Towards an Accurate Measure of Emotional Pupil Dilation Responses: A Model for Removing the Effect of Luminosity

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***Abstract*—Pupil dilation is a fundamental marker of emotional response, and indicates emotional arousal independently of stimulus valence. As such, pupil dilation provides invaluable insight into emotional engagement and arousal levels. One of the challenges faced when studying emotion response through pupil diameter is distinguishing between dilation caused by light and dilation caused by emotion. This is particularly challenging when examining emotional responses in individuals viewing videos, where luminosity changes constantly occur.**

To solve this problem, we propose a model that accurately predicts how pupil size changes with brightness, taking into account the nonlinearity of the relationship. Since effects of luminosity and emotion are additive without interacting [1], pure emotional effects on pupil size may be isolated by subtracting the model estimate from the total pupil size recorded in response to the visual stimuli. The general structure of the model was developed from findings in the literature and by analysing data collected from seven participants. The model was then tested on 10 subjects and different monitor models. We obtained an average error of 6.69% (SD:1.05%) and a maximum error of 23.29% (SD: 3.66%) between the actual pupil size and the pupil size predicted by the model. To the best of our knowledge, this is the only nonlinear model that has been validated on a sample of subjects. This research lays the groundwork for the accurate capture of emotional responses from pupil diameter under varying lighting conditions.

***Keywords*— Pupil dilation, Pupil size, Emotion Detection, Arousal, Mathematical Modelling**

I. Introduction

Emotions are fundamental elements of human life, profoundly impacting cognition and behaviour [2]. They affect memory [3], attention [3], perception, and learning [3], influence decision-making and regulate social behaviour [4]. Recognising emotions, whether one's own or others', is crucial in various domains such as social interaction, mental health and education [5]. Emotional changes are associated with physiological responses, facial expressions, body language, eye movements and pupil dilation [6].

In recent years there has been a growing interest in automating the recognition of people's emotions by monitoring and detecting changes in those indicators. Pupil diameter changes in response to emotionally charged or engaging visual stimuli [7] [8] has emerged as a reliable measure of emotional states, and particularly emotional arousal [9]. However, changes in pupil diameter are not solely elicited by emotional arousal; they are also influenced by fluctuations in ambient luminosity [10] and monitor screen brightness/contrast settings [11]. Robert H. Spector et al. (1990) [10], mentioned in his study that the pupil size variation has a difference of about 50% in bright light and dark light environments. Therefore, the influence of luminosity on pupil size dramatically complicates the interpretation of pupil behaviour, potentially leading to errors if solely attributed to emotional states [9] [12]. For example, the pupil shrinks in high light and dilates with increased mental activity and the two effects may neutralise each other, giving the impression that there is no emotional activation [13]. Therefore, it is crucial to account for and remove the influence of luminosity when assessing emotional responses using pupil size. This ensures accurate evaluation of pupil changes due to emotion. The two effects, luminosity and arousal, are additive [1], suggesting that a subtractive solution can isolate emotional effects on pupil size.

Researchers commonly mitigate the influence of luminosity on pupil size by using baseline data or controlling lighting conditions [14] [15]. For instance, in a study on emotional arousal [15], baseline pupil data from grey-scale stimuli were subtracted from data recorded during emotional stimuli to reduce luminosity impact. However, even when it is possible to keep ambient lighting constant and perform a baseline correction, the frames of a video can often have very different luminosity with respect to the baseline.

In [12], Tarnowski and colleagues proposed to calculate the pupil size from the luminosity of the screen and then subtract it from the recorded pupil size in order to get the effect of emotional arousal on pupil size alone. However, there are three important limitations in their work. First, a linear model was applied, whereas it is known that the relationship between pupil size and luminosity is non-linear [16]. Secondly, the accuracy of the linear model was not tested, e.g., as the difference between the pupil diameter value predicted by the model and the actual recorded diameter. Finally, the variation in luminosity due to different frames of the videos presented on the screen was taken into account without also taking into account possible variations in ambient luminosity.

