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Analysis Methods of EEG Signals: A Review in EEG Application for Brain Disorder

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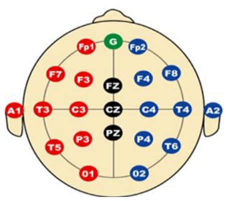
Graphical abstract



Abstract

The electroencephalograph (EEG) is a medical modality that plays crucial roles in detecting, displaying and recording electrical activity in the brain. This paper reviews the analysis method of EEG signal for common diseases in Malaysia which are autism, Cerebral Palsy (CP), Parkinson and schizophrenia from Malaysian and worldwide research paper that has been published. Fast Fourier Transform, Short Time Fourier Transform (STFT) and event-related potential (ERP) are some of the techniques used in analyzing EEG signal were discussed in this paper. It can be concluded that EEG plays its role as a detection tool to detect the disease in the early stage, rehabilitation, classification or as an assistive tool for the patient according to the needs of the diseases.

Keywords: EEG; autism; cerebral palsy; schizophrenia; parkinson; multiple sclerosis

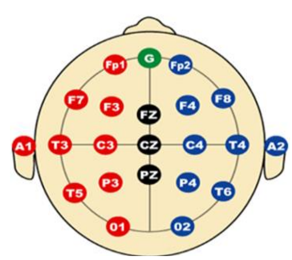
1.0 INTRODUCTION

Brain is an essential part of the body that receives messages from the senses. It can be divided into three parts; brain stem, cerebellum and cerebrum [1]. Cerebrum works as a control to voluntary movement, sensation and intelligence. Since cerebrum is big, it is divided into four lobes, frontal, temporal, parietal and occipital. Table 1 shows the functions of the cerebrum according to its parts [2].

Table 1 Part of cerebrum and its function

Part of cerebrum	Function
Parietal Lobes	Receive messages from the five senses, namely sight, touch, smell, hearing and taste.
Frontal Lobes	Control body movement and emotion. This part of the brain allows human to speak.
Occipital Lobes	Receive messages from the eyes.
Temporal Lobes	Receive messages from the ears. Temporal lobes allow human to recognize messages and sounds. Damage in this area will lead to epilepsy with severe behavioural disorders and aggressive outburst.

Electroencephalograph (EEG) is a powerful medical modality that can detect, view and record electrical activities in the brain. Although EEG produces high quality in capturing temporal information and cheaper compared to Positron Emission Topography (PET) and functional Magnetic Resonance Imaging (fMRI), the spatial resolution in EEG is low. This makes EEG the most suitable medical modality to investigate memory, learning, perception, emotion and information processing tasks [3]. EEG is a non-invasive testing method, which is safe to be used to a human body and can be recorded over a long period of time. The recorded EEG is called electroencephalogram. One of the methods to record EEG signal is by using a 10-20 EEG electrode placement technique established by the International Federation of EEG Societies. The head is divided into four standard points: the nasion (nose), the inion (external occipital protuberance or projection), the left preauricular points (ears) and right preauricular points. Figure 1 shows picture of standard EEG electrode attachment in the brain involved while taking the EEG recording.



KEY WORDS:

F-Frontal lobe
T-Temporal lobe
C- Central lobe
P-Parietal lobe
O-Occipital lobe
Z-Electrode place on midline
A-Ear clip reference node

Figure 1 Electrode placement method

The EEG device records and interprets the voltage fluctuations along the scalp which are generated by the brain. The voltage fluctuations is caused by the current that flows during synaptic excitations of activated neurons in the cerebral cortex [4, 5]. Generally, there are a few common steps in order to analyze EEG signal. The raw EEG signal that has been extracted will undergo preprocessing which includes acquisition of signal, removal of artifacts, signal averaging, threshold value of the output, enhancement of the resulting signal, and edge detection [6]. The next step is a feature extraction scheme where the most important features or information is chosen for classification exercise. Then, the signal will be classified using linear analysis, nonlinear analysis, adaptive algorithms, clustering and fuzzy techniques, and neural networks [6]. Figure 2 shows the flow chart for the whole system in EEG signal processing. The methods involved in signal processing will be explained briefly in the next section.

The result of frequency in the brain’s activity can be divided into five groups, delta (0.5 to 4 Hz), theta (4 to 8 Hz), alpha (8 to 13 Hz), beta (13 to 30 Hz) and gamma (31 to 100 Hz). Usually, alpha frequency, that shows the calmness of the subject and beta frequency which detects the attention of the subject, are used by researchers to determine the subject’s diseases. Figure 3 is a picture of the EEG raw signal and the signal that has been extracted according to the frequency (delta, theta, alpha, beta, gamma) [7].

