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EOG-Based Eye Movement Classification and Application on HCI Baseball Game

CHIN-TENG LIN[1], **JUANG-TAI KING**[2], **PRIYANKA BHARADWAJ**[1], **CHIH-HAO CHEN**[3], **AKSHANSH GUPTA**[4], **WEIPING DING**[5], **AND MUKESH PRASAD**[1]
[1]Centre for Artificial Intelligence, School of Computer Science, FEIT, University of Technology Sydney, NSW 2007, Australia
[2]Brain Research Center, National Chiao Tung University, Hsinchu 30010, Taiwan
[3]Institute of Imaging and Biomedical Photonics, National Chiao Tung University, Hsinchu 30010, Taiwan
[4]School of Computational and Integrative Sciences, Jawaharlal Nehru University, New Delhi 110067 , India
[5]School of Information Science and Technology, Nantong University, Nantong 226019, China

Corresponding author: Mukesh Prasad (mukesh.nctu@gmail.com)

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ABSTRACT Electrooculography (EOG) is considered as the most stable physiological signal in the development of human–computer interface (HCI) for detecting eye-movement variations. EOG signal classification has gained more traction in recent years to overcome physical inconvenience in paralyzed patients. In this paper, a robust classification technique, such as eight directional movements is investigated by introducing a concept of buffer along with a variation of the slope to avoid misclassification effects in EOG signals. Blinking detection becomes complicated when the magnitude of the signals are considered. Hence, a correction technique is introduced to avoid misclassification for oblique eye movements. Meanwhile, a case study has been considered to apply these correction techniques to HCI baseball game to learn eye-movements.

INDEX TERMS Eye movement classification, HCI, baseball game, EOG.

I. INTRODUCTION

The importance of eye movement tracking along with human-computer interaction (HCI) has been investigated in this paper. This approach has remained a promising method which is used in recent years to detect and analyze eye movements. Electrooculography (EOG) is an inexpensive technique used in recent years to record eye movements [1]. EOG signal classification is considered as the most useful control signals for human-computer interface [2]. Eight directional eye movement classification algorithm is an effective way to analyze the aftermath effect of noise in EOG signals. However, a thorough understanding of various characteristics of eye movements leads to a better understanding of eye-movement detection algorithm.

Following types of eye movements can be detected through EOG signals.

A. VERGENCE

Vergence eye movements are considered as, ‘‘slow disconjugate eye movements that allow the visual system to fuse targets moving in depth, giving a person the ability to perceive the world in all three dimensions’’ [3].

B. PURSUIT MOVEMENTS

Pursuit movement occurs while the eye tracks a moving object. It means that the image of an object can maintain focus on the fovea.

C. SACCADE

Saccades are classified as rapid eye movements where these eye movements observe the world without an externally driven feedback system [3]. Saccades are faster than Vergence and Pursuit eye movements.

D. BLINK

Blink can be described as a rapid eyelid movement which has a stimulant to the surrounding environment such as

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temperature, relative humidity, and brightness. Blink rate is directly associated with mental state, physical activity, or fatigue [4], [5].

E. FIXATION

Fixations are the stationary state of eyes. Visual gaze is maintained in a single location during fixation state. Fixations are the events that occur between two saccades. The average fixation time ranges from 100ms to 200ms [6].

In recent years, several eye tracking techniques have evolved which allow the detection and monitoring of eye movements. One of them is Infrared oculography (IR), which is generally used to quantify the difference between the amounts of infrared light reflected by the sclera and sensor (phototransistor) pair [7]. However, IR is not a reasonable technology to measure pursuit or saccades because of the nonlinearity problem. Many other techniques such as search eye coil [8], [9], video images [10], [11] and EOG have been proposed to track eye movements [12], [13]. EOG has been very popular due to its ease of signal acquisition approach. However, studies show that hybrid brain-computer interface utilizing hybrid signal are in practice [12], [14], [15], these papers concentrate on EOG based eye movement analysis. EOG measurement is based on the potential difference between electrodes from the skin it is placed. Human eyes act like a dipole with cornea acting as positive side and retina as a negative side. When eyeballs are rotated, the inner dipoles also move consequently. These movements of eye dipoles make electrical potential slightly change around the eyes. Thus the potential difference assessing eyeball rotation can be measured. Because of these characteristics, EOG signals are considered as an appropriate approach to develop human-computer interface (HCI). It also aids in translating eye movements into human understandable commands.

EOG has become a preliminary eye movement detecting technique in developing HCI systems such as voice recognition [16], [17], visual information [18], gesture control [19], [20], methods based on brain signals, infrared head-operated joysticks [21] and many other medical usages. Extensive research is being carried out in terms of non-medical applications such as gaming [22]–[25], and browsing internet [26]. However, this paper aims to utilize EOG based classification in gaming applications for practical consumption. It discusses an approach to have high accuracy and low computation for an EOG-based HCI baseball game.

II. MATERIALS AND METHODS

Figure 1 gives the overview of the proposed BCI system. BCI system focuses on aspects of extracting EOG signals. An EOG measuring device will be used to record the eye-movements from the subjects. A signal acquisition system is used to collect EOG signals from the devices and the processed signals are transmitted to personal devices with the aid of Bluetooth devices. Thereby, HCI computations are carried out. Classification algorithms are applied for eye-movement detections, and the output is represented by a graphical user interface.

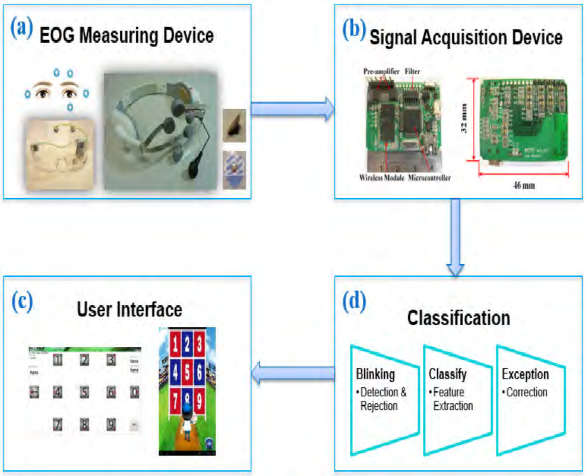

FIGURE 1. System Overview for extracting EOG signals.

