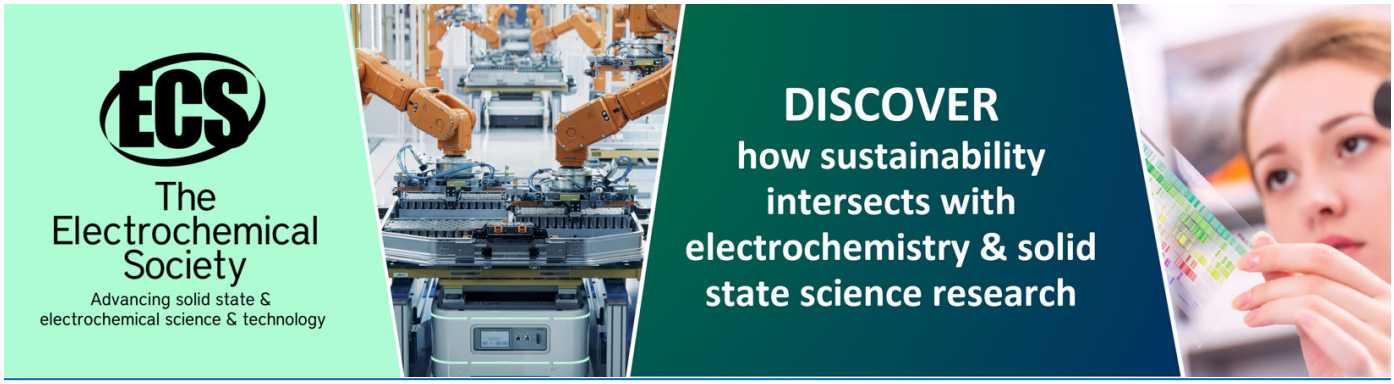
Detection of Drug Effects on Brain Activity using EEG-P300 with Similar Stimuli



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Detection of Drug Effects on Brain Activity using EEG-P300 with Similar Stimuli

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Abstract. Drug addiction poses a serious problem to our species. The worry that our significant family might be involved in drug use and are concerned to know how to detect drug use. Examinations of thirty taped EEG recordings were performed. The subjects consist of three group: addictive, methadone treatment (rehabilitation), and control (normal) which 10 subjects for each group. Statistical analysis was performed for the relative frequency of wave bands. The higher average amplitude is obtained from the addiction subjects. In the comparison with the signals source, channels P3 provide slightly higher average amplitude than other channels for all of subjects.

1. Introduction

Drug addiction poses a serious problem to our species. Consider the disastrous effects caused by the abuse of one of our oldest drugs, alcohol: automobile accidents, fetal alcohol syndrome, cirrhosis of the liver, Korsakoff's syndrome, increased rate of heart disease, and increased rate of intracerebral haemorrhage [1]. Moreover, drug addiction has been associated with a broad range of cognitive deficits in domains, including emotional regulation and motivation, attention and flexibility, working memory, learning, and decision making [2]. For example, cocaine addiction can cause psychotic behavior, brain damage, and death from overdose; and competition for lucrative and illegal markets terrorizes neighborhoods, subverts political and judicial systems, and causes many violent deaths. The drugs stimulate brain mechanisms responsible for positive reinforcement. In addition, most of them also reduce or eliminate unpleasant feelings, some of which are produced by the drugs themselves. What actually seems to happen is that the occurrence of an appetitive stimulus activates a reinforcement mechanism in the brain that increases the likelihood of the most recent response in the present situation. All natural reinforcers that have been studied so far (such as food for a hungry animal, water for a thirsty one, or sexual contact) have one physiological effect in common: They cause the release of dopamine in the nucleus accumbens [3].

