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Full Length Research Paper

Development of robust electrooculography (EOG)-based human-computer interface controlled by eight-directional eye movements

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Electrooculography (EOG) signal is one of the useful electro-physiological signals. The EOG signals provide information about eye movements that can be used as a control signal in human-computer interface (HCI). Usually, eight-directional movements, including up, down, right, left, up-right, up-left, down-right and down-left, are proposed. Development of the EOG signal classification has been shown more increasing interest in the last decade; however, the effect of noises on classification system is a major problem to degrade the usefulness of EOG-based HCI. A robust classification algorithm of the eight movements is proposed, in which this technique can conduct the effect of noises in EOG signal, particularly for involuntary movements and eye-blink artifacts. The proposed algorithm was based on the onset analysis, feature extraction, the first derivative technique and threshold classification. Eight beneficial time domain features were proposed including the peak and the valley amplitude positions, and the upper and the lower wavelengths of two EOG channels, vertical and horizontal channels. Based on the optimal threshold values and conditions, the results showed that classification accuracy reached 100% for three-subject testing. In addition, the first derivative technique was additionally implemented in order to avoid the eye-blink artifact and other eight time domain features, that is, peak amplitude and area under curve, have been investigated for use in advanced HCI interfaces, notably, eye activity and eye writing recognitions.

Key words: Electrooculography signal, eye motions, eye blink artifacts, feature extraction, interference, noises, non-pattern recognition, robustness, threshold analysis.

INTRODUCTION

Currently, many research studies are underway into means of enabling the disabled and elderly to communicate effectively with machine or computer. Depending on the users' capabilities, different types of interface have been proposed, such as speech recognition based on both voice (Raab et al., 2011) and surface electromyography (Fraiwan et al., 2011), lip movement control system (Shaikh et al., 2011), vision-based multiple gestures (Reale et al., 2011), sip-and-puff controller (Jones et al., 2008), tooth-click controller (Simpson et al., 2008), infrared and ultrasonic non-contact head controllers (Coyle, 1995; Evans et al., 2000), multifunction myoelectric control system (MMCS) (Phinyomark et al., 2011a) and brain-computer interface (BCI) (Panicker et al., 2011). However, due to the limitations of each interface, for example, speech recognition and vision-based head gesture have a major problem in outdoor and noisy environments (Ikuta and Orimoto, 2011), infrared and ultrasonic non-contact head controllers have a low classification performance, or MMCS and BCI have a problem with noise (Phinyomark et al., 2011b; Suresh and Puttamadappa, 2008); therefore,

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the electrooculography (EOG) signal is one of the sufficient candidate signals to be deployed in human-computer interface (HCI) (Ubeda et al., 2011). This interface is very useful for patients with amyotrophic lateral sclerosis (ALS). ALS patients may lose the oral speaking and hand movements abilities; however, their eye movement functions generally remain relatively intact and become the last resource for communication (Park et al., 2005; Tomita et al., 1996; Tsai and Chen, 2009).

EOG signal is one of the useful electro-physiological signals that provide information about activities of the human eye, detecting changes in eye positions. It is generated by the potential difference between the cornea and the ocular fundus, and it is known as the “cornea-retinal potential (CRP)” (North, 1965). This potential difference comes from large presence of the electrically active nerves in the retina equate to the front of the eye and can be considered as a steady electrical dipole with a positive pole at the cornea and a negative pole at the retina (Brown et al., 2006). Because of its relatively large signal-to-noise ratio (SNR) as compared to other electro-physiological signals, its amplitudes range between 15 and 200 µV, and a linear relationship between its amplitude and eye movement angle, the EOG signal may look like an ideal candidate for eye movement classification system.

In this study, we are promoting the usefulness of EOG signal to be used as an efficient hand-free control interface. Non-pattern recognition algorithm based on threshold analysis and time domain features to classify eight-directional eye movements has been investigated. The robustness of EOG-based HCI has been considered in developing classification algorithm (Bulling et al., 2008; Kim et al., 2007; Yagi, 2010). This technique can be used in noisy environment and can be availably implemented for a real-time application. The preliminary result of this algorithm is presented in Aungsakun et al. (2011). This study presented an extensive review of EOG applications and classification algorithms, after which the proposed EOG time domain features used for classification algorithm was described. This was followed by a report given on the results and discussion. Finally, summary and concluding remarks were given.

PREVIOUS RESEARCH

The EOG signals have been successfully and widely used in biomedical and rehabilitation engineering applications, particularly in HCIs. Many efficient HCIs have been developed in the last two decades, such as computer cursor control (Septanto et al., 2009), computer animation application (Krupiński and Mazurek, 2009), home automation (Harun and Mansor, 2009), multitask gadget control (Gandhi et al., 2010), electrical wheelchair control (Barea et al., 2002), mobile robot control (Kim et al., 2007), hospital alarm system (Venkataramanan et al., 2005), activity recognition based on eye movement analysis (Bulling et al., 2011), visual improvement system for the elderly (Yu et al., 2005) and eye writing recognition (Tsai et al., 2008). In order to develop all of these HCIs, various techniques have been proposed, which can be divided into two main types: pattern recognition and non-pattern recognition.

In pattern recognition, features extracted are discriminated by a suitable classifier (Brunner et al., 2007). Time-domain features that have been frequently used are mean value, peak duration, peak polarity and slope (Kherlopain et al., 2006). In addition, spectral analysis has been deployed as the useful features for eye movement classification (Bukhari et al., 2010; Lv et al., 2010). All of these features are usually implemented with two classifier types, that is, neural networks (Barea et al., 2000; Güven and Kara, 2006; Kikuchi and Fukushima, 2000; Lee and Lee, 1993) and support vector machine (Bulling et al., 2011; Shuyan and Gangtie, 2009). However, computational times and implementation complexity become a major limitation of algorithm based on pattern recognition, particularly for implementing in microcontroller devices. Several research studies have established better performance of EOG signal classification based on non-pattern recognition (Deng et al., 2010; Gandhi et al., 2010). This technique has a simple structure. The classifier module of pattern recognition algorithm has been degraded to a simple threshold comparison module. In this study, non-pattern recognition algorithm has been implemented in order to be used in microcontroller devices.

Eight-directional eye movements: up, down, right, left, up-right, up-left, down-right and down-left, are the basic movements for most of the HCIs (Yamagishi et al., 2006), especially the first four directions (Barea et al., 2002; Güven and Kara, 2006; Kim et al., 2007; Shuyan and Gangtie, 2009). The eight types of directional movements can be used as basis of various advanced movements, that is, eye activity and eye writing recognitions (Bulling et al., 2011; Tsai et al., 2008), thus the classification of these movements has become a challenge for many advanced EOG-based HCIs in the near future.

