Brain Dynamics in Response to Intermittent Photic Stimulation in Epilepsy

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Tahereh Najafi[1], Rosmina Jaafar[1](✉), Rabani Remli[2], Wan Asyraf Wan Zaidi[2], Kalaivani Chellappan[1]
[1] Dept of Electrical, Electronics & Systems Engineering, Universiti Kebangsaan Malaysia, Bangi, Malaysia
[2] Dept of Medicine, Hospital Canselor Tuanku Muhriz, Univeristi Kebangsaan Malaysia, Cheras, Malaysia
rosmina@ukm.edu.my

Abstract—Routine electroencephalogram (EEG) examinations uses intermittent photic stimulation (IPS) for investigation of the visual cortex EEG responses during resting time. This study aimed to discover brain dynamics effects of IPS in 28 generalized epilepsy patients and 28 healthy subjects. Signal processing techniques were used in feature extraction by Fast Fourier transform (FFT), feature dimension reduction by t-test (significant, $p<0.05$) and classification by nearest neighbor (k-NN) and support vector machine (SVM). The epilepsy group had higher level of amplitude in Theta waves compared to the healthy group. The Alpha waves in the resting time and for all IPS frequencies were observed with lower level of amplitude in healthy subjects compared to the epilepsy group. The k-NN (85.7% accuracy) classifier had the best discrimination of epilepsy from healthy group for resting time versus during IPS at 18 Hz IPS. However, using SVM (75.0% accuracy), IPS at 25 Hz yielded the best discrimination between resting time versus IPS in epilepsy where the healthy group responded similarly in all IPS frequencies. This study shows that IPS at 18 Hz and 25 Hz are suitable IPS frequencies for k-NN and SVM, respectively, to discriminate non-photosensitive generalized epilepsy from normal subjects during interictal.

Keywords—intermittent photic stimulation (IPS), electroencephalography (EEG), epilepsy; support vector machine (SVM), k nearest neighbor (k-NN)

1 Introduction

Epilepsy is a chronic disorder inducing subject to experience seizure due to impairment of excitatory and inhibitory pathway in neural activities. People with epilepsy face cognitive challenges, medical and psychiatric comorbidities, and social stigmatization and in some cases, lower annual incomes and physical limitations leading to poor quality-of-life (QOL) [1]. A recent study reported the prevalence of lifetime epilepsy is 7.8 per 1000 persons in Malaysia in 2021 [2]. The progress in brain cognition, epilepsy management and control can be achieved via anti-seizure medication (ASM) as part of the treatment strategies. Epilepsy diagnosis most of the time is investigated during interictal in the absence of seizure usually by clinical neurologists via visual inspection on the EEG waveforms. Normal EEG does not rule out epilepsy and the visual EEG evaluation has high false negative result from routine EEG analysis. Hence a more sensitive method shall be adopted to increase the sensitivity of epileptic detection using advanced software/algorithm.

Intermittent photic stimulation (IPS) is a form of visual stimulation accompanied by changes in neuronal activity by triggering specific visual stimuli [3]. Although the responses of IPS in each subject is varied [4], various investigations have been done in different studies such as epilepsy and generalized anxiety disorder and etc. [5]. Electroencephalography (EEG) is a non-invasive technique that can explore the responses of visual stimuli by measuring the electrical potentials on the head surface resulted by neural activities.

In epilepsy, visual stimuli are the stimulus which can provoke seizure, evoke paroxysmal discharges as spikes in particular brain regions or exhibit a normal phase-locked responses [6]. Although a variety of diagnostic methods are available, EEG as a non-invasive routine technique vastly used in diagnosis and visual stimulation as a diagnostic intervention that plays a valuable role in this journey specifically during interictal [7], [8]. The responses to visual stimulation are varied depending on the specifications of stimuli itself in the aspect of factors such as intensity, duration, distance from the source, background illumination, type of pattern, background illumination, contrast, and color [9]. Furthermore, it is demonstrated that subjects' biodiversity in the aspect of types of sensitivity; photo-induced seizure, photoparoxysmal response (PPR), photosensitivity and photomyoclonic response effects the responses [6].

