VOL. 10, NO. 3, FEBRUARY 2015 ISSN 1819-6608

ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

ADAPTIVE RECURRENT NEURAL NETWORK FOR REDUCTION OF NOISE AND ESTIMATION OF SOURCE FROM RECORDED EEG SIGNALS

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ABSTRACT

In recording the EEG signals are often contaminated by a large of signals called artifacts such that the brain activity (source) difficult to estimate. There are different kinds of artifacts such as power line noise, electromyogram, electrocardiogram and electrooculogram. In this research, an adaptive recurrent neural network (ARNN) for estimation of source and reduction of noise from recorded EEG signals is proposed. In the experiment, the EEG signals are recorded on three conditions, which is normal conditions, closed eyes, and blinked eyes. After processing, the dominant frequency of the EEG signal is obtained in the range of 12-14 Hz either on normal conditions, closed eyes, and blinked eyes. The experimental results show that the ARNN method was effectively estimated the brain activity according to the given stimulus and remove the artifacts from all subjects.

Keywords: EEG, adaptive, neural network, estimation, reduction.

INTRODUCTION

Electrical impulses raised by firing of neuron within the brain diffuse through the head and can be measured by placing the sensors (electrodes) on the scalp, is known as electroencephalogram (EEG) (first measured in humans by Hans Berger in 1929). The EEG signals contain information about the neural activity and has been non-invasively used for clinical or research application such as brain computer interface (BCI). A BCI has been defined as a communication system that does not depend on the brain's normal output pathways of peripheral nerves and muscles (Wolpaw et al., 2000). To increase the effectiveness of BCI systems it is necessary to find methods of increasing the signal-to-noise ratio (SNR) of the observed EEG signals. In the context of EEG driven BCIs, the signal is endogenous brain activity measured as voltage changes at the scalp while noise is any voltage change generated by other sources. These noise, or artifact, sources include: line noise from the power grid, eye blinks, eye movements, heart beat, breathing, and other muscle activity. Some artifacts, such as eye blinks, produce much higher amplitude of voltage changes than raised by brain activity. In this situation the data must be discarded unless the noise or artifact can be removed from the data.

There are two general methods for removing artifact from the EEG record. The simplest approach is to discard a fixed length segment, perhaps one second, from the time an artifact is detected. Discarding segments of EEG data with artifacts can greatly decrease the amount of data available for analysis. Regression using the EOG channel was attempted in the time and frequency domain (Gratton, Coles, & Donchin, 1983; Woestenburg, Verbaten, & Slangen, 1983). This method is fast, easy to implement, reliable, and still in use by modern researchers. Although this method can result in losing of certain information from the recorded data, it can be mitigated by doing the recording for a longer periods or larger numbers of trials. However, this method of artifact removable is not acceptable for many experiments and also is not practical in online or real-time application. However, as a reliable means of removing artifact from the EEG record and leaving clean data would be of tremendous value, there has been an ample amount of research toward this goal (Babiloni et al., 2011; Escudero et al., 2011; Turnip, Hong, & Jeong, 2011; Turnip & Hong, 2012). Many of these newer approaches involve techniques including independent component analysis, neural networks, Kohonen maps, and other methods which were either unavailable or much less well known during the early days of EEG signal processing. Techniques for removal of EEG artifact without rejecting other data are now prevalent in EEG processing software.

During the experiment, the electrodes is located in some significant distances away from the neural activity. Therefore, the EEG signal collected at any point on a person's scalp is a nonlinear mixture of the activities generated over a large brain area. The analysis of EEG data and the extraction of information from this data is a difficult problem. This problem is exacerbated by the introduction of extraneous biologically generated and externally generated signals into the EEG. In this paper, an adaptive recurrent neural network (ARNN) for estimation of brain activity sources and simultaneously reduce the additive noise from collected EEG signals is proposed. This problem can also be solved by optimisation algorithms such as ELPSO (Jordehi, 2015).

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The rest of this chapter is organized as follows. Section 2 presents the adaptive recurrent neural networks. Section 3 explains the experiment method. Results are discussed in Section 4, and conclusions are drawn in Section 5.