EXPERIMENTS AND DATA ACQUISITION

Two channel EOG signals, horizontal and vertical signals, have been commonly used to acquire information from human eye movements. Independent measurements can be obtained from both eyes. However, in vertical directional movements, two eyes move in conjunction, thus only one right eye was deployed. The procedure of recorded EOG signals is presented in the following. Five surface electrodes were placed around the eyes. All positions are as shown in Figure 1. Vertical-channel electrodes were placed above and below the right eye (Ch.V+ and Ch.V-) and horizontal-channel electrodes were placed on the right and left of the outer canthi (Ch.H+ and Ch.H-). Additionally, a reference electrode was placed on the forehead (G).

Recordings of all EOG signals were carried out using a commercial wireless system (Mobi6-6b, TMS International BV, Netherlands). The amplifier, with a gain of 19.5 and a band-pass

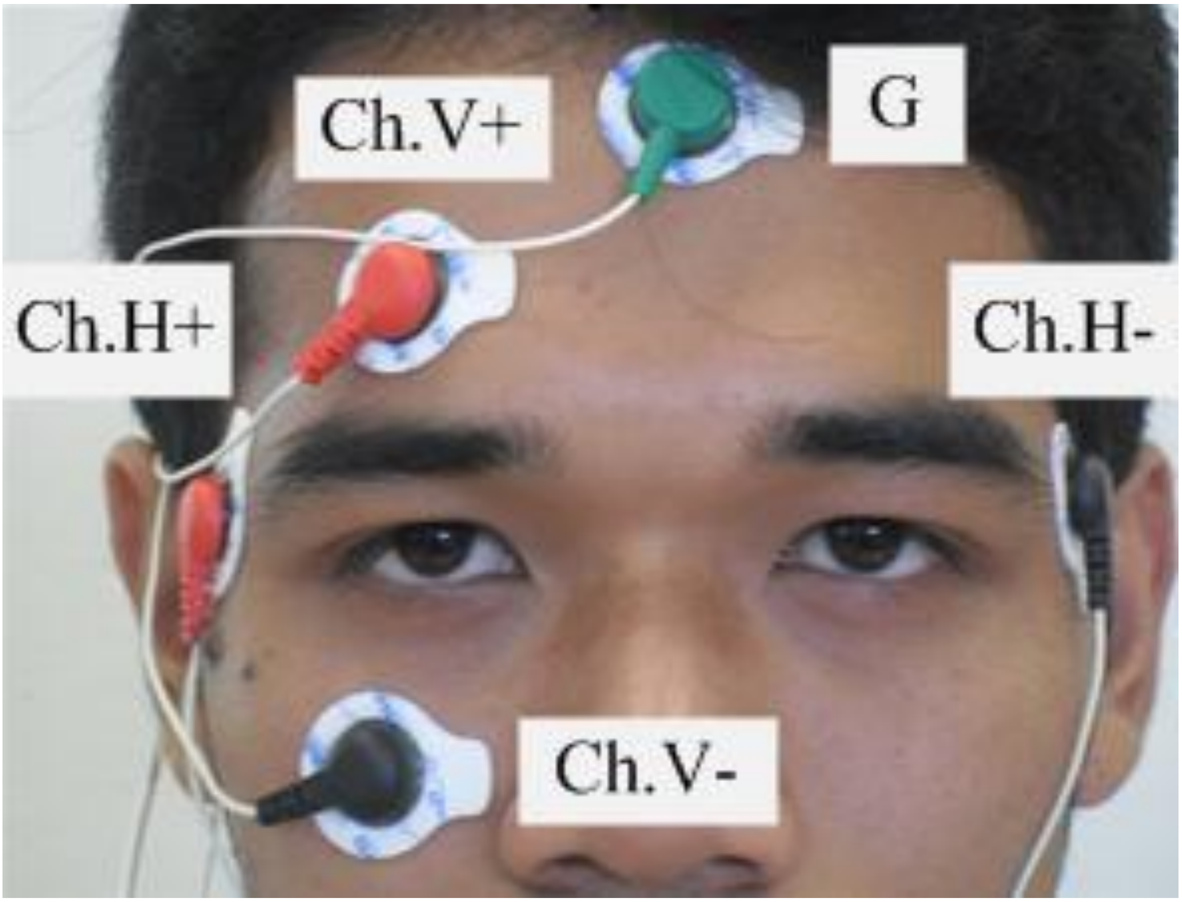

Figure 1. Five electrode positions: vertical channel (Ch.V+ and Ch.V-), horizontal channel (Ch.H+ and Ch.H-) and reference channel (G) (Aungsakun et al., 2011).

filter of 1 to 500 Hz bandwidth were set for the recording system.

The sampling rate was set at 1024 Hz for analog-to-digital conversion. However, the energy frequency bands of EOG signal are in range of direct current (DC) to 15 Hz, thus the sampling rate was reduced to 128 Hz in pre-processing stage. The EOG data were recorded from three normal subjects with 8 directional eye movements: eyes move -down (M1), –up (M2), -left (M3), -right (M4), -down and left (M5), -down and right (M6), -up and left (M7) and -up and right (M8). Each movement was held for 2 s and it was performed five times throughout a trial. In total, fifteen data sets were obtained from each directional movement.

Eye movement classification algorithm

To discriminate the aforementioned eight directional eye movements, the simple and effective non-pattern recognition algorithm based on threshold analysis and time domain features was proposed. Two main advantages of the proposed algorithm are that it can be availably implemented for a real-time system and can also be used in noisy environment. Procedures of the proposed algorithm are as follows:

1. Onset analysis was used to detect simultaneously starting point of eye movement, point-by-point, from both EOG signals, Ch.V and Ch.H, with a suitable threshold level THR_{ON}. Based on a preliminary result (Aungsakun et al., 2011), the value of THR_{ON} was set to 50 μV. It is approximately 25% of the maximum amplitude value, which is approximately 200 μV. This threshold is implemented in order to avoid background noise and small involuntary EOG movements. Further, THR_{ON} is implemented for both positive and negative values to detect either up/right or down/left movement, examples of the threshold levels can be observed as shown in Figures 2 to 4.

2. Firstly, eight types of time domain features were calculated: peak and valley amplitude values (*PAV* and *VAV*), peak and valley amplitude positions (*PAP* and *VAP*), upper and lower wavelengths (*UWL* and *LWL*) and area under upper and lower curves (*AUC* and *ALC*) for both EOG channels, vertical (V) and horizontal (H), are as shown in Figures 2 to 5, respectively. In total, sixteen features from two-channel EOG signals were obtained. Subsequently, eight features were selected to be used in the classification algorithm for eight-directional movements. There were PAP_V, PAP_H, VAP_V, VAP_H, UWL_V, UWL_H, LWL_V and LWL_H. The remaining features were deployed to be used in future classification algorithms which can classify other advanced movements.

3. Avoiding eye-blink artifact, the first derivative of UWL_V feature was implemented and then the artifact index (*AI*) was calculated with a pre-defined threshold, THR_{SF}. If the logical value of *AI* was defined as true, it means that more than one burst signals were found. In other words, the eye-blink artifact or involuntary eye movement was established. Then, step 1 will be repeated. Procedure of noise avoiding technique is as shown in Figure 6.

4. Suitable conditions were proposed in Table 1 in order to discriminate the eight movements from the eight features selected.