In most of epilepsy studies evaluating the effect of visual stimulation, the subjects had photosensitivity. In [10], twelve photosensitive epilepsy patients were examined in front of different colors of photic stimulation; white, red, blue, green and yellow light respecting to the evaluation of intensity of EEG activity. The achievement of study was benefitted in designing more appropriate sunglasses respecting seizure prevention. Rhythmic visual stimulation leads to a neural entrainment originated from synchronization of neural activity with the periodic properties of the stimuli [11]–[14]. The hypothesis was supported in [14] by presenting this importance that the exact synchronization of cerebral rhythms leading to a certain type of seizures which were out of step previously. Resting time and 14 Hz IPS focused on estimating power spectrum density and coherence profiles using autoregressive parametric model (AR) was investigated in [15] photosensitive idiopathic generalized epilepsy. The study resulted a significantly larger number of coherence peaks in the Gamma band in patients with respect to controls where in IPS coherent Gamma activity is mainly presented as IPS frequency harmonics. Alpha activity peaks appeared in controls but not in patients in confront of IPS. In [16], while simultaneous recordings of EEG and functional MRI (EEG-fMRI) were applied on photosensitive idiopathic generalized epilepsy patients revealing the activation of spike-wave discharges in thalamus and deactivation in frontoparietal areas. The result showed a significant activation in the visual cortex confronting IPS. Furthermore, while early regressor showed photo PPR in the parietal cortex and in the premotor cortex, standard regressor presented deactivation in early activated areas in all subjects and thalamic activation in one subject. Respecting to the hypothesis that the reduce of inhibitory effect of Alpha oscillations may be associated with PPR [17] investigated on photosensitive subjects. Linear and non-linear spectral characteristics of Alpha rhythms were studied during visual stimulation. Despite a desynchronization of Alpha power persistence over occipital region in both case and control groups, the activity appeared in central lobe for only case group. The study resulted a reduced bicoherence of the central Alpha frequency band in case group against the claim attributed by hypothesis.

In this study, the EEG from two groups; 28 normal and 28 patients with generalized epilepsy with no report of PPR, were investigated. The objective of the study was to discover the brain dynamics in the aspect of power of frequency band during resting time and visual stimulation. In this regard, IPS under nine continuous frequencies; 8, 10, 12, 14, 16, 18, 20, 25 and 30 Hz, were elicited to the groups. Brain signal processing concentrated on feature extraction, feature selection and classification were applied on the signals obtained from one channel from the visual cortex. The study is summarized in two approaches: 1) Discovering the differences between case and control groups in each experimental condition, 2) Figuring out the differentiations between resting time and each IPS within an individual group.

This study contains three main sections after introduction, brain signal processing techniques and the two well-known machine learning classifiers via k nearest neighbor (k-NN) and support vector machine (SVM) as described in the method section. Next, the focus of our study categorized in EEG dataset, feature extraction, feature selection and classification, will be explained. The study constitutes two approaches which are explained in each sub-branch of the methodology sections. The study will be concluded after discussing about the results of both approaches. The references will be indicated at the end of the paper.

2 Materials and methods

2.1 Brain signal processing

With the focus on EEG, brain signal processing is a technique that provides the condition to describe brain dynamics by analyzing the signals on the scalp recorded by EEG. The signals are electrical potential differences resulted by neuronal activity in intracranial in time series data between two electrodes placement on the scalp according to 10-10 or 10-20 systems [18]. In total, brain signal processing is summarized in three main steps after the acquisition; feature extraction for extracting the attributions from the signal, feature dimensionally reduction and classification [19]. EEG signals can be analyzed in time and frequency domain. Figure 1 shows a general overview of brain signal processing steps. Research shows that brain emits specific range of frequency bandwidths in certain times such as Delta (0.5-4 Hz); during deep and dreamless sleep, Theta (4-8 Hz); during relaxation and meditation, Alpha (8-12 Hz); in awake and calmness, Beta (12-30 Hz); lower beta where the subject is awake and higher beta confronting anxious, and Gamma (over 30 Hz); during hyper brain activity [20], [21]. Figure 2 presents various frequency bandwidths of the brain signals.

In a study by Najafi and et al, the role of brain signal processing is described in an epilepsy study [22]. The study reported that the technique was mainly performed well in detection with the focus on 1) epilepsy status; by extracting the features being able to classify various statuses of epilepsy such as interictal vs ictal, 2) epilepsy type; by finding the differentiation between various types of epilepsy based on the seizure type such as generalized vs focal, 3) epilepsy marker; by detecting the abnormalities in the epileptic signals and 4) surface localization; with a concentration on the standard of EEG electrode placements to discover the level of potential activities and the possibility of reporting seizure onset zone (SOZ). In addition, it has resulted that the analysis can be done in prediction towards notifying the seizure by processing the long-term EEG signals. In this study FFT in feature extraction step, t-test was applied for feature selection and the classifiers; SVM and k-NN, were utilized in the classification step.

