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Emotional Stroop Task Recognition by Band-Localize Fractal Dimension Method

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***Abstract*: This study aims to investigate the association between bipolar dimension emotional model (based on band-localize fractal dimension (BLFD) feature) and Stroop colour-word test (STW). Twelve healthy participants are voluntarily took part in this study. Participants' emotion during STW test was measured using a wireless electroencephalogram (EEG) sensor. Three STW sessions were introduced in this study based on different stress level induced. Alpha and beta frequency band were extracted from EEG signals using six-level wavelet decomposition. Then, BLFD features was computed based on Higuchi method. Lastly, valence and arousal levels were calculated and mapped to bipolar dimension model in estimating participant emotional states. Results showed that valence level was decreased at beginning of each session and increase towards the end of the session. On the other hand, decreasing trend was observed for arousal level at each session.**

***Index Terms*: arousal, band-localized fractal dimension (BLFD), emotion, valence.**

I. INTRODUCTION

Recently, many research have been carried out on the stress assessment in emotion recognition. The main principle reason to this fact is that emotions are present in many situations where humans are involved. There give are a great impact on (i) cognitive status, (ii) decision making and behavior, and (iii) physical and mental health (e.g. headache, cardiovascular and sleep disorder). Stress is regularly characterized as the body's response to a perceived mental, emotional or physical distress [1]. Meanwhile, emotion is a psychological state related with the nervous system expedited by chemical deviations associated with moods, judgements, social responses and level of preference and annoyance. Emotion is frequently interlaced with character, mood, attitude, aura and inspiration. It becomes one of the most important communication features in human-computer interaction (HCI) area. While cooperating with human, machine should most likely perceive human emotions from both types: affective behavior and verbal expression.

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Perceiving the signs of emotions from their affective behaviors is critical task in HCI [2]–[5].

Due to emotions complexity, the most well-known hypothesis to classify emotions is based on valence-arousal-dominance (VAD) model [6]. In [7], there is an understanding that valence and arousal is already sufficient to categorize human emotion. With measured valence and arousal dimensions, emotional states and intensity can be described by merging these two dimensions by mapping onto the space of bipolar dimension.

In emotions recognition, brain activity plays the central role. Physical procedures in the human brain change with certain ideas and affective behaviors. Consequently, researchers have been utilizing signals extracted from human brain in order to have better understanding on human emotions [8]. Numbers of quantitative researches have been conducted to measure human emotions by evaluating human physiological responses. However, EEG extracted from brain signals has promising outcome in measuring emotions compared to others [7], [9], [10] .

The objective of this study is to examine the association between bipolar dimension emotional model (based on band-localize fractal dimension (BLFD) feature) and Stroop colour-word test (STW). Specifically, bipolar dimension model is mapped based on participants' valence and arousal levels which are calculated using BLFD features during participants' ongoing STW tests.

II. METHODOLOGY

Participants

12 marine cadets from Maritime Technology programme of National Defense University of Malaysia are hired. Prior to the screening, all participants are free from any pre-existing medical condition, continuous medical use, and any other non-medical substances that may affected cognitive performance. Participants experienced with STW will be noted. All participants should give their concern voluntarily before any experiment to be conducted.

Experimental Protocol

As mentioned by [11], [12], STW is a reliable protocol to cause stress to participant in laboratory situation. The experiment protocol for this study was designed based on [12]–[14] and developed using MATLAB. Fig. 1 indicates the flow of STW test intended to cause four distinct concentrations of stress in RS, S1, S2, and S3 sessions. Details on this stress-based test session are as follows:

i. *Initial Session (IS)*: This situation permits the participants to familiarize themselves with the setting of the test.

The test method was described, and instructions were provided for the STW test administration. In order to subjectively measured the state of negative emotional (depression, anxiety and stress), participants were also asked to answer the questionnaires (42 *Depression Anxiety and Stress Scale* (DASS-42)) [15][16].

ii. *Inactive Session (RS):* This session is referred as baseline session. In this part, participants were asked to relax and stay with eyes open for 2 or 3 minutes. The participants were intended to be in the most relaxing state. They rested and tuned in to Bach's Harpsichord Concerto No. 5 in F Minor BWV 1056 during this moment. Earlier RS session is labelled as START, followed by BK1 and BK2.

iii. *Session 1 (S1):* This session caused a low state of stress with a straightforward, no time-limited assignment. There are twenty printed words describing various colours. Congruent (CS) and incongruent (ICS) sections refers to printed words with similar and dissimilar ink colours respectively. Whereas incongruent section. Participants were asked to acknowledge the ink colours instead of printed words. This session is labeled as S1CS (congruent) and S1ICS (incongruent).

iv. *Session 2 (S2):* This section was intended to prompt a mild stress state with a restricted response time set to 3 minutes. The fundamental test was the same with S1, but within the time limit (3 minutes) the participants were needed to respond to the font colours of the words. The participants were expected to be more stressed than S1. This session is labelled as S2CS and S2ICS.

v. *Session 3 (S3)*: This segment caused a greater stress state than S2, with less response time (1.5 minutes). The fundamental test was the same with S1 and S2, but within the lower time limit. This session labelled as S3CS and S3ICS.

