ARTIFACT REMOVAL IN EEG USING MORPHOLOGICAL COMPONENT ANALYSIS

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ABSTRACT

To reduce the effects of artifacts in electroencephalography (EEG), we propose the use of Morphological Component Analysis (MCA). Taking advantage of the sparse representation of data in overcomplete dictionaries, MCA decomposes EEG signals into parts that have different morphological characteristics. For denoising purpose, the parts related to artifacts are removed. An overcomplete dictionary is constructed using the discrete cosine transform, Daubechies wavelet basis, and Dirac basis. Movement-related potentials (MRP) and EEG signals contaminated by spikes, eye-blinks, and muscle artifacts caused by eye-brow raising are used to evaluate the performance of the method. The results demonstrate that MCA can be used to decompose the single-channel EEG signals into artifacts and MRP components. The correlation coefficient between the denoised MRP and the original MRP using MCA is significantly higher than that obtained using stationary wavelet transform.

Index Terms— Electroencephalogram, Artifacts, Brain-Computer Interface, Denoising, Morphological Component Analysis

1. INTRODUCTION

Electroencephalography (EEG) that measures the electrical activity of the brain can be used to operate a brain-computer interface (BCI) system. EEG signals are often contaminated by artifacts such as ocular artifacts, muscle artifacts, power line interference, and electrode artifacts. The removal of artifacts from the EEG signals is crucial as the artifacts can affect the detection of EEG features such as movement-related potentials (MRP), as well as event-related desynchonization of the mu and beta rhythms. This can cause false activations in a BCI system and cause frustration in users. Yet, little attention has been paid in BCIs to the detection and removal of artifacts in general, and to muscle artifacts in particular.

Regression analysis is widely used to remove ocular artifacts from EEG signals [1]. This method has the disadvantage of requiring the recording of source signals from the electrooculogram (EOG) channel. Moreover, it may also remove some useful information in the EEG signals. Blind source separation and independent component analysis have also been proposed for artifact removal [2, 3]. Such methods, however, require multi-channel data and long data epochs to produce reliable results [3]. An alternative artifact removal method, based on wavelet denoising, has been proposed. For example, it has been used to remove ocular artifacts from EEG signals [4]. This method can be applied to single-channel data. Unfortunately, suppressing the wavelet coefficients in the low frequency range may also remove the low frequency components of the EEG signals.

There is presently a growing interest in sparse signal representation in which the signals are decomposed into several sparse components. Xu and Yao [5] propose a sparse component decomposition algorithm based on a mixed overcomplete dictionary to improve the estimation of evoked potentials. The mixed dictionary is constructed with an overcomplete wavelet and an overcomplete discrete cosine function dictionary for the representation of the evoked potentials and the background noise respectively. However, artifacts also have transient properties that can be represented by the wavelet dictionary. The method may not be effective in the presence of artifacts.

In this paper, we present a method of removing artifacts using Morphological Component Analysis (MCA). MCA decomposes EEG signals into components that have different morphological characteristics. Each component is sparsely represented by different bases (discrete cosine transform (DCT), wavelet and Dirac basis). We demonstrate the potential of this method in reducing the effects of artifacts in EEG signals, especially MRP as this can be used to operate a BCI system. The proposed method has the advantage that it can be applied to single-channel EEG data and no source signals are required to remove the artifacts. To the best of our knowledge, MCA has not been applied to EEG signals to remove artifacts even though it has been shown to have interesting applications in image inpainting [6] and MEG signal decomposition [7].

2. METHODOLOGY

2.1. The MCA Concept

A dictionary $\mathcal{D}$ is a collection of waveforms or atoms, such as columns from wavelet, Fourier and Dirac basis [8]. A signal is sparse in $\mathcal{D}$ if it can be represented using a linear combination of a few atoms only. By merging several complete dictionaries, an overcomplete dictionary is contructed [8]. Although the signal representation is no longer unique, the class of signals that can be sparsely represented using the dictionary is much larger.

