WAVELET BASED HEAD MOVEMENT ARTIFACT REMOVAL FROM ELECTROOCULOGRAPHY SIGNALS

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ABSTRACT

Electrooculography (EOG) signals acquire different types of eye movements, which can be employed for human-machine interfaces (HMI) and also for diagnostic purposes. In realistic circumstances, EOG signals tend to be contaminated with noise due to unconstrained head movements. This noise degrades the signal quality as well as increases the misclassification rate of eye movement detection. General filtering and preprocessing techniques are unable to remove this noise. This paper presents a novel approach of head-movement noise removal from EOG signals by employing a biorthogonal wavelet transform to extract the level-4 approximation coefficients, which are also exploited as features classified by k- nearest neighbor (kNN) classifier. This approach enhances the classification performance remarkably. Even when this wavelet based technique is applied as denoising technique and features to the prior arts, it improves the performance of those existing techniques too. Moreover, the proposed technique is suitable for real time applications.

***Index Terms*—** electrooculography, wavelet transform, k-nearest neighbor, head-movement noise, signal denoising.

1. INTRODUCTION

Biosignal based human machine interfaces (HMI) have been one of the prime research areas in last two decades [1-3]. HMIs not only have the capability to improve the lifestyle of people suffering from neuro-muscular disabilities but also they have immense potential to enhance overall regime of healthy individuals [22-23]. Electroencephalography (EEG), electromyography (EMG) and electrooculography (EOG) are mostly utilized as biosignals for HMI applications [1-3]. EOG signals are acquired using surface electrodes placed above and below the eye lids for vertical eye-movement detection, and on the outer canthi of the eyes for horizontal movement detection [4]. The cornea remains at positive potential and the retina at negative potential. While the eye ball moves in various directions, a potential difference created due to the dipole between the cornea and retina causes generation of biopotential signal acquired as EOG. EOG signals have certain advantages over EMG and EEG signals for being utilized as control signals for HMI applications. Although EOG is not a zero mean signal, however EOG signals have fixed patterns for various movements, where the inter subject variability are also less compared to EEG signals. Even template based EOG analysis is possible, which are unfeasible for EEG and EMG signals.

In addition to application in HMIs, EOG can be used for reading speed analysis, gaze detection, autism study, cognitive ability analysis, dystonia detection, developing security systems to name a few [5-9]. For all these applications the prerequisite is appropriate detection of eye movements. The most common eye movement types that carry vital information and are utilized in most of the EOG related studies are eye blinks, comprising voluntary and involuntary, single and double blinks and winks, and eye ball directions, mainly, up, down, left and right.

Researchers generally carry out experiments in controlled lab environments, under constrained conditions so as to minimize any sort of contamination of the EOG signals [10-13]. However, if we aim to migrate the HMI technologies out of the lab, in real life scenarios, there will be possibility of many artifacts degrading the signal quality and in turn vitiate the eye movements detection system's performance. EOG signals can be affected by power line noise, facial EMG, loose electrode contact, and also head movement artifacts. Most of these artifacts can be removed by simple band pass, median, and/or moving average filtering. However the artifacts due to the head movements, in absence of chin rest or constraints of not moving the head, poses to be more problematic as it is in the same frequency range of EOG signals and also morphologically close to EOG. Researchers [14-15] have worked on removal of power line, blinks, and facial EMG noise from the EOG. To the best of authors' knowledge none of the existing works have concentrated on presence of head-movement noise in EOG signals and in turn removal of the same.

The objective of this paper is to develop a technology for reducing the effect of head movement artifacts and thus to improve the classification accuracy of eye movement detection from EOG signals. Furthermore the approach employed in this work can be exercised in online scenarios due to its very less run time. In this paper EOG data has been acquired from the same stimulus in two different conditions so as to acquire EOG without (WO) and with head-movement (HM) noise. The acquired EOG signals are preprocessed, followed by discrete wavelet decomposition of the signal and feature extraction, which are classified by supervised multi-class k-nearest neighbor (kNN) classifier. There exists works related to eye movements detection based on thresholding and template based measures [12, 16-17]. Yet they become exigent due to inter-subject and inter-session variability in thresholds and template and are also affected by eye fatigue and external noises. The threshold and template based algorithms, require some prior training and tuning of algorithm parameters, which is not the restriction for the approach implemented in the present study. Researchers have utilized wavelet transform as features and also for noise removal based on reconstructed signal from decomposed wavelets (although not for head-movement noise removal from EOG). However, in this current work, a wavelet schema is implemented for HM noise removal as well as feature extraction.