To address those limitations, in the present study we have developed a non-linear model which then we validated by calculating its accuracy from a sample of ten participants. To the best of our knowledge, this is the first time that a robust model to accurately separate luminosity-induced changes in pupil size is proposed and validated, thus enhancing the reliability of pupil-based assessments of emotional responses to complex stimuli like videos.

In our model, two parameters were considered: luminosity and pupil size. First, a method was developed to determine the luminosity of given images or video frames by using a sample of 1330 uni-colour images. Subsequently, a mathematical model was designed and fitted to predict pupil size based on various luminosity levels, using pupil size data from seven participants who were presented with uni-colour videos created at different luminosity levels. The final model was established to take three-dimensional data of the average contribution of RGB values for each image or video frame as input. Based on this input, the model predicts the luminosity and, in turn, predicts the pupil size due to luminosity. This predicted pupil size may then be subtracted from the pupil size measured while presenting emotional images or video frames, allowing for the isolation of the pupil size change due to emotional arousal. This model will be useful in accurately accounting for and removing the confounding effects of light, providing a clearer picture of the pupil's response to emotional stimuli. By refining this approach, the aim is to improve the fidelity of pupil-based metrics for measuring emotional responses. This advance contributes to the field of emotion research by enhancing the accuracy of tools available for studying emotion recognition from a wide variety of sources. In the remainder of this article, we refer to pupil size as the average of the sizes of the two pupils.

II. METHOD

The prediction of pupil size as a function of screen luminosity occurs in three phases:

1) The first phase is to predict the intensity of the light stimulus reaching the eye as a function of screen luminosity, such as when someone is watching a video.
2) The second phase consists of determining the size of the pupil as a function of the intensity of the light stimulus.
3) The third phase consists of combining the models developed in the first two steps to obtain a single model that can predict pupil size as a function of screen luminosity.

Below we describe the three phases in more detail.

1) Prediction of light intensity: Each pixel of an image consists of three pixels, one red, one green and one blue (RGB system) and is characterised by three RGB intensity values, one per colour, expressed as a percentage of the maximum possible value. In order to predict the intensity of the light stimulus (luminosity) as a function of the luminosity of the screen, the luminosity of a set of 1330 uni-colour images of different colours and luminosities was measured with a professional lux meter. The set of images was composed as follows: the first image of the set was completely black and each pixel had an RGB value of 0%, 0%, 0% (all colours off); the last image was white with maximum luminosity and each pixel had an RGB value of 100%, 100%, 100% (all colours at maximum intensity); all the other images had intermediate values uniformly distributed in the range [0%, 100%]. In a commercial monitor, the relationship between RGB intensity values and the luminosity values of the screen is non-linear. For example, considering a single colour, e.g. red, the luminosity corresponding to an RGB intensity value of 80% is not twice as high as that corresponding to a value of 40%. Instead the increase in luminosity as a function of RGB intensity is slower at lower intensity values and faster as the intensity approaches maximum. Furthermore, this non-linear relationship changes as more colours are used. We modeled this relationship by means of the following non-linear function:

$$L = k \cdot f(r, g, b) \quad (1)$$

where L is the luminosity value, k is a constant (scaling factor) depending on the brightness/contrast settings of the monitor, and $(r, g, b) \in [0\%, 100\%]$ are the RGB intensity values of a uni-colour image shown on the screen.

