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 environmental quality, was found to be a primary contributor to deficient indoor environments in today’s workplace. This resulted from the fact that current guidelines are derived from empirical values and neglect the prevalence of computer-based tasks in current offices. A personal visual comfort model was designed to predict the degree of an individual’s visual comfort, as a way of evaluating the indoor lighting of the environment. Development of the model relied on experimental data, including individual eye pupil sizes, visual sensations, and visual satisfaction in response to various illuminance levels used for tests of six human subjects. The results showed that (1) A personal comfort model was needed, (2) the personal comfort model produced a median accuracy of 0.7086 for visual sensation and 0.65467 for visual satisfaction for all subjects; (3) To develop a prediction model for the sample group, the Support Vector Machine algorithm, outperformed the Logistic Regression and the Gaussian Naïve Bayes in terms of prediction accuracy. It was concluded that a personal visual comfort model can use a building’s occupant’s eye pupil size to generate an accurate prediction of that occupant’s visual sensations and visual satisfaction that can, therefore, be applied with lighting control to improve the indoor environment and energy use in that building.

1. Introduction
It was estimated that people in the U.S. spend 90 percent of their time indoors.[¹] The indoor environmental quality (IEQ), nowadays, has become the most crucial contributor to occupants’ good health. A good IEQ gives rise to positive physical and mental conditions, that result in high productivity, which can be remediation for overworked situations today. Among the factors that define IEQ, lighting is closely related to an occupant’s visual perception. Visual perception is of great importance in an office environment because of the large amount of information that is input through the visual path. The sensation of light determines the quality of perception, while the comfort level of the lighting environment decides the efficiency of perception. Light is also significant for regulating human physiology, from a perspective of the non-visual path of human photoreception. Therefore, an office lighting environment should be designed deliberately designed.
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 tests, instead of from real-life scenes. The required value is uniform for each functional zone, without any emphasis on the diversity of the occupants. In addition, the existing lighting guidelines mainly focus on paper-based tasks, but neglect to address the popularity of computer-based work in current office environments.

To address the problems stated above, this study proposes a personal visual comfort model. This model depicts an individual’s perception of visual comfort in a specific lighting environment, and would permit assessment of the lighting from the perspective of an individual. The key characteristics of the personal comfort model are (1) Using a 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 program the model; (3) Adopting a data-driven method (e.g., machine learning) to allow testing of different algorithms and variables; (4) Adapting new data, provided by the personal comfort model, to describe individual desires for visual comfort that can be used to accommodate a diversity of comfort needs through integration with a physical lighting control system.

2. Background

2.1. The relationship between eye pupil size and visual comfort

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. 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. tested the eye pupil size patterns under different illuminance levels, wall spectral reflectivity (i.e., different wall colors), and light source spectral distributions. It was revealed that log pupil area is linearly dependent 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 corresponded to improved visual performance, even though they usually occur with increased disability glare in high-luminance conditions. For decades, eye pupil size has been discussed as the result of visual stimuli and then as a cause of variation in visual performance. However, no correlation has been investigated between eye pupil size and visual comfort.

Choi reported this research gap and conducted fundamental research to figure out the feasibility of utilizing eye pupil size as an assessment of occupants’ visual sensation. The research validated its hypothesis by conducting a human subject experiment and analyzing experimental data. A major finding was that, for an individual human subject, different ranges of normalized pupil sizes corresponded to various visual sensations (defined by a 7-point scale). However, all individuals did not exhibit the same pattern for this correlation since they each had a different range of value, even though the visual sensation level was identical. In addition, age was found to significantly influence the eye pupil size change pattern in response to different light conditions. This means that, when eye pupil size is used to evaluate an individual’s visual comfort, variations pertaining to that subject and other individuals can be accommodated. In other words, eye pupil size can be used as a parameter to construct a personal visual comfort model.

2.2. Human subject experiment as the source of data

The experiment using human subjects was designed to collect data as a basis for establishing a viable model. The principle goal of this experiment was to record visual sensations and visual satisfaction levels of a human subject, to develop a subjective report describing visual comfort in different lighting settings (e.g., illuminance level). The experiment was conducted in the environment chamber of Watt Hall at the University of Southern California’s University Park Campus (Figure 1a). For the sake of easy control, dimmable lamps provided the only sources of light.
Human subjects participated in the experiment to provide data for their visual comfort model. Each experiment, which only accommodated one participant, took 1 hour and 46 minutes. The experiment was divided into two parts. First, the subject was allowed 10 minutes to adapt to the environment in the lab (especially the lighting conditions) and then completed a pre-experiment survey. The survey was to provide a description of the subject and his or her impression of the real-world office environment.

