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Real Time Eye Blink Noise Removal from EEG signals using Morphological Component Analysis

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Abstract— **This paper presents a method of removing the noise caused by eye blinks from an electroencephalogram (EEG) signal in real time based on morphological component analysis (MCA). This method sparsely represents both the eye blink and the EEG signal basis matrices using a Short Time Fourier Transform (STFT). This approach has two main advantages: 1) fast computation of the estimation of the signal coefficients using the basis pursuit algorithm 2) less memory requirement. The obtained result shows that the correlation coefficient between the raw EEG and the cleaned EEG is between 0.72 and 0.94 which implies that it is possible to remove eye blink noise from the EEG signal in real time without affecting an underlying brain signal.**

I. INTRODUCTION

The electroencephalogram (EEG) signal is the composition of brain activities recorded as changes in electric potential at various locations on the scalp. Traditionally, EEG has been used for medical and medical brain computer interface (BCI) applications, but in recent years there has been a great interest of non-medical BCI applications such as device control, training and education, gaming and entertainment [1]. Most of these applications require portable and wearable EEG devices with a single or a few EEG channels to reduce the cost, power consumption, size and improve user comfort level.

The raw EEG signal is usually contaminated by artifacts from sources such as the heart, eyes, muscle movements and interference from electrical equipment, the mains supply and other electromagnetic sources. Removing these artifacts is essential as they can affect the detection and extraction of features from the EEG signal. Artifacts from eye blinks are particularly difficult to suppress due to their large amplitude which is of the order of ten times larger than a typical EEG signal [2]. Existing methods of removing eye blink artifacts from the EEG signal are based on regression [3] [4], principal component analysis (PCI) [5] and independent component analysis (ICA) [6] and are not suited to single channel non-medical applications. Regression based methods require an extra channel for recording eye blinks as a reference signal. Both PCI and ICA based methods require the EEG to have at least two channels. Morphological component analysis (MCA) [7] is another method which has attracted much attention in sparse signal processing. Yong et al. [8] demonstrated the feasibility of MCA for removing artifacts from an offline EEG signal. However, the author computed some of the basis matrices using SPARCO (a Matlab toolbox developed for testing and reconstruction algorithm) and estimated the coefficients of signal components using another optimization algorithm. Such an approach requires more memory than the presently reported method as basis matrices need to be stored during the estimation of the coefficients of the signal components. The size of memory required increases with the size of the matrices and the number of components to be estimated from the signal.

This paper presents a real time method to remove eye blinks from EEG signal based on MCA. Both eye blink and EEG signals are sparsely represented using basis matrices which are fast and efficiently computed using Short Time Fourier Transform (STFT). Computing basis matrices in real time offers the advantage of requiring low memory space. This paper is organized as follows: section II discusses the general concept of MCA, followed by the description of how the signal used in the experiment was acquired and then the steps followed to remove the eye blinks from the raw EEG signal is presented. Section III presents the results and finally, conclusions are drawn in section IV.

II. METHODOLOGY

A. The concept of Morphological Component Analysis

Morphological Component Analysis (MCA) is a method of decomposing a signal into its components. The method is based on the assumption that every signal component has a different shape (hence the term morphology) that enables its reconstruction using a sparse representation [9]. If a signal y has components $y_1, y_2, ..., y_N$ and each of these components is represented sparsely using the basis $\phi_1, \phi_2, ...\phi_N$ respectively, then the signal y can mathematically be written as:

$$y = \phi_1\alpha_1 + \phi_2\alpha_2 + ... + \phi_N\alpha_N \tag{1}$$

where $\alpha_1, \alpha_2..\alpha_N$ are the projection coefficients of $y_1, y_2, ..., y_N$ on basis $\phi_1, \phi_2, ...\phi_N$ and N is the number of signal components. In this paper, the signal y is considered as a linear combination of two signal components, y_1 and y_2 (henceforth, $N = 2$) where y, y_1 and y_2 correspond to the raw EEG signal, cleaned EEG signal and eye blink signal respectively. Therefore to meet the assumption of MCA, it is important that the dictionary of bases ϕ_1, ϕ_2 exists such that for each signal component in y is sparse in ϕ_1 and not, or at least not as sparse as, in ϕ_2 [7].

