A New Technique of Room Access Security based Brain Computer Interface

Artha Ivonita Simbolon, M Faizal Amri, M. Agung Suhendra and Arjon Turnip

***Abstract*— The use of the bio signal activity of the human brain which represented based on the EEG-P300 potential is proposed as a new technique for a room access security. The main purpose of this research is a detection of an information through the analysis of the bioelectric activity with the use of P300 potential amplitude and latency analysis of the brain in response to presented stimuli. In the experiment, eight subjects whose age are around 25 ± 2 years old were involved. The processed signals were classified with fuzzy logic inference system method. The results show that an application of brain computer interface based EEG-P300 signals as a new technique to access a room is successfully achieved with 75% accuracy.**

***Index Terms*—EEG-P300, ICA, brain-computer interface, stimuli**

I. INTRODUCTION

BRAIN-computer interface (BCI) is a collaboration between a brain and a device that enables signals from the brain to directly communicate with an external activity, such as control of a cursor or a wheelchair [1]. A BCI system is could be designed for medical purposes and helps people with disabilities especially patients with physical paralyses such as amyotrophic lateral sclerosis and spinal cord injury by providing tools that can be controlled directly by the patient's brain [2]. But today, the BCI system has expanded in applications for everyday life and shows an increasing trend in human-computer interaction applications. The BCI system is the result of integration from various disciplines, from the field of neuroscience, computer engineering, signal processing, even to psychology. Progress of research results from each field indirectly also helped improve the ability and reliability of the BCI system. In recent years, research activities on BCI have increased significantly compared to the early years of its developed.

By reading signals from an array of neurons and using signal processing system to translate the signals into action, BCI can enable a person suffering from paralysis to write a book, control a motorized wheelchair, or concealed information through thought alone [3]. There are several methods that can be used to measure the human brain activity which one of them is an electroencephalography (EEG).

Recently, one of the uses of the EEG based BCI system is to detect a concealed information of human based on brain signals activity. The study focused on the topography and the time domain of ERP (a form of brain activity). Around the 1980s, a detection of a concealed information has been committed to the analysis of evoked potentials (EP): A distinctive, time-specific bioelectric response of the brain, also known as the event (or stimulus) related potential (ERP) [4, 5]. ERPs are recorded from the central nervous system and are considered to be affected by the recognition of important events, which is more cognitively determined activity than autonomic responses.

There are many types of existing ERP or EEG signals, depending on the type of provided stimulus and experimental methods. For an example are motor imaginary, P300, SSVEP signals and others [6-17]. The P300 is a brain we that evoked whenever someone saw some objects or stimuli. The P300 wave component consists of latency and amplitude. Amplitude reflects the number of neurons allocated to generate the response to stimulants while latency reflects the cognitive functioning of the brain (cognitive processing speed). The P300 wave appears as a positive deflection with a 0-10 μv amplitude range and a latency of about 250-1000 ms [15]. For the first time, the P300 potential was described in the 1960s by Sutton and his team [16]. It is also worth mentioning that individual peaks are also known in the literature as potentials, hence the P300 peak is also referred to as the P300 potential, with the names being used interchangeably. As this peak has the greatest significance from the point of view of studies of the detection of concealed information, the following subchapter is devoted to its characteristic traits, and especially to its cognitive correlates.

The P300 potential is expected to follow its presentation. In the oddball procedure, a set of two different stimuli is randomly presented to the subject. One of them is very frequent called a standard stimulus and the other is very rare called a target. It is expected that the P300 potential will be greater in response to the rare stimulus than in the case of the frequent stimulus. The task of the subject is to react only to the target-type stimuli, ignoring all the others. Due to the cognitive correlates of P300 potential amplitudes and latencies, this research focus on the interest of studying memory and concealed information for accessing room application. There are two groups of the subject, the first group has been in the room before (experience) and the second group has not but know about the room (familiar). There are three types of used visual stimuli which are probe, target, and irrelevant. Probe stimulus is stimuli with related information with the accessed room, will only be known by the second

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group subjects and researchers. Target stimulus is known by anyone (will only be known by the first group subjects and researchers), and the subjects were given the command to perform some task when this stimulus appeared. Lastly, stimulation Irrelevant are stimuli that completely unrelated to the room, and thus is not known by all subjects. After the EEG-P300 signals information obtained, the next step to do is a classification of the EEG signals. The classification is needed for distinguishing between the EEG-P300 of subjects, that have been in the room or not. In the classification step, MATLAB based algorithm, a fuzzy logic system is used. Fig. 1 shows the scheme of recorded EEG signals for access security system.

