A Personal Visual Comfort Model: Predict Individual's Visual Comfort Using Occupant Eye pupil Size and Machine Learning

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Abstract. Lighting, as a significant component of indoor environment qualities, was found to be a primary contributor of deficient indoor environment in today's workplace. This is resulted from the fact that current guidelines are derived from empirical values and neglect the prevalence of computer-based tasks in the current offices. A personal visual comfort model was designed to predict the degree of occupant's visual comfort in order to provide a way of evaluating the indoor lighting environment. The model development draws from experimental data including occupant's eye pupil size, visual sensation and visual satisfaction in response to different illuminance levels collected from human subject test conducted for 6 participants. The results showed that (1) A personal comfort model is necessary for creating (2) the personal comfort model produced the median accuracy of 0.7086 for visual sensation and 0.65467 for visual satisfaction among all subjects; (3) For the current sample group, Support Vector Machine, as the algorithm used for developing the prediction model, outperformed Logistic Regression and Gaussian Naïve Bayes in terms of prediction accuracy. It was concluded that personal visual comfort models based on occupant's eye pupil size can generate effective prediction of individual's visual sensation and visual satisfaction and can therefore be applied with lighting control to improve the indoor environment and energy use in buildings.

1. Introduction

It was estimated that people in the U.S. spend 90 percent of their time indoors. The indoor environmental quality (IEQ), nowadays, has become the most crucial contributor to occupants' wellness. Good IEQ gives rise to positive physical and mental conditions, for example, high productivity, which can be remediation of the overworked situation today. Among all the factors defining IEQ, lighting is closely related to the occupant's visual perception. Visual perception is of great importance in the office environment because there is a large amount of information input through the visual path. The sensation of light determines the quality of perception and the comfort level of the lighting environment decides the efficiency of perception. Light is also significant for the human physiology regulation from a perspective of non-visual path of human photoreception. Therefore, office lighting environment should be designed deliberately.

However, the increasing demand for design with good IEQ has not been taken along with current interior lighting design guidelines. Requirements such as illuminance on the working plane are derived from either empirical values or experimental approaches in manipulated laboratory test instead of a real-life scenes. The required value is uniform for each functional zone which takes less account of diversity within occupants. In addition, the existing lighting guidelines mainly focus on paper-based tasks. It neglects the popularity of a computer-based work in current office environment.

The industry does pay effort to overcome the drawback of robust compliance with the guideline. For example, they use dynamic simulation tools (e.g. Radiance, Daysim) to better analyse the lighting condition. However, a frequent layout change afterwards stops the existing design being optimum even though the diagnosis achieves a comprehensive design during the design stage. Additionally, this kind of tool is unable to estimate the occupant's perception of the lighting environment.

To address the problems stated above, this study proposes a personal visual comfort model. A personal visual comfort model predicts individual perception of visual comfort for current lighting environment which provides assessment of lighting environment from the perceptive of occupants. The key characteristics of the personal comfort model are (1) Using single person as the unit of analysis instead of groups of people; (2) Using eye pupil size and survey results in response to different lighting settings to train a model; (3) Adopting a data-driven method (e.g. machine learning) which allows testing of different algorithms and variables; (4) Being able to adapt to new data. Personal comfort model provides a way of describing individual desires for visual comfort which can be used to accommodate a diversity of comfort needs by being integrated with a physical lighting control system.

2. Background

2.1. The relationship between eye pupil size and visual comfort

The pupil is a hole located at the center of the iris of the eye, giving light access to the retina. Physically, the variation of brightness will result in the dilation and contraction of the pupil, which is regulated by the iris to ensure that the right amount of light enters. In detail, the size of the pupil is determined by the activity of two kinds of smooth muscle in the iris – the sphincter pupillae and dilator pupillae. They operate in the opposite way. This physiological activity retains a stable physiological condition of the human body by reducing changes from the ambient environment.

