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Stress classification based on human electromagnetic radiation analysis

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ABSTRACT

Stress is a feeling of emotional or physical tension due to events that makes one feel frustrated, angry or nervous. It is a situation that trigger biological response when a person encounters a threat or challenge. This paper discussed stress classification based on human electromagnetic radiation (EMR). EMR frequency are captured at seven major chakra points and being analyzed using multivariate analysis of variance (MANOVA) to identify the significance points for the classification. Locally weighted learning (LWL) algorithm is used to classify the collected data. The results show stress classification using EMR based on third eye and throat chakra points obtained accuracy of more than 60%.

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1. INTRODUCTION

Stress is defined as a threatened condition to the human body system stability. Human body reaction towards stress is known as adaptive process which involves physiological, biochemical and cognitive behavioral responses to gain body system stability [1]. Adaptive ability in dealing with stress will affect the risk of disease. Stress is a condition in which a person fails to adapt to the right conditions [2]. Stressful events are inevitable in life and need to overcome obstacles as a result of success. A person has the ability to control what they perceive as stress and how to respond to it. Stress response is the body's proactive step in adapting to a situation to encourage survival or motivate success, and can also be catastrophic when the body's response to stress is inappropriate. For instant, when a person experiences excessive situations or recurrent negative trauma, it can cause excessive stress levels and result in an inappropriate stress response that will prolong cortisol secretion [3], [4]. Stress has been a major concern in the current situations as chronic stress can leads to health issues such as heart disease, depression and anxiety. There are several factors that can trigger stress which includes major life changes, financial problems, and work. Many techniques have been used to assess stress. One of the current stress assessment is a lengthy process where patients need to answer multiple sets of questionnaires to be diagnose with stress [5], [6]. Several attempts also have been proposed on assessment and recognition of stress included using electrophysiosignal analysis

[7], [8]. Therefore, this study proposed an alternative stress pre-assessment using human electromagnetic radiation (EMR) analysis.

Several evidences have shown the existence of energy field in the form of electric, magnetic, optical and acoustic emitted from and contained within the human body theoretically and experimentally [9]. Human energy field is defined as an extremely weak electromagnetic (EM) field but measurable EM that are formed from a collection of electromagnetic waves [10]. EM is produced around the human body due to the movement or rotation of particles. Cells, tissues and organs assemble molecules and each molecular interaction in the human body radiate unique energy spectrum. This spectrum is the EM radiation for each respective molecule [11], [12].

Alternative medicine philosophy such as chakra has practiced healing through energy field. It is mentioned that one's wellbeing is based on body energy balance and energy centered while any blockage or imbalance will affect the person's health condition. Chakra is derived from a Sanskrit word meaning 'wheel'. There are seven main chakras located from the perineum in the lower pelvis to the top of the head [13]. Each of these chakra points are associated with organs. When a person has an unresolved stress, this stress will cause disturbance to the body energy field which can contribute to physical illness. As the focus of this study is about stress, thus the chakra points that can be influenced by stress will be further discussed. There are several chakra points that are related to stress which are crown, third-eye, throat, solar plexus and root. Crown chakra is located at the top central of the skull. It is related to pineal gland which produces melatonin hormones for calming. Decreased melatonin production can cause anxiety or stress. Third eye chakra is located on the forehead between the eyebrows. This chakra externalizes the pineal gland thus treatment related to hormonal imbalance is done through this chakra as it governs lower brains, central nervous system, left eyes, ears and nose. Blockage of this chakra can lead to stress and anxiety [14]. Throat chakra is located in the throat to the base of the neck and collar bones. It is associated with communication and expression abilities. Weaken of this chakra can result to introvert behavior. Neck muscle tension due to stress is treated using acupuncture at this point. While throat is related to communication, solar plexus is associate to emotion which controls fear and anxiety. Thus, stress condition will inevitably influence the solar plexus chakra. It is located under the rib cage in the same area of diaphragm [15]. Root or base chakra is located at the base of the spine which is the chakra point that are closest to the earth. It responsible of anchoring the body on the physical plane and provide channel to express oneself. It is associated with adrenal medulla and cortex which produces adrenaline and cortisone. Blockage of this chakra will cause anxiety as the person is no longer grounded and reduced the gland secretion [14]. There were five chakra points that are relevant to stress, however the frequency of human EMR is captured at seven chakra points for this study. Further data analysis based on the frequency of human EMR is performed to confirm the points closely related to stress.