Given that it was impossible to determine the analytical expression for Equation 1, we described it by means of a lookup table with 1330 entries corresponding to the RGB intensities values of the uni-colour images that we used to explore the entire RGB space. When changing the brightness and contrast settings of the monitor, Equation 1 changes only for a scaling factor k. We calculated the values in the lookup table using a Dell Precision M6500 (1920x1080) monitor set to 100% brightness and 100% contrast, which we will refer to as the "reference monitor". When the value of contrast and brightness were changed, Equation 1 remained valid, except for the scaling factor k, which must be recalculated each time. Different models of monitors have different brightness capabilities. However, when testing four monitors of different sizes and brands, we consistently observed the same non-linear relationship in Equation 1, which therefore remained valid, while for each monitor we had to recalculate the scaling factor

k only, with a maximum error of 3 lux. This suggests that the non-linearity in the relationship between luminosity and RGB intensity values is a common characteristic of different monitors, regardless of their manufacturer and model. For the reference monitor, the value of k was 1, as re-scaling was not needed.

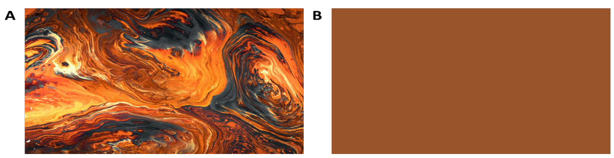

Fig. 1. *Example of original multi-colour image (A) and its corresponding uni-colour image (B).*

As mentioned before, we filled a look-up table using luminosity data from 1330 uni-colour images with different RGB intensities. We measured these luminosity values with a digital lux meter - LX1010BS (Dr.meter; [https://drmeter.com/]) in an unlit laboratory, maintaining a distance of 65 cm between the screen and the lux meter, in accordance with the typical requirements of standard eye-tracking technology. To predict the luminosity of an image, we provided the model with the RGB values of the image as input. Since the image is uni-colour, the model received three integers from 0 to 100, representing a point in three-dimensional space. If the given input 3D-point was found in the look-up table, the model returned the corresponding luminosity value. Otherwise, it calculated the weighted average of the values of the eight nearest RGB 3D-points in the look-up table, with weights inversely proportional to the distance of each of the eight 3D-points from the input 3D-point.

At this stage, we did not recalculate the scaling factor, so the predicted luminosity value was that of our reference monitor. We address the computation of the scaling factor and the discrepancy due to the use of different monitors with different settings in the next step.

So far, we have only discussed uni-colour images. In real applications, however, each pixel of an image has a different RGB value. In principle, one could calculate the luminosity of each pixel and average the values obtained. However, we observed that the luminosity of an image is similar to that of a uni-colour image with the average RGB value of the original image, calculated by averaging the RGB values of all its pixels. To verify this, we selected 100 images: 50 taken from the internet and 50 generated by assigning a random RGB value to each pixel. We then generated the corresponding uni-colour images using the average RGB value of each original image (see Figure 1). The luminosity of the original images differed from the luminosity of the corresponding uni-colour images by 1.5 lux on average, with a maximum difference of 3 lux, which is tolerable for our purpose. For computational reasons, using uni-colour images is preferred as it is much faster than calculating the luminosity for each pixel and then averaging.

The predicted luminosity value was then used to predict pupil size, as described in the next phase below.

2) Determining the pupil size: In order to determine the pupil size for different luminosities, we recorded the pupil size of seven participants (4 males, 3 females), ages 20-45 while they were watching four uni-colour videos, with each video only showing one fundamental colour (red, green, blue) and grey. Keeping the colour constant in each video, only luminosity could change from frame to frame. Our goal was to assess the pupil response either to one of the fundamental wavelengths (red, green, blue) or to the uniform combination of them (grey). Each video was presented full-screen (1920x1080) and lasted 102 seconds. The RGB intensity of each uni-colour frame changed every second, increasing from 0% to 100%. For example, the red colour video started from the darkest red (minimum red intensity) and progressed to the brightest red (maximum red intensity). The grey-scale video was composed of pixels with identical values across all three colours (RGB). We measured pupil size for each frame using a Tobii Nano Pro eye tracker in an unlit laboratory, maintaining a distance of 65 cm between the screen and the participant. Simultaneously, we measured luminosity during each video using a lux meter. Therefore, using this method, we recorded pupil size for each luminosity level and colour.