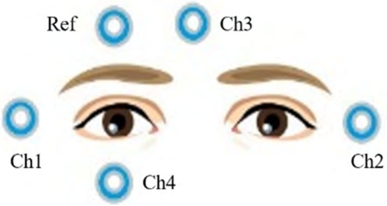

FIGURE 2. Schematic diagram of electrodes placement.

A. EOG MEASURING DEVICE

An EOG Mindo device from National Chiao Tung University Brain Research Center has been used to measure EOG signals from subjects. Electro-physiological signals are measured by placing electrodes around eyes as shown in the figure 2. Electrode placed on the forehead is a reference signal. Four channels are read by placing electrodes around eyes, where Ch1 and Ch2 collect horizontal signals, and Ch3 and Ch4 collect vertical signals.

B. SIGNAL ACQUISITION

The proposed wireless EOG signal acquisition device was approximately 45 × 32 × 8 mm3 in size. A Bluetooth module was employed to transmit the EOG signals wirelessly. The Bluetooth module BM0203 provided a sufficient transfer band rate (115 200 b/s) and was compliant with the computer's Bluetooth v2.0 with enhanced data rate (EDR) specification. Power was supplied by a lithium battery with an output voltage of 3V. A commercial 750 mA·h Li-ion battery has been used to supply power to the EOG acquisition circuit, which has capacity to operate continuously for 12 hours. EOG signals are measured by the wet or dry sensors which are firstly amplified by the preamplifier unit. The preamplifier amplifies the voltage difference between the reference signals and those of the EOG electrodes, while simultaneously rejecting common-mode noise (i.e., the power line noise). An instrumentation amplifier (INA2126, Texas Instruments,

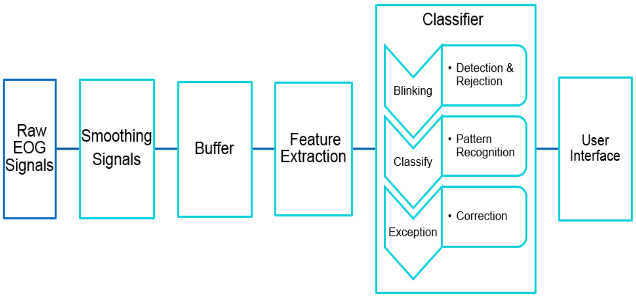

FIGURE 3. **A structural overview of classification algorithm.**

Dallas, TX, USA) was used for its extremely high input impedance and high common-mode rejection ratio (CMRR) (~90 dB) [27].

Instrumentation amplifiers have the ability to improve CMRR and amplify the EOG signals to a degree, where the minute voltage levels can also be detected. Gain of the preamplifier unit was set to 5.5 V/V. The cutoff frequency was regulated at 0.1 Hz by using a high-pass filter. Microcontroller program which is controlling preamplifier and filter stage has reduced the 60 Hz noise in the EOG signals employing a moving average. In addition, a 12-bit resolution ADC has been used to digitize the EOG signals. A microcontroller unit was also used to digitize the EOG signals, with a sampling rate of 256 Hz. The sync filter removed signals with frequencies higher than 62.5 Hz. After removing the noise and amplifying the EOG signals, the data was transmitted to the computer interface via a wireless module.

C. SIGNAL CLASSIFICATION ALGORITHM

EOG Classification algorithm is designed to reduce the overall calculation time and it also does not require signal down sampling. The structural overview of the classification algorithm is as shown in figure 3. A software program gathers four channels transmitted from a Bluetooth device. System reduces the common mode noise caused by electromyography (EMG) and environmental noise. Raw signals are obtained in horizontal and vertical form. In order to extract features from the eye-movement, raw signals need to be smoothened. Calculation amount of the signal has been reduced by introducing buffer in the classification phase.

1) RAW EOG SIGNAL

Electrodes are placed around the eyes to record EOG signals. During this process traces of EMG signals are found due to facial contact of electrodes. This paper intends to discuss extracting only the EOG signals. Hence, EMG signals needs to be removed from the raw signals. Equation (1) and (2) demonstrates the subtraction of channel 2 from channel 1 and channel 3 from channel 4. The signal processing is done by using these equations.

$$\begin{aligned} Horizontal\ Signal &= Ch1signal\ (Horizontal\ +) \\ &\quad - Ch2signal\ (Horizontal\ -) \end{aligned} \tag{1}$$

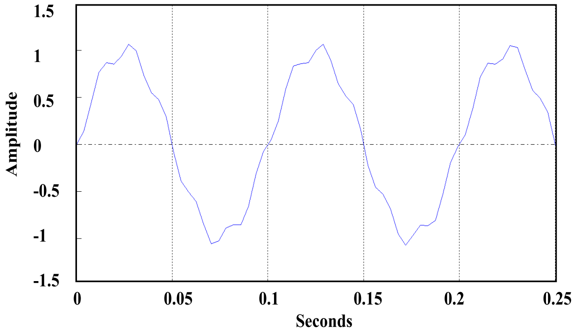

FIGURE 4. **Signal with 60 Hz noise before moving average method.**

$$\begin{aligned} Vertical\ Signal &= Ch3Signal\ (Vertical\ +) \\ &\quad - Ch4Signal\ (Vertical\ -) \end{aligned} \tag{2}$$

a: SIGNAL SMOOTHING

Some high frequency noise still could corrupt the signal in an unexpected way. Thus, to solve this problem, a filtering process in the firmware level is introduced. A moving average method is utilized, to fit the limitation of the hardware. Moving average also called rolling average, is the basic type of FIR filter in DSP domain. Moving average is most commonly used with time series data to smooth out short-term fluctuations and highlight long-term trends or cycles. The choice between short-and long-term, and setting of moving average parameters depends on the requirement of application. Mathematically, the moving average is a type of convolution and similar to a low-pass filter used in signal processing. The moving average filter is optimal for a common task: reducing random noise while retaining a sharp step response. This makes it as the premier filter for time domain signals. Now considering an M-point sequence $x[n]$, it needs to be transformed to a new sequence $y[n]$ through an N-point moving average for this sequence. It means that the each element of output $y[n]$ is the average of N values in order of input sequence $x[n]$. Its input-output relation can be represented in equation (3).