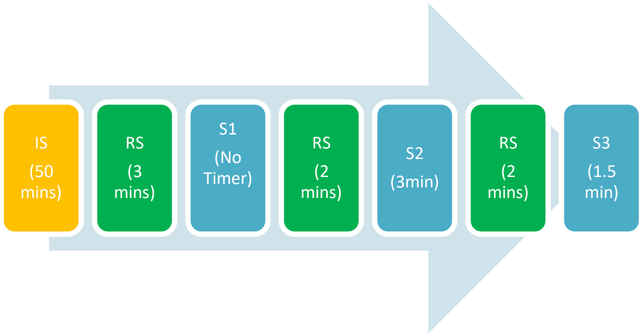


Fig. 1 STW test flow during EEG data collection

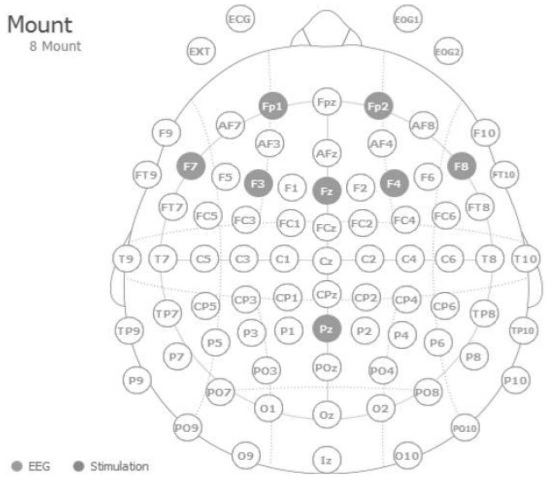


Fig. 2 ENOBIO 8 channel positioning system. Grey circle indicate channel used. The reference and ground locations used stick rode are not indicated

EEG Data

In this study, wireless EEG hardware, ENOBIO 8-channel is used. A neoprene cap with eight dry electrode is required to fix the channels in accordance to channel placement based on the 10-20 system [17]–[19]. Fig. 2 indicates channels used in these tasks are Fp1, F3, F7 (left region), Fp2, F4, F8 (right region), and Fz, and Pz (center region).

The electrical conduction of electrodes was ensured through proper installation of neoprene cap. Stick rode was used as the EEG reference electrode by placing it on the participant's bare skin mastoid. The ENOBIO equipment's features are as follows: resolution: 24 bits – 0.05μV; and sampling rate: 500 sample per second.

Wavelet-Based EEG Sub-band Decomposition

A wavelet filter is used to extract the specific EEG sub-bands as a substitute of traditional Fourier Transform since wavelet transform has the advantages in terms of multi-rate filtering, time-frequency localization, and scale-space analysis [20], [21]. Wavelet transform utilized a variable window size over the length of the signal in order to employ wavelet with any signals with different frequency [21]. Following studies by [21], the sub-band EEG (0.16-43 Hz) is decomposed into six bands using a six-level wavelet decomposition: gamma (>30Hz), beta-2 (20-30Hz), beta-1(12-20Hz), alpha (8-12Hz), theta (4-8Hz) and delta (0-4Hz).

Fractal Dimension Feature

Fractal Dimension (FD) which measure self-similarity and provide space filling information has been used in many researches [22]. There are numerous calculations of FD, however Higuchi method is used as its showed promising results in [23].

EEG Data Analysis

The method used to process EEG signals has been summarizing in Fig. 3. During the pre-processing phase, the linear trend was removed from the EEG signal without any changes to the information contents. The band-pass filter is then used to generate signals in frequencies between 0.16 Hz and 43 Hz as per gamma to delta frequency band range. Finally, six-level Daubechies order 4 (db4) wavelet transformation was applied to the filtered EEG signals.