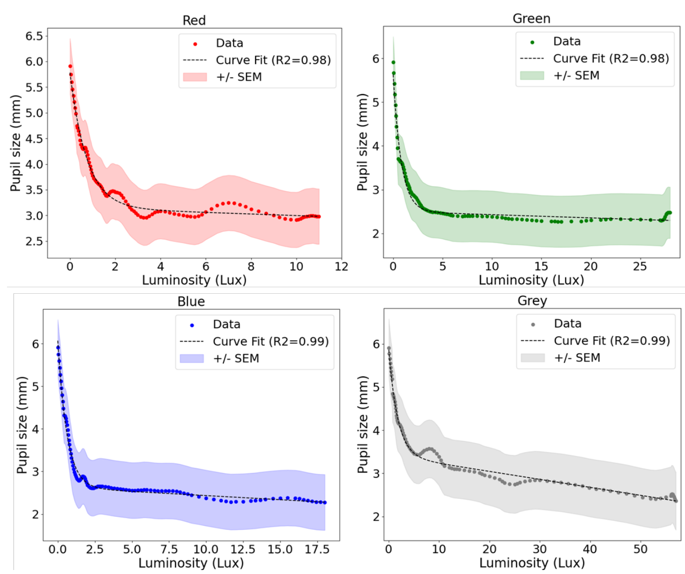

Fig. 2. *Pupil size as a function of luminosity for red, green, blue, and grey (dotted line for experimental data and continuous line for the fitted curve).*

In frames where there was an eye blink pupil size was replaced with the median value of the pupil size for the respective frame. We then averaged the pupil size data across participants for each luminosity level for all the different colours. Figure 2 illustrates the average (across participants) of pupil size against luminosity for each colour, and, as it can be seen, pupil size decreased exponentially as luminosity increased. This is consistent with what is widely accepted, i.e., that the relationship between luminosity and pupil size follows an exponential decay, as also demonstrated in [16].

To model the relationship between pupil size and luminosity for each color, we utilized the Python open-source platform with the SciPy library for curve fitting, employing the following equation:

$$PS = a_i \cdot e^{-b_i \cdot L} + c_i \cdot L + d_i, \quad i \in \text{red, green, blue, grey} \quad (2)$$

where PS is the pupil size, L is the luminosity value, and a, b, c, and d are coefficients to be determined by fitting the model to the recorded data. The four coefficients are shown in Table I and are different for each colour.

TABLE I
Values of the four coefficients in Equation 2, for each colour.

Colour	a_i	b_i	c_i	d_i
Red	2.631718881	1.337185719	-0.015263019	3.150067507
Green	3.125971983	1.232499771	-0.007369488	2.503629301
Blue	3.443025449	1.616759396	-0.019305937	2.62718504
Grey	2.446582212	0.563893338	-0.018479723	3.414006057

3) Determining pupil size from RGB values: Finally, to compute pupil size from RGB values the two models, luminosity prediction and pupil size prediction, were combined, according to the following Equation:

$$\begin{aligned} PS &= a \cdot e^{-b \cdot k \cdot f(r,g,b)} + c \cdot k \cdot f(r,g,b) + d \\ PS &= a \cdot e^{-g \cdot f(r,g,b)} + h \cdot f(r,g,b) + d \end{aligned} \quad (3)$$

where the pupil size is expressed as a function of the RGB intensity value k, and $g = b \cdot k$ and $h = c \cdot k$.

To fit the model, we need to compute four coefficients, a, d, g, and h, for each participant and for each experiment. [1]

We devised a calibration procedure to compute the four coefficients, taking into account all these sources of variability simultaneously. An experimenter using our method will have to precede the experiments with a calibration procedure, which consists of having the participant watch a uni-colour video. To keep the calibration procedure short, we designed a calibration video consisting of only 27 uni-colour images, each presented for 4 seconds, for a total of 108 seconds. Only three RGB values were used: 0%, 50%, and 100%. All possible combinations of these three values generate 27 possible images ranging from the darkest (0, 0, 0) to the brightest (100, 100, 100). The pupil size of a participant watching the video is then measured. The calibration procedure was used during the validation phase of our model, which we will now explain.