Previous study based on EMR frequencies analysis on gender classification shows that gender can be distinguished using k-nearest neighbour (kNN) classification method [16]. There are 13 out of 23 points that are significant to differentiate gender. Male and female have different distribution of frequency radiations. Males are observed to have higher range of frequencies on both left and right side of the body compare to females [17]. Several studies on human EMR also demonstrates significant result in classifying body segment on upper body, torso, arm and lower body [18], and on left, right and chakra [19]. In addition, studies shown that EMR can be classified based on the person's health condition [20], [21]. Significant results have been shown for down-syndrome and non-down syndrome person [20] and for stroke patients and to non-stroke participants, which support the assumption of human conditions can affect human EMR [21].

A recent comparative study shows that kNN classifier gives the lowest accuracy when comparing with J48, Bayes Net and locally weighted learning (LWL) algorithm in predicting breast cancer survival rate despite the high performance of kNN in previous studies. The LWL algorithm produces highest accuracy with 66.2% while kNN only able to predict at 56.1% accuracy [22]. The LWL performance also surpass kNN in identifying defective software modules using imbalanced dataset with 92.23% accuracy when validated with 10-fold cross validation and 91.08% accuracy when tested with percentage split of 66%. The result also has been validated using paired t-test with 99% confidence level [23]. Thus in this study, LWL algorithm will be used to classify the stress.

2. METHODOLOGY

The proposed study involved four steps which are data acquisition, statistical analysis for pre-processing, classification and validation. Further details about these steps are explained in the next subsections.

2.1. Sampling

The subjects for this study are students from Universiti Teknologi Malaysia, Kuala Lumpur. There are forty (40) volunteer students consist of twenty-nine (29) males and eleven (11) females are involves in this study. The stress is induced through virtual reality (VR) technology [24], [25]. The EMR frequencies are collected two (2) times, i.e before the stress is induced (before VR session) and after the stress is induced (after VR session). During data collection, the measurement room temperature is set constant at 24ºC and the data collection session is limited to four sessions per day. Session 1 is from 9.00am to 10.00am, session 2 is from 10.30am to 11.30am, session 3 is from 2.00pm to 3.00pm and session 4 is from 3.30pm to 4.30pm.

2.2. EMR data collection

The EMR data is collected at seven points using body radiation wave detector which are the crown, third eye, throat, heart, solar plexus, sacral and root chakra points. The points' label and location of each chakra points are described in Table 1. The EMR data acquisition is performed as shown in Figure 1. The EMR readings are taken five times at each point. The average EMR reading for each chakra points are calculated before further analysis.

Table 1. Location of chakra points

Chakra Points	Label	Location
Crown	CA	Top of the head
Third Eye	CB	Forehead between the eyes
Throat	CC	Throat
Heart	CD	Centre of chest just above the heart
Solar Plexus	CE	Upper abdomen in the stomach area
Sacral	CF	Lower abdomen, about two inches below the navel
Root	CG	Base of spine in tailbone area

