Online Brain Activity Extraction from EEG-P300 Signals with Nonlinear Autoregressive Model

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Abstract—**In this paper, an application of nonlinear autoregressive model for brain activity extraction from EEG-P300 signals is proposed. The extracted signals are then classified using adaptive neural network classifier method. To test the improvement in the EEG classification performance with the proposed method, comparative experiments are conducted by using Bayesian Linear Discriminant Analysis. All subjects achieve a classification accuracy of 100%.**

Index Terms—**Accuracy, adaptive neural networks, autoregressive, brain computer interface, EEG-P300, feature extraction, transfer rate.**

I. Introduction

A Brain Computer Interface (BCI) is a device that allows users to communicate with the world without utilizing voluntary muscle activity [1]. BCI systems utilize what is known about brain signals to detect the message that a user has chosen to communicate. These systems rely on the finding that the brain reacts differently to different stimuli, based on the level of attention given to the stimulus and the specific processing triggered by the stimulus. For this, brain activity must be monitored with various techniques. Among these techniques, EEG is the most preferred for BCI designs, because of its non-invasiveness, cost effectiveness, easy implementation, and best temporal resolution [1-3]. An event-related potential (ERP), which can be generated in the EEG during a stimulation paradigm, is a brain response directly resulted from a perception or a thought. Particularly, the P300 component refers to the wave peaking around 300 ms after a task-relevant stimulus [2-11]. While the P300 is elicited in many different ways, the most common factors influencing it are two stimulus-discrimination tasks presented to the subject in an unknown fashion. One occurs infrequently (i.e., target) and the other frequently (i.e., non-target).

The P300 has become a valuable tool for the measurement of cognitive function in medical and research applications. Numerous applications of P300 are as a disease diagnostic test [10], an evaluation of cholinesterase inhibitors treatment in demented patients, an intelligence test [13], a lie detector [14], as a communication tool by people with neuromuscular disorders (such as BCI spellers, BCI wheel-chair), Recently, a great variety of its potential applications has been widely studied such as smart homes, internet browsing, market researchers [15], BCI for controlling hand grasp [16], its correlation with the memory status of patients with mild cognitive impairment. Previous research has shown that several aspects of the ERP (especially the latency, magnitude, and topography) are highly variable across trials. Many techniques appeared in research area are intrended to resolve the problems of EEG (specifically for obtaining P300 components) are not sufficiently standardized especially for clinical usage.

One important task in designing a BCI is extracting relevant features from the EEG signals, which is naturally noisy and stochastic. In order to avoid the averaging processes and to remove the artifacts, which are computational complexity, poor generalization, and need a large number of training to achieve a desired accuracy and a communication rate, an adaptive neural network classifier (ANNC) of different brain activities is applied. To overcome the classifier of overtraining caused by noisy and non-stationary data, the extraction of the brain activities using nonlinear autoregressive model (NAM) is proposed. In order to examine the performance improvements of the proposed classification method, comparative experiments were conducted using Bayesian Linear Discriminant Analysis (BLDA). The contributions of this paper are as follow: (i) Enhancement and strengthen the EEG signal according to the small amplitude of the EEG-based P300 which is naturally noisy and stochastic (ii) Driving the tracking error converges to a small value around zero while the closed-loop stability is guaranteed.

The structure of the paper is as follows. In Section 2, the EEG data set and preprocessing are described. Feature extraction and classification using NAM and ANNC methods, respectively, are explained in Section 3. Results and discussions are presented in Section 4. Conclusions are drawn in Section 5.

II. Data Set and EEG Preprocessing

In the experiment, seven subjects (all males, age 32 ± 5 years, none of whom had any known neurological deficits) have participated. A seven-choice signal paradigm (i.e.,

Manuscript received August 8, 2015.

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forward, turn right, turn left, backward, backward right, backward left, and stop) is used to stimulate the seven subjects. The subjects are asked to count silently the number of times of the flashes of a preselected image on the screen while imagining a car moving in the direction of the flashed signal. The EEG signals are recorded continuously using eight electrodes (channels) at Fz, Cz, Pz, Oz, P7, P3, P4, P8 placed at the standard positions described in the 10-20 International System and digitized at a 256 Hz sampling rate. Each subject records four sessions; four different image-flash durations (i.e., 25 ms, 50 ms, 75 ms, and 100 ms, respectively) followed by a 300 ms blank screen. Hence, the inter-stimulus intervals (ISIs) in this work range from 325 ms to 400 ms.