The signal y can then be decomposed using MCA by finding the coefficients α_1, α_2 (from (1)) such that:

$$y = {\phi_1}^T\alpha_1 + {\phi_2}^T\alpha_2 = \hat{y}_1 + \hat{y}_2 \tag{2}$$

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Following the basis pursuit approach, the coefficients α_1 and α_2 in (2) can be estimated by l_1-norm minimization [10]. The problem can then be formulated as:

$$\arg\min_{\alpha_1,\alpha_2} \| \lambda_1 \odot \alpha_1 \|_1 + \| \lambda_2 \odot \alpha_2 \|_1$$

$$such\ that \quad y = {\phi_1}^T \alpha_1 + {\phi_2}^T \alpha_2 \tag{3}$$

where λ_1 and λ_2 are weighting parameters, and $\| .. \|_1$ is l_1-norm.

Several algorithms have been developed to solve the basis pursuit problem (equation 3), namely Iterative Shrinkage/Thresholding Algorithm (ISTA) [11], Fast ISTA (FISTA) [12], Split variable Augmented Lagrangian Shrinkage Algorithm (SALSA) [13], [14]. As the name suggests, FISTA is much faster than ISTA by several order of magnitude [12]. Afonso et al. [13] demonstrated that SALSA is faster than FISTA and therefore in this paper SALSA was chosen to solve the basis pursuit problem.

B. Signal acquisition and transmission

The electroencephalography signals were acquired using the MindWave Mobile headset from Neurosky Inc [15] . This device consists of a headset, an ear-clip and a sensor arm. The EEG electrode is on the sensor arm which rests on the forehead above the eye. According to the 10-20 International system of EEG electrode placement on the human head [16] this position is approximately equal to the Fp1 position (see Fig. 1). The headset's reference and ground electrodes are on the ear clip at A1 and at T4. The device also includes a Bluetooth module which sends the signals wirelessly to the computer at a sampling frequency of 512 Hz. EEG signals are typically below 256 Hz, hence the sampling frequency of this device meets Shannon's sampling theorem.

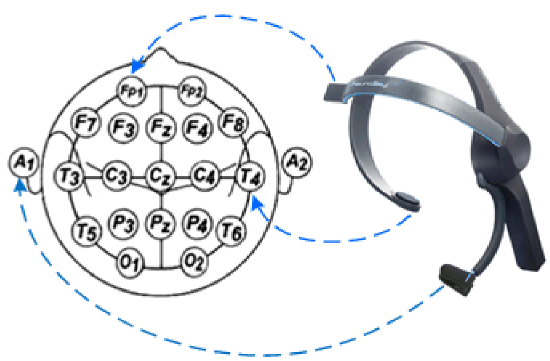

Fig. 1. Position of Mindwave Mobile headset [15] electrodes on 10-20 international system of electrode placement

Transmission Control Protocol/Internet Protocol (TCP/IP) server was used on the computer and was responsible for collecting the EEG signal from its Bluetooth receiver. The server was running JavaScript Object Notation (JSON) based protocol and the EEG signal was collected at a rate of 512 samples per second by the TCP/IP client that was implemented in Matlab.

C. Separating eye blinks from EEG signal using MCA

The EEG signal is non-stationary and its spectral content evolves slowly over time and can be analysed using STFT. A STFT performed on a signal $y[n]$ is described as

$$STFT\{y[n]\} = \sum_{n=0}^{R+1} \{y[n-m]\omega[n]\} e^{-j\omega n} \tag{4}$$

where $\omega[n]$ is the sliding window that emphasis local frequency components within it, and R is the length of the window; a long window length provides high frequency resolution and a short window length provides high time resolution.

The real time blink separation from the raw EEG signal was performed based on an algorithm shown in Fig. 2. The parameters such as basis matrices, $\phi = \{\phi_1, \phi_2\}$, maximum number of frames, F, and total number of samples per frame, S, were first initialized. The basis matrices which sparsely represented the EEG signal and eye blinks were computed by STFT using a large window length ($\approx 2\ s$) for the former and a short window length of about 500 ms for the later as most eye blinks have duration between 200 to 400 ms. The basis coefficients were estimated iteratively using a basis pursuit algorithm and were followed by reconstruction of the cleaned EEG signal using the obtained coefficients.

The performance of this method was evaluated by correlating the raw EEG signal obtained as described in section IIB and the cleaned EEG signal. The correlation coefficient of two signals is always between 0 and 1, whereas 0 means the signals are uncorrelated and 1 implies that they are strongly correlated. Although this method is commonly used as a comparative measure of likeness of two signals, it is important to point out that if the measured EEG contains many eye blinks, it will not correlate with the cleaned EEG even if the algorithm is 100 percent perfect.