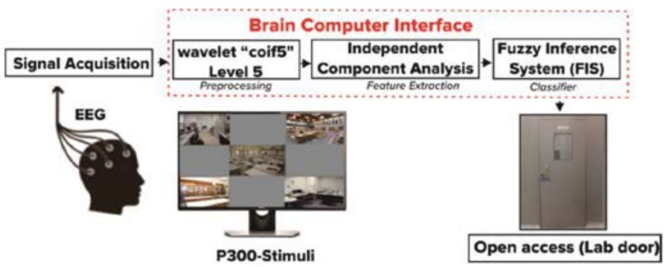

Fig. 1. Scheme of access security system based BCI

II. METHOD

A. Data Acquisition

In the experiment, the data was recorded from eight men healthy subjects with the age around 25 ± 2 years. The EEG data were collected from seven Ag/AgCl electrodes embedded in an elastic cap using the Mitsar 202 EEG system. The electrodes that used in this experiment are the frontal (Fz), central (Cz), parietal (Pz, P3, and P4), and occipital (O1 and O2) (Fig. 2). Further, WinEEG software for EEG recording and the stimuli displayed through PsyTask. Before the experiment, the subjects were trained on experimental procedures. The subjects were divided into two groups: Experience and familiar with the room. They must do some tasks when the objects the stimulus is displayed. The time interval between each stimulus is one second with two-second delay as shown in Fig. 3.

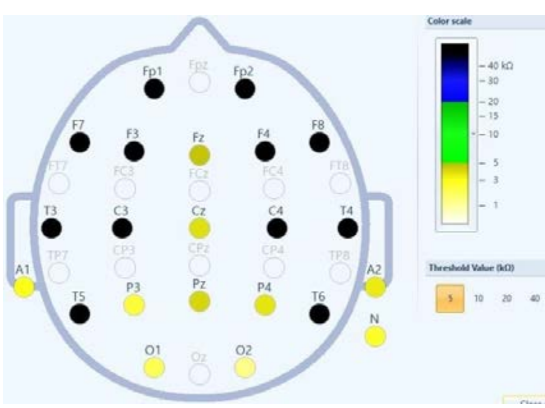

Fig. 2. Electrode position with impedance less than 5 kΩ

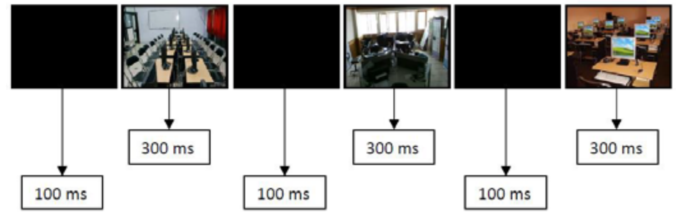

Fig. 3. Time interval of the stimulus

B. Signal Processing and Feature Extraction

Once the signals recording was complete, the continuous EEG data from each subject were inspected and filtered for artifacts using band-pass filter and Independent Component Analysis (ICA), respectively. Parts of the signals that contained noises by task-irrelevant movement or artifact be cut by band-pass filtered using 0.1 Hz and 30 Hz cut-offs and then the noises were removed by ICA.

The ICA is applied with the assumptions [18]: Data is a combination of stable space cerebral activity and independent artifact; Superposition of potentials on many parts of the brain, head skin, linear body of the electrodes, and propagation delay can be neglected; Number of sources is not greater than the electrode's. In this paper, the ICA method is used to separate the signals based on probe, target, and irrelevant stimuli. The ICA is important to blind signal separation. The separation of a set of source signals from a set of mixed signals, without the aid of information about the source signals.

