EEG-Based Emotion Assessment using Detrended Fluctuation Analysis (DFA)

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***Abstract*—Stroke patients suffer from emotional and behavioral changes. The emotion assessment of stroke patients is helpful to carry out appropriate treatment. Emotion assessment through Electroencephalogram (EEG) is reliable and can be applied to stroke patients. Fractal analysis using Detrended Fluctuation Analysis (DFA) is applied to detect the temporal correlation and the simplicity of EEG signals. Emotion contained-EEG signals of two groups of stroke patients, with left brain damage (LBD) and right brain damage (RBD), and a group of normal control (NC) were assessed using DFA in alpha, beta and gamma frequency bands. The EEG signals of the three groups show different degrees of temporal anti-correlation. Moreover, alpha and beta bands which exhibit larger brain oscillation have better performance in emotion classification than gamma band. The overall performance of DFA has achieved 92.00% classification accuracy in LBD, and 91.75% in RBD. Thus, DFA is useful in emotion assessment of stroke patients.**

***Index Terms*—Electroencephalogram (EEG); Emotion; Detrended Fluctuation Analysis (DFA); Stroke.**

I. INTRODUCTION

According to the statistic, there will be a person in the world has a stroke attack every two seconds [1]. Stroke survivors need to undergo the rehabilitation process to relearn skills and return to normal life. Meanwhile, stroke patients often suffer from emotional changes and depression following a stroke attack [2–4]. During the rehabilitation process, understanding the emotional states of stroke patients and their ability to recognize emotion helps physiologists to carry out appropriate treatment. Emotional assessment of stroke patients is made by carrying out the interview with patients, or standardized measures for mood disorder are used [5,6]. There is less engineering approach, and signal processing based method was reported for emotional assessment of stroke patients.

Recent years, researchers have been assessed emotion through Electroencephalogram (EEG) signals, they reported that EEG signals were able to classify emotional states of normal people [7,8] and has been used in classifying the emotion in Parkinson's disease patient [9]. In past studies, researchers studied the ability of emotion recognition of stroke patients by using Event-Related Potentials (ERP) components in a stroke patient with right brain damage [10], also EEG signals have been analyzed for left brain damage stroke patient in [11]. This work proposed the use of EEG signals to assess the emotion recognition of stroke patients with left brain damage (LBD), right brain damage (RBD) and normal control (NC).

This paper is organized as follows: Section I Introduction, Section II Literature Review, Section III Method, Section IV Results and Discussion, and Section V Conclusion.

II. LITERATURE REVIEW

The brain is a complex network with many different types of neurons, and the different connections between the neurons carry out functional interactions [12]. To study the complexity of the neural network, researchers have been applied fractal theory on EEG signals [13–15]. Fractal is characterized as self-similarity and scale-independent. One example that best illustrates the fractal geometry is the fern leaf, if the examination is taken in the detail of the fern leaf, the magnified detail is similar as the original shape of the fern leaf. The applications of fractal geometry in natural phenomenon, including biological sciences, were used to study the self-similarity and correlation of the phenomenon. In EEG signal processing, different fractal analysis has been applied, for example, Higuchi's Fractal dimension (FD) has been used by Klonowski [13], and the study has proven that fractal analysis is useful in EEG analysis. Furthermore, Krakovská used the power spectrum to analyze the exponential and power-law decay in EEG signals [14]. Hu Sheng et. al. studied the Hurst exponent (H) and Hölder exponent, H(t) as the scaling properties of fluctuations in the human sleep EEG signals [15].

Moreover, researchers reported that there is evidence of long-range temporal correlation (LRTC) in EEG signals by using fractal analysis [16–18], LRTC indicates that the event in the past had an effect on the future event, which implies that the neuronal dynamics are self-similar on a different time scale. Therefore, the LRTC in EEG signals infers that the interaction of the underlying neuronal population is able to operate over a broad temporal scale. The evidence of the existence of LRTC in EEG signals suggested that the oscillation of brain activity shows correlations after at least five seconds [16]. LRTC also has been used in the study of depression; the study shows there is an association between the LRTC and the severity of depression [18]. The LRTC in EEG signals can be characterized using scaling exponent, such as Hurst exponent[15,19] and detrended fluctuation analysis (DFA) [18–21]. In this paper, DFA is used to analyze the emotion-contained EEG signals of stroke patients.

