



Title	A user-friendly wearable single-channel EOG-based human-computer interface for cursor control
Author(s)	ANG, AMS; Zhang, Z; Hung, YS; Mak, JNF
Citation	The 7th International IEEE/EMBS Conference on Neural Engineering (NER 2015), Montpellier, France, 22-24 April 2015. In Conference Proceedings, 2015, p. 565-568
Issued Date	2015
URL	http://hdl.handle.net/10722/214827
Rights	International IEEE/EMBS Conference on Neural Engineering (CNE). Copyright © IEEE.

A User-friendly Wearable Single-channel EOG-based Human-Computer Interface for Cursor Control

A. M. S. Ang, Z. G. Zhang, *Member IEEE*, Y. S. Hung, *Senior Member IEEE*, J. N. F. Mak

Abstract—This paper presents a novel wearable single-channel electrooculography (EOG) based human-computer interface (HCI) with a simple system design and robust performance. In the proposed system, EOG signals for control are generated from double eye blinks, collected by a commercial wearable device (the NeuroSky MindWave headset), and then converted into a sequence of commands that can control cursor navigations and actions. The EOG-based cursor control system was tested on 8 subjects in indoor or outdoor environment, and the average accuracy is 84.42% for indoor uses and 71.50% for outdoor uses. Compared with other existing EOG-based HCI systems, this system is highly user-friendly and does not require any training. Therefore, this system has the potential to provide an easy-to-use and cheap assistive technique for locked-in patients who have lost their main body muscular abilities but with proper eye-condition.

I. INTRODUCTION

In recent years, numerous human-computer interface (HCI) systems have been developed as assistive technologies for improving life quality of the people with neuromuscular disabilities [1]. Examples of these assistive technologies include specially designed joystick, infrared-oculography, tongue-computer interface and brain-computer interface [2, 3]. Generally, all these HCI systems serve as the bridge between the human and the computer by translating or decoding the signals generated from physiological processes into control commands. Particularly, because the eyes and related facial muscles are rarely affected by neuromuscular mobility impairments, many HCI systems are developed by translating electrooculography (EOG) signals generated by intended actions of these intact organs to control commands. A majority of existing EOG-HCI systems [4-7] rely on multi wet electrodes, because they can achieve a high signal-to-noise ratio (SNR) of EOG and can provide more discriminative information for recognizing more types of eye activities. As a result, characteristic structure of EOG in temporal or spatial domain can be more accurately extracted by multiple wet electrodes, and hence the systems are more capable of classifying different types of eye-movements such as looking at different directions, resulting in a higher system performance score.

Although the HCI systems based on multi-channel EOG normally have a good performance, they are not considered as

user-friendly and practical. The overall quality of an assistive technology can be evaluated by two types of factors, the ergonomic factors and the system performance factors. System performance factors, such as the accuracy of classifying signals encoded by different intentions, the false alarm rate, the execution speed, and the information transfer rate, are often regarded as the most important factors when designing a HCI system, particularly, in laboratory. However, for practical applications for end users, the ergonomic factors such as comfortableness, portability, cost effectiveness, and time spent on training are crucial because a HCI system ultimately has to be used by an end user for a long period of time and in an easy-to-use manner. Ergonomic factors are less considered in many existing EOG-based HCI systems developed in laboratory, and therefore, these systems cannot provide a practical assistive technique for users. For example, current HCI systems based on EOG activities usually consist of a large bulk of hardware, such as wiring and amplifiers, which are not user-friendly for disabled people since they have a higher setup and preparation cost. Another important ergonomic factor is the time spent on training for users. Most EOG-based HCI systems require users to perform intensive practice in a training session, or to memorize certain kind of eye movements for specific control commands, which is not user-friendly and could not be achievable for patients with cognitive impairments.

