

Performance Metrics of Kanade-Lucas-Tomasi (KLM) filters on Users' Perception to Graphic Images through Data Generated from Pupillary Response

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Abstract

Most research focuses on determining the correlates of pupil dilation and constriction to changes in light intensity in contrast to bright and grey images of a visual interface and found that pupil response is highly correlated to high cognitive response related to problem-solving, which is the same as the response to strong light intensity. An experiment was conducted with the consent of forty participants whose pupil response was recorded in video frames in response to image stimuli, the aim was to generate response data while comparing their pupil response to bright and colored images to its greyscale version. The result indicates that bright and colored pictures are more appealing and preferable to their grey version and the pupil tends to dilate in reaction to comprehension. This is as opposed to using changes in light intensity and gives a novel definition to the cognitive response of users to a simple stimulus through pupillary response. The proposed model would help in generating response data that would be used in designing prototypical analytics for accessing and predicting users' responses to visual images and optimisation of visual aesthetics and cognitive elucidations.

Keywords : Kanade-Lucas-Tomasi filters, Viola Jones model, Performance metrics, Intelligent analytics, Pupil response, Baseline Response, User Cognition.

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1 Introduction

Recent research has found that there is a synchronous correlation between the different measures of cognitive ability and baseline pupil response of an individual [Causse et al. [7], Eckstein et al. [10], Kang and Wheatley [16], Muckschel et al. [24]]. The pupillary response is a kind of physiological response that changes the size of the pupil through the optic and cranial nerves, the pupil constriction is the narrowing of the

pupil and could be caused by attention or other responses to drugs, the pupil dilation (Figure 1) is the constant widening of the pupil which may be caused by adrenaline in an active state of cognition, also drug intake can also be the cause for it.

1.1 Objectives

The main objectives adopted here are :
— To conduct a brief review of KLM and Voila-Jones

method of feature selection on the pupillary motion.

- Design a framework for pupillary response generic data and its predictions for cognitive processes.
- Make a constructive comparison of both methods adopted for feature selection.
- Propose a model for user cognitive prediction with data analytics for eye movement predictions.

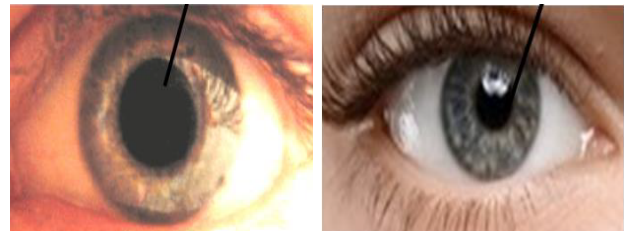
It has been determined that "*The eyes are the window of the soul*", and could also be the window to the brain according to research [Bozohora [5], Kwa [18], Panda [26]]. The pupil responds to more than just light intensity, they may indicate arousal state, mental state, or the cognitive state of a person, such as interest. Research [Bozohora [5], Kwa [18], Panda [26]], shows that the baseline pupil response is directly related to individual differences in cognition. The larger the size of the pupil, the higher the intelligence which is measured by testing the reasoning ability, memory, and attention of the person. Different motion detection algorithms have been used for predicting the pupil response to objects they viewed and KLM and Viola-Jones have been the most constantly utilised model for eye movement predictions.

2 Literature Review

The terminology in "*Cognitive Psychology*" was first introduced in late 1967 by [Barsalou [3], Bower [4], Hoffman [12], Hoffman and Deffenbacher [13]], and since then, a lot of inventions have emerged from this study. This has benefited the field of psychology and so many other related disciplines such as education, design, business, and Human-computer interaction. The concept in cognitive psychology is one of the major fields that has contributed to Human-computer interaction (HCI) research, by application of its principles to the understanding and development of models that explain the predictions of human performance [Carroll [6], MacKenzie [19], Olson and Olson [25]]. The major components in cognitive psychology are similar to those found in design and how it also deals with problems that are focused on goal-oriented and problem-focused design. The problem is first identified by the user which is then formulated to a specific goal for a self-purposed design frame.