The lighting setting (primarily illuminance on a working plane) was changed every 8 minutes and 12 times per test. The illuminance for each step was predetermined before the experiment began. Values were selected from 100, 200, 300, 500, 550, 650, 800, 950, 1,000, 1,150, and 1,250 lux. It should be noted that these levels fall within a range of 100 to 1,400 lux. This was determined based on previous research findings that 100–1,400 lux was the acceptable range for a majority of experimental subjects[5]. The order of lighting settings implemented in the experiment is shown in figure 1c. Visual satisfaction and visual sensations were surveyed for each step and lighting settings were labelled. The participants were asked to complete the survey during the last minute of each step to assure that they had received enough exposure to the current setting.

Each individual’s eye pupil sizes were recorded by a mobile tracking eye module manufactured by ASL. This module came with tracking glasses, a display transfer unit, and a laptop. The tracking glasses were mounted with two cameras – a view camera to catch what the wearer was looking at and an eye camera to capture image of eye pupil using a near-infrared light. Both cameras were installed on the side of the right eye, which meant that the device only collected data for a single eye. The sizes of eye pupil were measured in pixel and automatically saved as csv file.

Figure 1. (a) Fish-eye view of the chamber; (b) Layout of the chamber (Inch); (c) Illuminance levels in experimental order.

3. Methodology
3.1. Data preparation
All data were processed following the steps: (1) Data cleansing: The original pupil size data was sampled at a rate of 30Hz, which was a heavy and noisy process. The granularity was modified to 1 Hz, and missing values were replaced with a value from the previous time frame. All 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, 40s, 50s, 60s, 90s, and 120s gradient of the eye pupil size, with 30s as the moving average filter. According to Kenney[6],

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

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

\[\text{gradient}(x) = S_x - S_{x-n}\]
where $S$ is the processing of the absolute pupil size by moving the 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 the moving average filter; (3) Data integration: Survey data concerning visual sensations 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 be used to solve the problem. The research problem was defined as a classification of tasks for an individual’s visual sensations (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 levels of each individual, which also provided hints on how to improve current lighting conditions. Therefore, this process could be used to signal a physical lighting control system to enhance an individual’s visual comfort level. Eye pupil size data was used as input features for the visual comfort model.

#### Table 1. Parameter settings for algorithms

| Algorithm | Parameter Settings |
|-----------|--------------------|
| Gaussian NB | $\text{Var} \_\text{smoothing} = 1 \times 10^{-6}$ |
| LR | $C=1.0$, $\text{Class} \_\text{weight}=$None. It specifies the weight assigned to the classes. All classes are given weight one if it is not clarified. $\text{Random} \_\text{state}=$0. The seed of the pseudo-random number generator to use when shuffling the data. $\text{Solver}=$lbfgs. This tells the algorithm used in the optimization problem. $\text{Max} \_\text{iter}=100$. The maximum iteration allowed for convergence of learning. $\text{Multi} \_\text{Class}=$multinomial'. A multinomial loss function is assumed to fit the data. |
| SVM | $C=1.0$, $\text{Kernel}=$rbf'. The kernel type is Radial-basis function (RBF) kernel. $\text{Degree}=3$. $\text{D}=$The degree of the polynomial kernel function used for the model. $\text{Gamma}=$scale'. The coefficient used in the kernel function. The value equals $1 / (n \_\text{features} \times X \_\text{std}())$. $\text{Class} \_\text{weight}=$None. $\text{Max} \_\text{iter}=1$. -1 means no limit. $\text{Random} \_\text{state}=$None. |

The selection of a machine learning algorithm was closely related to the performance of the visual comfort model and was determined by the size of the input data, the number of input features, and the tasks implemented. Three machine learning algorithms were selected for this research to establish the model – Gaussian Naïve Bayes (Gaussian NB), Logistic Regression (LR), and Support Vector Machine (SVM). Mathematical theory is not elaborated on here, but parameters set for the algorithms are 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 for this research.

### 3.3. Feature selection & Performance evaluation

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[7], “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.

To evaluate the performance of the model, the accuracy of its predictions was adopted as the criterion, and defined as the percentage of correct predictions made for test data. Empirically, the original dataset was split into training and test data, with a ratio of 70:30.

### 4. Results and Discussion

#### 4.1. Feature selection
Pupil sizes, with a 30s moving average filter, 60s gradient, 90s gradient, and 120s gradient were selected as features for establishing the visual sensation prediction model. This decision was based on a summary of votes (shown in table 2). In detail, 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 and 120s gradient of pupil size were the most correlated features by all test subjects. The accuracy 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 absolute pupil size, 30s, 40s, and 50s gradients were filtered out because of the high standard deviation of votes.

