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Modeling phasmophobia (fear of ghosts) using electroencephalogram

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ABSTRACT

Extreme fears towards ghosts and entities are defined as phasmaphobia. Those diagnosed with phasmophobia symptoms should control their own fears to avoid phasmaphobia attack. In this work, we present the development of phasmophobia detection electroencephalogram database (PDED). PDED consists of an average of 45 minutes electroencephalography (EEG) recordings from eight electrodes situated on the frontal lobe of the brain area. A real-time fear assessment was conducted simultaneously with the EEG recording by the participant. Five different stimuli were used to induce fear in our experiment. 599 EEG epochs related to fear were extracted based on the timestamp recorded by each individual. Asymmetry relation ratio (ARR) techniques were used on these EEG to detect the presence of fear. The quality of long duration of EEG recording from PDED in recognizing fear was thoroughly presented based on ARR. In this study, 91.5% of fear emotion managed to be detected from these epochs. Using PDED, it is also proven that the changes of ARR reflected positive correlation towards the changes of the level of fear. Analysis using emotion recognition rate (ERR) curves indicated that, two electrodes, namely F7 and F8, were sufficient to recognized 88% of fear from the recordings.

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1. INTRODUCTION

Phasmophobia is an anxiety disorder, which involves the development of fears toward ghosts or entities at an extreme level [1]. This type of phobia occurs as a result of over exposure to ghost stories or horror films. It should be controlled, otherwise it can lead to other kinds of fears such as fear of night-time, fear of darkness or fear of sleeping alone. Neglecting treatment for this type of phobia would affect or influence the daily life of a person for years. This fear will cause one to be passive who always needs help in solving their problems, as he/she will be reluctant to be left alone [2], [3]. The ability to recognize fear automatically, is imperative to help phasmophobia patients control the level of their fears.

Phasmophobia can be recognized through cognitive, physiological, and behavioral reactions. The cognitive reactions are false perceptions of the situation, in this case, an individual belief that ghosts poses a real threat to them and they start to imagine the presence of such entity. This leads to behavioral reactions, such as wincing, crying, shouting, and shaking. There is also an emergence of avoidance behaviors such as a physical attempt to escape from a fearful situation or run away from their imaginary entity. Physiological reactions exist simultaneously with the cognitive and behavior reactions such as increased of heart rate, blood pressure, brain wave and skin conductance of the individual [4].

Recognizing emotions specifically fear using brain waves is the topic of interest in this paper. Electroencephalogram (EEG) is a signal recorded from the brain. There have been numerous studies conducted in recognizing emotion using EEG [5], [6]. The use of EEG for emotional recognition requires these signals to undergo several steps namely the pre-processing, feature extraction and finally classification.

This paper analyses the problems that exist in the process of extracting features. Generally, the extraction method can be categorized into time domain, frequency domain, and time frequency domain [7], [8]. The number of EEG signals used for each feature calculation varies, either generated from a single electrode, or combination of multiple electrodes. There are various features that have been used on EEG for emotion extraction in the time domain category. Event-related potential (ERP) [9], statistical measure [10], and higher order crossings [11] are among the time-domain characteristics that are widely used for emotional recognition. The most popular features within the context of emotional recognition using EEG are the power characteristics of different frequency bands. This feature belongs to the frequency-domain category. Based on frequency-domain category, in analysing the state of mind, the recorded EEG signals are usually decomposed into 5 different frequency ranges as tabulated in Table 1. Theta, alpha, and beta ranges are usually used in recognizing emotions [12].

Table 1. EEG frequency ranges and its representation of the state of mind

Rhythm	Frequency (Hz)	Amplitude (μV)	State of mind
Delta	0-4	20-200	Deep sleep
Theta	4-8	>20	Stress, drowsiness
Alpha	8-13	30-50	Relaxed, awareness
Beta	13-30	5-30	thinking, attention
Gamma	>30	<5	consciousness

The frontal brain area is a part of the brain which controls and influences personality, attitudes, emotions and self-awareness [13]. The difference of EEG alpha power spectrum, captured from the left and right sides of the frontal area, reflects the asymmetry of brain activity when emotion changes [14], [15]. The left frontal area is involved in the experience of positive emotions such as joy or happiness, whereas the right frontal region is involved in the experience of negative emotions such as fear or disgust [16].