Perhaps we worry that our significant family might be involved in drug use and are concerned to know how to detect drug use. Regardless of whom the person is and what his or her relationship is to us, it is important to understand how to detect drug use so we can get help for our child, loved one, or business associate. A drug test is a technical analysis of a biological specimen, for example urine, hair, blood, breath, sweat, or oral fluid/saliva to determine the presence or absence of specified parent drugs

or their metabolites. However, those technical analysis are not veasible applied without medical personel assistance. Previouss studies have shown that drug abuse is associated with altered brain function [3-10]. Electroencephalogram (EEG) power analysis are one of veasible tool for examining the effects of drugs on brain function. Due to its wide availability, relatively low-cost, superior temporal resolution, easy implementation, and non-invasiveness, intensive research has been performed on EEG as tool for cognitive processes in research and clinical diagnose [11-18].

The EEG pattern is constantly changing depending on mental activity, relaxation, drowsiness and sleep and this dynamic process is therefore an index of cortical activation, cognitive function and consciousness. The EEG may thus be considered an intermediate phenotype for complex behaviors and psychopathology in which arousal is implicated, such as anxiety, depression and addiction. Using the EEG signals to gain access to a neural correlate of brain activity could possibly be useful in the investigation of its relationship to the clinical syndrome of drug dependence, and ultimately in the development or selection of medications. The brain of drug abusers presents various structural and neurophysiological abnormalities, some of which may predate drug consumption onset. However, how these changes translate into modifications in functional brain connectivity is still poorly understood. To characterize functional connectivity patterns, the EEG activity from 20 drug abusers and 10 age-matched control subjects performing a simple counting task are recorded.

2. Data aquisition

Thirty male subjects were recruited from Hasan Sadikin General Hospital (HSGH) of Bandung-Indonesia. The subjects consist of three group: addictive, methadone treatment (rehabilitation), and control (normal) which 10 subjects for each group. At the time of testing none of the subjects was taking prescribed or non-prescribed medications. The healthy control subjects who never used any drug were recruited from treatment staff. Most drug dependent subjects had a history of additional drug use and ten subjects had ever been in methadone maintenance treatment. The study was approved by the Ethical Committee of the institution in which the the experiment was performed. All subjects provided written informed consent.

Subjects were asked to participate in a study concerning the measurement of brain function. They were informed that participation involved EEG measurements. Both the patients and control subjects received a remuneration of IDR 150.000. All subjects provided written informed consent. The experiment started with a short explanation of the procedure and informed consent was obtained. Personal data and history of drug use were recorded by the experimenter. Then the subject completed the questionnaires. After completion the subject was seated in the EEG chair and electrodes were attached. Instructions were to sit relaxed and concentrated on counting the total appear number in the screen. The appearance sequence of the stimuli (shown in Fig. 1) were randomly flashed. After EEG measurements, electrodes were removed and subjects received their financial compensation.

The EEG signals were measured with a digital Mitsar 202 amplifier using Electrocap Ag/AgCI electrodes at the 9 scalp sites according to the International 10/20 System (Fp1, Fp2, F7, F3, Fz, F4, F8, P3, P4) with green color as shown in Fig. 2. Ground was placed between A1 and A2. All signals were digitized without filtering on a PC with WinEEG software with a sample rate of 500 Hz and 16-bit A/D conversion. Off-line, an average reference channel was computed (all channels except A1/A2), and used for all analysis. For all electrodes, impedance was kept under 5 KΩ. With modern high input-impedance amplifiers such as used in the present study, and accurate digital filters for power line noise, high-quality EEG can be recorded. The experiment setup is given in Fig. 3.

Figure 1. The flashed similar stimuli represented of the drugs: (a) – (d) as non target and (e) as a target.

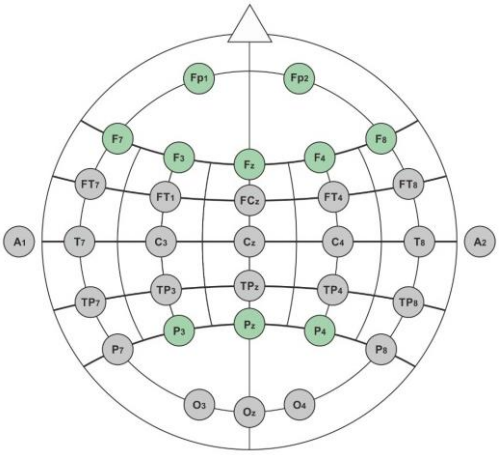

Figure 2. The electrodes position according to the International 10/20 System.