$$\begin{aligned} y\,[n] &= \frac{1}{N}\left(x\,[n] + x\,[n+1] + \ldots + x\,[n+N-1]\right) \\ &= \frac{1}{N}\sum\nolimits_{k=0}^{N-1} x\,[nk] \end{aligned} \tag{3}$$

As mentioned above, the recorded signals are easily interfered by 60Hz noise, especially when the acquisition circuit gets closer to the electric appliances. It has been showed in the figure 4, that the original sine wave had been contaminated by 60Hz power-line noise. After applying the moving average filter with a 5-point moving window, the moving average could be effectively removed by power-line noise, as shown in the figure 5.

Given a continuous noise signal $x(t)$ with frequency F Hz, it is apparently that the integral within 1/F sec is equal to zero. A digital situation is demonstrated here. Equation (3) can be extended to digital form. That means the summation of all

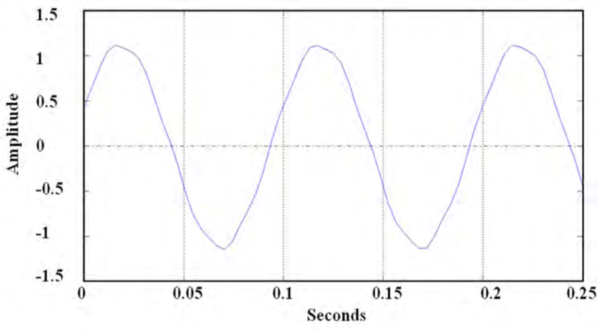

FIGURE 5. Signal with 60 Hz noise after moving average method.

discrete signals with one period is equal to zero as shown in equations (4) and (5).

$$\int_0^{1/x} x(t) = 0 \tag{4}$$

$$\sum_{k=0}^{All\ signals\ with\ one\ period} X[n+K] = 0 \tag{5}$$

The moving window size is decided by both sampling rate and the noise frequency as shown in equation (6).

$$Moving\ Window\ Size = \frac{Sampling\ Rate\ S}{Noise\ Frequency\ F} \tag{6}$$

b: BUFFER

Computational expense of the system can be reduced by introducing buffer which is employed to retrieve temporary data. Computation occurs only when the buffer is full. Hence, it avoids the unnecessary computation there by increasing the efficiency of classifier unit.

2) FEATURE EXTRACTION

In order to analyze the eye-movements from EOG, meaningful features needs to be recognized and extracted. Distinguishable patterns present in saccades makes it easy to be classified further. Primarily, blinks and saccades needs to be segregated. Secondly, more than one eye movement needs to be identified based on this study.

3) CLASSIFIER

Differentiation and peak detection play an important role in the classification algorithm. Differentiation is used to observe the variation of the slopes which can distinguish blinking and other eye-movement efficiently. Figure 6 demonstrates eye-movement classification based on magnitude variation technique. However, this approach is not used to detect certain eye-movements.

Hence, signal classification requires a novel approach to identify blinks in a comprehensive manner, and which can also decrease the correction rate. In this paper, a slope variation technique is used to distinguish blinks from other eye-movements. Figure 7 shows the slope variation of a look-up saccade and the slope variation of a blinking. The slope variation of the blinking is apparently larger than the look-up saccade when compared with the look-up saccade in figure 7 with the special blinking #2 in figure 6. It is discovered that their magnitude is both around 1000μV but the look-up saccade has longer duration than special blinking #2. That means the slope variation of the special blinking #2 is still larger than the look-up saccade. The slope variation method increases the efficiency to classify blinks from other eye-movements.

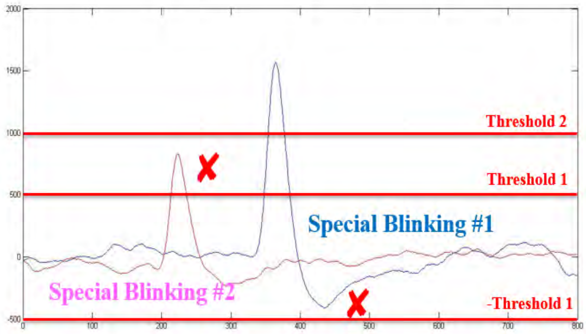

FIGURE 6. Special blinking types using magnitude classification.

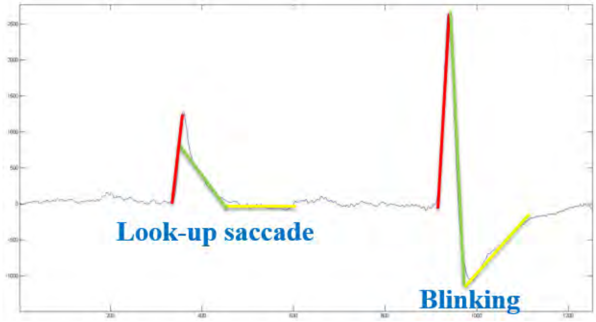

FIGURE 7. Feature of look-up saccade and blinking.

a: PEAK DETECTION

Peak detection is a method designed to reduce the calculation time and the number of misclassified cases by detecting the peak values of the vertical and horizontal signal. Classification algorithm will find peak values of the differentiated signals. The peak value detection is utilized to identify various types of eye-movements.

b: BLINKING DETECTION AND REJECTION

There is a need to overcome misclassification which might adversely affect the specific eye-movement detection. Blinks in the signal are identified and removed in order to avoid the interference of blinks with horizontal and vertical signals. Interference with horizontal and vertical signal will result in misclassification.

