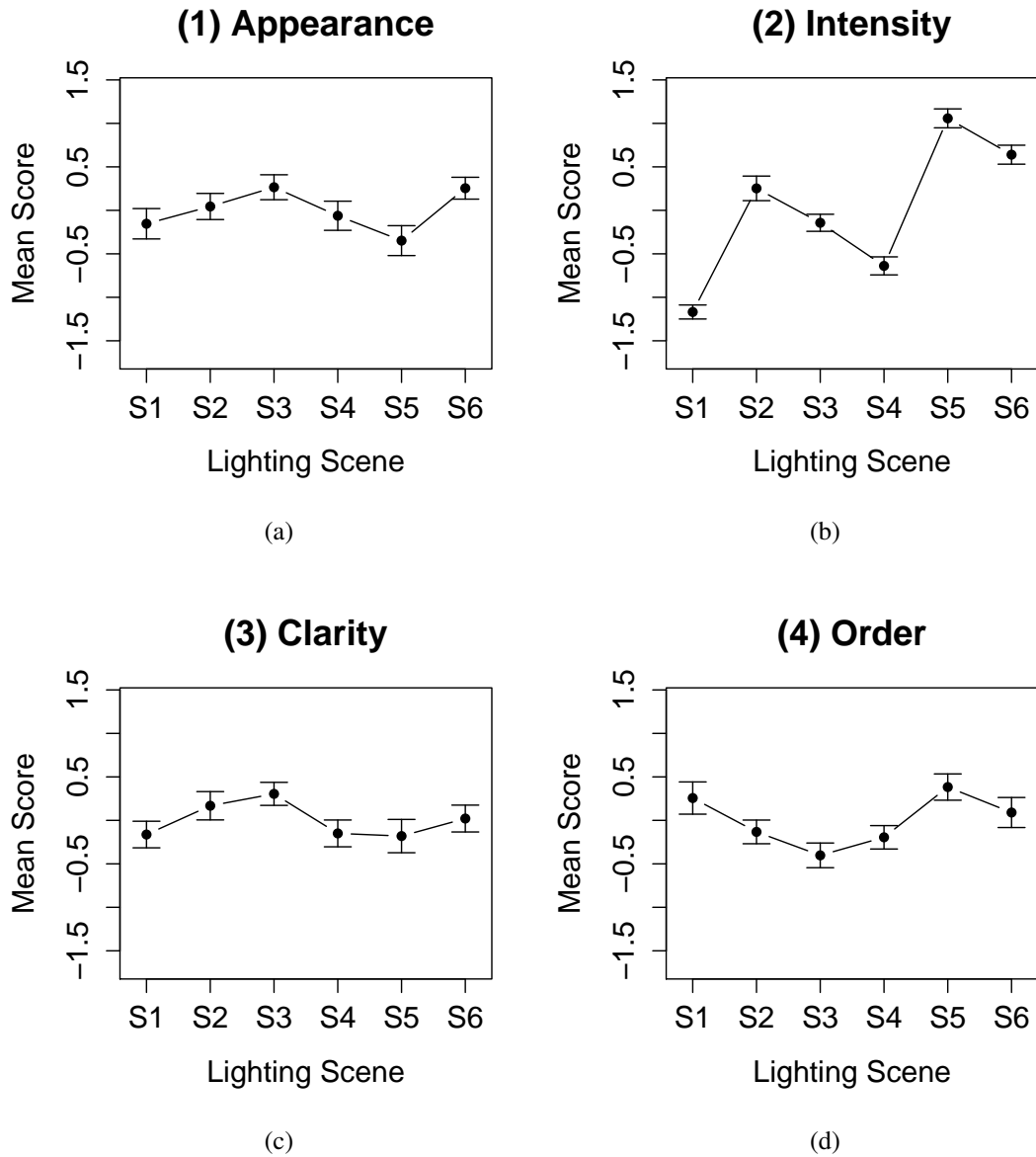


Figure 4.6: The mean scores (centered and scaled) for the four scales (appearance, intensity, clarity, and order) under different lighting conditions (scenes 1-6).

Comparison of 3 Fitting Methods: Principal Component Scores and Intensity for the Short Wall Wash Fixtures

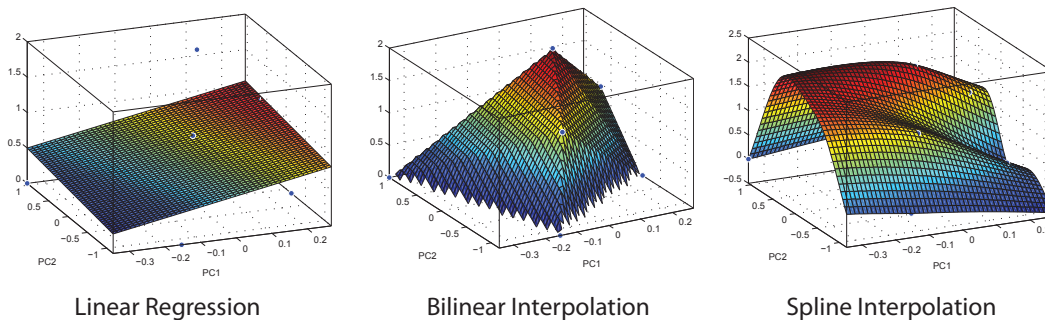


Figure 4.7: The interpolated surfaces fit using a linear regression, a linear interpolation, a spline interpolation for the short wall-wash fixtures. All three mappings yield different user-experiences during control.

all lighting scenes, according to the intensity scale, are statistically different ($.05 < p < .001$).

Clarity No significant effect was found ($F_{5,234} = 1.61, p = .16, \eta_p^2 = .03$).

Order Changing lighting conditions produced a significant effect on the order component ($F_{5,234} = 3.66, p = .05, \eta_p^2 = .07$). Two significant differences between lighting scenes were obtained with this scale. Scenes 3 and 1 ($p < .05$) and scenes 5 and 3 ($p < .01$) varied significantly.

4.3.4 Design of the 2-Axis Prototype

We present a visual summary of the fitted surfaces for a single fixture type (short wall-wash) in Figure 4.7. In the figure, the relative intensity of the short wallwash fixture (the z -axis) is estimated according to the location of the six lighting scenes. The principal components in the figure, PC1 and PC2 reference to the appearance and intensity components described previously. Importantly, each fitting procedure leads to every different energy profiles, via the superposition of the the four luminaire types. Thus, in a linear interpolation scheme, the enegy profile represents a plane. The resulting energy contour derived using either the linear or spline interpolant is non-linear.

Finally, we developed a prototype lighting controller using a mobile phone to control the lighting of the Unity game engine. We designed the axes using the touchOSC library and the phone transmitted wireless lighting control data to the in-game model of the room. We could then visualize the effects of the three fitting procedures. An early prototype (Figure 4.8) allowed control using the axes, and several buttons to evaluate different models.

Users could control the lighting in real-time, altogether, the prototype ran on a simple laptop and we demonstrated the initial concept (Figure 4.9).

4. HUMAN SUBJECTS TEST I: A CONTROL PROTOTYPE IN A VIRTUAL MODEL

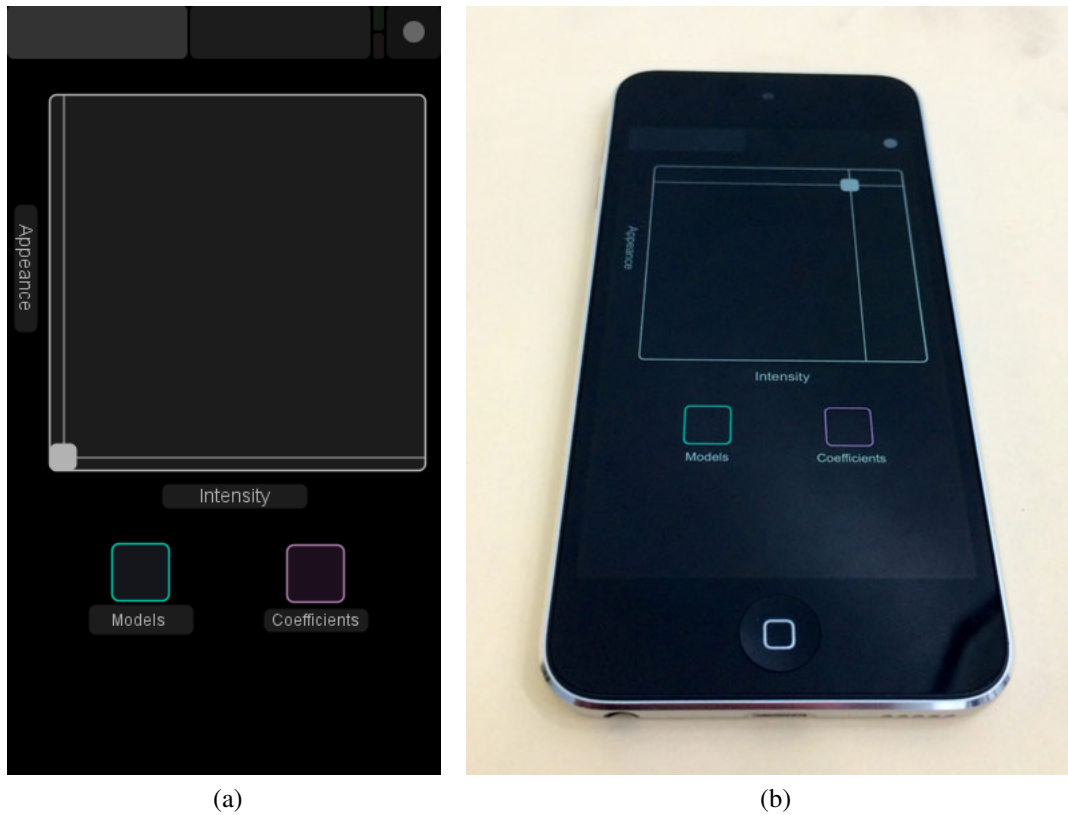


Figure 4.8: Early prototype of the lighting controller designed using the appearance and intensity axes.



Figure 4.9: The complete prototype.

4.4 Discussion

Overall, we designed a prototype lighting control system based upon the participants subjective impressions of lighting. This experiment serves as illustration that such a prototype system is feasible, which encouraged us to pursue the design of a system using a physical room. We observed several important pieces of evidence which were used guide the future studies.

First, in the post-hoc procedure we noticed the principal components interpreted as “appearance” and “order” appear to describe scenes in which participants responses depended on the physical configuration of the luminaires. For example, in the order component, we observed significant differences between scenes 1 and 3 and scenes 5 and 3. Using Figure 4.5 as a guide, we see the primary differences between scenes 1 and 3 are the use of overhead lighting versus wallwashing. In scenes 5 and 3, we observe the primary differences of what appears to be the effects of uniform wallwashing.

Ultimately, despite the subjective ratings of appearance using adjectives, it appears that participants discriminated between the brightness of the scenes and also the fixture types employed in the lighting scene. This promising result is suggestive of simpler means of collecting these subjective ratings, such as the use of pairwise comparisons in which participants simply rate the similarity between the scenes themselves. These findings are consistent with Newsham et al. (2004), in which Newsham et al. found that observes responses depended heavily on contrast between the ceiling illuminance and the walls. Our interpretation is also consistent with Houser and Tiller (2003) where Houser and Tiller found that participants were capable of discriminating between balanced and imbalanced lighting arrangements as well as downlight versus uplight configurations.

While we pursued an adjective-based description of the scenes, it appears that participants are more likely to observe the spatial variation of the room as affected by the different luminaire types. In a study where the color temperature of the lighting remains fixed, it is likely that participants can readily observe the differences between contrast (the ratio of the work surface to the walls and ceiling) and the overall brightness of the scenes. These results suggest a simpler framework. Evidence by Garner (1974); Shepard (1964), suggests that participants may be perceiving the brightness and contrast of the lighting arrangements integrally, that is simultaneously. In our experiment, the hue was fixed, however we varied the value (lightness) and chroma (saturation) of the scene. Our evidence is suggestive that there is a physical basis for measuring and analyzing these subjective impressions by varying these attributes in a controlled manner. These ideas will be explored in Chapter 5.

4.5 Summary

In this chapter, a method of collecting subjective responses about the lighting using a computer-based model was presented. We described the design of six lighting scenes in which participants rated 29 attributes of the scenes. We then described the four principal components extracted from this data and presented an approach which maps the intensity component of the lighting model to first two principal components, interpreted in this

4. HUMAN SUBJECTS TEST I: A CONTROL PROTOTYPE IN A VIRTUAL MODEL

work as appearance and intensity. We then described how we made these models useful to a user, and presented a description of the working prototype.

Human Subjects Test II: Physical Space

This chapter is the second of three empirical chapters describing the measurement and development of a lighting control user-interface designed analytically determined via human subjective impressions. The chapter details the use of multidimensional scaling to analyze the latent structure of pairwise comparisons of luminous conditions. The correspondence of this model with a objective model derived from sensor measurements is also discussed. Finally the the chapter presets the development of the user-interface employed in the performance testing and evaluation of the lighting controls.

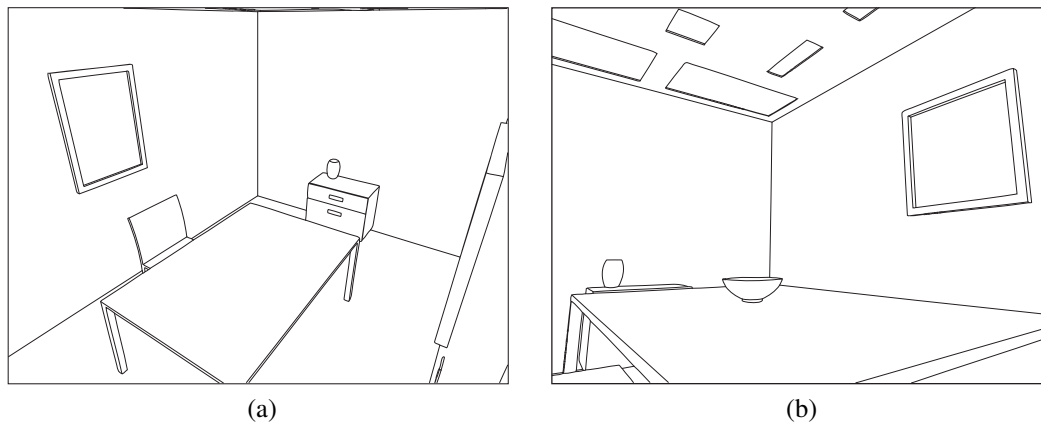


Figure 5.1: Illustrations of lighting room at the Media Lab. In (a), a perspective from the door of the room. In (b), a view across the table showing the ceiling recesses (ventilation and lighting).

5.1 Introduction

This chapter describes the design and measurement of human subjective impressions of lighting in the physical space. The goal of the analysis is to infer the dimensional basis (the latent variates) that subjects employ when rating the similarity of lighting scenes. A second goal of this chapter is describe an experiment in which physical measurements of the luminous are employed to derive an objective model of the room. It is shown in this chapter that the two approaches are similar. Finally, the analytical derivation of the user-interface is presented, determined directly from the subjective response data.

5.2 Experimental Setup

5.2.1 Office Room

A single, windowless office room with surface area 11.6 m^2 (length= 4.2m, width= 2.8 m) at the MIT Media Lab was converted into a lighting laboratory. The room height was 2.6m. The room temperature was maintained at $22 - 23^\circ\text{C}$ via building HVAC.

The room was furnished to provide a work space. A rectangular white table was positioned in the room centered underneath the downlights. A rectangular file cabinet was also included. A single dark gray office-type chair was placed at the work surface of the table for participants to sit at. The table height was approximately 0.70 m high (distance from ceiling to table was 1.9 m). Decorative furnishing consisted of artificial flowers in a flower stand, three paintings, and several colored decorative objects (a green bowl, a blue vase, and a yellow vase). During the experiments, office related materials were placed in the room such as magazines, books, and color photographs. The green bowl was filled with fruits (Figure 5.1)

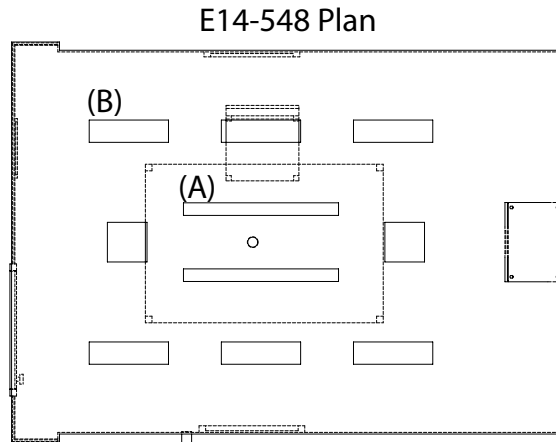


Figure 5.2: Room plan. The cutout designated (A) corresponds to the two linear downlight; cutout (B) corresponds to the six wall wash fixtures.