ADAPTIVE RECURRENT NEURAL NETWORKS

Let M be the number of measured EEG signals and N be the number of unknown input sources. Then, the measured signal at channel i, $x_i(k)$, can be represented as a linear combination of N unknown mutually statistically independent source signals $s_j(k)$, $j = 1,2,\ldots,N$, as follows (typically $M \geq N$) (Choi & Cichocki, 2000; Cichocki, & Amari, 2002).

$$x_i(k) = \sum_{j=1}^{N} a_{ij} s_j(k) + v_i(k), \tag{1}$$

or in matrix form,

$$x(k) = As(k) + v(k), \tag{2}$$

where $x(k) = [x_1(k), x_2(k), \ldots, x_M(k)]^T \in \mathrm{R}^M$ is a noisy sensor vector of EEG signals, $A \in \mathrm{R}^{M \times N}$ with entries a_{ij} is an unknown M x N mixing matrix, $s(k) = [s_1(k), s_2(k), \ldots, s_N(k)]^T \in \mathrm{R}^N$ is an unknown source vector signals, and $v(k) = [v_1(k), \cdots, v_M(k)]^T \in \mathrm{R}^M$ is a vector of additive noises.

When $x(k)$ is noisy such that $x(k) = \hat{x}(k) + v(k)$, where $\hat{x}(k) = As(k)$ and $\hat{y}(k) = W(k)\hat{x}(k)$ are the noiseless estimates of the input and output vectors respectively. It is easy to show that the additive noise $v(k)$ within $x(k)$ introduces a bias in the estimated decorrelation matrix W. In general, the problem of noise cancellation is diffcult or even impossible to handle, because we have (m+n) unknown source signals (m sources and n noise signals), but only m available or measured sensor signals. However, in many practical situations, the unbiased separating matrices can be estimated and the noise can be reduce or cancel (if some information about the noise is available). In this research, the additive noise in the i–th sensor is modeled as

$$v_i(k) = \sum_{y=0}^{L} \left[h_{ip} z^{-p}\right] v_r(k) = \sum_{y=0}^{L} h_{ip} v_r(k-p), \tag{3}$$

where z^{-1} is the unit delay operator. In this model, a reference noise which is added to each sensor (mixture of sources) with different unknown time delays and various unknown coefficients $h_{ip}(k)$ representing attenuation coefficients is assummed. Therefore, the unknown mixing can be described in matrix form as

$$x(k) = As(k) + h(z)v_r(k), \tag{4}$$

where $h(z) = [A_1(z), A_2(z), \cdots, A_n(z)]^T$ with $A_i(z) = h_{i0} + h_{i1}z^{-1} + \cdots + h_{iL}z^{-L}$. Analogously, the separating and noise deconvolutive process can be described as

$$\begin{aligned} y(k) &= W_x(k) - \overline{w}(z)v_r \\ &= WH_s(k) + Wh(z)v_r - W(z)v_r \end{aligned} \tag{5}$$

where $\overline{w}(z) = [w_1(z), w_2(z), \cdots, w_n(z)]^T$ with $W_i(z) = \sum_{p=0}^{M} \widetilde{w}_{ip} z^{-p}$. In order to develop a viable neural network approach for noise cancellation, we define the error vector

$$e(t) = x(t) - \widehat{H}\,\hat{y}(t), \tag{6}$$

where $e(t) = [e_1(t), e_2(t), \cdots, e_m(t)]^T$ and $\hat{y}(t)$ is an estimate of the source $s(t)$. To compute $\hat{y}(t)$, consider the minimum entropy (ME) cost function

$$E\{J(e(t))\} = -\sum_{i=1}^{m} E\{\log[p_i(e_i(t))]\}, \tag{7}$$

where $p_i(e_i)$ is the true pdf of the additive noise $v_i(t)$ and expressed as

$$p_i(e_i) = \frac{r_i}{2\sigma_i r(1/r_i)} \exp\left(-\frac{1}{r_i}\left|\frac{e_i}{\sigma_i}\right|^{r_i}\right). \tag{8}$$