Taking advantage of the sparse representation of data in overcomplete dictionaries, MCA assumes that a signal $s \in \mathbb{R}^N$ can be represented by a linear combination of m morphological components [6]:

$$s = \Phi\alpha = \sum_{i}^{m} \Phi^{(i)}\alpha^{(i)}$$

where $\Phi = [\Phi^{(1)} \ldots \Phi^{(m)}]$, $\alpha = [(\alpha^{(1)})^T \ldots (\alpha^{(m)})^T]^T$, and $\alpha^{(i)}$ is a coefficient vector corresponding to dictionary $\Phi^{(i)}$.

Each component, $s^{(i)} = \Phi^{(i)}\alpha^{(i)}$, represents a signal type that has different morphological structures. A morphological component that is sparse in a particular dictionary $\Phi^{(i)}$ will generally not be sparse in other dictionaries, $\Phi^{(k)}, i \neq k$. Therefore, $\Phi^{(i)}$ plays a role in discriminating different signal contents [6].

The problem of finding the sparsest representation can be formulated as [6]:

$$\min_{\alpha} \quad \sum_{i=1}^{m} \|\alpha^{(i)}\|_0 \quad \text{subject to} \quad s = \Phi\alpha$$

Because this problem is inherently combinatorial, and therefore intractable, the basis pursuit method:

$$\min_{\alpha} \quad \sum_{i=1}^{m} \|\alpha^{(i)}\|_1 \quad \text{subject to} \quad s = \Phi\alpha, \tag{1}$$

suggests the substitution of the ℓ_0-norm by the ℓ_1-norm that also promotes sparsity in the solutions [8].

2.2. Data Description

The EEG data used in this study were obtained from two different experiments:

- Data A: EEG data obtained from an EEG artifact study [9]. The EEG data contained artifacts caused by eye-brow raising, jaw clenching, swallowing, and eye-blinks. The EEG signals were recorded at the sampling rate of 256 Hz with electrodes placed over the primary motor cortex area.

- Data B: EEG data obtained from an asynchronous brain-controlled switch study [10]. MRP trials were collected in this study. During the experiment, the subject performed an actual right index finger flexion (by pressing a finger switch). The EEG signals were recorded at the sampling rate of 128 Hz with electrodes placed over the supplementary motor area and the primary motor cortex area.

2.3. EEG Signal Denoising Using MCA

The EEG signals are modeled using the MCA concept. We assume that a single-channel EEG signal ($s \in \mathbb{R}^N$) can be represented by a linear combination of three morphological components:

$$s = \Phi_{db}\alpha_{db} + \Phi_c\alpha_c + \Phi_d\alpha_d$$

where α_{db}, α_c, and α_d are the coefficient vectors corresponding to the complete dictionaries of Φ_{db}, Φ_c, and Φ_d, denoting respectively the Daubechies wavelet (db8), the discrete cosine transform (DCT), and the Dirac basis.

Spikes in the EEG signals can be caused by muscle artifacts, electronic noise, etc. The spikes can be represented sparsely by Dirac basis (an identity matrix). The background EEG signals and event-related potentials are represented by the DCT basis. Finally, artifacts such as ocular and muscle artifacts that have transient properties are represented by Daubechies wavelet basis (db8) with 5 levels of decomposition.

The mixed overcomplete dictionary $\Phi \in \mathbb{R}^{N\times 3N}$ consists of the three complete dictionaries mentioned above: $\Phi = [\Phi_{db} \quad \Phi_c \quad \Phi_d]$. Φ is constructed using SPARCO (a toolbox developed for testing reconstruction algorithms) [11]. In order to reduce the processing time and improve robustness, the basis pursuit denoise model is used [8]:

$$\min \quad \sum_{i=1}^{m} \|\alpha^{(i)}\|_1 \quad \text{subject to} \quad \|s - \Phi\alpha\|_2 \leq \sigma \tag{2}$$

where σ is an estimation of the noise level in the data. If $\sigma = 0$, the solution obtained is essentially the same as the one obtained using basis pursuit. In this study, we use SPGL1 [12], an optimization algorithm, to solve Equation (2). σ is set to 10 as this value is found not to affect significantly the performance of the method while reducing the processing time by approximately a factor of two. To find the value of σ that provides an optimal tradeoff in performance and fast processing speed, a more comprehensive study will be conducted in the future.

