A Multidimensional Continuous Contextual Lighting Control System Using Google Glass

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ABSTRACT

An increasing number of internet-connected LED lighting fixtures and bulbs have recently become available. This development, in combination with emerging hardware and software solutions for activity recognition, establish an infrastructure for context-aware lighting. Automated lighting control could potentially provide a better user experience, increased comfort, higher productivity, and energy savings compared to static uniform illumination. The first question that comes to mind when thinking about context-aware lighting is how to determine the relevant activities and contexts. Do we need different lighting for reading a magazine and reading a book, or maybe just different lighting for reading versus talking on the phone? How do we identify the relevant situations, and what are the preferred lighting settings? In this paper we present three steps we took to answer these questions and demonstrate them via an adaptive five-channel solid-state lighting system with continuous contextual control. We implemented a multidimensional user interface for manual control as well as an autonomous solution using wearable sensors. We enable a simple set of sensors to manipulate complicated lighting scenarios by indirectly simplifying and reducing the complexity of the sensor-lighting control space using human-derived criteria. In a preliminary user study, we estimated significant energy savings of up to 52% and showed multiple future research directions, including behavioral feedback.

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Categories and Subject Descriptors

H.1.2 [**User/Machine Systems**]: Human factors

Keywords

Context-aware; Lighting; Wearable Computing; Energy

1. INTRODUCTION

Artificial lighting is one of few examples, if not the most preponderant example of pervasive technologies. Lights are a given in today's urban environment. "They [have] weave[d] themselves into the fabric of everyday life [...]" similar to Weiser's description of Ubiquitous Computers [33]. Is artificial lighting truly ubiquitous? With growing pervasiveness and expanding configurability, the complexity of control of modern lighting systems has dramatically increased. To give an example, how often have we puzzled over the many sliders and buttons on the lighting control panel in our office buildings? Artificial lighting, especially indoor lighting, has not yet achieved invisibility in a way that allows one to only "[...] focus on the task, not the tool" [33].

One way to reduce complexity for the user is to simplify manual control using sensors, gestures, or a space model [5], [22], [26]. Another approach is automation, for instance based on user context. Many researchers have defined the term context [3], [11]. Less clear is how context is linked to specific needs. Under what circumstances is the change of lighting conditions desirable and when are they distracting or indifferent? In the field of psychology, many have studied preference, mood, and performance under different lighting conditions. Veitch et al. provide an extensive literature review on this matter [31]. She concludes that despite similarities among research outcomes, there is no consensus on concrete luminance levels, distributions, or degree of luminance contrast. Even if this information would be available, the results are only useful as general guidance for an "acceptable range" [31]. To find meaningful solutions for a specific space would still rely on the expertise of a lighting practitioner. In the field of HCI, research on lighting and context has sometimes chosen to focus on evaluating technology while using somewhat arbitrary mapping between context and lighting scenes [34], [29], [24], or focus on creating tools to explore different adaptive lighting scenarios [20], [21], [4]. Offermans et al. present a more holistic solution that addresses both the mapping and context recognition problems, but they limit the space of possible lighting settings, i.e., the solution space, to only 8 distinct settings and focus mainly on the integration of manual correction [25].

In this paper we present an approach towards multidimensional continuous contextual lighting control. A continuous control space gives the user freedom to go beyond a limited set of predefined lighting scenes and allows seamless transitions between contexts. Our system breaks context down into subjective components that we transform into continuous dimensions of lighting control. We did not manually select these dimensions. We rather developed a method, built upon findings in [6], to derive a multidimensional contextual model from user preference data. In this "fuzzy" representation of context, the control parameters become the extents of occupants' engagement in focused tasks, casual activities, and work with displays. A rather simple mapping of sensors as indicators for the reduced control parameters is now sufficient to navigate a complex set of lighting configurations. In a further step we implemented activity recognition using a wearable sensor platform. A preliminary study in our adaptive environment showed significant energy savings and positive user response.

Incorporating "humans as sensors" and thus taking into account what can only be experienced on site, we acknowledge spatial and user-group-dependent variance of lighting needs. We followed Veitch's advice to seek "integration between lighting and architecture" and go beyond simply designing for an "acceptable range" [31].

2. IMPLEMENTATION IN THREE STEPS

First, we conducted our experiment for a proof of concept in a 3-d virtual environment using a game engine. The goal of this step was to derive control parameters from user preference data (see figure 1). Encouraged by that initial success, we repeated the experiment in a physical space. We created a continuous contextual controller for the test environment (see figure 6). Finally, we prototyped an adaptive system using Google Glass for activity recognition (see figure 11). In a preliminary user study, we collected quantitative data on power consumption and qualitative data on user satisfaction. In this section we will describe in detail the three phases of our research.

2.1 Feasibility study of contextual mapping in a virtual environment

2.1.1 Method

We conducted a user study to collect participants' opinions on the suitability of 6 lighting conditions for 14 different tasks. We performed dimensionality reduction with Principal Component Analysis (PCA) to identify the underlying components in the preference response. We consider the eigenvectors the contextual control dimensions. Component scores indicate relevance of the lighting condition for each contextual dimension. We evaluated the results visually and in comparison to previous findings in lighting research.