Fig. 1. An overview of brain signal processing steps

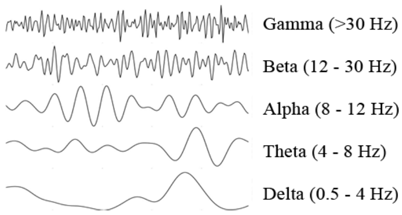


Fig. 2. Various brain frequency bandwidths

Support vector machine (SVM). The performance of the SVM classifier relies on the choice of the regularization parameter C or the box constraint and the kernel parameter or the scaling factor leading to a hyperplane parameter [23].

Mathematically, SVM refers to solving a quadratic problem (Q.P) with minimizing equation (1).

$$Q.P: min \ \frac{1}{n}\alpha^T H\alpha + f^T\alpha \ , \quad h_{ij} = y_i y_j \, x_i^T x \ , \quad \rightarrow \quad H[h_{ij}]_{n\times n} \ , \quad f_i = -1 \ , \tag{1}$$

Where H represents inputs and f considered as internal parameter equals to -1 and α which is multiplied to H in order to find the positive and negative lines that must be found. After finding α by solving Q.P, the biases of the SVM lines are needed to be found. Considering the equations (2) and (3) and the amounts of ω and S, the value of bias will be found based on equation (4).

$$\omega = \sum_i \alpha_i \, y_i x_i \ , \tag{2}$$

$$S = \{i \mid 0 < \alpha_i < c\} \ , \tag{3}$$

$$b = \frac{1}{|S|} \sum_{i \epsilon S} (y_i - \omega^T x_i) \, , \tag{4}$$

K-nearest neighbor (k-NN). The k-NN algorithm is a non-parametric learning method used to classify objects based on their closest training examples in the feature space. An object is classified by a majority vote of its neighbors [24]. The Euclidean distance metrics $d(x, y)$ between two points x and y is calculated using the equation (5). Where N is the number of features $x = \{x_1, x_2, x_3 \dots x_N\}$ and $y = \{y_1, y_2, y_3 \dots y_N\}$. The number of neighbors used to classify the new test vector was varied in the range of 1 to 10, and its effects on the classification performance is determined in the form of classification accuracy considering to the standard deviation [23].

$$d(x, y) = \sum_{i=1}^{N} \sqrt{x_i^2 + y_i^2} \tag{5}$$

2.2 Brain dynamics in response to IPS in epilepsy

In this study, IPS as the visual stimulation was elicited to provide a comparative condition for analyzing EEG signals between case and control groups. The analysis covered by brain signal processing techniques was concentrated on FFT for extracting features, t-test for significant feature selection; and k-NN and SVM for classification. The algorithms of each step were implemented on MATLAB R2020a which in detail, BrainStorm V.2021 and ClassificationLearner toolbox were employed in data acquisition and classification steps, respectively. The hardware system for this analysis was considered an Intel® Core™ i7 desktop with 2.20 GHz processor and 8 GB of RAM. In the next sections, the detail of brain signal processing techniques used in this study will be described.

EEG dataset. In this study, the retrospective data were collected from 56 subjects; 28 healthy subjects and 28 generalized epilepsy patients, who visited the Neuro Clinic of Hospital Canselor Tuanku Muhriz (HCTM), Universiti Kebangsaan Malaysia (UKM) in 2020. Age of the subjects recruited in this study was between 21-60 years for both case and control groups. Categorization of case and control groups was based on the EEG reports indicating epilepsy (evidenced by diffuse generalized cerebral disturbance) and normal EEG, respectively. Pregnant ladies, patients with retardation or having previous brain injuries were excluded. This study received ethics approval from the UKM Research Ethics Committee (UKM PPI/111/8/JEP-2021-177). EEG data were recorded during interictal. None of the subjects in both the healthy and epilepsy groups were reported having PPR. The subjects diagnosed as epilepsy were of category generalized epilepsy and no reports of the presence of epileptiforms in the recorded EEG.