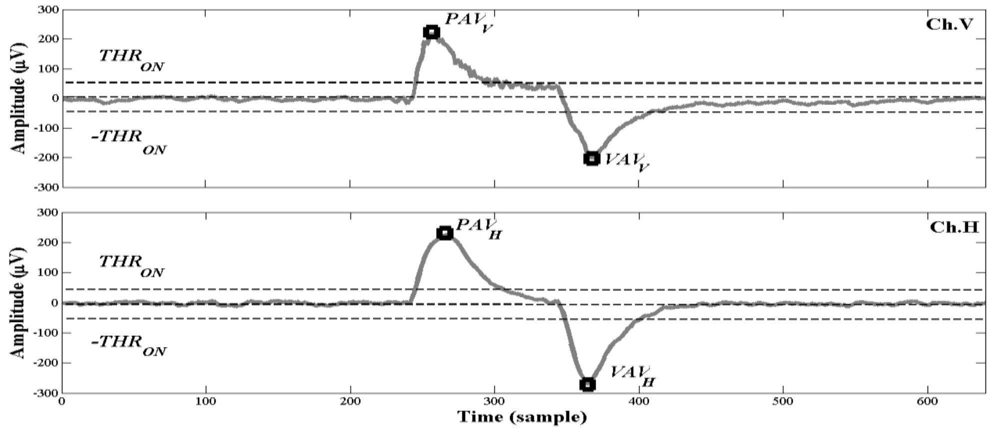

Figure 2. Peak and valley amplitude value (*PAV_V*, *VAV_V*, *PAV_H* and *VAV_H*) features.

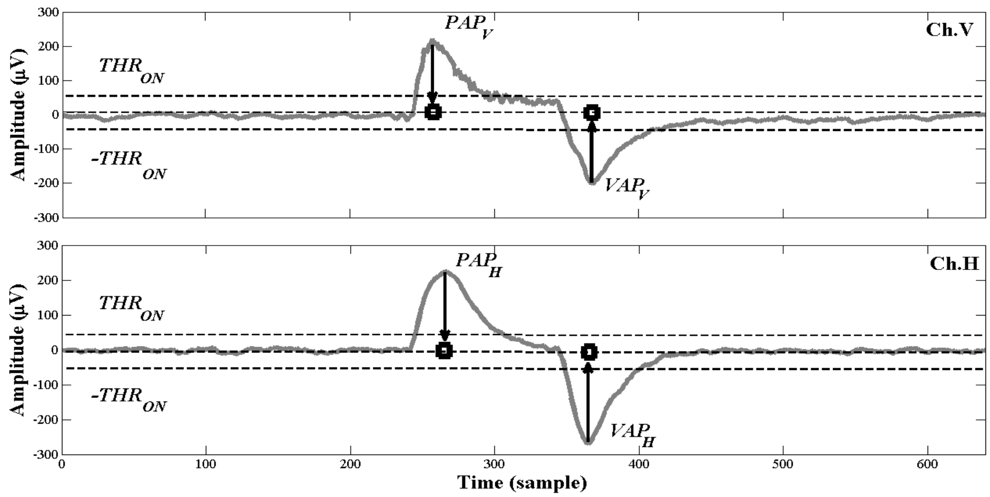

Figure 3. Peak and valley amplitude position (*PAP_V*, *VAP_V*, *PAP_H* and *VAP_H*) features.

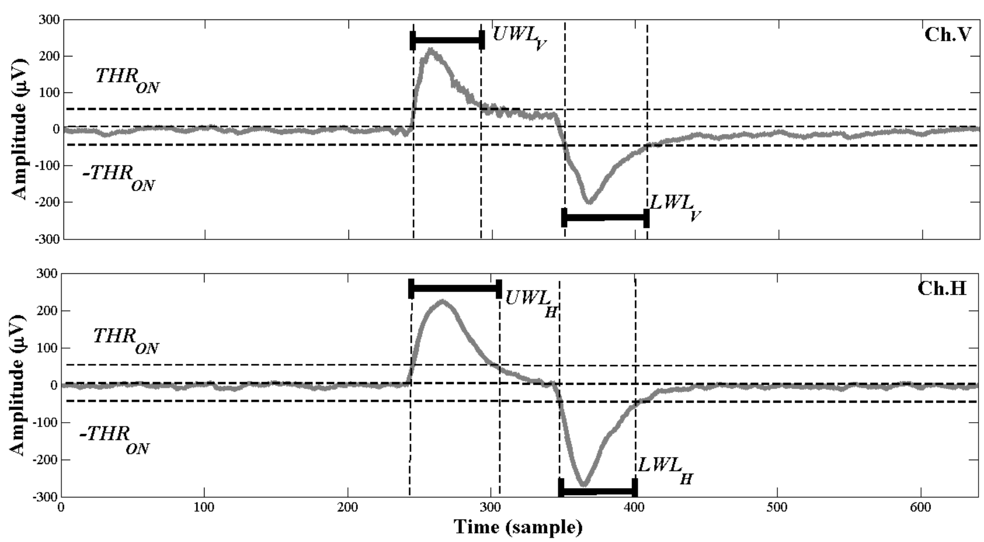

Figure 4. Upper and lower wavelength (*UWL_V*, *LWL_V*, *UWL_H* and *LWL_H*) features.