Several four-second EEG segments from Data A contaminated by 60 Hz noise, jaw clenching, eye blinks, eye-brow raising, and swallowing are down-sampled to 128 Hz and decomposed using MCA. Next, the averaged MRP obtained from Data B is then mixed with EEG segments that contain artifacts from Data A. The length of the EEG segments is four seconds. Only the EEG signals from channel C1 and FC1 are processed using both the MCA and stationary wavelet transform (SWT) algorithms. These electrodes are selected because they are positioned near the contralateral motor cortex area of the brain, which is activated during right finger flexion.

SWT (db8 with 5 levels of decomposition) using soft-thresholding is implemented in Matlab. For both the MCA and SWT, the difference between the denoised EEG signals of the two channels (bipolar) is computed. To quantify the performance of each method, the correlation coefficient (CC) between the bipolar averaged MRP and the bipolar denoised EEG signal is used in this study.

3. EXPERIMENTAL RESULTS

Fig. 1 shows an example of the morphological components obtained from an EEG signal contaminated by an eye-blink and muscle artifacts caused by swallowing (column 1), and an EEG signal contaminated by 60 Hz power line noise, an eye-blink, and muscle artifacts caused by jaw-clenching (column 2). The MCA method shows good ability to separate the background EEG signals from the artifacts (except 60 Hz noise because it is sparsely represented by the DCT basis). The results show that the selected dictionaries are suitable. The muscle and eye-blink artifacts are represented by both the Daubechies wavelet and Dirac bases. The effects of the artifacts on the EEG signals can therefore be reduced by removing the db8 and Dirac components. The 60 Hz noise can be easily removed by removing the DCT coefficients corresponding to that frequency. However, we should not assume that all EEG-related information are completely captured in the DCT component. When MCA is applied to EEG segments free of artifacts, the EEG signals are found to be represented by both the Daubechies wavelet and DCT.

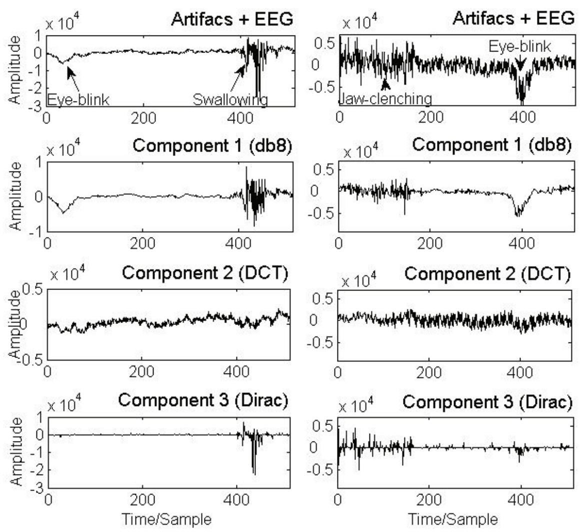


Fig. 1. Decomposition of the EEG signals contaminated by artifacts caused by eye-blink and swallowing (column 1), and power line interference, jaw-clenching and eye-blink (column 2) using MCA.

Fig. 2 shows the averaged MRP contaminated by eye-brow raising artifacts and the components obtained using MCA and SWT. The MRP can be observed in the DCT component obtained using MCA, but not in the SWT denoised MRP. The results obtained using SWT denoising method could possibly be improved if the threshold is carefully adjusted using prior knowledge of the signals. Nevertheless, the wavelet denoising method is not as flexible as the MCA because only one type of waveform is used in processing the signals. Different sources of artifacts such as spikes and ocular artifacts may have different morphological characteristics. For example, spike-like artifacts cannot be removed efficiently using SWT (with Daubechies wavelet).