A novel method has been introduced to overcome misclassification caused by blinks. An efficient way of classifying eye-movement is to differentiate signals and to extract peak value of signals is shown in figure 8. Once the peak values

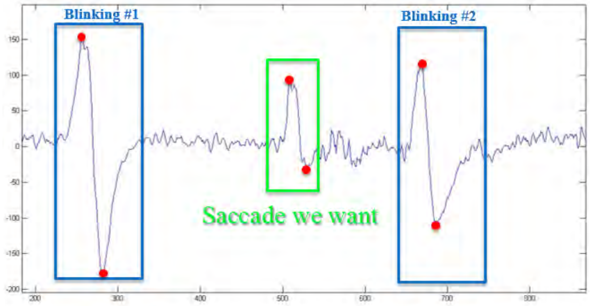

FIGURE 8. Differentiating blink and saccade.

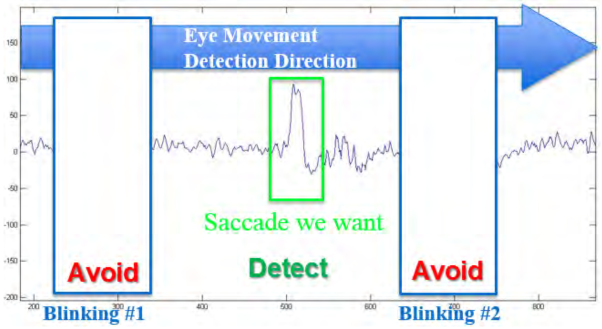

FIGURE 9. Process of rejecting the blinks.

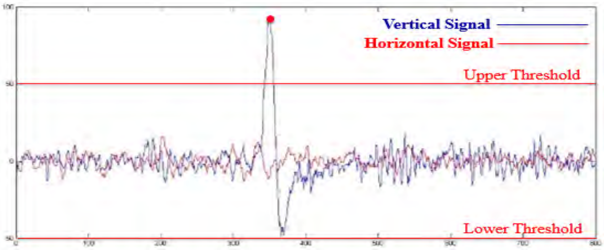

FIGURE 10. Representation of a look-up saccade.

has been verified, blinks can be easily rejected based on their threshold values. The eye-movement marked beyond their threshold values after the peak values are recognized are classified as blink. Once the blink has been identified, they are rejected to extract saccades. The system searches for peak values, and then the left signal of figure 8 is decided as a blink. System does not identify center signal, hence it is marked as a saccade. The blinking rejection process is shown in figure 9.

c: PATTERN RECOGNITION

Various eye-movement detection is done by observing the peak values of the signal. Figure 10 illustrates that the peak value of the vertical signal is marked above the upper threshold and hence the system considers it as a look-up saccade.

Four other eye-movements identified are look-up-and-left, look-up-and-right, look-down-and-left, and look-down-and-right as oblique saccades. System identifies a look-up saccade when the peak of vertical signal is marked beyond the upper threshold value. Similarly system can identify a look-left saccade when it encounters horizontal signal marked beyond its threshold value. Combination of look-up and look-left saccades forms a look-up-and-left saccade eye-movement as shown in figure 11. However, both look-up saccade and look-left saccade have to occur at the same time. A misclassification is created when there is a mismatch in the occurrence of two signals. This misclassification can be removed by applying the exception correction.

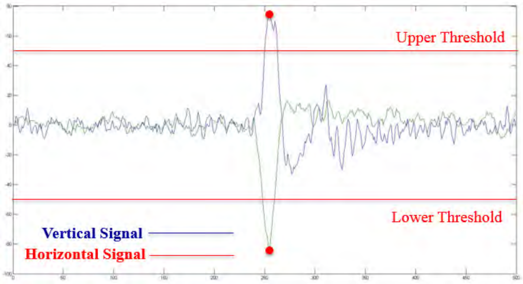

FIGURE 11. Representation of a look-up-and-left saccade.

Target of Mindo : SPP Slave - 0018003206E8

Time range to show the data : 5 sec

☐ Save as : C:\Users\lab540\Desktop\MINDO.txt

☐ Receive comport via RS232 :

Load a text file of the channel names :

Searching BT device is completed.

FIGURE 12. Setting interface.

D. GRAPHICAL USER INTERFACE DESIGN

This paper aims to present classification results on a HCI baseball game platform. An initial baseball game interface is shown in the figure12. A time range is set up to display the data, file and name. Once all the required information is gathered, device is paired with a Bluetooth device to stimulate interface. Figure 13. Simulating interface is activated by pressing start button and it will guide user through different steps. This will aid us to record user reaction and to recognize various eye-movements. The total number of eye-movements occurred during this session can also be registered.

III. EXPERIMENTAL SETUP

Three aspects of experimental set up has been discussed in this paper. First experiment set up is to verify the classification working capability by considering normal scale and cues. Second experiment setup tests the capability of the classification by eliminating cues and using the same scale

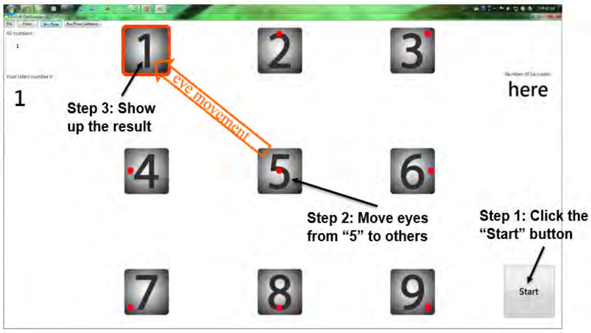

FIGURE 13. Stimulating interface and the user steps.