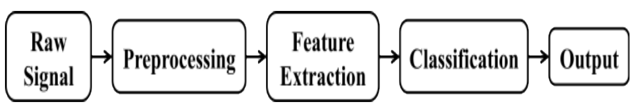


Figure 2 Steps of EEG signal processing

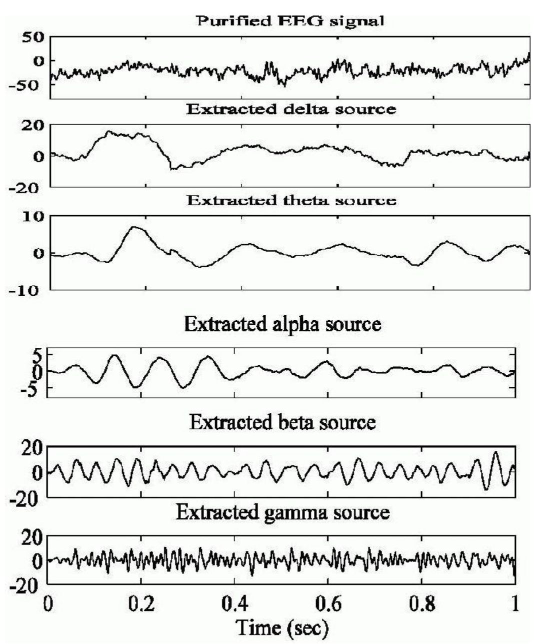


Figure 3 Raw EEG signal and the extractions of signal

This paper is divided into five sections. The first section covers the brief introduction on brain, functions of the cerebrum and general introduction on EEG. Section 2 describes the processing steps and the method involved in EEG analysis. In Section 3, a brief review on previous study on disease detected such as autism, cerebral palsy, multiple sclerosis, Parkinson and schizophrenia using EEG is presented. In Section 4, the methodology of each disease is compared accordingly. The final chapter concludes the whole paper regarding the widely use of EEG in detecting several types of disease based on their abnormal waveform.

■2.0 EEG SIGNAL PROCESSING

The raw EEG signals will likely be contaminated by undesirable non-cerebral origin signal called artifacts or noises. These artifacts are caused by biological sources and external sources. The existing of the artifacts in EEG signal attenuates the brain-originating signal which could lead to misinterpreting the brain activity and misdiagnosis of the brain disorder. Thus, the first step in analyzing EEG signal is to remove the artifacts while enhancing the brain signal. There are several techniques which have been used in separating and removing the artifacts, including notch filter and fixed linear filter. Notch filter is often used to filter the line interference noise in case the data acquisition system of the EEG is unable to cancel out the 50 Hz line frequency [4]. However, the use of filter such as a low - pass filter (LPF) and high-pass filter (HPF) are not advisable since linear filtering could possibly attenuate the brain signals as well, since the frequency band for both artifacts and brain signals could be overlapped. Researchers have developed many techniques for artifact removal, including regression-based methods, component-based methods and adaptive filtering methods. Regression analysis relies on a clean measure of the artifact signal to be subtracted out [8] thus, is not applicable for online processing. Independent Component Analysis (ICA) is one of the component-based methods which are extensively used in the pattern analysis and biosignal analysis. ICA separates the noises from the EEG signals by decomposing the signals into several independent components depending on statistical independence of signals [9]. The advantage of ICA is, it does not require an additional channel reference since the algorithm itself does not require a priori information. However, ICA needs a manual visual inspection to identify the artifact independent components [10, 11] make it time consuming and subjective. In the adaptive filtering method, the filter coefficients are updated using a recursive algorithm according to a given signal property to remove the noises. It requires a reference signal, which carries significant information and statistical properties about the artifacts. The filter coefficients are adjusted in an ongoing basis until the output has been minimized [12]. Adaptive filtering method is suitable for online applications due to its fast convergence.

