Artifacts Removal of EEG Signals Using Nonlinear Adaptive Autoregressive

Arjon Turnip and Iwan R. Setiawan

Abstract—**Analysis of EEG activity usually raises the problem of differentiating between genuine EEG activity and that which is introduced through a variety of external influence. These artifacts may affect the outcome of the EEG recording. In this paper, the Nonlinear Autoregressive (NAR) algorithm for artifacts removal of EEG signals in connection with the choice of the model structure (order) and computation of the system coefficients is proposed. The proposed method was tested in real EEG records acquired from eight subjects. The experimental result show that the proposed method can effectively remove the artifacts from all subjects.**

Index Terms—**Artifacts, nonliniear adaptive autoregressive, EEG.**

I. Introduction

When brain cells (neurons) are activated, the synaptic currents are produced within the dendrites. This current generates a secondary electrical field over the scalp measurable by Electroencephalogram (EEG) systems [1]. EEG is the noninvasive measurement of the electrical activity on the scalp over multiple areas of the brain. The measured of currents that flow during synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex is called EEG signal. EEG signal, which is important in clinical application such as diagnosing and in research field such as brain computer interface (BCI) application is widely affected by a variety of large signal contaminations or artifacts. In current data acquisition, eye movement and blink related artifacts are often dominant over other electrophysiological contaminating signals (e.g., heart and muscle activity, head and body movement), as well as external interference due to power sources. Eye movements and blinks produce a large electrical signal, known as electrooculogram, which spreads across the scalp and contaminates the EEG. These contaminating potentials are commonly referred to as ocular artifacts. Artifacts can dramatically alter the signal recorded at all scalp sites, especially those closest to the source of the noise [2]-[7]. Hence, a necessary stage in EEG processing is artifact removal.

In a BCI application that removed all data containing artifact might be left with too little clean data to be of practical use. The core components of a BCI system [8], [9] (can be invasive or non-invasive) are brain signal acquisition, pre-processing, feature extraction, classification, translation, and feedback control of external devices as shown in Fig. 1. Therefore, the use of artifacts removal algorithm to the EEG records and leaving clean data would be of tremendous value (there has been an ample amount of research toward this goal) [8]-[19]. Many of these newer approaches involve techniques including independent component analysis (ICA) [14], neural networks [16]-[19], principal component analysis (PCA) [12], and other methods which were either unavailable or much less well known during the early days of EEG signal processing. Statistically, PCA decomposes the signals into uncorrelated, but not necessarily independent components that are spatially orthogonal and thus it cannot deal with higher-order statistical dependencies. However PCA cannot completely separate eye artifacts from brain signals especially when they both have comparable amplitudes. A newer approach uses ICA, which was developed in the context of blind source separation problems to form components that are as independent as possible. Another class of methods is based on decomposing the EEG and EOG signals into spatial components, identifying artifactual components and reconstructing the EEG without the artifactual components.

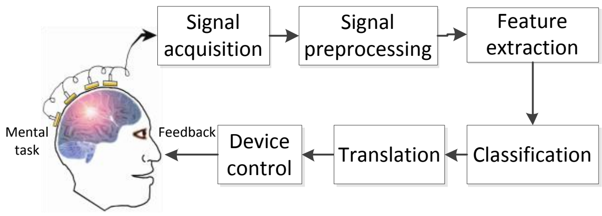

Fig. 1. Basic six key steps in BCI.

Techniques with an intelligent method for EEG artifacts without rejecting other data are remains difficult in EEG processing software but necessary one for BCI designers. In this paper, we introduce an intelligent method (i.e., Nonlinear Adaptive Autoregressive (NAR)) for EEG artifacts removal which can significantly enhance prominence of the spike in the clean EEG signals. This method is designed to adaptively derive a relatively small number of mean square error of a set of model parameters while retaining as much of the information from the original data as possible.

The structure of this chapter is the following. Section II presents the data acquisition. Section III presents the application of the Nonlinear Autoregressive for Noise Cancelation. Section IV shows the discussions of the experimental results. Section V draws conclusions.