5.2.2 Measurement Equipment

The spectral power distribution (SPD) of the light settings was measured using a USB4000 spectrometer from Ocean Optics calibrated using an Ocean Optics HL-2000 Tungsten Halogen (NIST traceable S/N F-211). The detector is a Toshiba TCD1304AP (200 – 1100nm). The spectrometer was calibrated before measuring the scenes. Work surface illuminance on the table was derived directly from the SPD of the lighting scenes. The surface illuminances were measured by a Konica Minolta LS-100 Luminance Meter. These equipment comprise the “sensor” portion of the experiment.

5.2.3 Luminaires

Ceiling-recessed luminaires consisted of two linear recessed downlights (Color Kinetics Skyribbon Linear Direct Powercore) with dimensions $1.2\text{ m} \times 0.10\text{ m}$, and six recessed wall-washing fixtures (Color Kinetics Skyribbon Wall Washing Powercore) with dimensions $0.56\text{ m} \times 0.10\text{ m}$. Each luminaire had five controllable wavelengths and capable of both intensity and color temperature (2500 K – 10000 K) adjustments. Color consistency across both fixture types/intensity was maintained internally by the luminaires. Precision control of color temperature was not requirement in the design of the lighting experiments. The lighting plan is provided in Figure 5.2.

The lighting system was controlled by a Color Kinetics Data Enabler Pro which was wired into the local area network at the Media Lab. The lighting system was controlled via software written at the Media Lab running on a PC which sent data packets to the Data Enabler. Control of the lighting via wireless devices (e.g., tablets and phones) was also possible by transmitting data directly to the PC, which in turn sent the data to Data Enabler. Real-time lighting control was possible.

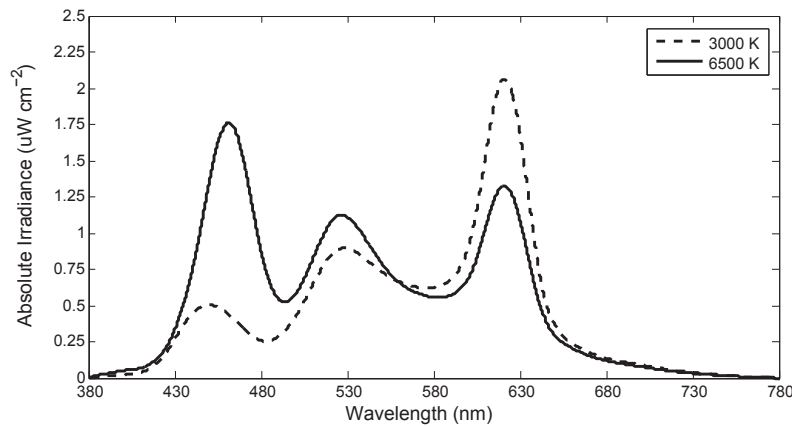


Figure 5.3: Spectra collected at the work surface for 3000 K and 6500 K at 600 lx.

Table 5.1: Photometric characteristics of the 8 lighting scenes.

Scene ID	CCT	Downlight contribution (%)	Wallwash contribution (%)	Average horizontal illuminance (in lx)	Power demand (W)
1	6500 K	90	10	202 (180 + 22)	82
2				602 (541 + 61)	138
3		10	90	203 (21 + 182)	102
4				604 (52 + 542)	215
5	3000 K	90	10	205 (182 + 23)	78
6				595 (542 + 63)	124
7		10	90	205 (23 + 182)	96
8				604 (63 + 541)	196

5.2.4 Lighting Scenes (Stimuli)

In order to acquire the psycho-visual data, eight lighting scenes were created. The eight scenes represent a balanced sampling amongst two color temperatures (3000 K and 6500 K), two work surface illuminances (200 lx and 600 lx) and, two contrast configurations (wallwash and downlight). Example spectra, measured at the work surface are provided in Figure 5.3 .

The contrast variable was designed such that, for either of the two illuminance levels, 90% of the illuminance was contributed by one fixture type and 10% of the illuminance was contributed by the other. This design, including the measured work surface illuminance, and power consumption of these set points is given in Table 5.1.

The lighting scenes presented to the subjects is reproduced in Figure 5.4.

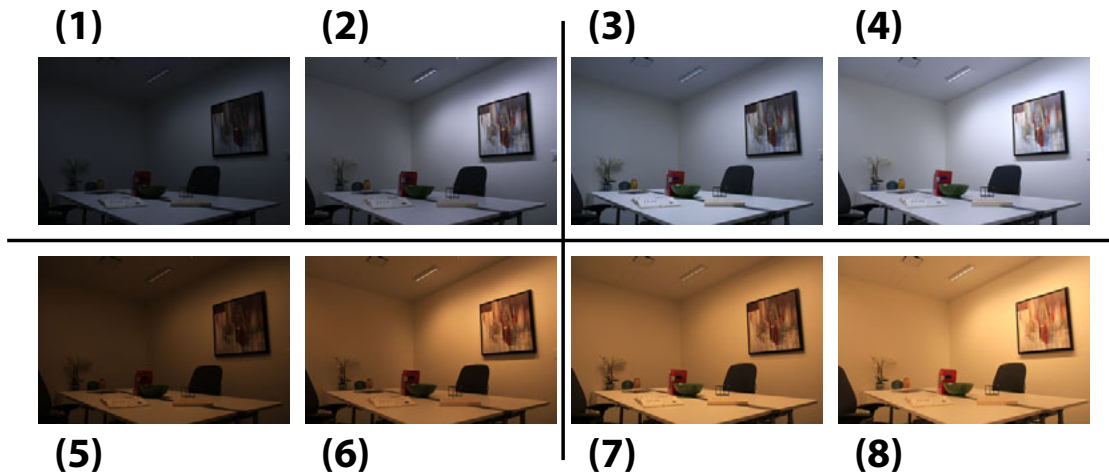


Figure 5.4: The eight lighting scenes tested in the experiment.

5.2.5 Participants

In total, 32 participants from the university were involved in the experiment, including 20 students and 12 persons from the staff (either from administration or other research labs). Participants ranged from 19 to 60 years of age with roughly 15% of the participants wearing glasses. All subjects reported normal color vision. About 9 subjects reported familiarity with lighting basics, and two considered themselves experienced in lighting design. All participants can be considered inexperienced in subjective perceptual studies.

5.2.6 Procedure

The procedure section can be decomposed into two procedures: (1) An *objective* procedure to collect sensor data to subsequently derive a model of the room and (2) a *subjective* procedure of collecting data to derive an appearance model using the study participants.

5.2.6.1 Objective Test Protocol

The spectral power distribution was collected using the spectrometer for each of the eight lighting scenes. In addition, for each of the 4 walls, ceiling, and table, five brightness measurements were collected using luminance meter. These five measurements correspond to each corner of the room facet and the middle point (see Figure 5.5).

Thus, the protocol details a sampling procedure that describes changes in illuminance, color, and contrast of the room.

5.2.6.2 Subjective Test Protocol

A single protocol was employed for the subjective evaluation; during the experiment the subjects were asked to compare the similarity of two lighting scenes and also, indicate

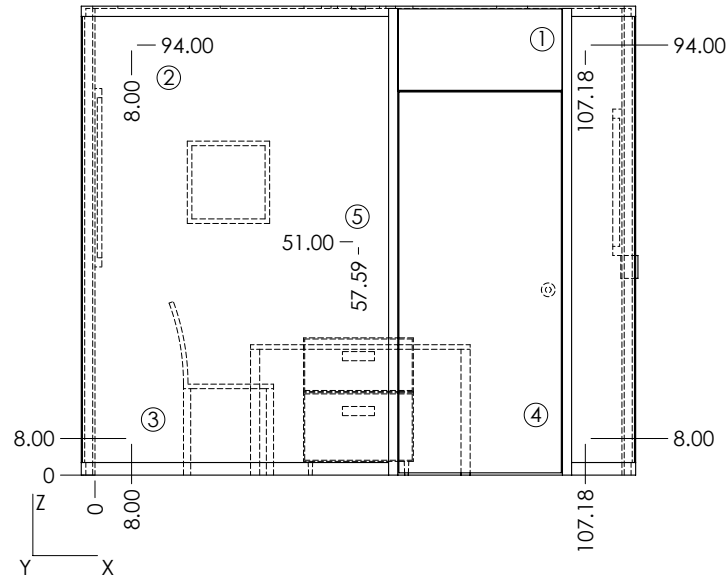


Figure 5.5: Schematic of measuring brightness data. Points 1-5 correspond to the sampled points. This process was repeated for all 4 walls, ceiling, and table.

which of the two lighting conditions they preferred. Subjects were instructed that to consider themselves in a typical office environment.

To measure similarity, the participant compared two lighting scenes and indicated their impression of similarity. The subject was given the prompt, “indicate on a scale of 1 to 7, where 1 is the same and 7 is the most different, the similarity between the two lighting scenes.” Altogether, each participant completed 28 comparisons. The order in which the pairs of lighting scenes were presented were varied randomly across the participants. For any given comparison, scenes were presented sequentially to each participant, and the participant could go back and forth between the scenes as many times as needed.

To measure preference, subjects indicated whether they preferred the first or second scene in the comparison.

5.2.7 Evaluation

The evaluation can be decomposed into four primary objectives. First, we seek a model of appearance using the sensor data. Second, we seek a model of appearance using the subjective (human) data. Third, we relate the objective and subjective models using linear regression. Fourth, we seek a mapping of the subjective impressions of lighting data that can be employed to control the lighting in the room.

Crucially, the third objective demonstrates the possibility of relating subjective impressions of lighting conditions with those as measured using the sensors. The third objective provides the means to generalize the regimes. The fourth objective embodies all facets of this work; it represents a new lighting user-interface based on a subjective mapping of lighting conditions. As stated earlier, we seek a solution comprised of two

dimensions.

5.2.7.1 Derivation of a Sensor-Based Model

The sensor-based (the objective data) model is a crude approximation of how humans may judge the simple changes in lighting stimuli. Therefore, the basic requirement is that the model must describe the differences in brightness between the facets of the room, as well as, changes in illuminance and color. To explore this idea, principal component analysis was selected to initially extract and model independent dimensions of variation in the dataset. In this study, a model is derived using a both illuminance and spectral data. The dataset is comprised of 96 row entries and 18 column entries. In all, 1728 points were collected (96×18).

Each scene is comprised of 6 row entries in the matrix. Each of these six entries corresponds to the facets of the room (left wall, right wall, front wall, back wall, ceiling, and table, respectively). The first five columns of each row correspond to the four corner and center luminance measurements. The remaining 13 columns corresponds to spectral data down-sampled to 25 nm increments (range 400 nm to 700 nm). This simple structure is then replicated for all 8 scenes (see Figure 5.5 on the facing page for an illustration of the corner measurements).

Thus, the dataset is designed so that the variation in brightness is described in the first five columns and the variation in color and work surface illuminance in the remaining 13 columns. We believe this to be a straightforward approach to modeling the room's appearance using a sensor network, it is capable of describing – in a linear fashion with PCA – how a machine might learn unique scenes and describe presets.

When the data are projected onto their first two eigenvalues, we obtain a representation of the scenes in two dimensions. This approach represents an unsupervised approach to organizing and subsequently, controlling lighting.

5.2.7.2 Derivation of a Human-Based Model

The pairwise comparisons of similarity (the subjective data) represent a simple “distance” measurement of the difference between two lighting conditions. Rather than propose an a priori model using scales (see Chapter 4), subjects are free to use their own criteria. Since our experimental stimuli are well controlled, we expect participants' impressions of similarity will be influenced by the variations in color temperature, brightness, and contrast. Thus, we are interested in modeling the extent to which changes in these variables affect the participants.

The goal of the analysis is to deduce (1) the independent dimensions in which subjects perceived the experiment and (2) the distance between all eight lighting scenes in this latent basis. In other words, we seek a model in which the subjective data can be mapped to a coordinate system, such that the resulting coordinate systems reflects the perceived distance between all 8 stimuli. The resulting mapping is known as a configuration. A representation in two-dimensions represents a viable configuration for lighting control.

Multidimensional scaling (MDS) is a modeling approach specifically intended to solve these problems. It is common procedure in analysis psychophysical data collected in pairwise fashion. Specifically, in this analysis, we model the data using the INDSCAL algorithm (Carroll and Chang, 1970) which is specialized form of MDS intended for use in datasets comprised of repeated measurements of subjects. This algorithm assumes that individuals share a common space (i.e., geometry) but that respondents may individually weight some dimensions differently (or not at all).

In this analysis, we analyze both two and three dimensional representations of the data; the two dimensional configuration being of critical importance for the design of a lighting user-interface.

5.2.7.3 Correspondence of Both Models

One would like to relate the models derived using both the objective and subjective data. For example, in future work, a model of the subjective response might be constructed entirely from sensor-based models (or vice versa). In order to accomplish this endeavor, one must relate the two models and test if they measure similar things. This can be accomplished through simple linear regression and hypothesis testing; the resulting model then describes the weighting, β_i , required to linearly transform the input. Classical tests of significance then follow.

Furthermore, one might wish to test both the objective and subjective approaches in different rooms with different lighting configurations, perhaps replicating the experiments described in this chapter. Such an approach would in turn, generalize the relationship between the models. The belief in this case, is that the β s derived in such a model were stable across all lighting configurations and rooms.

In this analysis, we outline a simple approach for testing the relationship between the objective and subjective models in a single room. We employ a simple linear model: Let m represent the number the lighting scenes described by both X and Y . Let x_1, x_2, \dots, x_r be a set of r predictors, where r corresponds to the dimensionality of X believed to be related to response variable $Y_1, Y_2 \dots Y_p$ where p corresponds to the dimensionality of Y . In this formulation, we have a simple multivariate regression problem,

$$Y_1 = \beta_{01} + \beta_{11}x_1 + \dots \beta_{r1}x_r + \varepsilon_1 \tag{5.1}$$

$$Y_2 = \beta_{02} + \beta_{12}x_1 + \dots \beta_{r2}x_r + \varepsilon_2$$

$$\vdots \qquad \qquad \qquad \vdots$$

$$Y_p = \beta_{0p} + \beta_{1p}x_1 + \dots \beta_{rp}x_r + \varepsilon_3 \tag{5.2}$$

where β_{0p} corresponds to the p th intercept and β_{ip} the estimated coefficients of X_{rp} for Y_p .

For example, assume we estimate a configuration of eight lighting scenes ($m = 8$) using the subjective responses in three dimensions using the INDSCAL algorithm. Let X represent this data with $m = 8$ rows and $r = 3$ columns. Similarly, let Y represent a matrix of the average component score for scene m_i using the first three eigenvalues

($p = 3$). As long as the p dimensions of Y are independent, the model above holds. Thus, solving these 3 regressions requires estimating 3 β s per regression. This can be done using ordinary least squares.

One last comment is in order: there is no requirement that $p = r$, in fact likely solutions may have $p > r$, and in the example above, might correspond to $p > 2$, indicative of a higher-dimensional sensor model and a two-dimensional subjective model.

5.2.7.4 Modeling A 2-Axis Lighting GUI

The final objective of the analysis is to find a maps the configuration of points, Ω (e.g., the principal components) and the corresponding setpoints of the luminaires Γ (e.g., their red, green, and blue control values). In other words we seek a solution of the form $f : \Omega \rightarrow \Gamma$ where f is the mapping between our configuration of the lighting scenes and their control values. The intent is the function f provides a mapping for control of the luminaire setpoints, such that the function provides a means to manipulate the state-space of Γ . Thus, this section describes the design of a lighting user-interface derived from either objective or subjective mappings of the lighting scenes. In particular, we focus on solutions where Ω is two-dimensional.

We can make no apriori assumptions about the regularity of the points in Ω , which precludes the use of classical linear and cubic interpolants. Furthermore, in a two-dimensional configuration of Ω , a linear fit (fitting a hyperplane) to Γ is prohibitively restrictive (i.e., fitting a plane through Γ is unlikely to map the full dynamic range of control values). We are relegated to the use of splines to model f to find a smooth surface passing through the irregularly sampled points in.

In a two-dimensional lighting GUI, we seek a solution that maps distinct points $x_1, x_2, \dots, x_N \in \mathbb{R}^2$ and the corresponding control value $z_1, z_2, \dots, z_N \in \mathbb{R}$ in a “sufficiently regular” fashion such that $f : \mathbb{R}^2 \rightarrow \mathbb{R}$. This leads to a series of interpolation equations $f(x_k) = z_k$ for $k = 1, 2, \dots, N$. One approach to solve such problems is bi-harmonic spline interpolation (Sandwell, 1987). We employ Sandwell’s method in this work.