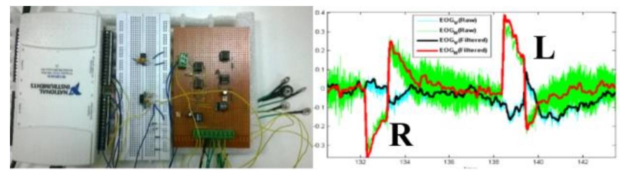
The next section describes the EOG signal acquisition, followed by the signal processing and intelligent classification techniques in section 3. Results and comparison with related existing works are presented in section 4, while concluding remarks are outlined in the final section 5.

2. EOG ACQUISITION

This section presents acquisition of EOG signal by a custom made system and the data acquisition following specific experimental framework.

2.1. Development of EOG Acquisition System

As shown in Fig. 1(a), a two channel, one for the vertical eye movement signals and the other for its horizontal counterpart, EOG acquisition system is developed. The system is USB powered, with a provision of signal isolation achieved by isolated DC/DC converter, which isolated the circuit from the USB 5V power and generates a ±12V, which powers the rest of the circuit. Thus the safety issue of the subjects has been ensured. The amplitude and frequency range of EOG signals are 5-30μV and 0.01-20Hz respectively. Thus the developed circuit has a total gain of 2400 given in three stages to avoid any possibility of signal saturation due to noise. The circuit is composed of three parts. The 1st part consist of an instrumentation preamplifier with a gain G1=100. The output of this preamplifier goes to a passive high pass filter with low cut off frequency of 0.1Hz, which also helps to reduce the DC drifts. The HPF is followed by an active low pass filter of high cut off 40 Hz and gain G2=2.4. Finally, an amplifier with a gain G3=10 has been implemented. The EOG signals are transmitted to PC through 16bit ADC, NI USB 6216. The two channel circuit has a current consumption of 9mA. The sampling rate is 100Hz. Ag/AgCl electrodes are utilized. The signals are further processed in MATLAB environment. The raw EOG signal for right and left eye movement are depicted in Fig. 1(b), EOG_V in cyan and EOG_H in green.



(a) (b)

Fig. 1.(a) Developed an EOG acquisition set up, (b) EOG signal, for right (R) and left (L) eye movement, raw signal (EOG_V in cyan and EOG_H in green) and filtered signal (EOG_V in black and EOG_H in red

2.2. Experimental Paradigm

Thus developed EOG system is utilized to acquire data from six subjects, four male and two female (27±5years). The subjects are informed about the objective of the study and their written consent has been obtained prior to the experiments. The experiments have been carried out according to Helsinki declaration [18]. The subjects are seated in comfortable position, 120cm in front of a 17" rectangular computer screen (height: 10inch, width: 13inch, approximately), and are presented to visual cues. The stimuli started with a fixation cross in the middle of the screen for 20 seconds, to mark the origin of subjects' gaze. This is followed by a ball (60pixel size) in the middle of the screen, then the ball either moved up/down/left/right and the subject has been instructed to follow the ball with their eyes. The sequence of ball movement in any direction followed the pattern: center (5 seconds)→left/right/up/down(1sec)→ center (5seconds). For each direction there were 20 trials per session, and there were total two sessions, thus total 40 trials for each movement type per subject. In addition to this the instruction "BLINK" or "BLINK TWICE" (in font size 97) also appeared on screen, each 20 times in a session, where the subjects needed to blink voluntarily, once or twice, respectively. These two experimental sessions are conducted under two conditions, i) constrained condition, where the subjects were directed not to move their head at all during the experimental session, thus acquiring EOG signal without (WO) head movement and ii) unconstrained condition, here the subjects were told to sit at their free will, with permission to move their head naturally, thus acquiring EOG signal contaminated with head-movement (HM). For both the conditions, 2 experimental sessions per subject were conducted.

3. METHODOLOGY

The EOG signals thus acquired comprises of 6 movement types, two types voluntary blinks, single (SB) and double (DB), and up (U), down (D), left (L) and right (R) directions with and without HM, as shown in Fig. 2. This study concentrated on only these signals since most of the EOG based HMIs can be driven by control signal generated by these movements and for diagnosis of eye pathologies, cognition study also these movements need to be extracted. If all these eye movements can be deciphered from EOG signal then eye gaze tracking can also be achieved suitably.