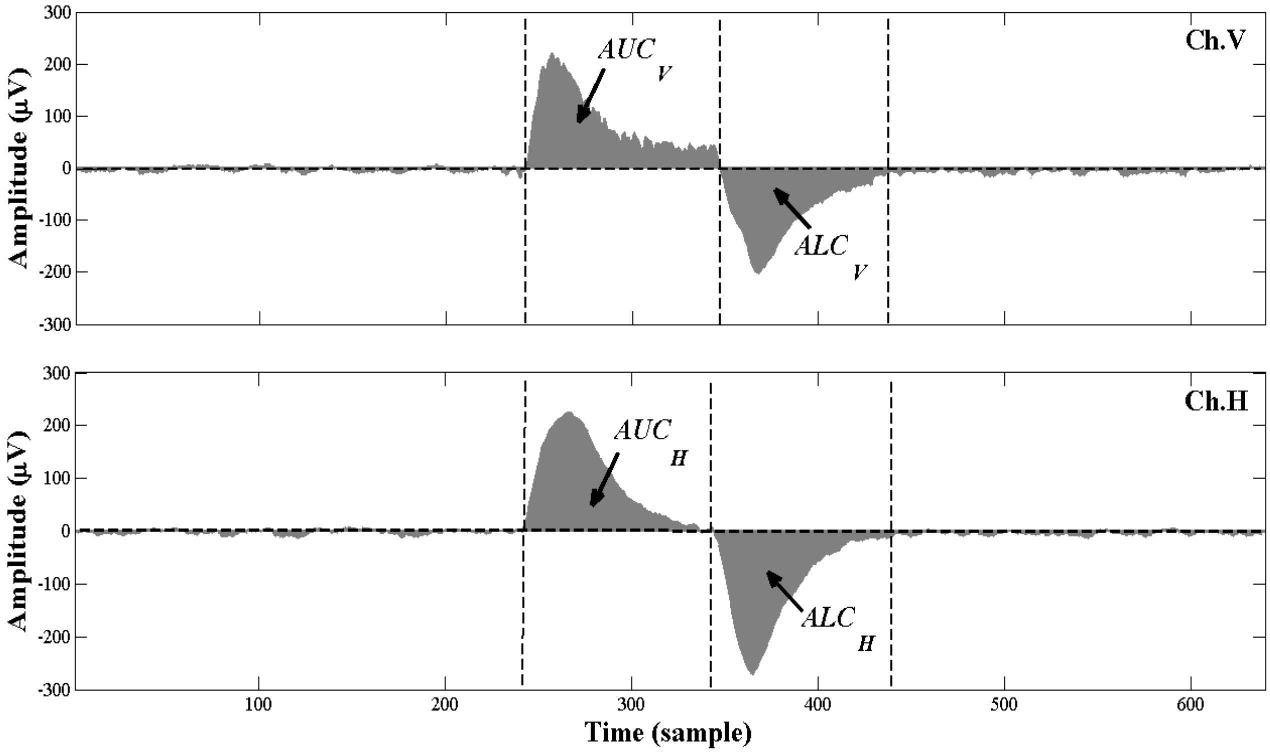

Figure 5. Area under upper and lower curve (AUC_V, ALC_V, AUC_H and ALC_H) features.

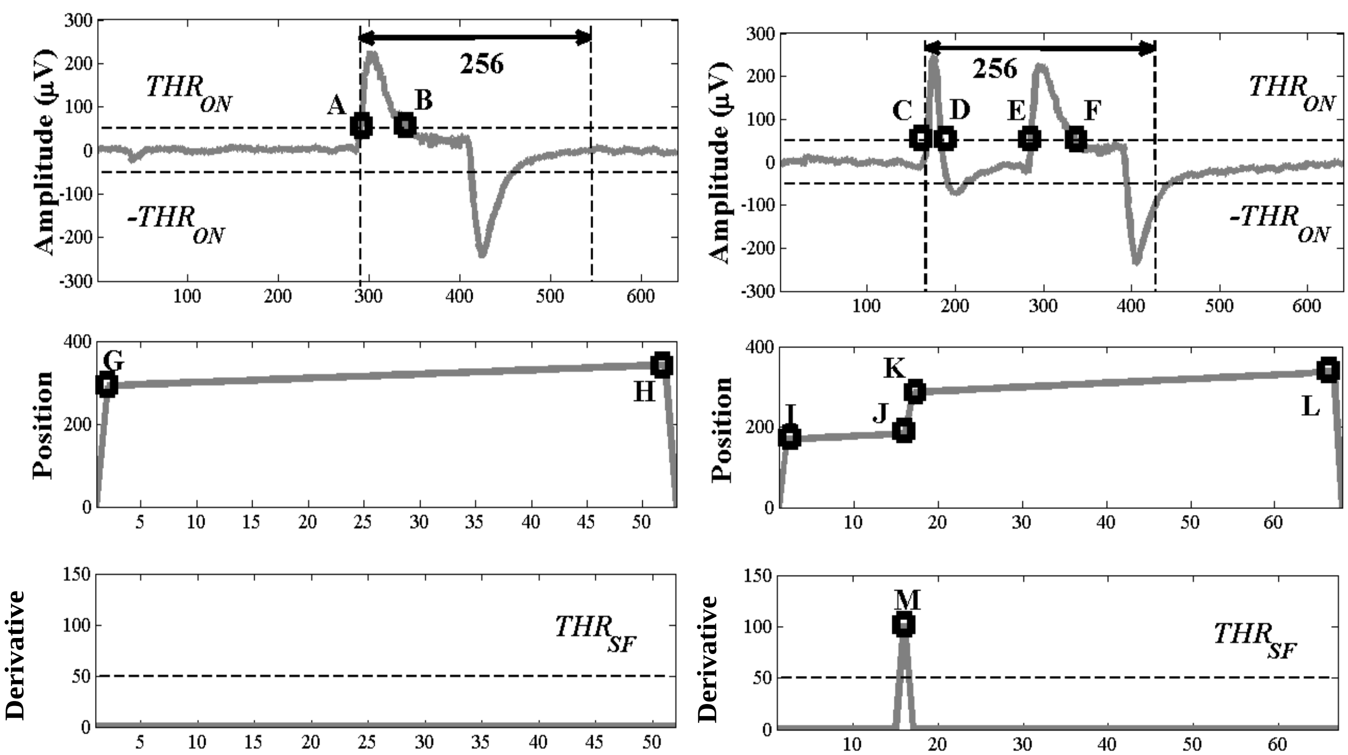

Figure 6. Procedure of the noise avoiding technique. The case example of only eye movement in feature length shown in the left panel, whereas on the right panel, it showed a case example of one blinking and one eye movement in feature length. The positions of point A to F are shown with point G to L in the middle panel, respectively. In addition, the value of M is the derivative of J-K.

Table 1. Discrimination rules.

If $PAP_V > VAP_V$ and $UWL_V <= THR_{UV}$ *or* $LWL_V <= THR_{LV}$ and $UWL_H >= THR_{UH}$, and $LWL_H >= THR_{LH}$, then OUT = M1	If $PAP_V > VAP_V$, $PAP_H > VAP_H$ and $UWL_V <= THR_{UV}$, $LWL_V <= THR_{LV}$ and $UWL_H <= THR_{UH,}$ and $LWL_H <= THR_{LH}$, then OUT = M5
If $PAP_V < VAP_V$ and $UWL_V <= THR_{UV}$, $LWL_V <= THR_{LV}$ and $UWL_H >= THR_{UH}$, and $LWL_H >= THR_{LH}$, then OUT = M2	If $PAP_V > VAP_V$, $PAP_H < VAP_H$ and $UWL_V <= THR_{UV}$, $LWL_V <= THR_{LV}$ and $UWL_H <= THR_{UH}$, and $LWL_H <= THR_{LH}$, then OUT = M6
If $PAP_H > VAP_H$ and $UWL_V >= THR_{UV}$, $LWL_V >= THR_{LV}$ and $UWL_H <= THR_{UH}$, and $LWL_H <= THR_{LH}$, then OUT = M3	If $PAP_V < VAP_V$, $PAP_H > VAP_H$ and $UWL_V <= THR_{UV}$, $LWL_V <= THR_{LV}$ and $UWL_H <= THR_{UH}$, and $LWL_H <= THR_{LH}$, then OUT = M7
If $PAP_H < VAP_H$ and $UWL_V >= THR_{UV}$, $LWL_V >= THR_{LV}$ and $UWL_H <= THR_{UH}$, and $LWL_H <= THR_{LH}$, then OUT = M4	If $PAP_V < VAP_V$, $PAP_H < VAP_H$ and $UWL_V <= THR_{UV}$, $LWL_V <= THR_{LV}$ and $UWL_H <= THR_{UH}$, and $LWL_H <= THR_{LH}$, then OUT = M8 Otherwise OUT = M0

The PAP and VAP features were used to detect the arrival of the positive and negative amplitudes. If the positive amplitude has occurred before, the output is expected to be up or right. On the other hand, the output is expected to be down or left if the positive amplitude occurred after. Discrimination between up and right or down and left can be conducted by information from two channels. In addition, up and down are vertical movements and right and left are horizontal movements. The other four directional movements can be seen as a combination of four basic movements. In order to avoid classifying uninterested and involuntary eye movements, four threshold values have been proposed, including THR_{UV}, THR_{LV}, THR_{UH} and THR_{LH}. These thresholds were implemented for application with the UWL and LWL features. Throughout the experiments, optimal values of all thresholds were defined.