Detrended Fluctuation Analysis (DFA) is a useful method to analyze the long-range dependency of a time series, the scaling exponent, α, of DFA works as an indicator for the self-affinity of the EEG signal. DFA was first proposed by Peng et. al. in analyzing the organization of DNA [22]. DFA is a modified version of root mean square analysis of a random walk and has been applied to non-stationary time series such as DNA sequences and heartbeat [22, 23]. The authors reported that DFA reveals the long-range power-law correlations in DNA sequences. Therefore, fractal analysis of non-stationary biomedical signals can be analyzed through DFA. Moreover, DFA algorithm has been reported as a useful method in the study of neuronal dynamics of EEG signals [19, 20].

The α value of DFA is defined as anti-correlation of the time series if the α value is between 0 and 0.5, α between 0.5 and 1 indicates the long-range correlation of the time series, whereas α equal to 0.5 indicates no correlation in the time series.

The scaling exponent, α of DFA can be computed as follows [1–3]:

Let $x(n)$ be a time series with length N, where n = 1, 2, 3, …., N. First, integrate the time series $x(n)$, the integrated time series, $y(k)$ is then divide into boxes of equal length, l. Then, a least square line is fit to the data in each box of length l, which represent the local trend, $y_l(k)$ in that box. Next, detrend the integrated time series $y(k)$, by subtracting the local trend, $y_l(k)$, in every box, the detrended series is $Y(k)$.

The root mean square fluctuation of this integrated and detrended time series is calculated by

$$F(l) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}[Y(k)]^2} \tag{1}$$

$F(l)$ is calculated for all window sizes, then a log-log plot is plotted for $F(l)$ *vs* l. The plot is expected to be a positive linear line, and the slope of the line is calculated as α, the scaling exponent of DFA.

III. Method

A. EEG Data

EEG database used in this study was collected from the stroke patients at Hospital Canselor Tuanku Muhriz (HCTM), Kuala Lumpur with formal approval from UKM Medical Center and Ethics committee for human research. The analysis was done on 15 subjects from each group, stroke patients with left brain damage (LBD), right brain damage (RBD) and normal control (NC), respectively. All the subjects passed the Mini-Mental State Examination (MMSE) and the Beck Depression Inventory (BDI), to exclude the subjects with dementia and psychological problems.

The stimuli used to evoke the emotions in subjects were audio-visual stimuli in the form of video clips, the source of the video clips were from International Affective Picture System (IAPS) and International Affective Digital Sound (IADS). The video clips were used to stimulate six discrete emotions, anger (A), disgust (D), fear (F), happiness (H), sadness (S), and surprise (SU). The EEG device used for data collection was a 14 channel wireless EEG Epoc Emotiv headset with sampling frequency 128 Hz, the electrode placement was the international standard 10-20 system. The experimental setup and procedures have been described in[25].

B. Preprocessing

The artifacts due to eyes blink were removed by offsetting the potential higher than 80μV and lower than -80μV from each EEG raw signal[26]. A 6th order Butterworth bandpass filter was used to filter the EEG signals with cut-off frequencies from 0.5Hz to 49Hz to extract the delta to gamma frequency band[26].

C. Feature Extraction

The preprocessed EEG signals had a length of 5000-time series data per channel. Each of the channels was segmented into six seconds length and refers as an epoch, each epoch contained 768 data. The alpha (8-13) Hz, beta (13-30) Hz and gamma (30-49) Hz frequency bands were selected for analysis. DFA was calculated from each epoch with the smallest window size as 4, and the largest window size as 76, in this work, the maximum window size is 1/10 of the epoch length[19,24], the increment of the window size is 4. Thus, there were total 19 different window sizes analyzed in each epoch.

D. Statistical Analysis

The DFA in the three groups (LBD, RBD and NC) were analyzed by using one-way ANOVA. The ANOVA test is to reject the null hypothesis that all the variances are the same in the six emotional states in the three groups, respectively. If the p-value is smaller or equal to 0.05, the null hypothesis will be rejected.

E. Classification

A Probabilistic Neural Network (PNN) classifier was used to classify the six emotional states of LBD, RBD and NC. Spread values of 0.01 to 2.00 with an increment of 0.01 were used to obtain the most suitable spread value for the probabilistic distribution function (PDF) of PNN[27,28]. The performance of the classifier in classifying the emotional states was validated by using a 10-fold cross-validation and the sensitivity of the classifier.