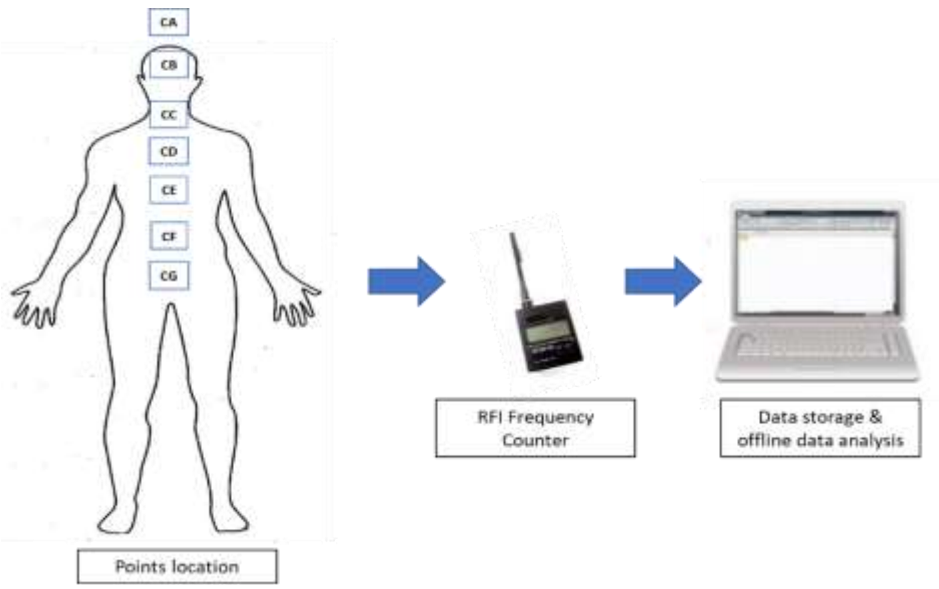

Figure 1. EMR data acquisition

2.3. Statistical analysis

The collected EMR data is analyzed using multivariate analysis of variance (MANOVA) in SPSS Statistics software version 23 to find significant points for the classification of stress state. MANOVA is a generalization of the general linear model of statistical analysis to situations where there are multiple dependent measures. In this study, the independent measures are VR stress session (before and after the stress is induced) and the dependent measures are EMR readings on chakra points of CA to CG. The analysis results in the F-ratio statistic is calculated for the EMR readings to indicate whether different values of before and after VR stress session have statistically significant effect on the EMR readings on chakra points. MANOVA are based on F-test, the larger F value and the smaller *p*-value (less than 0.05 for the sig. value). Hence, the F value and P value is evaluated to identify which points are significant in identifying the stress.

2.4. Data classification

The datasets with significant attributes are classified using waikato environment for knowledge analysis (WEKA) software tool by utilizing the locally weighted learning (LWL) classifier. LWL classifier is one of the lazy learner classifiers. Lazy learners are advantageous when performing prediction using single training sets because only the immediate sections of the instance space are occupied by objects to be classified will be modeled. It can improve prediction accuracy by allowing the system to focus on deriving possible decision for exact points of the instance space for prediction. LWL refers to supervised learning of continuous functions which are in the context of kernel regression [26]. LWL forms lazy model around a point of interest whereby only training data that is local to that point is used during classification. LWL can be observed as approximation method function [27]. It is formulated as:

$$F(x_q) = w_0 + w_1 a_1(x_q) + \cdots + w_n a_n(x_q) \tag{1}$$

Where $a_i(x_q)$ is the i^{th} attributes of point x_q, w_i is the coefficient for each $a_i(x)$ and $F(x)$ is the target function determined by $a_i(x)$ and w_i. The lazy model is used to fit nearby data points by defining the error criterion as expressed in (2):

$$E(x_q) = \frac{1}{2}\sum_{x\in D}\left(F(x) - f(x)\right)^2 K(\frac{d(x_q,x)}{\beta}) \tag{2}$$

Where x_q is the query point, the data point set containing k-nearest data point. K is the kernel function to calculate weight for each data point to the distance. While $d(x_q, x)$ is the distance between query point x_q to each data point x. The favorable approximation for the function output $F(x)$ can be obtained by determining the w_i. Gradient descent method is used to get the best estimation of w_i with minimal error criterion (x_q) . The training criterion is formulated as:

$$\Delta w_i = \eta \sum_{x\in D} K(\frac{d(x_q,x)}{\beta})(F(x) - f(x))a_i(x) \tag{3}$$

Where η is the learning rate and β is the bandwidth. The new weight is obtained through as (4):

$$w_i = w_i + \Delta w_i \tag{4}$$

2.5. Data validation

The classification training set is validated using k-fold cross validation. Cross validation is used to evaluate the accuracy of the classifier by repeating the classification process based on define numbers of k. The initial dataset will be randomly partition into k mutually exclusive or also known as folds, $D_1, D_2, ⁝⁝⁝, D_k$, each of approximately equal size. The training and testing is executed for k times. For each iteration i, partition D_i will be used as test set while the remaining partitions are used to train the model. The accuracy estimate is based on the overall number of correct classifications from k iterations and divided by total number of tuples in the initial data [28].

The classification evaluation are measured by true positive (TP) which refer to positive tuples that were correctly labeled by the classifier, true negative (TN) which is the negative tuples that were correctly labeled by the classifier, false positive (FP) are the negative tuples that were incorrectly classified and false negative (FN) are the positive tuples that were incorrecly labeled by the classifier.