5. As a result, eight movement classes (M1 to M8) were examined for the output parameter (*OUT*). In addition, if resting and other movements were detected, output *OUT* is set to M0. The procedure of the proposed algorithm is as shown in Figure 7. Note that in this figure, $\{x(i)\}$ is EOG signal time series and i is the position of time samples.

RESULTS AND DISCUSSION

Generally, when the eyes move to the left, the positive cornea moves closer to the left electrode which becomes more positive with zero potential at the right electrode, and vice versa. As a result, eye movement will generate voltage in horizontal direction. This finding can also be observed from up and down movements in vertical channel. From this knowledge and amplitude shape observed, the detection algorithm was designed as presented in the study's results and discussion.

Throughout the experiments, THR_{ON} as 50 μV was optimized for both detecting the starting point of movement and avoiding the background noise. Afterwards, all features were calculated for two EOG channels. The features calculated were presented as shown in Tables 2 to 4 with their mean and standard deviation values. All subjects showed that values of the selected eight features, PAP_V, PAP_H, VAP_V, VAP_H, UWL_V, UWL_H, LWL_V and LWL_H, are useful enough for discriminating eight-directional movements. Based on the results obtained, the suitable thresholds of THR_{UV}, THR_{LV}, THR_{UH} and THR_{LH} were defined, and the optimal threshold values were dependent on each subject. To be easily used, however, universal threshold can be defined. Approximately, 10% of the window size features was recommended, that is, in this study, the feature length was set at 256 samples. Interestingly, the resting eight features, PAV_V, PAV_H, VAV_V, VAV_H, AUC_V, AUC_H, ALC_V and ALC_H are useful for discriminating other advanced eye movements. For instance, peak and valley amplitude values can distinguish the movement associated with EOG signals at different angles (10, 20 and 30°) as shown in Figure 8. Note that its behaviour is practically linear for gaze-movement angles of ±30°.

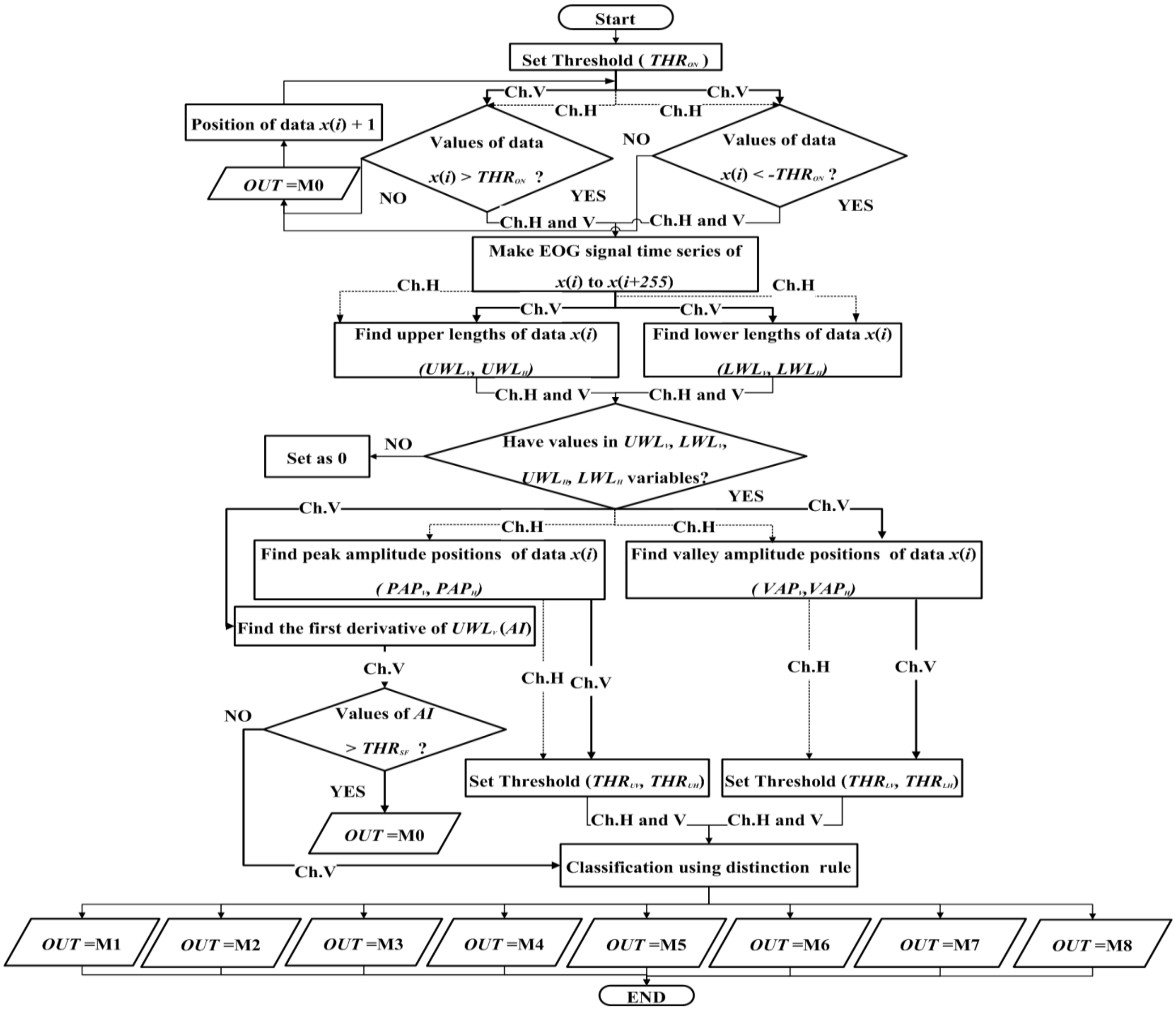

Figure 7. Flowchart of the proposed EOG classification algorithm.