Stochastic gradient descent of the ME function yields stochastic independence of the error components as well as the minimization of their magnitude in an optimal way. The resulting system of differential equations is

$$\frac{d\,\hat{y}(t)}{dt} = \mu(t)\widehat{H}^T \psi[e(t)], \tag{8}$$

or in a discrete-time algorithm as

$$\hat{y}(k+1) = \hat{y}(k) + \mu(k)\widehat{H}^T(k)\psi[e(k)], \tag{9}$$

where $\psi[e(t)] = [[\psi_1[e_1(t)], \cdots, \psi_m[e_m(t)]]^T$ with nonlinearities $\psi_i(e_i) = -\dfrac{\partial \log p_i(e_i)}{\partial e_i}$. The functions $\psi_i(e_i)$ (i=1,2,...,m) can be implemented via nonlinear filters that perform filtering and nonlinear noise shaping in every channel such that

$$\psi_i(e_i(k)) = \psi_i\left(\sum_{p=0}^{L} b_{ip} e_i(k-p)\right), \tag{10}$$

where the parameters of filters $\{b_{ip}\}$ and nonlinearities $\psi_i(e_i)$ are suitably chosen depends on the noise

VOL. 10, NO. 3, FEBRUARY 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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distributions. In this paper, any value of $r_i \geq 1$ is selected, in which case the locally-optimal nonlinear activation functions are of the form $\psi_i(e_i) = e_i / [|\sigma_i|^{r_i} |e_i|^{2-r_i} + \varepsilon]$ where ε is a small positive constant to avoid the singularity of the function at $e_i = 0$. The proposed algorithm can be considered as a form of nonlinear post-processing that effectively reduces the additive noise component in the estimated source signals.

EXPERIMENT METHODS

EEG is most commonly recorded according to the international 10-20 electrode placement system (Jasper, 1958). The 10-20 system was developed to standardize the collection of EEG and facilitate the comparison of studies performed at different laboratories. When only a few channels of EEG are collected the electrodes are placed at a subset of the sites. The EEG data were collected from eight healthy adult subjects (all men, ranging in age between 20-22 years old). Five subjects have slight hair and the rest are thick hair. All subjects were asked to complete the standard task by following three stimuli contition which are baseline (normal), closed, and blink eyes.

During the experiment, the participant were sitting in a comfortable chair in front of 14" monitor at a distance of about 1 m. Continuous EEG signals were recorded (sampling frequency about 128 Hz) from 6 electrodes placed on the scalp using Emotiv wireless EEG. The desired brain activity is focused in the F7, F8, T7, T8, O1 and O2 channels which represent the visual of human brain. The the OpenVibe software is used to perform the data acquisition, stimulus visualization, and EEG recording with the built in function block. The experiment consists of two sessions with period of 130 second (two stimuli: normal and closed eyes condition) and period of 66 second (two stimuli: normal and blink eyes condition). The stimuli arrangement is built based on a scenario in Table-I. The picture of all subject during the experiment are shown in Figure-1.

The first sessions is started with baseline (no movement) condition for 30 seconds. At the 31-32th second, OpenVibe will show the '+' sign indicating the preparation for first movement. Then, the arrow is shown at the 33-63th second to indicate the subject to do closed eyes. These stimuli are repeated for twice. The second scenario is started with baseline (no movement) condition for 18 seconds. At the 19-20th second, OpenVibe will show the '+' sign indicating the preparation for second movement. Then, the arrow is shown at the 21-23th second to indicate the subject to do blink eyes. Two-second interval is added to finish the current movement. These continue until the 10th stimulus appeared.

Table-I. Scenario for EEG sample recording.