Figure 3. Experiment setup.

3. Signal processing

The flowchart of the signal processing is given in Fig. 4. One session for each subject consist of 20 seconds (i.e., each ten blank and number). One trial or epoch length is processed for 2 seconds. Prior to feature extraction, several preprocessing operations including filtering were applied to the raw data. For filtering, a 6th-order band pass filter (BPF) with cutoff frequencies of 3 Hz and 30 Hz was used.

Wavelet theory is a relatively new concept developed. The properties of the wavelet are given as follow: The time complexity is linear. Wavelet transform can be done perfectly with the time that is linear; Wavelet coefficients that are rarely elected. Practically, most of the wavelet coefficients of low value or zero. This condition is very beneficial, especially in areas of compression or data compression. Wavelet can be adapted to different types of functions, such as functions that are not continuous, and the function defined on bounded domains [19]. In general, a common function of wavelet is defined as [20 - 23].

$$\psi_{s,t}(t) = \mid s \mid \frac{1}{2} \psi \left[\left(\frac{t - \tau}{s} \right) \right] \tag{1}$$

where s and τ , $s \neq 0$, denotes the scale and translation parameters, and t indicates time. In the continuous wavelet transform, the signal is analyzed using a set of basic functions that are related to scaling and simple transition. The development of the CWT is presented in the following equation.

$$X_{WT}(\tau, s) = \frac{1}{\sqrt{\mid s \mid}} \int x(t) \psi \left(\frac{t - \tau}{s} \right) dt \tag{2}$$

Wavelet decomposition is embodied in the input signal and the filtered, lowpass fileter generates a waveforms called approximation and highpass filter generates a random waves called detail. The correlation of both filter with wavelet functions arranged in a hierarchy scheme called multiresolusi decomposition, where decomposition separates the signal into details at different scales and approximation.

