EEG based Automated Detection of Six Different Eye-Movement Conditions for Implementation in Personal Assistive Application

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Abstract

Contemporary human-machine-interfaces (HMIs) employ a wide range of human expressions to provide assistive support to the elderly and disabled population. Based on the disability type, expressions conveyed in terms of eye movements are often found to provide the most efficient way of communication. Nowadays, standard Electroencephalogram (EEG) based arrangements, used to analyze neurological states are also being adopted for the detection of eye movements. Although, a majority of the EEG-based state-of-the-arts researches either detects eye-movements in a lesser direction or uses a higher feature dimension with limited classification accuracy. In this study, a robust, simple and automated algorithm is proposed that uses the analysis of the EEG signal to classify six different types of eye movement. The algorithm uses discrete wavelet transform (DWT) on the EEG signals acquired from six different leads to eliminate a wide range of noise and artefacts. Then, two features per lead are extracted from the reconstructed wavelet coefficients and combined to form a binary feature map. Finally, a unique feature obtained from the calculated weighted sum of the binary map is used to classify six types of eye movements via a threshold-based technique. The algorithm presents high average accuracy (Acc), sensitivity (Se), specificity (Sp) of 95.85%, 95.83% and 95.83% respectively, using a single feature value only. Compared to other state-of-the-art methods, the adopted simple methodologies and the obtained results indicate the immense potential of the proposed algorithm to be implemented in personal assistive applications.

Full Text

Due to technical limitations, full-text HTML conversion of this manuscript could not be completed. However, the latest manuscript can be downloaded and [accessed as a PDF](#).

Figures

Figure 1

Block diagram of the proposed methodology to classify six different types of eye movements. After removal of the power line components, a Discrete Wavelet Transform (DWT) based methodology is adopted to eliminate a wide range of noises and artefacts of the EEG signal acquired from six different leads. For every lead, two features are extracted from the chosen wavelet coefficients and are unified to

form a binary feature map. Then, a weighted sum of the unified binary map is computed and used as a single unique feature to classify six different types of eye movements via a simple threshold-based classification technique.

Figure 2

A representative EEG signal record of a subject obtained from six different leads.

Figure 3

Overall experimental setup to investigate the process of eye-movement. During the experiment, each of the subjects is instructed to follow the circular marked positions sequentially by moving their eyes at a specific visual angle. The movement of the eye in each direction is essentially carried out based on an external auditory command.

Figure 4

Power line artefact removal from a representative EEG signals. The dotted line represents the EEG signal corrupted with power line artefact and the dark line represents the same EEG signal after removal of the power line artefact.

Figure 5

(a) The presence of baseline artefact in a specific EEG band; (b) the extracted baseline artefact component; (c) and a resulting EEG signal after removal of the baseline components.

Figure 6

Wavelet decomposition process using DWT, noise removal and selection of proper wavelet coefficients.

Figure 7

The occurrence of an eye blink artefact obtained from an EEG band. The beginning and the end of the artefact is indicated in the figure within a marked window.

Figure 8

Representative EEG signal bands, corrupted with eye blink artefact are presented in the figures (a), (c) and (e) respectively. The same EEG signal bands are shown in the figures (b), (d) and (f) after removal of the eye blink artefact using the proposed technique.

Figure 9

The calculated power values obtained for six different conditions of the eye.

Eye condition	APF					WAP				
	Delta	Theta	Alpha	Beta	Gamma	Delta	Theta	Alpha	Beta	Gamma
Open	0	0	1	0	0	0	0	1	0	0
	0	0	1	0	0					
	0	0	1	0	0					
	0	0	1	0	0					
	0	0	1	0	0					
	0	0	1	0	0					

(a)

Eye condition	Unified binary feature map				
Open	0	0	1	0	0
	0	0	1	0	0
	0	0	1	0	0
	0	0	1	0	0
	0	0	1	0	0
	0	0	1	0	0
	0	0	1	0	0

(b)

Figure 10

(a) A representative binarized form of the extracted two features for a particular eye-condition. The WPF row feature is marked by gray; (b) the unified binary feature map after appending the WPF row vector as the seventh row with the binarized APF feature matrix

Figure 11

The overall average (a) Accuracy, (b) Sensitivity and (c) Specificity performance of the classifier for each fold of the classification algorithm is presented in terms of the bar plots.