Based on this physiological principle, researchers have conducted several experiments to study the reaction of eye pupils to different visual stimulations. Berman et al.[1] tested the eye pupil size patterns under different illuminance level, wall spectral reflectivity (e.g. different wall colors) and light source spectral distribution. It was revealed that log pupil area is linearly depended on log scotopic illuminance which is measured in the plane of the viewer's eyes. They used visual performance to label the eye pupil size, that is, smaller pupils correspond to improved visual performance even though it usually occurs with increased disability glare in the high luminance condition. Navvab[2] extended the research scope and included color temperature as other potential factors affecting visual acuity. He didn't measure the occupants' eye pupil size in his study but considered the pattern discovered by Berman that high illuminance level results in smaller eye pupil size and enhanced visual performance. He kept the illuminance level identical for two studied lamps with different color temperature. It was proved that full spectrum lamp of high color temperature outperforms conventional warm color temperature lamp in terms of visual superiority. For decades, eye pupil size has been discussed as the result of visual stimuli and then as a cause of variation in visual performance. There is no correlation investigated between eye pupil size and visual comfort.

Choi[3] reported such research gap and conducted fundamental research to figure out the feasibility to utilize eye pupil size as an assessment of occupants' visual sensation. The research validated its hypothesis by conducting the human subject experiment and analyzing experimental data. A major finding was that, for an individual human subject, different range of normalized pupil size corresponded to different visual sensation which was defined by a seven point scale and different subjects showed different patterns of this correlation, that is, different range value was found for identical visual sensation level for different human subjects. In addition, It was found that age can significantly influence the eye pupil size change pattern in response to the different light conditions[4]. This means eye pupil size, as a way of evaluating occupants' visual comfort, can accommodate variation within and between individuals. In other words, it can be used as a parameter to construct personal visual comfort model.

2.2. Human subject experiment as the source of data

The human subject experiment was designed to collect the data for the establishment of the model. The principle of the experiment was to record visual sensation and visual satisfaction level of a human subject, as a subjective report of visual comfort, under different lighting settings (e.g. illuminance level). The experiment was conducted in the environment chamber of Watt Hall at the University of Southern California University Park Campus (Figure 1a). The dimmable lamps (Figure 1c) were the only light sources for the sake of easy control.

Human subjects participated in the experiment to provide data for their visual comfort model. Each experiment could only accommodate one participant. Each experiment took 1 hour and 46 minutes and seated one human subject only. The experiment was divided into two parts. Firstly, the human subject took 10 minutes to adapt to the environment in the lab, especially the lighting condition, and filled in the pre-experiment survey. The pre-experiment survey aimed to provide a description of the human subject and his or her impression about his or her real-world office environment.

The lighting setting, primarily the illuminance on the working plane, was changed every 8 minutes and 12 times per test. The illuminance for each step was predetermined before the experiment. The values were picked from 100, 200, 300, 500, 550, 650, 800, 950, 1000, 1150, and 1250 lux. It should be noted that these levels fall within the range from 100 to 1400 lux. This was determined based on previous research finding that 100–1400 lux is the acceptable range for the majority of experimental subjects[5]. The order of lighting settings implemented in experiment was shown in figure 2a. Visual satisfaction and visual sensation were surveyed for each step to label lighting settings. The participants were asked to fill in the survey during the last minute of each step to make sure they had gotten enough exposure to the current setting.

Occupant's eye pupil size was recorded through entire experiment. Eye pupil size was captured by a mobile tracking eye module manufactured by ASL (Figure 2b). The module comes with tracking glasses, a display transfer unit, and a laptop. The tracking glasses are mounted with two cameras – a view camera to catch what the wearer is looking at and an eye camera to record the eye pupil size data. Both cameras are installed at the right eye side, which means the device only allows a single eye's data to be collected.

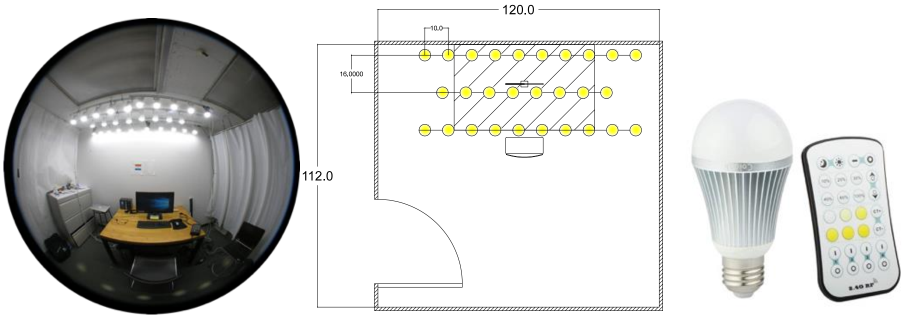

Figure 1. (a) Fish-eye view of the chamber; (b) Layout of the chamber; (c) Coidak 9W E26 dimmable LED light bulb