The proposed algorithm has two advantages as compared to other publication algorithms for a classification of eight-directional movements based on EOG signals. Firstly, the proposed algorithm provided a high accuracy as shown in Figure 9. The figure showed the detection of 8 eye movements (M1 to M8) on the top panel from both Ch.V on the middle panel and Ch.H on the bottom panel. The classification accuracy of 8 eye movements is 100% resulting from three healthy subjects, whereas the accuracy from other publications is less than 100%. Examples from previous publications showing the results from 4 directional eye movements are as follows. In a study by Deng et al. (2010), 90% classification accuracy was achieved for applications in game control, eye test and Television controller. In Merino et al. (2010), 94% average rate was achieved when the derivative and amplitude levels were used for detecting the direction. Examples from previous publications showing results from eight-directional eye movements are as follows. In a study by Yamagishi et al. (2006), 90.4% classification accuracy was achieved for applications in screen keyboard when algorithm based on logical combination was realized. In Itakura and Sakamoto (2010), 96.7% classification accuracy was obtained from algorithm based on the integration method when EOG data were acquired from six subjects.

Secondly, the algorithm was not affected by various noises and involuntary movements, that is, single blinking (SB), double blinking (DB) and involuntary eye closing (IEC). Figure 10 showed the detection of left eye movement (M3) on the top panel using the EOG signals from Ch.V and Ch.H on the middle and bottom panels, respectively. Although, there are SB, DB and IEC noises as shown in thick lines generated in Ch.V, the proposed algorithm can

Table 2. Mean (μ) and standard deviation (σ) values of all features from subject 1.

Feature	Down		Up		Left		Right	
	μ	σ	μ	σ	μ	σ	μ	σ
PAP_V	100.8	23.9	13	4.1	n/a	n/a	n/a	n/a
VAP_V	14.0	1.0	110	11.1	n/a	n/a	n/a	n/a
PAP_H	n/a	n/a	n/a	n/a	101.8	15.1	12.6	0.5
VAP_H	n/a	n/a	n/a	n/a	14	1.6	102.8	12.6
UWL_V	50.8	6.4	71.4	11.3	n/a	n/a	n/a	n/a
LWL_V	56.0	1.7	56.4	14.1	n/a	n/a	n/a	n/a
UWL_H	n/a	n/a	n/a	n/a	57.6	8	51.4	1.9
LWL_H	n/a	n/a	n/a	n/a	62.6	9.5	53	6.2
PAV_V	393.9	44.8	33.42	21.1	n/a	n/a	n/a	n/a
VAV_V	-289.6	11.8	-355.8	26.7	n/a	n/a	n/a	n/a
PAV_H	n/a	n/a	n/a	n/a	353.9	8.0	280.6	5.7
VAV_H	n/a	n/a	n/a	n/a	-303.6	8.0	-298.7	41.1
AUC_V	10045.6	701.5	11814.2	409.6	n/a	n/a	n/a	n/a
ALC_V	9676.2	113.7	9326.2	817.6	n/a	n/a	n/a	n/a
AUC_H	n/a	n/a	n/a	n/a	9419.0	385.6	8020.0	158.5
ALC_H	n/a	n/a	n/a	n/a	9769.0	251.7	8193.6	420.3

Feature	Down-left		Down-right		Up-left		Up-right	
	μ	σ	μ	σ	μ	σ	μ	σ
PAP_V	50.8	10.5	33.4	5.4	65.6	3.8	61.2	1.9
VAP_V	62.6	17.8	41.2	5.4	59.8	2.4	53.6	2.1
PAP_H	44.4	2.5	50.8	3.8	55.4	2.4	54.4	2.3
VAP_H	57.2	3.9	46.8	5.3	58.8	4.3	53.4	3.2
UWL_V	97	38.3	102.4	9.6	12.6	1.1	10.6	0.9
LWL_V	30.2	32.9	15.8	1.6	121.4	11.7	107	13.6
UWL_H	82.6	59.9	13.4	1.3	116.6	11.1	15.4	1.7
LWL_H	24.6	34.3	105.4	8.6	18.8	2.3	99.2	7.9
PAV_V	398.8	59.0	285.5	40.8	355.9	58.5	259.5	20.4
VAV_V	-285.5	10.6	-191.4	31.6	-425.9	28.8	-259.9	128.9
PAV_H	231.8	9.8	193.1	35.3	304.2	15.2	274.8	5.5
VAV_H	-33.7	164.4	-237.2	29.4	-250.2	20.2	-289.7	13.2
AUC_V	9133.6	1047.5	5483.8	922.1	11727.0	1023.8	7566.4	474.3
ALC_V	8863.6	258.5	5577.8	1037.7	11796.8	872.4	6948.8	3381.1
AUC_H	5893.0	266.2	6356.4	956.5	9011.6	701.1	9035.6	203.0
ALC_H	6309.8	168.3	6234.4	947.3	9078.2	1127.8	8505.2	511.0

Note that n/a is information in a field that is not provided or is not available.

still detect the motion with 100% accuracy as shown in the top panel. The value of threshold THR_{SF} was set at 30, in order to keep away from small fluctuation during eye movement. The threshold value is approximately 12% of the feature length. Several noise removal techniques have been presented in the past few years, for instance, a simple median filter and a wavelet packet approach, using Daubechies wavelets at level nine (Bulling et al., 2008), a velocity shape algorithm and a threshold and correlation technique (Kim et al., 2007), a calibration technique and a low-pass filter (Yagi, 2010). More attention should be paid to the development of noise removal techniques in future studies, since it is still an active topic of research.

Conclusions

EOG signal is widely employed in various clinical applications, such as diagnosis of the eye diseases and evaluation of the eye injuries, and in various engineering applications, such as eye-controlled cursor mouse and

Table 3. Mean (μ) and standard deviation (σ) values of all features from subject 2.

Feature	Down		Up		Left		Right	
	μ	σ	μ	σ	μ	σ	μ	σ
PAP_V	183	20.1	19.4	11.1	n/a	n/a	n/a	n/a
VAP_V	18.6	3.4	183.8	26.2	n/a	n/a	n/a	n/a
PAP_H	n/a	n/a	n/a	n/a	204.4	29	33.4	35.7
VAP_H	n/a	n/a	n/a	n/a	32.8	28.1	172.6	35.9
UWL_V	46.8	5.4	41.6	3.6	n/a	n/a	n/a	n/a
LWL_V	64.4	3.4	49.6	4.6	n/a	n/a	n/a	n/a
UWL_H	n/a	n/a	n/a	n/a	46.8	9	69.8	7.3
LWL_H	n/a	n/a	n/a	n/a	63.6	5.1	67	4.5
PAV_V	570.6	83.8	335.8	53.6	n/a	n/a	n/a	n/a
VAV_V	-353.3	36.5	-355.2	36.9	n/a	n/a	n/a	n/a
PAV_H	n/a	n/a	n/a	n/a	395.9	25.5	410.1	9.8
VAV_H	n/a	n/a	n/a	n/a	-309.4	43.9	-470.0	21.9
AUC_V	14604.8	2133.9	12743.4	1538.7	n/a	n/a	n/a	n/a
ALC_V	12939.6	2374.9	11654.8	1858.8	n/a	n/a	n/a	n/a
AUC_H	n/a	n/a	n/a	n/a	11434.2	519.1	14454.4	338.2
ALC_H	n/a	n/a	n/a	n/a	31490.0	44816.3	14443.4	276.0

