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Lighting Quality Research using Rendered Images of Offices

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Abstract

Forty participants viewed a series of high-quality, colour images of a typical open-plan partitioned office, and rated them for attractiveness. The images were projected at realistic luminances and 33% of full size. The images were geometrically identical, but the outputs of four lighting circuits depicted in the renderings were independently manipulated. Initially, the lighting circuit outputs were random, but a genetic algorithm was used to generate new images that retained features of prior, highly-rated, images. As a result, the images converged on an individual's preferred scene. Luminances in the preferred image were similar to preferred luminances chosen by people in real settings. A sub-set of images was rated on Brightness, Non-Uniformity and Attraction scales. Ratings were significantly related to simple photometric descriptors of the images. In particular, around 50% of the variance in Attraction ratings was predicted by average image luminance and its square, or by average image luminance and a measure of luminance variability.

1. INTRODUCTION

The traditional method of exploring preferred luminous conditions involves participants evaluating full-scale spaces lit in different ways. These studies are expensive, especially if one wishes to manipulate the lighting design between evaluations. There has been some interest, from both researchers and lighting designers, in other presentation methods, such as scale models, photographs, or computer renderings. Research in areas such as forestry, architecture and urban design [e.g. Daniel & Meitner, 2000; Danford & Willems, 1975; Rohrmann & Bishop, 2002; Bishop & Rohrmann, 2003] have established that images can be a reasonable surrogate for the real space, particularly on ratings related to aethestics. The limited lighting research on this topic concurs with this, when using photographs [Hendrick et al., 1977], or highly-detailed simulations [Mahdavi & Eissa, 2002].

However, these studies were limited to the evaluation of predefined scenes. With this approach one can compare ratings of images to real spaces, find which of a set of images is most preferred, and look for general trends, but one cannot easily find the *optimal* scene. Johnston [1999] and Johnston & Franklin [1993] described an interesting method using computer-generated images of faces to arrive at an optimally attractive face. Software initially presented a series of faces with random variations of features (e.g., hair colour, size of chin, separation of eyes). A participant rated each face for attractiveness. Using a genetic algorithm, the software then combined the most attractive faces to produce new combinations of faces and the rating process was repeated until a face with an optimal rating was arrived at. This proved to be an effective method of finding an optimally attractive face from a vast combination of possible faces. Furthermore, the features of the preferred faces correlated well with the results of studies using real faces. In this study we applied Johnston's method to computer-generated images of lit scenes.

We are not the first team to apply genetic algorithms to lighting problems. Ashdown [1994] described a process for using genetic algorithms in non-imaging optics to find optimal luminaire designs. Eklund & Embrechts [2001] used genetic algorithms to optimize filter design to develop energy-efficient light sources with desired spectral output. Chutarat & Norford [2001] described an inverse method utilising genetic algorithms to derive the physical parameters of a room to produce desired daylighting performance. Corcione and Fontana [2003] used genetic algorithms to optimize the lighting designs for outdoor sports facilities. However, all of these studies used physical performance measures as criteria for success, not subjective evaluation.

Deterministic optimization techniques, rather than genetic algorithms, have been applied to illumination in the computer graphics domain. In Kawai et al. [1993], a user specified target luminous conditions and software generated the optimal luminaire focussing and output. Schoeneman et al. [1993] allowed the user to "paint" lighting patterns on a rendered scene and then determined the light outputs and colours from a set of fixed luminaires that would most closely match the desired pattern. One drawback of these techniques is that they are based on the user's pre-existing biases towards a desired solution. The genetic algorithm approach does not assume that participants can describe their preferred solution in advance, it only requires that they will know their preferred conditions when they see them.

Moeck [2001] developed software to directly manipulate the luminance and chromaticity of surfaces in a computer-generated image. These surfaces served as light sources themselves with realistic inter-reflections. However, Moeck's software tool was designed for trial-and-error exploration as a teaching tool, and not as an optimization tool.

In a previous study Newsham et al. [2004] used software to present images to participants who rated them on an attractiveness scale. Successive images varied only in the luminance of important surfaces. The software used a genetic algorithm to develop the optimally attractive combination of luminances for each participant. The results were encouraging: the method was efficient in producing attractive images, and the preferred luminances chosen were consistent with preferred luminances chosen in experiments conducted in real spaces. Further, ratings of image brightness, uniformity and attractiveness were significantly related to simple photometric descriptors of the image.

This work, although promising, suffered from the limitation of using an image of low realism. Although derived from a photograph of a real office, it was displayed in greyscale only. Luminance modifications were made to surfaces in the image independent of other surfaces, and therefore with no inter-reflection. Also, there were no visible sources of illumination. These were all deliberate choices to simplify the work. In this study we applied similar techniques to a more realistic image. The image used in this experiment was a high-quality colour rendering of an office space. Instead of manipulating the luminances of independent surfaces, we manipulated the output of four independent groups of luminaires, thus introducing realistic illuminance sources and inter-reflections.

The general goal of this experiment was to replicate and extend the findings of Newsham et al. [2004] using a more realistic image. Specifically, this experiment was designed to test these hypotheses:

- The genetic algorithm is an efficient method to generate a highly attractive image
- Highly attractive images are rated differently than non-optimal images
- Preferred luminances derived from images are the same as those derived in experiments in real spaces
- Subjective ratings correlate with photometric descriptors

2. METHODS & PROCEDURES

2.1 Participants

The 40 participants were non-research staff from within our organization, and were naive with respect to lighting. Participation was voluntary, and the reward for participation was limited to a free drink and snack. Data was collected in August and September, 2003. Participants could choose to do the experiment in either English or French; data from both language groups were pooled for analysis. Participant characteristics are shown in Table 1.

Participants were given a general description of the experiment both verbally and on paper, and asked to sign a consent form. All further information, instructions and tasks were presented on screen.

2.2 Image Evaluation

During the experiment, participants were asked to rate a series of images of an open-plan, partitioned office space, with a single workstation (or “cubicle”) in the foreground. These are increasingly common workspaces, and we have also conducted experiments in real spaces of this kind.

We used Lightscape™ to generate the basic images used. An example image is shown in Figure 1. The geometrical content of all images used was identical; only the lighting depicted changed from image to image.

The lighting was changed by varying the output of four independent groups of luminaires:

- an undershelf task lamp in each workstation: max. intensity 624 cd
- direct/indirect suspended direct/indirect fixtures on a 5ft x 10ft grid:
    - up component: max. intensity 811 cd
    - down component: max. intensity 1828 cd
- ceiling-recessed wall-washers at the perimeter of the room: max. intensity 1543 cd

Figure 2 shows the model used for the renderings, showing dimensions and luminaire location. The viewpoint used to render the images was at the entrance to the cubicle at the top left. Most workstation objects not visible from this viewpoint were excluded from the model, reducing rendering time without substantially affecting the luminous conditions.

2.2.1 The software used

Software was written to present the images, to conduct the image manipulation according to the genetic algorithm, to administer questionnaires, and to store data. A flow diagram is shown in Figure 3.

Participants saw an initial set of 12 images, and rated each one for attractiveness, on a scale of 1 to 10. Images were presented one at a time, separated by 10 seconds when the screen was blank. Ten of the initial 12 images were random combinations of luminaire outputs, and were therefore different for every participant. The other two images were the same for all participants: an image with all luminaires at maximum output, and an image with all luminaires at a low (non-zero) output (labelled '*Maximum*' and '*Minimum*' in Figure 4). These images were randomly ordered within the other 10, and were included to give an early indication of the range of possible luminances. This set of 12 formed the initial "population" of images. Then the genetic algorithm process began.

2.2.2 The genetic algorithm

The algorithm was designed to mimic the process of Darwinian evolution. "Parent" images were selected from the population. One parent was the image with the highest attractiveness rating. The second parent was selected randomly from the population, but selection was weighted according to the image's attractiveness rating. These parent images "reproduced", creating "child" images, and passing on successful "genes".

To describe the process mathematically, first we define "genes" for an image. We had four groups of luminaires each of which had 32 possible levels of output, arranged between 0 to 100%. In binary terms, the output of each luminaire group varied between 00000 and 11111 (i.e., between 0 and 31 in decimal terms). For example, an output level of 9 (or ~29% of full output) was represented by the gene 01001, a level of 22 (or ~71% of full output) by 10110, and so on. Five binary digits for each of four luminaire groups resulted in a 20-digit binary string, or "phenotype" uniquely representing the luminaire outputs in a particular image (see Figure 4 for examples).