In the specification of the lighting scenes, we distinguished between downlighting and wallwashing luminaires. These two groups require separate interpolants. Furthermore, in the specification of the lighting control system we must fit six different interpolations (the red, green, and blue channels for each of the fixture distinctions). In other lighting configurations, the amount of interpolated surfaces to calculate will vary, but the approach remains the same.

5.3 Results

The results are organized as follows: first, the principal components of the lighting scenes derived using the objective study (sensor mapping) are presented. Second, the results of the subjective study (human study) are presented. Third, the relationship between the two scales is presented. Finally, a sample configuration of the subjective mapping of lighting scenes and control values is presented.

5.3.1 Appearance Derived Using Sensor Data

First an interpretation of the component loadings is given. Next, the component scores of the eight lighting scenes as learned by the model is presented and interpreted. Finally, an example configuration of a two-dimensional representation of the model is given and interpreted.

5.3.1.1 Component Loadings

As described previously, the sensor data is a two dimension matrix of 96×18 data points describing the variation of the lighting conditions. Recall that the first 5 columns of the matrix describe the variation in brightness and the remaining 13 describe the variation in the spectral power distribution. The data are measured on difference scales, hence, before processing the data was centered and scaled (e.g., the z-scores were calculated). We present an unrotated loading of the principal components in Table 5.2 and describe the loading on each of the columns. A parallel analysis suggested the first three eigenvalues were sufficient, hence three principal components are presented.

In the first component, we see a loading characteristic of brightness, all the variables in the analysis load positively in the first dimension. This is expected. Next, in the second component we see a loading in the first four variables related to brightness, the variation in the room's facets accounts for the variations in contrast of original eight lighting scenes. Finally, in the third component, we see that the major variations are accounted for by the changes in the 465 nm and 615 nm wavelengths. Referring back to Figure 5.3 on page 58, we find this is a plausible explanation as these wavelengths discriminate between the warm (3000 K) and cool (6500 K) color temperatures.

In a rotated solution, we expect to find a large amount of variance explained by the first eigenvalue (typically 80%). We find that the first three components represent 78%, 11%, and 10% respectively.

5.3.1.2 Component Scores for the Lighting Scenes

Next, we interpret the component scores of the PCA analysis. Recall these component scores are merely a linear transformation of the scaled sensor data with the principal components. We are primarily interested the mean component score for each lighting scene for each of the three components (Table 5.3). The group-means describe the location in the component space of the lighting scenes. In other words, these mean-scores allow us to interpret the relationship and proximity of the lighting scenes in a lower-dimensional basis.

Recalling the lighting scenes (Figure 5.4 on page 59) and using the sign of the scores in Table 5.3, the learned structure of the scenes closely follows the experimental design. For example, scenes 1 and scenes 2 differ in their contrast variable, but are both cool white and of low illuminance (200 lx). Similarly, scenes 7 and 8 differ in contrast, have similar illuminance values (600 lx) and are both warm white (3000 K).

Given the pattern of signs in Table 5.3 closely follows the experimental design, it is highly plausible that the configuration of data in this analysis is an adequate representation of the variation of the room. Using this approach, we have derived a rudimentary

Table 5.2: Unrotated component loadings of the room model based on sensor readings of the 8 lighting scenes.

No.	Variable	PC1	PC2	PC3
Illuminance				
1	Top Left Corner	0.77	0.51	–
2	Top Right Corner	0.78	0.58	–
3	Bottom Right Corner	0.71	0.63	–
4	Bottom Left Corner	0.73	0.62	–
5	Center	0.68	–	–
Spectral Power				
6	390 nm	0.90	–	–
7	415 nm	0.89	–	–
8	440 nm	0.97	–	–
9	465 nm	0.60	–	0.76
10	490 nm	0.86	–	–
11	515 nm	0.98	–	–
12	540 nm	0.98	–	–
13	565 nm	0.96	–	–
14	590 nm	0.93	–	–
15	615 nm	0.79	–	-0.58
16	640 nm	0.92	–	–
17	665 nm	0.94	–	–
18	690 nm	0.95	–	–
% Variance Explained		78	11	10

Note: Only loadings above a 0.5 criterion are shown

Table 5.3: Mean component scores of the 8 lighting scenes for each of the first three 3 principal components using the sensor-based model.

Scene	Sensor (3D PCA)		
	Dim 1	Dim 2	Dim 3
1	-0.95	-0.26	0.55
2	-0.83	0.40	0.68
3	0.66	-1.01	0.92
4	1.38	0.27	1.42
5	-1.11	0.05	-0.56
6	-0.94	0.63	-0.28
7	0.74	-0.96	-1.49
8	1.05	0.88	-1.25

model of appearance – changes in brightness, gradient or contrast, and color temperature are measured and learned by the unsupervised method (in this case principal component analysis). The approach of using PCA is straightforward, but not exhaustive of other machine learning algorithms for dimensional modeling.

5.3.1.3 Visualization of the PCA model

We are now ready to interpret the lighting scenes using these derived components. Although the configuration of points in Table 5.3 on the previous page matches the experiment design, graphing these solutions with the corresponding lighting scenes leads to an immediate conclusion – the variation as modeled using the sensor data will rarely reflect our actual perception of a logical configuration (this issue is discussed and remedied in Section 5.3.3 and requires a model of our subjective responses in addition to the objective measures). This incongruency is depicted in Figure 5.6.

Studying this figure, the discord between our senses and the sensor-model is apparent yet, easily explained. In the solution which graphs the first two components (according to the loadings in Table 5.2 on the preceding page, the choice of y -axis is arbitrary), we see that in two dimensions, the first component corresponds to brightness and the second component, contrast. In two dimensions, the effect of color temperature is marginalized; immediately at odds with how we actually perceive the lighting scenes.

If instead, one were to graph the second and third components, we now achieve a solution that matches our perception of the scenes. Color temperature now dominates the y -axis and contrast spans the x -axis. Intensity (see the dotted lines connecting scenes in Figure 5.6b) spans the diagonal elements of the space.

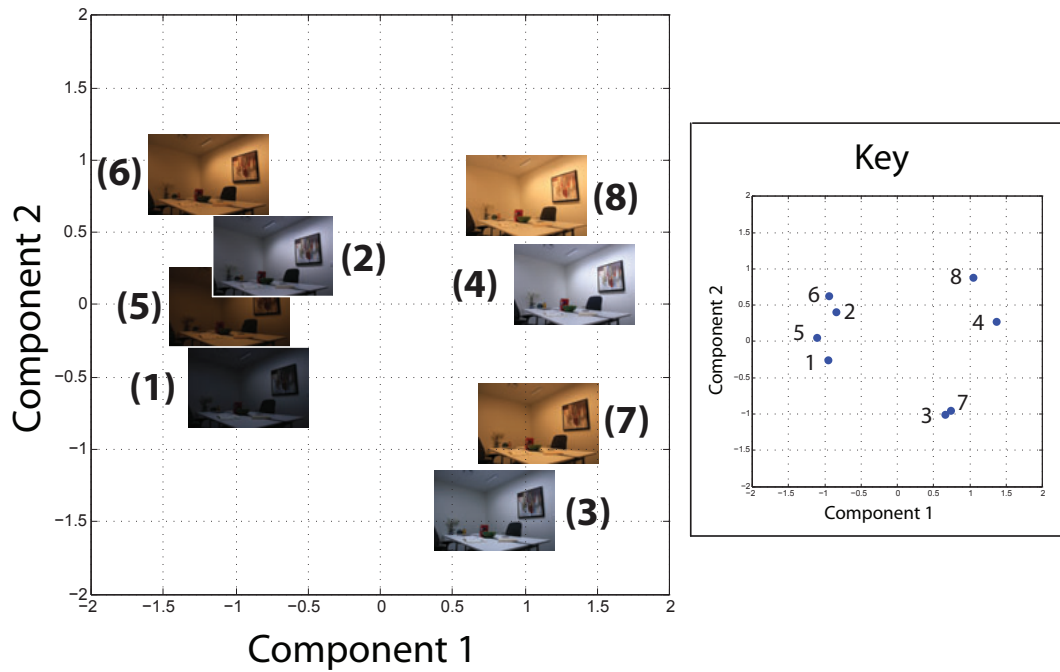
One conclusion is immediately obvious: it is very difficult to design an intuitive lighting controller using sensor data alone; it is a dead-end. The sensors can only describe the difference between the physical signal, and not anticipate our interpretation (however, in Section 5.3.3, evidence will be given that shows how this data is a required component in future analysis).

5.3.2 Appearance Derived Using Human Data

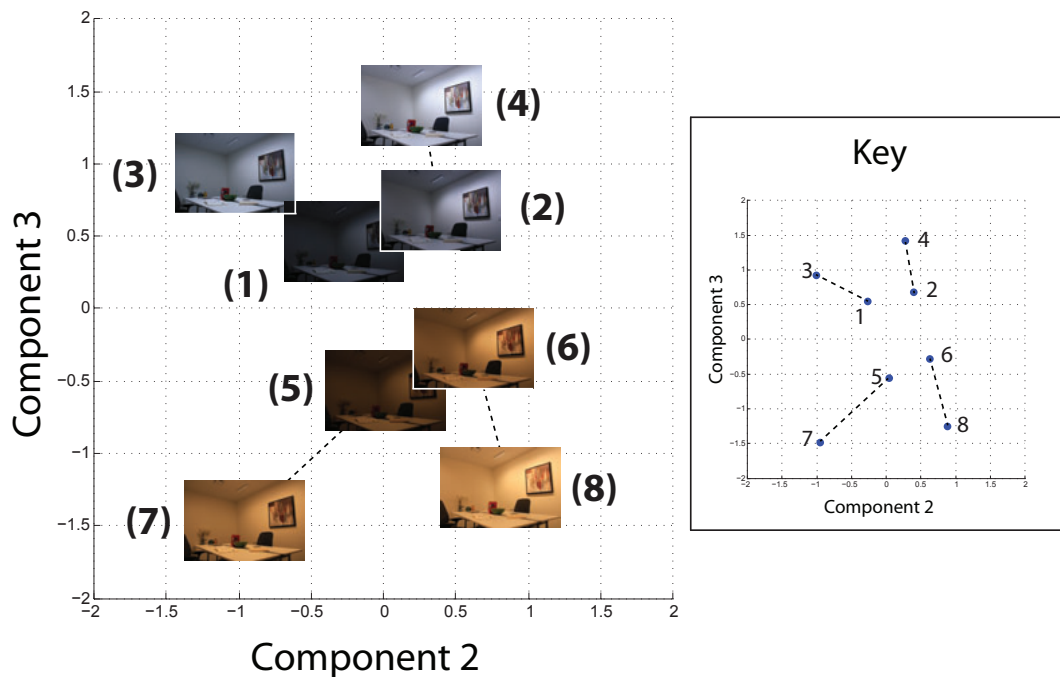
The similarity data obtained in the subjective experiment with humans was analyzed using the INDSCAL algorithm (Carroll and Chang, 1970). The goal of the analysis was to determine a configuration of the 8 lighting scenes according to their similarity scores obtained in the user study. This approach recreated – directly from the pairwise data of similarity – as estimate of the perceived structure (either in 3 dimensions or 2 dimensions) of the experiment using the “distances” reported by the participants. An illustration of the method (the first 12 random paired comparisons) is given Figure 5.7.

The mean scores of the 32 participants are presented in Table 5.4. This table represents the average dissimilarity score in the study, it can be read in a column-row type fashion. For example, scene eight and scene seven were reported more similar, than scene eight and one.

For instance, it was hypothesized that participants would perceive the experimental stimuli in three dimensions, but, it was unknown to what extent manipulations of color



(a)



(b)

Figure 5.6: Example 2D projection of the objective (sensor-based) 3-dimensional PCA solution. In (a), the first two components and in (b), components 2 and 3. The mapping in (a) uses the first two components but leads to a solution in which a human would find confusing.

5. HUMAN SUBJECTS TEST II: PHYSICAL SPACE

M

ID No: 11 Test No: 11 **SIMILARITY SCORES**

For each row, place an X in the box (between the dashed lines) according to how similar or different the two lighting scenes are.

Very Similar 0 1 2 3 4 5 6 **Very Different**

Comparison #

1						X		
2						X		
3					X			
4							X	
5				X				
6				X				
7					X			
8					X			
9						X		
10		X						
11		X						
12			X					

Figure 5.7: Subjects indicated their impression of similarity on a paper survey (the first 12 responses of 28 are shown).

Table 5.4: Average dissimilarity ratings of 8 lighting scenes collected from 32 participants; reported on a 7-point scale (7: very different).

scene	1	2	3	4	5	6	7	8
1	–							
2	2.19	–						
3	2.59	2.22	–					
4	3.03	2.78	2.26	–				
5	3.53	3.72	4.41	4.53	–			
6	3.94	3.50	4.28	4.44	2.28	–		
7	4.31	4.34	3.97	3.84	2.72	2.24	–	
8	4.69	4.09	4.32	3.75	3.31	2.91	2.22	–

temperature, brightness, and contrast would affect the participants.

The results of the subjective experiment are presented as follows: first, a full three-dimensional solution is presented and discussed. A visualization, of the configuration of points is presented to aid in the understanding of how changes in color temperature, brightness, and contrast affected participants. Second, the results of a two-dimensional fit are presented and discussed.

For brevity, the discussion of the modeling errors and evaluation of the fits are discussed in Appendix C.

5.3.2.1 Configuration in Three Dimensions

Given our prior hypothesis that variations in color temperature, brightness, and contrast are perceived in independent dimensions by observers, we first sought a configuration of the lighting scenes in three dimensions. An important assumption in this analysis – regardless of the dimensionality of the space – that intra-scene distances are Euclidean; this has practical importance in the design of a lighting user-interface, as well as, implications on the performance of the such a user-interface (see Chapter 3).

We proceeded by fitting a model that describes the distances between the pairwise comparisons. Like any exploratory statistical analysis, the number of dimensions sought is guided by prior theory and some measure of the algorithms performance (see App. C).

What was not known prior to the analysis was the extent to which changes of these three variables affected the study. For example, was a change in color temperature perceived as a larger effect than brightness, or contrast? A fully factorial design (see Table 5.1) is often presumed to sample from stimuli found along vertices of some linear space. The goal of this analysis was to then recreate this space via the pairwise similarity data.

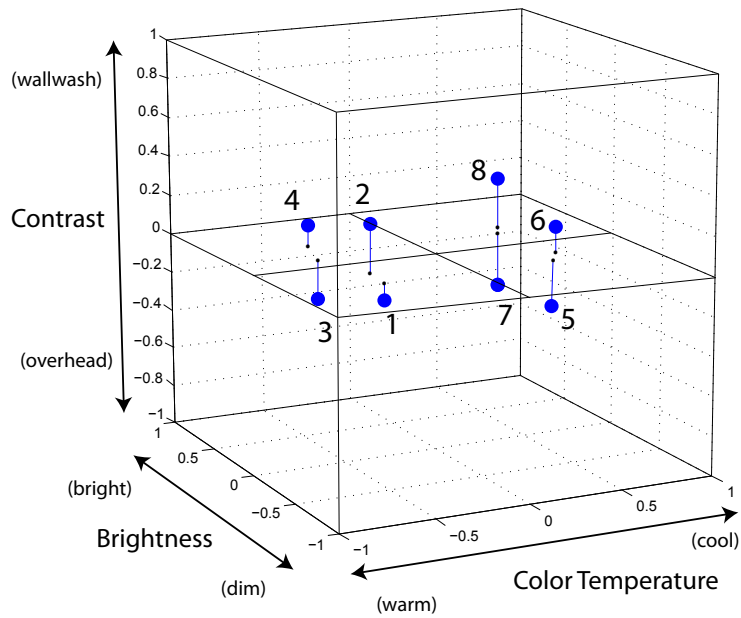
Most importantly, the analysis of the subjective experiment indicated the effects of the changing one, two, or three attributes simultaneously – the similarity of the lighting scenes depends simultaneously on (a), the attributes varied and (b) the number of attributes varied. One presumes the perceived differences of the lighting stimuli thus resemble some cubic structure. In Figure 5.8, the resulting structure of the stimulus as inferred by the algorithm is displayed.

A stem plot (Fig. 5.8a) shows the group-configuration of the lighting scenes and logically follows the design of the experiment. Changes in the warm/cool dimension were perceived as the most different, followed by intensity, and finally, contrast. In other words, the perceptual space was not a cube, but perceived somewhat like a rectangle. A visualization of the lighting stimuli coordinates is also presented in Figure 5.8. The six figures describe a rotation of this structure, the longest distance due to a change in color temperature.

