Electrocardiogram (ECG) based stress recognition integrated with different classification of age and gender

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ABSTRACT

Good mental health is important in our daily life. A person commonly finds stress as a barrier to enhance an individual's performance. Be reminded that not all people have the same level of stress because different people have dissimilar problems in their life. In addition, different level of age and gender will affect unequal amount of stress. Electrocardiogram (ECG) signal is an electrical indicator of the heart that can detect changes of human response which relates to our emotions and reactions. Thus, this research proposed a non-intrusive detector to identify stress level for both gender and different classification of age using the ECG. A total of 30 healthy subjects were involved during the data acquisition stage. Data acquisition which initialize ECG data were divided into two conditions; which are normal and stress states. ECG data for normal state only need the participant to breath in and out normally. In other hand, the participants also need to undergo Stroop Colour word test as a stress inducer to represent ECG in stress state. Then, Sgolay filter was selected in the pre-processing stage to remove artifacts in the signal. The process was followed by feature extraction of the ECG signal and finally classified using RR Interval (RRI), different amplitudes of R peaks and Cardioid graph were used to evaluate the performance of the proposed technique. As a result, Class 5 (age range between 50-59 years old) marks the highest changes of stress level rather than other classes, while women are more affected by stress rather than men by showing tremendous percentage changes between normal and stress level over the proposed classifiers. The result proves that ECG signals can be used as an alternative mechanism to recognize stress more efficiently with the integration of gender and age variabilities.

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1. INTRODUCTION

Health status is important in preparing productive employees of developed county. Challenging global economic conditions keep increasing day by day. A global workspace provider, formerly known as Regus summarized that 70% of Malaysian workers reported experiencing stress due to the economic downturn [1]. At the same time, the number of workload by their employer will keep increasing in achieving company's mission without concerning on the employee capability limit. Unfortunately, this situation will affect the health of the employees especially when it is related to their emotion. If the workload is over the limit of their capability, they will feel the burden and simultaneously invoke them to feel stressful especially when the workload is approaching the estimated dateline.

Stress can be defined as an abnormal emotion which can lead to irresponsible reaction and affecting the mental health. According to World Health Organization (WHO), mental health is well-defined as a state of comfort upon which an individual realizes his or her potential, can manage with normal stress every day, work productively and contribute to society [2]. So, if the person feels that they can't manage to contribute which is over their potential limit, they will keep feeling uneasy and aggravate stress.

This issue has gain attention from researches as previous studies found out that 60% of human diseases are caused by stress. In fact, some of us do not realize that they are emotionally stressed. In addition, three out of four people consults the doctor for stress related disorder in the United States as reported by the Employee and Family Resources (EFR) [3]. Meanwhile, about 200,000 cases of work related diseases which includes stress and mental health disorders were reported in European Agency for Safety and Health at Work [4] which shows the seriousness of this matter.

In Singapore, a stress management organization created an online support system which the person who is under stress can share their emotion and hardship called Samaritans of Singapore (SOS). It is a non-profit organization which aims to support individuals facing problem in crisis, emotional problem and suicidal attempts. SOS Straits Times Graphics reported on suicide cases summarized that majority of the victim were in stress condition due to the effect of higher pressure on job, academic and family related issues [2]. This article also concluded that people with the age range between 50 to 59 years old were the highest suicidal victim as shown in Figure 1. Thus, this issue is significance to be explored further to identify the level of stress in different age level.

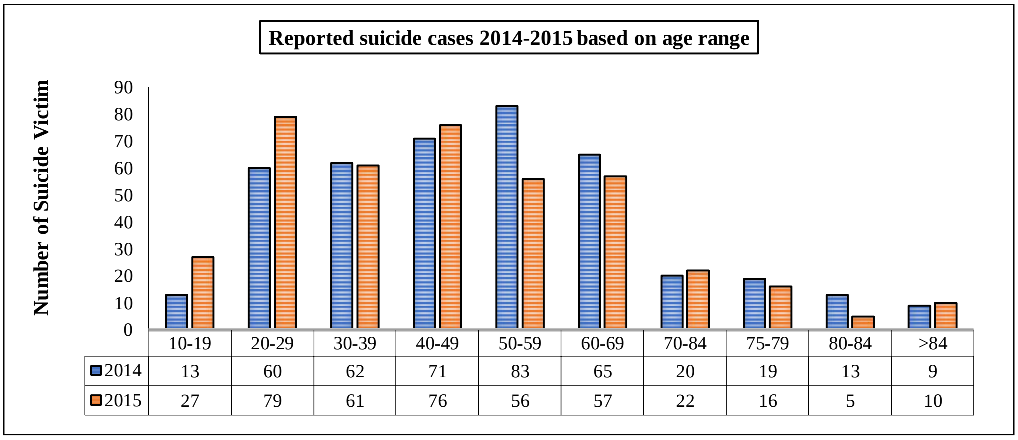

Figure 1. Reported suicide cases 2014-2015 based on age range [2]