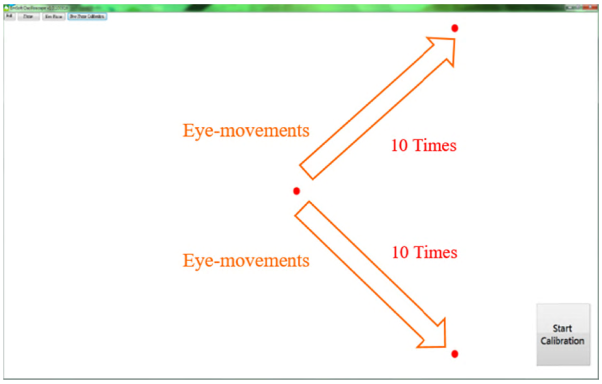

FIGURE 14. Calibration interface and using procedure.

as the first test experiment. Third experiment is to test the classification functionality on a tablet by reducing original scale size to half of its size as to make it work on a tablet while considering the cues. Eye-movement is detected based on the horizontal and vertical threshold values of EOG signals. A Matlab based approach has been utilized to analyze the recorded EOG signal. The calibration interface utilized in this project can distinguish various eye-movements based on the threshold values.

Figure 14 shows a simple and effective calibration interface system. Initially user needs to press ''Start calibration'' button, and the calibration will show the cue in the center of the frame. Then the up-right red dot will show up, now the user will have two seconds to move their eyes to the up-right position. Similarly, experiments will be repeated for down-right position. This experiment position will be repeated for 10 times for the system to collect sufficient data to set up an appropriate threshold value.

An experimental environment is set up to mimic the day to day computer usage. Hence, a distance of 50cm is maintained between the viewer and the monitor. Look-up and look-down distances from eyes and monitor are maintained at 11cm. Look-right and look-left distance from eye to monitor is 13cm. This experiment is set up on a 22'' monitor. Figure 15 shows the experiment set up. Since the magnitude and accuracy [28] of EOG signal depends on the angular velocity, distance is transferred into the angle which is convenient to establish the relation between EOG signal and the scale of screen. Table 1 illustrates the calculated angle of view. The above equation can be extended to digital form. That means the summation of all discrete signals with one period is equal to zero.

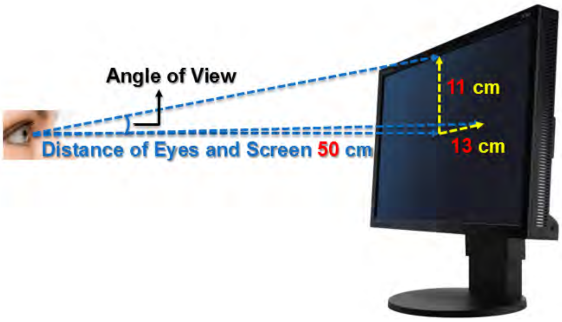

FIGURE 15. Experiment environment.

TABLE 1. Angle of view.

Direction	Angle of View	Direction	Angle of view
Up	12.4°	Up-right	18.8°
Down	12.4°	Up-left	18.8°
Left	14.6°	Down-right	18.8°
Right	14.6°	Down-left	18.8°

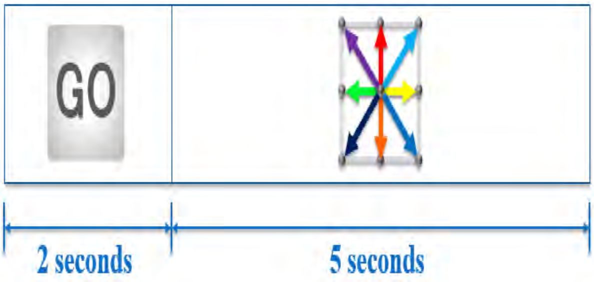

FIGURE 16. Color code representation for experiment procedure with cues.

A. EXPERIMENT PROCEDURE WITH CUES

In day-to-day activities, eight directional saccades and fixation are observed. Different color code is assigned for respective eye-movements as shown in figure 16. Look-up, look-down, look-right, look-left, look-right-up, look-right-down, look-left-up and look-left-down are represented by red, orange, green, yellow, blue, aqua blue, violet and navy blue respectively.

B. EXPERIMENT PROCEDURE WITHOUT CUES

This experiment is designed to simulate an intuitive technique while using the EOG application. Cues have been eliminated so that the user don't have to limit their eye moves in a particular direction. Process of this experiment is empty for initial 2 seconds. For the next 5 seconds the subject is

FIGURE 17. Experiment procedure without cues.

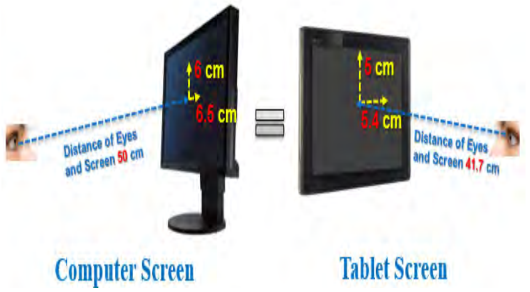

FIGURE 18. Computer screen and tablet screen.

asked to move eyes in any direction. Color code represents the respective eye-movement as described in the previous section. Figure 17 shows the experimental set up without cues. Primarily, this experiment is intended to provide a natural approach to play HCI game by allowing user to have an independent eye-movement.

C. EXPERIMENT PROCEDURE WITH CUES USING SMALL SCALE

This experiment is repeated similar to the previous set up by narrowing down the scale. A challenge has been encountered while narrowing the scale, as the scale is narrowed the distance between eye and the monitor is also reduced. This will cause the signal to be smaller in amplitude and it becomes difficult to classify the signal. It will also raise misclassification due to the signal direction being deviated from the expected direction. In order to use this EOG classification algorithm on a tablet, the scale is narrowed about half of the original size. Figure 18 shows that as we deflate the scale to 6 cm X 6.5 cm, it allows users to see the tablet from 41.7 cm distance.