EEG recordings were performed in the neurology laboratory where each subject was placed in a low lighted room at normal room temperature. Nicolet-One EEG device was utilized to record EEG signals at 500 Hz sample rate based on the 10-20 system in the conditions of resting time and variable IPS frequencies. To prevent signal distortions, impedances at each electrode contact with the scalp was kept below 5 kohm. Intermittent photic stimulation specified by white light is divided in a set of 12 series of frequencies: 1 Hz, 3 Hz, 6 Hz, 8 Hz, 10 Hz, 12 Hz, 14 Hz, 16 Hz, 18 Hz, 20 Hz, 25 Hz and 30 Hz. The IPS signal radiated from a strobe light located in front of the subjects' face with the distance between 20 to 30 cm. The potential difference between electrode O1 (located in left occipital lobe) and the reference; placed on the right fronto-central region, was recorded in 10 seconds for each event. For the resting time, 10 seconds signal before the first IPS was considered the zero frequency and baseline signal. In this study, due to the condition of flickering response-coverage by a maximum of 250 milliseconds, nine IPSs (between 8 Hz to 30 Hz) are studied [25]. As 1 Hz IPS is induced once in a second whereas the response of IPS is; by maximum, 250 milliseconds equal to ¼ of second, the whole one second will be contained IPS responses (¼ second) and non-IPS responses (¾ second) as the rest. The response by inducing 3 Hz IPS with three stimuli in a second, passes the threshold as well. In order to eliminate analyzing the mixture of responses, the IPS with low frequencies were ignored. Although, 6 Hz IPS by inducing six stimuli in a second can cover the whole one second full of IPS response, regarding more confidence in analysis, the investigation was started since the 8 Hz frequency of IPS. Figure 3 depicts the detail of EEG recording of left occipital lobe where the shaded areas are presented as the study experimental events; first 10 seconds with no stimulation represents resting time (R.T) and 90 seconds for IPSs (8 Hz to 30 Hz).

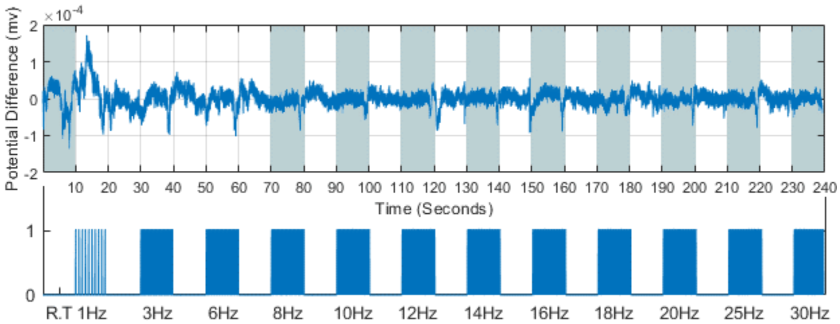


Fig. 3. Detail of EEG recording during resting time (R.T) and various IPS frequencies

Feature extraction was concentrated on frequency domain analysis to explore the amplitude of each brain frequency bandwidth. Although, the effect of IPS is not merely related to the occipital lobe in epilepsy [6], the channel O1 in primary visual cortex (the main region for processing visual information) was chosen to be analyzed using brain signal processing techniques. FFT was applied on EEG signal of each subject for the events separately and the average of magnitude referred to each bandwidth is computed to produce the average of amplitudes. By applying FFT for all EEG recordings, the waves with different range of frequency that compose the original signal are discovered. Considering the range of each frequency bandwidth; e.g., 8 to 12 Hz for Alpha waves, the average of amplitudes observed in all subjects are calculated. Figure 4 illustrates the detail of feature extraction step starting with signal acquisition from O1 in 10 seconds of recording for each experimental event. Therefore, the features were extracted from all subjects in both groups for each experimental event. In the next step, the features supplying the significant meaning between groups were selected.

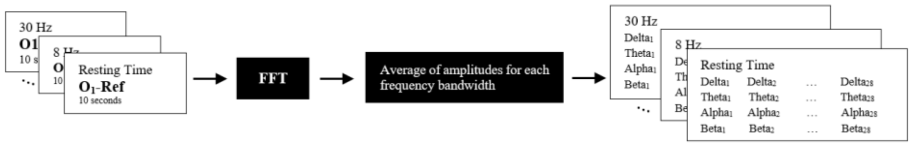


Fig. 4. Feature extraction step for each subject

Feature selection. Statistical test by independent samples t-test of $p<0.05$ (targeting 95% of hypothesis confirmation) presented a significant meaning to differentiate case and control groups in particular events were selected for the first approach. The events were summarized in resting time and 8 Hz to 30 Hz IPS where case and control groups were compared in each event separately. Analysis between two group mean differences were conducted in two approaches in this study. Figure 5a shows the detail of feature selection step for the first approach that compares the case and control subjects. Further, in the second approach, the features in resting time (R.T) were compared to the features in each IPS frequency within the individual group. Figure 5b shows the detail of feature selection step for the second approach.