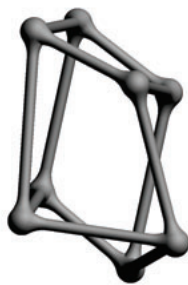
5.3.2.2 Configuration in Two Dimensions

The results of a two-dimensional procedure are presented in Figure 5.9. In this configuration, the solution can be interpreted as a two-dimensional projection of the contrast variable onto the brightness and color temperature axes. Scenes 2,4,6, and 8 consist of

Group Stimulus Space: INDSCAL 3D



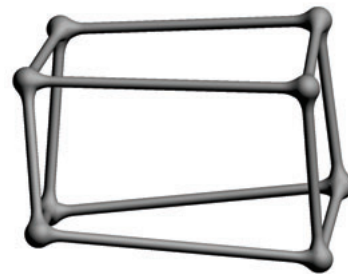
(a) 3D stem plot of configuration



(b) Left



(c) Top



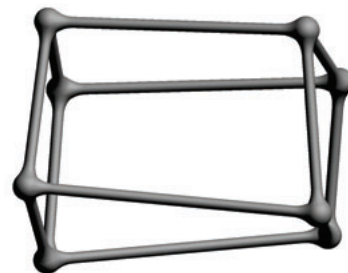
(d) Front



(e) Right



(f) Bottom



(g) Back

Figure 5.8: Results of MDS algorithm; in (a), a stem plot of the x,y,z configuration of the stimuli with interpreted dimensions for change. In (b)-(g), a visualization of the fitting procedure and resulting 3-dimensional map.

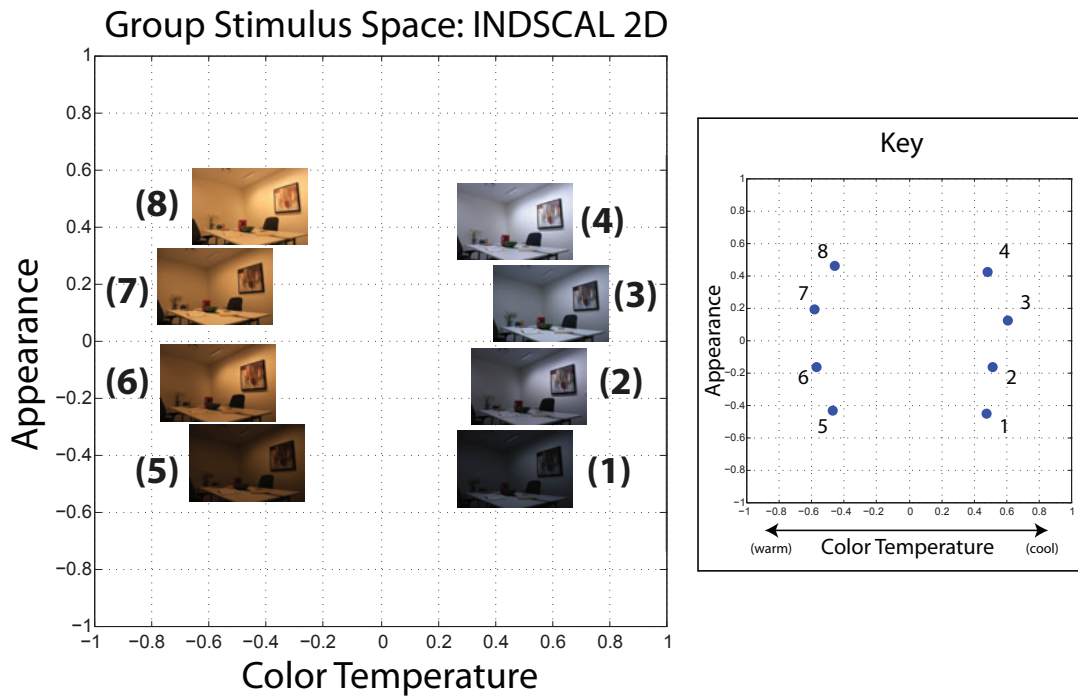


Figure 5.9: MDS representation of the 8 lighting scenes described by a two-dimensional configuration. The contrast variable is folded into the solution; visually, the representation of the 8 scenes is logical and ordered.

90% wallwash and 10% downlight variations of low and high illuminance and cool and warm color temperatures. Similarly, scenes 1,3,5,7 describe scenes consisting of 10% wallwash and 90% downlight configurations. Interpretation of the axes is simple: the horizontal axis corresponds to varying the color temperature (warm and cool) and the vertical axis varies both brightness and contrast. Scenes 5-8 and scenes 1-4 reflect stimuli consisting of both illuminance and contrast manipulation, which leads to a natural interpretation that the vertical axis adjusts “appearance.” Thus, along the vertical axis, changes in brightness are no longer strictly monotonic. Understanding the implications of this mapping for lighting control – both quantitatively and qualitatively – are studied extensively in Chapter 6.

5.3.3 Correspondence between the Objective and Subjective Mappings

Using the model of Eq. 5.1, we provide statistical evidence of the generality of this approach. The results in this section provide crucial evidence of a methodology that can be used to automatically derive the perceptual dimensions (axes) of a human-based appearance model for lighting. The analysis suggests that a simple linear rescaling of a sensor-based mapping of lighting conditions is sufficient to derive an intuitive mapping of lighting control.

Table 5.5: Derived mean-component scores for the 3 dimensional PCA, and the scene configurations for both the 3D MDS and 2D MDS model fits.

Scene	Sensor (PCA)			Human (3D MDS)			Human (2D MDS)	
	Dim 1	Dim 2	Dim 3	Dim 1	Dim 2	Dim 3	Dim 1	Dim 2
1	-0.95	-0.26	0.55	-0.49	-0.43	-0.07	0.48	-0.45
2	-0.83	0.40	0.68	-0.45	-0.18	0.25	0.52	-0.16
3	0.66	-1.01	0.92	-0.57	0.17	-0.20	0.61	0.13
4	1.38	0.27	1.42	-0.49	0.43	0.11	0.48	0.43
5	-1.11	0.05	-0.56	0.44	-0.39	-0.22	-0.47	-0.43
6	-0.94	0.63	-0.28	0.56	-0.21	0.13	-0.57	-0.16
7	0.74	-0.96	-1.49	0.48	0.27	-0.27	-0.58	0.19
8	1.05	0.88	-1.25	0.52	0.34	0.27	-0.46	0.46

We present the results of two different procedures. First, we present the estimated model coefficients which map a three dimensional PCA solution (i.e., the principal components) of the sensor to the estimated configuration in the three dimensional MDS solution (Model A). Second, we present the estimated model coefficients which map a 3-component sensor-model to the two dimensional MDS model (Model B). In this analysis, the dependent variables are the subjective dimensions and the independent variables are the principal components. For reference, the group-means and coordinates of the results are reference in Table 5.5.

5.3.3.1 Model A (3 Subjective Dimensions)

In model A, we regressed the three principal components of the sensor-data with the corresponding three subjective dimensions derived using MDS. In total, 3 models were parameterized (one for each dependent variable of the subjective experiment). The results and statistical significance of the fitting procedure are given in Table 5.6.

All three models suggested an effect of at least one principal component (see the F -scores), and we note the distinct effects of the orthogonal (e.g., unrotated) principal components. Since the mean score of any of the MDS dimensions in Table 5.5 are zero, we expect that the estimated β_0 (the constant, or mean score) in each model to be zero, and indeed, we find this fact. Thus, the statistical significant of the estimated β s for the principal components is tested against zero.

For example, the first model (designated (1) in Table 5.6) describes the color temperature dimension of the subjective experiment and we find the estimated coefficient of the third principal component of the sensor-model is statistically different than zero ($p < .01$) and suggests that this component is correlated with the color temperature dimension in the subjective model. A similar interpretation then follows for all three models presented. One could seek a more parsimonious solution by testing model fits using fewer principal components. In general, we find evidence that supports the notion of a linear rescaling from one scale to another.

To further aid in the interpretation of these results, consider the application of these

Table 5.6: Multiple regression results using the 3D-MDS configuration.

	<i>Dependent variable:</i>		
	D1 (Warm/Cool)	D2 (Brightness)	D3 (Contrast)
	(1)	(2)	(3)
PC1	-0.028 (0.094)	0.323*** (0.031)	0.042 (0.043)
PC2	0.175 (0.142)	0.041 (0.046)	0.282** (0.065)
PC3	-0.450*** (0.092)	-0.013 (0.030)	0.043 (0.042)
Constant	0.000 (0.091)	-0.000 (0.030)	-0.000 (0.042)
Observations	8	8	8
R ²	0.868	0.965	0.829
Residual Std. Error (df = 4)	0.258	0.084	0.118
F Statistic (df = 3; 4)	8.748**	37.124***	6.485*

Note:

*p<0.1; **p<0.05; ***p<0.01

models to estimate the subjective x, y, z location of scene 1 using the principal components referenced in Table 5.5 In this case we have:

$$\begin{aligned}\hat{d}_1 &= -0.03(-0.95) + 0.18(-0.26) - 0.45(0.55) \\ &= -0.27\end{aligned}\tag{5.3}$$

$$\begin{aligned}\hat{d}_2 &= 0.32(-0.95) + 0.04(-0.26) - 0.01(0.55) \\ &= -0.32\end{aligned}\tag{5.4}$$

$$\begin{aligned}\hat{d}_3 &= 0.04(-0.95) + 0.28(-0.26) + 0.04(0.55) \\ &= -0.09\end{aligned}\tag{5.5}$$

Thus, using the coefficients in Table 5.6, one can estimate \hat{d}_i for all $i = 1, 2, \dots, 8$ lighting scenes. With no loss of generality, if a varimax rotation was applied to the principal components (the components are no longer orthogonal), we would then expect to find that multiple principal components were then correlated with the subjective dimensions presented in Table 5.6.

5.3.3.2 Model B (2 Subjective Dimensions)

In model B, we regressed the three principal components of the sensor-data with the corresponding two subjective dimensions derived using MDS. The data used in this analysis (PCA and 2D MDS) are reported in Table 5.5. Also, for reference, recall the

visualization of the lighting scenes estimated using the 2D-MDS fit on on page 71. In total, 2 models were parameterized (one for each dependent variable of the subjective experiment). The results and statistical significance of the fitting procedure are given in Table 5.7. For reference, the data used in this analysis is given in Table 5.5.

Table 5.7: Multiple regression results using the 2D-MDS configuration

	<i>Dependent variable:</i>	
	D1 (Warm/Cool)	D2 (Appearance)
	(1)	(2)
PC1	0.032 (0.107)	0.338*** (0.032)
PC2	-0.136 (0.161)	0.119* (0.048)
PC3	0.473** (0.105)	-0.021 (0.031)
Constant	0.00000 (0.103)	-0.00000 (0.031)
Observations	8	8
R ²	0.845	0.966
Residual Std. Error (df = 4)	0.292	0.088
F Statistic (df = 3; 4)	7.270**	37.542***
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01	

Interpreting this model proceeds similarly – we find evidence here that suggests our prior interpretation of the 2D configuration of lighting scenes is correct. The horizontal axis in Figure 5.9 corresponds with the third principal component, that is color temperature. Unsurprisingly, we find evidence that the vertical axis (designated “appearance” in Figure 5.9 corresponds primarily with PC1 and to a lesser extent, PC2.

Again, we find no evidence contrary to our hypothesis that a linear rescaling is sufficient to move between the objective and subjective regimes according to the simple lighting scenes evaluated in this study.

5.3.4 The 2-Axis Mapping for Performance Testing

During the experiment, the red, green, and blue set-points for the fixtures were recorded. As stated earlier, the primary goal was to develop a two-axis lighting control interface based upon the participants’ subjective responses in the study. After determining the locations of the 8 lighting scenes, the surface fitting was performed.

Altogether, six interpolants were estimated. These six interpolants correspond to the red, green, and blue channels for both the downlights and wallwash fixtures. For illustration and interpretation, Figure 5.10 and Figure 5.11 depict the surface interpola-

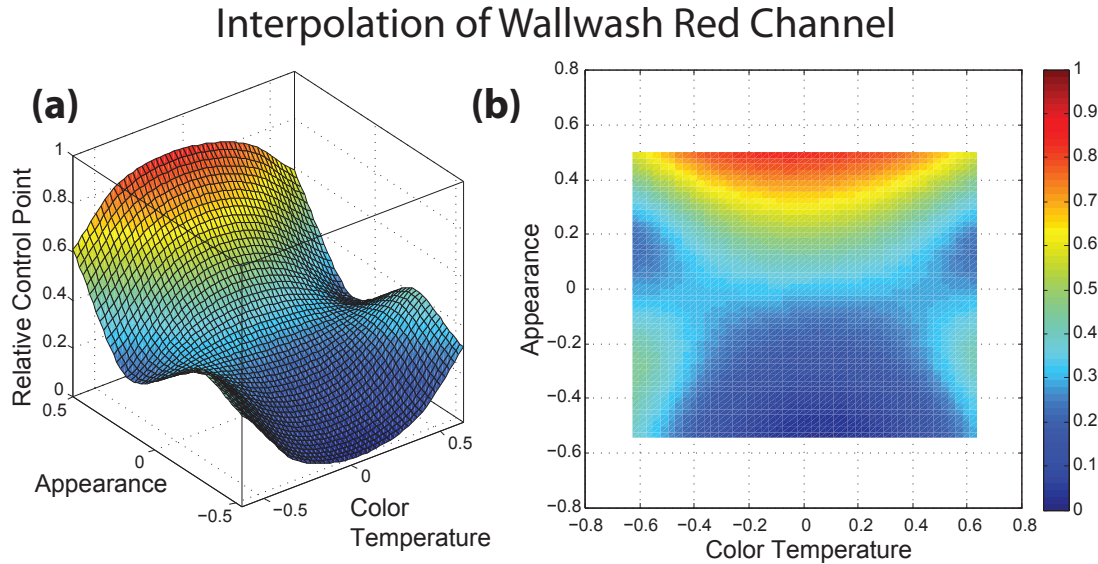


Figure 5.10: Interpolated control settings for the wallwash red channel using the point-configuration of the 2D MDS fitting procedure (the setpoint is normalized to 1). In (a), the surface is plotted. In (b), the contour is plotted.

tion of the red and blue channels for the wallwash type of fixtures. These images were chosen to illustrate the fitting procedure because they both illustrate non-monotonicity of the appearance axis, and when viewed together, allow interpolation of the warm/cool direction of the color temperature axis.

In the graphs, the z -axis, labeled “relative control point” is merely the normalized setpoint (e.g., an 8 bit value) for the respective color channel of the luminaires. In the appearance axis, at the positive-most and negative-most regions, we notice an increased intensity in the red channel. Decreasing on the appearance axis, one encounters a “ripple” due to the arrangement of scenes 7 (more downlight) and 6 (more wallwash).

The effect of adjusting the color temperature is also present, as the color temperature axis is increased, we notice that the blue channel setting is increased.

5.4 Discussion

We find evidence that when subjective impressions of lighting are measured in a pairwise fashion, participants easily detect changes in the luminous conditions of the room without the need for rating multiple scales. This is a clear advantage of applying MDS to the study and derivation of the lighting axes. These results appear to be consistent with Flynn (1977); Flynn et al. (1973), in which Flynn et. al. found that participants were likely to describe the physical changes in the room along the dimensions of intensity, warm and cool, and uniform/non uniform.

The work described here measures the participants perceived distances using a set of eight well-controlled luminous conditions. This fact leads to the regularity and symmetry of the ordinated lighting scenes in two-dimensions. Given that participants easily

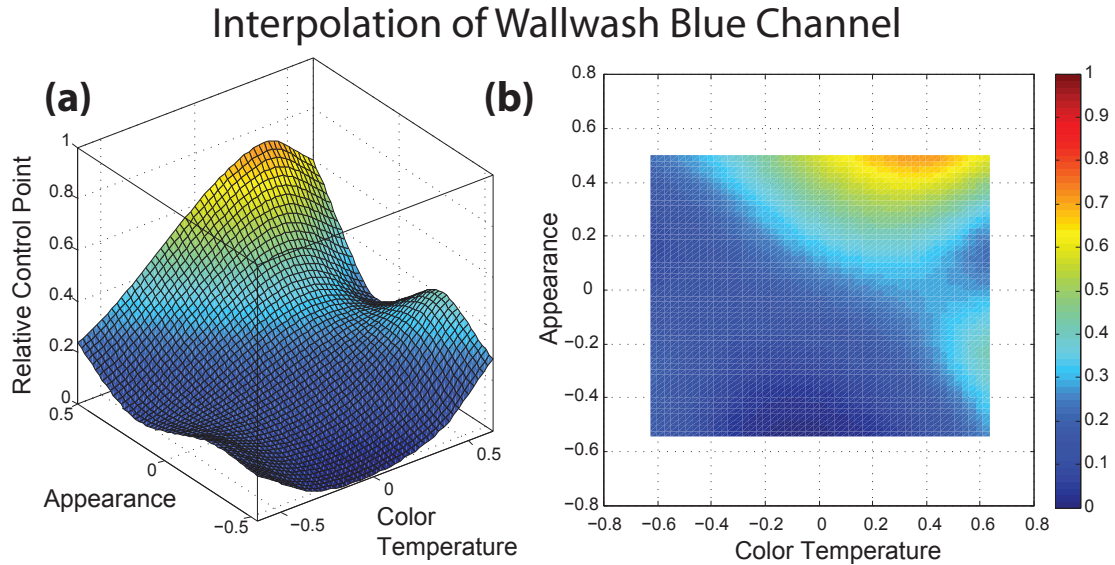


Figure 5.11: Interpolated control settings for the wallwash blue channel using the point-configuration of the 2D MDS fitting procedure (the setpoint is normalized to 1). In (a), the surface is plotted. In (b), the contour is plotted.

describe the physical changes in the lighting configurations, it is expected that sensor measurements consisting of luminous spectra and the brightness of the facets of the room yield a sensor-based PCA solution that is highly correlated with the subjective responses. Not only does this validate the procedure, it suggests there is a physical basis to measurement of these subjective dimensions. This approach is different than the derivation of a uniform color space (e.g., CIE 1931 and CIE 1964) because we did not focus exclusively on color. In our measurements we also incorporate some information regarding the different configurations of the luminaires.