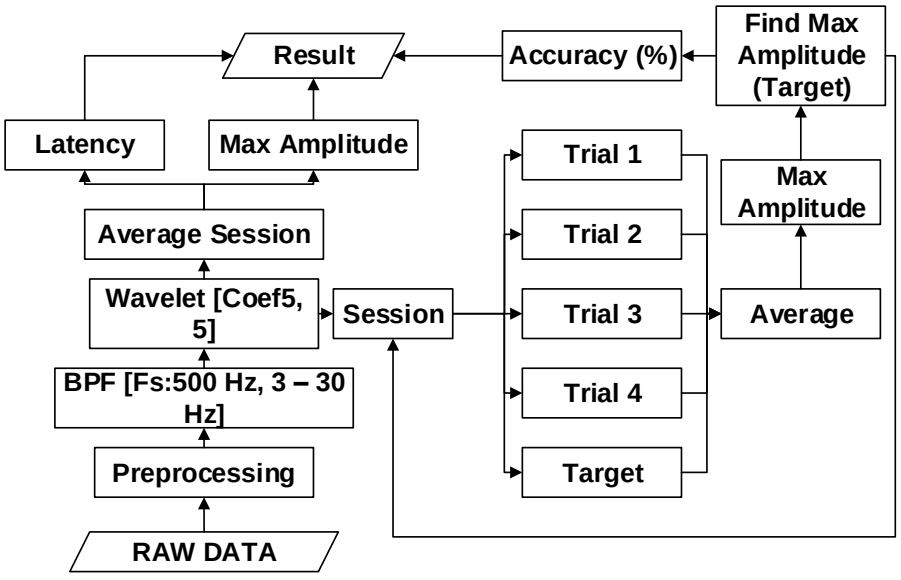

Figure 4. Signal processing processes

4. Results and discussions

The recorded EEG signals of addiction subject 2 from 10 channels (Fp1, Fp2, F7, F3, Fz, F4, F8, P3, PzP4) is shown in Fig. 5. For the raw data of all subject are generally similar which are mostly corrupted by noise. Fig. 6 indicate the filtered signals using band pass filter which the noise signals have been higly remove. The input signal is the raw EEG data then decomposed by the decomposition of the signal with noise on wavelet bases where there is information on signal wavelet coefficient. Denoising can be obtained by thresholding wavelet coefficients. Denoising is done by separating the wavelet coefficients with the download threshold. Wavelet group is used to pass the signal through wavelet transform blocks for the decomposition process, then the signal will be decomposed into wavelet coefficients which will be in thresholding and denoising where the process occurs. Thresholding function to eliminate noise and preserve the information that is important to the maximum signal.

Fig. 7 is the extracted signal using wavelet denoising. By applying the fast Fourier transform (FFT) algorithm, the peak amplitude of P300 component for each considered channels is obtained as Fig. 8. The higher amplitude is obtained from channels P3 and P4. The drug abuse has the lower amplitude in prefrontal cortex. People with a long history of drug abuse not only show the same deficits on tasks that involve the prefrontal cortex as do people with lesions of this region, they also show structural abnormalities of this region.

Fig. 9 and Fig. 10 are the comparison of the average latency and amplitude of the P300 component (addiction, control, and rehabilitation) for each channels. The control subjects has the shorter latency compare with the others group onthe target. It is indicates that, the control subject is faster to make a decision and others especially the rehabilitaion group are need more time to make a decision. Compare with the control one, the addiction subject need more power to get focus or concentrate. These EEG abnormalities may reflect underlying changes in brain function due to long-term drug use. The high amplitude is provided by the addiction subjects and the lower amplitude is provided by the rehabilitation subjects. It is indicate that the brain activities especially in the prefrontal cortex of the adicitive group is higher. It is suspected that the adictive subjects were still affected by the drug.

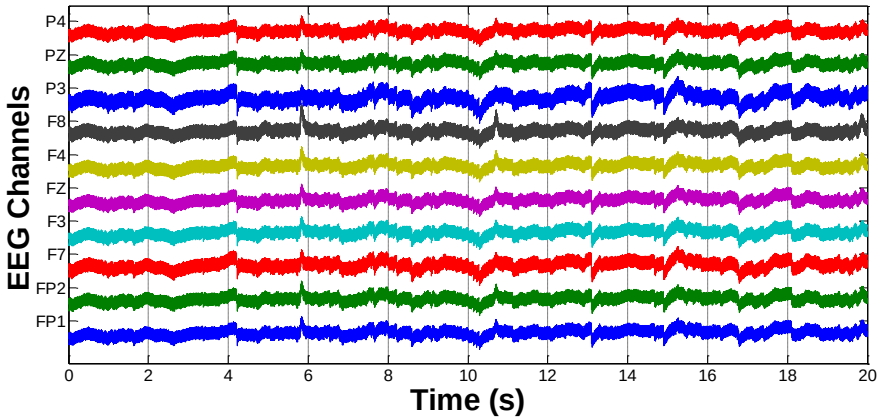

Figure 5. Raw data of addiction (subject 2).