IV. Results and Discussion

Figures 1 to 3 show the average values of the scaling exponents, α, of the three groups (LBD, RBD and NC) in alpha, beta and gamma bands, respectively. The α values indicate that the EEG signals exhibit anti-correlation in temporal scale. The three frequency bands have a different range of average α value for all groups. The average α values of the three groups are in the range between 0.48 and 0.50 in alpha band, the average α values in the beta band are in the range of 0.18 to 0.20, whereas, the average α values of gamma band range from 0.03 to 0.04. Therefore, gamma band is the most anti-correlated frequency band since the average α values are the most near to 0. Next, the beta band is the second in the degree of anti-correlation, and the least anti-correlated frequency band is the alpha band.

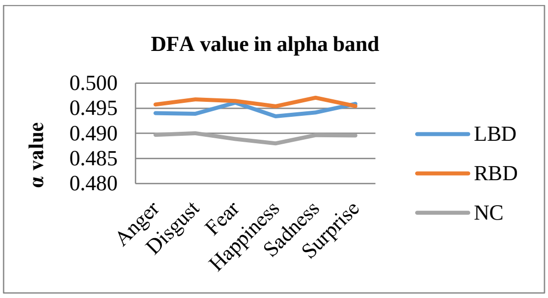

Figure 1: Average DFA scaling exponents in alpha band

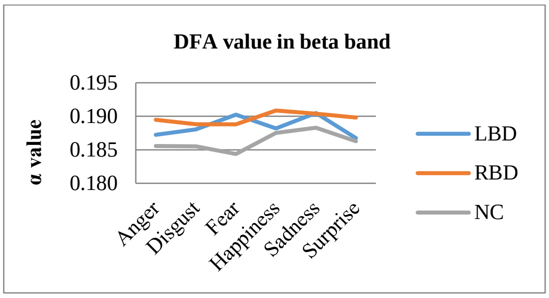

Figure 2: Average DFA scaling exponents in the beta band

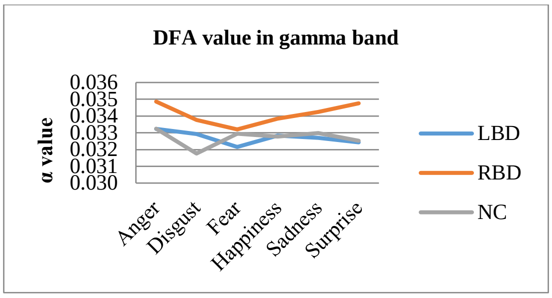

Figure 3: Average DFA scaling exponents in the gamma band

From Figure 1 and 2, the LBD and RBD have higher DFA exponent values compared to NC in all frequency bands. Also, RBD patients' EEG signals exhibit less anti-correlation (larger α) in alpha and beta bands, and the most anti-correlation (smaller α) occurred in NC in alpha and beta frequency bands. In Figure 3, RBD exhibits least anti-correlation whereas LBD and NC have a higher degree of anti-correlation compared to RBD in the gamma band.

The anti-correlation in the temporal scales of the EEG signals implies that for larger time scale, the fluctuations are smaller. In past studies, researchers have been revealed the autocorrelation in the temporal scale ($\alpha>0.5$) of depressive patients' EEG signals[18]. However, in a related study of emotional states of stroke patients has also reported the anti-correlation in EEG signals by using Hurst exponents in time-frequency domain [25], unlikely, the researchers stated that the LBD group exhibit highest degree of anti-correlation compared to RBD and NC.

The anti-correlation shows persistent in beta and gamma bands in all three groups. Although, the average DFA exponents of alpha band for all groups exhibit anti-correlation, however, some EEG channels in LBD and RBD patients, particularly in frontal region (F3, F4, F8 and AF4) have α values that are approximate to 0.5, which indicates no correlation in the temporal scale, as shown in Figures 4 to 6. In this case, no correlation implies that the activity of the underlying neuronal population does not have a pattern that can be recognized on a larger timescale.

The frontal region has been related to emotional control [29,30], people with frontal lobe deficits were observed to suffer from emotional problems, such as anxiety and depression [31]. Moreover, past studies have been revealed that stroke patients are suffering from emotional problems[2–4]. Therefore, the difference between the correlation of LBD, RBD stroke patients, and NC can be inferred as the presence of the emotional impairment in stroke patients.