2.1 The Kanade-Lucas-Tomasi (KLM) filters

The KLT algorithm is a motion and action detection in feature tracker T(k) on computer vision and imagery as an approach to feature extraction. Its purpose is to deal with the assumption that traditional object detection registration techniques are generally complex and expensive [Al-Najdawi et al. [1], Jabar et al. [14], Matikainen et al. [21], Uemura et al. [30]]. The KLT makes use of data spatial intensity information to trace the search for positions and movements that yield the best



(a) Pupil dilates in response to low light intensity or in high cognition. (b) Pupil constricts in response to bright or low cognition.

FIGURE 1 – Pupil dilation and constriction in response to light intensity and cognition.

match to its pattern. Its procedure is faster than the normal traditional methods for body movement and motion tracking that identifies potential matches between objects they track. It is given to have a negative normalized correlation as in Equation 1.

$$\frac{-\sum_{x \in R} F(x+h)G(x)}{norm_{l_1} norm_{l_2}} \quad (1)$$

where $norm_{l_1} = \sum_{x \in R} |F(x+h) - G(x)|$, and $norm_{l_2} =$

$\sqrt{\sum_{x \in R} [F(x+h) - G(x)]^2}$ The process used the object registration problem that is characterised as two functions $F(x)$ and $G(x)$, representing pixel values in video frames at each location x in two different objects on a visual screen, where x is a vector. To define the disparity vector h , we minimize some of the measures of the difference between $F(x+h)$ and $G(x)$, for x in the region of interest R . The measure of the difference between $F(x+h)$ and $G(x)$ is given as : $norm_{l_1}$ and $norm_{l_2}$.

2.2 Viola-Jones Algorithm

The Viola-Jones motion prediction is based on an object tracking framework [Dahirou et al. [8], Mayank and Mukhopadhyay [22], Safaldin et al. [28], Weng et al. [32]], it trains a set of the generated data records for motion detection on a variety of object classes. An exemplary problem here to be solved is detecting pupillary response by tracking iris positions. The computation method requires precise instructions and constant constraints. The object to be detected must be pointed toward the camera for the video frame, each step is followed by a recognition step. The learning process involves the speed with which the features are evaluated and can compensate for their numbers measured in pixels sub-window. The framework employs a variant scheme of learning processes to select the best possible features and train the classifiers (strong and weak) such as :

$$h_j(x) = \text{sgn} \left(\sum_{j=1}^M \infty_j h_j(x) \right) \quad (2)$$

Each of the weak classifiers is a formed threshold of functions based on the selected feature $f_j h_j(x) = \begin{cases} -s_j & \text{if } f_j \leq \theta_j \\ s_j & \text{otherwise.} \end{cases}$ The threshold θ_j and polarity value of detection $s_j \epsilon \pm$ are obtained in the training, in synchronous with ∞_j .