Mathematically, the ICA method could be represented in the linear standard model form. The observed signals are represented as $xp(t)$ $\left(i.e., x_1(t), \ldots, x_p(t)\right)$, the desired or pure signals of EEG without noise (i.e., the recording hardware is not capable of detecting s) are represented as $s_n\ (t)\ \left(i.e., s_1(t), \ldots, s_n(t)\right)$, and A linear mixtures of the sources a_{ij} , for the time t. So each $x_p(t)$ is a linear combination of the source signals $s_n(t)$. The following Equation 1 represents this mixing of sources in matrix form.

$$x(t) = As(t) \quad (1)$$

The task of ICA is to find a de-mixing matrix, commonly referred to as a separating matrix, W, such that observed signals can be translated into the original source signals. The matrix W can be multiplied by the observed signal vector $x(t)$ to yield the independent components, $u(t)$, as in Equation 2. [19]

$$u(t) = Wx(t) \quad (2)$$

There are several ways of determining the matrix W. In this paper, Matrix W is obtained by minimizing the mutual information I between components. The following Equation defines mutual information for a random vector X, where $p(x)$ is the probability density function of:

$$I(x) = \int p\ (x) \log \frac{p(x)}{\prod_{i=1}^{n} p_i(x)} dx \quad (3)$$

When the sources are independent, $p(x) = \Pi_{i=1}^{n} p_i(s_i(t))$, then Equation 3 will go to zero (the log of one is zero). The main objective of the ICA algorithms is to acquire the independent components of $u_i(t)$ $(i.e.,$ share tu i (i.e., share little mutual information). In other words, the goal of ICA is to minimize the value of Equation 3. Obtaining independent components can also be considered of in terms of maximizing the entropy of H between components. The information between two signals X and Y can be expressed in terms of the entropy of the signals, where entropy of X is defined as $H(X) = H(p(x)) = -\int p(x) \log p(x) dx$. The following equation relates entropy to mutual information:

$$I(X,Y) = H(X) - H(X|Y) \tag{4}$$

It can be seen from Equation 4 that maximizing $H(X|Y)$ is equivalent to minimizing $I(X,Y)$.

The feature extraction can be applied to produce five characteristics of signal P300; minimum amplitude, maximum amplitude, mode amplitude, median amplitude, and mean amplitude. In this research, discrete wavelet transform (DWT) with level 5 is used as an extraction method. The DWT is a transformation that can be used to analyze the temporal and spectral properties of nonstationary signals. The reason why the wavelet transform has been selected because the component of ERP signal-to noise ratio is low and not stationary. The DWT uses multi filter banks and special wavelet filters for the analysis and reconstruction of signals. The DWT provides a compact representation of a signal in time and frequency that can be computed efficiently. In the pyramidal algorithm, the signal is analyzed at different frequency bands with the different resolution by decomposing the signal into a coarse approximation and detail information. The method calculates the wavelet coefficients at discrete intervals of time and scale instead of at all scales [20, 21].

III. RESULT AND DISCUSSIONS

Most investigations were devoted to the amplitude and latency of the P300 peak. Taking into account the localization of electrodes, it was discovered that its

amplitude is highest in the central line, with the value growing from the Fz lead over frontal lobes to the Pz lead over occipital lobes [9]. Another researcher observed that the value of the P300 potential amplitude is affected by the number of cognitive factors by mean the emergence of the P300 potential in response to a new stimulus is related to the updating of the mental representation [10, 11]. It was observed that this concept of emergence of the P300 potential is close to the description of the rudiments of the orientation response (the changes registered at the level of functioning of the autonomous nervous system, and in the behavior of a person in response to the novelty or change of the stimulus). The functioning level of the autonomous nervous system will change based on the change of the stimulus.