We mimicked sexual reproduction with operations on the binary strings called crossover and mutation (see Figure 5). The two parents (the "father" and the "mother") produced two offspring (the "son" and the "daughter"). To create the son's phenotype, we started with the first binary digit in the father's phenotype. For each digit, reading from left to right, we randomly tested to see if crossover occurred, if it did not, the son's digit was a copy of his father's and the next digit of the father's phenotype was tested. If crossover did occur the son's digit was a copy of his mother's and the next digit of the mother's phenotype was tested. The possibility of crossover at each digit was set at 25%.

We also included random mutation, which could create gene combinations which otherwise would not occur. The possibility of mutation at each digit was set at 4%. The daughter was created in the same way as the son, except the process began with the mother's phenotype.

An extra element was introduced to help the participant guide the genetic process – they indicated for each of four surfaces in an image whether they preferred it brighter, the same, or darker. The interface is shown in Figure 1. Because participants were unfamiliar with lighting technology, we articulated the luminaire outputs in terms of surface brightness. Therefore Undershelf brightness preference affected the output of the task light; Ceiling brightness preference affected the direct/indirect up component; Desk brightness preference affected the direct/indirect down component; and Far Walls brightness preference affected the wall washers. The image did not change directly with these preferences, but when the next child was created, it was checked against the participant's brightness preference for each surface. If the child did not meet the set of preferences it was rejected and another child created and tested, until a satisfactory child was created. The approach of guiding the genetic process can increase the efficiency of a genetic algorithm [Caldwell & Johnston, 1991].

The children were then presented to the participant and rated for attractiveness. If they were rated more highly than the lowest rated images in the existing image population then they replaced these images, otherwise they were discarded. The process of parent selection and child creation continued until one of three end conditions was reached:

- An image received an attractiveness rating of 10;
- A participant preferred no brightness changes for all four surfaces;
- Neither of the latest two child images were rated more highly than the least attractive member of the existing population.

2.2.3 Semantic differential ratings

After the end condition was reached, participants rated the appearance of six images on a series of semantic differential (adjective pair) scales. Two of the images rated were the image with the highest attractiveness rating in the final population (*Best* image), and the image rated third highest from the initial population (*75th percentile* image), both of which were (potentially) different for every participant. The other four images rated were identical for all participants. These were the *Maximum* and *Minimum* images described above, an image designed to give similar, mid-range, luminances on all surfaces (*Neutral* image), and an image designed to have the same overall luminance as the *Neutral* image but with higher luminance on the ceiling and far walls (*Ceiling Boost* image). These latter four images are shown in Figure 4.

Newsham et al. [2004] used 15 adjective pairs for semantic differential ratings. Factor analysis of their data suggested three basic factors related to attractiveness, uniformity, and brightness. We wanted to keep the time required of each participant to 30 minutes, so we used only nine individual rating scales in the present study. These nine scales were made up of three sets of three, each set designed to load on factors of Attraction, Non-Uniformity[1], and Brightness. The three Attraction scales were: *ugly* –

[1] This label is expressed in this way because higher values of the final variable indicated more variability, whereas lower values indicated uniformity.

beautiful; pleasant – unpleasant; comfortable – uncomfortable. The three Non-Uniformity scales were: *varied – unvaried; simple – complex; non-uniform – uniform*. The three Brightness scales were: *bright – dim; dark – light; radiant – murky*. The six images were presented in random order, with each adjective pair presented one at a time next to the image. Participants gave their rating by moving a cursor on a continuous scale between the two adjectives; the value recorded ranged from 0 to 100.

Finally, the *Best* image was recalled to the screen and the participant was asked to indicate, for each surface in turn, whether they would prefer it to be A lot Brighter, a little Brighter, No Change, a little Darker, or A lot Darker. The image did not change in response to this input.

Completion of the on-screen part of the experimental procedure took a mean time of 19:12 (min:sec); s.d. = 5:53.

2.2.4 A note on image rendering

Four lighting circuits each with 32 levels of output means 32^4 , or 1.05 million possible unique images. Rendering high quality images on-demand, or pre-rendering all of the images in advance were not possible. Instead, we rendered all combinations of light output from the four circuits at four levels: 0, 33, 67 and 100% of full output, which gave 256 images. We then devised an interpolation scheme to generate any other possible combination of luminaire outputs from these 256 images in less than 10 seconds with low error (more information on this process is available at: http://irc.nrc-cnrc.gc.ca/ie/lighting/office/images_e.html).

2.3 The Experimental Space

Images were projected onto a viewing screen using an InFocus LP530 data projector (see Figure 6). Participants sat in a chair and viewed the image through a height-adjustable rectangular slot. The inside of the space was completely black except for the image. The participant had access to a keyboard and a mouse for questionnaires and ratings.

The distance from the projector to the viewing screen affected both the size of the image and the maximum brightness of the image. We chose a distance that gave an image that was 1.30m (51") wide and 0.83m (33") high; the computer monitor in the image was 0.125m (5") corner to corner, or about 33% of full size. Luminances in the image were then up to ~140 cd/m^2, a typical maximum for most surfaces in a non-daylit office.

2.4 Luminance Measurements

To calibrate the display we projected a target onto the screen with five blocks of uniform grey, and measured their luminance values used a Topcon BM3 luminance meter. We adjusted the brightness and contrast settings on the projector to get a condition where the 0 grey level ("black") was close to 0 cd/m^2, the 255 grey level ("white") was close to a typical maximum luminance, and the relationship between grey level and luminance was close to linear in the most common luminance range (20 – 80 cd/m^2). The final calibration is shown in Figure 7.

With the brightness and contrast levels fixed, we made the same calibration measurements prior to each participant's experimental session. These measurements are also shown in Figure 7. These data show that the projector's output was not constant between sessions, and could vary by 10 – 15%. This seemed to be part of normal projector functioning. This effect does create error in the experimental process. However, the effect was largest at the high end of possible luminances, which were not achieved very often (only 24% of the *Maximum* image area was greater than 80 cd/m^2), and were much smaller than the possible luminance range created by lighting circuit output settings.

After the experimental sessions were completed, the *Best* and *75th percentile* images for each of the participants, as well as the *Maximum*, *Minimum*, *Neutral*, and *Ceiling Boost* images, were re-projected in a different laboratory. These images were measured using a Radiant Imaging Prometric video photometer, which took a digital picture of these stimuli and provided a luminance measurement for every pixel.

3. RESULTS & DISCUSSION

3.1 Did the Genetic Algorithm Lead to a Highly-Rated Image?

The mean attractiveness rating of the *Best* image (scale of 1 to 10) was 8.6 (s.d. = 1.3), and the modal rating was 9. When offered the opportunity to express a final preference in surface brightnesses of their *Best* image, 44% of the 160 votes (4 surfaces x 40 participants) were for 'No Change', and 89% for the three middle categories of 'No Change', 'A little darker' or

‘A little brighter’. A large majority of those wanting change preferred an increase in brightness, and preferences for change were not evenly distributed by room surface. For example, the number of participants wanting no change to the desk brightness was low; on the other hand, satisfaction with the brightness of the perimeter was high, with few people wanting change.

A measure of the efficiency of the algorithm is the number of images seen by the participants. Five participants gave an attractiveness rating of 10 to one of the 12 images in the initial population. The mean number of images seen was 21.7 (s.d. = 10.3), small compared to the number of possible images.

Although the *Best* image was not perfectly optimal, it was rated very highly. Participants were viewing an image of a relatively uninspiring office space, and some might not have given a rating of 10 in any circumstances. The *Best* image was achieved after viewing relatively few images. However, many participants desired further small brightness changes to their final *Best* image, particularly an increase in desk brightness. The mean dimmer setting for the downward component of the direct/indirect fixtures, the circuit that most affected the desktop, was only 56%. This suggest that the optimization process did not allow participants to achieve high desktop brightness without compromising other preferences. Therefore, there is room for improvement.

3.2 Are the Optimal (*Best*) Images Rated Differently than Non-Optimal Images?

We explored this was through the semantic differential appearance ratings of the images. Figure 8 shows the mean ratings for the six images for each of the adjective pairs. The mean brightness-related ratings for the *Maximum* image are close to 100, and for the *Minimum* image are close to 0, therefore including the *Maximum* and *Minimum* images in the initial population to establish a brightness scale was successful. The *Neutral* and *Ceiling* Boost images were designed to have the same overall luminance, and their mean brightness-related ratings are very similar. Also as expected, the *Best* image has the highest mean scores on the attraction-related ratings (*ugly – beautiful, unpleasant – pleasant, uncomfortable – comfortable*), whereas the *Minimum* image rates poorly.