Algorithm 1 Viola Jones Feature extraction.

```

1: procedure SET OF  $N$  POSITIVE AND NEGATIVE
   TRAINING ON IRIS MOVEMENT WITH PARAMET-
   TERS( $(X^i, y^i)$ )      ▷ User faces mobile camera
   lens
2:   if the shape of each eye is  $y^i = 1, Y^i = -1$  then
3:   else if negative then
4:     Initialise weight  $w_1^i = \frac{1}{N}$  to each pupil move-
     ments  $i$ 
5:     For each feature  $f_n$  with  $j = 1 \dots M$ 
6:       Normalise  $\sum w_1^1 = 1$ 
7:       Apply feature to each pupil change in the training
       set
8:       Find optimal threshold and polarity
9:       For  $j, i = 1 : N$ 
10:      Set  $\theta_j, s_j = \underset{\theta_{js}}{\text{argmin}} \sum_{i=1}^N w_j^i \epsilon_j^i$  where  $\epsilon_j^i =$ 
       $\begin{cases} 0 & \text{if } y^i = h_j(x^i, \theta_j, s_j) \\ 1 & \text{otherwise} \end{cases}$ 
11:      Assign  $\theta \rightarrow h_j$  best feature selection
12:      Next  $w_{j+1}^i$ 
13:      End
14:      End
15:      set final classifier  $h(x) =$ 
       $\text{sgn} \left( \sum \infty \sum_{j=1}^M \infty_j h_j(x) \right)$ 
16:      End

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Different methods have been adopted for motion and feature selection for object detection using the above-mentioned algorithms and performance in detection rate has proven optimal. The custom method here applies both methods in feature extraction on data generated from pupil dilation, this can be remodified from previous techniques on the cognition of users from observed pupil changes.

Three studies [Eckstein et al. [9], Marshall [20], Unsworth et al. [31]] have shown that the difference in baseline pupil change between individuals who have a high score on the cognitive test and the others with a low score was great enough to be determined by an unaided eye. The study is based on the mental effort needed from people to complete a memory card task. The pupil dilata-

tions were used as an indicator of mental effort, and the result was a significant correlation between baseline and pupil response intelligence, though a definite conclusion was not given. Several tests were also conducted on large-scale studies where the pupil size of a lot of participants was carried out using an eye tracker. The measures were taken, while they stared at a blank screen of the monitor for four minutes. The eye tracker was used to calculate the participants' average pupil size.

The pupil size is the diameter of the black circular aperture at the center of the eye. These range from 2–8 millimeters per second. It is mostly surrounded by the iris and this is responsible for controlling the muscle of the pupil [Kolb [17], McDougal and Gamlin [23]]. Other experiments [Au et al. [2], Tranter and Koutstaal [29]] were conducted where participants had to complete a series of cognitive tests designed to measure their fluid intelligence. i.e. the capacity to reason through problems, the working memory capacity often demonstrate in most research regarding pupil measurement to cognition. This is mostly the ability to recall certain information over time-based attention and control motor on the brain and gives the ability to focus attention on certain interference and distractions [Au et al. [2], Jaeggi et al. [15]]. The participants were asked to avoid looking at a bold asterisk on the computer screen to avoid distraction and lay their focus on a letter. The eye movements were steady on the letters and lay off the screen. The results obtained show that humans are prompted to react to objects that pass through their vision and this process can present a procedure for the learning patterns toward behaviour predictions on a visual field [Au et al. [2], Jaeggi et al. [15]].

Baseline pupil response was also found to be correlated with a greater expanse of fluid intelligence, memory, attention control, and working memory, this indicates a significant relationship between the brain and eye coordination. The findings also reflect a negative correlation between eye and age; i.e. younger participants have larger constricted pupils than older participants based on cognitive correlations. The relationship between pupil size and cognitive ability is constant when ages are homogenous [Falch and Sandgren Massih [11], Roda [27]].