A calibration procedure was used to compute the four coefficients, considering all sources of variability simultaneously. Experimenters must precede experiments with this calibration, which involves having participants watch a uni-color video.

To validate our method (our models and our calibration procedure), we conducted a validation experiment, in an unlit laboratory with 10 new participants. Ethical approval was obtained by the University of Essex Ethics Committee (approval ETH2223-0795). They were seated 65 cm away from the computer screen (described above). Five participants sat in front of a Dell OptiPlex 5070 monitor (1920 x 1080), and the other five were seated in front of a Dell G15 laptop (1920 x 1080). Both monitors were different from the reference monitor.

[1] Given that each participant has a different response to light, each monitor is different, and each experimental setting is different (e.g. distance of the participant from the screen, monitor's settings, etc.).

Before the experiment, there was a calibration procedure consisting of the calibration of the eye-tracker (Tobii Nano Pro) used for measuring the pupil diameter, followed by our previously mentioned luminosity calibration video. The experiment consisted of watching 40 uni-colour test images each of them presented for 4 seconds, without any emotional content. The 40 test images were generated to cover RGB intensity values equally distributed from the minimum to the maximum luminosity of the screen and across all the colours. An example is an image with values (64, 86, 45), where the green colour is slightly more intense than the red and the blue colours. We asked the participants to remain relaxed throughout all phases of the experiment to maintain constant arousal activation. We measured the participants' pupil size using the eye-tracker with the procedure mentioned above.

We fitted the model represented by the Equation 3 independently for each colour in order to obtain the contribution to the pupil size given by the luminosity at each colour:

$$\begin{aligned} PS_{\text{red}} &= a_{\text{red}} \cdot e^{-g_{\text{red}} \cdot f(r,0,0)} + h_{\text{red}} \cdot f(r,0,0) + d_{\text{red}} \\ PS_{\text{green}} &= a_{\text{green}} \cdot e^{-g_{\text{green}} \cdot f(0,g,0)} + h_{\text{green}} \cdot f(0,g,0) + d_{\text{green}} \\ PS_{\text{blue}} &= a_{\text{blue}} \cdot e^{-g_{\text{blue}} \cdot f(0,0,b)} + h_{\text{blue}} \cdot f(0,0,b) + d_{\text{blue}} \end{aligned} \quad (4)$$

where PS is the pupil size, a_{red}, g_{red}, h_{red}, d_{red} are the coefficients for the red colour, a_{green}, g_{green}, h_{green}, d_{green} are the coefficients for the green colour, a_{blue}, g_{blue}, h_{blue}, d_{blue} are the coefficients for the blue colour.

To find all the coefficients we fitted the three independent models described by Equations 4 using the pupil sizes recorded during calibration, and corresponding RGB intensity values of the following images: one black image (0, 0, 0), two red images (50, 0, 0), (100, 0, 0), two green images (0, 50, 0), (0, 100, 0), two blue images (0, 0, 50), (0, 0, 100). We considered only nine images of the calibration video and we will use the other 18 images to try alternative methods in the future. However, to fit the model represented by Equation 4 we needed more data points and we computed additional points as described below.