Our plan was to reduce these nine ratings to the three concepts related to Attraction, Non-Uniformity, and Brightness. It is clear from Figure 16 that the mean values of ratings related to Attraction and Brightness were very consistent. It is equally clear that the scales intended to relate to Non-Uniformity neither agree with each other, nor discriminate very well between the six images[2]. The single scale *uniform-non-uniform* does order the mean ratings in the expected manner: the *Minimum*, *Maximum*, and *Neutral* images are the most uniform, and the *Ceiling Boost* image is the least uniform. Therefore, for further statistical tests, our measure of Non-Uniformity was the single item rating *uniform – non-uniform*. Descriptive statistics for the three scales are shown in Table 2.

We conducted statistical analyses on these three subjective outcomes to test differences between the images. There were *a priori* reasons for the following comparisons:

- *Best* vs. *Neutral* – a test of whether optimal images differed in ratings from another image, in this case the comparison is to a non-optimal, "average" image;
- *Best* vs. *75th percentile* – a more rigorous test of whether optimal images differed in ratings from another image, in this case the comparison is to a non-optimal, but relatively attractive image;
- *Best* vs. *Maximum* – previous research [Newsham et al., 2004] suggested that brighter images were more attractive; this comparison tests whether the optimal image, which is not maximally bright, differs in ratings from the maximally bright image;
- *Neutral* vs. *Ceiling Boost* – previous research [Newsham et al., 2004] suggested that brighter ceilings were more attractive; this comparison tests whether images with the same brightness overall differ in ratings when the ceiling is brighter in one of the images.

We first conducted overall multivariate analyses of variance (MANOVA) for the planned comparisons to test for an overall difference across outcomes. It is usual practice (to control for Type I statistical errors) to test for univariate differences (differences on single outcomes) only if the overall MANOVA is significant. Only two of the planned comparisons had significant MANOVAs; the results of the tests are shown in Table 3.

The *Best* image was rated significantly brighter and more attractive than the *Neutral* image, as expected. On average, the *Best* image had higher

[2] These impressions were supported by the Cronbach's Alpha statistic of scale reliability.

luminance (see Table 4): 36.9 cd/m^2 vs. 28.4 cd/m^2. The *Best* image was rated significantly less bright than the *Maximum* image, and the *Maximum* image had a higher luminance (55.6 cd/m^2). Nevertheless, the *Best* image was significantly more attractive than the *Maximum* image, suggesting that images that are too bright are less attractive. Previous research [Newsham et al., 2004] suggested that images that are too uniform are also less attractive, and the *Maximum* image was rated as significantly more uniform than the *Best* image.

There was no significant difference between the *Best* and *75th percentile* images on the room appearance ratings. There was little difference between the images in luminance (*75th percentile* image mean was 35.6 cd/m^2). Note that the ratings of image attractiveness made on a scale of 1 – 10 used during the optimization process did differ significantly between the two images (*Best*: Mean=8.6, s.d. 1.3; *75th percentile*: Mean=6.6, s.d. 1.5; $F(1,39)=69.98$, $p<0.001$, $\boldsymbol{\eta^2}_{\textit{partial}} = 0.64$). In Newsham et al. [2004] the *75th percentile* image was much less realistic than the *Best* image, and there were significant differences in room appearance ratings. Perhaps the use of more realistic images meant the range of appealing images was wider.

The MANOVA showed no significant difference in ratings between the *Neutral* and *Ceiling Boost* images. Therefore the finding of our previous work, which indicated the primacy of ceiling luminance in determining attractiveness, was not supported. This could have been because the images were both too dim, or because we did not boost the ceiling luminance enough in the *Ceiling Boost* image.

3.3 Are Preferred Luminances the same as Those Derived from Experiments in Real Spaces?

Table 4 presents a summary of the luminance information from the images, and Figure 9 shows how the image was divided into surfaces for analysis. Table 4 also contains a physical measure of image luminance non-uniformity, labelled RMS, calculated as follows:

$$RMS = \sqrt{\left(\sum_i ((Lum_i - WAV)^2 \cdot N_i) \,/\, (\sum_i N_i) \cdot WAV\right)}$$

where,

i = surface label for 1 to 9 surfaces
Lum_i = mean luminance of surface i (cd/m^2)

WAV = weighted average luminance of image (cd/m^2)
N_i = number of data points (relative area) for surface i

RMS accounts for the difference between the individual surface luminances and mean luminance. It is scaled by the mean luminance, so that images do not have higher values just by virtue of being brighter. The higher the value of RMS the higher the physical non-uniformity.

We compared the preferred luminous conditions in the *Best* images to those derived from experiments in real spaces. All of the studies we refer to in this section excluded daylight, analogous with our study.

Loe et al. [1994] had observers rate a small conference room from a point equivalent to the room's entrance. Lighting conditions were manipulated by the experimenters using a variety of luminaires. They concluded that for 'visual lightness' the preferred average luminance in a horizontal band 40^o wide should be >= 30 cd/m^2. We have approximated an equivalent average luminance, shown in Table 4 with the label '40-deg band'. This is the weighted mean luminance of the far walls, other cubicles, partitions, desk, and computer screen. The median value in the *Best* images was 37.7 cd/m^2, and only 9 participants chose *Best* images with the 40-deg band luminance below 30 cd/m^2.

Veitch and Newsham [2000] conducted a study in a similar workstation in a laboratory. Participants had dimmable control over three lighting circuits (one indirect and two direct) as well as on-off control over an undershelf task light. Participants occupied the space for an 8-hour day and conducted typical office tasks. One value reported was the mean luminance in an area that included the partitions behind the computer and under a binder bin, part of the desktop and part of the binder bin – chosen to represent the 40^o horizontal band of field of view from Loe et al. [1994]. The median luminance in this area resulting from participants' choices was 39.2 cd/m^2 (min. = 11.5, max. = 61.0). The median luminance of the partitions and 40-deg band in the *Best* images was 35.5 cd/m^2 (min. = 12.3, max. = 55.9), and 37.7 cd/m^2 respectively.

Berrutto et al. [1997] gave participants dimming control over various luminaires in small private offices. Exposures were limited to 20 minutes, and data were collected separately for different tasks. They concluded that for non-VDT tasks wall luminance at eye level should be around 60-65 cd/m^2, and for VDT tasks the luminances around the screen should be equal or lower than the luminance of the screen. In our study, the median screen luminance in the *Best* images was 30.6 cd/m^2 and the partitions had a median luminance of 35.5 cd/m^2.

Van Ooyen et al. [1987] presented participants with different office luminous environments by manipulating light distributions and changing the reflectivity of surfaces; working plane illuminance was maintained at around 750 lux. The spaces were private two-person offices, and data were collected separately for different tasks. For non-VDT tasks, preferred wall luminances were 30 to 60 cd/m^2, and preferred working plane luminances were 45 to 105 cd/m^2. For VDT work the values were reduced: preferred wall luminances were 20 to 45 cd/m^2, and preferred working plane luminances were 40 to 65 cd/m^2. In our study, the median partition luminance of the *Best* images was 35.5 cd/m^2, and the median desktop luminance was 52.5 cd/m^2. Van Ooyen et al. reported that the preferred ratio of working plane luminance to wall luminance was 1.33. In our study, the equivalent ratio, desk:partitions, was 1.49. Note that with the lighting systems we modelled, a low desk:partition ratio was very difficult to achieve.

Finally, we looked at the variability in individual preference. We observed a wide variety of preferred luminances in the *Best* images. This is encouraging because studies of individual preference in real spaces also report wide variety. We performed a quantitative comparison to the results of Veitch and Newsham [2000]. Figure 10 shows a plot of two measures of the frequency of preferred luminance: for Veitch and Newsham we plot the mean luminance in the (approx.) 40^o horizontal band of field of view (as described above). For this study, we plotted the derived value labelled '40-deg band' in Table 4. The two curves show remarkable agreement.

Taken together, these comparisons show that the preferred luminances derived from our study compare well with the preferred luminances from studies in real spaces. As such, these comparisons reinforce the hypothesis that the images are perceived in the same way as real spaces.

3.4 Do Subjective Ratings Correlate with Photometric Descriptors?

Lighting researchers have often sought to correlate occupant ratings of luminous environments with photometric descriptors. This task has proven difficult, though some progress has been made [for example: Flynn et al., 1979; Loe et al., 1994; Veitch & Newsham, 1998; Newsham & Veitch, 2001].