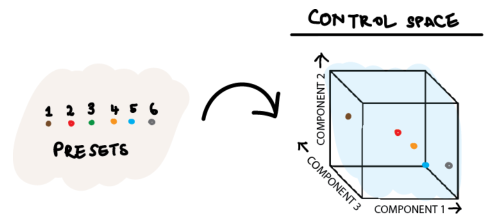

Figure 1: This diagram illustrates the first phase in the implementation of the adaptive lighting system. The first step is to establish the contextual control space and the corresponding mapping of the preset scenes.

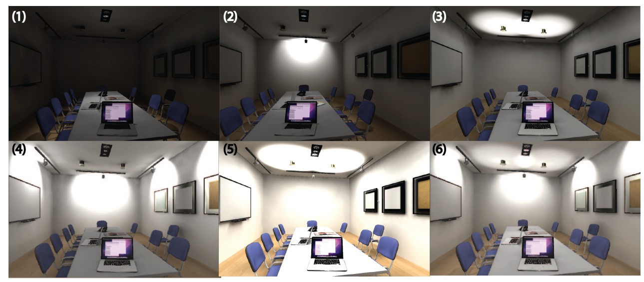

Figure 2: Virtual test environment in 6 unique lighting scenes.

Inspired by Flynn's work on lighting and perception [12], which introduced multivariate statistics in lighting research, we chose a board room with four luminair types to be our testing environment. We chose the tasks according to our guesses of potentially relevant contexts in the space. They could be classified as creative, executive, relaxing, demanding, social, individual, visual, non-visual, formal, and informal (see table 1 to find the complete list of tasks). We designed 6 unique lighting scenes by varying intensity and contrast (see figure 2). In this experiment we used one color temperature and four groups of luminaires. The 6 initial scenes are mapped to the control space using the average value of the component scores. The analysis was performed using the PSYCH package in R [1] and the Varimax rotation method [17].

2.1.2 Principal Component Analysis

PCA is a technique commonly used for face recognition and feature detection in machine learning applications. In social sciences, it is used for multivariate statistical problems, for example to reduce the number of variables [13]. In lighting research specifically, PCA is often applied to investigate perception and preference [8], [10], [32]. Wang et al. used PCA to study the dimensions of atmosphere perception for dynamic lighting [32]. The researchers identified three principal components: *tenseness*, *coziness*, and *liveliness*, for both female and male participants and used the factor loadings to analyze differences between the two groups. In our study, we are not looking for generalization, but rather a mathematical model to incorporate preference feedback into the controller design.

2.1.3 Panel

The panel consists of 40 participants, 21 women and 19 men, between 21 and 45 years old. The participants were staff and students from the university, thus familiar with the technology we used and the tasks in the questionnaire.

2.1.4 Study setup and protocol

The experiment was conducted in a dark windowless office (4.2m in length, 2.8m in width, and ceiling height of 2.6m). Participants set at a desk and looked at a 3D display (Asus VG236H) with active-shutter glasses (Nvidia P854) at a distance of 0.5m. A virtual work space was rendered using Unity. Figure 2 shows the six virtual lighting scenes that were used. The virtual room is furnished with a white table in the center and ten chairs. On the table there a few office supplies. On the walls there are three decorative paintings and one white board. The room is equipped with four groups of luminaires, down-lights, wall-washing on the short wall, wall-washing on the long wall, and diffused overhead.

The 6 lighting scenes as well as the associated 14 questions were presented in random order. Participants were able to move around as an avatar and look at objects such as a newspaper, pencil, writing paper, and laptop computers. They recorded their opinions on a 5 point Likert scale from strongly disagree to strongly agree. They were also given the option to give no answer.

2.1.5 Results

Parallel analysis suggests 3 principal components (see figure 5). We named the components: *casual*, *presentation*, and *visually demanding* (see table 1). Taking into account a 4th component, the visual component is split into tasks done with and without computers. Our results agree with previous findings in lighting and psychology. Biner et al. observed different preferences for visual and non-visual tasks as well as varying social contexts [7]. Butler et al. found out that a higher brightness level is preferred for visually demanding tasks such as reading and studying, and a lower level is preferred for relaxing activities such as talking to a friend or listening to music [9]. Differences were also shown for VDT and paper-based tasks [27] and [30].

Figure 4 illustrates the resulting control space. It shows that participants prefer to have a mix of light sources for a casual contexts. If the situation is casual but also involve visually demanding work, they'd rather increase the brightness of the wall washers than the defused down lighting (Figure 4 right diagram, upper right corner). In a less casual but visually demanding context, participants chose to have primarily down-light (Figure 4 right diagram, upper left corner).

2.2 Implementation of continuous contextual lighting control in a physical environment

2.2.1 Method

We repeated the human subject study similar to section 2.1 in a physical environment. In collaboration with a lighting practitioner we designed six lighting configurations for the test environment to accommodate for tasks as shown in table 2. Figure 7 presents the resulting six scenes. Following the method described in section 2.1.1, we established the

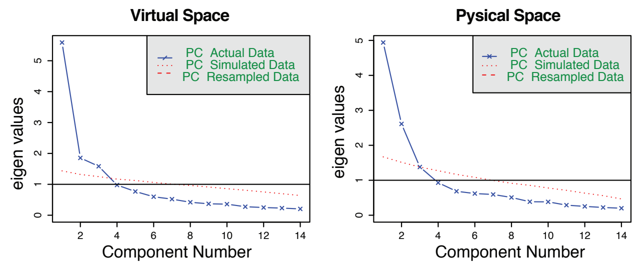

Figure 5: Plot of parallel analysis, left for the experiment in the virtual room, right for the physical room, 3 component were used in both cases