Prior to feature extraction, several preprocessing operations including filtering and down-sampling were carried out. To filter the data, a 6th-order band-pass filter (BPF) with cut-off frequencies of 1 Hz (i.e., to remove the trend from low frequency bands) and 12 Hz (i.e., to remove unimportant information in high frequency bands) was used.

III. Feature Extraction and Classification

In order to select the most appropriate classifier for a given BCI system, it is essential to clearly understand what features are used for extract in, what their properties are and how they are used. This section aims at describing the common BCI features and more particularly their properties as well as the way to use them in order to perform the desired task according to the stimulus.The extracted signals should encode the commands made by the subject but should not contain noises or other interfering patterns (or at least should reduce their strength) that can impede classification or increase the difficulty of analyzing EEG signals. The scheme of online brain activity exraction to wireless driving toy-car is given in Fig. 1.

Adaptive filter commonly uses the principle used in noise elimination. The method uses a primary input containing the corrupted signal and a reference input containing noise correlated in some unknown way with the primary noise. By identifying a non-linear model between a measurable noise source and the corresponding immeasurable interference, the adaptive filter process remove the interference signal. In all the signal modeling problems, including nonlinear signal processing, the general problem is to find a good model structure and then to estimate the parameters of some basis signals from the observations. Going from linear to nonlinear system processing also makes this problem much harder since the set of nonlinear models is much richer than the linear one.

An autoregressive model of order-n can be represented as follows [18-20].

$$A(q)x(t) = \gamma(t) \tag{1}$$

or

$$x(t) = \sum_{i-1}^{n} a_i x(t-i) + \gamma(t) \tag{2}$$

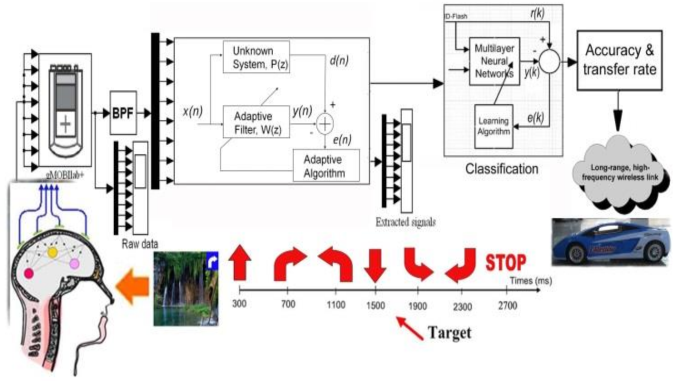

Fig. 1. The scheme of online brain activity extraction to wireless driving toy-car.

A natural generalization of the linear autoregressive model to the nonlinear case can be written as:

$$\begin{aligned} x(t-1) &= f(h_x^T(t), \theta_a(t)) + \\ & f_{chl}(n(t), n(t-1), \ldots, n(t-k)) + \omega(t) \end{aligned} \tag{3}$$

$$y_m(t) = g(x(t)) + \vartheta(t) \tag{4}$$

and

$$h_x^T(t) = h(x(t), x(t-1), \ldots, x(t-k)) \tag{5}$$

$$\theta_a = \theta(a_1, a_2, \ldots, a_n)^T \tag{6}$$

where $f(\cdot)$, $g(\cdot)$, and $f_{hcl}(\cdot)$ are known matrix-valued functions of some unknown data $x(t)$ and a_i, and the noise passage channel, respectively, k is the order of the predictor, $\omega(t)$ and $\vartheta(t)$ are uncorrelated zero mean white noise processes not necessarily Gaussian with variances Q and R respectively and $a_i : i = 1, \ldots, n$ are the predictor coefficients. Based on the measurement $y_m(t)$, the order of the predictor is selected, and then the signal *x(t)* is computed. Since $f(\cdot)$, $g(\cdot)$ and $f_{hcl}(\cdot)$ are unknown, neural networks can be used to learn in order to approximate these functions and to generate a suitable filter. The NAF technique is then used for estimating the desired signal from the corrupted signal. The following assumptions are made in the process: x and n are zero mean processes (statistical, stationary and zero means); x is uncorrelated with γ and n; γ and n are γ correlated by the function $f_{hcl}(\cdot)$. The clean EEG signal $s(t)$ serves as the recovered signal in the NAM, and it is given as follows:

$$s(t) = y_m(t) - \hat{\gamma}(t) \tag{7}$$

where $\hat{\gamma}(t)$ is the estimated output from the filter.

It has been proven that a HONN has the function approximation ability [3, 17, 20-22].

$$\varphi(W,z) = W^T H(z),\ W \text{ and } H(z) \in R^l \quad (8)$$

$$H(z) = [h_1(z), h_1(z), \ldots, h_l(z)]^T \quad (9)$$

$$h_i(z) = \prod_{j \in l_i} [h(z_j)]^{d_j(i)},\ i = 1,2,\ldots,l \quad (10)$$

where $z = [z_1, z_2, \ldots, z_n]^T \in R^n$, the positive integer l indicates the neural network node number, $d_j(i)$ stands for non-negative integers, W is an adjustable synoptic weight vector, and $h(z_j)$ is a hyperbolic tangent function such that

$$h(z_j) = \frac{e^{z_j} - e^{-z_j}}{e^{z_j} + e^{-z_j}} \quad (11)$$

According to Girosi and Poggio [17], there exists an estimate weight $\hat{W}$ such that the function $\varphi(z)$ can be approximated by an ideal neural network as

$$\varphi(z) = W^{*T} H(z) + \varepsilon_z \quad (12)$$

where ε_z is the neural network approximation error. The ideal neural network weight W^* is not known and needs to be estimated. Let $\hat{W}$ be the estimated of W^* and $\hat{s}(k)$ be the estimated of $\varphi(z)$. Therefore, the extractor and the updating law for the estimate of weight $\hat{W}$ are chosen as

$$\hat{s}(k) = \hat{W}^T H(\bar{z}(k)), \quad (13)$$

$$\hat{W}(k+1) = \hat{W}(k_1) + \Gamma[H(\bar{z}(k_1))(y(k+1) - r(k+1)) + \rho\hat{W}(k)] \quad (14)$$

where $k_1 = k - n + 1$, diagonal gain matrix $\Gamma > 0$, and $\rho > 0$. In this paper, the following parameters are chosen: the number of neurons l = 40, $\hat{W}(0) = 0$, $\Gamma = 0.06I$, and $\rho = 0.008$. Thereby, by increasing the approximation accuracy of the neural network, the tracking error is made to converge to a small neighborhood of zero.

IV. EXPERIMENTAL RESULT

Fig. 2 shows the application of online feature extraction and classification on BCI: EEG-P300 signals for driving a toy-car. In the figure, the subject was asked to focus on one out of seven-choice signal paradigm which indicates the flashed traffics light (i.e., forward, turn right, turn left, backward, backward right, backward left, and stop) as a target. In online, the actual signals were recorded in an eight-channel configuration and using NAM algorithm, the EEG-P300 components were extracted. The raw data were first pre-processed using a sixth-order band-pass filter (BPF) with cut-off frequencies of 1 Hz and 12 Hz, respectively, see Fig. 3. It can be seen that the signals were corrupted by noises. Since the P300 signal to the EEG power (noise) ratio is small, a method of extracting and classifying the P300 component from the EEG is desirable. One way of gaining further insights into EEG signals is by applying NAM techniques. Fig. 4 shows the feature extraction results of the linear adaptive filter (LAF). The features were extracted every 400 ms interval (one trial) for about 22 target trials. Although there is a noticeable improvement, it remains difficult to identify the associated signals with respect to the given stimulus.