Therefore we examined whether photometric measures of the images (such as those in Table 4) were predictive of Attraction, Non-Uniformity, and Brightness ratings, using linear regressions. We began by including ratings and photometric values for all six images rated using the semantic differential scales. This gave us 240 data points per regression (6 images x 40 participants). Because each participant provided six data points, the points are not independent and simple regressions would provide misleading results. Two of the six images varied between participants, making traditional analysis-of-variance techniques inappropriate. The relatively new statistical technique of Hierarchical Linear Modelling (HLM, or mixed regression) [Bryk & Raudenbush, 1992; Hox, 1995] accounts for the within-subject effects in this kind of analysis. Conceptually, this analysis consists of creating separate regression lines for each participant, and then testing the distribution of regression weights (slopes and intercepts) against the null hypothesis that the average regression weight equals zero. The technique also produces a single best-fit regression line across all data points[3]. The results of the HLM analyses are summarized in Table 5.

We expected that images with a higher average luminance (labelled 'WAV' in Table 5) would have higher Brightness ratings. The HLM analysis showed the linear trend was significant, and the proportion of variance explained was high (0.72). Note that the intercept was close to the origin, as expected: an image with a luminance of zero should get a zero rating of Brightness.

We were concerned that the linear relationship between Brightness and WAV was being driven by ratings of images at the extremes of the luminance range: the *Minimum* and *Maximum* images. We therefore repeated the analysis with these images removed. The linear trend was still significant and strong, with coefficients similar to those from the analysis with all six images: intercept = -6.8; slope = 1.71 ($t = 8.59$, d.f. = 39, $p < 0.001$); proportion of variance explained = 0.51. Similarly, in the

[3] The model we generally used was a random intercept and random slope model with no centering, with one or more photometric predictors at level-1, and no level-2 predictors; we were interested in explaining whether photometric variables predicted appearance ratings (level-1), and not in investigating what participant characteristics might have led to differences in ratings between participants (level-2).

analyses of Uniformity and Attraction below, we found that removing the data from the *Minimum* and *Maximum* images did not substantially affect the results. Therefore, all analyses in Table 5 include data from all six images.

The weighted average luminance was highly correlated (r > 0.85) with all the other luminances shown in Table 4. This is almost inevitable with real lighting systems. We did repeat the HLM analysis on Brightness ratings using the other luminances as predictors, but found that all were very similar in predictive power. Therefore, we conducted other analyses with WAV as the luminance predictor.

Previous work using the genetic algorithm method [Newsham et al., 2004], and using brightness matching and rating scales methods in real spaces [Tiller & Veitch, 1995; Tiller et al., 1995] found a significant relationship between ratings of brightness and photometric uniformity: less uniform images were rated as being more bright. Data from this study supported this. Table 5 shows a significant relationship between Brightness rating and RMS, with a positive slope. However, using WAV and RMS together as predictors of Brightness ratings did not increase the predictive power over using WAV alone. WAV and RMS are correlated (r = 0.37), with more luminous images tending to be less uniform. The relationship between Brightness and RMS might have resulted from this confound, although this seems unlikely given that the relationship between brightness and uniformity was observed in two experiments in which uniformity varied while average luminance was held constant [Tiller & Veitch, 1995; Tiller et al., 1995].

We also found a significant relationship between Brightness rating and the ratio between desk and partition luminance (labelled DSK:PAR in Table 5). The slope was negative, indicating that the lower the luminance difference between these two surfaces the higher the Brightness rating. However, using WAV and DSK:PAR together as predictors of Brightness ratings did not increase the predictive power over using WAV alone. WAV and DSK:PAR were highly correlated (r = -0.83), with more luminous images tending to feature desks and partitions with more similar luminances. The relationship between Brightness and DSK:PAR might have resulted from this confound.

For Non-Uniformity, the obvious first predictor was RMS. The relationship between Non-Uniformity ratings and RMS was significant and in the expected direction. The intercept was very close to zero, as expected: an image where all surfaces had the same mean luminance should be subjectively rated as very uniform. This result supports the relationship found in Newsham et al. [2004], but is not as strong. This is likely because in the previous work the range of photometric variability between images was much larger.

Whereas there were obvious photometric predictors for ratings of Brightness and Non-Uniformity, there were no such obvious predictors for ratings of Attraction. Newsham et al. [2004] showed that brighter images were rated as more attractive, so we began there. Table 5 shows that the relationship was significant, WAV explained 30% of the variance in Attraction ratings. Figure 8 suggests that the relationship with WAV was not linear, the *Maximum* images received lower average attractiveness-related ratings then the *Best* images, despite having a higher average luminance. This implies a quadratic component to the relationship, and therefore we examined Attraction vs. WAV and WAV^2. This relationship was also significant, and explained 50% of the variance in Attraction ratings, substantially more than WAV alone. The coefficients were also in the expected direction: positive for WAV so that Attraction increases with luminance at low luminances, and negative for WAV^2, resulting in a penalty on Attraction if average luminance is too high.

Newsham et al. [2004] also suggested that some non-uniformity increased attractiveness, but excessive non-uniformity decreased attractiveness. Therefore, we examined the Attraction vs. RMS relationship. The relationship was significant with a positive coefficient, the more non-uniform the image, then more attractive it was rated. To test if excessive non-uniformity was negative for attractiveness, we examined Attraction vs. RMS and RMS^2. This relationship explained 27% of the variance in Attraction ratings, a little more than RMS alone. The coefficients were also in the expected direction: positive for RMS so that Attraction increased with non-uniformity at low non-uniformity, and negative for RMS^2, resulting in a penalty on Attraction if non-uniformity was too high. However, although the RMS coefficient was significant, the RMS^2 coefficient just failed the significance test ($p = 0.059$). Normally we do not comment on non-significant tests (and this test is not included in Table 5), but we comment here because of the theoretical interest in this trend. The lighting design we used to create the images did not generate a large range of values photometric uniformity. Images with more variability might produce a significant Attraction vs. RMS and RMS^2.

As noted above, WAV and RMS are positively correlated, and it could be that the significant relationship between Attraction and RMS arose because images with higher RMS values also tended to be brighter. Therefore we examined Attraction vs. WAV and RMS. Table 5 shows that this relationship was significant, and explained 47% of the variance in Attraction ratings, substantially more that either WAV or RMS alone. This result suggests that RMS is contributing unique explanatory power.

The obvious next step would be try WAV, WAV^2 and RMS together as predictors. Unfortunately, given the data we had, the HLM analyses were not stable for three predictors. Future studies with more participants observing more images might allow for HLM analyses with more predictors.

The models of Attraction vs. WAV and WAV^2, and Attraction vs. WAV and RMS both explained about the same proportion of variance. We encourage others to explore these relationships in future studies, both with images and with real spaces as stimuli. We also recommend ensuring a wider range for the photometric predictor values.

4. CONCLUSIONS

The general goal of this experiment – to replicate and extend the findings of Newsham et al. [2004] using a more realistic image – was met. The results demonstrated that the genetic algorithm approach was quite successful in obtaining a participant's preferred luminance patterns in a high-quality, realistic colour image of an office space. Further, the preferred luminances from the projected images were very similar to those from experiments conducted in real settings.

Importantly for lighting quality research, subjective ratings of room appearance in the image were significantly related to photometric descriptors of the image. Ratings of image brightness were predicted by the average luminance of the image (WAV), and by a measure of photometric non-uniformity (RMS). Ratings of image non-uniformity were predicted by RMS. And, in particular, ratings of image attractiveness were predicted by various combinations of WAV, WAV^2, RMS, and RMS^2. The latter result indicates that an attractive image of an office space is one that is bright, but not too bright, and that has some non-uniformity but is not too non-uniform.

Our results suggest that evaluation of images has value as both a research tool and a method of presenting lighting design solutions to clients and occupants. If future work reinforces our findings that image evaluation is equivalent in many ways to the aesthetic evaluation of real spaces, this method might, in some circumstances, be able to replace much more expensive studies in real settings.

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Table 1. Participant characteristics.

	Total responses					
Sex		*Female*	*Male*			
	40	28	12			
Age		*18-29*	*30-39*	*40-49*	*50-59*	*60-69*
	40	2	9	16	13	0
Correction Lenses		*None*	*Reading Glasses*	*Distance Glasses*	*Bi- or Trifocal Lenses*	*Gradual or Multifocal Lenses*	*Contact Lenses*
	40	10	3	12	8	5	2
Principal Occupation		*Administrative*	*Technical*	*Professional*	*Managerial*	
	40	22	0	15	3	
Language		*English*	*French*			
	40	32	8			

Table 2. Descriptive statistics for the three scales used in statistical tests.