II. Data Acquisitions

In the experiment, eight healthy adult subjects (all men,

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ranging in age between 20-22 old years) participated in this study, which are 5 subjects have slight hair and the rest are thick hair. All of the subjects do same experiment with three stimulus which are baseline, closed eye, and blink eye condition. It has been made sure that every participant was not in a stress mental condition while the experiment was being conducted. All participant pictures are shown in Fig. 2. During the experiment, all participant were sitting in a comfortable chair in front of 14" monitor at a distance of about 1 m. To build the experiment setting used in the EEG sample collecting process, we utilize the Open Vibe software to perform the data acquisition, stimulus visualization, and EEG recording with the function block that already built in. This experiment consists of two sessions, first session had a period of 130 seconds with 2 stimulus (i.e., baseline (eye normal) and closed eye condition). Second sessions had a period of 66 seconds with 2 others stimulus (i.e., baseline (eye normal) and blink eye condition). The EEG signals are recorded continuously using six electrodes (channels) at F7, F8, T7, T8, O1 and O2 that represent the visual of human brain and digitized at a 128 Hz sampling rate. The six electrodes configuration is shown in Fig. 3.

Fig. 2. Eight subjects participated in the experiment.

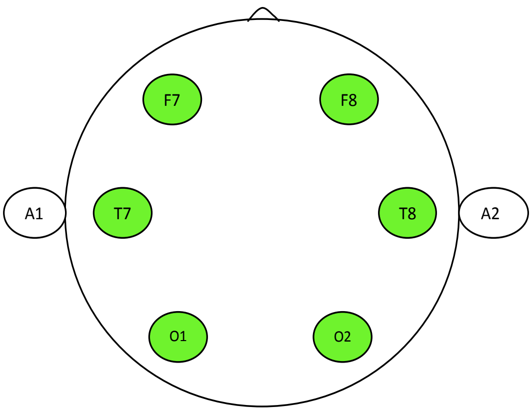

Fig. 3. Six channels of electrode configuration in the experiment.

III. Nonlinear Autoregressive for Noise Cancelation

In all the signal modeling problems, including nonlinear signal processing, the general problem is to find a good model structure and then estimate the parameters of some basis signals from the observations. A nonlinear autoregressive (NAR) model can be written as [14]:

$$x(t-1) = f_t\left(h_x^T(t), \theta_a(t)\right) + e(t) \tag{1}$$

$$y(t) = g_t\left(x(t)\right) + u(t) \tag{2}$$

and

$$h_x^T(t) = h\left(x(t), x(t-1), \ldots, x(t-n)\right) \tag{3}$$

$$\theta_a = \theta(a_1, a_2, \ldots, a_n)^T \tag{4}$$

where f_t and g_t are known matrix-valued functions of some unknown data $x(t)$ and a_i , n is the order of the predictor, $e(t)$ and $u(t)$ are uncorrelated zero mean white noise processes not necessarily Gaussian with variances Q and R (estimated using a technique described in [14]) respectively and a_i n_i: =1, ..., n are the predictor coefficients.

Let replaced the coefficients $a_i : i = 1, \ldots, n$ by $a_i(t)$ to reflect the possibility that the coefficients are subject to random perturbations and define the vector of coefficients $\vartheta(t)$ as follows:

$$\xi(t) = [a_1(t) a_2(t) \ldots a_n(t)]^T \tag{5}$$

where $0 \le t \le N$, N denotes the number of samples. Notice that the coefficients $a_i : i = 1, \ldots, n$ have been replaced by $a_i(t)$ to reflect the possibility that the coefficients are subject to random perturbations. This fact can be modeled by assuming that:

$$\xi(t+1) = \xi(t) + \omega(t) \tag{6}$$

where $\omega(t)$ is also a zero mean white noise process not necessarily Gaussian with variance V (we assume that processes $e(t)$, $u(t)$ and $\omega(t)$ are independent).

Given a set of observations $y(t)$ where $0 \le t \le N$, then from an NAR(n) process we have to determine the unknown parameter vector:

$$\zeta = \left[x(t), \xi(t), n, Q, R, V\right] \tag{7}$$

Assuming that the signal coefficients are slowly varying in time ($V = 0$), equation (6) is replaced by:

$$\xi(t+1) = \xi(t) \tag{8}$$

We consider that the signal $x(t)$ and the predictor coefficients are collected in the (n +1)×1 parameter vector $Q(t)$ as follows:

$$Q(t) = \begin{bmatrix} x(t) \\ \xi(t) \end{bmatrix} \tag{9}$$

The system model of equations (1) and (2) together with equation (9) can be reformulated as the nonlinear model:

$$Q(t) = F_t\left(Q(t)\right) + H_t\left(Q(t)\right) \tag{10}$$

$$y(t) = G_t\big(Q(t)\big) + u(t) \tag{11}$$

where,

$$H_t\big(Q(t)\big) = \begin{bmatrix} e(t) \\ \mathrm{O}_{n\times 1} \end{bmatrix} \tag{12}$$

The notation $\mathrm{O}_{n\times1}$ denotes the $n \times 1$ zero vector, n is the order of the model and $Q(t/t;n)$ is the a conditional MMSE state vector estimate that is obtained by the corresponding Extended Kalman Filter.