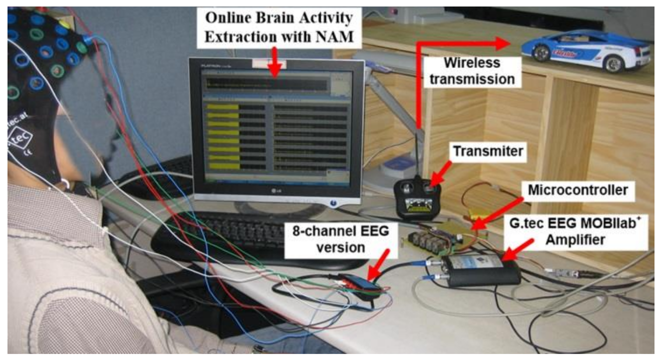

Fig. 2. An experiment setup of online brain activity extraction with NAM for driving toy-car

In order to track the dominant waves, the extracted results using NAM is demonstrated in Fig. 5. Fig. 5 shows the extracted signals from eight-electrode of the P300 component using the NAM algorithm for each ISI. Although the signals were still corrupted by noises (manifested as the high amplitudes of non-targets in some sessions), the behaviors of the extracted signals clearly represented in the P300 components. The observed signal was of the P300 event-related potential signal form. Overall, for the ISI of about 350 ms (Fig. 5 (b)), the target and non-target amplitudes were clearer and easier to be distinguished than for the other ISI.

Although the amplitude of the P300 component with the ISI of about 325 ms was higher than for the other ISI, the best P300 signal in amplitude with ISI 350 ms was achieved. Also, Fig. 5 (a)-(d) show that the extracted signal amplitudes decreased (i.e., from the Fz to the P8 channel) as the distance of the electrodes increased. This result is consistent with the previous works in the literatures. Dealing with the typical low-amplitude and low SNR potentials, the removal of other biological signals becomes one of the major challenges in the study of ERPs. To resolve this problem, the averaging method of extracted EEG-P300 signals can be applied.

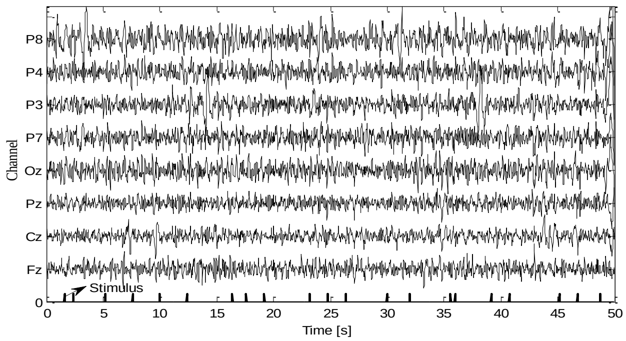

Fig. 3. Preprocessed EEG Signals: 350 ms ISI

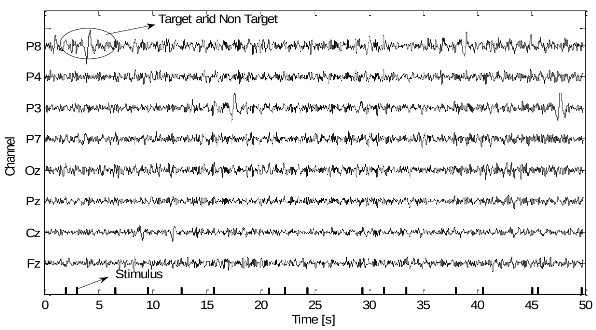

Fig. 4. Extracted EEG Signals using LAF

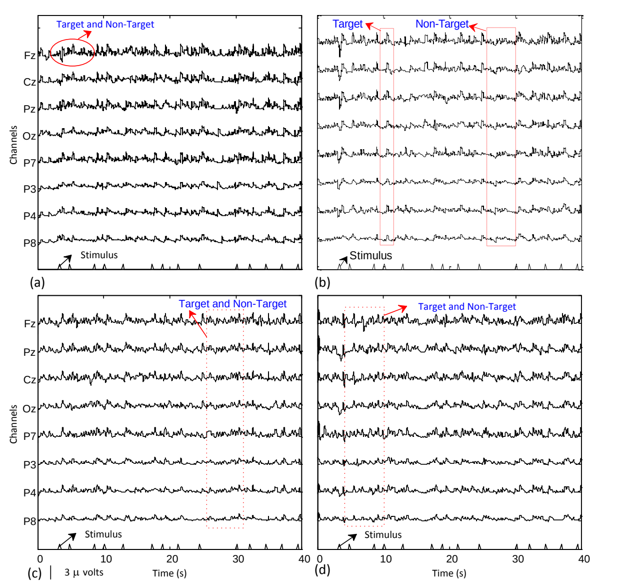

Fig. 5. Extracted P300 components using NAM: (a) 325 ms ISI, (b) 350 ms ISI, (c) 375 ms ISI, (d) 400 ms ISI