### Table 2. Score of feature importance for visual sensation prediction

| No. | Abs. Size | Max. Ave. 30s | Grad. 30s | Grad. 40s | Grad. 50s | Grad. 60s | Grad. 90s | Grad. 120s |
|-----|-----------|---------------|-----------|-----------|-----------|-----------|-----------|-----------|
| 1   | 0.0289    | 0.4161        | 0.0957    | 0.0820    | 0.0664    | 0.1403    | 0.0749    | 0.1118    |
| 2   | 0.0420    | 0.7398        | 0.0982    | 0.0958    | 0.0677    | 0.0878    | 0.1272    | 0.1730    |
| 3   | 0.0415    | 0.3639        | 0.0741    | 0.0752    | 0.0547    | 0.1295    | 0.1081    | 0.1528    |
| 4   | 0.0505    | 0.2576        | 0.1311    | 0.0748    | 0.0490    | 0.0927    | 0.1642    | 0.1821    |
| 5   | 0.0289    | 0.4190        | 0.1284    | 0.0612    | 0.0563    | 0.0921    | 0.1495    |           |
| 6   | 0.0294    | 0.3134        | 0.0937    | 0.0895    | 0.0430    | 0.0962    | 0.1795    | 0.1720    |

**Table 2. Score of feature importance for visual sensation prediction**

**Table 3. Score of feature importance for visual satisfaction prediction**

| No. | Abs. Size | Max. Ave. 30s | Grad. 30s | Grad. 40s | Grad. 50s | Grad. 60s | Grad. 90s | Grad. 120s |
|-----|-----------|---------------|-----------|-----------|-----------|-----------|-----------|-----------|
| 1   | 0.0103    | 0.4005        | 0.0768    | 0.0776    | 0.0580    | 0.1241    | 0.0839    | 0.1486    |
| 2   | 0.0626    | 0.1094        | 0.1121    | 0.0549    | 0.0473    | 0.0663    | 0.1415    | 0.2049    |
| 3   | 0.0597    | 0.4185        | 0.0893    | 0.0769    | 0.0527    | 0.1066    | 0.1155    | 0.1029    |
| 4   | 0.0525    | 0.2338        | 0.1299    | 0.0683    | 0.0612    | 0.1103    | 0.1542    | 0.1900    |
| 5   | 0.0263    | 0.3990        | 0.0921    | 0.0782    | 0.0557    | 0.1147    | 0.1071    | 0.1898    |
| 6   | 0.0198    | 0.3619        | 0.0949    | 0.0628    | 0.0491    | 0.0783    | 0.1779    | 0.1666    |

**Table 4. Prediction accuracy of visual satisfaction**

| No. | Data Size | Gaussian naïve bayes | Logistic Regression | Support Vector Machine |
|-----|-----------|----------------------|---------------------|------------------------|
| 1   | 2276      | 0.54005              | 0.56808             | 0.71303                |
| 2   | 2308      | 0.67388              | 0.70428             | 0.68975                |
| 3   | 2279      | 0.59355              | 0.62261             | 0.67836                |
| 4   | 2294      | 0.63560              | 0.74020             | 0.73237                |
| 5   | 2307      | 0.74499              | 0.76190             | 0.80000                |
| 6   | 2266      | 0.73888              | 0.78076             | 0.82500                |

**Table 5. Prediction accuracy of visual satisfaction**

| No. | Data Size | Gaussian naïve bayes | Logistic Regression | Support Vector Machine |
|-----|-----------|----------------------|---------------------|------------------------|
| 1   | 2276      | 0.55507              | 0.59151             | 0.63590                |
| 2   | 2308      | 0.61039              | 0.48485             | 0.62771                |
| 3   | 2279      | 0.83772              | 0.83190             | 0.89237                |
| 4   | 2294      | 0.53556              | 0.61538             | 0.60377                |
| 5   | 2307      | 0.71140              | 0.67244             | 0.79221                |
| 6   | 2266      | 0.80294              | 0.83129             | 0.85882                |

**Table 4. Prediction accuracy of visual sensation**

**Table 5. Prediction accuracy of visual satisfaction**

4.2. Performance evaluation

Table 4 summarizes the prediction accuracy of visual sensations from three algorithms. The red shading highlights the algorithm generating the highest accuracy for each test subject. The sizes of the test data were different for each participant and details are listed in the table.

It can be seen that the prediction model of visual sensations, that adopted the SVM algorithm, possessed the highest accuracy for five out of six participants. Each algorithm performed differently for various 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 variations in the performance of the three algorithms were 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 was 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) was 0.0303. These facts revealed that, even though SVM performed 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 when individual differences are considered.

*The shading highlights the algorithm with the highest accuracy.
5. Conclusion
It was found that a personal visual comfort model provided an accurate prediction of an individual’s visual comfort with a median accuracy of 0.7086 for visual sensation and 0.65467 for visual satisfaction. Pupil sizes 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. A support vector machine was revealed as the algorithm that could produce the most accurate predictions. However, its statistical significance should be verified by additional data from a larger group.

It is suggested that a larger group of human subjects should be investigated to verify the universality of current personal visual comfort model. The verification will accelerate the application of this personal comfort model in combination with physical lighting control, which provides a customized solution to lighting design with consideration of individual well-being and work productivity. Additionally, it contributes to building energy saving by varying the luminance of light according to the occupants’ demand.

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