A large alpha band power in the brain reflects resting or calm conditions. When certain parts of the brain become more active (due to emotional changes), the power of the alpha band reduces [17]. Thus, activity in the brain region is inversely proportional to the power of alpha. Higher alpha power from the right frontal area compared to the left represents negative emotions state and vice versa. Asymmetry relation ratio (ARR) is used to measure these differences and mathematically it can be described as (1) [18]:

$$ARR = \frac{P_{\alpha R} - P_{\alpha L}}{P_{\alpha R} + P_{\alpha L}} \tag{1}$$

where $P_{\alpha L}$ is the left alpha power and $P_{\alpha R}$ is the right alpha power. Alarcao *et al.* [5] summarize that, out of 63 literature studies conducted by her on emotion recognition, 44.6% of them involve fear. Pictures or videos have been used in most of these studies to stimulate the emotion. On top of that, only one of these studies specifically focuses on fear [19]. For the rest, various emotions have been stimulated simultaneously to a subject in an experimental session. Videos and pictures are very useful stimulants for inducing fear in a subject. However, this stimulus only exists as a result of the watching and listening reactions. There are still many forms of stimuli that have not yet been considered to generate fear. In this work, the fear will be stimulated not only through watching and listening activities, but also through odour and recitation.

Furthermore, Alarcao *et al.* [5] also reported that the duration of the video or photo being displayed to stimulate the fear is between 5 seconds and 5 minutes. As a result, the extracted features from the EEG can only detect the presence of fear, without considering its magnitude. In our study, participants were stimulated continuously until they fail to control their fear. This level is defined as the phobia threshold. Section 2 will further explain the procedures in generating our EEG database under the above conditions. The average duration of our EEG recordings is up to 45 minutes. The level of fear for each EEG recording, will be simultaneously evaluated by each participant, on a scale of 1 to 10 throughout the recording process.

To extract the unique EEG features in representing fear, asymmetry relation ratio (ARR) as in (1) will be used. ARR is thought to be relatively stable over time [20]. Although, there are studies indicating that ARR is highly dependent on the analysis method, as described in [21], many studies have shown that good classification results are attainable using ARR [13], [14], [22]. The effectiveness of the ARR has never been tested in a long EEG recording, especially involving continuous stimuli of fear. So far, ARR is capable of detecting the presence of fear. In this paper, the ARR will be used to analyse the changes of magnitude of fear. Our process of extracting EEG features to classify fear is described in section 3. Different procedures have been reported in calculating the alpha power. Niemiec and Lithgow [13] use a clear peak in the 8-13 Hz as the alpha power. The total power and relative power at alpha bands had also been used as features as in [23]. The average spectral power is the most usable methods in calculating the alpha band power [24].

Performance comparison to recognize fear between single and average spectral power is also discussed in section 3. We introduce the concept of an emotion recognition rate (ERR) curve in this work, as it has never been discussed by other researchers. The concept is important to reduce the weakness of ARR in recognizing emotion. This can be done because our database is deliberately designed to capture the presence of fear continuously by our candidates. Finally, section 4 concludes the paper.

2. METHOD

Quantifying fear is a challenge in this study due to several factors. First, fear is a subjective experience. Not everyone is afraid of the same thing at the same level. Second, fear in this study is very specific. It relates to the fear of ghosts or entities. This is the result of individual beliefs, cultural and environmental influences, and experience of an individual towards these entities. The criterion of survey and questionnaire to identify phasmophobia candidates is set based on the american psychiatric association (APA) requirement [1]. Basically, there are four levels of diagnostic test in identifying phasmophobia patients as shown in Figure 1.

