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Evaluating Feature Extraction Methods of Electrooculography (EOG) Signal for Human-Computer Interface

S. Aungsakul*, A. Phinyomark, P. Phukpattaranont, C. Limsakul

Department of Electrical Engineering, Faculty of Engineering, Prince of Songkla University, Songkhla, 90112, Thailand

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Abstract

Electrooculography (EOG) signal is a widely and successfully used to detect activities of human eye. Use of the EOG signals as a control signal for human-computer interface (HCI) plays a central role in the understanding, characterization and classification of eye movements which can be applied to a wide variety of applications consisting virtual mouse and keyboard control, electric power wheelchairs and industrial assistive robots. The advantages of the EOG-based interface over other conventional interfaces have been presented in the last two decades; however, due to a lot of information in EOG signals, the extraction of useful features should be done before the classification task. In this study, fourteen useful features extracted from two directional EOG signals: vertical (V) and horizontal (H) signals have been presented and evaluated. There are the maximum peak and valley amplitude values (PAV and VAV), the maximum peak and valley position values (PAP and VAP), the area under curve value (AUC), the number of threshold crossing value (TCV), and EOG variance (VAR), which are derived from both V and H signals. In the experiments, EOG signals obtained from three healthy subjects with eight directional eye movements were employed: up, down, right, left, up-right, up-left, down-right and down-left. The mean feature values and their standard deviations have been reported. Most features show the difference between the mean feature values. Using the analysis-of-variation test, the differences in mean features between the movements are statistically significant for ten features ($p < 0.0001$), particularly for the VAV, VAP, AUC, TCV and VAR of V signal, and the PAV, VAV, AUC, TCV and VAR of H signal. The combination of these features may be useful for the classification of EOG signals in both class separability and robustness point of views. Using multiple features with sufficient classifiers or threshold techniques is recommended to be evaluated in further analysis. These features can be useful for various advanced HCI applications in future researches, notably eye-exercise and eye-writing recognitions.

Keywords: Classification; Electrooculogram; Eye gesture recognition; Eye motion; Eye movement analysis

* Corresponding author. Tel.: +66-74-558831; fax: +66-74-459395.
E-mail address: siriwadee.a@hotmail.com.

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1. Introduction

Many human-machine interfaces (HMIs) have been established during the last two decades such as vision based head/hand gesture, speech recognition, sip and puff, head or chin controller, ultrasonic non-contact head controller and brain-computer interface [1-6]. However, each HMI has its limitations. For instance, speech recognition and vision based head/hand gesture have a major problem in noisy and outdoor environments. Ultrasonic non-contact head controller has low classification accuracy. For patients with amyotrophic lateral sclerosis (ALS), a few HMIs can be used. One of the challenging HMIs is electrooculography (EOG) signal. EOG signal is a widely used to detect activities or movements of human eye. The use of EOG signals as a control signal for HMI [7-12] plays a central role in the understanding, characterization and classification of eye movements which can be applied to a wide variety of applications such as electrical wheelchair control [7], mobile robot control [8], cursor mouse control [9], eye writing recognition [10], eye activity recognition [11] and eye exercise recognition [12]. In order to yield the high performance in recognition of EOG signal, various techniques have been proposed such as derivative technique [13], threshold analysis technique [14], slope analysis technique [10] and peak detection analysis [15]. One of the most important components in the classification of EOG signal is feature extraction. In this study, the evaluation of EOG feature extraction is proposed. All features are calculated based on time domain and are used for discriminating the eight commonly used directional eye movements.