Context	RC1	RC3	RC2
casual conversation with a friend	0.82		
coffee break	0.80		
reading a magazine	0.75		
informal phone conversation	0.66		
brainstorming in a group	0.62		
formal presentation with slides			0.85
informal presentation with slides			0.85
programming/CAD or video editing on a computer		0.81	
creative task using a computer		0.78	
(routine) email on computer		0.70	
study/memorization		0.66	
sketching on paper		0.62	
hand-craft		0.56	
formal phone conversation			
Proportion Explained	0.41	0.36	0.23

Table 1: Rotated component (RC) loadings of the 14 contexts, only loadings above a 0.5 criterion are shown, we named RC1, RC2, and RC3 *casual*, *presentation*, and *visually demanding*.

control axes and mapping of the initial scenes. In a further step, we used superposition of the presets to implement continuous control. The algorithm is described in detail below.

In a n dimensional control space, the operating point is $u \in \mathbb{R}^n$. In this section, vector u is set using a manual controller interface. v is the corresponding lighting setting. The test environment is equipped with 6 individually-addressable luminaire groups with adjustable color temperature. As a constraint, color temperature can only change uniformly for all fixtures. This results in 7 controllable parameters, and $v \in \mathbb{R}^7$. $v_{0i} \in \mathbb{R}^7$ represents the lighting setting of the ith preset. The mapping function between input u and output v is

$$F(u) = \frac{\sum_{i=1}^{6}(a_i(u) * v_{0i})}{\sum_{i=1}^{6} a_i(u)} = v \qquad (1)$$

The factor $a_i(u)$ describes the relevance of the ith preset for the current input. We define

$$a_i(u) = a(\|u - p_i\|) = \exp(\frac{-\|u - p_i\|^2}{2 * \sigma^2}). \qquad (2)$$

$p_i \in \mathbb{R}^3$ is the component scores of the ith lighting preset and $\|u - p_i\|$ the respective euclidean distance to the current input. $a(\|u - p_i\|)$ is the Gaussian Function with $a(0) =$

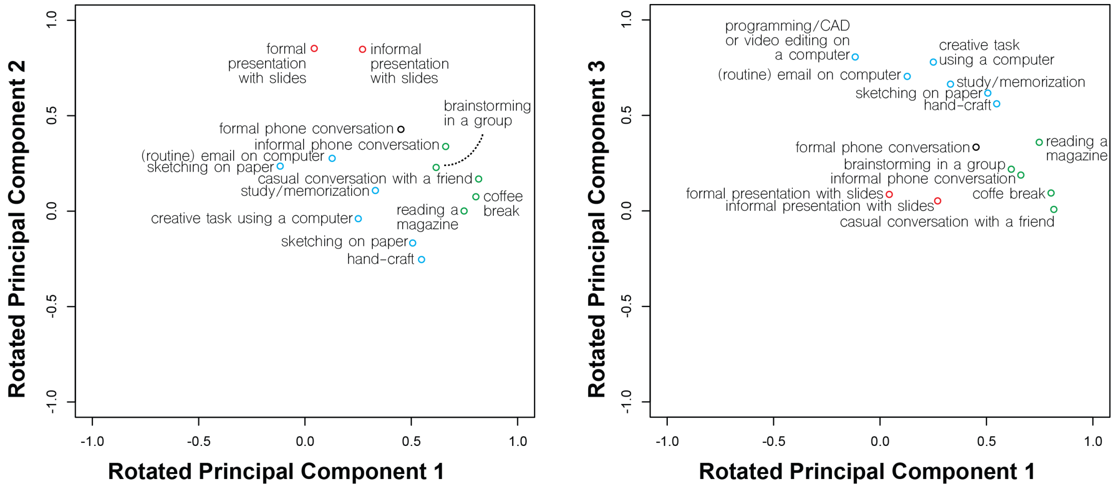

Figure 3: Graphical illustration of the factors in the control space: component 1 (green) *casual*, component 2 (red) *presentation*, and component 3 (blue) *visually demanding*.

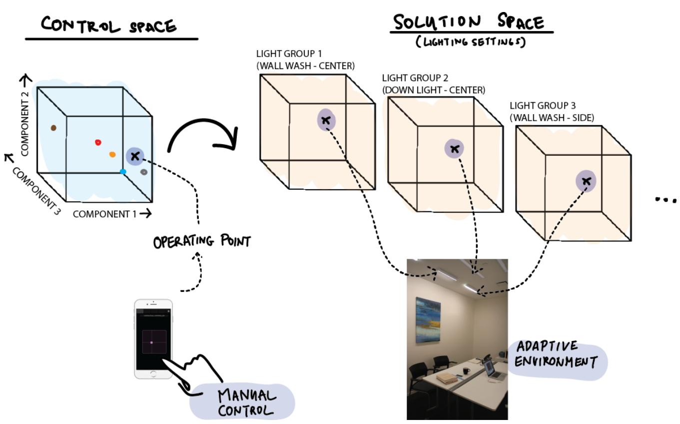

Figure 6: This diagram illustrates the second phase in the implementation. The second step is to establish continuous mapping between user input and lighting settings.