Based on band localization, FDs were calculated throughout the intertrial interval. EEG time series were split into 50% overlapping 3s windows size. As the EEG signals were sampled at 500 sample per second, the sliding window size was 1500 point. For each window, FDs were acquired using the Higuchi technique. To assess valence and arousal levels, two channels in frontal region (F3 and F4 as indicated in Fig. (2)) are used to calculate the mean FD values of alpha and beta frequency ranges using equation (4) and (5) [24].

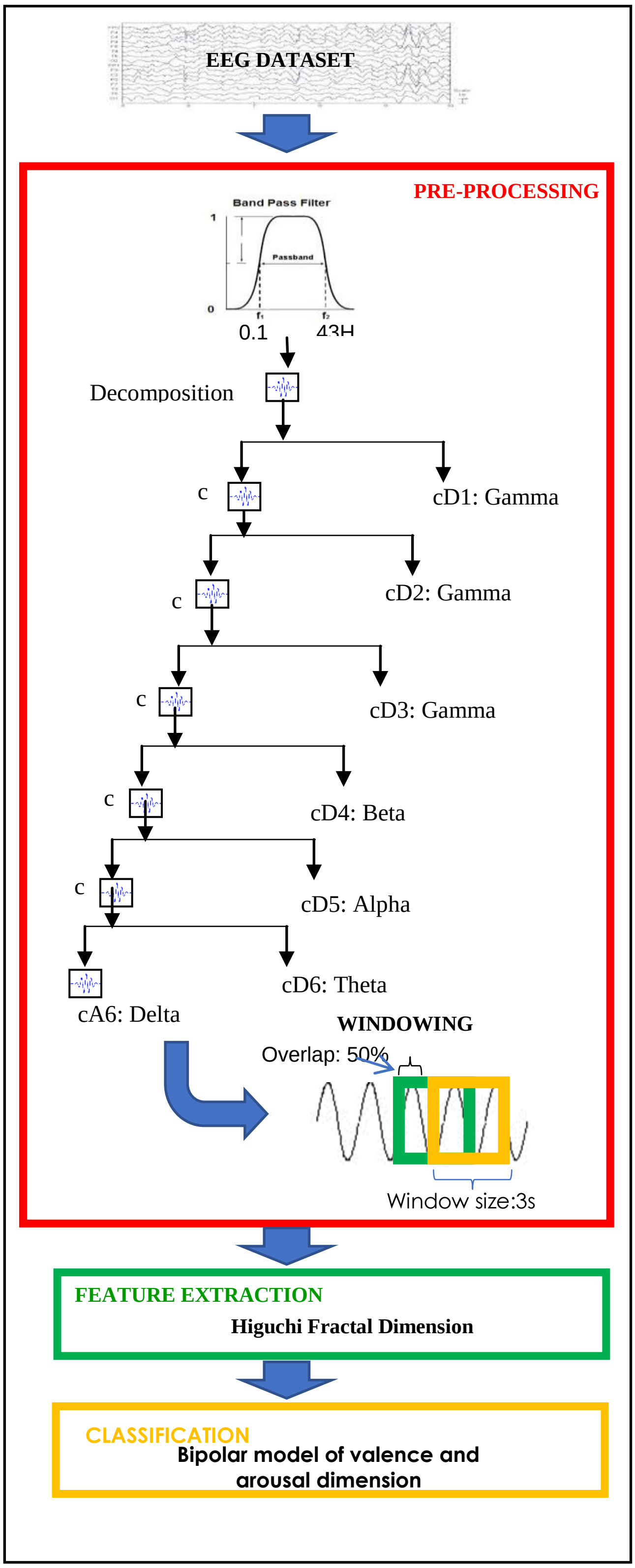


Fig. 3 Emotion quantification process block diagram where cAn -wavelet decomposition approximation coefficient level n and cDn – detail coefficient level n. n= 1,2,3,4,5, and 6.

In particularly, high activation of left frontal area region is related to positive valence, while high activation in right frontal area region demonstrates negative valence. Valence level as indicated in equation (4) shows a relative difference of two activation regions. In spite of the fact that valence levels did not have any predefined range, an increasingly positive valence esteem implies progressively more pleasant emotion with higher activation in the left region than the right region. Besides that, equation (5) demonstrates the arousal level by computing the alpha/beta ratio [24].