Feature	Down-left		Down-right		Up-left		Up-right	
	μ	σ	μ	σ	μ	σ	μ	σ
PAP_V	165.6	22.5	169.8	63.9	22.6	17.1	14	2.5
VAP_V	20.6	5	20.2	2.8	209	18.8	188.8	13.7
PAP_H	172.4	23.5	54.4	82.5	209.4	18.4	17.8	1.5
VAP_H	13.6	2.4	203.6	22.7	26	18	187.8	12.9
UWL_V	46.8	5.4	41.6	3.6	61.8	2.2	61.8	8.5
LWL_V	64.4	3.4	49.6	4.6	50.6	10.8	52	7.2
UWL_H	45.2	3.7	65.6	6.6	46.8	9	69.8	7.3
LWL_H	46.6	7.6	54.4	13.4	63.6	5.1	67	4.5
PAV_V	435.6	63.7	492.2	38.0	284.8	12.1	193.2	63.2
VAV_V	-276.3	23.0	-265.9	22.5	-280.9	15.3	-208.6	41.1
PAV_H	232.9	9.9	230.3	17.1	352.2	22.8	328.3	29.3
VAV_H	-184.3	18.4	-256.3	10.5	-277.4	6.6	-381.8	41.8
AUC_V	9471.0	1025.1	10875.0	572.8	8495.4	118.7	6016.0	1375.1
ALC_V	10826.2	487.3	10934.8	657.9	8120.2	271.2	6693.4	1372.5
AUC_H	6280.2	412.0	8126.8	728.8	10230.0	364.9	13315.2	851.4
ALC_H	5095.6	627.5	7756.6	782.6	10872.8	677.7	12941.6	588.7

Note that n/a is information in a field that is not provided or is not available.

wheelchair. In this study, we have proposed a non-pattern recognition algorithm to classify eight eye directional movements from EOG signals. From experimental results, the features proposed (peak and valley amplitude values and upper and lower wave-lengths) and threshold classification algorithm showed the best performance to be used in discrimination of EOG signal. Avoiding artifact method that was defined from the first derivative technique, can be effectively used to avoid most noises in EOG signal. The resting features (peak and valley amplitude positions and area under upper and lower curves) have shown that they can be added to increase the classification performance of advanced movements, such as eye movements with different angles (10 to 30°), eye writing 0 to 9, A to Z, +, -, x, /) and activity based on eye movement (reading, typing and browsing). Interestingly, more interest should be paid on two issues in future studies for real-world applications: (1) noise removal or (noise avoiding techniques (Bulling et al., 2008; Kim et al., 2007; Yagi, 2010) and (2) minimi-zation of EOG electrode positions (Usakli and Gurkan, 2010) and design of wearable EOG goggles (Bulling et al., 2009).

Table 4. Mean (μ) and standard deviation (σ) values of all features from subject 3.

Feature	Down		Up		Left		Right		Down-left		Down-right		Up-left		Up-right	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
PAP_V	100.6	12.3	30	45.8	n/a	n/a	n/a	n/a	83.8	8.4	127.6	71.9	24.4	30.6	11.2	4.1
VAP_V	15.4	1.1	159.2	46.4	n/a	n/a	n/a	n/a	18.6	1.1	43.8	61.1	121	34.9	129	17.5
PAP_H	n/a	n/a	n/a	n/a	109.8	19.7	14.8	0.4	88	7.4	44	59.9	121	34.7	18.8	2.5
VAP_H	n/a	n/a	n/a	n/a	13.4	0.9	117.2	15.1	14.6	2.4	134.2	68.3	27.2	29	128.2	18.9
UWL_V	43.8	8.9	51.6	1.3	n/a	n/a	n/a	n/a	48.2	7.5	33	4.4	45.8	1.3	57.8	17.3
LWL_V	53	3.7	50	8.8	n/a	n/a	n/a	n/a	56.8	2.2	51	10.3	49.8	8.6	57.6	6.6
UWL_H	n/a	n/a	n/a	n/a	57.6	4.6	66.4	5.5	51.6	4	53.6	2.9	54	4.2	61.6	5.5
LWL_H	n/a	n/a	n/a	n/a	58.6	3.2	65	3.6	61.6	5.4	40	21.4	62	2.3	55.8	5.6
PAV_V	326.4	28.7	227	6.2	n/a	n/a	n/a	n/a	336.5	38.9	347.2	49.6	235.8	33.4	227.7	29.2
VAV_V	-213.2	7.5	-248.9	23.8	n/a	n/a	n/a	n/a	-265.2	17.9	-201.6	13.7	-261.8	10.7	-195	13
PAV_H	n/a	n/a	n/a	n/a	343.5	21.6	373.9	13	259.7	12.7	216.1	18	318.4	40	195.6	97.2
VAV_H	n/a	n/a	n/a	n/a	-307.7	17.3	-437.3	25.9	-211.8	5.3	-238.8	56.6	-202.4	100.7	-290.6	16.6
AUC_V	20359	29769.9	7110.8	291.1	n/a	n/a	n/a	n/a	8362.8	426.4	1489.2	1553.9	5459.8	1804.2	7040.4	2155.5
ALC_V	6934.4	469	6848	798.7	n/a	n/a	n/a	n/a	8840.6	447.7	5809.6	1162.8	7144	146.4	6592.8	656.8
AUC_H	n/a	n/a	n/a	n/a	9489	525.2	6237	1051.1	7170	184.5	5489	1133.7	9029.8	502	8975.2	547.4
ALC_H	n/a	n/a	n/a	n/a	9980.4	744.5	4676.6	3038.2	7534.4	422.3	2407.4	2346.3	9003.4	167.4	8859.2	1009.7

Note that n/a is information in a field that is not provided or is not available.

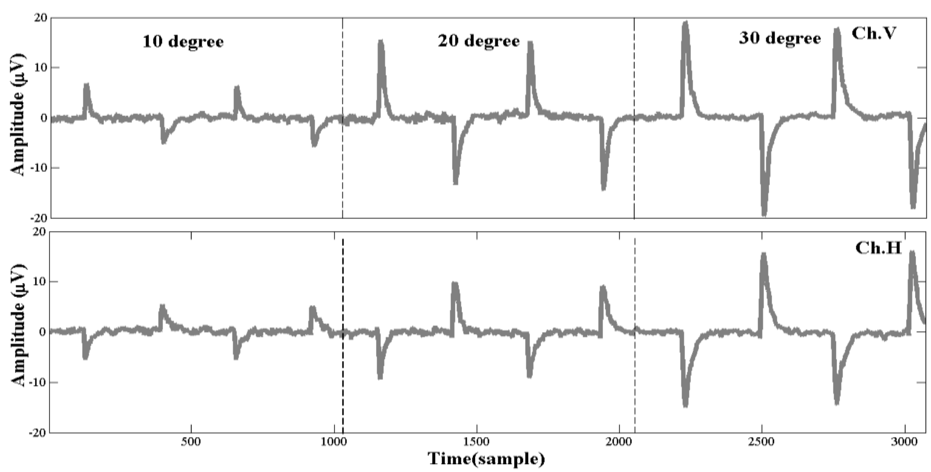

Figure 8. Up-left movement associated with EOG signals at 10, 20 and 30 degrees from two channels, Ch.V and Ch.H.