A previous study also found that age is one of the factor in differences of emotional responses to stress which comes from broader physiological context in our daily life. (Section: Age Differences in Emotional Response to Events) [5]. This concludes that different people in different varying classification of age reflects to dissimilar amount of stress.

Furthermore, gender also affects the physiological response in conjunction with stress. Moreover, cardiovascular responses proved to be particularly different when incorporating with gender [6]. Essentially, influence of acute stress of the heart have been done in previous research which proved that stress decrease complexity of the heart rate [7], reduce heart rate variability [8, 9] and rapidly increases the heart rate [10]. Issues in stress which are related to gender were supported in [11] stated that different gender will reflect different reaction either in biologically nor psychologically conditions.

Their study selected HPA axis and SAM activities as indicators in measuring stress by inducing acute stressors. Male and women participant were instructed to be involved in a public speaking session as the physiological stressor. As a result, female participants had lower acute responses Hypothalamus Pituitary Adrenal (HPA) and Sympathetic Adrenal Medullary (SAM) response as compared to male participants. This result also has been supported in [12] which summarized that men are more susceptible to develop coronary heart disease rather than women who suffers more from autoimmune illness which are reflected from sex-specific prevalence rates from numerous diseases. Thus, this study reveals that gender plays a significant role to the stress level, which can be further investigated. Next, this research proceeds with reviewing related paper from previous researcher to identify the limitations of current stress recognition system to can be improved.

2. LITERATURE REVIEW

This section discusses on related works regarding stress recognitions using physiological signals including Photoplethysmography (PPG), Electromyogram (EMG), Electroencephalogram (EEG) and Electrocardiogram (ECG).

Banerjee et al. in [18] takes PPG morphological features to identify stress by proposing a two-step Gaussian modelling induced by modified TSST. The outcome shows that width of diastolic wave (C2) is narrowed during stress states. It is suggested that more decision-making techniques were needed to support the accuracies of the proposed method. Luijcks et al. in [19] used EMG reading at both trapezius muscles to identify stress impact based on ACEs in two age categories; (0-11 years as youngsters old and 12-17 years old as adolescence). The result shows that ACEs in youngsters for both trapezium muscles (left and right) gain high value of T and P rather than adolescence. It is recommended that the age range could be extended as elders (40 years old and above) might influence the outcomes since they are more exposed to the major health problems.

Gaikwad and Paithane proposed a novel method in recognizing stress using EEG signals in different stages of Stroop test [20]. The research obtains 72.3% of data accuracies in different stress levels (low, medium and high). However, different stages of Stroop test might interfere in evaluation of stress states. Research in [21] by Zhang et al. measure stress using ECG to identify weak (long duration of winter break) and strong (during final examination) stresses. Consequence of the research shows that weak and strong stresses gain accuracies of 93.75% and 87.5%, respectively. Nevertheless, long duration of winter break might differ in any situation.

In [22], Tripathi et al. estimate changes of autonomic response including HRV, GSR and RR. This research summarized that slower beat to beat (HRV), more sweat produced (GSR) and faster heart rate (RR) in stress conditions. However, the study only mentions on the trend of the result, regardless the reliability of the proposed method. Hwang et al. proposed a novel technique to identify stress by arithmetic test in short term window (10 second) as the spectral features in ECG signal [23]. The classification technique using Naïve Bayes acquire the highest accuracies which could reach up to 81.16%. In contrast, arithmetic test has limitation in the impact of it; which might give confusion rather than act as stress inducer.

Munla et al. apply HRV analysis in Stress Recognition in Automobile Driver database including warning sensor to identify early stage of stress [24] which leads to 83% data accuracies on stress detection. Yet, neglect the amount of stress affected to the driver as a threshold for early detection. In [25], Goel et al. focussed on designing optimal filtering techniques for increasing accuracy in stress detection by varying the polynomial order. This research attained a recognition accuracy of 87% when tested over 17 drivers. However, different result can be obtained if the study integrates with both gender.