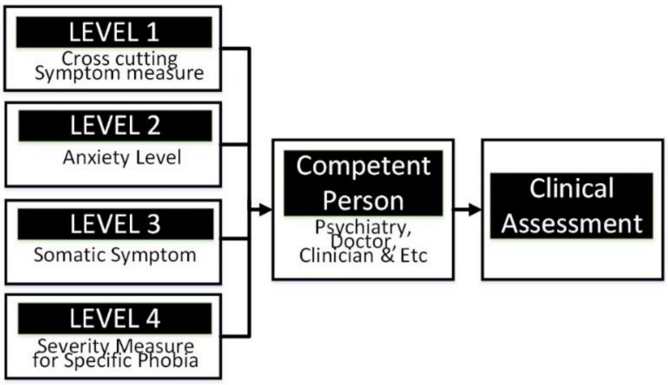

Figure 1. Clinical assessment to identify phasmophobia patients

The first step was to understand the psychological states of the candidates for the past two weeks prior to the recording session. In Figure 1, this assessment is called 'cross cutting session'. The selection criteria assessed were like their anxiety level, somatic symptoms, and repetitive thoughts or behavior. There were 23 questions that should be answered by the participant and each item was rated on a 5-point scale. All these criteria have correlations that tend to make a person feel anxious, uneasy, feels afraid and can be a possible trigger to one of the symptoms of phasmophobia. Questionnaires were then developed to score these criteria based on the manual from american psychiatry association [1]. In, this work, candidates with the average score number between three and four were chosen for the next process. This range represents a moderate and severe psychological problem in the candidates' daily life for the past two weeks.

The second step of the assessment is on the candidate level of anxiety. Anxiety test for past seven days prior to the recording session was also assessed through the questionnaire. This test consists of 22 questions and each question answered based on Likert-scale assessment [25]. Clinically, the third step of the assessment is to detect and identify the somatic symptoms such as stomach pain, back pain, shortness of breath, dizziness, feeling tired or low level of energy. A high score on these two assessments indicates most likely that the person has some psychological problems that require further attention.

The final step is to assess the candidate using specific diagnosis of the phobia. Apart from taking the characteristics provided in [5], additional features need to be taken into consideration in our list of survey and questionnaire in order to identify the criteria for fear of ghosts. In our study, the characteristics of the fear of ghosts are taken from [26], [27]. This step is designed according to the characteristics of phasmophobia symptom and to ensure their level of fear towards ghosts and entities are measurable. In our experiment, 124 questionnaires were distributed to 124 students, aged between 21 to 25 years old. Based on their results, 90 students passed the first step. From that, only 62 students passed the anxiety assessment. A total of 49 students passed the third assessment for somatic symptom. Finally, 40 students were identified with a possibility of phasmophobia symptoms. From these 40 candidates, only 10 of them agreed to undergo the next experimental process. All of them are male.

According to Alarcão and Fonseca [5], almost 50% of published works related to emotion recognition use less than 15 subjects in their studies. These are works using their own emotion database. 30% of research works on emotion uses at least 30 subjects in their studies which come from publicly available database such as DEAP [28] and SEED [29] databases. In our work, the final number of subjects who completed all our experiments was 10.

We started the experiment by briefing all candidates in a large room situated 50 meters from the recording site. All candidates were briefed about the whole process of data collection and what they need to do during the recording process as described in Figure 2. We also explained the possibilities of risks or discomforts associated with this research such as phasmophobia attack, fear of being possessed by entities, tendency to hurt themselves, urge to lose control or unconsciousness and feeling scared of entities. If they felt exposed to any of these discomforts, the counter measure that we provided was through our psychologist and our on-site Islamic medical practitioner. They would also be sent to nearby hospital for further examination. All candidates signed a consent form as a sign of understanding the consequences as voluntary candidates for this research. Each candidate was then requested to undergo the EEG recording process independently.