Image	**Attraction** *(ugly – beautiful, unpleasant – pleasant, uncomfortable – comfortable)*	**Non-Uniformity** *(uniform – non-uniform)*	**Brightness** *(dim – bright, dark – light, murky – radiant)*
Best			
Min.	0.0	0.0	6.0
Max.	100.0	100.0	100.0
Med.	67.8	39.5	57.8
M	63.8	42.6	58.1
SD	26.2	28.6	24.7
75th percent			
Min.	0.0	0.0	5.3
Max.	100.0	100.0	100.0
Med.	53.0	49.0	49.7
M	53.3	41.4	55.6
SD	29.2	28.1	29.0
Neutral			
Min.	0.0	0.0	0.0
Max.	88.0	80.0	100.0
Med.	36.3	40.5	38.3
M	39.8	36.6	41.3
SD	25.4	22.0	27.3
Ceiling Bst.			
Min.	0.0	0.0	0.0
Max.	100.0	100.0	91.7
Med.	34.5	50.0	35.0
M	37.5	45.0	41.2
SD	24.4	27.6	26.5
Maximum			
Min.	0.0	0.0	0.0
Max.	100.0	97.0	100.0
Med.	28.7	20.5	94.3
M	41.4	25.4	89.6
SD	37.4	26.4	13.6
Minimum			
Min.	0.0	0.0	0.0
Max.	85.7	92.0	34.3
Med.	5.3	10.5	1.7
M	11.8	24.2	5.1
SD	19.9	27.8	7.6

Table 3. Result of MANOVAs and univariate effects on appearance ratings. Statistical tests were within-subjects on a single independent variable: image type; with two levels in each comparison. Only statistically significant effects are shown ($p < 0.01$). $\eta^2_{partial}$ is a measure of effect size, or proportion of variance explained by the effect.

Outcome	***Best* vs. *Neutral***		***Best* vs. *Maximum***	
	F(1,39)	$\eta^2_{partial}$	**F(1,39)**	$\eta^2_{partial}$
Attraction	28.24	0.42	9.76	0.20
Non-Uniformity			7.98	0.17
Brightness	9.68	0.20	55.79	0.59
	MANOVA: Wilks' $\Lambda = 0.528$; $\eta^2_{partial(ave)} = 0.22$; $F(3,37) = 11.01$		MANOVA: Wilks' $\Lambda = 0.362$; $\eta^2_{partial(ave)} = 0.32$; $F(3,37) = 21.69$	

Table 4. Luminance-related information for the six different images (cd/m^2). Values from the Best and 75^{th} percentile images were different for each of the 40 participants, therefore measures of variability are shown. Values for the Neutral, Ceiling boost, Maximum and Minimum images were the same (within experimental error) for every participant. Values for combinations of surfaces were calculated by weighting each surface's contribution according to its size.

***Best* image**	**Min.**	**Max.**	**Median**	**Mean**	**s.d.**
Ceiling	7.9	57.5	40.5	37.5	14.3
Far walls	13.6	62.4	42.1	39.8	14.2
Other cubicles	12.4	54.0	32.1	32.9	11.7
Left partitions	9.3	54.4	34.7	34.4	11.4
Left desk	15.2	74.1	55.3	53.3	14.3
Right partitions	10.5	57.0	33.9	34.5	12.9
Right desk	12.6	73.5	50.2	48.5	16.5
Computer Screen	17.5	43.3	30.6	30.3	7.0
Other Image Areas	14.0	45.4	31.1	30.3	8.6
Weighted Average	13.8	57.4	36.6	36.9	11.7
Left partitions + Left desk	11.2	60.7	41.0	40.4	12.2
Right partitions + Right desk	11.3	63.0	39.4	39.5	14.1
Left partitions + Right partitions	12.3	55.9	35.5	34.4	11.9
Left desk + Right desk	19.9	73.8	52.5	50.3	14.6
40-deg band	14.7	60.2	37.7	38.3	12.3
Desk : Partitions	1.32	1.76	1.49	1.50	0.11
RMS	1.0	2.3	1.2	1.4	0.3

Table 4. continued …

***75th percentile* image**	**Min.**	**Max.**	**Median**	**Mean**	**s.d.**
Ceiling	7.2	52.6	44.4	38.1	13.5
Far walls	9.6	56.7	45.0	39.0	15.1
Other cubicles	6.9	48.6	33.9	31.7	10.4
Left partitions	4.7	49.4	33.8	31.5	10.4
Left desk	7.3	68.6	52.8	49.2	15.2
Right partitions	6.8	50.7	33.8	32.8	11.0
Right desk	10.4	68.8	50.1	47.0	14.7
Computer Screen	14.2	38.4	29.9	29.4	5.9
Other Image Areas	9.5	41.3	29.9	29.2	7.6
Weighted Average	8.0	51.9	38.5	35.6	11.0
Left partitions + Left desk	5.5	55.6	39.8	37.1	11.9
Right partitions + Right desk	8.1	56.7	39.4	37.9	12.3
Left partitions + Right partitions	6.0	50.1	33.5	32.2	10.5
Left desk + Right desk	9.3	67.0	50.1	47.8	14.2
40-deg band	7.8	54.3	38.7	36.5	11.5
Desk : Partitions	1.34	1.76	1.48	1.50	0.09
RMS	0.7	1.7	1.2	1.2	0.2

	Image Type			
	Neutral	***Ceiling Boost***	***Maximum***	***Minimum***
Ceiling	29.4	38.0	56.8	7.4
Far walls	32.6	41.8	61.7	10.8
Other cubicles	25.6	26.2	52.5	7.0
Left partitions	20.7	19.9	51.5	4.8
Left desk	32.5	28.6	70.3	7.6
Right partitions	27.3	24.3	55.7	6.9
Right desk	41.9	33.9	71.6	10.8
Computer Screen	25.9	24.8	41.0	15.2
Other Image Areas	24.6	23.2	42.9	10.1
Weighted Average	28.4	29.1	55.6	8.2
Left partitions + Left desk	24.5	22.7	57.5	5.7
Right partitions + Right desk	32.6	27.8	61.4	8.3
Left partitions + Right partitions	24.5	22.4	53.9	6.0
Left desk + Right desk	38.3	31.9	71.1	9.6
40-deg band	29.0	28.3	58.3	7.9
Desk : Partitions	1.57	1.42	1.32	1.59
RMS	1.0	1.3	1.1	0.7

Table 5. Results of the HLM analyses. Each line shows a separate regression model, using the predictor variables indicated. All coefficients (slopes) shown are statistically significant ($p < 0.05$). All intercepts shown were also are statistically significant ($p < 0.05$), unless shown in italics. WAV=Weighted Average Luminance; DSK:PAR=Desk:Partitions.

Outcome	Predictor	Intercept	*t (d.f. = 39)*	Coefficient	*t (d.f. = 39)*	Proportion of Variance Explained
Brightness	WAV	-7.8	-2.49	1.75	22.37	0.72
	DSK:PAR	352	15.74	-205	-13.48	0.48
Non-Uniformity	RMS	*-1.3*		32.6	4.73	0.26
Attraction	WAV	20.0	3.59	0.62	3.62	0.30
	WAV, WAV^2	*-5.4*[F]		2.66, -0.032	5.94, -3.99	0.50
	RMS	*-13.7*		48.2	6.86	0.21
	WAV, RMS	*-11.2*		0.41, 32.8	2.09, 4.27	0.47

Note, in this analysis the proportion of variance explained refers to variance at level-1, at the level of the individual ratings. The total variance at level-1 is calculated using a 'random intercept model' that is, an HLM model with no predictors; call this σ_1^2. We then add the level-1 photometric predictor, which reduces the unexplained level-1 variance to σ_2^2. The proportion of variance explained at level-1 is then $(\sigma_1^2 - \sigma_2^2)/ \sigma_1^2$.

[F] This is a fixed intercept model, meaning that when HLM calculates regression equations for each participant, it assigns each participant the same (best-fit) intercept. Our general preference is to use a non-fixed (random) intercept for our models, but this particular model is not stable without a fixed intercept. Nevertheless, a fixed intercept, with a value close to zero, is not unreasonable in this case. With a luminance of zero it is a reasonable assumption that all participants would give an Attraction rating of zero.