This simple fact makes generalization about the widespread applicability difficult, but we suggest that a simple linear rescaling of the sensor data is adequate to describe the perceptual space. Thus, we have presented a methodology that can be extended to testing in multiple rooms with different lighting configurations. This is a key area of future work.

We also demonstrated the ability to fit a non-linear manifold with the set Ω , the ordained scenes on a lower dimensional basis. Future work entails replicating this experiment with additional color temperatures and validating the accuracy of this technique to reproduce accurate white points along the blackbody curve. It is anticipated that this problem is readily solvable.

5.5 Summary

This chapter presented the analysis and results of both a subjective study using well controlled stimuli using humans and objective measurements of luminous conditions using sensors. The latent basis of both approaches was derived and presented. A linear

model was proposed, which relates both the objective and subjective was presented and studied. It was found, using the stimuli tested, that a simple linear rescaling of the objective measures sufficiently maps sensor-based measurements onto the subjective space. Using a two-dimensional mapping, a prototype lighting control-system to interpolate between the eight luminous conditions was presented. It was argued that these eight conditions sufficiently represent the basic characteristics of office-type lighting.

Human Subjects Test III: Performance Testing

The work detailed in this chapter is the third and final experiment presented in this thesis. In this experiment, subjects are randomly assigned to complete a series of lighting tasks using either the proposed two-axis lighting interface or using a set of traditional linear faders to adjust the lighting. The analysis therein describes the strong effect of the axes in decreasing task time as well as self-reported tiredness. A full comparison of the exit questionnaire given to both groups is presented. The results are linked to other theories of user-interface design and future work is presented

6.1 Introduction

In the prior chapters, the intent has been to measure and extract the resulting arrangement of luminous conditions using several different approaches. In this chapter, I present the results of an experiment designed to measure the performance of the a two-axes lighting controller derived using the results of Chapter 5.

6.1.1 Pre-Experiment Background

In a prior subjective study designed to derive the specialized axes of control, a series of experiments were carried out in which subjects rated the perceived similarities of the lighting conditions (Section 5.3). Using a specialized technique (multidimensional scaling), the pairwise comparison data were analyzed with the goal of determining a configuration of the tested lighting scenes that described the original pairwise data collected in the experiment. In other words, we transformed the pairwise data into a geometry in which eight distinct lighting scenes were ordinated on a Euclidean coordinate system. In this new geometry, the inter-scene distance is made as close as possible to observed pairwise similarity data. A visualization of this procedure which arranged the 8 lighting scenes in 2 dimensions is given in Figure 5.9.

Using these two dimensions, an interpolation procedure (biharmonic spline fitting) determined the corresponding control-surface mapping for the red, green, and blue channel of both the downlighting and wallwashing fixtures in the room (Figures 5.10 and 5.11). Thus, for any (x,y) -pair on the derived axes, the state of the luminaires in the room was exactly known. In effect, this dual procedure of first ordinating the lighting scenes, and then deriving the corresponding set-points along this surface enables one to adjust the lighting in the room via interpolating over their lighting presets.

6.2 Experimental Setup

Using the same office and same luminaires as described in Section 5.2, a user-experiment was conducted to determine if the derived lighting control axes were an improvement over the direct-control of intensity and color as commonly provided used a set of sliders and buttons.

6.2.1 Equipment

In this experiment, the user-interface (GUI) under test ran on an Apple iPod device capable of capacitive touch and control. The lighting control software available to the user was written using the touchOSC library available for mobile devices. This device transmitted data wirelessly to a data logging PC which monitored the elapsed-time in each trial and kept a log of the adjustments made by the participant, per-trial. The communication interface between the data logging PC and the iPod was bidirectional, so that the state of the lighting conditions and user-interface were capable of being synchro-

Time	X	Y
0.084	0.71825	0.25198
0.088	0.70039	0.25992
0.105	0.6865	0.26785
0.123	0.67063	0.27777
0.139	0.65873	0.28571
0.167	0.65079	0.29365
0.172	0.64285	0.2996
0.189	0.63888	0.30753
0.205	0.63293	0.31547
0.223	0.62896	0.32738
0.239	0.625	0.3373
0.255	0.62103	0.34722
0.272	0.61904	0.35912
0.289	0.61507	0.37103

Figure 6.1: Software interface for logging time and position of the finger on the control-device. Similarly, slider number and intensity were also logged. Bidirectional communication was possible between the host-computer and the control-device.

nized by the experimenters in each trial. The custom-written software for recording the experiments is shown in Figure 6.1

The PC, in turn, transmitted lighting control data back to the Color Kinetics control module (the Data Enabler Pro). These data were used to adjust the lighting conditions in the room (for details, see Sec. 5.2.3).

The lighting interface provided real-time control of the luminaires.

6.2.2 The Lighting Control User-Interface

Two lighting control graphical user-interfaces were designed for this experiment. The first user-interface is the experimental interface derived using subjective impressions of lighting. The second user-interface is the control, it consists of single degree-of-freedom sliders which adjust the individual luminaire's flux and buttons to toggle the color temperature. The description of each interface follows.

6.2.2.1 The Two-Axis Lighting Control GUI

The domain of the two-dimensional lighting configuration was linearly rescaled and normalized to $[0, 1] \times [0, 1]$. This did not fundamentally change previous findings, but allowed for the mapping to span the entire range of the GUI running on the ipod. The user-interface was designed such that the original eight lighting scenes (Fig. 5.4) are reachable (from a controls standpoint) and the (nonlinear) interpolated control values follow from the two-dimensional interpolation of these original conditions. The tested interface is presented in Figure 6.2. The axes were unlabeled in the experiment.

In this control system, the user was capable of adjusting the appearance of the room (brightness and contrast) and color temperature. To visually illustrate this mapping,

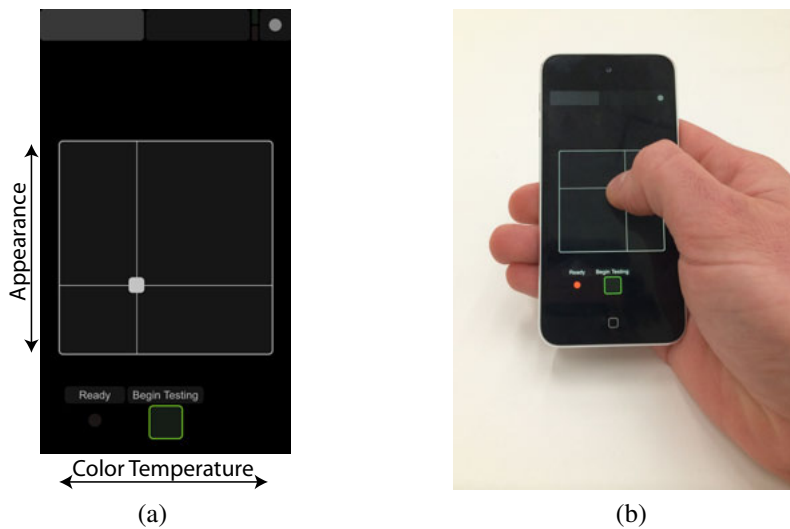


Figure 6.2: The axes lighting control GUI. In (a), a description of the layout. In (b), the tested layout.

nine control were selected from the GUI and photographed (Figure 6.3). The range of brightness and change in appearance is shown. In the center of the two axes, the scene is neutral (approximately 5000 K and 300 lx).

6.2.2.2 The Linear Slider GUI

The linear slider interface is the familiar collection of sliders used to adjust the intensity of the luminaires. It was decided that a fair model of the slider user-interface was a direct mapping of intensity to each of the 8 luminaires. Therefore, intensity control was set to a 1:1 mapping, with 9 degrees of freedom (eight sliders and warm/cool adjustment). Adjustments in color-temperature were possible by pressing the warm or cool button on the GUI. This interface and the mapping between sliders and the corresponding luminaires are presented in Figure 6.4.

6.2.3 Participants

Altogether, 20 subjects were recruited across the MIT campus (8 female, and 12 male) ranging in age (20-43 years). Half of the participants were students and researchers, the remaining half were from administration and MIT (non technical) staff. Participants were given a \$5 dollar coffee card for their time and sessions lasted approximately 20 minutes. The participants were randomly assigned to either the control group (consisting of experiments with the slider interface) and or the treatment group (the axes interface), such that each interface was tested by 10 different participants. All subjects reported being familiar with the use of capacitive-touch screens and graphical-user interfaces.

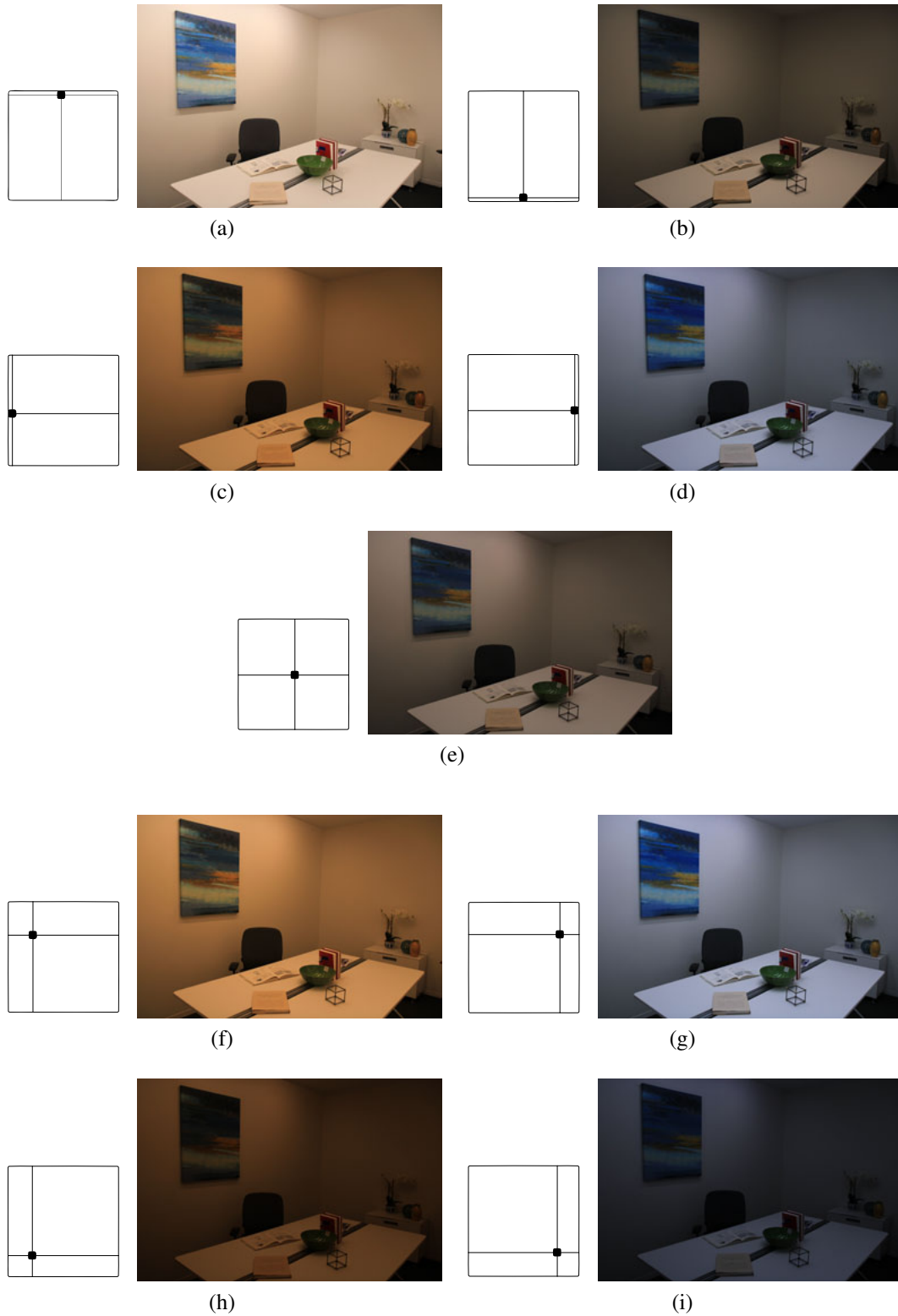


Figure 6.3: Visualization of axes setpoints and corresponding lighting conditions.

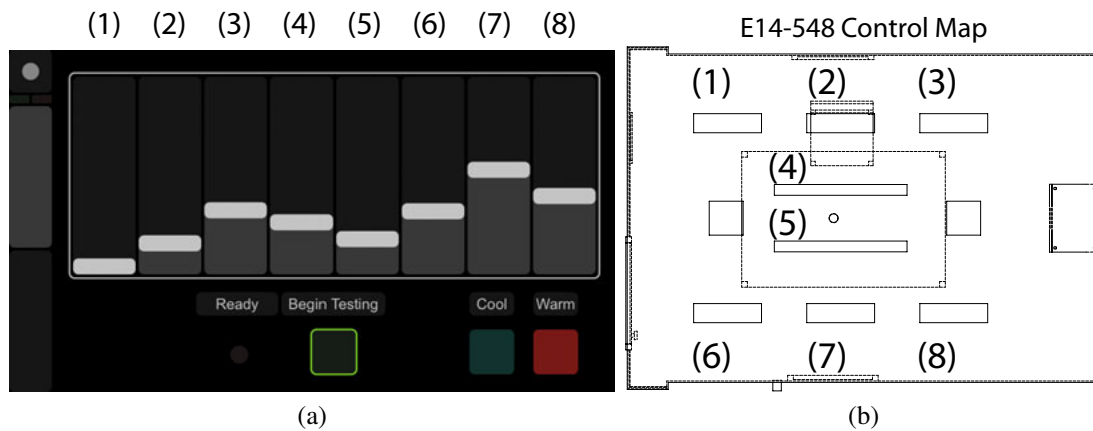


Figure 6.4: Linear slider interface and corresponding luminaire map.

6.2.4 Procedure

Two protocols were utilized across all trials. The first protocol, the task-time protocol, was designed to measure the participants performance using either the axes or the sliders. The second protocol, the exit questionnaire, the consisted of five Likert items designed to measure the participant’s attitude about the user-interface, administered at the conclusion of the study. Subjects then completed an optional question and answer session about the experiment.

6.2.4.1 Task-time Protocol

The experiment utilized a mixed between and within-variable design. The twenty subjects were randomly assigned to either the sliders group or axes group for testing. Thus, the between-subjects variable, controller-type consisted of two levels, sliders and axes. Since illumination control is ultimately a subjective process for each user, users were tested with lighting prompts using natural language. The first within-subjects variable, prompt-type, described whether the type of prompt was an instructional or contextual lighting task. The second within-subjects variable was task-number. Each subject completed 5 instructional and 5 contextual lighting tasks during the study. The prompts read to the users are listed in Table 6.1.

The experiment instructions were read to the participants by the experimenter and the user was given two basic training tasks to become familiar with the lighting controls and the experimental procedure. These training tasks were not included in the analysis of task-time. Each subject then completed 10 lighting tasks, in which the participant was read a prompt by the experimenter, and then adjusted the lighting until they were satisfied with their response. These ten tasks were presented in a random order to each participant. During each testing period, the task-time and user-manipulation history were recorded for later analysis. Logging did not begin until pressed both the “begin-testing” button and interacted with at least one control-element. Subjects indicated they were complete with the task by pressing the “begin-testing” button a second time. After

Table 6.1: Task instruction.