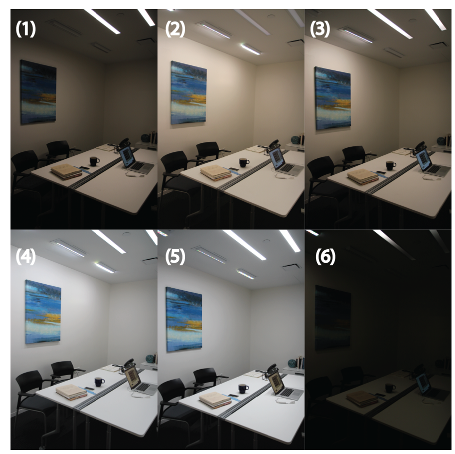

Figure 7: Physical test environment in 6 unique lighting scenes. We named the selected scenes warm down-light (1), warm wall-wash (2), warm gallery lighting with spotlight on the paintings (3), cold wall-wash (4), cold down-light (5), and presentation with projection (6).

1 and $a(\overline{\|u-p\|}) = 0.01$. $\overline{\|u-p\|}$ is the average distance between all presets.

For the manual controller, we chose to focus mainly on the first two principle components. This simplification allows us to implement a two-dimensional controller interface that lets the user manipulate both axes simultaneously. This type of representation has shown advantages in related research (see 2.2.2). We created a simple smart phone application featuring a 2D touch controller. Using this application, the user can easily manipulate the position of the operating point. User input is streamed in real-time to a central control server. Following the mapping strategy described above, the central control unit computes the corresponding lighting settings and sends commands to the lighting server. The lighting server is able to control all luminaires on the local area network. Communication between the application, control unit, and lighting server are implemented using the Open Sound Control (OSC) protocol [2].

2.2.2 *Complex-to-Simple Mapping*

In lighting control [6] as well as sound design [28] multidimensional interfaces have been identified to be more effective than slider-type, one-dimensional controllers. In [6] and [28], the speed of performance improved by 100% and 9% respectively using a two-dimensional controller compared to a slider bank. The mapping strategy between manual input and system output is essential to creating an engaging experience. Existing lighting controllers in majority map technical parameters, such as color and intensity, directly to control input. Hunt et al. investigated how complex mapping strategies for digital instruments allow the player to forget about the technical meaning and thus “promote [...] holistic thinking” [15]. Aldrich observed similar response for a lighting interface derived from user perception data [6]. Study participants using the abstract lighting control were

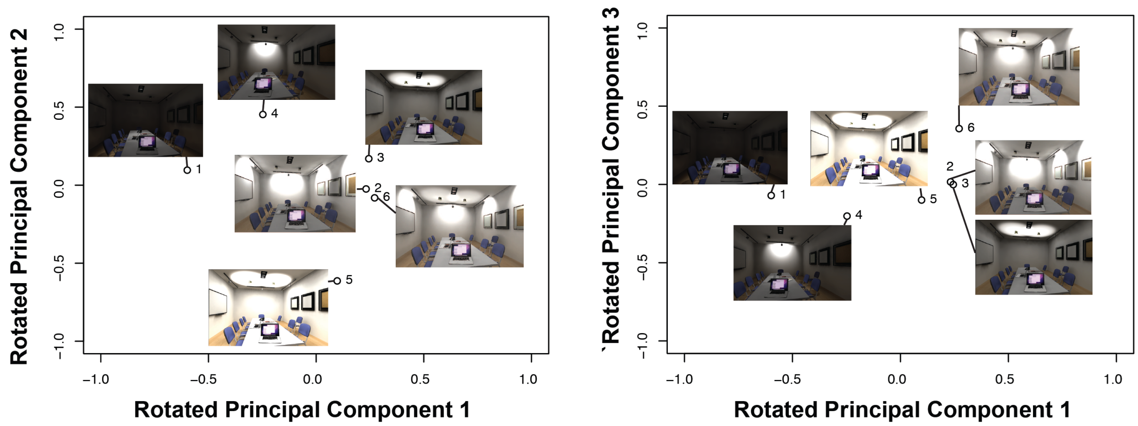

Figure 4: Graphical illustration of the control space in 2D. On the left the six presets are projected onto the first (*casual*) and second (*presentation*) component. On the right they are shown against the first (*casual*) and and third (*visually demanding*) component.

less focused on the luminaires and directed more attention to the lighting effects. A controller mapped to context prompts the user to think about what they want to do or achieve rather than light levels or color. Our continuous approach generates a wide range of possible solutions, which can be navigated easily using the two dimensional interface.

2.2.3 Panel

The panel consists of 17 participants from 20 to 35 years old. The participants are students and staff of the University.

2.2.4 Study setup and protocol

The physical study was conducted in a windowless, rectangular office room (4.2m x 2.8m, with a height of 2.6m). The room is furnished with a white desk in the center positioned underneath the downlights. The table height is 0.7m. There are books, a LEGO object, sketching paper, pens, an office phone, a mug, a laptop computer, and some other office supplies on the table. In addition, there are 3 decorative paintings on the walls, a white file cabinet with books, and three chairs distributed around the table. There are two types of luminaires, two ceiling-recessed luminaires (Color Kinetics Skyribbon Linear Direct Powercore) in the center and six wall-washing fixtures (Color Kinetics Skyribbon Wall Washing Powercore) along the long wall. Both types of luminaires have five controllable wavelengths. They are managed through the Color Kinetics Data Enabler Pro over the local area network and a lighting server that processes incoming commands from any OSC-enabled device. The lights are set up as 6 individually addressable luminaire groups with programmable color temperatures between 2300K and 7000K.