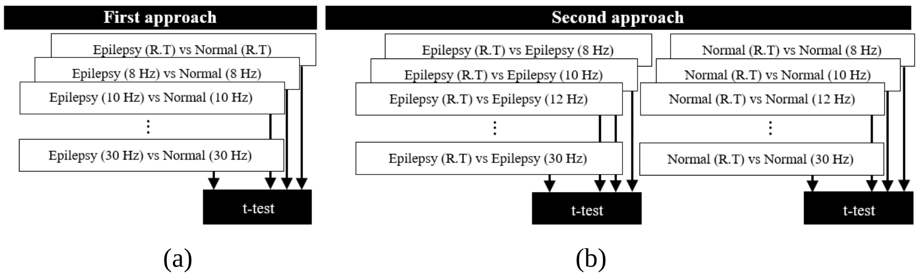


Fig. 5. Feature selection step regarding to the first approach (a) and the second approach (b)

Classification. Towards completing the first approach, besides finding the differences between groups in each IPS, a sub-question was introduced: which IPS will be the most efficient event among all IPSs? Based on the results from the first approach, the amplitude of Theta frequency was considered as the feature that can provide meaningful differences between case and control groups for all IPSs. In this study, SVM and k-NN were chosen to answer the mentioned question using internal kernels assisted by k-fold cross validation (k=10). In brief, 28 normalized amplitudes of selected frequency band for each group and IPS were assigned to the classifier, separately. The second approach aim at analysis of comparison for the normalized amplitude of selected frequency bands between the resting time and each IPS within each of the study groups. This step is important as it will determine the right classifiers for each of the SVM and k-NN.

3 Results

3.1 Feature extraction and feature selection

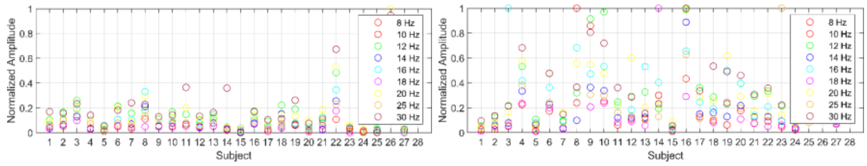
The research was concentrated on EEG analyzing on two groups of subjects with generalized epilepsy and normal EEG reports, which was considered as the case and control groups, respectively. In this regard, IPS as a visual stimulus with the focus on stimulation in a set of continuous frequencies (9 IPSs; 8 to 30 Hz) was applied. FFT was applied on the signals for both groups to recognize the average amplitude of brain frequency bandwidths in Delta, Theta, Alpha and Beta as the signal features. In this study, statistical t-test was applied on the feature selection process to discover the feature(s) of significant difference between the groups of subjects to discriminate the case from control group.

Feature selection for the first approach. Table 1 presents t-test significant difference for two approaches of study in feature selection step., The symbol "×" represents no difference whereas "✓" represents there is significant difference. In the main first column, none of the features could exhibit significant discrimination between case and control groups. However, the brain frequency features could present meaningful discriminations for majority of the IPS frequencies. Furthermore, it is observed that Theta frequency has significant differentiations between case and control groups for all IPSs. This provides a comparative common information on the best IPS frequency for discrimination feature. Figure 6 (a and b) presents how Theta frequency band behaves in the subjects of each group. A brief comparison between Figure 6a and Figure 6b shows that a higher level of Theta frequency band in the case group compared to the control group in spite of significant different behaviors in some subjects.

Feature selection for the second approach. The main second column of Table 1 illustrates the t-test significant difference for comparing R.T versus IPS for the normal and epilepsy groups. Only Alpha frequency band was the feature with the significant difference between groups for all IPS (except 8 Hz) for both study groups. Figure 7 (a and b) presents how Alpha frequency band behaves in the subjects of each group. The comparison between Figure 7a and Figure 7b results a sharp difference in confronting IPSs in the aspect of Alpha frequency band in the control group which is higher than the case group. Although the comparison between two groups in resting time is not reliable (according to the result of t-test reported in first approach column of Table 1 ($p>0.05$)), the comparison can be done between the responses of IPS revealing lower values in control group comparing to case group.

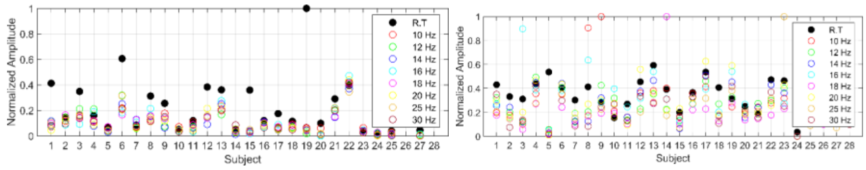
Table 1. Result of t-test for two approaches (First: normal vs epilepsy; Second: R.T vs IPSs in each group) in feature selection step