To show the performance of the extraction, the extracted signals were then passed to the classifier (i.e., back-propagation neural networks [3]). After classification, BCI performance can be evaluated from the stand point of (i) speed and accuracy in specific applications or (ii) theoretical performance measured in the form of the information transfer rate. The information transfer rate is the amount of information communicated per unit of time. The transfer rate is a function of both the speed and the accuracy of selection. Comparative plots of the classification accuracies and transfer rate for the seven subjects were provided in Fig. 6. All subjects achieved an average classification accuracy of 90% after three blocks of stimulus presentations were averaged (i.e., 8 sec). In this regard, the subject intention was recognized after ten seconds in online and after eight seconds in offline of the first given stimulus. The same methods were applied in the online and offline cases but in the online case, classifier was connected with other hardware such as microcontroller which is developed with different platform algorithm. Clearly, the figure shows that the offline results were only slightly better than that of in online results. The interface between the two systems might be the reason of the delay and the accuracies. Briefly, the best classification accuracy in both cases (online and offline) was achieved using ISI 350 ms.

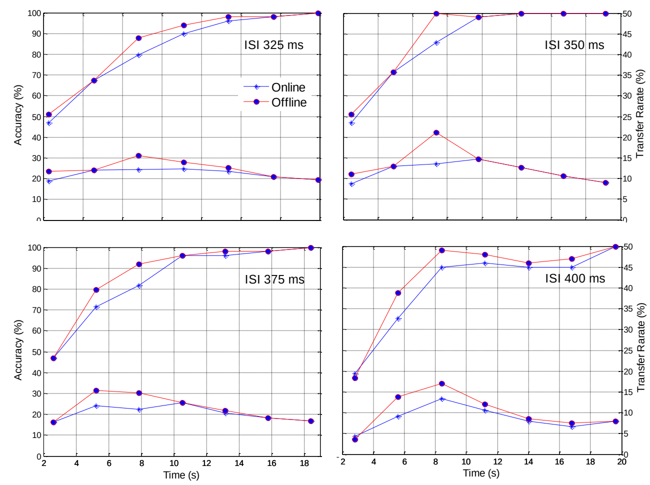

Fig. 6. Comparison of average classification accuracies and transfer rate along seven stimuli (four ISIs, seven subjects): ISI 350 ms was the best out of four

V. Conclusions

The developed nonlinear autoregressive model applied at the feature extraction step had the advantage of much less training time and provided significantly better classification accuracy. The application of the proposed feature extraction method can identify the P300 components (i.e., without down-sampling and averaging) and it was applied for BCI to run the toy-car. Using the proposed method, the offline results were only slightly better than that of in online results. Similarly, the proposed method should work and can be a viable tool for other applications.

Acknowledgment

This research was supported by the thematic program through the Bandung Technical Management Unit for Instrumentation Development (Deputy for Scientific Services) and the excellent program through the Research Center for Physics (Deputy for Engineering Sciences) funded by Indonesian Institute of Sciences, Indonesia.

References

[1] M. Hamalainen, R. Hari, R. J. Ilmoniemi, J. Knuutila, and O. V. Lounasmaa, "Magnetoencephalography - theory, instrumentation, and applications to noninvasive studies of the working human brain," *Reviews of Modern Physics*, vol. 65, issue 2, pp.413-497, 1993.

[2] A. Turnip, and K.-S. Hong, “Real-time feature extraction of P300 component using adaptive nonlinear principal component analysis,” *BioMedical Engineering OnLine*, vol. 10, issue 83, 2011.