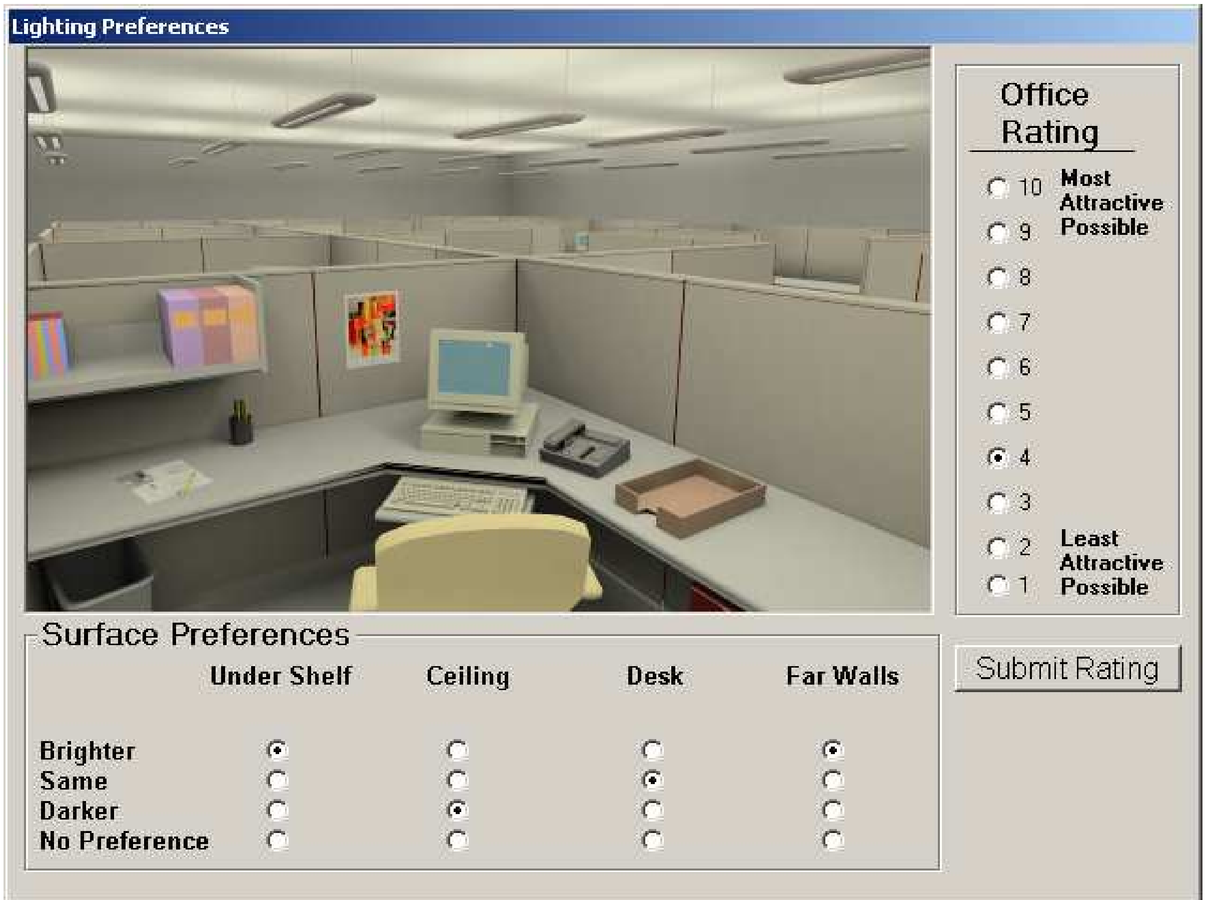


Figure 1. Interface for the experimental task. Participants rated the image for overall attractiveness on a scale of 0-10. They then used the boxes at the bottom to indicate their brightness preference for each surface. Example images can be viewed in colour at: http://irc.nrc-cnrc.gc.ca/ie/lighting/office/images_e.html

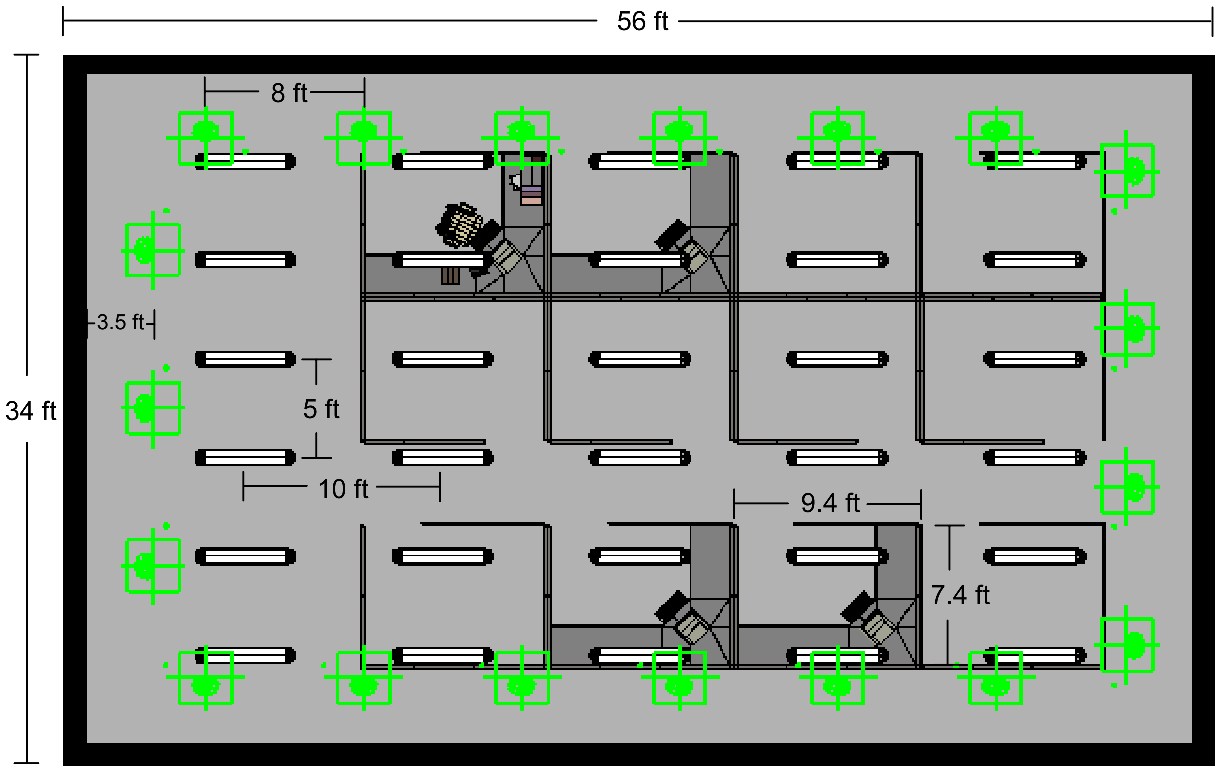


Figure 2. A plan view of the model used for the Lightscape™ renderings. The suspended direct/indirect fixtures are clearly visible as the white rectangles. The crosshairs show the centre of the wall washers.