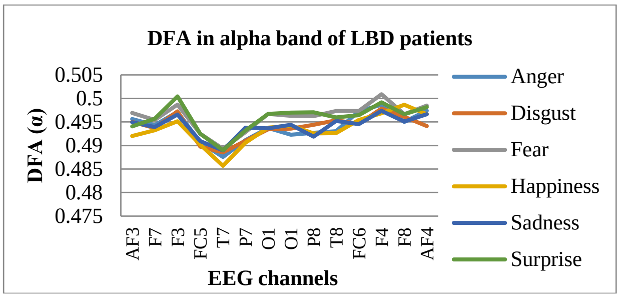

Figure 4: DFA scaling exponents for LBD in the alpha band

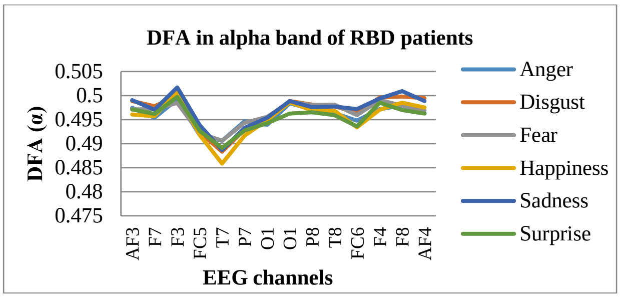

Figure 5: DFA scaling exponents for RBD in the alpha band

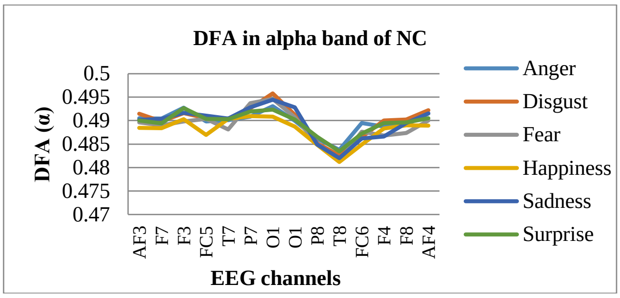

Figure 6: DFA scaling exponents for NC in the alpha band

From Table 1, the ANOVA results showed that only alpha and beta bands are statistically significant in the DFA exponents in different emotional states for all three groups (LBD, RBD, and NC), with p-values that less than 0.05. The gamma band does not show statistical significance in NC and LBD groups (the shaded values). However, gamma band is analyzed by using a PNN classifier to prevent the Type II error of ANOVA, which is the error when failing to reject a false null hypothesis.

Table 1
ANOVA Test Between Emotions, Statistically Significant at $p \leq 0.05$

Frequency band / Group	p-value		
	Alpha	Beta	Gamma
NC	<0.001	<0.001	0.214
LBD	<0.001	<0.001	0.488
RBD	<0.001	<0.001	<0.001

The PNN classification of the DFA exponents was conducted by using the three individual frequency bands (alpha, beta and gamma) and the four different combinations of the frequency bands, which were alpha and beta (Al + Be), alpha and gamma (Al + Ga), beta and gamma (Be + Ga), and also alpha, beta and gamma (Al + Be + Ga).

The sensitivity of the classifier was tabulated in Tables 2 to 4. The PNN classifier has achieved 90-95% accuracy in classifying the six emotional states. The classification results of gamma band for all three groups were above 90%.

However, the gamma band shows the lowest in classification accuracy among all frequency bands.

Previous studies have shown that alpha band and beta bands are more oscillatory [20, 21]. Hence the temporal correlation can be analyzed in the alpha and beta bands. In this work, the α values for gamma band are so small and approximate to 0. Hence, the variations of α values in gamma band are small and therefore not oscillatory as alpha and beta bands. Furthermore, although the gamma band is significant in classification, it is not statistically significant in ANOVA test.

Table 2
Performances of the Emotion Classification of LBD Patients

Frequency bands	Accuracy (%)						
	A	D	F	H	S	SU	Mean
Alpha	91.17	91.23	90.98	91.36	94.49	91.44	91.78
Beta	92.55	92.85	92.01	91.84	94.23	91.08	92.43
Gamma	92.75	90.92	91.53	92.48	90.90	90.96	91.59
Al + Be	92.42	91.55	92.34	93.47	93.94	91.66	92.56
Al + Ga	92.63	90.59	91.89	91.27	91.46	92.28	91.69
Be + Ga	92.12	90.83	91.88	94.25	91.55	91.25	91.98
Al + Be + Ga	91.73	91.59	91.32	93.39	91.29	92.46	91.96