Time (s)	Activity	Time (s)	Activity
Sessions-1		31-33	Blink eye
0-30	Normal	34-35	+
31-32	+	36-38	Blink eye
33-63	Closed eye	39-40	+
64-65	+	41-43	Blink eye
66-96	Normal	44-45	+
97-127	Closed eye	46-48	Blink eye
128-130	End	49-50	+
Sessions-2		51-53	Blink eye
0-18	Normal	54-55	+
19-20	+	56-58	Blink eye
21-23	Blink eye	59-60	+
24-25	+	61-63	Blink eye
26-28	Blink eye	64-65	+
29-30	+	66	End

Figure-1. Eight experiment participant. Participant 2 and 5 showing blink eyes activity, and the rest are showing closing eyes activity.

ANALYSIS RESULTS

The matrix equation $x(k)$=H$s(k)$+$v(k)$ is used to create $x(k)$, where each $v(k)$ is a Gaussian random noise with the covariance matrix $\widehat{R}_{vv} = \hat{\sigma}_v^2 I$ with $\hat{\sigma}_v^2 = 0.01$. Twenty trials were run, in which W(0) were different random orthogonal matrices such that $W(0)W^t(0) = 0.25I$ and ensemble averages were taken in each case. Figure-2 shows the evolution of the performance factor $\rho(k)$ defined as

$$\rho(k) = \frac{1}{n}\sum_{i=1}^{n}\left\{\left(\sum_{k=1}^{n}\frac{|g_{ik}|}{\max_j |g_{ij}|} - 1\right) + \left(\sum_{k=1}^{n}\frac{|g_{ki}|}{\max_j |g_{ji}|} - 1\right)\right\} \quad (11)$$

where n = 6. g_{ij} is the (i,j)-element of the global system matrix $G = WH$ and $\max_j g_{ij}$ represents the maximum value among the elements in the ith row vector of G. $\max_j g_{ji}$ is the maximum value among the elements in

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the ith column vector of $\boldsymbol{G}$. The value of $\rho(k)$ measures the average source signal crosstalk in the output signals $\{y_i(k)\}$ if no noise is present. Crosstalk is usually caused by interferece of undesired signal effect from channel to another. As can be seen, the original algorithm yields a biased estimate of $W(k)$, whereas the bias removal algorithm achieves an average crosstalk level that is about 5 dB lower except for subjects 5 and 6. Also shown for comparison is the original algorithm with no measurement noise, showing that the performance of the described algorithm approaches this idealized case for small learning rates for all subjects.

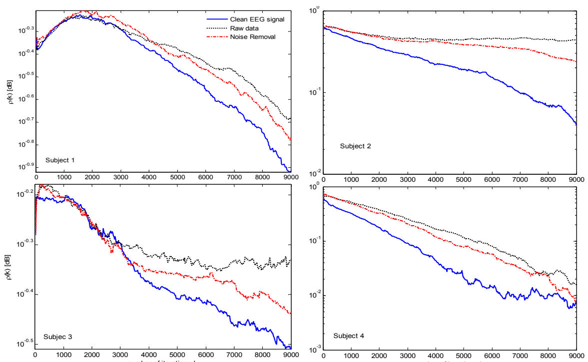

Figure-2. Ensemble-averaged value of the performance index for uncorrelated measurement noise (subjects 1 – 4).

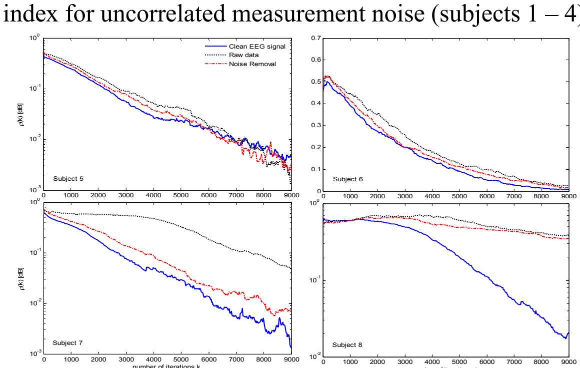

Figure-3. Ensemble-averaged value of the performance index for uncorrelated measurement noise (subjects 5 – 8).