The scenes and questions were presented in random order. Participants were able to move around and interact with objects, make sketches, work at the computer, and talk to the instructor to simulate the tasks. A neutral scene was shown between each test scene. Participants recorded their opinion on a 5-point Likert scale, from strongly disagree to strongly agree. They were also provided the option to give no answer.

2.2.5 Results

Parallel analysis suggested 3 principal components (see figure 5). We named the components: *attentive*, *casual*, and *work with displays* (see table 2). Figure 10 illustrates the respective control space. We can see that cold high-intensity lighting is preferred for focused tasks. Gallery lighting with spotlight on the paintings, which creates a more interesting atmosphere, is preferred for casual tasks. For tasks at computers, wall-washers are preferred over down-lighting. Figure 8 shows the intensity setting of one lunimair group against the first two contextual axes. Here we can see that this light group is nearly turned off for non-focused and non-casual tasks and highest for focused and non-casual activities.

2.3 Implementation of activity recognition and adaptive lighting control using Google Glass

2.3.1 Method

Finally, we implemented activity recognition and autonomous control for the adaptive lighting system. The goal in this section is to rapid-prototype a context-aware environment that will help us to understand further research directions. It was neither our goal to improve existing or identify new activity recognition methods, nor to evaluate the reliability of the method we chose. Alternative solutions can be found in [19]. A large body of research covers indoor activity recognition using wearable sensors. We chose Google Glass as our prototyping platform because head-mounted sensors are especially suitable for recording user-centric lighting and gaze-related contexts. Ishimaru et al. was able to identify activities such as reading, talking, watching TV, mathematical problem solving, and sawing using the embedded inertial measurement unit (IMU) and infrared proximity sensor in Google Glass, analyzing both eye-blinking frequency and

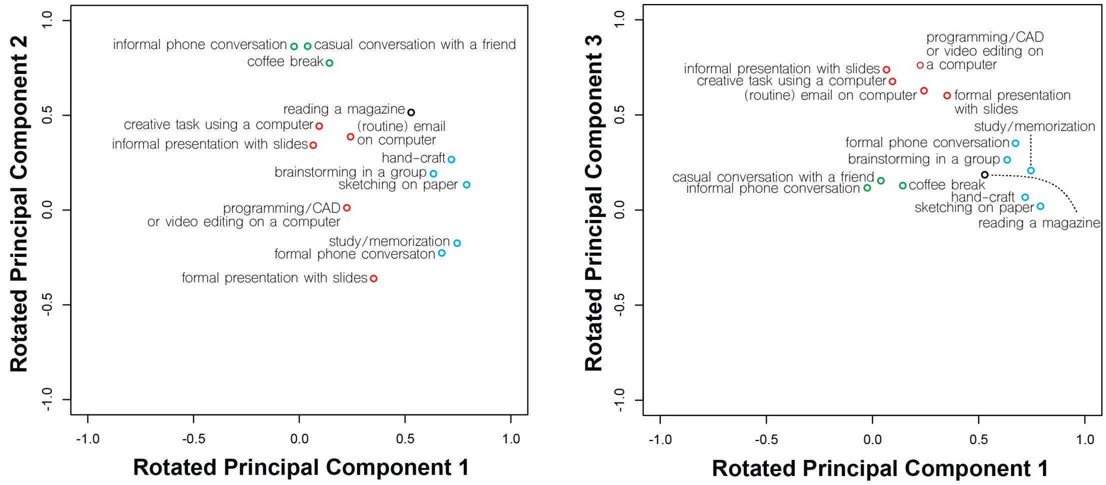

Figure 9: Graphical illustration of factors in the control space: component 1 (blue) *attentive*, component 2 (green) *casual*, and component 3 (red) *work with displays*.

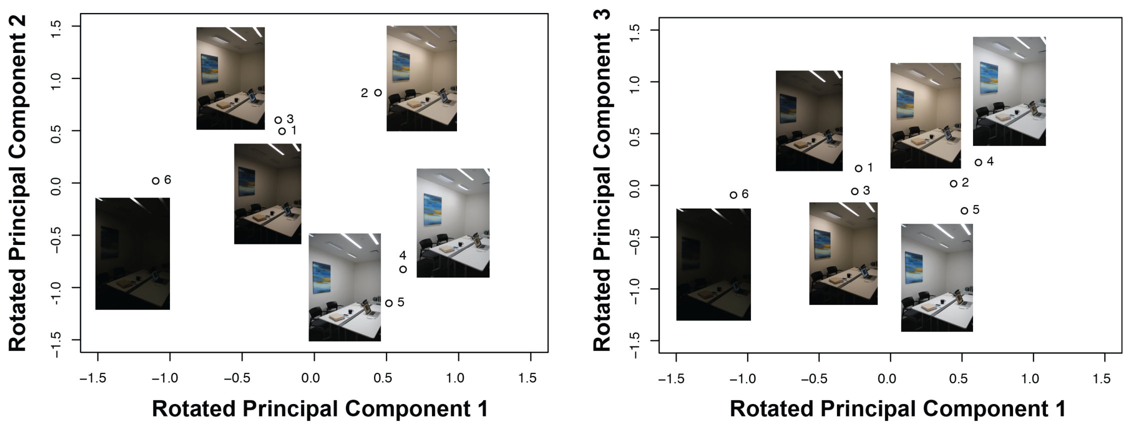

Figure 10: Graphical illustration of the control space in 2D. On the left the six presets are projected onto the first (*attentive*) and second (*casual*) component. On the right they are shown against the first (*attentive*) and and third (*work with displays*) component.