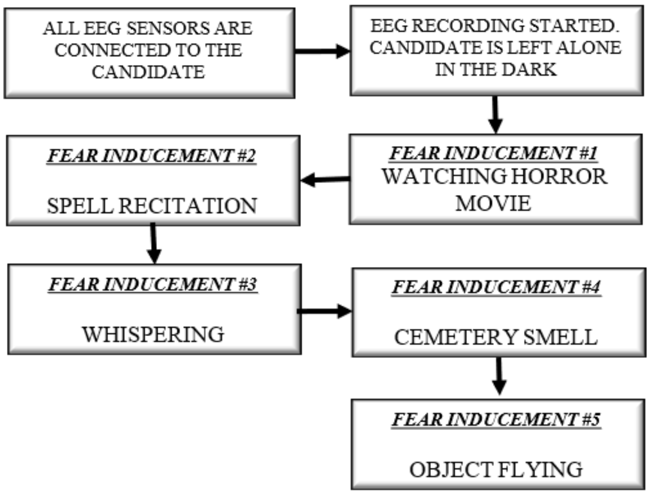

Figure 2. Fear inducement procedure

The candidate was given several minutes to relax and adapt to the test environment once all EEG electrodes were placed on them. The candidate was asked to sit still. When the candidates were in a relaxed mode, we started the EEG recording and left them alone in a dark room. A graphical user interface (GUI) was created to record the scale of fear, *Fscale* of these candidates as shown in Figure 3. Throughout their experience in this study, they would self-rate their fear between 0 and 10.

There were no activities within the first 2 minutes after they were left alone. A horror film was then automatically switched on for the duration of 15 minutes. This was to stimulate the feeling of fear of ghost for the candidates. Once the film finished, we started the process to induce them with the fear of ghosts. First, the candidate was made to believe they were reciting spells in calling ghosts. We created our own 15 sentences in Javanese as spells and the candidate was required to recite these sentences as loud as possible for a maximum of 5 minutes. While the recitation was in process, we induced a whispering sound from outside the room. This was to trigger the phasmophobia symptoms of the candidate.

We continued provoking the candidate fear by calling their name for a few times. Fear of ghosts from the presence of smell was then induced to the candidate. We burnt a Chinese joss stick which was usually present in a cemetery from outside the room. We let the smells entering the room to stimulate their fear. Finally, after 10 minutes stimulating their fear through sounds and smells, a flying object was set to appear and made visible through the room windows. This object was mechanically and electronically engineered to resemble the appearance of a ghost. It was not a must for every candidate to go through all of the above experience. If the candidates felt that they were no longer able to control their fear, they could click the STOP button on the GUI to stop the experiment. After completing the experiment, the GUI generated a data-log which recorded the activity of the candidate, time, and self-rated fear level for that activity. Samples of output from the data-log are presented in Table 2.

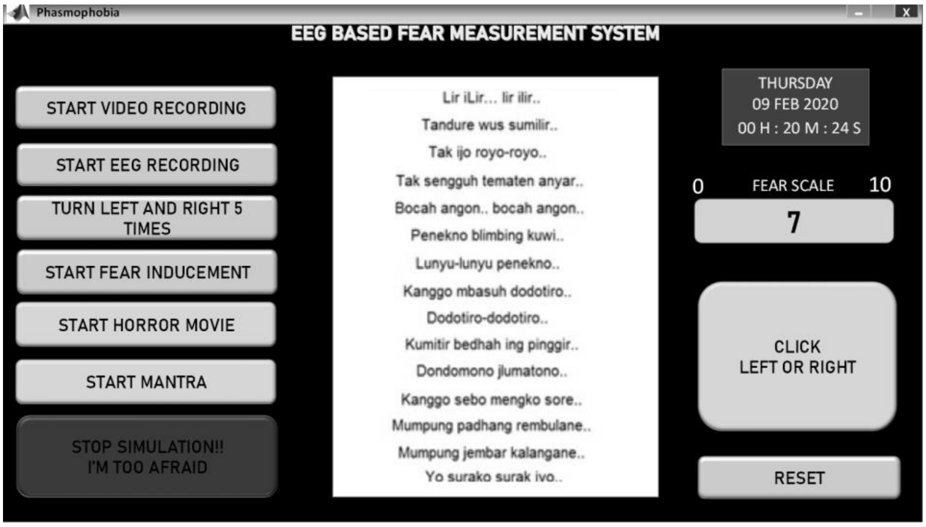

Figure 3. GUI of fear scale

Table 2. Output of the GUI to record the fear scale

Activity	Time Stamp	*Fscale*	Remarks
3	10:16:39 PM	0	Step 3: EEG start
4	10:16:57 PM	0	Step 4: Turn left and right
5	10:20:26 PM	0	Step 5: Left Alone
6	10:21:07 PM	0	Step 6: Watching Horror Movie
8	10:25:27 PM	2	
7	10:25:46 PM	1	Step 7: Fear Inducement Started
8	10:33:43 PM	3	
8	10:53:21 PM	5	
9	11:01:25 PM	5	Phobia Threshold