2. Materials and Methods

2.1. Data acquisition

Eight directional eye movements were used: up, down, right, left, up-right, up-left, down-right and down-left, while the EOG signals are recorded from two EOG channels: vertical (V) and horizontal (H). Commonly, independent measurements can be obtained from both eyes, V and H. However, in V channel, either left or right side gives the similar EOG signal. Hence, only one right eye was used in the experiments. Five surface electrodes were put around the eyes as can be observed in Fig. 1. Vertical leads were acquired on the above and the below of the right eye, Ch.V+ and Ch.V-. Horizontal leads were acquired by two electrodes on the right and the left of the outer canthi, Ch.H+ and Ch.H-. A reference electrode was placed on forehead, G. All EOG signal recordings were carried out using a commercial wireless system (Mobi6-6b, TMS International BV, Netherlands). A band-pass filter of 1-500 Hz bandwidth and an amplifier with 19.5 times were set for the acquisition system. The sampling rate was set to 1024 Hz. However, the energy frequency bands of the EOG signal are fallen in range of 1 to 10 Hz, thus the sampling rate was reduced to 128 Hz in pre-processing process. The EOG signals were recorded from 3 normal subjects with 8 directional eye movements as mentioned above. All of these activities were held for 2 s. Each activity was performed 5 times throughout a trial. As a result, 15 datasets were obtained from each directional movement.

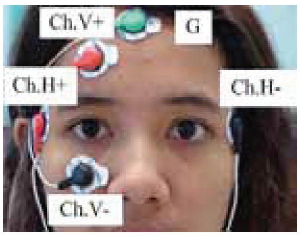


Fig. 1. EOG electrode placements

2.2 Feature Extraction Methods

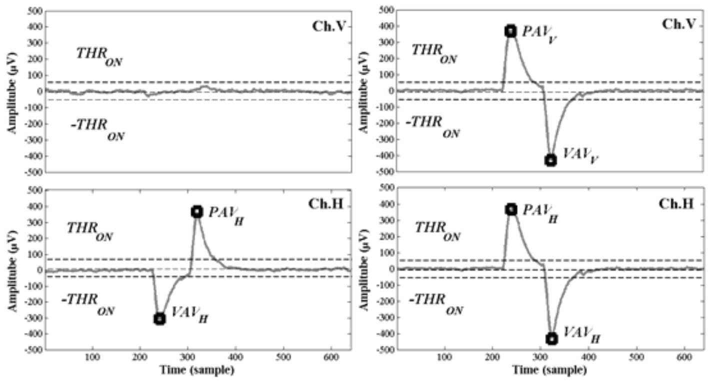
Fourteen features are evaluated in this study. They are a combination between seven techniques and two EOG channels. All features are calculated based on time domain in order to yield a computational simplicity. The definition of seven techniques has been described in the following:

1. Maximum peak amplitude value (PAV): It is a measure of the EOG signal amplitude value at the highest point, maximum positive value, in both V and H channels, as shown in Fig. 2.
2. Maximum valley amplitude value (VAV): It is a measure of the EOG signal amplitude value at the lowest point, maximum negative value, in both V and H channels, as shown in Fig. 2.
3. Maximum peak amplitude position value (PAP): It is a measure of the EOG signal amplitude position value at the highest point, maximum positive value, in both V and H channels, as shown in Fig. 3.
4. Maximum valley amplitude position value (VAP): It is a measure of the EOG signal amplitude position value at the lowest point, maximum negative value, in both V and H channels, as shown in Fig. 3.
5. Areas under curve value (AUC): AUC of EOG signal is a summation of absolute value of the amplitude under both positive and negative curves in both V and H channels, as shown in Fig. 4. It can be expressed as