head motion [16]. Head-mounted motion sensors can also be used to measure physiological parameters, such as heart beat [14]. Kunze et al. demonstrated the possibility of using eye tracking to distinguish reading different document types such as novels, manga, magazines, newspapers, and textbooks [18]. Using the front camera, one can capture the user's first-person view and identify, for example, when she is working with her hands [23]. We consider these examples as possible future features of the lighting system. In our current approach, we mainly focus on context recognition using the IMU and microphone.

We determined two contextual indicators: activity and sound level. While performing a visual task with high visual attention, the head is more likely to remain steady and look down. During a conversation and other non-visual tasks, we are more likely to gesture and move. This phenomenon is summarized as the activity level. It is calculated by integrating acceleration magnitude with a variable leak rate depending on head pitch angle. We used this value as an indicator for the first component - engagement in focused tasks. As opposed to this dimension, the second axis (*casual*) is more likely to involve speech and social interactions. This dimension includes activities such as casual conversation with a friend, casual phone conversation, and a coffee break. Therefore, we chose sound level as an indicator for the second component. Due to its position, the microphone on Glass is most sensitive to the wearer's voice.

Activity and sound level are measured and processed locally on Glass and streamed in real-time to the central control unit using the OSC protocol. A simple low-pass filter is then applied to the incoming data. The filter constant is a very crucial parameter for the overall user experience. It determines the responsiveness of the adaptive system. Fast response can be distracting and unpleasant. Slow, seamless changes are preferred. The speed of transition will be discussed further in section 3. Similar to the previous section, we mainly focus on the effect of the first two axes. The third dimension (*work with displays*) can be adjusted using a manual control interface. In future work, this control parameter could be derived from an activity tracking application on

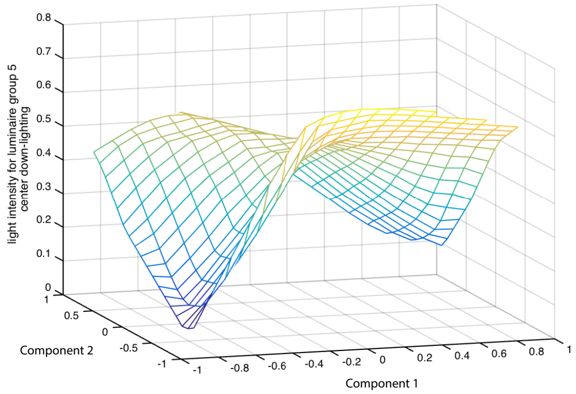

Figure 8: Light intensity settings of the center down-lights for various inputs of the first two components and constant third component $u_3 = 0$. Settings range from 0 to 1 where 1 is the brightest.

Context	RC2	RC1	RC3
casual conversation with a friend	0.86		
informal phone conversation	0.86		
coffee break	0.78		
sketching on paper		0.79	
study/memorization		0.75	
hand-craft		0.72	
formal phone conversation		0.67	
brainstorming in a group		0.63	
programming/CAD or video editing on a computer			0.76
informal presentation with slides			0.74
creative task using a computer			0.68
(routine) email on computer			0.63
formal presentation with slides			0.60
reading a magazine			
Proportion Explained	0.35	0.35	0.30

Table 2: Rotated component (RC) loadings of the 14 contexts, only loadings above a 0.5 criterion are shown, we named RC1, RC2, and RC3 *attentive*, *casual*, and *work with displays* respectively.

the user's personal computer, using the first person camera on Google Glass, or advanced light measurements.

A GUI control interface is available to the user for manual correction. This interface has a combination of three sliders and one 2D pad (see figure 11). Using the 2D pad, the user can adjust the position of the operating point similarly to the smart phone application. Using the three sliders, the user can independently adjust the 3rd axis, light intensity, and color temperature. User input is treated as an offset to the sensor-driven operating point.

We used the embedded light sensor on Google Glass for closed-loop feedback. A proportional-integral (PI) controller keeps brightness level in the field of vision at a constant. Reference brightness is set to a high level initially and can be adjusted manually. This design choice reduces the context-dependent variation of brightness, but this mainly applies for the illumination of close-by objects. The light sensor is less responsive to the overall appearance of the room. For example in a scenario where the user is looking at the table,

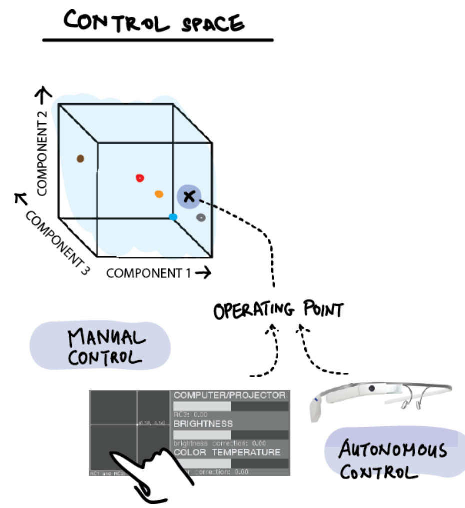

Figure 11: This diagram illustrates the final phase of implementation. Using wearable sensors for activity recognition, we autonomously determine the operating point. Manual correction is possible.

the sensor value can remain constant for down-light illumination on the table or illumination with wall-washers. In the first case, the room will appear dark and for the latter bright. In a future version, we would like to also couple the reference brightness to user context.