IV. Simulations and Analysis

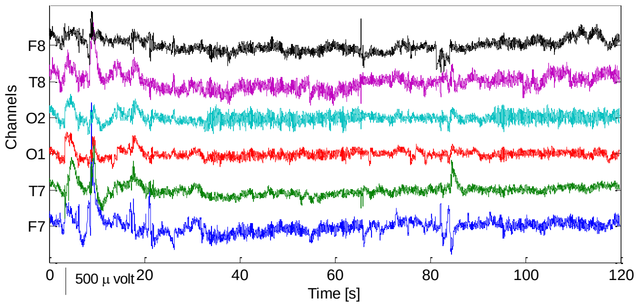

Fig. 4. Recorded EEG signals from 1st subject.

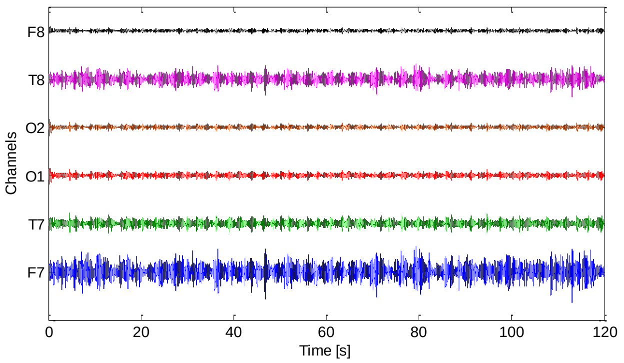

Fig. 5. Filtered EEG signals using BPF.

Preparatory to an analysis of the features of ERPs components from EEG signals, actual signals were recorded in a six-channel (F7, F8, T7, T8, O1 and O2) configuration. The raw data (see Fig. 3) were first pre-processed using a wavelet denoising. Wavelet method is performed to enhance artifacts removal by eliminating high frequency in order to obtain the final result of clean EEG signals with amplitude 2-6 μV range of values where the value is smaller than the signal Raw EEG signal. Therefore, the value of the amplitude of the wavelet denoising result is closer to the EEG signal amplitude range. The denoised EEG signals, therefore, were filtered using a sixth-order band-pass filter with cut-off frequencies of 3 Hz (i.e., to remove the trend from low frequency bands) and 13 Hz (i.e., to remove unimportant information from high frequency bands), respectively (see Fig. 4). Since the ERPs power (signal) to the EEG power (noise) ratio is small, a method of extracting and classifying the ERPs component from the EEG is desirable. One way of gaining further insights into EEG signals is by applying NAR allgorithm. At every iteration, the algorithm selects the model that corresponds to the maximum a posteriori probability as the correct one. This probability tends (asymptotically) to one, while the remaining probabilities tend to zero. If the model structure changes, the algorithm senses the variation, increases the corresponding a posteriori probability, while decreasing the remaining ones. Thus the algorithm is adaptive in the sense of being able to track model changes in real time. The extracted signal is given in Fig. 5.

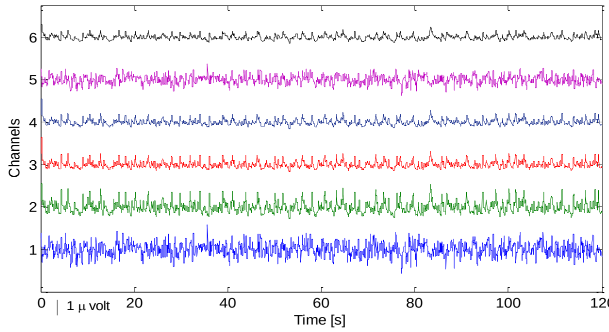

Fig. 6. Extracted EEG signals using robust PCA based moving average.

V. Conclusions

In this paper, an intelligent method of the nonlinear AR model for artifacts removal and refine raw EEG signals has been addressed. The superiority of this method is that is adaptive, identifies the model parameters in a sufficiently small number of iterations and tracks successfully changes in the model structure. Finally, the results using the proposed illustrate the effectiveness of the proposed algorithm removing the artifacts and other non-even-related sources, and increasing the visibility of the ERPs on all subjects.

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