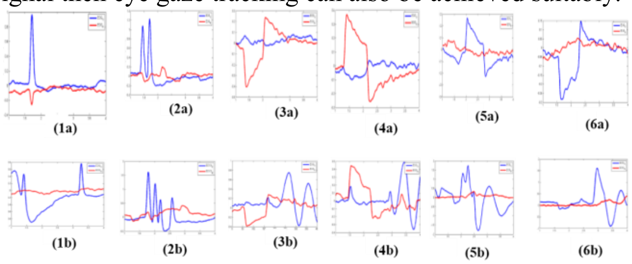


Fig.2. Six types of eye movements SB, DB, R, L, U and D in 1,2,3,4,5,6 respectively, the first row depict EOG WO and row 2 EOG HM. (EOG_H in red, EOG_V in blue)

3.1. Preprocessing

The acquired EOG is filtered using 4th order FIR bandpass filter with Hamming window according to the eqn. (1).

$$h(n) = h_d(n)\, w(n),$$

$$\text{and } w(n) = 0.54 - 0.46\cos\left(\frac{2\pi n}{M}\right) \qquad (1)$$

where, *w(n)* is the Hamming window function of finite duration, *h(n)* is the practical FIR filter, $h_d(n)$ is desired IIR filter prototype and *M* is the filter order. The lower and upper cut-off frequencies are set as 0.5 and 20Hz respectively.

The bandpass filtered signal is smoothened by applying 1-dimensional, 4th order median filter, which smoothens the signal and at the same time preserves distinctive edges.

The acquired EOG signal contains some DC drifts as well as some non-linear patterns throughout, which are not inherent to the EOG signal. These trends need to be removed from the signal as they pose glitches in the following processing and analysis stages. Thus the EOG signals entail to be detrended. For this purpose, a 6th order polynomial is fitted separately to the median filtered vertical (EOG_V) and horizontal (EOG_H) channels of EOG and the best fitted polynomial is subtracted from the EOG signals. This operation removes the redundant patterns and DC drifts from the median filtered EOG signals.

Prior to wavelet analysis, eye movement epochs are extracted from the EOG signal, where each epoch was of 4 seconds window. During real time processing (i.e. online classification), then instead of epoch extraction, signals will be buffered for each 4 seconds. All the other procedure remains same.

3.2. Wavelet transform for noise removal and feature extraction

The Fourier Transform contains only frequency domain information, and short time Fourier transform has the demerit of fixed window lengths. Thus encountered problems are overcome by wavelet transform, which has the capability to discriminate between both time and frequency domain characteristics. These reasons contribute to wavelet transform becoming an effective tool in signal processing domain.

A single archetype wavelet, referred to as the mother wavelet is subjected to contraction, dilation, and shifting operations to obtain wavelets. Particular location and scale are the distinctive characteristic of each wavelet. The obtained wavelets are the origin functions that are segregated with respect to time and frequency, and are used to decompose a signal. This approach forms the basis of wavelet transformation [19-20]. Mother wavelet can be represented by eq. (2)

$$\psi_{(sc,sh)} = \frac{1}{\sqrt{sc}}\,\psi\left(\frac{t - sh}{sc}\right) \qquad (2)$$

where *sc* is the scaling factor and *sh* is shifting parameter, $sc, sh \in R$, i.e. the wavelet space.

In this work, discrete wavelet transform is utilized for both noise (i.e. head movement artifact) removal and feature extraction. This is one of the major uniqueness of the present work. EOG signals are acquired at a sampling rate of 100Hz. Power spectral density analysis of the acquired EOG signal suggest that maximum power of the EOG signals are contained below 15Hz. Thus decomposition of the wavelets are performed till level 4. The level 4 approximation coefficients retain the signal morphology, related to the various eye movements, and simultaneously attenuated the HM noise. Here biorthogonal ‘*bior2.8*’ mother wavelet is implemented for decomposition as it resembles the eye movement signals very closely and biorthogonal wavelets provide more degrees of freedom and orthogonal counterparts. The current approach performs wavelet transformation based decomposition only and utilizes thus obtained approximation coefficients for further processing, unlike [19], which has used wavelet based reconstruction to extract features. Thus the signal reconstruction time and computational load is also reduced in this current approach. Three types of features are being exploited in this study: i) FS1: the obtained approximation coefficients serve as feature set to the classifier, ii) FS2: some time-domain features and statistical parameters (viz. area under the curve, peak to peak amplitude, maximum and minimum value in a particular epoch window, Hjorth parameters, standard deviation, mean, Skewness, Kurtosis, Shannon’s entropy) are extracted from the level 4 approximation coefficients, and iii) FS3: same time domain and statistical features as FS2, extracted from preprocessed EOG, prior to wavelet decomposition. These three feature sets, FS1, FS2 and FS3 are separately classified. Fig. 1(b), EOG_V in black and EOG_H in red denotes the preprocessed and filtered EOG.