Estimating the power consumption was the result of a joint collaboration between the researchers and the lighting equipment suppliers. The power consumption of each light fixture was estimated from data obtained from the OEM during the analysis stage of this project. Future work entails directly measuring the power consumption at the AC feeder in the lighting testbed. For the following analysis we used the linear model below for power P

$$P(v_R, v_G, v_B, t) = v_R(t) * \alpha + v_G(t) * \beta + v_B(t) * \gamma. \quad (3)$$

The coefficients α, β, γ are determined with linear regression using 16 power measurement points at two different color temperatures, 3000K and 6500K, and 8 different brightness levels, from 20lx to 600lx. This linear model gives us a fair estimation for a limited range of intensities and colors. We define $\overline{P}$ the average power over time for the span of the experiment session.

2.3.2 *Panel*

The panel consists of 5 participants from 20 to 36 years old. The participants are affiliated with the University and thus familiar with wearable technology.

2.3.3 *Study setup and protocol*

The test environment is identical to that of section 2.2.4.

We invited each participant to work in the office for 30 to 60 minutes on their normal work tasks. These include programming, reading, writing, being on the phone, and crafting. They were also able to have casual conversation with the interviewer. At the beginning of the study the manual control interface was explained in detail to the participants and they were asked to familiarize themselves with it. They were allowed to adjust the lighting conditions manually at anytime. Participants wore Google Glass during this entire study. The device was running the activity recognition application in the background and did not give the user any visual feedback on the head-mounted display. We did not explain which sensors were used to control the lights.

The interviewer was present in the office space during the span of the entire study, working independently or interacting with the participant in a colleague-like fashion. The interviewer did not wear Google Glass or change the lighting manually, and at the end we discussed the experience with the participant in an informal conversation. Beside the qualitative study, we recorded system behavior and estimated total power consumption as described in equation 3.

2.3.4 Results

The average estimated $\overline{P}$ across all subjects is 145W with standard deviation of 24W. The participants performed casual tasks as well as focused tasks, each person in a different ratio. We think the activities were representative for common office work. In a non-adaptive scenario, scene two is most likely to be chosen because, according to figure 10, it is suitable for attentive and casual tasks. Compared to scene two, the adaptive controller enabled 38.15% of estimated energy savings. Compared to the brightest preset, we achieved 52.09% estimated energy savings. One explanation is that the brighter scenes are positioned towards the edge of the control space. High brightness settings are activated only during highly attentive tasks. Social tasks and less focused activities call for settings with less energy consumption such as scene 1 and 3.

	P (in W)	Average horizontal illuminance (in lx)
Scene 1	57.20	176
Scene 2	235.09	376
Scene 3	108.69	224
Scene 4	303.46	568
Scene 5	167.93	636
Scene 6	46.52	60

	$\overline{P}$ (in W) Average	Standard deviation
Experiment	145.40	24.07

Table 3: Estimated power consumption and average horizontal illuminance level measured at table height.

During the interview, we learned that the participants overall agree with the adaptively chosen lighting conditions. They described different reasons why they thought the lighting supported their activities. Subject 1 described the lighting as a indicator for social interaction. The lighting configuration revealed the state of social interaction in the shared office space. When both interviewer and participant were focusing on individual tasks and not interacting, the operation point was low on the casual axis and high on the focus axis. In this situation the participant felt encouraged to keep on focusing on his task and to not disturb the state that both users of the office had implicitly agreed on. This effect was enhanced by the slow control adaptation, which created contextual inertia. A different participant saw the lights as an reminder to go back to work when the lighting slowly adapted to a more casual setting. Subject 4 mentioned that the conversation felt nicer with the adaptive system, but showed concerns that there might be a situation where that is not the desired effect, for example in a very formal conversation. The same participant also noted that he enjoyed that the light focused on the table when he looked down to work. Participant 5 described the system as following: "when I am multitasking, the lights are not trying to do something in particular, but trying to compensate for multitasking, therefore the effects are subtle. Maybe, if I spend more time in here, I will notice the effect more". Overall the adaptive process was described as slow, natural, and subtle. In rare cases, the system performed fast transitions, which were noticeable and not preferred by the participants. Two out of 5 participants used the manual controller to correct the lighting settings. In both cases, the user explained that they prefer a different color temperature. The input was recorded as an offset and applied thereafter.

3. DISCUSSION

Slow adaptation allowed the adaptive lighting system to move from high to low energy settings without disturbing the user. The speed of adaptation is an important variable. In our preliminary study, participants described impact on comfort and social behavior. Some transitions were described as especially pleasant or supportive, because they provided feedback to the user's action, for example as a focus indicator. In this study, the lighting scene was controlled solely by the participant. The influence of lighting as a social indicator is especially interesting for further studies, where multiple users would be equipped with a wearable like Google Glass. In that case the room could be dynamically split into multiple lighting zones or perform multi-objective optimization.