After the elimination of the artifacts, the significant features of the EEG signals will be extracted using feature selection techniques. The feature extraction and selection techniques are important to identify certain properties that can effectively be used in classifying the EEG signals. There are several approaches used in feature extraction including time-domain analysis, frequency-domain analysis and time-frequency domain analysis. The features such as minimum, maximum, mean, standard deviation and energy are commonly used in time-domain analysis. The disadvantages of time-domain approach are high sensitivity of the selected features and the demand for higher storage capabilities. In frequency-domain analysis, EEG signals are first transformed into frequency domain using Fast Fourier Transform (FFT). In certain cases, it is not enough to provide signal characteristic for classification using merely frequency information, thus time-frequency analysis is an alternative to improve the classification performance. Ling *et al.* proposed the time frequency space analysis using Discrete Wavelet Transform (DWT) in [13]. Carlos *et al*. presented a method based on the time-frequency distributions (TFDs) and partial tracking called tracks extraction in [14].

In feature classification state, the selected features from EEG signals will be used as input to classifier models. The number of features, linearity between input and output, and data distribution, are among the factors, which will affect the accuracy of the classification. Up until today several classifier have been proposed in the literature, including the method using Support Vector Machine and Neural Networks [15], Linear Discriminant Analysis (LDA), Hidden Markov Modelling [16], and K Nearest Neighbors [17].

3.0 DISEASES

3.1 Autism

Dolah *et al*. characterized autism by social disconnectedness; failure to identify and read the astuteness of human communication behaviours and interactions, an obsessive addiction to routines and repeatable behaviour, the repetitions of sentences and words without regard to their significance or context [18]. Since autism is a spectrum disorder, each autistic child is special and will have different characteristics from each other. Three categories of autism are mild, moderate and severe. However, some studies classify autism into three functions, Low Functioning Autism (LFA), Medium Functioning Autism (MFA) and High Functioning Autism (HFA). It is reported that in the 1970s, the rates of autism spectrum disorder was less than 3 per 10,000 children and increased to more than 30 per 10,000 in the 1990s [19]. In another study made by local survey indicated that one in every 625 children in Malaysia is autistic [18]. Current research [20] states that roughly one in every 150 children is diagnosed with some form of autism while according to Behnam *et al*.[21], autism affects 1 in 66 births.

Most of the research towards autism use frequency-domain and time-domains in analyzing EEG signals. However, the analysis in the frequency domain was more significant compared to time-domains technique [22]. Malaysian researcher, Sudirman *et al.* [23] indicates that the diagnosis of alpha value (10 Hz) using Fast Fourier Transform (FFT) in visual simulation for autistic children is lower than normal children. The Fast Fourier Transform (FFT) method is used to analyze the characteristics of the acquired EEG by power spectral density (PSD) estimation. The low value of alpha is a result of lower relaxation and insecure feeling of respondents towards his environment. It is also stated that most autistic children experienced eye disorders since the age of 3 which makes them wear spectacles and undergo eye treatment. Hoole *et al.* [22] came out with the results stated that the abnormalities in EEG alpha waves are related to the early age of autism. Listening to relaxing music helps increasing the alpha level and reduces the beta level in autism children.

Behnam *et al.* [21] discovered the EEG background activity of autisms and normal children by using Fast Fourier Transform (FFT) and Short Time Fourier Transform (STFT). By using mean and standard deviation as the extracted features, the result gives 82.4% of original grouped cases that is correctly classified. According to Wang *et al* [24], autistic children show abnormalities of EEG waveform in the limbic system and cerebellum. The resting EEG studies reveal that 20% of individuals with autism show epileptiform discharges at rest, commonly without the existence of clinical seizures besides an increase in alpha power coherence. There is an exception for severe autism where studies reported unaffected alpha power. Thus, an adult will have low in delta and theta frequency bands compared to children.

Alhaddad *et al.* [25] presented a method to diagnose the autism using Fisher Linear Discriminant Analysis (FLDA) to classify the extracted FFT features. A method using Fourier methods to extract EEG features and k nearest neighbours (kNN) in classifying between normal and autistic children shown 82.4% accuracy was presented by Sheikhani *et al.* in [26]. William *et al*. demonstrated a classification between typically developing and high-risk group autism using multiclass support vector machine and modified multiscale entropy (mMSE) as a feature vector [27]. Razali *et al*. applied Gaussian mixture model (GMM) to extract feature in frequency-domain and multilayer perceptron (MLP) to classify the data [28]. Further research was done by Duffy [29] to differentiate between Aspenger Syndrome (ASP) and autism disorder which shows that Aspenger diagnosis does not show symptom of impairment in communication and does not have lack of difficulty in language compared to autistic children. This result of studies is crucial as Aspenger's syndrome is always debated by researchers on whether it is a part of autism or another unique entity.