$$Valence = \frac{\alpha(F4)}{\beta(F4)} - \frac{\alpha(F3)}{\beta(F3)} \quad (4)$$

$$Arousal = \frac{\alpha(F3+F4)}{\beta(F3+F4)} \quad (5)$$

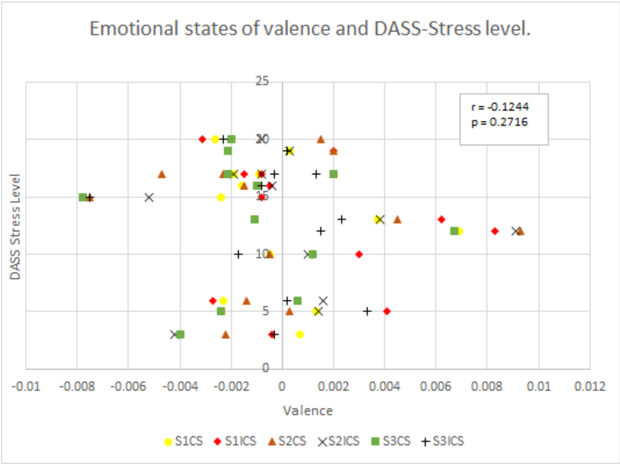
where $\alpha(n)$ and $\beta(n)$ is FD of alpha and beta frequency range obtained from n^{th} channel of EEG signals.

III. RSULTS AND DISCUSSION

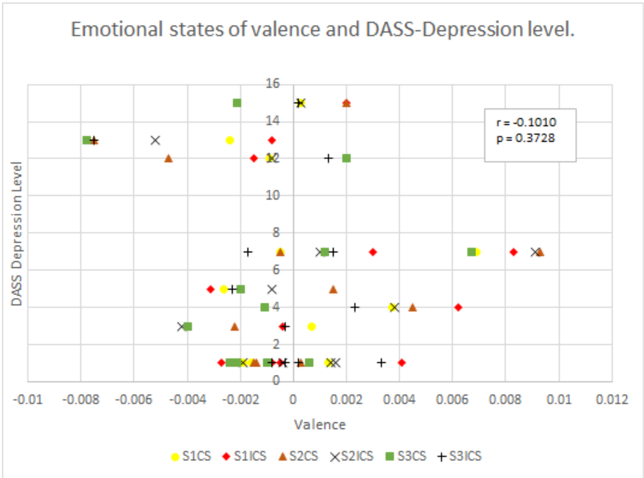
Fig. 4 shows the relationship between valence levels and DASS level scores (stress, depression and anxiety) for 12 data sets (session S1CS, S1ICS, S2CS, S2ICS, S3CS and S3ICS). Pearson product-moment are used to calculate the *r* value. The *r* and *p* values are determined between valence level and DASS scores (stress, depression and anxiety). No significant correlation is found between DASS scores and valence levels (stress: r = -0.1244; p>0.05, depression: r = -0.1010; p>0.05, and anxiety: r = 0.0072; p>0.05). A higher valence level shows more positive and pleasant emotions (e.g., joy, excitement, pleasure, or fulfillment) whereas negative and unpleasant feelings (stress, anxiety, or depression) express when DASS score is higher. This indicates that, there is no correlation exhibits the STW emotion session result which did not affected by participant's feeling/emotion before the test. Therefore, STW is practically suitable for emotional state under control environment.

In view of estimated emotional states of participants using EEG, the authors did detailed examination on how participants' emotions change according to induce stress level. Fig. 5 summarizes the changes of nine sessions level for different stress level induced (S1CS, S1ICS, S2CS, S2ICS, S3CS, S3ICS, START, BK1, and BK2) of valence and arousal levels on average. Fig. 6 indicates the emotional states under various stress level induced during STW session mapped on bipolar dimension emotion model.

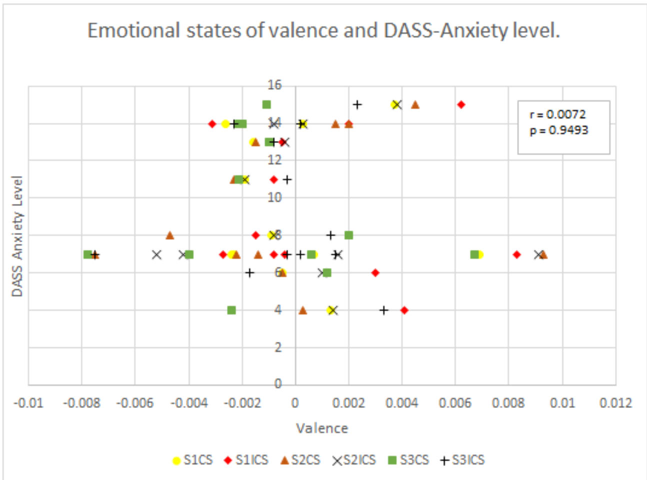
Participants experienced less stressful session: START, BK1, BK2, S1CS, S1ICS and S2ICS , indicate more positive emotions compare to with participants under more stressful circumstances (e.g. session S1CS, S2CS, S3CS, S3ICS). Valence level was found to be decreased at the beginning of each session and increased towards the end of the session. Otherwise, decreasing trend is observed at each session for arousal level. Such outcomes confirmed numerous past hypothetical and observational that measure the effect of working hazards on emotions [25], [26].