	First approach				**Second approach**							
	Normal vs Epilepsy				**Normal (R.T) vs Normal (IPS)**				**Epilepsy (R.T) vs Epilepsy (IPS)**			
	Delta	***Theta***	***Alpha***	***Beta***	***Delta***	***Theta***	***Alpha***	***Beta***	***Delta***	***Theta***	***Alpha***	***Beta***
R.T	×	×	×	×	-	-	-	-	-	-	-	-
8 Hz	×	✓	✓	×	✓	×	✓	×	×	×	×	×
10 Hz	×	✓	×	×	×	×	✓	×	×	×	✓	×
12 Hz	×	✓	✓	×	✓	×	✓	×	✓	✓	✓	✓
14 Hz	✓	✓	✓	×	×	×	✓	×	×	×	✓	×
16 Hz	×	✓	✓	×	✓	×	✓	×	×	×	✓	×
18 Hz	×	✓	✓	×	✓	×	✓	×	×	×	✓	×
20 Hz	✓	✓	×	×	×	×	✓	×	✓	✓	✓	✓
25 Hz	×	✓	×	×	×	×	✓	×	×	×	✓	×
30 Hz	✓	✓	✓	×	×	×	✓	×	✓	✓	✓	✓



(a) (b)

Fig. 6. Distribution of Theta frequency band in normal (a) and epilepsy (b) subjects for different IPS frequencies (8 to 30 Hz)



(a) (b)

Fig. 7. Distribution of Alpha frequency band in normal (a) and epilepsy (b) subjects during resting time (R.T) and different IPS frequencies (10 to 30 Hz)

3.2 Classification

Classification for the first approach. How Theta frequency band can discriminate the groups for each IPS frequency and which IPS frequency causes the most difference? The amplitudes of Theta frequency for both the case and control groups for all IPS frequencies were delivered to SVM and k-NN. Table 2 shows the accuracy of discriminations achieved by each classifier. The table shows that among all IPSs, 18 Hz produced the best accuracy of discrimination between groups with 85.7% accuracy estimated by k-NN whereas SVM produced the best at 16 Hz IPS with 75% accuracy (10% lower than k-NN). However, both classifiers claim that case and control groups behaved more uniquely at middle range of IPS frequencies (16 Hz and 18 Hz). The difference of results was due to the differences between algorithms of classifiers and their internal parameters. SVM performed constant parameters in bordering the classes under soft margin condition (C and scaling factor equal to 1). Whereas, k-NN used cubic kernel to find the neighbors in classification. In general, one of the purposes of study was to select the trustable classifier tool with the best result; here k-NN with 85.7% of accuracy, 84.6% of sensitivity and 80.0% of specificity have been chosen for the 18 Hz IPS as the one leading these differences between normal and epilepsy groups. Figure 8 illustrates the normalized amplitudes of Theta frequency band for 18 Hz IPS for all subjects for the normal and epilepsy groups.

Table 2. Accuracy of discriminations between epilepsy and normal groups by SVM and k-NN for all IPS frequencies

Classifier	8 Hz	10 Hz	12 Hz	14 Hz	16 Hz	18 Hz	20 Hz	25 Hz	30 Hz
SVM	55%	69.6%	71.4%	73.2%	75%	70.1%	67.9%	67.9%	69.6%
k-NN	71.4%	70%	63%	55.6%	75%	85.7%	67.9%	67.9%	62%

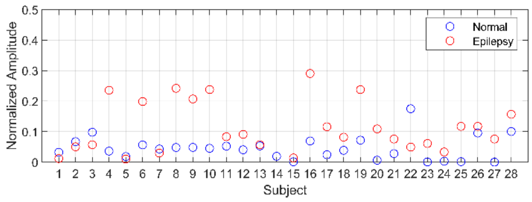


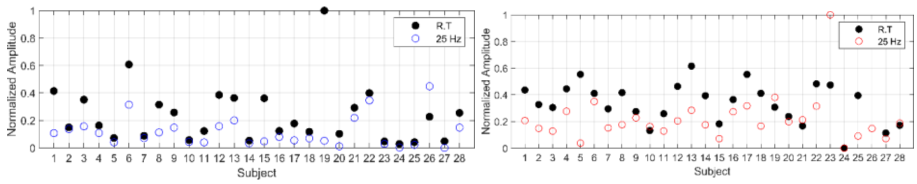
Fig. 8. Distribution of Theta frequency band in 18 Hz IPS for normal and epilepsy subjects