In this paper, we develop a novel EOG-based HCI system which is aimed at maximizing both ergonomic factors (usability, less training time, etc.) and system performance factors (accuracy, information transfer rate, etc.). The proposed system only use EOG produced by one type of eye activity, double blink (DB), to encode user's intentions. In the proposed system, EOG activities are captured by a single-channel commercial headset, the NeuroSky MindWave Mobile Headset (NeuroSky, CA, US). The headset is basically a single-channel sensor with a dry electrode made of stainless steel. The sensor is attached on the forehead of the user to collect electrical signals generated by the brain and muscles continuously. The system then sends the collected signals wirelessly through a Bluetooth communication protocol to a computer for processing. The processing blocks consist of filtering, activity detection and classification. The recording will first be filtered to remove noise and any undesired components, and then the continuous recording will go through an activity detector to extract a short data segment containing EOG activities. The extracted data segment will be analyzed to yield a set of discriminative features to be fed into a classifier. Finally the classification output is used to control the mouse cursor for multiple applications in a computer. The control of the cursor is based on the following switching control scheme : (1) the mouse cursor will keep moving either vertically (from top to bottom) or horizontally (from left to

Research supported by a Hong Kong RGC GRF Grant (HKU 785913M)

A. M. S. Ang and Y. S. Hung are with the Department of Electrical and Electronic Engineering, the University of Hong Kong, Pokfulam Road, Hong Kong (email: angms@hku.hk; yshung@eee.hku.hk).

Z. G. Zhang is with the School of Chemical and Biomedical Engineering and the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore (zg Zhang@ntu.edu.sg).

J.N.F. Mak is with NeuroSky Hong Kong, Science Park, Sha Tin, Hong Kong, (e-mail: jmak@neurosky.com).

right) on the screen with a constant speed if no double blink is detected; (2) when the first double blink (i.e. a control command) is detected from EOG, the cursor will switch its moving direction (from vertically to horizontally, or from horizontally to vertically); (3) when the second double blink occurs, a clicking action will be performed on that current cursor location and the mouse cursor will be reset to the top-left corner of the screen and move again.

As compared with existing EOG-based HCI systems, the advantages of the new system are three folds. First, it is based on a commercial device, NeuroSky MindWave headset, so that it has a high mobility and can be potentially used in more scenarios. Second, the system only uses one eye action, double blinks, to encode users' intentions so that the control strategy is simple and user friendly. Third, because of the high inter-subject consistency of double-blink EOG signals, the system is capable of performing cross-subject decoding, which means that no training is required for new users.

Unlike other multi-channel counterparts, the proposed system only has one single electrode to collect information, and therefore, the proposed system is more sensitive to noise and hence having a lower SNR. To handle these problems, the system adapts some advanced signal processing methods (such as wavelet filtering and support vector machine) to boost the system performance.

The rest of the paper is organized as follows. In Section II, the system architecture, data analysis methods and implementations of the new EOG-based system are proposed. The experimental results and discussion are given in Section III. Summary is drawn and discussed in Section IV.

II. METHODS

A. System Architecture

Fig. 1 shows the structural diagram of the proposed system. EOG signals generated from the user are collected by the NeuroSky MindWave Mobile headset with a sampling rate of 512Hz. The raw digital signals are packed and then transmitted into a computer through Bluetooth communication protocol. Data packet parsing is then performed in the computer to obtain the raw numerical values of the signals. These raw signals then go through pre-processing blocks, which include de-trending and wavelet de-noising to remove noise and un-desired components. The filtered signals then pass through an activity detector to extract the signal segments that contain double blinks (or other major eye activities) and store the extracted signal segment into a buffer of 1 second. Subsequently, feature extraction is performed for each buffer and the features extracted are fed into the SVM classifier. All the functional blocks are cascaded, once a non-interested activity is detected, the system will throw away that segment immediately to save computational resources.

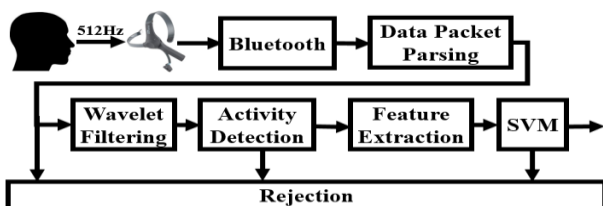


Fig. 1. The cascade architecture of the whole system.

B. EOG Signals

EOG signals are the electrical activity generated by the movements of the eyeballs or the eyelid muscles. As shown in our previous study, various kinds of EOG signals, such as looking towards different directions and blinking in different ways, can be used to indicate the user's intentions [8]. However, because the system proposed in this paper is primarily focused on practical aspects and is aimed at providing an alternative communication pathway for the disabled people, only both-eye double blinks (DB) will be used as control signals in this paper.