(a)



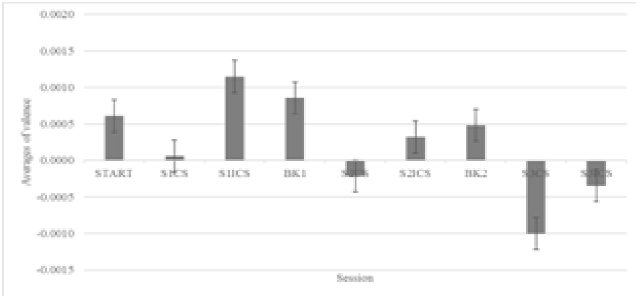
(b)



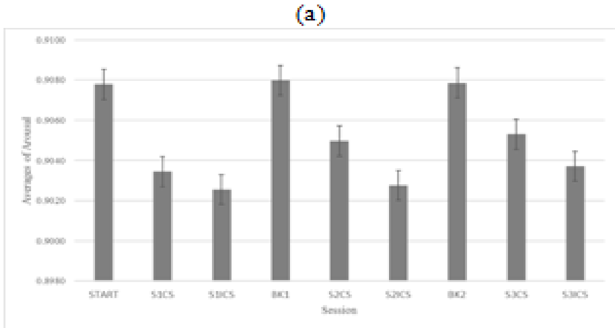
(c)

Fig. 4 Emotional states of valence and DASS level scores for (a) stress level, (b) depression level and (c) anxiety level

Among two dimension of emotions, participants' valence levels tend to be influenced by the level of stress induced (Fig. 5(a)). START, BK1, BK2, S1CS, S1ICS and S2ICS show positive valences [mean = 0.0006, 0.0009, 0.0005, 0.0001, 0.0012, 0.0003 with standard deviation (SD) =0.0030, 0.0035, 0.0029, 0.0028, 0.0036, 0.0037], whereas those induced stress such as S2CS (mean = -0.0002 with SD = 0.0043), S3CS (mean = -0.0010 with SD = 0.0035), and S3ICS (mean = -0.0003 with SD = 0.0028) show negative valences. The highest positive valence levels are found when participant performed no time-limited assignment on session S1ICS (mean = 0.0012 with SD = 0.0036). It appears, therefore, that such positive valences are connected to positive emotions (Fig. 6) and coherently.



(a)



(b)

Fig. 5 Average of participants' emotion during STW in various sessions (a) valence and (b) arousal

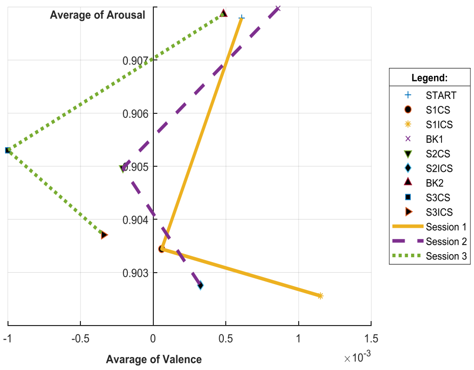


Fig. 6 Average of participants' bipolar dimension of emotions while doing STW

This study displayed the ability to estimate and understand the emotional changes of participants during STW. No significant correlations between valence levels and DASS scores demonstrated in Fig. 4. Furthermore, Fig. 6 shows changes of emotions as per level of stress induced increased. Particularly, a participant's positive valence level led to positive emotions under a less distressing circumstance (e.g. START, BK1, BK2 and S1ICS). It is also clearly indicated in Fig. 6 that given new test (e.g. S1CS) and limited time test (e.g. S2CS, S2ICS, S3CS, or S3ICS) are likely to make participants stressful with negative valences.

The explanation behind a positive valence level for S1ICS and S2ICS should be analysed further because it stays unclear whether a participant feel relax or stress using other physiological markers such as cortisol, heart rate or electrocardiogram.

IV. CONCLUSION

This study has successfully explored the possibility of measuring participant's emotions during STW based on two dimensions of emotions (i.e. valence and arousal levels) using a wireless EEG sensor. The outcomes confirmed that participants' emotions can be dependably estimated, especially valence levels, which remain significant to evaluate participants' emotional states, through a comparison with questionnaire (i.e. DASS). The outcome also proved that participants' feeling is inline when stress element is induced during test.

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