To fit the three independent models, we used eight 3D-points for each colour (model), with RGB intensity values ranging from 0% to 100%. The points were not equidistant because the curve described by Equation 2 and shown in Figure 2 has a larger variability for smaller luminosity values. For example, for the red colour, we used (0, 0, 0), (10, 0, 0), (25,0, 0), (50,0,0), (65, 0, 0), (75, 0, 0), (86, 0, 0), (100, 0, 0), and similarly for the other two fundamental colours. The strategy of using non-equidistant points led to a good fit (on average R2 = 0.995 ± 0.00935 across our 10 participants and the three Equations to be fit per each fundamental colour). For each fundamental colour, out of these eight points, the pupil size was recorded only for three points during the calibration video, as mentioned above. However, as we know the shape of the relationship between pupil size and luminosity for each colour (Equation 2 and coefficients in Table I), we used that information to calculate the remaining five points. [2]

We performed all experiments in the unlit laboratory, and the maximum luminosity reaching the eyes of our participants was 60 lux, which is the maximum luminosity of the screens that we used to validate the model. As we did not have measurements taken in daylight [3], we made an assumption to better fit the curves: per each colour we assumed that the pupil size value at 100 lux, which is typical of daylight conditions, was 80% of the pupil size at the maximum screen luminosity recorded by the calibration video [16].

After fitting the three models for each participant and related monitor, we predicted the pupil size for each test image as if presenting one colour per time: given a uni-colour test image with RGB intensity values (r, g, b), we considered three different uni-colour images, with RGB intensities (r, 0, 0), (0, g, 0), (0, 0, b), in three different moments. The idea was to disentangle the effect of each wavelength (colour) on the pupil size. For example, for the test picture with RGB intensity (64, 86, 45), we pretended to have only the red component (64, 0, 0), then the green one (0, 86, 0), and then the blue one (0, 0, 45). Using the Equations 4 we obtained three different predicted pupil sizes PS_{red}, PS_{green}, and PS_{blue}. We computed the final pupil size as a weighted average of these three contributions:

$$PS = (\frac{\text{r}}{\text{Tot}}) \cdot PS_{\text{red}} + (\frac{\text{g}}{\text{Tot}}) \cdot PS_{\text{green}} + (\frac{\text{b}}{\text{Tot}}) \cdot PS_{\text{blue}} \tag{5}$$

where PS is predicted pupil size and Tot = r + g + b.

It is important to note that our method allows the coefficient k of Equation 1 relating to phase one and the coefficients a,b,c,d of Equation 2 to phase two to be computed in one go, using the calibration procedure. In the next section we present the results from our model validation experiment.

III. Results

As discussed above, our model predicts the pupil size from the RGB intensity of an image, provided this is preceded by a calibration procedure. Our method is applicable in any dark environment and for any screen. It has been validated on a sample of 10 subjects, who were shown a video of 40 uni-colour images varying in luminosity and colour, while the pupil size was measured using an eye-tracker. Each image was shown for 4 seconds resulting in a 160-second video.

Figure 3 shows the pupil size recorded from one of our participants throughout the video, the average pupil size measured for each of the 40 frames, and the pupil size predicted by our models. The average difference between the predicted and recorded pupil size was, for this participant, 5.05% ± 4.47%. The maximum difference was 16.80%.

Figure 4 shows the average pupil sizes for each frame recorded for all 10 subjects and for all 40 images (400 points in total) in relation to our model's predictions. The Pearson correlation coefficient is r = 0.89 and indicates a substantial alignment between model predictions and real-world pupil size measurements. Further supporting this, the determination coefficient R2 value of 0.80 ± 0.12 suggests that nearly 80% of the variance in the measured pupil size can be explained by our model. The average difference between measured and predicted pupil size across all participants was 6.69% ± 1.05%, and the maximum difference was 23.29% ± 5.66%.