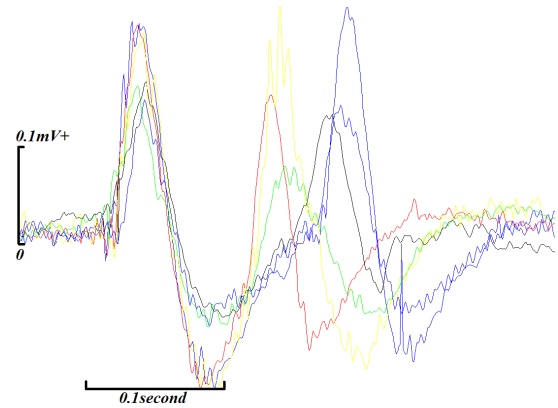


Fig. 2. The raw double blink EOGs collected from 6 subjects (denoted by different colors). Signals are aligned by the first peaks.

C. Filtering and Real-time Detection

Although the EOGs look highly consistent, filtering is necessary for noise removal and enhancement of the reliability of the detector and the extracted features. Wavelet filtering is used instead of traditional bandpass filtering to remove noise from raw recordings because of its better de-noising ability and smaller phase distortion. As a result this improves the performance of the system.

Activity detection is used in the system to isolate DB signals from continuous recordings. Because there is a great difference in terms of magnitude between the DB signals and the background recording, a magnitude-based detection method is used. When the signal magnitude exceeds a certain threshold, a 1-second segment of that instant will be extracted out and stored into a buffer. To handle the non-stationarity of DB signals, the threshold value γ is dynamically updated by adjusting previous threshold value with the current estimated magnitude of background recordings. That is, γ is calculated as follows:

$$\gamma^{\text{New}} = \gamma^{\text{Previous}} \times \frac{\text{new noise magnitudes}}{\text{previous noise magnitude}}. \quad (1)$$

Experimental data shows that the dynamic threshold γ for the DB signal is $0.0498\text{mV} \pm 0.0072\text{mV}$ (mean \pm sd).

D. Feature Extraction and Classification

From the 1s data segments we extract features that can differentiate DB signal of interest from signals generated by other eye movements, such as single blinks. We extracted numerous features (either in time domain or in frequency domain) from data segments and performed feature selection

by comparing the inter-cluster distances of each feature. Finally, the following three features are selected for classifying DB activity and non-DB activity: L1-norm, Kurtosis and Entropy. L1-norm measures the magnitude of the signal by summing up the absolute values of all the samples in the signal vector. Kurtosis measures the peakedness of the signal and entropy measures the amount of information in the signal.

After feature extraction, three features are fed into the classifier, which is basically a kernelized support vector machine (SVM). In training the SVM, both regularization and cross-validation are performed. The classification output will be translated to digital commands for controlling the mouse cursor.

E. Cursor Control

DB signals are used as a switch in the system to control the following two actions: (1) the switching of the moving direction of mouse cursor and (2) left-clicking. Suppose the mouse cursor has the coordinate of (X,Y) on the screen with an initial condition of X=Y=1 (the top left corner of the screen). When the system starts running, the mouse cursor will start moving horizontally (i.e., Y is kept constant but X is kept increasing with a step size of δ_x). When a DB activity is detected, the cursor will stop at the current location and start moving in vertical (i.e., X is kept constant and Y is kept increasing with step size of δ_y). When the second DB activity is detected, the mouse will left-click at that location (X,Y), and then its coordination will be reset to X=Y=1. The whole process repeats so that complex functions, such as text input, can be realized. The cursor control paradigm is summarized in Table I.

TABLE I. FLOWCHART OF CURSOR CONTROL USING DOUBLE BLINKS

```

BEGIN
  XMax ← Screen X ; YMax ← Screen Y;
  δx ← XMax / 300, δy ← YMax / 100;
  X ← 0; Y ← 0;
  WHILE running
    IF Direction == Horizontal
      X ← mod(XMax, X + δx);
      IF Double-Blink detected
        Direction ← Vertical;
      END IF
    ELSE IF Direction == Vertical
      Y ← mod(YMax, Y + δy);
      IF Double-Blink detected
        Mouse click;
        Direction ← Horizontal;
        X ← 0; Y ← 0;
      END IF
    END IF
  END WHILE
END BEGIN

```

The default values of X_{Max} and Y_{Max} are the screen sizes, while δ_x and δ_y are the step sizes along horizontal and vertical directions, respectively. These values affect the cursor moving speed and thus can be tuned to meet different people's need. In this paper the screen resolution is 1920×1080.