III. RESULTS

The method of removing eye blinks presented in this paper was tested by acquiring more than 60 frames of EEG signal and processing each frame in real time. Fig. 3 is a segment of four frames showing the raw EEG, the processed EEG, and eye blinks which were removed from the raw EEG. A closeup of raw EEG, processed EEG and the eye blinks is shown in Fig. 4 to allow easy visual inspection of the results.

The results show that MCA is capable of separating the eye blinks from the raw EEG signal in real time. Although MCA is an iterative algorithm, the average cleaning time of one frame (512 samples) of raw EEG was 26.9 ms with standard deviation of 0.8 ms on a desktop computer running a 64 bit operating system with 3.4 GHz processor. The correlation of the raw EEG and cleaned signal found to be between 0.72 to 0.94 depending on how heavily the signal is contaminated by the eye blinks with worse contamination as the number of eye blinks increased. These values are higher than those reported in [8] and comparable to those previously reported in [2] and [17].

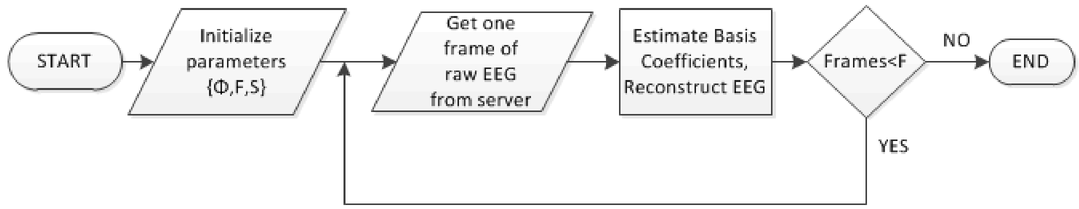

Fig. 2. Algorithm of separating eye blinks from raw EEG in real time

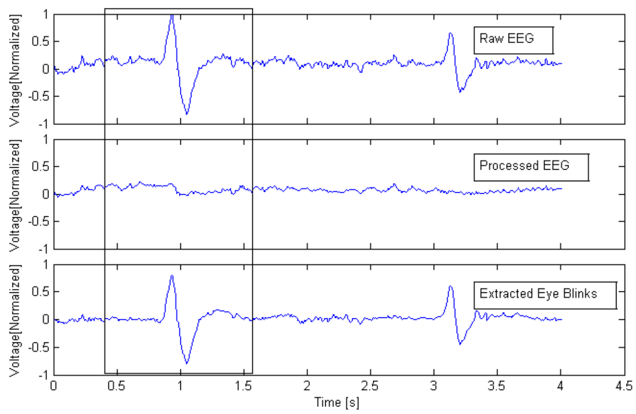

Fig. 3. Separation eye blinks from raw EEG signal

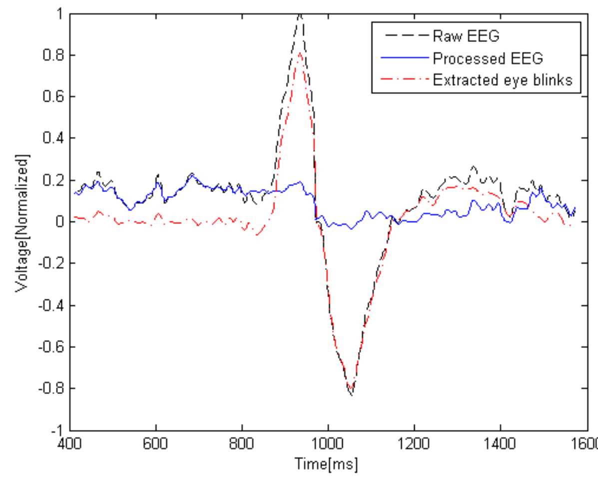

Fig. 4. Close look of section of signals presented in Fig. 3

TABLE I
PERFOMANCE EVALUATION

Perfomance Indicator	Value
Correlation Coefficient	0.72 to 0.94
Execution Time/Frame	26.90 ms

IV. CONCLUSIONS

In this paper, the implementation of MCA based method of removing eye blinks from single channel EEG signal is demonstrated. Taking advantage of fast computation of the basis matrices using STFT, it was possible to remove eye blinks from the EEG signal at real time. This approach is particularly useful as it is real time and requires less memory, which is limiting factor for most microcontrollers. In the future, this work will be extended and be implemented in our in-house low power wearable EEG targeted for non-medical BCI applications.

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