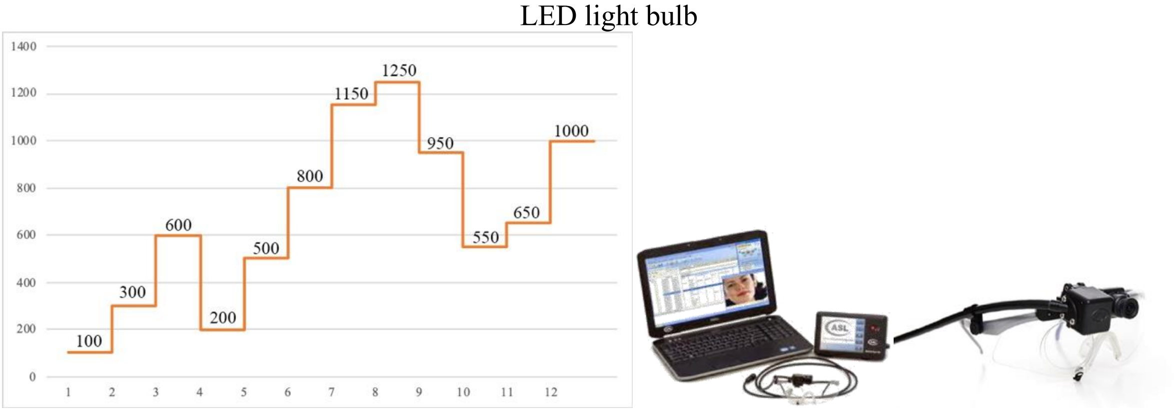

Figure 2. (a) Illuminance levels in experimental order; (b) Mobile tracking eye module

3. Methodology

3.1. Data preparation

The data was processed using the following steps: (1) Data cleaning: The original pupil size data was sampled at a rate of 30Hz which is heavy and noisy for processing. The granularity was modified to 1 Hz. The missing values were replaced with a value from the previous time frame. The unlikely values (i.e., beyond the expected range) were discarded; (2) Feature creation: Seven features were created based on the absolute pupil size recorded by the pupilometer. They were 30s moving average, 30s, 40s, 50s, 60s, 90s, and 120s gradient of eye pupil size with 30s moving average filter.

"Given a sequence $\{a_i\}_{i=1}^{N}$, an n- moving average is a new sequence $\{s_i\}_{i=1}^{N-n+1}$ defined from the a_i by taking the arithmetic mean of n terms, $s_i = \frac{1}{n}\sum_{j=i}^{i+n-1} a_j$".

The moving average filter filters out the short-term fluctuations within raw data but keeps the long-term data trend. In this case, the time window (n) was determined to be 30s because it reduced the noise at a maximum extent where the data sensitivity was still accessible. The gradient was defined as the difference between the moving average of eye pupil size at two individual timeframes, that is,

$$gradient\ (x) = S_t - S_{t-n}$$

where S is absolute pupil size processed by moving average filtering, t is the current time, and n is the time difference. The value of n should not be less than the time window size of moving average filter; (3) Data integration: Survey data about visual sensation and visual satisfaction were merged with eye pupil size data for every test subject.

3.2. Machine learning algorithms

This study adopted machine learning as the data driven method to solve the problem. The research problem was defined as a classification tasks of an occupant's visual sensation (Too dark/Dark/Neutral/Bright/Too Bright) and visual satisfaction (Very Dissatisfied/Dissatisfied/Neutral/Satisfied/Very Satisfied). These two labels were used to describe the visual comfort level of the occupant which also provides hints for how to improve current lighting condition, therefore, can be used to signal physical lighting control system to enhance the occupant's visual comfort level. Occupant's eye pupil size data was used as input feature for the visual comfort model.