Type	Task No.	Description
Training		
	1	Create a dimly lit, but comfortable, scene where the table is brighter than the walls using reddish (warm) lighting.
	2	Make this room optimal for illuminating the painting in front of you.
Context		
	1	Make this room optimal for reading a magazine or newspaper.
	2	Make this room optimal for computer-based work.
	3	Make this room optimal for socializing with friends.
	4	Make this room optimal for drawing attention to the objects on the table.
	5	Make this room optimal for relaxation.
Instruction		
	1	Create a dimly lit, but comfortable, scene where the walls are brighter than the table using reddish (warm) lighting.
	2	Create a brightly lit, but comfortable, scene where the table is brighter than the walls using blueish (cool) lighting.
	3	Create a brightly lit, but comfortable, scene where the table is brighter than the walls using reddish (warm) lighting.
	4	Create a dimly lit, but comfortable, scene where the walls are brighter than the table using blueish (cool) lighting.
	5	Create a scene of comfortable brightness and, using your choice of color, keep both the table and walls at the same brightness.

completing every task, the lighting and controls were reinitialized to an a common state (3000 K with a work surface illuminance of 200 lx).

6.2.4.2 Exit Questionnaire

After participants completed the 10 lighting tasks, we asked them to complete the questionnaire in Table 6.2. This questionnaire consisted of five Likert questions measured on a seven-point scale (1=strongly disagree, 7=strong agree) and was designed to measure the users' attitudes towards the lighting control GUI they tested.

Table 6.2: Exit Questionnaire.

No.	Question
1	This method is a natural way to control indoor lighting.
2	This method reflects my intent well.
3	A lot of training is necessary to use this method.
4	This method makes me feel tired.
5	I want to control the indoor lighting using this method.

6.3 Results

The analysis of the proceeds with a presentation of the descriptive statistics, an analysis of variance to determine which variables affected the average task-time during the study, and finally, a non-parametric analysis of the exit questionnaire.

6.3.1 Descriptive Statistics of Task-time

Altogether, 20 participants were tested 10 times each for a total of 200 data points. Irrespective of the independent variables, the median task-time was 25 s. Fifty percent of the participants finished their tasks between 15 s and 41 s with seventy-five percent of the participants finishing their lighting tasks within 41 s. A summary of the data is presented in Table 6.3, and the difference between the median and mean of the task times suggest the task-time data are right skewed (as expected).

User-task times are known to be right skewed, with the control group variance often times much greater than the treatment group's variance. Therefore, proceeding with the mixed-design analysis of variance (ANOVA) requires a variance stabilizing transformation (e.g., to ensure homogeneity of variance). Candidate transformations of the task time include the natural log and the square root transformation. In this analysis we proceed by first log-transforming the task time. The final results are then back-transformed to an arithmetic scale.

6.3.2 Analysis of Performance Time

Data were analyzed using a mixed-design ANOVA with a within-subjects factor of type (instructional, contextual) and task (prompts 1-5) and a between-subjects factor of controller-type (sliders, axes). See Table 6.4 for reference. The data were analyzed using the EZanova package using the R language. Recall that the estimated partial effect size η_p^2 describes the size of the effect measured in the experiment (e.g., small = .01, medium = .06, and large = .14). Large effect sizes are likely to be noticed by eye by a novice.

The analysis indicated that the average log-task time of participants depended on the controller-type ($F_{1,18} = 14.76, p < .001, \eta_p^2 = .45$). This effect was observed regardless of the type of prompt ($F_{1,18} = 2.15, p = .159, \eta_p^2 = .11$) and also irrespec-

Table 6.3: Experiment summary statistics. Column ctrl is the tested controller-type; "A" and "S" correspond to the axes and sliders. The column labeled type refers to the task, "I" and "C" correspond to instructional or contextual, resp.

	Ctrl	Type	Task	N_r	Mdn	M	SD	Skew
1	A	I	1	10	15.9	22.5	18.4	1.6
2	A	I	2	10	12.5	20.1	18.6	1.3
3	A	I	3	10	10.9	14.8	11.5	1.8
4	A	I	4	10	19.2	20.6	10.5	1.3
5	A	I	5	10	15.5	18.4	11.7	0.7
6	A	C	1	10	18.2	25.9	18.4	0.7
7	A	C	2	10	22.1	23.6	18.6	1.2
8	A	C	3	10	12.5	17.6	14.0	0.9
9	A	C	4	10	16.3	16.5	7.5	0.2
10	A	C	5	10	13.3	17.7	11.9	1.0
11	S	I	1	10	33.5	35.2	16.9	0.3
12	S	I	2	10	20.9	28.5	20.9	0.8
13	S	I	3	10	29.0	30.6	14.4	0.4
14	S	I	4	10	35.8	36.4	13.0	0.4
15	S	I	5	10	42.4	45.8	23.0	0.4
16	S	C	1	10	47.5	45.8	22.0	0.3
17	S	C	2	10	39.4	43.3	19.1	0.5
18	S	C	3	10	41.4	49.7	22.4	0.5
19	S	C	4	10	33.2	32.2	15.7	-0.0
20	S	C	5	10	40.4	44.1	27.7	1.6

Table 6.4: Results of the mixed ANOVA; the effect and interaction of independent variables in the experiment

Effect	F	P -value	η_p^2
Controller	$F_{1,18} = 14.8$	$< .001$	0.45
Prompt	$F_{1,18} = 3.8$	$= 0.07$	0.17
Task No.	$F_{4,72} = 1.3$	$= .30$	0.06
Controller \times Prompt	$F_{1,18} = 2.2$	$= 0.16$	0.11
Controller \times Task No.	$F_{4,72} = 2.0$	$= 0.10$	0.10
Prompt \times Task No.	$F_{4,72} = 3.5$	< 0.05	0.16
Controller \times Prompt \times Task No.	$F_{4,72} = 0.56$	$= 0.70$	0.03

tive of task ($F_{4,72} = 2.01$, $p = .102$, $\eta_p^2 = .10$). The analysis also indicated that mean log-task time differed by task ID and whether the type was instructional or contextual ($F_{4,72} = 3.47$, $p = .012$, $\eta_p^2 = .16$). No corrections to the data were required; Mauchly's test of sphericity on the within-subject variables was $p > .05$.

Since no other experiment variables interacted significantly with the effect of controller type, we could safely average the effect of the controls over all the interactions with prompt and task, to finally derive the estimated effect of the controller type on the mean task time (Figure 6.5). Recall that the model was fit using $\log(\text{task-time})$, therefore, we expect, after exponentiating these results, that the confidence intervals on an arithmetic scale are no longer symmetric; indeed this is the case.

A post-hoc test of the differences between the average log-task time revealed a statistical difference ($M = 0.65$, $SD = 0.19$, $z = 3.38$, $p < .001$). Recall the simple

Estimated Effect of Controller-Type on Task-Time

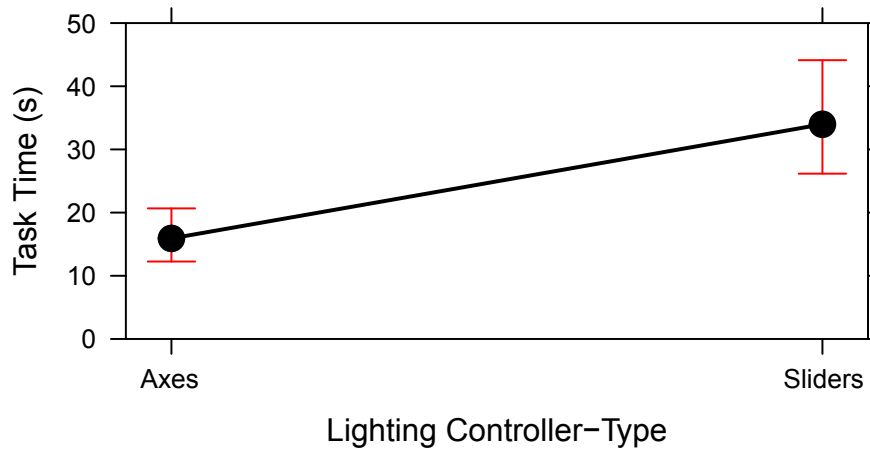


Figure 6.5: The estimated effect of the controller-type on task-time in this study. Asymmetric confidence intervals are expected since the model estimated mean $\log(\text{task-time})$ and the results are presented on an arithmetic scale.

property that exponentiating the difference between two log variables has the property $\exp(\log(x) - \log(y)) = x/y$. In other words, this post-hoc comparison, once exponentiated, yields the odds ratio between the sliders and axes groups. Interpreting these results, the estimated odds-ratio is 1.9 (1.3, 2.8). Thus, participants in the sliders group completed tasks nearly 100% slower than participants who were given the axes.

For example, if a task was known to require 20 s to complete using the axes, we expect, on average, this same task to require nearly 40 s using the sliders. In this example, uncertainty in this estimate suggests the difference in task times in may be as small as 26 s and as large as 56 s.

Summarizing, we obtained a positive finding suggesting that the axes allow the user to perform lighting tasks in half the time – regardless of the lighting task – than the sliders. As expected, we also observed an interaction between within-subject variables task and type, as instruction and context tasks had varying degrees of difficulty for the participants.

6.3.3 Analysis of Exit Survey

6.3.3.1 Non-Parametric Analysis

Overall, we find that participants in the study reported positive feelings toward their respective controllers. Recall the exit questionnaire was designed using a seven-point scale (7: strongly agree), and that questions two and three are negative questions (e.g., a positive affirmation is a low score). Statistical differences between the two groups were analyzed with a non-parametric Mann-Whitney U test. The median scores and statistical results are presented in Table 6.5.

Table 6.5: Questionnaire analysis using Mann-Whitney test. Columns designated “S” and “A” refer to the sliders and axes group, resp.

	Q 1		Q 2		Q 3		Q 4		Q 5	
	S	A	S	A	S	A	S	A	S	A
	7	6	7	6	1	2	4	2	7	6
	5	6	5	6	2	1	5	2	6	6
	2	5	4	6	3	5	5	2	3	7
	3	5	4	6	4	2	2	1	3	7
	5	5	5	6	2	2	2	2	7	7
	6	3	5	5	2	1	5	2	5	6
	4	6	4	7	5	1	6	1	1	6
	6	3	4	2	2	4	3	3	7	5
	2	5	6	5	1	3	2	2	6	4
	5	3	6	4	1	2	2	4	6	3
Median	5	5	5.5	5	2	2	3.5	2	6	6
U	53.5		55.5		49		22		56	
N_r	20		20		20		20		20	
Z-score	0.274		0.441		-0.079		-2.268		0.471	
significance	-		-		-		$p < .05$		-	
effect-size	-		-		-		0.51		-	

Both groups agreed ($Mdn = 6$) with the statement “I want to control the indoor lighting using this method” despite only reporting they somewhat agreed ($Mdn = 5$) with the statements “This method is a natural way to control indoor lighting” and “this method reflects my intent well.” In these three questions, the median score was positive.

Self-reported tiredness (Q 4: “This method makes me feel tired.”) was greater for subjects who were tested using the sliders ($Mdn = 3.5$) than for subjects who used the axes ($Mdn = 2$) during the experiment. We evaluated the difference between the two groups on our 7-point Likert scale using a Mann-Whitney U test. We found a significant effect of controller-type (the mean ranks of sliders and axes were 13.3 and 7.7, respectively; $U = 22$, $Z = -2.27$, $p < .05$, $r = .51$). No other significant differences were found between controller groups on the other 4 questions (see Table 6.5).

Altogether, the results of the questionnaire suggest that the sampled population (MIT students and staff) viewed both the sliders and axes lighting controllers as something they would like to use to control lighting and that both systems reflected their intent well and were natural ways of adjusting lighting. However, the axes users were more likely to report a lower tiredness score than the sliders. Most importantly, the non-monotonic appearance axis of the axes group did not negatively affect the scores of the questionnaire, an important fact.

6.4 Discussion

6.4.1 Task Time

As expected, we are pleased to report that the axes-based method of control allowed participants to control the lighting in the room nearly twice as fast as those who used the sliders. In some regard, this is to be expected. From an information-theoretic standpoint, the user-interface comprised of the two axes is a lower-entropy interface compared to that of a system consisting of nine degrees of freedom.

However, there is a much deeper connection between the results presented in this Chapter and the fields of psychology and human-computer interaction research. First, recall that the two axes describe the perceived Euclidean distance between the original eight lighting scenes. More importantly, a Euclidean geometry most often suggests that the stimuli are perceived integrally. For example, it is well known that brightness, saturation, and hue are perceived together (integrally) (Garner, 1974). In the axes-controller, the contrast dimension is folded into the appearance and color temperature axes, yet the general interpretation that test subjects reported was “brightness and color.”

Importantly, the results of task time support the conclusions Jacob et al. (1994) who studied manipulation of computer-based objects using gestural control. In this work, the group found that performance time is significantly decreased when the user-interface matched the perceptual structure of the stimuli (e.g., the stimuli are perceived integrally or separably and subsequently controlled using the appropriate interface).

In light of research above, we now interpret the the task time results. First consider the arrangement of the slider interface. The arrangement of sliders to control the brightness, contrast, and color of the room treats the perception of the room as it consisted of 3 distinct separable stimuli (e.g., that manipulation and perception of these attributes resembles a city-block type distance). The important contribution of Jacob et al. (1994) was that they found, in their experiments, that when a user-interface incorrectly specifies control of the underlying structure of the stimuli incorrectly, one finds a significant degradation of performance. This theory helps explain why the performance of the sliders-group was much slower than the axes group.

We now turn our attention to the axes-control. Anecdotally, one subject responded that the axes “felt as if I were designing and painting with the light” and that they were “amazed by how the shadows varied on objects in the room using the control system.” Several subjects commented on how easy it was to use the sliders, especially once they completed instructional-type tasks during the experiment. We interpret these comments as suggestive evidence that the lighting control axes matched the perceptual structure of the stimuli. Indeed, our quantitative analysis of task-time supports these conclusions.

6.4.2 Exit Questionnaire

The entire cohort appeared to respond favorably to both implementations of the lighting control, regardless of whether the user-interface consisted of integral or separable control. We attribute this fact to the novelty of the personalized lighting control, the fact that it was wireless, and also portable. Drawing conclusions about the MIT population,

it suggests the group would enjoy some form of digital and wireless lighting control. Without additional testing, it is unclear whether statistical differences between groups in questionnaire would arise. For example, it is possible that user who are inexperienced with graphical user interfaces may find both user-interfaces difficult to use.

Importantly, we measured a statistical difference between the groups when asked about tiredness. Participants who used the axes self-reported a statistically different and lower score of feeling tired. This conclusion certainly seems possible, as subjects completed tasks twice as fast as their slider-based cohort.

6.5 Limitations and Future Work

Regarding our comments on the entropy of the control solutions, one would like to know how task time in this study is affected by the degree of freedom of the sliders. This would allow us to compare our two axes results against a range of slider task times. Perhaps we would find that eventually decreasing the degree of freedom in the sliders-configuration led to a similar result as the axes. Ideally, we would hope to find this task time decreases logarithmically rather than linearly, which would be suggestive about the “compression” of the possible decision space. Specifically, to address the question if decreasing sliders offers logarithmic or linear utility for potential users. With this information in tow, one could compare the compression rates of the two the approaches to understand the efficiency of the two approaches.

In light of this fact, one can argue that the results presented here represent some form of “lighting control compression,” in that, by restricting the configuration of the lighting scenes to range of interpolated presets, one achieves a higher channel capacity, e.g., controlling the lighting using the axes requires a substantially lower bandwidth than using the sliders. The decompression routine is then, of course, the organization of the scenes within the axes.

We would like to eventually comment on the efficiency of compressing the state space of lighting control. For now, it must suffice to know that such a method of “compression” is possible and leads to increased performance without a discernible difference in human attitude towards the restricted state-space. This is an encouraging step.

Importantly, we must acknowledge that the state-space of the axes control was derived apriori. A logical extension of this work is to consider how participants could first, choose their lighting presets, provide similarity scores of the their chosen scenes, and then quantitatively and qualitatively evaluate the derived axes. This idea is also the basis for future work.

6.6 Summary

This chapter details the performance of two lighting control configurations. It presents quantitative evidence that apriori specification of interpolated lighting presents, presented to the user as two-dimensional interface offers substantial improvements in efficiency compared to a traditional, direct control method, using linear sliders. We also

6. HUMAN SUBJECTS TEST III: PERFORMANCE TESTING

find evidence that users who were given the lighting control axes in the study were less tired than those who completed the same tasks user the sliders. We relate these findings to the corresponding literature on human performance with user-interfaces in the requisite HCI and psychology domains.

Conclusions

In this chapter the hypothesis from Section 1.6 are discussed on the basis of the findings in this work. The outlook identifies future work.

7.1 Feasibility

The perception of luminous conditions, whether observed in a virtual or physical space, tend to be the same. Regardless of the underlying stimuli, or the method in which the data are analyzed, the experiments described in Chapter 4 and Chapter 5 suggests that luminous conditions can be represented by a simple structure. Furthermore, the evidence suggests that when the perceived differences are small (i.e., changes in contrast), these weaker dimensions can be folded into a simple two-dimensional representation of the luminous conditions.