The participants overall agreed with the lighting changes, yet 2 of 5 participants readjusted using the manual controller, explaining that they preferred warmer or colder light. Considering preferences on an individual level, the system could take into account user identity or individual user ratings extracted from the survey data, or learn from manual adjustments. Offerman, et al. [25] show varying preferences across groups. Different mappings of individual and collective preferences should be explored in future research.

Furthermore we want to mention that during the design of our experiments we tried to be conscious about the complexity and interdisciplinary nature of this problem in the real world. In public or office buildings, lighting design is part of the architect's work, sometimes in collaboration with lighting designers or lighting technicians. It is important to ensure an aesthetic appearance in line with the design of the building. Lighting designers have in-depth knowledge and intuition for illumination needs of a space, but in most cases the design process happens before the inhabitants of the space are known; as a result, there is often no communication between designer and user, and the level of customization is limited. Despite attempts to provide flexibility with reconfigurable lighting tracks, pre-programmed lighting scenes and zones, it remains difficult to meet the needs of the dynamic, modern meeting and work environments. The application designer, in this case the creator of the Google Glass application, is normally not involved during this process.

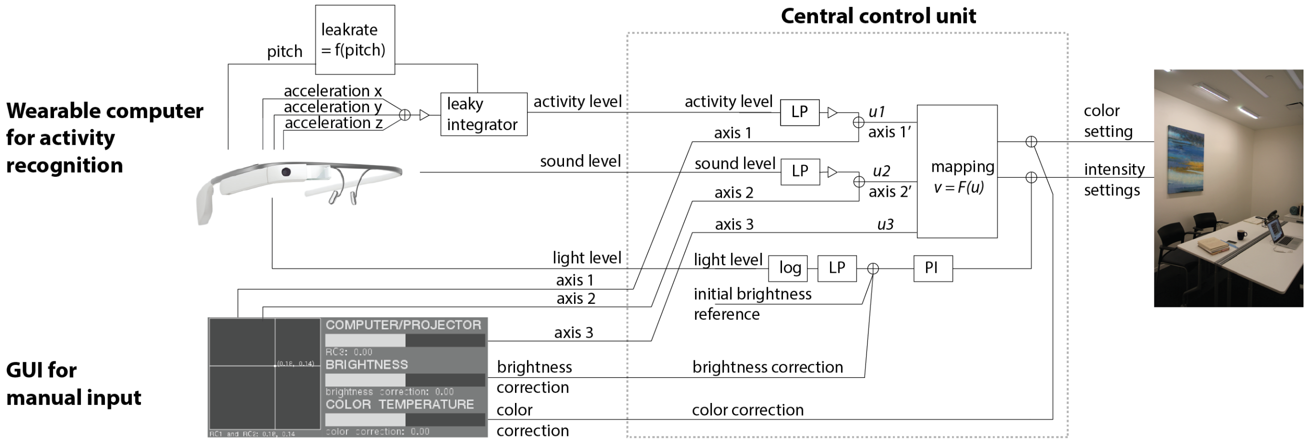

Figure 12: This diagram illustrates system architecture and signal path and processing.

In our approach, we tried to bridge the gaps in today's practice. Therefore we invited a lighting designer to choose the presets based on limited information about the use of the space, given as the 14 example tasks. With the preference survey, a time-delayed communication channel between lighting designer and user is simulated. Finally, based on the information obtained though user feedback, the application designer is able to optimize context adaptation according to the specific needs of the space and the users. The differences between the results from the studies in the virtual and the physical environment could be interpreted as an indicator of space-specific needs.

To take this idea a step further, the level of customization can be increased, for example by allowing the user to add or subtract items from the list of relevant tasks, or design their own lighting scenes. The application designer could label each of the relevant tasks, rather than the component axes, with appropriate activity recognition features. This way, the final selection of features could be automated without knowledge about the meaning of the components. In our paper we described the integration of Google Glass and manual control using a two dimensional representation. Other kinds of sensors or control methods, e.g. gesturing, pointing, etc. can be easily mapped to the control space and opens up many possibilities for the application designer. [6] has shown the potential of using an array of sensors to substitute the initial user survey. Using a sensor based approach to synthesize and map the control space for arbitrary rooms could potentially speed up the setup process. Ideally, the process would combine expert knowledge, sensor based initial calibration, and user input over time to achieve a best fit with maximal customization.

4. CONCLUSION

In this paper we demonstrated an approach and implementation for continuous, context-aware lighting control. The results of our experiments confirmed the potential of such a system to improve comfort, performance, and energy consumption. We applied dimensionality reduction on user ratings of preset lighting scenes for different tasks to generate continuous contextual control axes. We used superposition to map the control space to lighting settings. We furthermore implemented activity recognition with Google Glass to create an adaptive lighting environment. In our preliminary user study with the adaptive system, we estimated significant power savings of up to 52%. We believe this approach works not just for Google Glass but for any array of sensors. Because we used continuous adaptation, we were able to adjust lighting conditions without interrupting the user. The transitions were described as slow, natural, subtle, and pleasant overall. The speed of adaptation had a perceivable impact on comfort and social behavior, and is an interesting variable for further research.

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