The selection of machine learning algorithm is closely related to the performance of the visual comfort model and is determined by the size of input data, number of input features and tasks implemented. This research chose three machine learning algorithms for the establishment of the model – Gaussian Naïve Bayes (Gaussian NB), Logistic Regression (LR), and Support Vector Machine (SVM). Mathematical theory was not elaborated here but parameters setting for the algorithms were shown in table 1. Scikit-learn, a machine learning library for the Python programming language, was utilized as the main source of machine learning algorithms in this research. The major advantage of using a library is that the algorithms have been optimized for usage. For researchers outside the computer science domain, it allows machine learning to be easily accessed as a data analytic tool.

Table 1. Parameter settings for algorithms

Gaussian NB	**Var_smoothing = 1×10^{-9}**.
LR	**C=1.0**. It is the inverse of regularization strength. **Class_weight=None.** It specifies the weight assigned to the classes. All classes are given weight one if it is not clarified. **Random_state=0.** The seed of the pseudo-random number generator to use when shuffling the data. **Solver='lbfgs'.** This tells the algorithm used in the optimization problem. **Max_iter=100.** The maximum iteration allowed for convergence of learning. **Multi_Class='multinomial'.** A multinomial loss function is assumed to fit the data.
SVM	**C=1.0.** **Kernel='rbf'.** The kernel type is Radial-basis function (RBF) kernel. **Degree=3.** D=The degree of the polynomial kernel function used for the model. **Gamma='scale'.** The coefficient used in the kernel function. The value equals 1 / (n_features * X.std()). **Class_weight=None.** **Max_iter=-1.** -1 means no limit. **Random_state=None.**

3.3. Feature selection

The purpose of feature selection is to filter out the less relevant features in order to improve model performance. A boosted decision tree, called XGBoost in Python, was used as the primary method. It computes the score of importance of each feature in the construction of the boosted decision tree, allowing attributes to be compared with each other. According to Brownlee[6], "Importance is calculated for a single decision tree by the amount that each attribute split point improves the performance measure, weighted by the number of observations the node is responsible for." Therefore, the score is presented in a range between 0 and 1. It was expected that only four features would be kept for the establishment of the prediction model.

3.4. Performance evaluation

To evaluate the prediction performance of the model, prediction accuracy was adopted as the criterion. It was defined as the percentage of correct predictions made for the test data. Empirically, the original dataset was split into training and test data, with a ratio of 70:30. The dataset was prepared initially in a random state for the separation, in this case, to eliminate the time series effect of the data. Testing the model on a group of new data provided a more reliable demonstration of its performance. The mathematical expression of the prediction accuracy is shown below:

$$Prediction\ accuracy = \frac{number\ of\ correct\ predictions}{Total\ number\ of\ predictions\ made}$$

4. Results and Discussion

4.1. Feature selection

Table 2. Score of feature importance for visual sensation prediction

No.	Abs_ Size	Mov_ Ave_ 30s	Grad_ 30s	Grad_ 40s	Grad_ 50s	Grad_ 60s	Grad_ 90s	Grad_ 120s
1	0.0289	0.4161	0.0597	0.0820	0.0664	0.1403	0.0749	0.1318
2	0.0420	0.3798	0.0827	0.0598	0.0477	0.0878	0.1272	0.1730
3	0.0415	0.3639	0.0743	0.0752	0.0547	0.1295	0.1081	0.1528
4	0.0503	0.2556	0.1311	0.0748	0.0490	0.0927	0.1642	0.1821
5	0.0289	0.4190	0.1204	0.0612	0.0363	0.0921	0.0928	0.1493
6	0.0291	0.3814	0.0537	0.0895	0.0430	0.0962	0.1795	0.1276
Vote	0	6	2	1	0	4	5	6

Table 3. Score of feature importance for visual satisfaction prediction

No.	Abs_ Size	Mov_ Ave_ 30s	Grad_ 30s	Grad_ 40s	Grad_ 50s	Grad_ 60s	Grad_ 90s	Grad_ 120s
1	0.0303	0.4003	0.0768	0.0776	0.0580	0.1245	0.0839	0.1486
2	0.0636	0.3094	0.1121	0.0549	0.0473	0.0665	0.1413	0.2049
3	0.0397	0.4185	0.0893	0.0769	0.0527	0.1066	0.1135	0.1029
4	0.0525	0.2338	0.1299	0.0681	0.0612	0.1103	0.1542	0.1900
5	0.0263	0.3590	0.0921	0.0752	0.0357	0.1147	0.1071	0.1898
6	0.0393	0.3619	0.0569	0.0628	0.0411	0.0745	0.2170	0.1466
Vote	0	6	2	0	0	4	6	6