[3] A. Turnip, and K.-S. Hong, “Classifying mental activities from EEG-P300 signals using adaptive neural network,” *Int. J. Innov. Comp. Inf. Control*, vol. 8, issue 7, 2012.

[4] W. M. Bukhari, W. Daud, and R. Sudirman, "Wavelet approach on frequency energy distribution of electrooculograph potential towards direction," *Internetworking Indonesia Journal*, vol. 3, no. 1, pp. 3-9, 2011.

[5] A. Turnip, and D. E. Kusumandari, “Improvement of BCI performance through nonlinear independent component analysis extraction,” *Journal of Computer*, vol. 9, issue 3, pp. 688-695, 2014.

[6] A. Turnip, Haryadi, D. Soetraprawata, and D. E. Kusumandari, “A Comparison of Extraction Techniques for the rapid EEG-P300 Signals,” *Advanced Science Letters*, vol. 20,issue 1, pp. 80-85(6), 2014.

[7] A. Turnip, S. S. Hutagalung, J. Pardede, and, D. Soetraprawata, “P300 detection using multilayer neural networks based adaptive feature extraction method,” *International Journal of Brain and Cognitive Sciences*, vol. 2, issue 5, pp. 63-75, 2013.

[8] A. Turnip, D. Soetraprawata, and D. E. Kusumandari, “A comparison of EEG processing methods to improve the performance of BCI,” *International Journal of Signal Processing Systems*, vol. 1, issue 1, 2013.

[9] D. Soetraprawata, and A. Turnip, “Autoregressive integrated adaptive neural network classifier for EEG-P300 classification,” *Journal of Mechatronics, Electrical Power and Vehicular Technology*, vol. 4, issue 1, pp. 1-8, 2013.

[10] A. Turnip and D. Soetraprawata, “Electrooculography Detection from Recorded Electroencephalogram Signals by Extended Independent Component Analysis,” *Advanced Science Letters*, 21 (2), 173-176, 2015.

[11] A. Turnip, “Comparison of ICA-Based JADE and SOBI Methods EOG Artifacts Removal”, *Journal of Medical and Bioengineering*, Vol 4 (6), 2015.

[12] Belitski et al., “P300 audio-visual speller,” *Journal of Neural Engineering*, vol. 8, issue 2, 025022, 2011.

[13] Rosenfeld et al., “A modified, event-related potential-based guilty knowledge test,” *Int. J. Neurosci.*, vol. 42(1-2), pp. 157-161, 1988.

[14] Abootalebi et al., “A new approach for EEG feature extraction in P300-based lie,” *Computer Methods and Programs in Biomedicine*, vol. 94, issue 1, pp. 48-57, 2009.

[15] Mugler et al., “Design and implementation of a P300-based brain-computer interface for controlling an internet browser,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, issue 6, pp. 599-609, 2010.

[16] M. Kh. Hazrati, and A. Erfanian, “An online EEG-based brain-computer interface for controlling hand grasp using an adaptive probabilistic neural network,” *Medical Engineering & Physics*, vol. 32, issue 7, pp. 730-739, 2010.

[17] F. Girosi, and T. Poggio, “Networks and the best approximation property, artificial intelligence laboratory memorandum,” *1164, MIT*, Cambridge, 1989.

[18] P. J. Brockwell, and R. A. Davis, *Time series: Theory and methods*, Springer Science, 2nd ed, Business Media, LLC, New York, 2006.

[19] Erla et al., “Multivariate autoregressive model with instantaneous effects to improve brain connectivity estimation,” *International Journal of Bioelectromagnetism*, vol. 11, issue 2, pp. 74-79, 2009.

[20] A. Turnip, and D. Soetraprawata, “Performance of EEG-P300 Classification Using Backpropagation Neural Networks,” *Journal of Mechatronics, Electrical Power and Vehicular Technology*, vol. 4, issue 2, pp. 81-88, 2013.

[21] Isidori, A., *Nonlinear Control System*, 3rd ed., Springer-Verlag, London, 1999.

[22] L. Giles, and T. Maxwell, “Learning, invariance and generalization in high order neural networks,” *Applied Optics*, vol. 26, issue 23, pp. 4972-4978, 1987.

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