With the experiment scenario in the previous section, an application of brain computer interface for room access security is developed. In the experiment, Fig. 4 shows the recorded raw data of subject 2 which is still highly contaminated by the artifacts. By applying the preprocessed signals with wavelet method (coif 5 with level 5), the artifacts were reduced as shown in Fig 5. It can be seen that the amplitude was reduced into about 25 micro volts. The processed signals were then fed into extraction step with an independent component analysis method and the result is given in Fig. 6. It is still corrupted by some noises, but the P300 potential amplitude and latency have been detected. An example of the detected P300 amplitude and latency for opening and closing the room are shown in Fig. 7 and 8, respectively. The maximum amplitude and latency for all subjects from each channel are given in Table 1. It can be seen that Therefore, the average of the maximum amplitude and latency are used as an input to the classifier (Fuzzy interference system) with the membership function design as shown in Fig. 9. When the average maximum amplitude greater than 0.2 micro volts and the average latency greater than 160 ms and less than 450 ms then the room is opened, otherwise the room is closed. The P300 amplitude is related to the processing of significant information and memory processes, recognition of a stimulus learned earlier, a number of attention resources available and involved in the execution of the task (the more demanding the task, the greater the amplitude of the potential). The value of the P300 potential amplitude also depends on the distance between the successive stimuli and is inversely correlated to the frequency of presentation of the stimulus by mean the rarer and significant the appeared stimulus is, the greater of the P300 amplitude will be. However, the increase of difficulty of the subject to differentiate the stimulus will reduce the amplitude of the P300 potential. When the average latency is too short, then it is assumed that the peak amplitude is not caused by the stimulus and when it is too long (more than 450 ms), then the subject is only familiar with the room. The latency is highly related to the complexity of the stimulus or and the cognitive capacity (intelligence) of a subject to recognize the stimulus among each other. In this experiment, all participant subjects were provided average short latency, however, the maximum amplitude was relatively small. Finally, the classification accuracy about 75% is achieved.