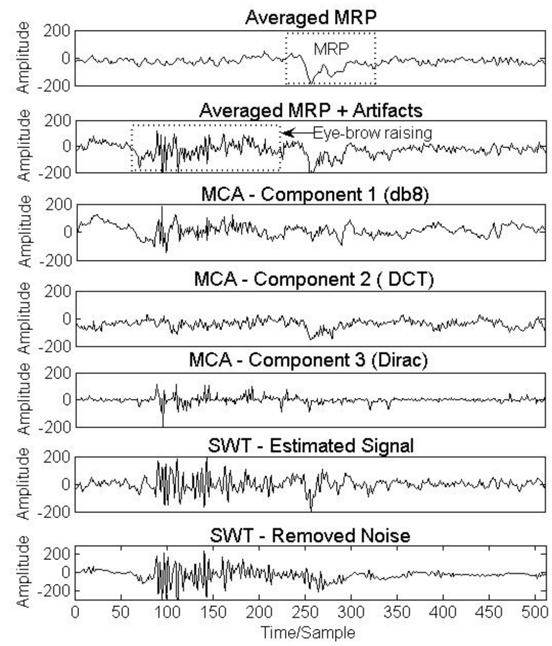
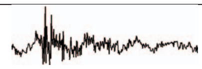
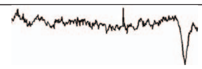


Fig. 2. Decomposition of the averaged MRP contaminated by muscle artifacts (eye-brow raising) using MCA and SWT.

The correlation coefficient (CC) values between the original averaged MRP and the estimated MRP obtained using MCA and SWT are presented in Table 1. The CC value in general is not very high because the MRP is not mixed with pure artifacts but with EEG segments contaminated with artifacts. Hence, the estimates obtained from MCA and SWT may contain the background EEG signals in both the MRP and the contaminated EEG signals. As shown, the results obtained are promising because the CC values of MCA are significantly higher than SWT. MCA has a better performance than SWT due to the use of several waveforms in the overcomplete dictionary, which can help to explain the data better.

MCA can possibly be applied to shorter segments of data. In our preliminary study, we use MCA to decompose a one-second single-trial MRP contaminated by an eye-blink, as shown in Fig. 3. The MRP is well represented by the DCT basis and the eye-blink by the db8 basis. Future experiments will study these findings in more detail.

Table 1. CC values of MCA and SWT obtained from Test 2.

Artifacts		MCA	SWT
Eye-brow raising		0.5485	0.2925
Eye-blink + spike		0.5524	0.2944

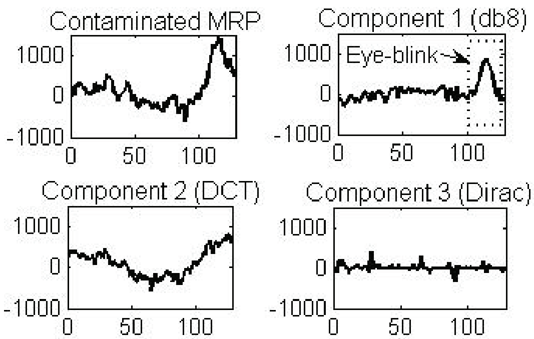


Fig. 3. Decomposition of the single-trial MRP contaminated by eye-blink artifacts using MCA.

4. CONCLUSIONS

The concept of decomposing the signals into atomic parts that have different morphological characteristics is appealing. In this study, we focus on demonstrating the feasibility of using the morphological diversity of the signals to reduce the effects of artifacts such as ocular and muscle artifacts in the EEG signals. This is achieved by using an MCA that decomposes EEG signals into Dirac, DCT and wavelet components. Components related to the artifacts are then discarded. The proposed method shows the advantage of representing the signals by a mixed overcomplete dictionary over the conventional methods such as wavelet denoising that uses only a single type of waveform. In the future, we plan to look into the construction of an overcomplete dictionary that is more flexible, and the use of algorithms such as K-SVD [13]. We are also interested in extending the problem to the case of multichannel EEG signals. A better way of evaluating the performance of the algorithm is required as correlation coefficient alone is not sufficient for this purpose. For example, we can apply feature extraction and classification algorithms to the EEG signals and find the error rate of a BCI system when MCA is used to preprocess the signals.

5. REFERENCES

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