When the hue of the lighting remains fixed (Chapter 4), perception of the luminous conditions is described by two independent axes, “intensity” and “appearance.” The appearance axis is simply a derived scale that measures the perceived distance between proportional differences of flux between the luminaires. The intensity axes is a scale that describes the perceived brightness of the stimuli.

When the hue can vary (Chapter 5), changes in color lead to large perceptual differences in the underlying lighting conditions (e.g., the blackbody locus spanning CIE 1931). In these situations, observers still detect changes in intensity and contrast. Changes in the proportions of luminaires (contrast) – in the presence of changing hue and brightness – are perceived as smaller distances. In two dimensions, the weaker effect of contrast, can be analytically “folded into” a representation comprised of hue and appearance. In turn, the appearance axis is non-monotonic and simultaneously describes changes in brightness and contrast. Yet for the participants who evaluated the control system, the overwhelming majority of subjects described the axes as “color” and “brightness.” In such a representation, changes in contrast represent “fine-grained” control; color and brightness represent easily found global optima, and contrast is achieved by small perturbations about this chosen operating point.

There also exists a physical basis for these perceptions. The major difference between the subjective and objective models is simply the scale. For example, changes in hue may be influenced by only a few dominant wavelengths, yet the perceived difference in humans is large. This fact was demonstrated in Chapter 5.

Using these facts, I conclude that it is feasible

- to remove unnecessary complexity from a lighting-control interface by creating a perception-based representation of the luminous conditions;
- to represent a set of lighting presents in two-axes and allow a user to interpolate between those presents;
- to automate objective measurements of luminous spectra and brightness and estimate the location of these luminous conditions in a subjective space.

7.2 Justifiable Effort

First, this work presents evidence that the study of subjective impressions of lighting can be applied to the design of the user-interface for lighting control. Second, this work

demonstrates how these impressions may be emulated by building a simple model of appearance using a sensor-network.

The design of the user-interface requires an apriori configuration of lighting scenes and a subsequent evaluation, carried out using either (a) spectrometer and luminance measurements, or (b), comparative ratings of scenes. This thesis demonstrates how an objective model of luminous conditions relates to the subjective impressions of lighting. These findings suggest a general approach – a sensor-based model for example, those suggested in Chapter 5, can approximate our impressions of the luminous conditions. Although the tested scenes were not extremely complicated, the relationship between the objective and subjective approaches is encouraging.

When one linearly regresses these two data sets, a correspondence between the major dimensions are found. In other words, using the data collected and presented in this thesis, I offer evidence that a linear rescaling may be a suitable way to approximate the lighting user-interface using sensor-based measurements.

These findings show that

- The subjective impressions of lighting can be inferred through the use of a simple computerized model consisting of photometric and radiometric measurements.
- The objective model described in this thesis corresponds well with the subjective data and vice versa.

7.3 Relevance

The affordance of the user-interface is formally tested in Chapter 6. The results of the user-study demonstrate the significant and substantial effect of the proposed axes-based user-interface on performance time to adjust luminous conditions. Importantly, this methodology can be implemented at this present time, by simply redesigning the user-interface to reflect the dominant ways we experience lighting.

In a user-study, it was empirically determined the proposed lighting control interface (the axes) offered substantial performance increases over traditional slider-based forms of control. Across all lighting tasks, the axes enabled users to set and control the lights in half the time of the sliders with less fatigue.

Tangential, but related, are the results of a simple pilot study of preference in Appendix A. Participants evaluated both user-interfaces and indicated their preferred method of control. In the evaluation, 93% of all users preferred the axes. Although this result is significantly different than equal preference of the two user-interfaces, it is important to also realize that novelty and simplicity of the interface may also bias this preference. However, given the substantial increase in performance, one would also expect that preference is also influenced by the overall utility provided by the axes.

All these results show that

- According to the test conditions and evaluated GUIs, the axes are the preferred method of lighting control. The methodology and approach in this thesis led to

the design of a lighting control interface that offers substantial performance gains without fatiguing the users.

7.4 Outlook

A number of advances have been realized during the course of this work, yet further steps are necessary to foster the broader interpretation and application of this user-interface in lighting.

Evaluating a set of heuristics In the most basic form, the axes are a parametric form of control – is the full calibration by either the human or sensor network required? For example, in a system with a fixed hue, and both wallwashing and overhead luminaires, how do users’ attitudes vary compared to the axes presented in this thesis? Commercializing this work may be as simple as parametric control of the luminous conditions.

Learning from the user In this approach, the system learns and infers the user-interface over time by studying the configuration of lighting presets by the user. Rather than force the user into a parametric form of control, the system, either using apriori specified model, could build the UI by finding the best representation of the presets (e.g., states of the sliders) that the user has specified. Additionally, since the sliders and axes are complimentary, it is foreseeable that broad changes to the lighting could be made by adjusting the axes and local, more fine-grained changes could be made using the sliders. In such an approach, the system would keep track of the state between the two user-interfaces.

A full-scale implementation In these experiments, the lighting presents were chosen apriori, in structured fashion, to measure and validate a lighting user-interface derived from subjective impressions, this led to heuristics discussed above. A logical starting place would be to evaluate a system in which the user creates a variety of presets, then using either sensor-based measurements, or similarity measurements, the system would derive a personal set of axes for the user. Given that users enjoyed controlling lighting with the interface, and the performance gains of such a system, it is logical conclusion to evaluate if users are willing to spend the time to create this form of control. The goal would be a full evaluation of the system “in-the-wild” test the suitability of this approach *en masse*.

Energy On average, do the axes and the interpolated presets consume more or less power than traditional sliders. Concerns from building councils recommend that personalized control in office environments leads to higher power consumption, but this stance, at least according to Veitch and Newsham suggests users typically prefer lower brightness levels than what is typically recommended. In this case, one could study the effects power consumption, while using the axes in two forms. In the present implementation, the axes abstract all visual cues about the intensity of the room, whereas,

with sliders, there is visceral and visual implication of a limit, what are the effects of overlaying a contour map of energy density with the present axes UI? Does this lead to lower power levels? Do user's still prefer the interface?

The evolution of lighting: luminous displays If certain parameters of the room are changed, for example, the reflectivity or color of the paint, how does this impact our impressions? The theory of integral stimuli should still hold, which loosely implies our methodology could be used to evaluate and build UIs in these unusual rooms. The complexity of this thought experiment can certainly explode – ultimately one would like to generalize and continue the researching the objective models derived using sensor-measurements as a suitable basis for anticipating our reactions to new forms of lighting, and small perturbations of the room's appearance. This endeavor likely suited to computer-based analysis and CGI to understand our impressions of unusual and new forms of lighting. For example, what might these subjective data look like when the experiment in Chapter 5 is replicated, but conducted using an entirely different lighting medium (e.g., large displays).

Deriving a general subjective mapping The present results suggest that a sensor-network is capable, after a simple rescaling of the objective-room model, of anticipating the (x, y) location of luminous conditions in a perceptual space. How might one continue to evaluate this theory? First, using the same room described in Chapter 5, the tested luminous conditions could be expanded to include a wider range of color-temperature and contrast variables. Asymmetric lighting configurations would also be evaluated. Using the same experimental procedure outlined in Chapter 5, participants would only be tested in a subset of the configurations. After some months of collecting responses, the coefficients of Eq. 5.1 would be estimated. One would subsequently derive a general two-axes model for control describing a wider range of luminous conditions.

A broader research plan would extend this procedure to different rooms and different luminaire configurations amending the procedure and analysis to account for these changes. Such a research endeavor could span multiple Universities with a common goal of deriving a common set of axes for user-based control of lighting.

Experts versus non-experts Using the same methodology described in this thesis, a research program could be designed in which lighting designers (experts) created the luminous presets and provided subjective scores of the scenes. In this approach, I would attempt to extract the dimensions and structure of their impressions of lighting. How might these configurations vary versus those made by non-experts? Thus, I could formalize an approach in I quantified the critical components of lighting design – drawing conclusions about the similarities and differences of the two groups. Using the methodology discussed in this thesis, is it possible for non-experts to build interfaces and mappings that are preferred more than those by experts?

Applying this approach and mapping in other domains Conceptually, audio equalization is an analogous problem, the main difference is the stimuli are auditory and not

7. CONCLUSIONS

visual. The approach and methodology described in this work can also be used to build new audio user interfaces. Parameter mapping has been studied (Hunt et al., 2003), but the novelty of my approach is that the techniques can generalize any n -parameter mapping. For example, parametric configuration of analog synthesizers could be easily distilled into the first two dominant axes. Again, system exists in dual-form, such that we estimate \hat{f} between Γ , the underlying physical parameters and Ω , the orthogonal basis that represents the geometry of these parameters. One would test how stable this configuration against perception of pitch and ADSR.

Pilot Study of Lighting Controller Preferences

Abstract

A preference study was conducted using fourteen participants to evaluate their preferences of two lighting control options. In a controlled study users indicated they preferred the axes-based user-interface 93 % of the time, CI95% = (.66, .99), significantly more than would be expected by chance, exact binomial p (two-tailed) = .001. In addition, users selected one of five hypothetical setup-times to configure the lighting user-interface. The test did not reveal a difference in preferred setup-time, $\chi^2(5, N = 14) = 4.82, p = .44$.

A.1 Purpose

A short pilot study was designed to follow up the questionnaire results presented in Section 6.3.3 in which participants rated five questions designed to measure their attitude about a specific user-interface. In this prior experiment, participants were randomly assigned to a single lighting user-interface.

This study primarily designed to measure which interface the participants preferred after evaluating both interfaces. Recall in Section 6.3.3, the attitudes are positive towards both user-interfaces but no between-group difference in attitude was detected. Therefore, in this short pilot study, it was hypothesized that, after evaluating both user-interfaces, participants would reveal a significant difference in preference of lighting controls.

Given that users were less tired and lighting tasks were performed twice as fast as those using the sliders, it was assumed that resulting preference of a single interface would be strong. A power analysis was conducted ($\alpha = .05, \beta = .80$) assuming a null hypothesis that both user-interfaces were preferred equally ($H_0 = .50$) and the alternative proportion (to be empirically measured) is $H_1 = .85$. Under these assumptions, fourteen participants are required. The approach to determine the number of participants is after Fleiss et al. 1981, pp. 13-15.

Table A.1: Task instruction.

Type	Task No.	Description
Context		
	1	Make this room optimal for reading a magazine or newspaper.
	2	Make this room optimal for socializing with friends.
Instruction		
	1	Create a dimly lit, but comfortable, scene where the walls are brighter than the table using reddish (warm) lighting.
	2	Create a brightly lit, but comfortable, scene where the table is brighter than the walls using blueish (cool) lighting.

A.2 Method

Fourteen subjects from MIT (ages: 23-34) were recruited to evaluate two lighting user-interfaces (for a full description of the method see Sec. 6.2).

The testing procedure was modified and participants evaluated both types of user-interfaces. Participants performed a total of four lighting tasks using each of the two interfaces (the sliders, and the axes, see Fig. 6.2 and Fig. 6.4).

The lighting tasks (a subset of the original tasks) are presented in Table A.1. The type of question (context, or instruction) and the task no. were presented randomly to the participants. Altogether, the fourteen participants performed eight lighting tasks; four using the sliders and four using the axes. Counterbalancing was applied to the order in which the interface was presented; half the subjects were presented with the axes first and half were presented with the sliders first.

When subjects completed all eight tasks, they were presented with a sheet of paper which instructed them to mark their preferred lighting control interface. They were also asked to report how much additional time they were willing to spend to train a computer to build the axes interface.

A.3 Results

A.3.1 Preference of Lighting Controls

A binomial test of proportions was performed to determine if, after using both types of lighting user-interfaces, users preferred both controllers equally (Table A.2). Users indicated they preferred the axes-based user-interface 93 % of the time, $CI_{95\%} = (.66, .99)$, significantly more than would be expected by chance, exact binomial $p(\text{two-tailed}) = .001$.

Table A.2: Preferred lighting control user-interface.

Order	ID	Choice
axes→sliders	1	A
	3	A
	5	A
	7	S
	9	A
	11	A
	13	A
sliders→axes	2	A
	4	A
	6	A
	8	A
	10	A
	12	A
	14	A
Total		(A=13,S=1)

*Note:*A: Axes, S: Sliders

Table A.3: Setup-time responses.

	N_r	Proportion (%)
< 5 minutes	4	29
5–10 minutes	1	07
11–15 minutes	5	36
16–20 minutes	2	14
> 20 minutes	2	14
Total	14	1

A.3.2 Setup Time

A chi-square test of independence was performed to determine if the five axes-calibration times were equally preferred (Table A.3). The test did not reveal a difference in preferred setup-time, $\chi^2(5, N = 14) = 4.82, p = .44$.

A.4 Discussion

As expected, a strong preference for controlling the lighting using the axes was found. For the respondent who selected the sliders, they commented that they preferred precise control. These reactions to new and unique interfaces are not uncommon. Recently, Noh et al. found that a “painting interface” for lighting control was preferred by the users in the study, yet some users preferred the simple and direct control of the sliders.

Overall, any lighting related user-interface must afford the users simultaneous “broad” and “short” strokes – such that a majority of the time adjusting the room is with the simple approach, and special design or aesthetic design can be accomplished with more

A. PILOT STUDY OF LIGHTING CONTROLLER PREFERENCES

control. The axes offer a compromise, since the approach blends the perceived aspects of the lighting conditions in one simple interface.

Description of Lighting Scales

B.1 Survey Items in Human Subjects Test I

Chapter 4 describes the measurement of subjective impressions of CGI-based lighting scenes using human subjects. The original scales used to conduct this research are drawn from Flynn et al. (1973); Hawkes et al. (1979). The scales and collection of the ratings were presented and recorded digitally using a computer (Table B.1).

For more information regarding the use of semantic differential scales in lighting research see Rea (1982). The use of the semantic differential was first proposed by Osgood (1957).

B. DESCRIPTION OF LIGHTING SCALES

Table B.1: The 29 bipolar adjective scales used in lighting ratings.

	-3	-2	-1	0	+1	+2	+3	
ugly	○	○	○	○	○	○	○	beautiful
unpleasant	○	○	○	○	○	○	○	pleasant
dim	○	○	○	○	○	○	○	bright
monotonous	○	○	○	○	○	○	○	interesting
discord	○	○	○	○	○	○	○	harmony
informal	○	○	○	○	○	○	○	formal
frustrating	○	○	○	○	○	○	○	satisfying
small	○	○	○	○	○	○	○	large
cluttered	○	○	○	○	○	○	○	uncluttered
tense	○	○	○	○	○	○	○	relaxed
angular	○	○	○	○	○	○	○	rounded
faces obscure	○	○	○	○	○	○	○	faces clear
dull	○	○	○	○	○	○	○	radiant
playful	○	○	○	○	○	○	○	serious
complex	○	○	○	○	○	○	○	simple
unfocused	○	○	○	○	○	○	○	focused
dislike	○	○	○	○	○	○	○	like
dynamic	○	○	○	○	○	○	○	static
vague	○	○	○	○	○	○	○	distinct
somber	○	○	○	○	○	○	○	cheerful
vertical	○	○	○	○	○	○	○	horizontal
hazy	○	○	○	○	○	○	○	clear
hostile	○	○	○	○	○	○	○	friendly
noisy	○	○	○	○	○	○	○	quiet
short	○	○	○	○	○	○	○	long
cramped	○	○	○	○	○	○	○	spacious
unusual	○	○	○	○	○	○	○	usual
unsociable	○	○	○	○	○	○	○	sociable
private	○	○	○	○	○	○	○	public

MDS Modeling Error

C.1 Background

In Chapter 5, subjective impressions in lighting were studied using multidimensional scaling (MDS). The procedure involved participants indicating the perceived dissimilarity between pairs of lighting scenes. This approach is very different than the method and procedure of Chapter 4. Namely, participants rated attributes of lighting in a multi-dimensional array.

The important distinction is that multidimensional scaling maps proximities p_{ij} into corresponding distances $d_{ij}(\mathbf{X})$ of the latent basis \mathbf{X} . Using the terminology and model of Borg (2005), we have a representation function

$$f : p_{ij} \rightarrow d_{ij}(\mathbf{X}), \quad (\text{C.1})$$

where a particular choice of f specifies the MDS model. Borg, 2005, pp. 39-40 explains, “an MDS model is proposition that given proximities, after some transformation f , are equal to distances among points of a configuration \mathbf{X} :

$$f(p_{ij}) \rightarrow d_{ij}(\mathbf{X}). \quad (\text{C.2})$$

Thus, the multidimensional scaling technique, using some f , attempts to fit the underlying proximity data with some user-specified number of dimensions m , such that the fitted distances d_{ij} match the observed proximities p_{ij} as close as possible.