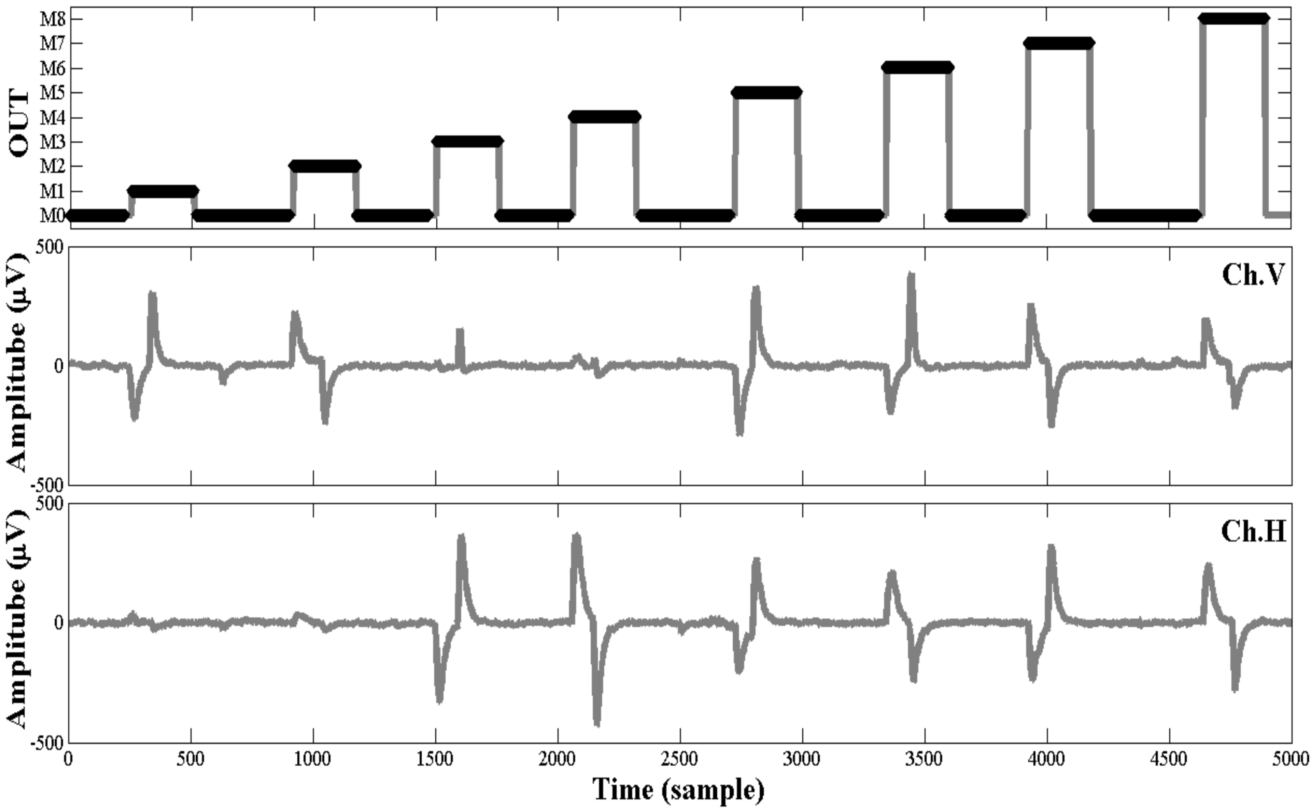

Figure 9. Example result of the proposed EOG classification algorithm for discriminating eight-directional movements.

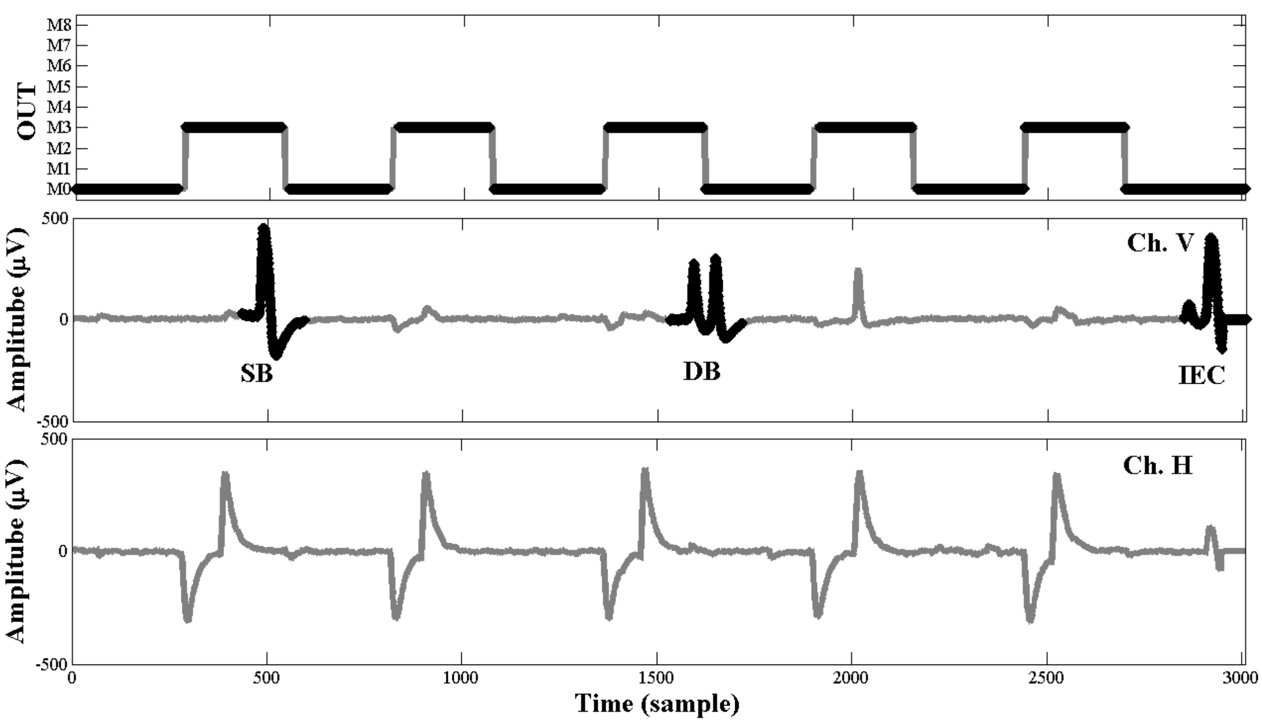

Figure 10. Effect of noises on the vertical EOG signal: single blinking (SB), double blinking (DB) and involuntary eye closing (IEC).

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