Pupil size with a 30s moving average filter, 60s gradient, 90s gradient, and 120s gradient were selected as features for the establishment of the visual sensation prediction model. This decision was based on a summary of votes, which is shown in table 2. In details, XGBoost would calculate the feature importance for predictive modeling of visual sensation for each participant. According to the scores, the ranking of features could be derived, and an effective vote would entitle the top 4 features for each test subject. By counting the votes for each feature, the top 4 would be selected for model establishment.

It can be seen that there were differences among participants in terms of features' ranking. The 30s moving average and 120s gradient of pupil size were recognized as the most correlated features by all 6 boosted decision trees constructed for each test subject. The importance computed for the 30s moving average was 0.3693on average, with a maximum of 0.4190 and a minimum of 0.2556. The 120s gradient of pupil size showed a lower average score of importance, which was 0.1528, with a maximum of 0.1821 and a minimum of 0.1276. Besides, the 90s gradient of pupil size was the third significant one, losing votes from human subject 1. The 60s gradient of pupil size was the last feature selected, with 4 votes. The 30s, 40s, and 50s gradients of pupil size got 2, 1, and 0 votes, respectively, and were filtered out because of the handful of votes. No vote was given to absolute pupil size.

Features selected for visual satisfaction prediction were identical.

4.2. Performance evaluation

Table 4. Prediction accuracy of visual sensation

No.	Data Size	Gaussian Naïve Bayes	Logistic Regression	Support Vector Machine
1	2276	0.54905	0.56808	0.71303
2	2308	0.67388	0.70418	0.68975
3	2279	0.53655	0.62281	0.67836
4	2294	0.68360	0.74020	0.75327
5	2307	0.78499	0.76190	0.80090
6	2266	0.73088	0.78676	0.82500

*The shading highlights the algorithm with the highest accuracy.

Table 5. Prediction accuracy of visual satisfaction

No.	Data Size	Gaussian Naïve Bayes	Logistic Regression	Support Vector Machine
1	2276	0.53587	0.59151	0.63690
2	2308	0.61039	0.48485	0.62771
3	2279	0.83772	0.85380	0.89327
4	2294	0.53556	0.61538	0.60377
5	2307	0.71140	0.67244	0.79221
6	2266	0.80294	0.83529	0.85882

*The shading highlights the algorithm with the highest accuracy.

Table 4 summarizes the prediction accuracy of visual sensation from three algorithms. The red shading highlights the algorithm generating the highest accuracy for each test subject. The size of the test data was different for each participant and is listed in the table for details.

It can be seen that prediction model of visual sensation adopting the SVM algorithm possessed the highest accuracy for 5 out of 6 participants. For the Each algorithm performed differently among individuals. For example, SVM produced an accuracy of 0.67836 for Participant 3 but an accuracy of 0.82500 for Participant 6. For different test subjects, the variation of performance among the three algorithms can be either remarkable or negligible. For example, Gaussian NB, LR, and SVM produced prediction accuracies of 0.54905, 0.56808, and 0.71303 for Participant 1. The difference between the highest and lowest values is 0.16396. However, the situation was different for Participant 2: The accuracy difference between the highest (LR = 0.70418) and the lowest (Gaussian NB = 0.67388) is 0.0303. These facts reveal that even though SVM performs the best for the majority of test subjects, the hypothesis that SVM would be the best option for the whole population is likely to be rejected in consideration of the individual differences.

5. Conclusion

It was found that personal visual comfort model provides an effective prediction of occupant's visual comfort. The median of prediction accuracy for visual sensation was 0.708605 and that for visual satisfaction was 0.65467. Pupil size with a 30s moving average filter, 60s gradient, 90s gradient, and 120s gradient of eye pupil size were selected as the most important features for the personal visual comfort model. Support vector machine was revealed as the algorithm that can produce the most accurate prediction, however, the statistical significance should be verified by a larger group of data.

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