The raw EEG data (see Figure-4) were first pre-processed using a band-pass filter with cut-off frequencies of 0.5 Hz (i.e., to remove the trend from low frequency bands) and 49 Hz (i.e., to remove unimportant information from high frequency bands), respectively (see Figure-5). Using only band pass filter, the signal amplitude has been highly reduce from about 5000 μ volts into about 60 μ volts. This result indicate that the raw data was cantaminated by a large of variety artifacts. Since the artifacts can randomly occur and are unexpected, they are difficult to identify. Thus, instead of detecting and removing artifacts, our approach is to extract the event-related components based on a global pattern that encapsulates models for signals of interest.

One way of gaining further insights into EEG signals is by applying ARNN techniques. In this algorithm, brain activity is estimated and the noise is simultaneously reduce. The signal after applied estimation and noise reduction techniques are shown in Figure-6. As shown that a view of brain activity is slightly reconizable in the each channels except channels 1 and 3 from the top (i.e., contaminated by noise or artifacts). These channels are predicted as accumulation of the noise or artifact after separation. Therefore, it can be concluded that the left channels can be used for the analysis or further application. It demonstrates that the proposed algorithm can effectively extract the brain activity from even when the background artifact or noise amplitude is very high in the original signals.

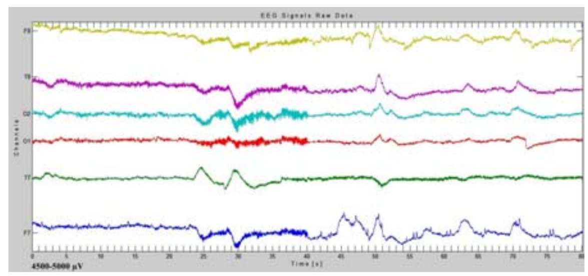

Figure-4. Raw EEG data (subject 1).

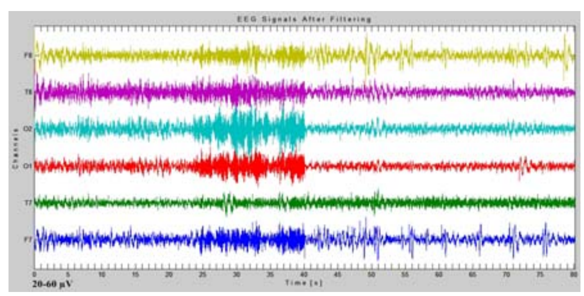

Figure-5. EEG data after band pass filtering with cut off frequency about 0.5 – 49 Hz (subject 1).

CONCLUSIONS

An adaptive recurrent neural network to estimate the brain activity according to the given stimuli and simultaneously reduce the noise from recorded EEG signals is proposed. The best noise reduction by minimizing the generalized energy of all its output signals under some constraints and simultaneously to enforce their mutual independence are achieved. The performance index of removal algorithm achieves an average crosstalk level that is about 5 dB lower.

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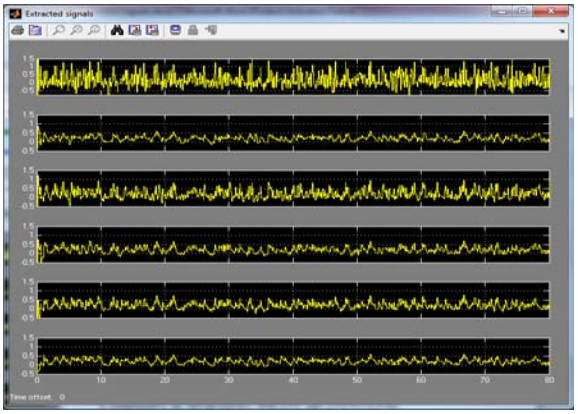

Figure-6. Estimated brain activity with simultaneously noise reduction using ARNN method.

ACKNOWLEDGEMENTS

This research was supported by the thematic program (No. 3425.001.013) through the Bandung Technical Management Unit for Instrumentation Development (Deputy for Scientific Services) and the competitive program (No. 079.01.06.044) through the Research Center for Metalurgy (Deputy for Earth Sciences) funded by Indonesian Institute of Sciences, Indonesia.

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