3. RESULTS

Table 2 shows the result of MANOVA analysis for the overall data. The results demonstrate that throat chakra is the most significant to differentiate stress state as the sig. or p-value is less than 0.05, then followed by third eye and solar plexus chakra. The overall classification results by each chakra points are tabulated in Table 3. The third eye chakra has the highest accuracy with 65% correctly classified and 90% TP Rate for classification of before VR session and 40% TP Rate for after VR session. The second highest correctly classified accuracy is the throat chakra with 53.80% and followed by root chakra with 52.50%.

The overall classification results by combination of multiple chakra points are displayed in Table 4. Combination of chakra points are based on significant points found in the statistical analysis. The combination of third eye (CB) and throat chakra (CC) produce a highest accuracy of classification up to 66.25% and 90% of TP rate for before VR session. The second highest correctly classified accuracy is followed by combination of crown (CA), third eye (CB), throat (CC), sacral (CF) and root (CG) with 65% accuracy.

Table 2. MANOVA analysis for overall data

Chakra	Points	F	Sig. (p-value)
Crown	CA	1.839	0.179
Third Eye	CB	3.883	0.052
Throat	CC	6.881	0.011
Heart	CD	2.007	0.161
Solar Plexus	CE	3.586	0.062
Sacral	CF	1.684	0.198
Root	CG	1.414	0.238

Table 3. Classification of chakra points

Chakra	Points	Correctly Classified	Incorrectly Classified	TP Rate (After VR session)	TP Rate (Before VR session)
Crown	CA	50.00	50.00	0.300	0.700
Third Eye	CB	65.00	35.00	0.400	0.900
Throat	CC	53.80	46.20	0.200	0.900
Heart	CD	42.50	58.50	0.200	0.600
Solar Plexus	CE	43.80	56.20	0.300	0.400
Sacral	CF	46.30	54.70	0.400	0.600
Root	CG	52.50	48.50	0.500	0.500

Table 4. Classification of combination chakra points

CA	CB	CC	CD	CE	CF	CG	Correctly Classified	Incorrectly Classified	TP Rate (After VR session)	TP Rate (Before VR session)
√	√	√	√	√	√	√	63.75	36.25	0.400	0.875
√	√	√	-	√	√	√	63.75	36.25	0.400	0.875
√	√	√	-	-	√	√	65.00	35.00	0.400	0.900
√	√	√	-	-	-	√	62.25	37.75	0.375	0.850
-	√	√	-	-	-	√	62.50	37.50	0.375	0.875
-	√	√	-	-	-	-	66.25	33.75	0.425	0.900

3.1. EMR stress data

The result of MANOVA analysis for EMR stress subject's shows no significant difference between before and after VR stress session. The chakra points that are close to significant are solar plexus, throat, heart, third eye and sacral as shown in Table 5. The classification result for stress subject's is shown in Table 6. The results indicate throat chakra has the highest classification accuracy of 63.64% with 100% TP rate for before VR stress session. The next highest accuracy is sacral chakra with 59.09% and solar plexus chakra with 54.55% accuracy.

In Table 7, the combination of throat (CC), solar plexus (CE) and sacral (CF), and combination of throat (CC) and sacral chakra (CF) produces a highest accuracy of correctly classified up to 59.09%. The combination of throat and sacral chakra yields a highest TP rate up to 90.9% for classification before VR session. Meanwhile, combination of throat, solar plexus and sacral chakra produces slightly lower TP rate at 81.8%. This finding is consistent with previous studies showing the relation of several chakra points to stress [19].