Now the shrinking scale will change the threshold that classifies eye-movements because the distance and the angle of view are smaller. A calibration interface has been designed to fit the screen size. This has been stimulated on the PC as shown in figure 19. As shown in figure 19 each of them has three red points. First user needs to focus on the center red point, after the cue vanishes, the user will now have two seconds to make an eye-movement. The user is asked to look at the right-up red point for five times. Each time the user is given two seconds to look at the point. Later, the user is asked to follow the similar pattern in the right-down direction. The system will acquire required information from these eye-movements.

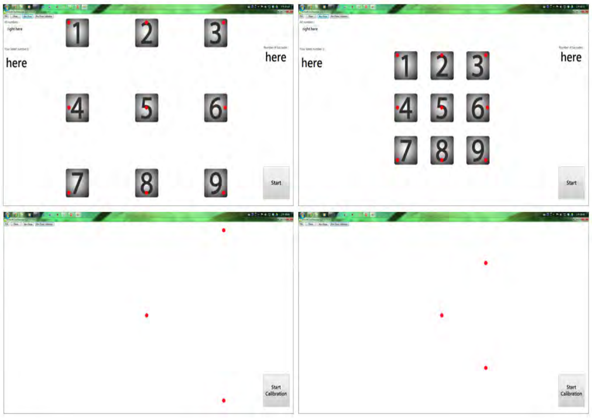

FIGURE 19. Calibration interface.

TABLE 2. Results of experiment procedure with cues.

Eye Movement Type	Correct rate (%)
Number 1 (↖)	83.33%
Number 2 (↑)	96.67%
Number 3 (↗)	81.67%
Number 4 (⟵)	91.67%
Number 5	N/A
Number 6 (⟶)	91.67%
Number 7 (↙)	85%
Number 8 (↓)	96.67%
Number 9 (↘)	78.33%

IV. RESULTS

EOG signal is considered in this study to differentiate various eye-movements of the subjects. A classification technique is provided which removed 90% of blinks along with extracting required saccades. Hence, it is effective in removing blinks. Overall computational time has been reduced by eliminating down sampling of the EOG signals. This has increased efficiency of the classification system.

A. RESULTS OF EXPERIMENT PROCEDURE WITH CUES

Experiment procedure with cues result in high correct rate. The current classification technique yields higher accuracy when compared with the historical data and classification techniques. It is evident from the comparison results listed in table 2 and 3. The classification result is more stable for number 2, number 4, number 6 and number 8. Number 1, number 3, number 7, number 9 have resulted in stable oblique eye-movement.

B. RESULTS OF EXPERIMENT PROCEDURE WITHOUT CUES

In this experiment procedure without cues, the correct rate decrease apparently. Results showed in table 4 indicates that

TABLE 3. Results of previous classification.

Eye Movement Type	Correct rate (%)
Number 1 (↖)	96%
Number 2 (↑)	98%
Number 3 (↗)	96%
Number 4 (←)	96%
Number 5	100%
Number 6 (→)	100%
Number 7 (↙)	96%
Number 8 (↓)	98%
Number 9 (↘)	94%

TABLE 4. Results of experiment procedure without cues.

Eye Movement Type	Correct rate (%)
Number 1 (↖)	92%
Number 2 (↑)	96%
Number 3 (↗)	94%
Number 4 (←)	90%
Number 5	92%
Number 6 (→)	96%
Number 7 (↙)	90%
Number 8 (↓)	90%
Number 9 (↘)	92%

correct rates are slightly deteriorated from that procedure with cues. The correct rate of the number 5 has lowered significantly.

C. RESULTS OF EXPERIMENT PROCEDURE WITH CUES ON SMALL SCALE DEVICE (SSD)

Result obtained by procedure with cues on a small scale device show that there is a decrease in the correct rate. Table 5 shows that the correct rates of number 2, number 4, number 6 and number 8 have increased from that of previous results. It signifies that the proposed classification techniques works appropriately for small scale screens. However, the correct rate of number 1, number 3, number 7, number 9 are considerably low. This classification can fit the small scale, it can be applied on the tablet.

TABLE 5. Results of experiment procedure with cues SSD.

Eye Movement Type	Correct rate (%)
Number 1 (↖)	92%
Number 2 (↑)	100%
Number 3 (↗)	94%
Number 4 (←)	98%
Number 5	100%
Number 6 (→)	92%
Number 7 (↙)	92%
Number 8 (↓)	94%
Number 9 (↘)	90%

TABLE 6. Results of application on HCI baseball game.

Rounds (10 trials)	Correct rate (%)
Round 1	90%
Round 2	90%
Round 3	100%
Round 4	90%
Round 5	80%

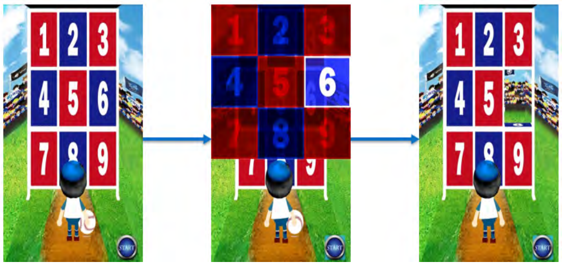

FIGURE 20. HCI game processing.

D. RESULTS OF APPLICATION ON HCI BASEBALL GAME

The setting up for the HCI Baseball game is as shown in figure 20. Firstly, press the "START" button to enter the HCI Baseball game. A translucent panel with the numbers will show up. Number 5 in the center on the panel is brighter than other numbers. Subsequently, the next number will randomly light up and it will blink. While the number is blinking, we move the eyes towards the blinking number, from the center of panel. If the blinking number is 5, eyes still stand on the center of the panel.