The main research question here is : *Why does the pupillary response correlate to basic intelligence?* This question can be answered through the understanding of the brain process using training procedures on data generated. The pupil size is found to be related to most brain activity by the synchronous representation of maintained brain cells that coordinate the process of memory, perception, attention, and learning [Falch and Sandgren Massih [11], Roda [27]].

To relate the cognitive response of a user to both pupil dilation and constriction, the correlates have to correspond to motor control of the muscles of the iris (Table



(a) RGB graphic images with color (b) Grayscale graphic image.

FIGURE 2 – Similar pictures with different contrasts were used as stimuli for the experimental study.

1), like specifying when a person’s cognitive response is of intense focus, comprehension, indecisive and deceive based on the direction of muscle reflex for both dilation and constriction. Table 2 indicates the estimated cognitive response to both bright and grey images depicting the same message.

Since the pupil changes are also responsive to bright and low light, we experimented to determine the cognitive response of four participants to the bright color and grey color of an image (Figure 2) that depicts the representation of different objects that are collected and used in the regular everyday activity of a person. The following section describes the method adopted.

3 Method

An experimental setup was conducted involving forty users who sat in front of a webcam lens of a PC which uses a set module to zoom the right pupil of the eyes by looking directly at the lens during calibration. Two different images (Figure 2) were presented to them on the visual screen. While the participants try to absorb the image in front of them, the lens captures and measures the pupil area and diameter using a function (Equation 2) that calculates the eye distance from the lens and the pupil size in diameter. Matlab was used to define the iris as an object detector bounded by the area around the pupils. The changes in light and cognitive response are also determined. The table (Table 1) below shows the estimated cognitive response of the participants concerning the images they viewed. The main aim is to try and define the terms *dilation* and *constriction* to the same images but with the difference in color using the baseline of both pupil constriction and dilation to the cognitive response of the participant in response to the two images. The rationale for using the image is to induce spikes or pupillary responses from the participant’s cognition to bright and grey color.

3.1 Performance Metric

To determine the performance in motion detection for both algorithms, each participant is labeled $X_i \dots X_n$, and a total time interval of thirty seconds was used for each subject in each frame. The data matrix generated for each subject on each video frame is simulated ($Y_i \dots Y_n$) (Figure 3). The best fit is selected and used as the training and testing data matrix with attributes and features from the pupillary measure in the area and centroid of the iris. This will help to determine the optimal performance for both original and simulated scenarios.

The simulation of the entire process was carried out where the diameter of the pupil is recorded as it changes with time in response to the images they viewed. The task is simply to look at the two images one at a time and tell the difference between the two. The decisions of the participant are reflected in the movement of the eyes and activation of the iris dilator muscle close to the eye region.