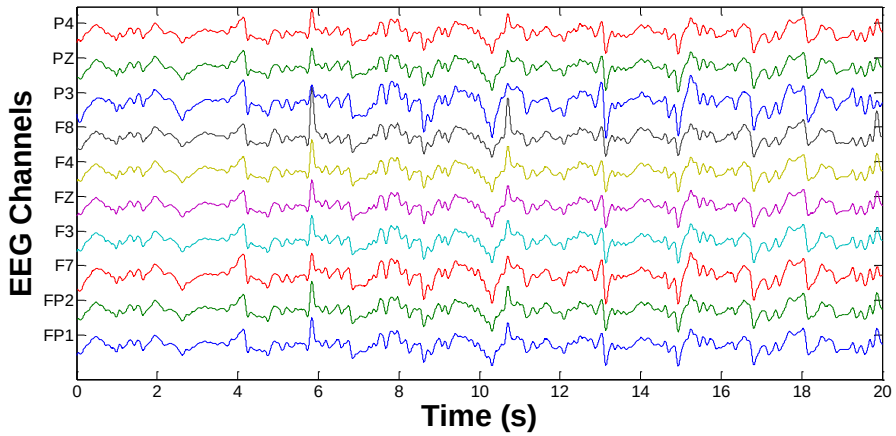

Figure 6. The EEG signals preprocessed using the BPF.

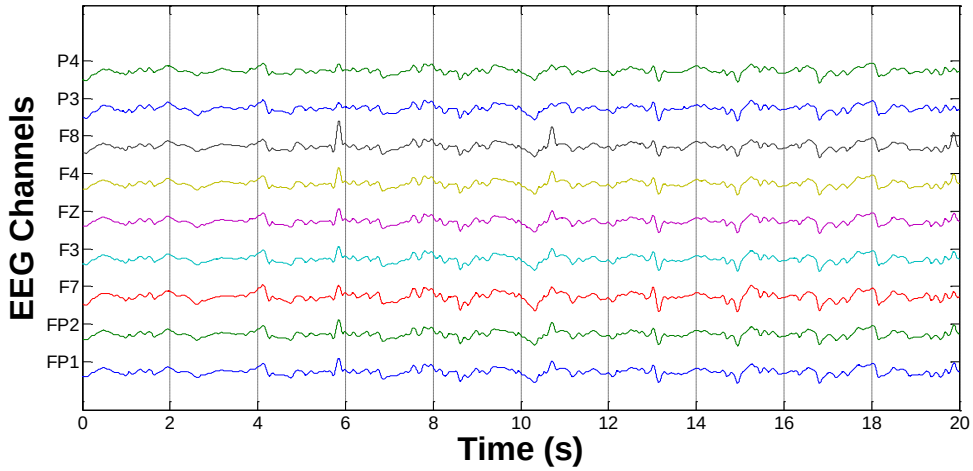

Figure 7. The EEG signals preprocessed using the Wavelet.

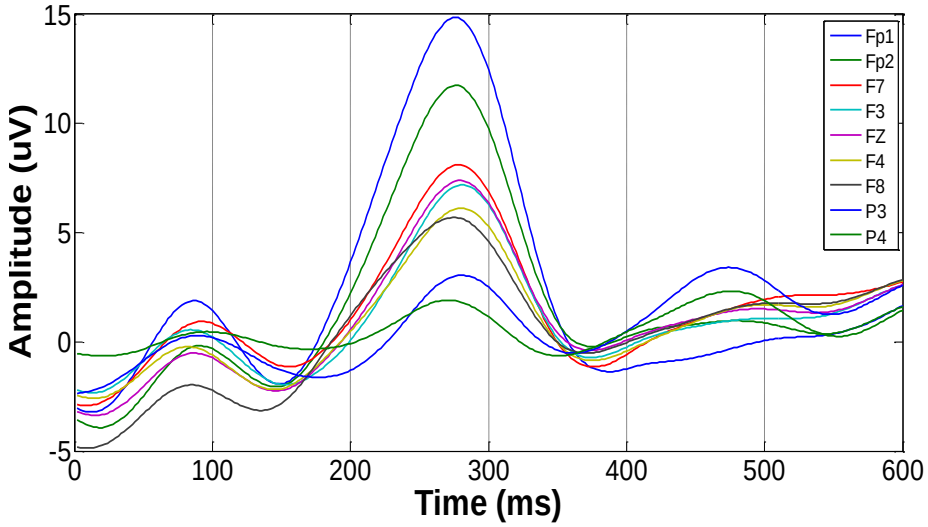

Figure 8. Extracted EEG-P300 signals from each considered channels.