Table 5. MANOVA analysis for stress subjects

Chakra	Points	F	Sig. (p-value)
Crown	CA	0.565	0.461
Third Eye	CB	1.931	0.180
Throat	CC	2.475	0.131
Heart	CD	2.048	0.168
Solar Plexus	CE	4.147	0.055
Sacral	CF	1.655	0.213
Root	CG	0.64	0.433

Table 6. Stress subjects classification by chakra points

Chakra	Points	Correctly Classified	Incorrectly Classified	TP Rate (After VR session)	TP Rate (Before VR session)
Crown	CA	40.91	59.09	0.273	0.545
Third Eye	CB	45.45	54.55	0.545	0.364
Throat	CC	63.64	36.36	0.273	1.00
Heart	CD	50.00	50.00	0.273	0.727
Solar Plexus	CE	54.55	45.45	0.364	0.727
Sacral	CF	59.09	40.91	0.364	0.818
Root	CG	50.00	50.00	0.636	0.364

Table 7. Stress subjects classification by combination of chakra points

CA	CB	CC	CD	CE	CF	CG	Correctly Classified	Incorrectly Classified	TP Rate (After VR session)	TP Rate (Before VR session)
√	√	√	√	√	√	√	36.36	63.64	0.273	0.455
-	√	√	√	√	√	√	40.91	59.09	0.273	0.545
-	-	√	√	√	√	√	40.91	59.09	0.273	0.545
-	-	√	-	√	√	√	50.00	50.00	0.273	0.727
-	-	√	-	√	√	-	59.09	40.91	0.364	0.818
-	-	√	-	-	√	-	59.09	40.91	0.273	0.909

3.2. EMR result based on subjects' feedback

Based on the subjects' feedback on stress after the VR stress session experiment, majority of the subjects shows doesn't feel stress. Figure 2 illustrates the finding. There is only 19% of the male subjects and 43% of female subjects were experienced stress after VR stress session, giving a total of 11 subjects out of 40 subjects. From the findings, it demonstrates gender differences on stress experiences in which female more susceptible of developing stress when exposed to physiological stress as compared to male. This finding is in line to previous studies [6], [8]. Studies also shows that females have slower rate of adapting to virtual reality environment compared to the males, indicating that VR or any type of stressor will give higher impact in females with compared to males [29], [30].

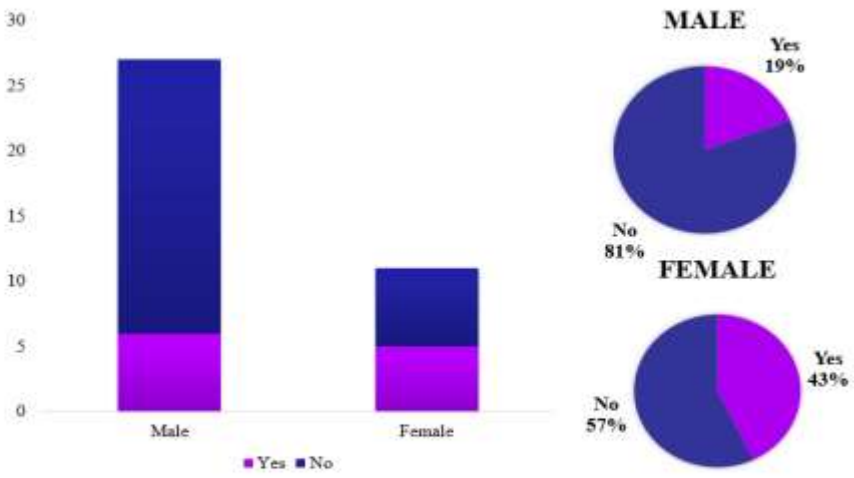

Figure 2. Post VR experience feedback on stress

4. CONCLUSION

Stress has been a major concern in the current situations as chronic stress can leads to health issues such as heart disease, depression and anxiety. This paper discussed stress classification based on human electromagnetic radiation (EMR) analysis. There are twenty-nine males and eleven female's student involved in this study. The human EMR data are analyse using statistical analysis of MANOVA and classified using LWL algorithm. Based on the overall EMR dataset, the finding shows that throat is the most significant point and followed by third eye. The result shows that the classification accuracy of this combinations is more than 60% accuracy. This finding in line with the previous studies indicating the relation of several chakra points to stress. However, since the number of subjects are unbalanced with the majority of the subjects are males, and based on the subjects' feedback on stress after the VR stress session, most of male subject's did not feel stressed while using VR. This factor may contribute to the percentage accuracy obtained of correctly classify. Although this study is capable of classifying stress using human EMR, further investigation with more and balance number of subject will be performed to distinguish and classify the human EMR on stress. In addition, this study will be associate with a well-established bio feedback instruments on stress identification such as electroencephalogram (EEG) for future research.

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