In Table 2, activity recorded as ’8’ indicates that the participants were in the process of rating their fear. In the GUI of Figure 3, the input for this activity is by clicking left and right of the mouse (on the right area of the GUI). In this study, 14 channels of EMOTIVE EEG headset [30] were used as the main recording devices. Fourteen EEG electrodes were connected to the scalp of each candidate based on configuration as in Figure 4. The sampling frequency for each signal was 128 Hz.

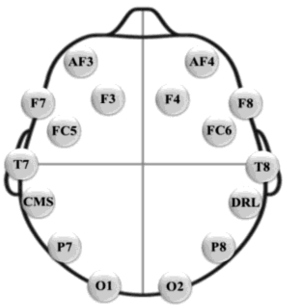

Figure 4. 14 channel EEG electrode configuration

This configuration is important to avoid signal interference from other physiological signals such as from the heart or due to muscle movement [31]. The EEG signals were subjected to a bandpass finite impulse response (FIR) filtering, to retain only the frequencies within the alpha (8-12 Hz), as these are the frequency bands that convey the emotion- related information [32]. The influence of eye movement or blinking was most dominant below 4 Hz, heart-functioning caused artefacts around 1.2 Hz, whereas muscle artefacts affected the EEG spectrum above 30 Hz. Non-physiological artefacts caused by power lines were clearly above 30 Hz (50–60 Hz). Consequently, by extracting only the alpha frequency bands from the acquired EEG recordings, the most part of the noise influence was circumvented [33].

According to the American Society of Electroencephalographic (ASE), the letter of the electrodes in Figure 4 relates to the position of the electrodes. Letters A, C, F, Fp, O, P, and T are for electrodes respectively placed at ear lobe, central lobe, frontal lobe, frontal polar, occipital lobe, parietal lobe, and temporal Lobe. As the focus of this paper is on EEG signals from the frontal area of the brain, only 8 signals data were used for our analysis. They were electrodes with the letter F namely AF3, AF4, F7, F8, F3, F4, FC5, and FC6. Figure 5 illustrates a sample output of phasmophobia detection electroencephalogram database (PDED). In this example, the EEG signals plotted came from the electrode of F3. For the purpose of illustration, we normalized the *Fscale* to the maximum and minimum value of F3.

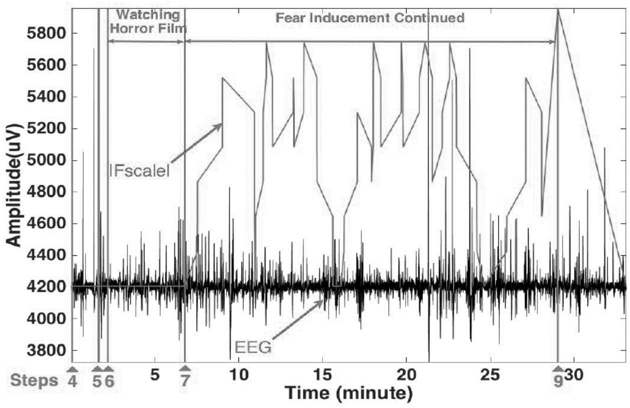

Figure 5. Raw EEG signals

3. RESULTS AND DISCUSSION

There are various analyses that can be done using PDED. In our work, we consider the concept described in section 1 is true when classifying emotions. This means that using (1), positive ARR indicates the presence of fear, vice versa. True fear recognition rate (TFRR) measures the level of accuracy, for the extracted EEG features, in representing the presence of fear. In our work, TFRR is measured in the EEG between steps 6 and 9 as shown in Figure 5. This location is selected based on the fact that the experiment was designed to induce the participants with all five stimuli as described in Figure 2 within this location. In addition to that, during this period, all participants recorded the presence of fear at different *Fscale*. The recording process is indicated by the number ’8’ in the activity column of Table 3. Five seconds of EEG were extracted every time participants recorded their *Fscale* for further processing. This was done by including 2 and 3 seconds of EEG recording, respectively before and after the recorded time stamp.