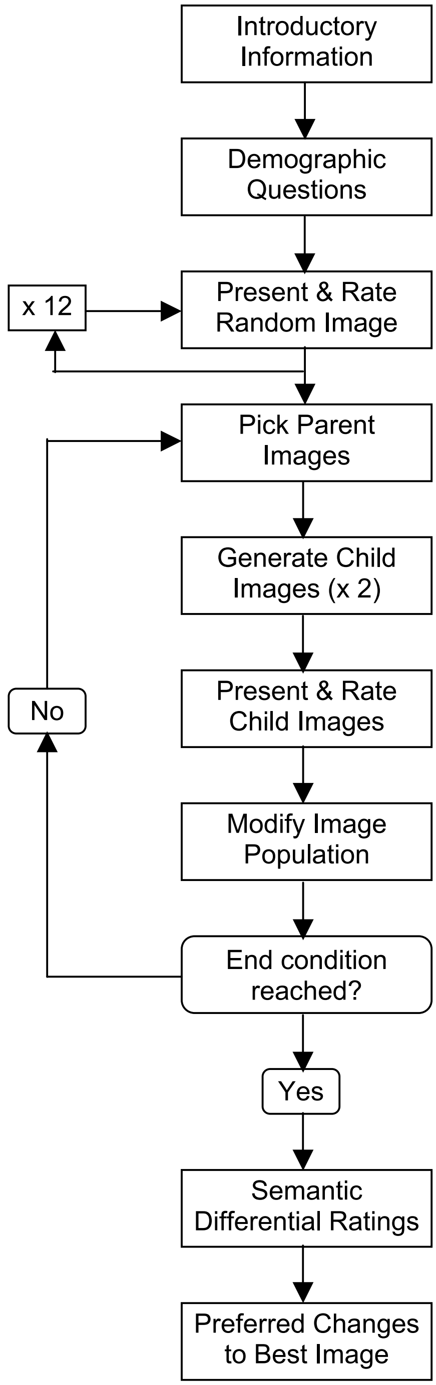


Figure 3. Overall flow diagram of software used in experiment

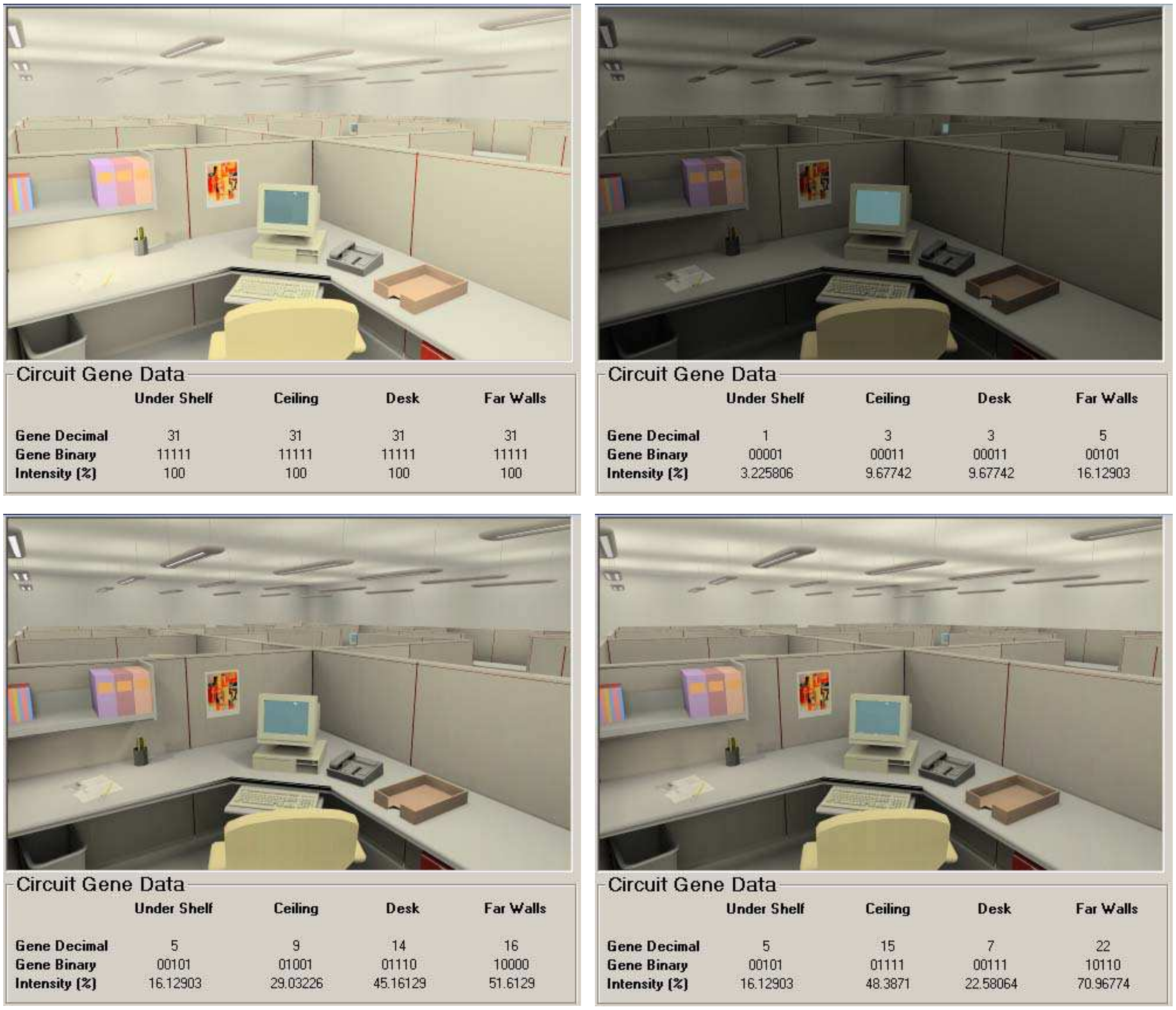


Figure 4. Four of the images used in the semantic differential ratings. Images are (from top left, clockwise): Maximum, Minimum, Ceiling Boost, Neutral.

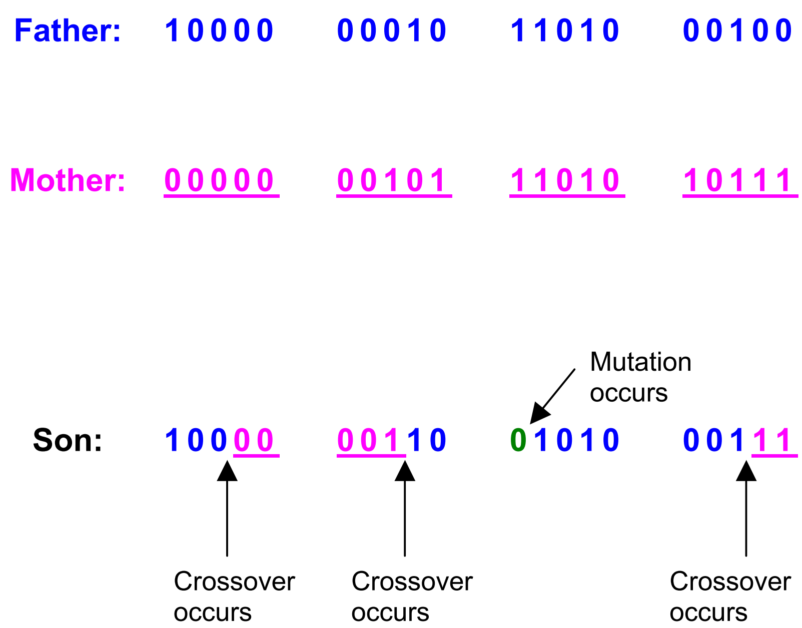


Figure 5. Crossover and mutation from parents' phenotypes (lower two images in Figure 4) to create a son phenotype; mother's genes are underlined. Resulting combination of surface luminances is shown.

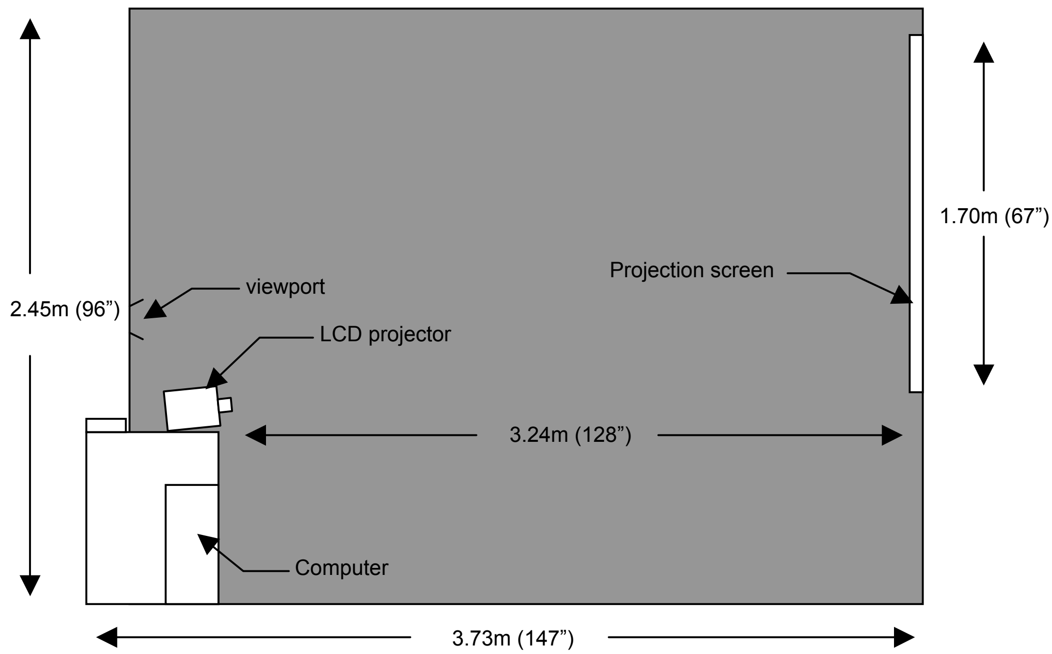


Figure 6. Experimental set-up. Participants viewed the projected image through a viewport (photo on left). The space into which they looked was black except for the projected image. Diagram shows side elevation, approximately to scale.