Accuracy rate as shown in figure 21. Since every run has 10 trials, each run of the interface will show a number and the user repeats the task 10 times. A correct rate is obtained by dividing it by ten trials. The correct rate has increased and hence this EOG classification can be leveraged into real life scenario.

V. DISCUSSION

Experimental results have demonstrated that the proposed classification techniques provide high accuracy and have improved the fluency of HCI game interpretation methods. Stable classification is obtained by conducting experiments

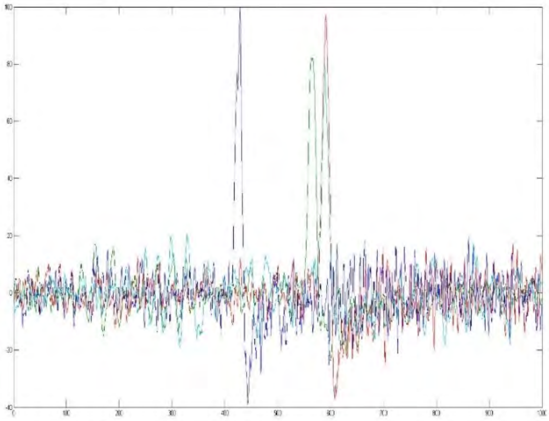

FIGURE 21. Look-up saccade and look-right saccade compared with look-up-right saccade.

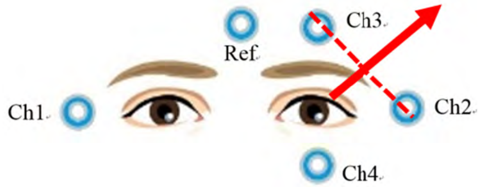

FIGURE 22. The electrode placement with the oblique eye-movement.

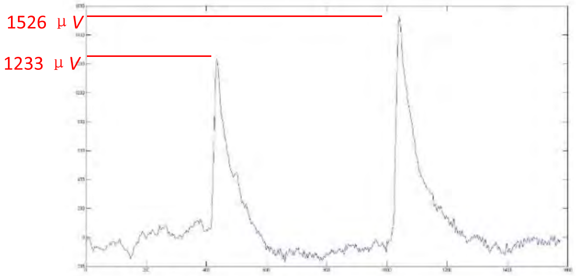

FIGURE 23. Two look-up saccades without differentiation.

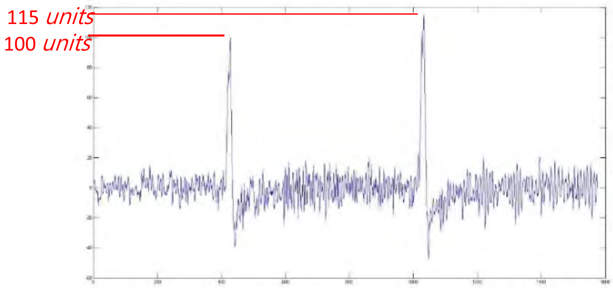

FIGURE 24. Two look-up saccades with differentiation.

with cues. Most of the blinks were removed during this classification technique and the oblique eye-movements are well classified with the above method. When the experiment was conducted without cues, blinks were not removed effectively due to processing time. Hence, a buffer was implemented which aided in classifying eye-movements. This system will split the signal when it encounters a blink before passing it through buffer. This will cause misclassification. This factor explains the decrease in correctness rate for experiment procedures without cues for number 5.

The average correct rate of the result for experiment with cues in the small scale is lower than the average correct rate of the result for experiment with cues. This can be observed for the correct rate of number 1, number 3, number 7 and number 9. This circumstance will explain that the angle of view is smaller, which can make the EOG signal smaller and the EOG signal is proportionate with the angle of view. When the oblique eye-movement distance is longer from the screen, the signal of the vertical and the horizontal are smaller than the up, down, right and left eye-movements.

It is evident from figure 21 that the oblique eye-movement signal is smaller than the look-up saccade or look-right saccade. This occurrence demonstrates that the signal scale is about ten times smaller than the original signal and it is caused by electrode displacement.

Figure 22 explains a look-up-left saccade. For look-up-left saccade signal is captured by channel 2 and channel 3. If there is only a look-up saccade, signal is captured by channel 3. Channel captured for look-up saccade is clear and hence appear large. When an oblique eye-movement occur, the left eye will not directly approach the channel 2 or channel 3. Therefore, vertical and the horizontal signal of the oblique eye-movement are smaller than the up, down, right and left eye-movements. Small scale has the smaller angle of view than the normal scale, apparently the signal in small scale is smaller than normal scale. The other key point is that if there is a slight disturbance while using the tablet, this classification can tolerate a bit of deviation. That is because, classification applies differentiation. This will shrink the magnitude of signals which makes deviation smaller.

Figure 23 shows two saccades without differentiation, and the deviation is 293 micro-volt. In figure 24 we can observe two saccades with differentiation, and the deviation is 15 units. When a threshold is set by the calibration, the error probability of the two saccades without differentiation is higher than two saccades with differentiation. It aids differentiation to shrink the scale of the signals and this can shrink the deviation at the same time which in turn decreases the error probability.

VI. CONCLUSION

It is evident from the HCI Baseball game that the classification can be utilized in everyday life. Usability and simplicity of the classification is made efficient due to online computation. The performance accuracy of the system has been improved by scaling down the measurement to fit a tablet. The proposed method has established that by utilizing eight eye-directional movement the accuracy and performance of the system can be increased. Research conducted based on procedures without cues and small scale measurements calls for a further study in terms of improving the accuracy.

In future, we focus on developing descriptive alternatives for all directions and even smaller scale eye-movements classification and also on the implementation of a stable classification on the circuit board. This EOG device can work freely like a remote controller or a joystick.