ARR for these 5-second EEGs was calculated using an (1). If the ARR value was positive, the EEG feature was classified as ’Fear’. The result of this classification was then compared to the actual emotion expressed by the participants, which was based on *Fscale*. For the moment, the value of *Fscale* was ignored. The actual emotion of the participant was categorized as ’Fear’ for *Fscale* with values not equal to 0. If both classification result and actual emotion were labelled as ’Fear’, we defined this condition as ’True Fear’. Table 3 shows the True Fear Recognition Rate for EEG recorded from 8 electrodes as described in section 2. Four (4) sets of ARR, namely F4-F5, F8-F7, AF4-AF3, and FC6-FC5 were calculated for all 6 frequencies within the alpha band. In this experiment, the number of EEG epochs that was studied was 599.

Based on the ARR value shown in Table 3, it can be seen that EEG with 10 Hz frequency component, recorded from the F8 and F7 electrodes yields the highest ARR value, compared to other frequencies in the alpha band. It can also be seen from this table, that EEGs recorded from these electrodes, regardless of their frequency, produce higher ARR values compared to those recorded from other sources. For this experiment, it can be concluded that the F8 and F7 electrodes are more likely to embed the features of ’True Fear’ in the EEG signal, if individual frequency of alpha band is considered independently.

The investigation then continued by looking at the performance of the TFRR, where the EEG power spectrum for several frequencies was being averaged. In this study, we categorized frequencies between 8 Hz and 10 Hz as lower alpha band, 9 Hz to 12 Hz as middle alpha band and 11 Hz to 13 Hz as higher alpha band. Table 4 shows the performance of TFRR when the EEG power spectrum, for lower, middle, and alpha bands, being averaged before equation, which (1) was used to calculate the ARR. The average EEG power spectrum for all alpha band frequencies was also considered.

Table 3. Percentage of true fear recognition rate (TFRR) between steps 6 and 9 using ARR on individual alpha band frequency

Frequency	F4-F3	F8-F7	AF4-AF3	FC6-FC5
8 Hz	79.13	91.82	77.63	81.80
9 Hz	75.96	92.99	73.79	81.80
10 Hz	78.96	94.32	72.45	81.80
11 Hz	78.46	92.82	71.95	81.80
12 Hz	78.63	91.32	72.79	81.80
13 Hz	73.79	94.16	67.45	81.80

Table 4. Percent of fear recognition rate between steps 6 and 9 using ARR by averaging the power spectrum of several frequencies

Frequency	F4-F3	F8-F7	AF4-AF3	FC6-FC5
Average 8-10 Hz	82.64	94.33	79.47	87.48
Average 9-12 Hz	83.30	94.99	75.79	85.64
Average 11-13 Hz	82.13	93.82	76.30	87.48
Average 8-13 Hz	84.30	95.83	83.97	91.32

The comparison of the TFRR performance between Tables 3 and 4, indicates that by averaging several frequencies within the alpha band, increased the TFRR performance, compared to using the individual spectrum to recognize the presence of fear. From Table 4, it was also observed that by averaging all alpha band power spectrums, generated better TFRR performance for all frontal area electrodes. Electrodes F8 and F7 still embedded the highest fear features within the EEG signals.

As described in section 2 and shown in Figure 5, EEG within steps 4 and 5 reflects the action of moving the head to the left and right for 5 times. The EEG within steps 5 and 6 on the other hand, reflects the action of sitting still for 1 minute. In our study, all candidates indicated the *Fscale* values of zero, throughout this period. Indirectly, it shows that they had no fear when EEG was recorded within these steps. Theoretically, the calculated ARR for each EEG epoch, within this period should show a negative value. According to [30], muscle artefacts only affect EEG with frequency components greater than 30 Hz. Eye blinking, on the contrary, is most dominant for frequencies below 4 Hz. Since we were extracting alpha rhythm from the EEG, the effects of eye blinking and muscle movements should be at a minimal. Therefore, the calculated ARR during this period only reflected the emotional features embedded in EEG.