Moreover, this approach can be extended to three-way models, for example, if the rating procedure is replicated over K subjects, this leads to a proximity matrix $p_{ijk} = (i, j = 1, \dots, n; k = 1, \dots, K)$. The data in Chapter 5 are treated as three-way data, in which any participant K has their own configuration in n dimensions as well as a group configuration, in which each individual configuration can be accounted for by stretching the configuration along the specified dimensions (see Borg 2005, Ch. 21). One such algorithm to fit these three-way data is INDSCAL developed by Carroll and Chang (1970).

In Chapter 5, the three-way data collected was analyzed using the INDSCAL algorithm using the implementation by de Leeuw and Mair (2009) in the R statistical language (2014).

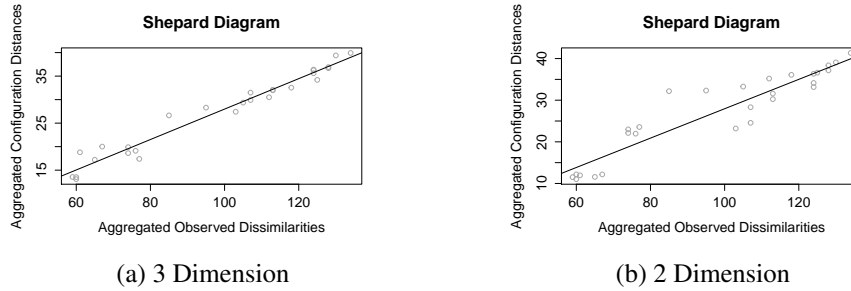


Figure C.1: INDSCAL fitting procedure using interval data assumptions in three and two dimensions.

C.2 Discussion of Model Fitting Procedure

Following the notation and discussion of Borg (2005), the following metrics for evaluating the fitting are presented. The squared error of representation is defined as

$$e_{ij}^2 = (f(p_{ij}) - d_{ij}(\mathbf{X}))^2. \quad (\text{C.3})$$

Summing e_{ij}^2 over all the pairs (i, j) yields the error for the entire MDS representation. This metric, known as *raw stress* is an error metric that is sensitive to the scale of the underlying data Borg (2005). The recommended metric discussed in by Borg is known as “Stress-1” proposed first by Kruskal (1964). The error, *Stress-1* in the analysis is formally defined as

$$\sigma_1 = \sqrt{\frac{\sum (f(p_{ij}) - d_{ij}(\mathbf{X}))^2}{\sum d_{ij}^2(\mathbf{X})}}. \quad (\text{C.4})$$

Minimizing σ_1 requires finding an optimal configuration \mathbf{X} given some dimensionality m .

C.3 Fitted Results

The fitted results of the eight scenes are presented in two ways. Aggregate stress diagrams (due to the use of INDSCAL procedure are presented. The fitting procedure assumed the responses of dissimilarity were collected on a interval scale. In Figure C.1, the fitting error is presented. A stress of zero implies that the points in the figures (the grey circles) fall along the bisector – as expected, as the dimensionality is decreased the stress increases. The respective aggregate σ_1 s in three and two dimensions are 1.44 and 1.25. Recall these are aggregate measures of stress and are not comparable with the standard ranges of stress found using metric MDS.

Interpretation of the fitting procedure is a subjective process, therefore a formal performance evaluation of the user-interface was carried out (Chapter 6).

Fitted Splines for 2-Axis Controller

The two-axis lighting user-interface discussed in Chapter 5 and tested in Chapter 6 required estimating a mapping between two perceived attributes of lighting (e.g., color and appearance) the control parameters of the luminaires (e.g., the red, green, and blue setpoints). For completeness, the red, green, and blue interpolants for both downlighting and wall-washing luminaires are illustrated below.

The method is after Sandwell (1987) and is implemented in MATLAB.

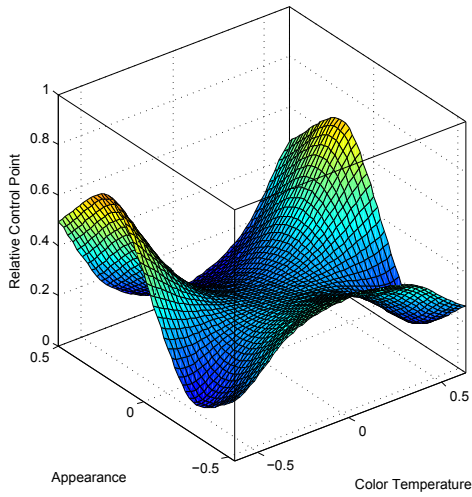
D.1 Control Surfaces

Refer to Figure D.1.

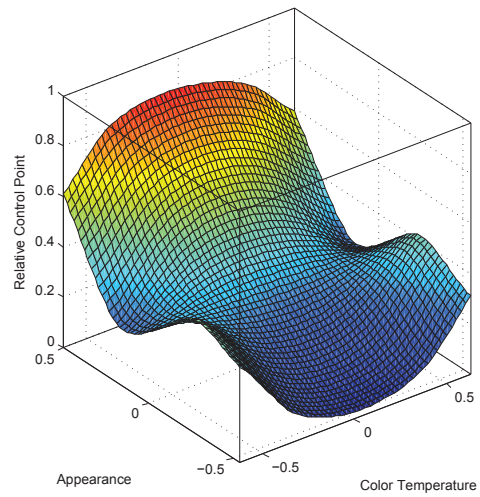
D.2 Control Surface Contour Plots

Refer to Figure D.2.

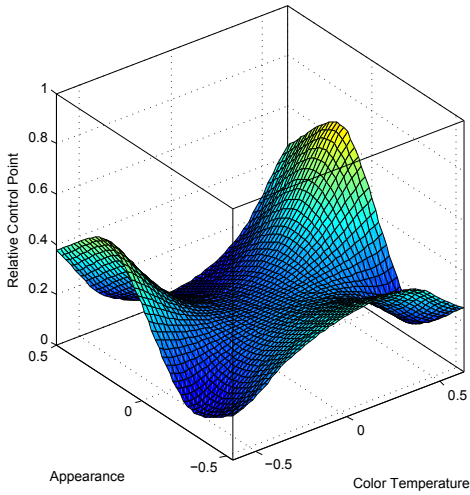
D. FITTED SPLINES FOR 2-AXIS CONTROLLER



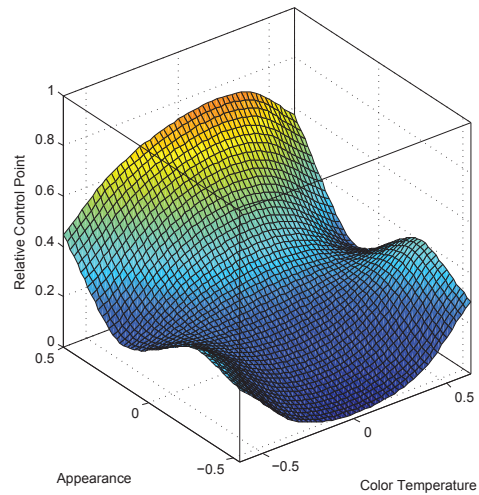
(a) Downlighting: red channel



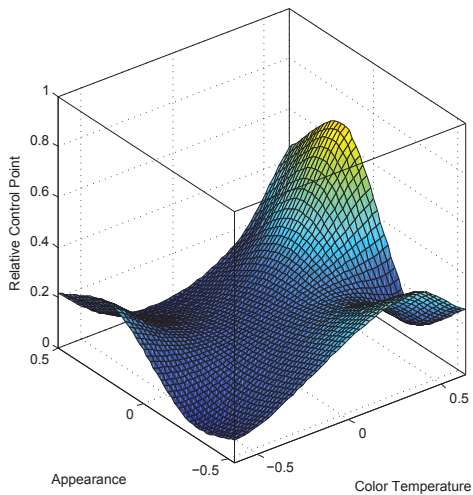
(b) Wallwashing: red channel



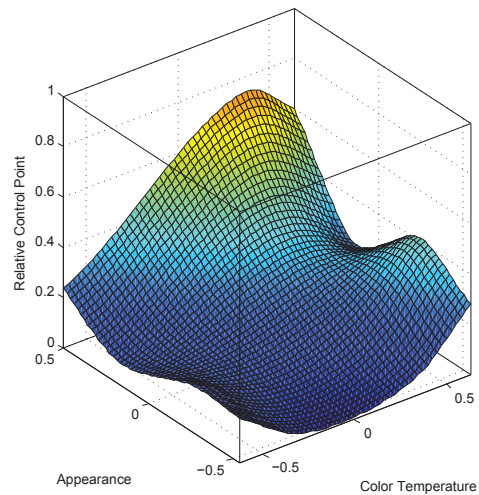
(c) Downlighting: green channel



(d) Wallwashing: green channel



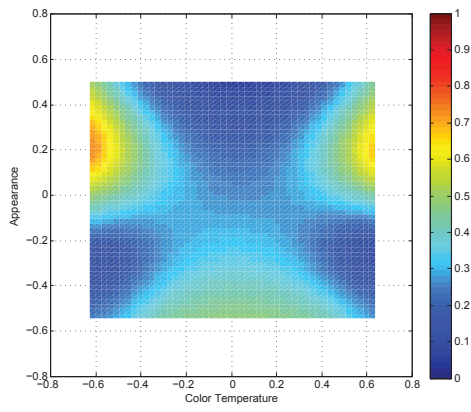
(e) Downlighting: blue channel



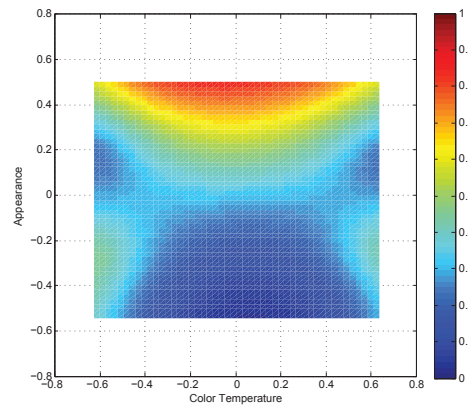
(f) Wallwashing: blue channel

Figure D.1: Interpolated surfaces.

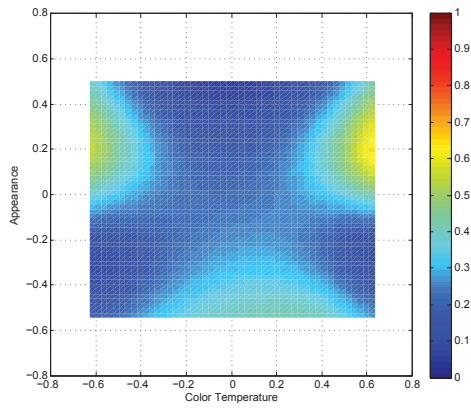
D.2. Control Surface Contour Plots



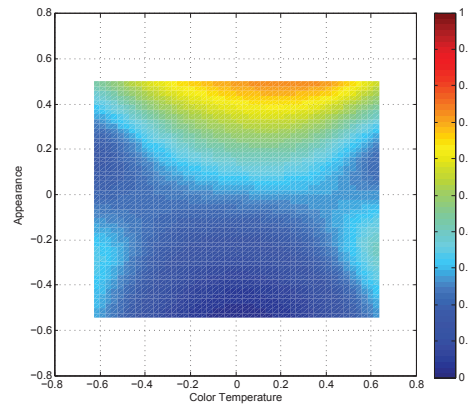
(a) Downlighting: red channel



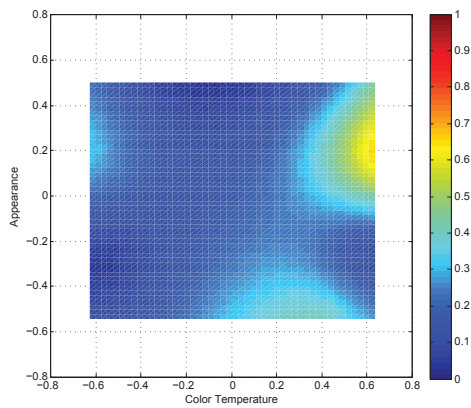
(b) Wallwashing: red channel



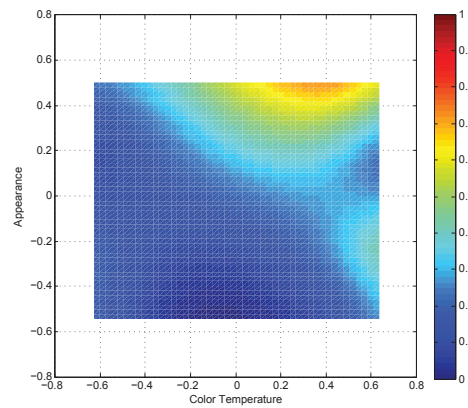
(c) Downlighting: green channel



(d) Wallwashing: green channel



(e) Downlighting: blue channel



(f) Wallwashing: blue channel

Figure D.2: Contour plots of the interpolated control surfaces.

— E —

Raw Datasets for Analysis

The raw data (in .csv form) can be found here

<http://web.media.mit.edu/~maldrich/thesis/data/>

Please refer to the `notes.txt` for descriptions of the datasets. The datasets correspond to the three human subject experiments discussed in this thesis. The data are available for any subsequent use and analysis with proper attribution.

Please use the following `BIBTEX` citation:

```
@PHDTHESIS{mhaldrichPhD,  
author = {Matthew H. Aldrich},  
title = {Experiential Lighting: Development and Validation of Perception-based  
Lighting Controls},  
school = {Massachusetts Institute of Technology},  
year = {2014},  
month = {September}  
}
```


— F —

IRB Approval Forms

F. IRB APPROVAL FORMS

MIT Committee On the Use of Humans as
Experimental Subjects

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
77 Massachusetts Avenue
Cambridge, Massachusetts 02139
Building E 25-143B
(617) 253-6787

To: Joseph Paradiso
E14-548P

From: Leigh Finn, Chair
COUHES 

Date: 09/09/2013

Committee Action: Expedited Approval

COUHES Protocol #: 1308005863

Study Title: Human Judgement of Computer Designed Spaces

Expiration Date: 09/08/2014

The above-referenced protocol was approved following expedited review by the Committee on the Use of Humans as Experimental Subjects (COUHES).

If the research involves collaboration with another institution then the research cannot commence until COUHES receives written notification of approval from the collaborating institution's IRB.

It is the Principal Investigator's responsibility to obtain review and continued approval before the expiration date. You may not continue any research activity beyond the expiration date without approval by COUHES. Failure to renew your study before the expiration date will result in termination of the study and suspension of related research grants.

Adverse Events: Any serious or unexpected adverse event must be reported to COUHES within 48 hours. All other adverse events should be reported in writing within 10 working days.

Amendments: Any changes to the protocol that impact human subjects, including changes in experimental design, equipment, personnel or funding, must be approved by COUHES before they can be initiated.

Prospective new study personnel must, where applicable, complete training in human subjects research and in the HIPAA Privacy Rule before participating in the study.

COUHES should be notified when your study is completed. You must maintain a research file for at least 3 years after completion of the study. This file should include all correspondence with COUHES, original signed consent forms, and study data.

MIT Committee On the Use of Humans as
Experimental Subjects

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
77 Massachusetts Avenue
Cambridge, Massachusetts 02139
Building E 25-143B
(617) 253-6787

To: Matthew Aldrich
E14-548S

From: Leigh Finn, Chair 
COUHES

Date: 04/16/2014

Committee Action: **Exemption Granted**

Committee Action Date: 04/16/2014

COUHES Protocol #: 1404006319

Study Title: Evaluation of Solid-State Lighting Control Methods

The above-referenced protocol is considered exempt after review by the Committee on the Use of Humans as Experimental Subjects pursuant to Federal regulations, 45 CFR Part 46.101(b)(2) .

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

If the research involves collaboration with another institution then the research cannot commence until COUHES receives written notification of approval from the collaborating institution's IRB.

If there are any changes to the protocol that significantly or substantially impact the rights of human subjects you must notify the Committee before those changes are initiated. You should retain a copy of this letter for your records.

F. IRB APPROVAL FORMS

MIT Committee On the Use of Humans as
Experimental Subjects

MASSACHUSETTS INSTITUTE OF TECHNOLOGY
77 Massachusetts Avenue
Cambridge, Massachusetts 02139
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(617) 253-6787

To: Matthew Aldrich
E14-548S

From: Leigh Finn, Chair 
COUHES

Date: 04/16/2014

Committee Action: Exemption Granted

Committee Action Date: 04/16/2014

COUHES Protocol #: 1404006318

Study Title: Measurement of Subjective Opinions of Lighting

The above-referenced protocol is considered exempt after review by the Committee on the Use of Humans as Experimental Subjects pursuant to Federal regulations, 45 CFR Part 46.101(b)(2) .

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

If the research involves collaboration with another institution then the research cannot commence until COUHES receives written notification of approval from the collaborating institution's IRB.

If there are any changes to the protocol that significantly or substantially impact the rights of human subjects you must notify the Committee before those changes are initiated. You should retain a copy of this letter for your records.

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