The module is used to generate pupil response in diameter records and detects when the participant is highly responsive and concentrated on the image (Figure ?? and ??). The nature of the images can be confusing at first glance due to the complexity of their representation, it usually takes a while before a person can understand what the image stands for and finally learn how to recognise the different objects assembled to create the color and grey-scale version of the image. Sometimes, pupil detection can be obstructive, this is due to the length of the video and the capture of the image. Each eye movement changes with time are analysed based on the number of frames. Figure 3 shows an example of an error in pupil size detection in an eye. The estimated cognitive response can be accurate even if the detected centroid is overlapping in some cases.

4 Result

From the result of the test runs, it was determined that the cognitive response of a person can be correlated with the shift in the iris muscle of the eye depending on whether the pupil dilates or constricts towards the top or bottom boundary of the iris muscle. Figure 4 shows four cases of the cognitive response of the participants’ pupil response to the images. Intense focus suggests that the pupil is dilated and circular. This can also mean the participant is in a high comprehension cognitive state which is similar to attentiveness. Three out of the four cases fall under intense focus with dilated pupils. The response to the image also signifies that a person is always alert when a complex image that draws their attention is shown to them and they respond by trying to understand the scenario and classify their mood of expression. The pupil normally gets constricted and focused at this stage and finally gets dilated at the comprehension stage.

TABLE 1 – The different categories of pupillary response to stimuli based on constriction and dilation.

Motor reflex	Constriction	Dilation
Muscle mechanism	Relation of the dilator muscle Activation of the iris muscle	Activation of the dilator muscle Relaxation of the iris muscle
Pupillary response to light	Increase in light	Decrease in light
Cognitive physiological response	Accommodation reflex	Flight response
Non-Cognitive physiological response	Mioses	Mydriasis

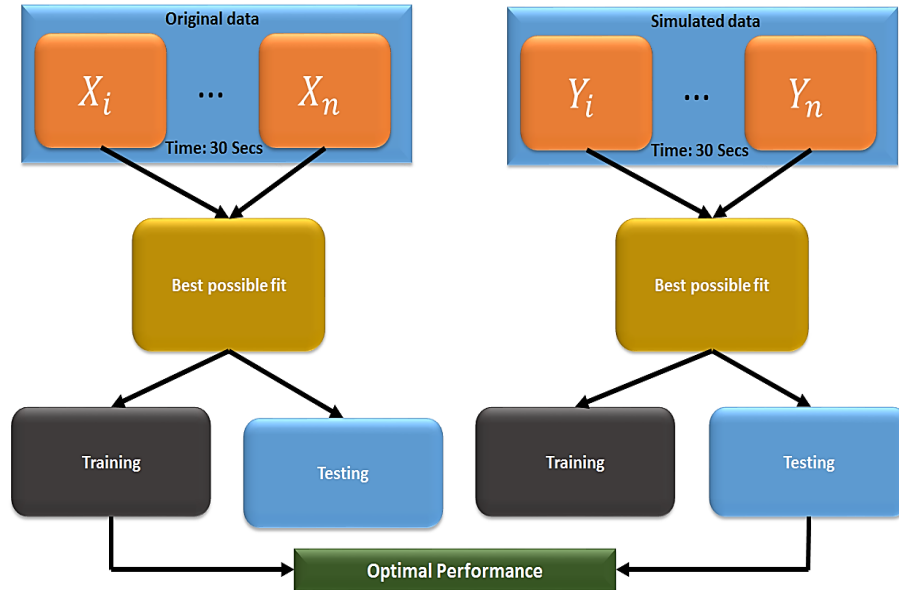


FIGURE 3 – Framework for performance metric.

TABLE 2 – Estimated cognitive response of participant in response to image stimuli to the resultant direction of pupil changes.

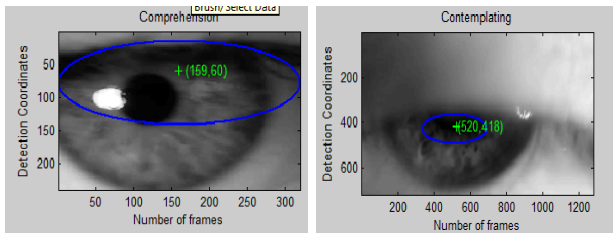
Direction of gaze	Cognition	Diameter	Dilation	Constriction
Top left	Indecisive	11.4	Present	Absent
Top right	Comprehension	11.4	Present	Absent
Bottom left	Contemplating	11.4	Absent	Present
Bottom right	Intense focus	11.3	Present	Absent

The baseline estimates can also tell us more about the correlates to visual attention (Figure 6) for the participants; the baseline is the average pupil response for an individual and this varies for every eye movement. The pupillary response is both physiological and iris motor reflex. The current computation of the baseline of pupil response is based area and diameter of the pupil. Some of the pupils were captured close to the lens and hence the area and diameter vary. The most accurate means for detecting pupil movement is based on the centroid in the middle of the pupil and iris region because this represents a value in a static motion state. Figure 6 and 5 shows the baseline response of the four participants in synch with their pupillary response, the constriction of the pupil indicates a decrease in diameter and area of

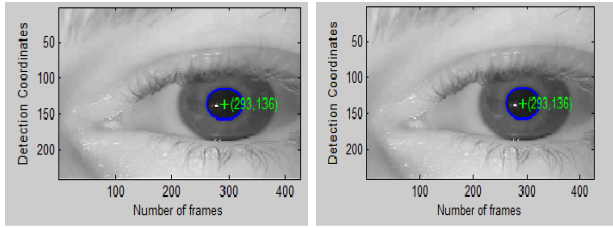
the pupil size, and it is found to be below baseline in a relaxed state of the iris muscle reflex. This demonstrates the low cognitive response of a participant in an indecisive mood. The high cognitive response is generally relaxed-instant comprehension with a dilated pupil to visual stimuli. But this is not known for certain till a higher number of participants is involved.

4.1 Error in Performance for Learning Process