No fear recognition rate (NFRR) is defined as accuracy rate for which the ARR value is calculated for an EEG epoch, resulting in negative values, and at the same time the value of *Fscale* expressed by the candidate is equal to zero. To calculate the NFRR, EEG within steps 4 and 6 are segmented for every 5 seconds. ARR is calculated using the (1) for each epoch. If the calculated ARR is negative and the value of *Fscale* is zero, we classify the emotion for that particular epoch as 'No Fear'. In this investigation, NFRR calculated for the four ARR sets described in section 3 is as follows: F4F3 (38.87%), F8F7 (29.97%), AF4AF3 (49.44%), and FC6FC5 (28.49%). We consider the power spectrum for all alpha band frequencies (8Hz to 13 Hz) has been averaged, for all epochs before the ARR is calculated. This result means that although F8F7 is the best combination of electrodes, which successfully accurately classifies up to 95.83% 'of True Fear', as shown in Table 4, it only recognizes 29.97% of 'No Fear' from the EEG recording.

Most research work using the ARR to detect the presence of fear fail to take into account the relation between ARR and emotions before any stimulus is induced to participants. Figure 6 shows an example of ARR distribution between steps 4 to 6 and 6 to 9. In Figure 6, note that all ARRs between steps 6 and 9 have a positive value, thus generating 100% TFRR. Between steps 4 and 6, it is observed that only 50% ARRs have negative value, which is equivalent to 50% NFRR. The accuracy of NFRR can be enhanced by subtracting the actual ARR_{Actual} with the values of k multiplies with the maximum ARR within the steps 4 and 6, ARR_{S46} as (2).

$$ARR_{New} = ARR_{Actual} - k \times max(ARR_{S46}) \quad (2)$$

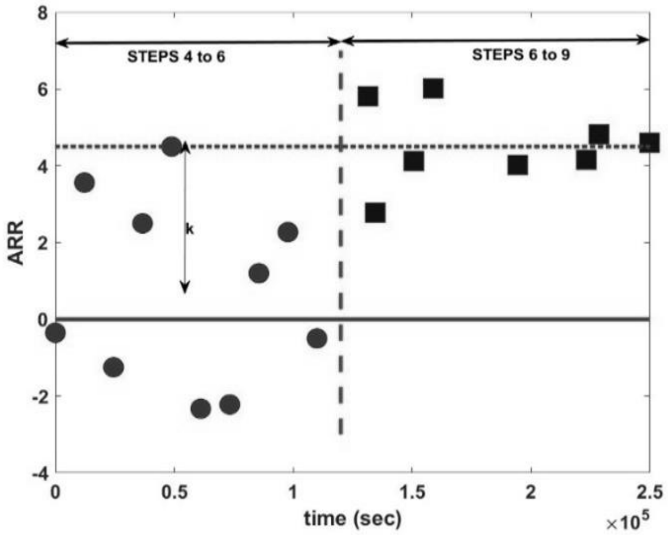

Figure 6. Example of ARR

k is set between 0 and 1. If k is set to 1, NFRR will become 100%. However, by doing this, TFRR has decreased to 40%. Tolerance between NFRR and TFRR is important in developing a Fear Recognition System. The target is to obtain the highest percentage of NFRR and TFRR at the same time. It can be achieved by plotting the emotion recognition rate (ERR) curve as shown in Figure 7. ERR is developed based on the concept of receiver operating characteristic (ROC) as explained in [34].

The ERR plot is a function of k in (2), which plots the rate of 'True Fear' on the x-axis, against the rate of 'No Fear' on the y-axis. The TFRR and NFRR of PDED for all 4 sets of electrodes described in section 2 is shown in Figure 7. We used average power spectrum values for all alpha band frequencies in calculating ARR in the (2). *k* is ranged between 0 and 1. The area under an ERR curve (AUE) was used for comparing ERR curves. The equal emotion recognition rate (EERR) is defined as the rate at which the TFRR equals the NFRR. Higher AUE and EERR values are desirable for practical systems. Table 5 shows the EERR and AUE values for the ERR curve as shown in Figure 7. As can be seen from Table 5, EEG generated from electrodes F7 and F8 generate the highest AUE and EERR. These electrodes were further used in modelling the relation between the magnitudes of *Fscale* and the ARR features.