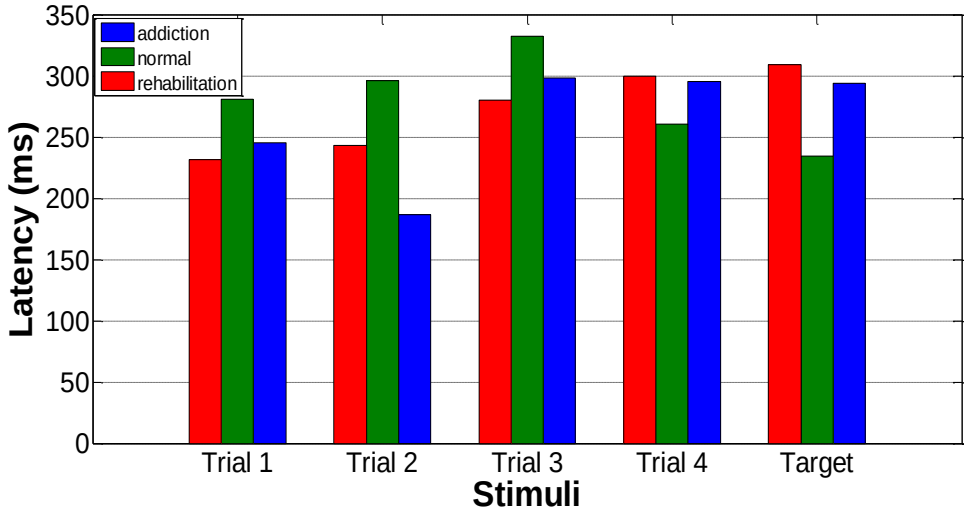

Figure 9. The comparison of the average latency (addiction, control, and rehabilitation) for each channels

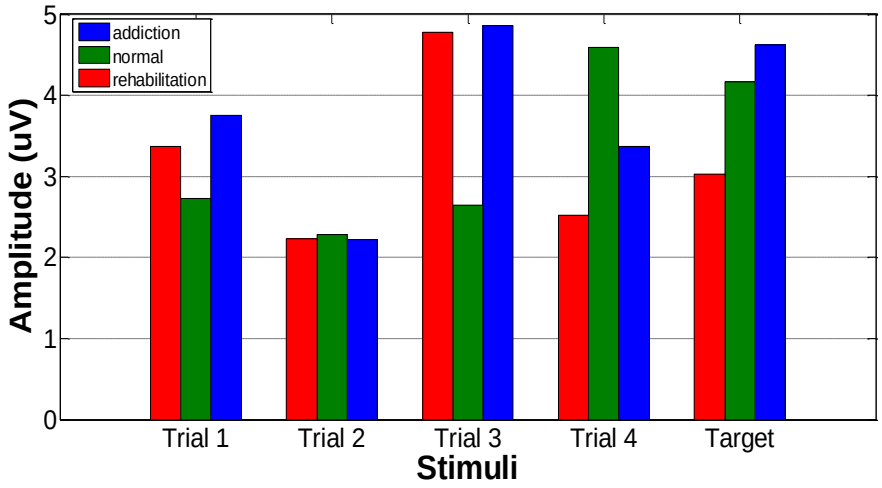

Figure 10. The comparison of the average amplitude (addiction, control, and rehabilitation) for each channels

5. Conclusions

The current study shows that excessive drug use subjects have an enhanced relative average amplitude compared to healthy control subjects. It has been suggested that a physiological relevance of the brain signal as a reflection of neural activity and the evidence of abnormal neural activity in drug dependence suggest the possibility that the brain signals might reflect abnormal neurobiology in drug dependence. These results indicate that chronic drug use may lead to distinct patterns of cognitive impairment that may be associated with dysfunction of different components of cortico-striatal circuitry.

Acknowledgments

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