F. Experiment Setup

Eight subjects (aged 18-40; all males) with proper eye conditions participated in the experiment. Data were recorded from two scenarios: indoor (in a quite laboratory) and outdoor (in a canteen with different sources of noise to stimulate real-life situation). We collected indoor data from 6 subjects, and outdoor data from 2 subjects. The subject is seated in a chair and the headset sensor is attached to the forehead with a sampling frequency at 512Hz. A computer was placed about 50-100cm in front of the subject. The experiment consists of two sessions: a calibration session and a testing session. In the calibration session, we collected a few (less than 5) DB signals from each subject and the signals are used to check whether the sensor is detached from the subject's forehead as well as to calibrate threshold as (1). No training is performed after the calibration. Then system is tested using the virtual on screen keyboard. All subjects gave their written informed consent, and the local ethics committee approved the experimental procedures.

G. Performance Evaluation

To evaluate the system performance, the accuracy, the information transfer rate (ITR) and the processing time will be used. The accuracy is the ratio of correctly classified trials to the total number of signal trials. ITR is a measure of amount of bits transferred per minute. It is calculated as

$$ITR = \frac{60}{T} [p \log_2(p) + (1-p) \log_2(\frac{1-p}{N-1}) + \log_2(N)], \quad (2)$$

where T is the time interval between two consecutive commands, N is the number of commands, and P is the classification accuracy. In the proposed system $N=2$ and $T=2.02s \pm 0.59s$. Notice that ITR is a function of time intervals between commands and accuracy, thus high accuracy does not always implies a higher ITR.

Finally, the processing time required for the user to input a short English phrase is also evaluated. To test the control of the cursor on texting, the Windows On-Screen Keyboard is used as shown in Fig. 3. When the mouse moves to the corresponding button, the user performs a DB to "press" the button. The English phrase "hello world" which contains 11 characters (space included) is used to simulate daily usage of the computer for word input.

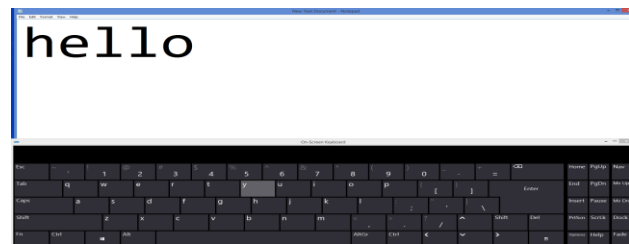


Fig. 3. The user interface based on the on-screen keyboard in Windows 7.

III. RESULTS

On average, the accuracy and ITR for indoor and outdoor testing are (84.41%, 45.47 bits/min) and (71.50%, 41.39 bits/min) respectively. The following tables show the results for each subject in indoor and outdoor environment. It is important to note that, the SVM classifier is trained on Subject 1 and applied to all subjects. In another word, the performance

of Subjects 2-6 listed in the following tables is from cross-subject prediction and these subjects did not undergo any training phase before they used the EOG-HCI system.

TABLE II-A. IN DOOR SYSTEM PERFORMANCE OF THE EOG-HCI SYSTEM

Subject	1	2	3	4	5	6
Accuracy (%)	95.12	80.00	88.10	85.29	88.00	70.00
ITR (bit/min)	54.60	48.15	50.68	39.78	38.37	38.70
$t_{\text{hello-world}}$ (min)	2.1	3.3	3.1	3.5	4.0	3.8

TABLE II-B. OUTDOOR SYSTEM PERFORMANCE OF THE EOG-HCI SYSTEM

Subject	7	8
Accuracy (%)	69.00	74.00
ITR (bit/min)	40.00	42.77
$t_{\text{hello-world}}$ (min)	5.5	5.2

The times spent ($t_{\text{hello-world}}$) on typing “hello world” from different subjects are largely different, which is due to the following reason. Because of the advanced signal processing algorithms used in this system, the computational complexity of the proposed system is moderately high. As a result, there is a small amount of time delay (0.1~0.5 seconds), which made it possible for the users to click at the wrong location on the screen. Therefore, the time spent on typing “hello world” actually includes the time spent on pressing “backspace” to delete the wrong inputted characters. To address the problem of lagging, the following improvements can be made: (1) δ_x and δ_y should be smaller, (2) a larger cursor (by changing the operating system setting) should be used, (3) the computer screen size should be larger so that the button size of the virtual on screen keyboard can be larger and becomes easier to press. It is also suggested that the movable range of the cursor position should be constrained. For example, when initializing the cursor position, the top-left corner of the virtual on-screen keyboard should be used instead of the position (0, 0).