$$\mathrm{AUC} = \sum_{i=1}^{N} |x_i| , \tag{1}$$

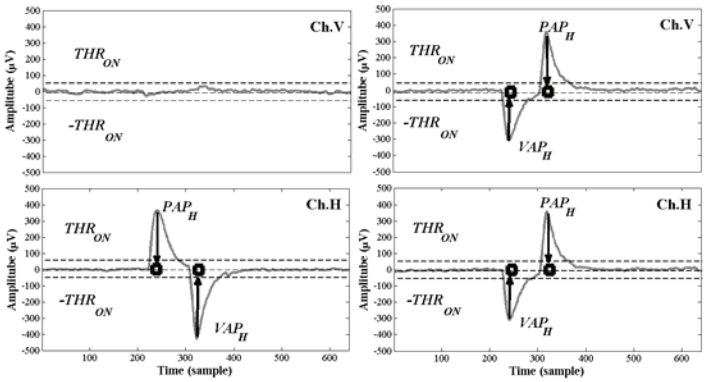
   where x_i is the ith sample of EOG signal and N is the window size for computing features.
6. Number of threshold crossing value (TCV): It is the number of times that the EOG signal passes the threshold amplitude value for both positive and negative threshold values, in both V and H channels, as shown in Fig. 5.
7. Variance of EOG signal (VAR): The variance is a measure of the signal power and calculated as

$$\mathrm{VAR} = \frac{1}{N}\sum_{i=1}^{N}\left(x_i - \bar{x}\right)^2 . \tag{2}$$



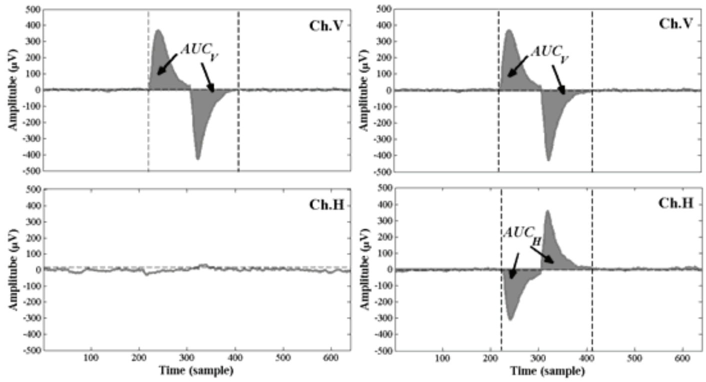
(a) (b)

Fig. 2. Maximum peak and valley amplitude values (PAV_V, VAV_V, PAV_H and VAV_H) (a) left (b) up-right



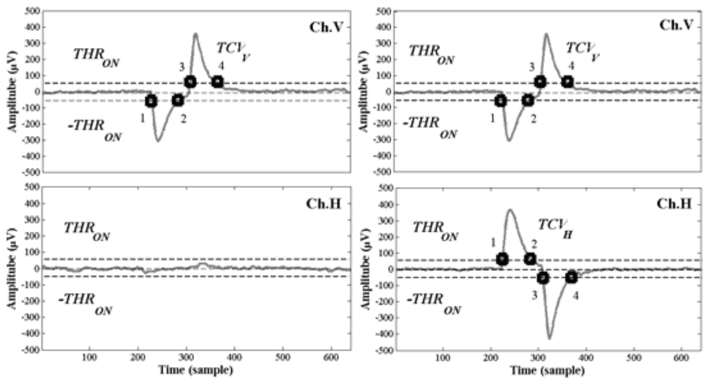
(a) (b)

Fig. 3. Maximum peak and valley amplitude position values (PAP_V, VAP_V, PAP_H and VAP_H) (a) right (b) down-left



(a) (b)

Fig. 4. Areas under curve values (AUC_V, AUC_H) (a) up (b) up-left



(a) (b)

Fig. 5. Number of threshold crossing values (TCV_V, TCV_H) (a) down (b) down-right

3. Results and Discussion

From the observation of EOG waveform shape, the extraction of useful features should be done before the classification task. Waveforms of eight eye directional movements can be observed in Fig. 2 through Fig 5. In order to avoid a background noise and involuntary eye movements, the onset threshold value is set at 50 μV in the study [12] for using as a starting point of eye movements in both eyes and also using as a starting point in extracting feature. The mean feature values and their standard deviation of all features have been shown in Table 1. In order to find the better feature, the analysis-of-variation (ANOVA) test is used to present the difference between the mean feature values of eight movements. The results obtained from ANOVA are presented in Table 2 for all features. The results showed that the differences in mean feature values between the movements are “statistically significant” for ten features ($p < 0.0001$), consisting the VAV, VAP, AUC, TCV and VAR of V signal, and the PAV, VAV, AUC, TCV and VAR of H signal.