Classification for the second approach. Which IPS causes the most difference for the groups in the aspect of Alpha frequency band? The k-NN and SVM were applied, and the results show that 25 Hz IPS using SVM presented a better discrimination with the best performance (75% accuracy) in epilepsy group where this difference in normal group for all IPSs were fairly similar. Hence, the differences for both groups at 25 Hz IPS were evaluated. Table 3 shows the results of SVM for the control group where x-axis is the IPS frequencies between 10 Hz to 30 Hz; and y-axis shows the accuracy between 55% to 100%. A brief glance resulted that epilepsy group in total in this approach, exhibited a higher percentage of differentiation rather than normal group for the majority of IPSs. It is demonstrated that the lowest and the highest differentiations belong to the IPSs frequencies of 10 and 25 Hz with the accuracy of 64.3% and 75%, respectively. Whilst discriminations in normal is behaving approximately consistent, the epilepsy group resulted a slightly increase by rising the IPS frequency. Furthermore, for IPSs of 14, 16, 18 and 20 Hz, both groups behaved approximately similar with the accuracies between 66.1% to 69.6% (with very small difference by 3.5%). The results of k-NN represents an instability of changes between resting time and each IPS in the normal control group. The table claims that the behavior of normal group in front of different IPS frequencies is not predictable whereas the same paradigm is slightly stable in the epilepsy group. Referring to SVM respecting to a stability for both groups, it can be concluded that IPS with 25 Hz of frequency may lead to the best discrimination for comparison of IPS and resting time for the epilepsy group.

Figure 9 demonstrates normalized amplitude of Alpha frequency band in the normal group (Figure 9a) and epilepsy group (Figure 9b) for all subjects during resting time and at 25 Hz IPS. In separate comparisons between responses of different IPS frequencies and the resting time in each group show a slightly more distance in the case group compared to the control group. The similarity between groups is a higher level of Alpha in both groups during the resting time comparing to the same paradigm in 25 Hz IPS. Furthermore, comparison between IPS responses in both groups shows a higher Alpha wave during the IPS condition in the case group compared to the control group.

Table 3. Accuracy of discriminations between epilepsy and normal groups by SVM and k-NN for all IPS frequencies

Classifier	Groups	10 Hz	12 Hz	14 Hz	16 Hz	18 Hz	20 Hz	25 Hz	30 Hz
SVM	Normal	69.3%	65.9%	66.1%	66.1%	69.6%	69.0%	66.0%	69.6%
	Epilepsy	64.3%	70.0%	66.1%	69.5%	69.6%	70.2%	75.0%	70.3%
k-NN	Normal	68.0%	55.0%	67.0%	66.9%	66.7%	71.8%	55.0%	60.0%
	Epilepsy	60.0%	68.0%	63.4%	67.2%	67.0%	66.9%	70.0%	72.0%



(a) (b)

Fig. 9. Distribution of Alpha frequency during resting time (R.T) and 25 Hz IPS for normal (a) and epilepsy (b) subjects

4 Discussion

In this study, the EEG records of two groups; 28 normal and 28 generalized epilepsy with no report of PPR, during resting time and elicited by intermittent photic stimulation (IPS) were evaluated. The photic stimulation as a standard procedure during routine EEG recording was expected to produce the changes in frequency in the visual cortex. The analysis of the changes was performed on power of frequency analysis on the occipital lobe [26]. In this study, two approaches were conducted to determine: 1) first approach; the comparison between normal and epilepsy in all experimental conditions and 2) second approach; the efficacy of IPS in each group separately comparing IPS responses to the resting time.

The result indicated a nonsignificant difference comparison in resting time between the normal versus epilepsy group. However, it was found a significant difference based on different frequencies of IPS where the Theta frequency band had the best differentiation between case and control groups for 18 Hz IPS. It was observed a higher power of Theta frequency in epilepsy compared to the normal group. Due to inadequate research evidence on non-photosensitive epilepsy subjects, this study is focused on the efficacy of visual stimulation on normal subjects compared to previous studies done by other researchers. The reduction of Theta frequency in normal subjects in confronting photic stimulation and in occipital lobe was confirmed by [27]. In their study, 15 normal subjects were monitored by 16-channel EEG during resting time and 10 sec continuous light or tone stimuli. With the focus of visual stimulation, the changes of topographical cortical were evaluated according to the power of frequency bands of the left hemisphere. After the statistical analysis they reported a reduction of Theta and Alpha frequency band in front of stimulations in occipital region. In [28], the responses to long-term audio-visual stimulation (AVS) in normal subjects were assessed on six normal participants during 25 AVS program sessions, each of 20-min length. Visual stimulation was provided by rectangular red-light pulses with different frequencies. Although they did not detect a rise of lower frequencies in parieto-occipital region, they reported a significant decreased in total power, frequency band powers, spectral edge frequency and spectral entropy in parieto-occipital region of cortex (from approximately 22.5 to 19 Hz). Their significant observation referred to a rather shifted frequency range (4-10 Hz) merging the Theta-1, Theta-2 and Alpha-1 ranges. The reason why 18 Hz IPS resulted the best discrimination from this study must be further investigated in vitro.