3.3. Classification

Classification of 6 eye movements from the extracted feature sets FS1, FS2 and FS3 are carried out by multiclass kNN [21], with k=5 and Euclidean distance as the distance metric. Features extracted from EOG signals of session 1 (S1) are used for training and session 2 (S2) is used for testing, also results of S2 as training set and S1 as test set are obtained.

TABLE 1. CM for FS1

CLASSES		PREDICTED					
		R	L	U	D	SB	DB
TRUE	R	**30**	0	0	8	2	0
	L	0	**26**	1	12	0	1
	U	2	2	**30**	5	0	1
	D	1	0	1	**37**	0	1
	SB	1	0	5	9	25	0
	DB	0	0	9	2	10	19

TABLE 2. CM for FS2

CLASSES		PREDICTED					
		R	L	U	D	SB	DB
TRUE	R	28	0	1	8	0	3
	L	9	13	3	13	1	1
	U	3	1	22	13	0	1
	D	0	3	2	34	0	1
	SB	5	2	0	1	23	9
	DB	3	2	1	0	3	**31**

TABLE 3. CM for FS3

CLASSES		PREDICTED					
		R	L	U	D	SB	DB
TRUE	R	18	11	1	4	0	6
	L	8	27	1	1	1	2
	U	3	0	18	15	1	3
	D	2	0	3	30	2	3
	SB	0	0	0	2	**33**	5
	DB	2	1	0	2	4	31

4. RESULTS AND DISCUSSION

Classification results, in the form of confusion matrices (CM), averaged over all subjects for features sets FS1, FS2 and FS3 for 40 trials for each movement type are depicted in Table 1, 2 and 3 respectively. The runtime for classification using feature set FS1, FS2, and FS3 is 0.11 sec, 4.72 sec and 2.55 sec respectively. It is evident from Table 1, 2 and 3 that the system performed best with FS1 followed by FS2 and FS3, moreover FS1 took the least time. Thus the proposed wavelet transform (WT) based denoising as well as feature extraction improves the performance of eye movement recognition system.

TABLE 4. Performance Compared with Related Prior Works

	CA in % (SD)	
Approach	WO	HM
A1 [11]	86 (2.2)	81.6 (2.7)
A2: WT+A1	**98.3 (0.9)**	**93.3 (1.8)**
A3 [12]	92.5 (8.6)	56.2 (4.6)
A4: WT+A2	**95 (7.07)**	**72.5 (3.3**
A5: [13]	77.6 (4.7)	72.3 (4.8)
A6: WT+A5	75 (8.3)	**80.5** (4.8)

4.1. Comparison with related literature

Researchers have extracted eye movements from EOG signals, but the noise due to head movements in practical scenarios have not been taken in account till date. This paper has implemented wavelet transform based denoising as well as feature extraction, which has improved the performance. Table 4 represents comparison with related work. Approaches A1, A3 and A5 when applied on the present data set, without (WO) and with head movement noise (HM) have been presented. In Approaches A2, A4 and A6, prior to applying A1, A3 and A5 respectively, our wavelet (WT) based denoising has been implemented, which has improved the classification accuracies (CA) in each of the cases, and the standard deviations (SD) are given in parenthesis have decreased. Moreover, unlike other wavelet transform approaches, instead of utilizing the reconstruction signal from wavelet transforms, we have utilized the approximation coefficients only. This reduces the time and computational complexity.

5. CONCLUSION

EOG signals related to six types of eye movements are acquired under constrained and unconstrained condition, considering out of the lab scenarios for EOG. The EOG signals contaminated with head movement noise tends to increase misclassification rate of eye movement recognition. The approximation coefficients are extracted by wavelet transformation as features to denoise the signal as well as increase the accuracy of the classification of the eye movement. The implemented approach is suitable for employing in real time systems too. Even compared with related prior work, the present approach increased the accuracy of the existing works, both classification based (Approach A1 and A3) as well as threshold based techniques (Approach A2).

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