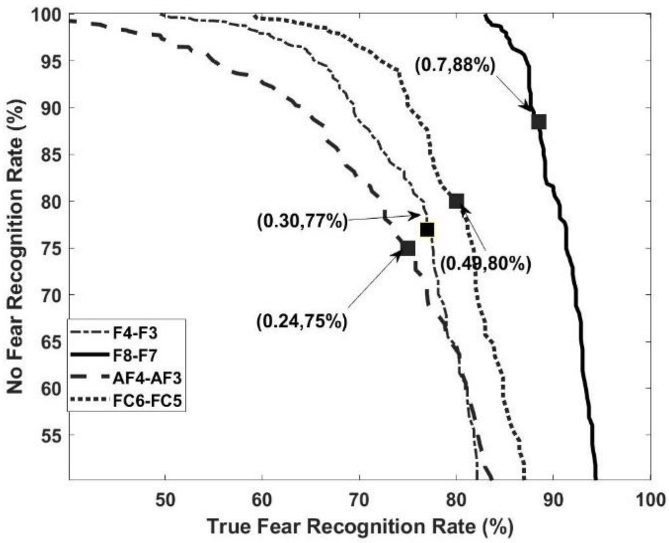

Figure 7. Emotion recognition rate (ERR) curve

Table 5. Equal emotion recognition rate and area under ERR curve

ERR	F4-F3	F8-F7	AF4-AF3	FC6-FC5
AUE	80%	92%	78%	85%
EERR	77%	88%	0.75%	80%
k	0.30	0.70	0.24	0.49

Based on our experiments described in section 2, participants were given the opportunity to express their fears, *Fscale* while their EEG was recorded. The fear quantization process was based on a scale of 0 to 10, of which 10 represented the most feared state they had ever experienced. However, the magnitude of the value expressed by a person, translated different information compared to another. *Fscale* with a value of 5 for a person, possibly equal to 2 for the other, although they were induced using the same stimulus (i.e., watching horror films). It depended on their experience. Therefore, the use of ARR features to model fears is difficult to be standardized for all subjects. Nevertheless, the outcome of our study suggests that there is a correlation, ρ between changes in magnitude of fear and ARR, which can be calculated using the following equation true fear recognition rate.

$$\rho = corr\left(\frac{\partial F_{SCALE}}{\partial t}, \frac{\partial ARR}{\partial t}\right) \tag{3}$$

$\partial F_{SCALE} / \partial t$ and $\partial ARR / \partial t$ are the first derivative value for *Fscale* and ARR respectively, during activity labelled as '8' in Table 2, that is recorded in sequence. The correlation result between these 2 variables is shown in Table 6. From this table, it is observed that the average correlation value for all participants, using (3) is 0.1952. This shows that there was a positive correlation between the changes *Fscale* and ARR. ARR value will increase if the magnitude of fear is increased.

Table 6. Correlation between magnitude of fear with ARR

Subject	Correlation	Subject	Correlation
S001	0.5	S006	-0.19
S002	0.78	S007	0.58
S003	-0.15	S008	-003
S004	0.40	S009	0.03
S005	-0.02	S010	0.06

4. CONCLUSION

This paper elaborates the process of developing a new EEG based emotion database which specifically focuses on fear. Asymmetry relation ratio (ARR) is used to detect and measure the brain activity, and is relatively compared to the magnitude of fear, *Fscale* indicated by 10 participants. 599 epochs for the duration of 5 seconds were extracted and used in our experiment. The results showed that up to 91.5% of fear emotion declared by all participants were correctly recognized using ARR. A study between 'True Fear' and 'No Fear' characteristics within an EEG recording was also presented. Emotion recognition rate (ERR) curve was also introduced to compare the system performance in recognizing fear. From our database, EEG recorded from electrodes F8 and F7 had the highest accuracy for fear detection. It is also shown in this work that the changes of *Fscale* had a positive correlation with the changes of ARR. As the magnitude of fear increased, the ARR also increased.

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