With the help of campaign and active non-government organization like National Autism Society of Malaysia (NASOM), there is an increase in awareness of autism in Malaysia for the last few years. However, more research needs to be done to give an efficient support system to families having autistic members [18].

3.2 Cerebral Palsy

Cerebral palsy (CP) is one of the most prevalent chronic disabling states of childhood and affected 1.2 to 2.5 per 100 school age children [30]. CP is a class of non-progressive group, motor impairment syndromes secondary to lesions or oddities of the brain that arise in the early stage of growth [31]. CP is often related to epilepsy, mental retardation, vision and hearing problems [32]. Although no data are available in Malaysia, Lim *et al.* [30] believed that cerebral palsy is one of the most typical chronic disabling childhood, affecting the health status or quality of life (QOL).

According to Rönnqvist *et al.* [33], CP children show more segmented reaches and need a longer time to reach and grasp during the movement execution when using the affected limb. However, when using the unaffected limb, the children will have more segmented movements in the task given. Typically, motor impairment in hemiplegic CP originates from contralateral brain damage which consequently changes motor control by the contralateral lesioned brain side. Rigoldi *et al.* [34] states that there are statistical differences in EEG between two conditions: the first condition is regarding the affected and less affected arms in CP patients and the second condition is between the less-affected arm in patients and the normal arm in control. The EEG analysis in this study also shows that CP children can be divided into two groups; one group of children (52.38%) shows bilateral electrical activation in the mu band when conducting the task while the other group (47.61%) showed a common unilateral activation with front central, central, centroparietal or parietal localization. Mu rhythm is a sensorimotor rhythm with frequency 7.5 until 12.5 Hz. Faria *et* *al.* [35] developed an intelligent wheelchair for CP patients with the help of EEG in assisting transmission between machine and patient. By using Hjorth parameters as signal preprocessing, the wheelchair helps the patients to handle the wheelchair by using facial expressions and thoughts. CP is also often related to epilepsy where almost 50% of children with CP also develop epileptic disorder [36, 15]. EEG reading may be abnormal when there is no history of clinically recognizable seizures [37]. Hundozi-Hysenaj *et al*. suggest that EEG should be implemented to detect epilepsy in CP patients and not as a tool to detect CP in patients.

In Malaysia, most of the researches in cerebral palsy work on the medical aspect and social science to improve the patients' life.

3.3 Parkinsons

Parkinson's disease is the second most common disease for an elderly after Alzheimer's disease [38]. According to Thanasyan [39], Parkinson's is a degenerative disease of the nervous system which gives impact to the brain and can affect the younger adults. It affects about 1% of the worldwide population over 55 years of age with an increasing number of patients for all the years recorded [40].

In Malaysia, a research by Yuvaraj *et al.* [41] revealed that Parkinson's patients show interhemispheric theta, alpha and beta ratios. This study that used Infinite Impulse Response (IIR) Butterworth bandpass Fast Fourier Transform (FFT) as methodologies stated that the Parkinson's patients displayed lower power values than normal in processing happiness, sadness, fear, anger and surprise. Another study by Soikkeli *et al.* [42] said that Parkinson's patients will have slow EEG signal. Parkinson's patients without dementia will have more theta activity and low frequencies compared to a normal person. Jiang *et al.* [40] shared that the delta-band relative power of 20 EEG channels for Parkinson's patient is increased while in alpha- and beta-band, the relative power declined. Nonetheless, theta-band relative power does not show consistent trend. Relative power in electrodes channel such as Fp_1, Fp_2, F_7, F_3, F_z and O_z were decreased while in another electrode channel were increased. Handojoseno *et al.* [43] used EEG as a tool to detect the freezing of gait (FOG), one of the most distressing sign of schizophrenia using Wavelet decomposition and patterns recognition technique. The classifying data samples based on features was conducted using MLP. The result showed that all the subbands of wavelet energy for schizophrenia patients at channel P_4 differ from the normal person. In channel P_4, the degree of order of wavelet energy continuously decreases in regularity, which expresses the freezing sign contrast with the occipital region which shows a significant increase. Besides that, the subband alpha shows more importance for dual task performance compared to beta band, which differ from Palmer's [44] study.