In addition, we did a survey on the user-friendliness of the system. All subjects agreed that there is no any discomfort or pain during the experiment, and they all agree that the system is very easy to use.

The following table shows the comparison of the proposed system to other established systems on the literature. It can be seen that the new system has an acceptably high accuracy, but the usability of the system is higher than other existing counterparts (mainly because of the use of the single-electrode NeuroSky headset). Hence, the proposed EOG-HCI system can improve the ergonomic factor while keeping the system performance at an acceptably high level.

TABLE III. PERFORMANCES OF DIFFERENT SYSTEMS

System	1. ([9])	2. ([5])	3. ([6])	4. ([7])	This paper
Accuracy (%)	95	82-100	78-97	86	72-84
#channels	3	16	5	8	1

IV. CONCLUSION

This paper presented a computer-access solution for people who can only move their eyes to control the computer by translating eye-blinks into a series of mouse cursor control sequence. With only single channel, the system has a higher degree of usability but still can achieve an acceptable accuracy rate. Not just in laboratory, the system can be used in outdoor environment. The system only requires double-blink action, which is natural to those with proper eye-condition and causes no discomfort. Thus in terms of performance, both ergonomic factors and system performance factors are maximized. The system has the potential to find many applications in daily computer usage such as cursor control, text processing and web-browsing. In this paper, only DB signals are utilized in the EOG-HCI system. In future, the proposed system can be extended further into a more powerful system by utilizing other non-DB eye-muscle activities, to achieve a system with a higher information transfer rate.

REFERENCES

- [1]. A. D. N. Edwards, ed. *Extraordinary Human-Computer Interaction: Interfaces for Users with Disabilities*. vol. 7. CUP Archive, 1995.
- [2]. L. N. S. Andreasen Struijk, “An inductive tongue computer interface for control of computers and assistive devices.” *IEEE Trans. Biomed. Engineering* vol. 53, no. 12, pp. 2594-2597, 2006.
- [3]. J. R. Wolpaw, D. J. McFarland, G. W. Neatb, and C. A. Fornerisa, “An EEG-based brain-computer interface for cursor control,” *Electroencephalography Clin. Neurophysiology*, vol. 78, no. 3, pp. 252-259, 1991.
- [4]. E. English, A. Hung, E. Kesten, D. Latulipe, and Z. P. Jin, “EyePhone: A mobile EOG-based human-computer interface for assistive healthcare,” in *Proc. IEEE Conf. EMBS NER*, 2013.
- [5]. S. L. Wu, L. D. Liao, S. W. Lu, W. L. Jiang, S. A. Chen, and C. T. Lin, “Controlling a human-computer interface system with a novel classification method that uses electrooculography signals,” *IEEE Trans. Biomed. Eng.*, vol. 60, no. 8, pp. 2133-2141, Aug. 2013.
- [6]. Y. Nam, B. Koo, A. Cichocki, and S. Choi, “GOM-Face: GKP, EOG, and EMG-based multimodal interface with application to humanoid robot control,” *IEEE Trans. Biomed. Eng.*, vol. 61, no. 2, pp. 453-462, Feb. 2014.
- [7]. T. Yagi, Y. Kuno, K. Koga, and T. Mukai, “Drifting and blinking compensation in electro-oculography (EOG) eye-gaze interface,” in *Proc. IEEE Conf. SMC*, 2006.
- [8]. J. F. Wu, A. M. S. Ang, K. M. Tsui, H. C. Wu, Y. S. Hung, Y. Hu, J. N. F. Mak, S. C. Chan, and Z. G. Zhang, “Efficient implementation and design of a new single-channel electrooculography-based human-machine interface system,” *IEEE Trans. Circuit and Systems II*, in press.
- [9]. Y. Punsawad, Y. Wongsawat, and M. Parnichkun, “Hybrid EEG-EOG brain-computer interface system for practical machine control,” in *Proc. IEEE Conf. EMBS*, 2010, pp. 1360-1363.