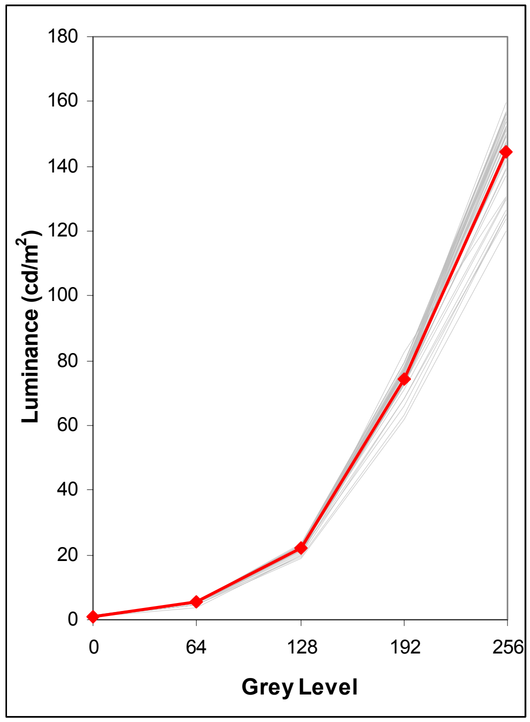
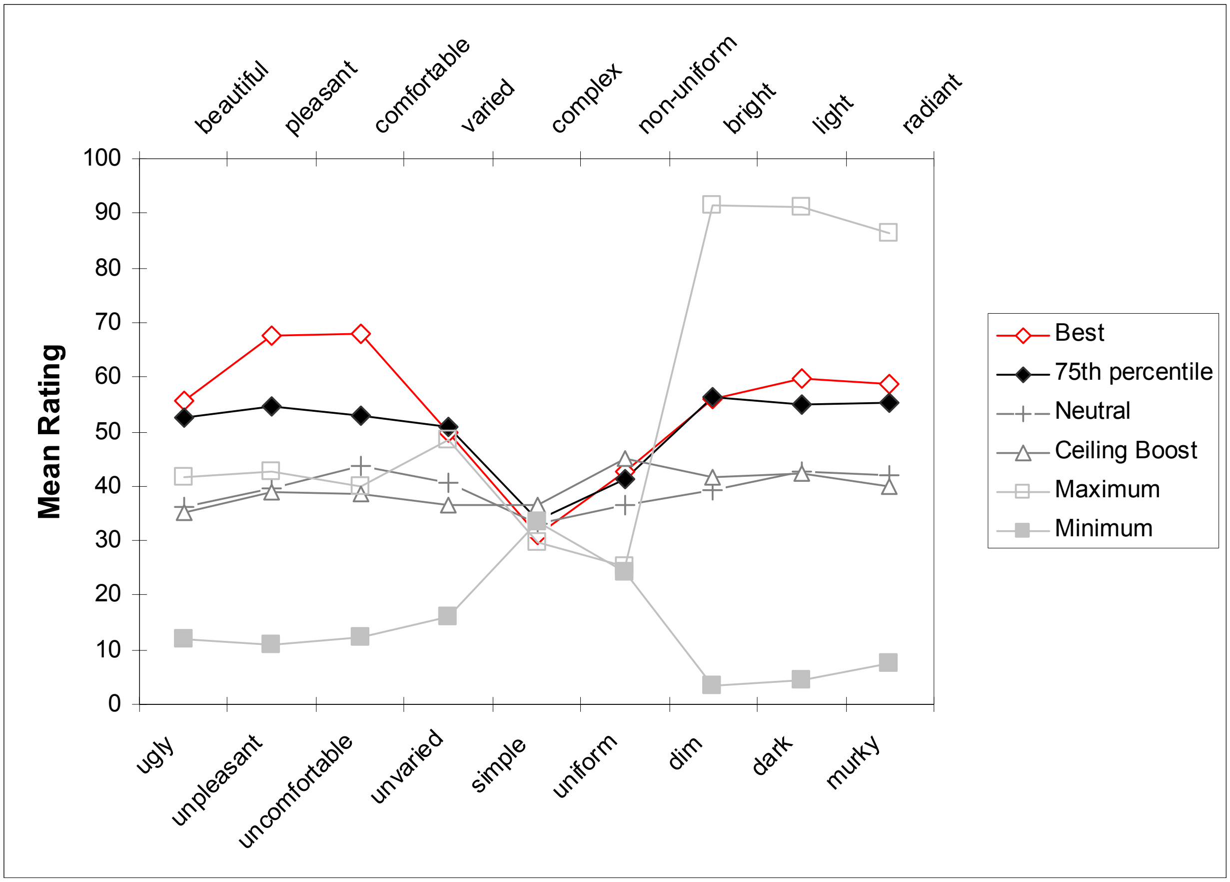
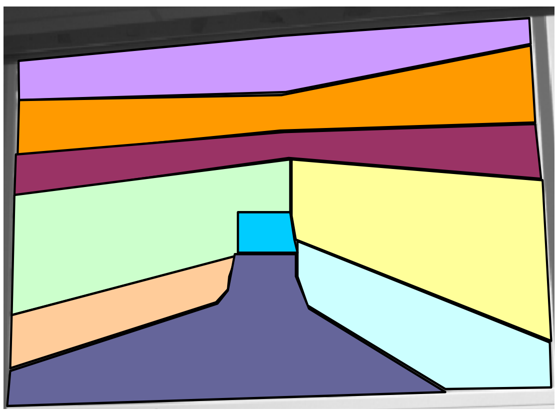


Figure 7. Calibration of projector screen luminance vs. image pixel grey level. Shown upper right is the image that was projected onto the screen to make the calibration measurements. Diamond symbols with heavy (red) line shows original calibration. Lighter lines show measurements made prior to each participant doing the experiment.



ugl-bea	unp-ple	unc-com	unv-var	sim-com	uni-non	dim-bri	dar-lig	mur-rad	**Image**
30.0	26.5	26.8	27.1	27.7	28.6	28.5	28.6	22.4	Best
30.1	32.6	30.9	29.7	25.1	28.1	30.3	32.5	29.4	75^{th} percentile
25.3	27.8	28.8	23.8	24.1	22.0	28.1	29.4	26.8	Neutral
25.7	27.7	24.4	26.3	26.9	27.6	27.8	29.3	26.5	Ceiling Boost
35.7	39.2	39.3	33.3	32.6	26.4	15.0	14.6	16.9	Maximum
17.0	21.1	23.5	19.5	35.6	27.8	6.8	7.0	12.0	Minimum

Figure 8. Comparison of mean semantic differential appearance ratings for the Best, 75^{th} percentile, Neutral, Ceiling Boost, Maximum, and Minimum images. Table shows standard deviations associates with each graph point.



	Surface	Pixels
	Ceiling	623
	Far walls	396
	Other cubicles	502
	Left partitions	437
	Left desk	205
	Right partitions	581
	Right desk	330
	Screen	42
	Miscellaneous	592

Figure 9. How the image was divided into areas for luminance analyses. Also shown are the number of data points for each surface from the Prometric output file, indicative of the relative area of each surface.

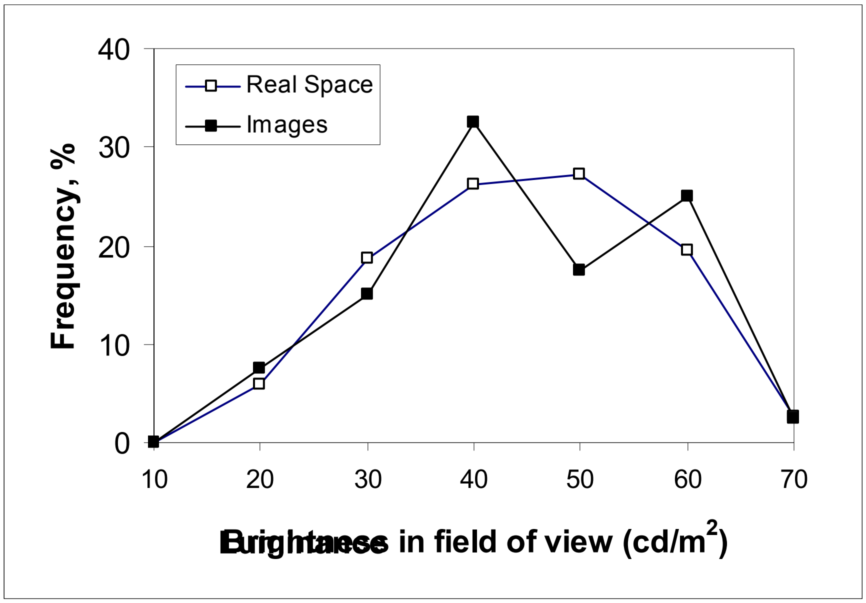


Figure 10. Preferred luminance in the field of view, for this study and a study done in a real space [Veitch & Newsham, 2000].