3.4 Schizophrenia

Schizophrenia is a popular mental disorder that affects 1 in 100 people worldwide and gives numerous burdens on the individual [25]. Individuals affected usually will have a poor quality of life, increased morbidity and mortality, disrupts interpersonal relationships and family structures, and has significant economic costs to society. There is an increasing number of patients in Malaysia which affects social functioning [45]. EEG is used in schizophrenia patients to measure the brain's response and the wave's tone that is different in length. Mismatch field (MMF) in the event-related potential (ERP) of the patient is reduced compared to a healthy person [46]. ERP is a measurement for brain response due to the result of specific sensory cognitive. For another group of people that show developing psychosis, the individual will have smaller MMF compared to other group who do not. Hoffman *et al*. [47] reveals that the power coherence in inter-hemispheric decreased while according to Mann *et al.*[48], power coherence in intra-hemispheric coherence increased.

Besides that, a study by Tika *et al.* [49] reveals that schizophrenia patients with higher minor physical anomalies (MPA) have higher low-gamma band (30-50 Hz) in the intra-hemispheric and inter-hemispheric regions compared to patients with low MPA and normal patients. Schug *et al.* [50] states that schizophrenia patients with record in violence will have an increase in gamma power (30 to 50 Hz) compared to patients who do not. Sun *et al.* [51] divided gamma oscillations into two conditions, resting paradigms (subjects in a state of awake relaxation with eyes closed or open) and active behavioural paradigms which refer to the condition of subjects who are busy processing information. The outcome shows less gamma power in the frontal region of schizophrenia's patient compared to the normal person during the resting paradigm. In contrast, for active behaviour, the schizophrenia patients show anomalous high in low working memory state and does not increase in a load dependent fashion [51, 52]. Basar *et al.* [53] in his review divided the study of schizophrenia into five paradigms; steady-state auditory/visual evoked oscillations in schizophrenia patients, somatosensory/auditory/visual sensory evoked oscillations in schizophrenia patients, the applications of transcranial magnetic stimulation- EEG combination in schizophrenia research, evoked/ event-related oscillations upon application of wavelet transform paradigms in schizophrenia patients and general remarks and summary of evoked/event related studies of schizophrenia. He summarized that most of the research in auditory-steady-state study are on gamma response oscillations. Furthermore, most of the researches agreed that schizophrenia patients show a reduction in the phase-locking factor (PLF) across the test for 40-Hz response to 40-Hz auditory tones. Hall *et al*. [54] in his study stated that event-related gamma power is reduced throughout an auditory oddball task in schizophrenia patients and their normal identical twins. Besides that, Spencer *et al*. [55] released that the left hemisphere source PLF in schizophrenia was positively related with auditory hallucination symptoms.

■4.0 DISCUSSION

All of the diseases have one common characteristic of EEG signal, which is abnormal EEG waveform. The abnormal EEG waveform is divided into two categories, epileptiform pattern and non-epileptiform pattern. Epileptiform pattern shows for spike and sharp wave, which can be seen in CP and autism patient. For the non-epileptiform pattern, the waves show focal slow waves, diffuse slowing and asymmetry in amplitudes and frequency. This pattern is shown on Parkinson and schizophrenia patients. However, the methodologies in analyzing the signal differ between each disease. Autism and Parkinson EEG waveforms are analyzed by using Fast Fourier Transform (FFT) or Short Time Fourier Transform (STFT). Frequency-domain analysis in autism gives more significant result compared to time-domain analysis. It is suggested to focus the analysis at the exact frequency and analysis on spectrum per channel itself for better outcome in distinguishing between control and autistic group. Since Parkinson's diseases involve faulty in movement, the analysis of this disease is done on the evoked reaction potential (ERP) using mu rhythm. It proposed that using the integration of features in the space-time-frequency analysis improves the sensitivity of the classifier for event prediction application for Parkinson's. Besides Parkinson's, analysis of schizophrenia's diseases also involved evoked relative potential in inter- and intra-hemisphere. Some patients may experience a combination of diseases. For example, 15% to 55% patient with cerebral palsy may have epilepsy [37]. EEG contributes to the development of the technology for cerebral palsy patient where it is used to detect their brain electrical activity when moving the wheelchair.

■5.0 CONCLUSIONS

The EEG is used as the analysing tool of diseases, classification and rehabilitation. The methodologies of the analysing diseases also differ according to the diseases. Some of the technique to analyse EEG waveform is using time-frequency pre-processing while others use focal wave to detect the active side in the EEG signal. There are many usage of EEG in Malaysia but still it is limited in terms of disease detection compare to other county. More research and development needs to be done to improve the usage of the EEG.

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