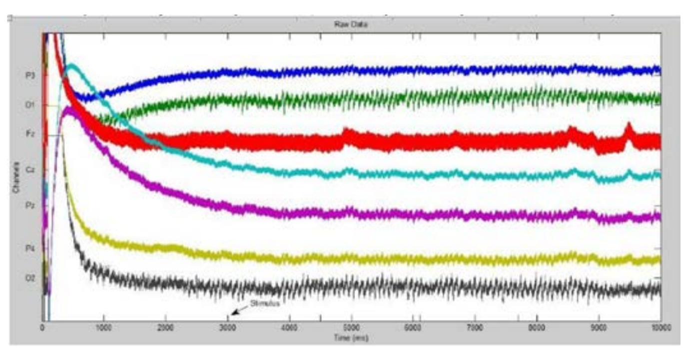

Fig. 4. Recorded raw data of EEG-P300 potential

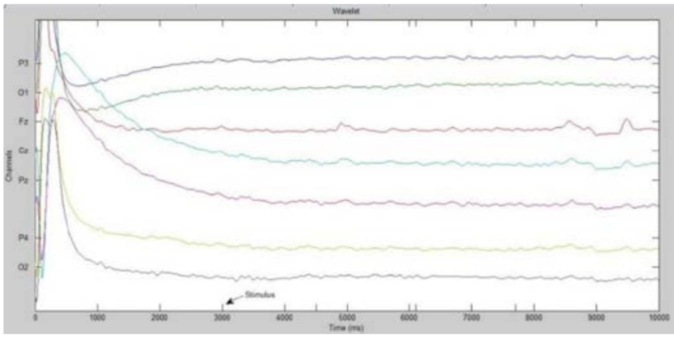

Fig. 5. Preprocessed signal using Wavelet method

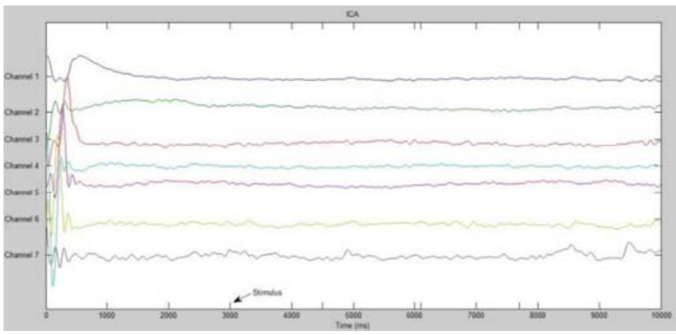

Fig. 6. Extracted signals using ICA method

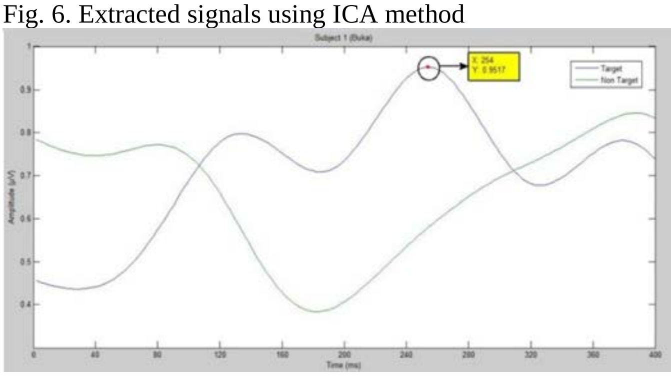

Fig. 7. The detected P300 potential feature for opening the room

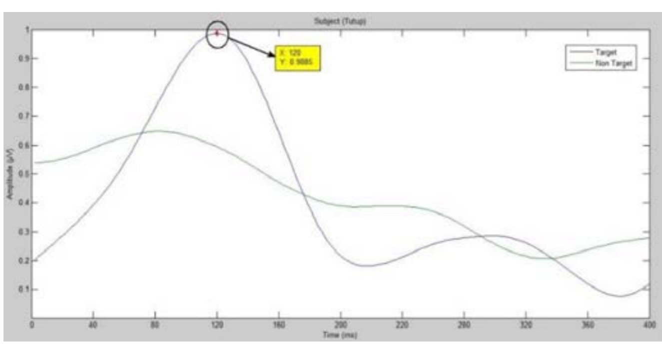

Fig. 8. The detected P300 potential feature for closing the room

TABLE I
MAXIMUM AMPLITUDE AND LATENCY OF EACH SUBJECT

Subjects		P3	O1	Fz	Cz	Pz	P4	O2	Average
1	Latency (X)	150	150	158	185	195	150	191	168.429
	Amplitude (Y)	-0.88	-3.11	-0.17	0.92	0.19	-0.28	-0.32	-0.523
2	Latency (X)	158	195	192	172	158	186	166	175.286
	Amplitude (Y)	-0.22	1.27	1.50	-0.33	0.24	2.05	-1.57	0.420
3	Latency (X)	156	150	152	186	184	180	185	170.429
	Amplitude (Y)	0.16	1.16	-1.61	-1.1	-0.06	0.79	0.55	-0.010
4	Latency (X)	196	150	192	150	185	150	150	167.571
	Amplitude (Y)	-0.51	1.09	-0.99	2.90	-1.24	0.37	1.87	0.498
5	Latency (X)	150	180	188	150	176	187	175	172.286
	Amplitude (Y)	-0.15	0.97	0.60	-1.95	-0.01	0.78	4.48	0.675
6	Latency (X)	153	180	150	187	159	166	188	169
	Amplitude (Y)	0.34	-0.18	0.70	0.73	0.67	-0.64	0.28	0.272
7	Latency (X)	162	150	170	150	186	193	188	171.286
	Amplitude (Y)	-0.01	-0.38	0.83	1.88	3.78	0.52	1.88	1.217
8	Latency (X)	156	190	190	160	188	160	158	171.714
	Amplitude (Y)	-0.01	1.38	-0.57	-0.37	0.71	1.11	-0.41	0.264

Fig. 9. Membership function design with Fuzzy interference system in classification

IV. CONCLUSION

This paper presented an experiment on the P300 amplitude and latency detection based on ICA-based blind source separation, wavelet analysis, and a fuzzy classifier. The results presented in this paper are part of a project with the ultimate goal of designing and developing brain computer interface systems and is applied for room access security. The subsequent analyses showed that the average value of the P300 amplitude was significantly greater in the group of the familiar subjects, who tried to enter the room than in the group of the innocent. Due to the correlation between the cognitive capacities with the P300 potential amplitudes, then the use of memory and concealed information on security system based brain computer interface become interested.

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