Tracking pupillary response using both visions cascaded object detection method can be very tricky with eye movements which usually is very unpredictable, especially when most of the captured eye video frame is

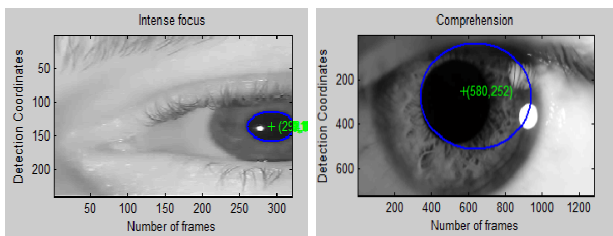


(a) Comprehension expression (b) Contemplating eye movement.

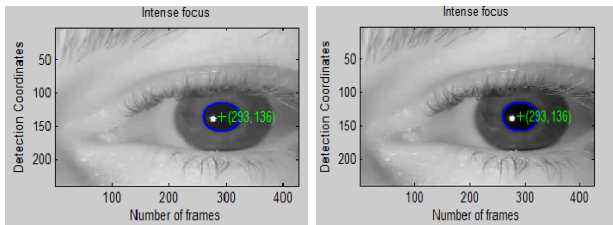


(c) Intense focus. (d) An Intense focus.

FIGURE 4 – Pupil detection for four eyes in response to image stimuli : object detector can vary depending on the length of the video.



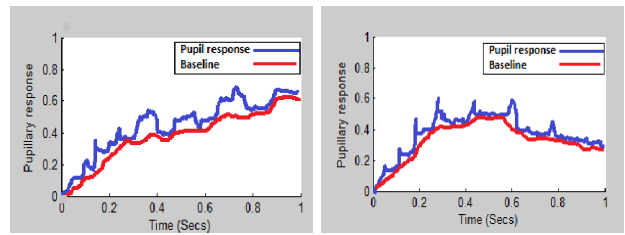
(a) Comprehension expression (b) Contemplating eye movement.



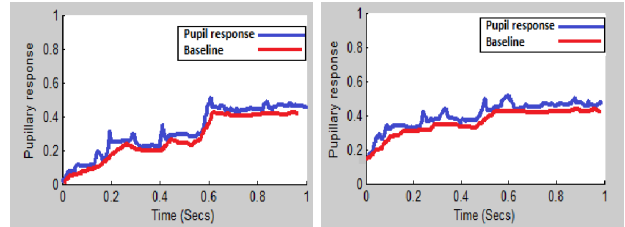
(c) Intense focus. (d) An Intense focus.

FIGURE 5 – Test runs show the cognitive correlates of the pupil changes as in a mood of comprehension, intense focus, and decisions.

depends on the distance between the lens and the iris location. The learning process is therefore prone to recording errors and might fall under false positive scenarios in detection. The cognitive response is based on shift cascading and motion detection from the centroid of the area pupil. To detect a pupillary response in cognition the iris muscle shifts upward or downward depending on the cognitive state. The cognitive state is then classified



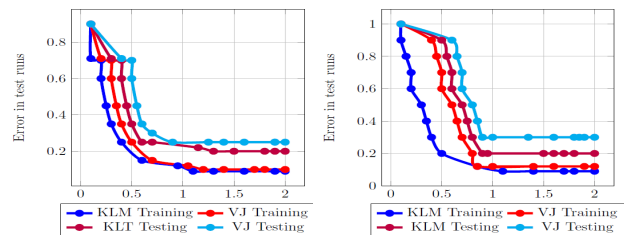
(a) Comprehension expression (b) Contemplating eye movement.



(c) Intense focus. (d) An Intense focus.

FIGURE 6 – The computed pupil response in synchronous effect to the baseline estimate in response to stimuli.

as contemplating, comprehension, intense focus, and in-decision.



(a) Error in movement detection for the original set. (b) Error in pupil response detection for the simulated data-set.

FIGURE 7 – Error in the learning process for both KLM and Viola-Jones detection algorithm.

The performance in the learning of both motion detection algorithms is determined by original and simulated data matrix generated. Figure 7 shows the list error in performance for both data matrices in the learning process lies between 0.09% to 0.1% for original data and 0.08% and 0.09% for the simulated scenario. The KLM model has the least performance for both the detection process. Object tracking is seen to show a similar and accurate score to motion tracking and this is adopted in most eye movement and tracking algorithms. The performance rate depends mostly on the distributional data attributes for both image and video output processing and can be controlled using complex computational models for rapid and vivid data visualisation for cognitive behaviour prediction.

5 Conclusion

The paper tries to investigate the performance metrics of Kanade-Lucas-Tomasi (KLM) filters on users' perception of graphic images through data generated from the pupillary response, a comparative data analysis was made for both KLM and Viola-Jones object detection that reports on the best the training set for KLM for pupil response recognition to changes in color representation. Most research focuses on determining the correlates of pupil dilation and constriction to changes in light intensity in contrast to bright and grey images of a visual interface through objects and motion predictions using the methods adopted in this paper, they found that pupil response is highly correlated to high cognitive response related to problem-solving, which is the same as the response to strong light intensity. This paper looks at this phenomenon from a different perspective by comparing bright and colored images to its grey-scale version with the two methods. The result indicates that bright and colored pictures are more appealing and preferable to their grey version and the pupil tends to dilate in reaction to comprehension with great accuracy using KLM. Future work would be to determine the performance of pupillary measures using different metrics relating to pupil detection based on centroid, area, diameter and radius of the pupil as an indicator of pupil response to cognitive interpretations.

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