Our result showed that the power of Alpha frequency in normal group is reduced for all IPS frequencies compared to the resting time. The result is in line with [29] where it was reported a persistence of EEG Alpha frequency entrainment under steady-state visually evoked potentials (SSVEP) in normal subjects. The visual stimulation consisted of a sinusoid light which are terminated at one of four different phases eliciting on 19s healthy study participants. The result was reported in parieto-occipital region measured by low-resolution electromagnetic tomography analysis (LORETA) in discovering the source localization of neuronal activity. The majority of hypotheses agree that induced and ongoing Alpha frequency band in EEG oscillations represent a general inhibitory mechanism revealing a perceptual and cognitive processes in brain [30]–[33]. In addition, photic stimulation can induce relaxation [34] and the increase of lower frequency bands may be correlated with the physiological findings during resting time of meditation which leads to an internal positive emotions and internalized attention [35]. Theta might deal with integrative cognition and association functions whilst alpha rhythm might be functionally correlated to several sorts of cognitive, sensory, and motor behaviors [36].

According to the present research, it seems that patients suffering from epilepsy with generalized epilepsy do not follow the same experiences as the normal subjects' responses to visual stimulation. Nevertheless, a greater number of subjects and more signal features; specially in the time domain, can be conducted for a better condition in making the result more reliable and comprehensive. For the next step, it is suggested to focus on neurophysiological aspects and discovering the probability of synaptic plasticity manner under neuronal membrane modeling during resting time as baseline and in front of specific frequency of visual stimulation which impacts on visual pathways. In this regard, designing a model of correspond to intracranial components and implementing functional networks in the accordance of anatomical connectomes based on atlas; after decoding, lead to valuable achievements in epilepsy and brain recognition. Hence, brain signal processing was used to extract the features of EEG oscillations under visual stimulation accompanied by the data from MRI; representing regional activities, can assist to simulate and model the system.

The major questions: what the epilepsy is and why the seizure occurs, are still undergoing investigation and need more comprehensive research. The study suggests deep investigations on the possible reasons how visual stimulation conducts EEG oscillations in diagnostic procedure between healthy control group and epilepsy group. For the next investigations in the aspect of neurophysiology and the manner of synaptic plasticity, it seems that designing a model of corresponded intracranial components and implementing functional networks in the accordance of anatomical connectomes based on atlas may lead to valuable achievements in epilepsy and brain recognition. In this regard, brain signal processing was adopted to extract reliable features of EEG oscillations under visual stimulation as well as MRI data representing regional activities can assist to model the system.

5 Conclusion

This study investigated how intermittent photic stimulations (IPS) influence the EEG signals of normal subjects and generalized epilepsy patients during interictal. Despite individual-based responses to IPS, we have performed two experiments based on groups of subjects and within groups evaluation via significant difference between groups feature analysis. EEG signals from the visual cortex were obtained and analyzed based on brain signal processing techniques. The results showed the most differences between normal and epilepsy groups were for IPS at 18 Hz with higher Theta frequency in the case group compared to the control group. In addition, the significant difference between resting time and IPS was belonged to IPS with 25 Hz with higher Alpha in the epilepsy group where the control group responded similarly for all IPS frequencies. In this study, the limitation in EEG dataset was retrospective data where all recordings were performed during early morning after waking up. In general, considering the concept of Theta that is originated from calmness, it seems that epilepsy group feels more calmness confronting to the IPS compared to the normal subjects. Furthermore, the consistent level of Alpha frequency in healthy control group was observed for all IPS frequency shows a homogeneous awareness and consideration lower than resting time where in epilepsy group, the paradigm in resting time is observed approximately similar for all IPS with the highest discrimination at 25 Hz IPS. Therefore, the presence of waves with low frequency bandwidth was unavoidable. In conclusion, it seems that IPS causes more composure in normal group comparing to the base line resting time. Nevertheless, in epilepsy the consideration is similar to the resting time.

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8 Authors

Tahereh Najafi is with Dept of Electrical, Electronics & Systems Engineering, Universiti Kebangsaan Malaysia, Bangi, Malaysia.

Rosmina Jaafar is with Dept of Electrical, Electronics & Systems Engineering, Universiti Kebangsaan Malaysia, Bangi, Malaysia.

Rabani Remli is with Dept of Medicine, Hospital Canselor Tuanku Muhriz, Univeristi Kebangsaan Malaysia, Cheras, Malaysia.

Wan Asyraf Wan Zaidi is with Dept of Medicine, Hospital Canselor Tuanku Muhriz, Univeristi Kebangsaan Malaysia, Cheras, Malaysia.

Kalaivani Chellappan is with Dept of Electrical, Electronics & Systems Engineering, Universiti Kebangsaan Malaysia, Bangi, Malaysia.

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