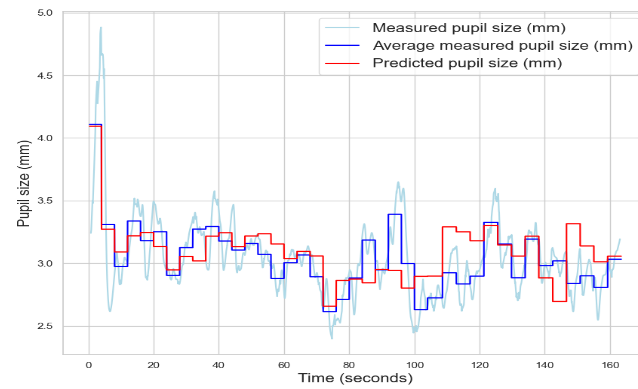

Fig. 3. *Actual and predicted pupil size for one participant.*

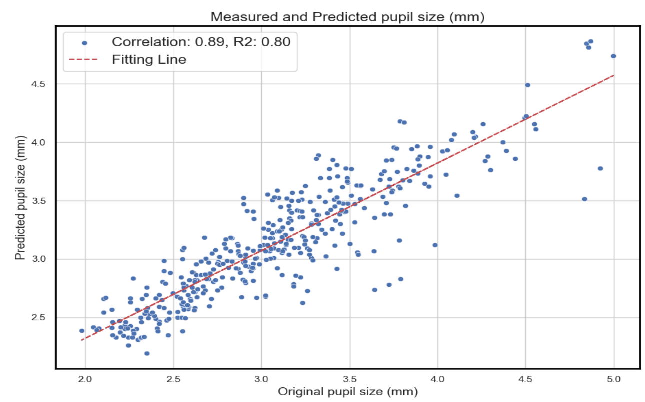

Fig. 4. *Correlation between measured and predicted pupil size with the colour-based approach.*

IV. Discussion

The primary goal of this study was to systematically measure the effect of luminosity on pupil size. This is very important, as changes in pupil size caused by luminosity are a confounding variable when assessing emotional responses from pupil size. Since the effects of luminosity and emotion are additive without interacting [1], emotional effects on pupil size may be isolated by subtracting the model estimate from the pupil size recorded in response to the visual stimuli. We developed a robust model that accurately predicts pupil size at

[2]An alternative would be to use a longer calibration video.

[3]In a future development of our method, we will perform the experiment in daylight too.

different luminosity levels in an unlit laboratory. The model was validated and achieved an average difference between actual and predicted pupil size of $\pm 6.69\%$. This is the first time, to our knowledge, that such a model has been proposed and validated.

One limitation of our model is that it is currently applicable only in unlit settings. The next stage will involve applying our model to different lighting conditions. Previous research, such as Aracena et al. (2015) [14] and Bradley et al. (2008) [15], normalised pupil size using a fixed grey colour under controlled lighting to account for luminosity effects. This method is inadequate as pupil size varies significantly with different lighting conditions, as we have demonstrated (see Figure 2).

In future developments, we will also not consider the average brightness of the whole screen uniformly but give more weight to the brightness of the portion of the screen the eyes are looking at, utilizing the information recorded by the eye-tracker. We will also make better use of the 27 frames of the calibration video to improve accuracy.

Tarnowski et al. (2020) [12] proposed a linear regression model to correct the pupil size data for luminosity. This approach has two problems: the relationship between luminosity and pupil size is known to be non-linear [16] and the accuracy of their model was not calculated by comparing recorded data with predicted data. Our model overcomes these limitations by taking into account the non-linear relationship of pupil size to luminosity, and the different effect that fundamental colours and grey have on pupil size. Furthermore, our method takes individual differences and different monitor models into account through the use of a calibration video. Considering that the variation of pupil size with light can be as much as 50%, and that the variation of pupil size with emotional activation can have values much smaller than 50% (typically 10% - 20%), the average error of about 6.6% of our model must be considered satisfactory, although there is still room for improvement, especially in reducing the maximum error of the model (about 23.3%). By subtracting the predicted luminosity-influenced pupil size from the measured pupil size during emotional stimuli, arousal information induced by emotion can be obtained without external artifacts, leading to a more accurate understanding of how emotions influence pupil dilation, and enhancing the reliability of emotion research.

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