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CHIN-TENG LIN received the B.S. degree from National Chiao-Tung University (NCTU), Taiwan, in 1986, and the master's and the Ph.D. degrees in electrical engineering from Purdue University, USA, in 1989 and 1992, respectively. He is currently the Chair Professor of Faculty of Engineering and Information Technology, University of Technology Sydney, Chair Professor of Electrical and Computer Engineering, NCTU, International Faculty of University of California at San-Diego (UCSD), and Honorary Professorship of University of Nottingham. He was elevated to be an IEEE Fellow for his contributions to biologically inspired information systems in 2005, and was elevated an International Fuzzy Systems Association (IFSA) Fellow in 2012. He has been elected as the Editor-in-Chief of the IEEE TRANSACTIONS ON FUZZY SYSTEMS, since 2011. He also served on the Board of Governors with the IEEE Circuits and Systems (CAS) Society in 2005-2008, the IEEE Systems, Man, Cybernetics (SMC) Society in 2003-2005, the IEEE Computational Intelligence Society (CIS) in 2008-2010, and Chair of the IEEE Taipei Section in 2009 – 2010. He is the Distinguished Lecturer of the IEEE CAS Society, from 2003 to 2005, and CIS Society, from 2015 to 2017. He served as the Deputy Editor-in-Chief for the IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS-II, in 2006 – 2008. Prof. Lin was the Program Chair of the IEEE International Conference on Systems, Man, and Cybernetics in 2005 and General Chair of 2011 IEEE International Conference on Fuzzy Systems. He is the coauthor of Neural Fuzzy Systems (Prentice-Hall), and the author of Neural Fuzzy Control Systems with Structure and Parameter Learning (World Scientific). He has published more than 200 journal papers (Total Citation: 20,155, H-index: 53, i10-index: 373) in the areas of neural networks, fuzzy systems, multimedia hardware/software, and cognitive neuro-engineering, including approximately 101 IEEE journal papers.

JUNG-TAI KING received the B.S. degree in psychology from National Cheng-Chi University in 1998, the M.S. degree in criminology from National Chung-Cheng University in 2001, and the Ph.D. degree in neuroscience from National Yang-Ming University (NCTU) in 2010. He is currently an Assistant Research Fellow with Brain Research Center, NCTU, Taiwan. His research interests include psychophysiology, cognitive, and social neuroscience and neuro-marketing.

PRIYANKA BHARADWAJ received the B.S. degree from Visvesvaraya Technological University, Belgaum, Karnataka, India, in 2012, and master's degree from the State University of New York, USA, in 2014. Additionally, she was a Software Engineer in the USA and Singapore before joining UTS as a Visiting Fellow. Her research interests include signal processing, machine learning, and data analytics.

CHIH-HAO CHEN received the master's degree from Institute of Imaging and Biomedical Photonics, National Chiao Tung University, Hsinchu, Taiwan. His research interests include brain computer interface, machine learning, and signal processing.

AKSHANSH GUPTA received the master's and Ph.D. degrees from the School of Computer and Systems Sciences, JNU, in 2010 and 2015, respectively. He is currently a Postdoctoral Research Fellow with the School of Computational and Integrative Sciences, Jawaharlal Nehru University (JNU), New Delhi, India. His research interests include signal processing, brain-computer interface, cognitive science, and healthcare.

WEIPING DING received the M.S. degree in software engineering from Soochow University, Suzhou, China, in 2005, and the Ph.D. degree in computer application from Nanjing University of Aeronautics and Astronautics, Nanjing, China, in 2013. His current research interests include granular computing, data mining, machine learning, and their applications in medicine. He was a Visiting Researcher with the Department of Mathematics and Computer Science, University of Lethbridge, Alberta, Canada, in 2011. In 2014, he was a Postdoctoral Researcher with the Brain Research Center, National Chiao Tung University (NCTU) with Professor Chin-Teng Lin, Hsinchu, Taiwan. In 2016, he was a Visiting Scholar with National University of Singapore (NUS), Singapore. From 2017 to 2018, he was a Visiting Professor with University of Technology Sydney (UTS), Ultimo, NSW, Australia. He is currently an Associate Professor with the School of Information Science and Technology, Nantong University, Nantong, Jiangsu, China. He is a Senior Member of CCF. He is Chair of Task Force on Granular Data Mining for Big Data, the IEEE Computational Intelligence Society. He has authored or coauthored more than 60 papers in top journals and prestigious conference proceedings. He was a recipient of the National Natural Science Young Foundation of China in 2013. He was awarded as High-Level Talent (Six Talent Peak) of Jiangsu Province in 2016, and a Middle-aged and Young Academic Leaders (Qing Lan Project) of Jiangsu Province in 2019. Dr. Ding currently serves on the Editorial Advisory Board for Knowledge-Based Systems and Editorial Board of Information Fusion. He serves/served as an Associate Editor for several prestigious journals, including the IEEE TRANSACTIONS ON FUZZY SYSTEMS, *Information Sciences*, *Swarm and Evolutionary Computation*, IEEE ACCESS and *Journal of Intelligent and Fuzzy Systems*, Co-Editor-in-Chief of *Journal of Artificial Intelligence and Systems*, as well as the leading guest editor in several international journals. He serves/served as a program committee member for several international conferences and workshops.

MUKESH PRASAD received the Ph.D. degree in computer science from National Chiao Tung University (NCTU), Hsinchu, Taiwan, in 2015 and master's degree in computer application from Jawaharlal Nehru University, New Delhi, India, in 2009. He was a Principle Engineer (Research and Development) with Taiwan Semiconductor Manufacturing Company, Hsinchu, Taiwan. He is currently a Lecturer with the School of Computer Science, Faculty of Engineering and Information Technology, University of Technology Sydney, Australia. He has published 35 peer reviewed journals and 40 conference articles. His current research interests include machine learning, data analytics, pattern recognition, fuzzy systems, neural networks, artificial intelligence, and brain computer interface.

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