Table 3
Performances of the Emotion Classification of RBD Patients

Frequency bands	Accuracy (%)						
	A	D	F	H	S	SU	Mean
Alpha	91.12	91.91	91.35	93.40	91.68	90.44	91.65
Beta	92.82	91.95	91.50	92.86	93.42	91.03	92.26
Gamma	93.71	90.76	90.56	91.29	91.71	90.89	91.49
Al + Be	92.06	92.72	91.30	92.50	92.39	90.56	91.92
Al + Ga	90.61	93.39	90.33	91.48	93.06	90.47	91.56
Be + Ga	92.82	91.93	90.91	91.62	92.66	90.11	91.67
Al + Be + Ga	91.11	92.84	90.32	92.10	92.75	90.89	91.67

Table 4
Performances of the Emotion Classification of NC

Frequency bands	Accuracy (%)						
	A	D	F	H	S	SU	Mean
Alpha	91.63	92.80	91.54	91.65	92.77	92.81	92.20
Beta	91.65	91.45	92.42	93.01	91.95	92.48	92.16
Gamma	94.95	90.54	91.28	90.68	91.45	91.17	91.68
Al + Be	92.94	92.44	91.06	92.45	91.39	91.27	91.93
Al + Ga	93.19	91.97	91.46	90.39	91.91	91.39	91.72
Be + Ga	92.45	92.35	91.01	92.63	95.05	90.78	92.38
Al + Be + Ga	91.89	93.71	92.09	91.85	93.11	91.58	92.37

Table 5
Overall Performances of the PNN Classifier in Classifying the Six Emotional States

Group	Average Accuracy (%)						
	A	D	F	H	S	SU	Average
LBD	92.20	91.36	91.71	92.58	92.55	91.59	92.00
RBD	92.04	92.22	90.90	92.18	92.52	90.63	91.75
NC	92.67	92.18	91.55	91.81	92.52	91.64	92.06

Table 6
Ranking of Emotional States in LBD, RBD and NC

Rank	LBD	RBD	NC
1	Happiness	Sadness	Anger
2	Sadness	Disgust	Sadness
3	Anger	Happiness	Disgust
4	Fear	Anger	Happiness
5	Surprise	Fear	Surprise
6	Disgust	Surprise	Fear

Table 5 shows the average accuracy of all the frequency bands to classify each emotional state. The group that achieved the highest average accuracy to classify the six emotions is the NC, which has 92.06% average accuracy, following by LBD, 92.00% average accuracy and RBD, 91.75% average accuracy. Meanwhile, an emotion ranking as shown in Table 6 is made based on the average accuracy of the emotional states recognized for the three groups; each group has a different ranking of the six emotions. Happiness, sadness and anger emotions are ranked as the first in LBD, RBD, and NC, respectively. The sadness emotion is ranked in the top three emotions in the three groups, which achieved first ranking in RBD, and the second ranking in LBD and NC, respectively.

V. CONCLUSION

In this work, DFA has been used as the fractal analysis in the analysis of emotional states of the EEG signals of stroke patients (LBD and RBD) and normal controls (NC). The DFA analysis of the temporal correlation in the emotions contained in EEG signals show anti-correlation in the six emotional states and the three frequency bands, alpha, beta, and gamma. The anti-correlation in the temporal scale is persistent in beta and gamma bands for all emotional states. However, some EEG channels in the frontal region show no correlation in alpha band in LBD and RBD. Since all the channels in NC are anti-correlated in alpha band, the EEG signals that show no correlation in the frontal region are inferred as the consequences of emotion deficit in stroke patients.

The frequency bands have a different range of correlation in the three groups since the variation of the α values between the six emotional states for all frequency bands is small. Hence no comparison is made between the degree of correlation of the emotional states. However, it is worth mentioning that the degree of anti-correlation between the LBD, RBD, and NC have significant differences in alpha and beta bands. In gamma band, only RBD has a remarkably different degree of anti-correlation compared to LBD and NC. Therefore, the degree of correlation given by DFA is associated with the types of the group (LBD, RBD, and NC), particularly in alpha and beta bands. In this work, the ranking of anti-correlation is NC, LBD, and then RBD.

In spite of that, the simplicity of EEG signals can be done by applying the DFA algorithm. The PNN classification rate for all frequency bands and all groups show average accuracy above 91%. Therefore, the assessment of emotional states of stroke patients can be analyzed through EEG signals.

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