In order to find the best feature the value of the F statistical obtained from the ANOVA test can be used. As we know that F value is the ratio between the variance of the group means and the mean of the within group variances. Hence, the best feature is yielded if its F value is higher than the F value of other features. Based on fourteen features extracted, the VAP of V signal has the highest F value ($F = 1055$), followed by the AUC of H signal ($F = 594.76$) and the PAV of H signal ($F = 259.25$). On the other hands, the PAP features contain the lowest F values. The F values of PAP_V and PAP_H are only 4.03 and 7.08, respectively.

Table 1. Mean (μ) and standard deviation (σ) values of all features from three subjects. Note that n/a is information in a field is not provided or is not available.

Movement types	Vertical (V) channel													
	PAV		VAV		PAP		VAP		AUC		TCV		VAR	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
Up	301	24	320	7	13	6	144	23	23346	4008	9	2	17599	4839
Down	430	28	285	16	128	19	16	2	22792	1916	5	1	20563	3483
Right	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Left	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Up- left	292	23	323	9	12	2	145	16	20070	1050	5	1	15772	1530
Up- right	227	23	221	60	12	3	142	15	17454	2293	7	2	9720	1928
Down- left	390	13	276	6	110	13	18	2	20994	1580	5	1	17220	2593
Down-right	375	6	220	9	123	12	17	2	17332	1396	4	0	13701	1754
Movement types	Horizontal (H) channel													
	PAV		VAV		PAP		VAP		AUC		TCV		VAR	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
Up	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Down	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Right	364	9	307	23	153	19	16	6	22851	1356	4	1	18423	5022
Left	355	4	402	30	15	2	126	17	26079	499	4	0	24469	7297
Up- left	325	13	243	43	144	16	16	2	20845	1216	4	1	14007	2986
Up- right	266	48	321	24	16	4	138	13	22557	1202	4	0	17577	4406
Down- left	241	2	143	63	113	13	14	3	15198	463	4	1	7544	2164
Down-right	213	10	244	32	15	2	129	12	16563	1407	4	0	9161	3672

Table 2. Average *p*-value of fourteen features.

Feature extraction	Average *p*-value	
	V	H
PAV	> 0.0001	< 0.0001
VAV	< 0.0001	< 0.0001
PAP	> 0.0001	> 0.0001
VAP	> 0.0001	> 0.0001
AUC	< 0.0001	< 0.0001
TCV	< 0.0001	< 0.0001
VAR	< 0.0001	< 0.0001

Based on the finding results, four features including VAV, AUC, TCV and VAR showed the statistically difference for both EOG channels. Thus in future algorithms, these features should be considered to use in the classification of EOG signal, because usually, in order to classify eight directions, the classification algorithm needs information from both EOG channels, V and H. On the other hands, PAV and VAP features showed a statistical difference only for one channel; however, it may be necessary to help the main features to discriminate the advanced movements such as in eye-writing, eye-exercise and activity recognitions [10-12]. In addition, both features showed the higher value of F statistical compared with other features. For the PAP feature, there is no significant for both EOG channels, therefore it is not recommended to be used as an EOG feature in future research.

4. Conclusion

In this study, several frequently used and newly proposed EOG features have been evaluated. The study provides a relatively comprehensive comparison of a variety of the EOG features in the class separability viewpoint which has not been reported before. It found that the VAP_V, AUC_H and PAV_H appear effective to discriminate the eight EOG movements. In order to extract the useful features for both eyes, VAV, AUC, TCV and VAR features are recommended. All of these features have a statistically significance at $p < 0.0001$. The combination of these features may be useful for the classification of EOG movements in future research works, particularly in class separation point of view. Using multiple-feature set with the sufficient classifiers or threshold analysis techniques is suggested to be evaluated in future works. Although this study did not include any classification algorithms, some researchers have applied some of them in the past, and we plan to apply them in the future.

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