Based on the previous literatures, this study can summarize that ECG are the most potential biosignal to reflect heart activity even though in the stress states. However, most of the study neglect the influence of age that can affect the reliability of the proposed method. Thus, this study takes the limitations to overcome those issues with an alternative scheme to recognize stress recognition integrating with age variabilities u sing ECG.

3. METHODOLOGY

The steps for the proposed study involved four staged which are data acquisition, pre-processing, feature extraction and classification as shown in Figure 2 were explain in the next subsections.

Figure 2. Methodology in ECG based stress recognition integrated with different classification of age

3.1. Data Acquisition

A total of 30 participants are included during this research which consists of 6 participants in each level of age. Age categories are classified into 5 groups, which consists of those who are in the range of i) 10-19, ii) 20-29, iii) 30-39, iv) 40-49 and v) 50-59 years old. There are two situations that the participants need to convey with. The first one is the resting state. Participants were instructed to normally breathe in and breathe out, in order to collect their ECG data for the normal condition which takes around 1 minute.

Second situation is the stress state. Each of the subject will undergo a Stroop Colour Word Test which has been recommended by the previous research as an effective way to induced stress. The stress condition will take around 3 minutes while the subjects feel stress until the end of the test. As for now, the heart activity from both states will be affected and differentiated for normal and stress conditions. Hence, this study proposed ECG based stress detection from different classification of age in both situations.

3.2. Pre-processing

Raw signal collected might not be in a smooth waveform due to the occurrence of the noise which is caused by the surrounding environment during the data collection. In order to remove the unwanted signal, data processing is performed by using Savitzky-Golay filter (also known as Sgolay filter) into the raw signal since the selected filter is broadly utilized in smoothing signals.

The main advantage of Sgolay filter in ECG is this filter tends to preserve the original signal such that P wave will not be affected during the noise removal [26]. Although the amplitude of QRS complex is shrinking, high amount of noise was successfully denoised and all the key features are preserved.

3.3. Feature Extraction

ECG signal is well known as PQRST morphology. Some interval were extracted during the transition which is known as feature extraction in order to detect wave changes in each human response from the overall ECG signal. The extracted signal includes PR interval, PR segment, ST segment, QT interval and the commonly used feature extractor is the QRS complex.

One of the most prevalent QRS detection algorithm is the Pan Tompkins algorithm. Pan and Tompkin introduced this method to extract QRS complex from the ECG signal. Essentially, the process begins with the ECG signal which will go through the low pass and high pass filters. Then, the filtered ECG signal will pass through the derivative filter, squaring and window integration processes. A research in [27] proved that Pan Tompkins gain higher sensibility in QRS detection rather than based wavelet transform which are 99.81% and 98.28% respectively.

3.4. Classification

There are three classifiers that been proposed in extracting the data which are i) RR Interval (RRI), ii) Difference of amplitudes at R peak and iii) Cardioid based graph by analyzing on the area, perimeter and Euclidean distance of both normal and stress graph. Each of these decision-making techniques is described below.

a) RRI

Previous studies prove that RR Interval (RRI) can be used as an indicator for HRV analysis [28]. RRI is the period between the first R peak and the next R peak. RRI can be used to measure stress since the R peak is less affected by noise that leads to small error and accurate measurements than the other points.

b) Difference of Amplitudes at R Peak

Amplitude of R wave is the most potential indicator which can be used to analyze the ECG signal since the R peak is less affected by noise that leads errors on other measurements. ECG signal clearly shows that amplitude of R is the highest peak in QRS complex.

c) Cardioid

It is proven by previous studies that Cardioid based graph can increase the accuracy of the results to support other classification algorithms [29]. By differentiating ECG signal, this method capable on calculating perimeter, area, Euclidean distance for this research study to differentiate between normal and stress conditions.

Hence, this section discussed on the details of the proposed methodology for this research study. The steps begin with the data acquisition, preprocessing, feature extraction and classification which were particularly described in each subsection. Next, the experimentation and results were shown to ensure the reliability of the suggested system.

4. RESULTS AND ANALYSIS

This section is divided into two subsections which are experimentation and results of stress recognition using ECG based on a) Different classification of age and b) with respect to both gender.

4.1. ECG Based Stress Recognition Integrating with Different Classification of Age

The experimentation begins with data processing. ECG signal from 20 participants out of 30 (4 subjects/class) were randomly chosen for age variability test. The age levels were classified based on

Table 1. During data acquisition, two examples of raw ECG signals from classes 1 and 5 were shown by subjects 2 and 28 in Figures 3 and 4 (a) respectively.

Table 1. Classification of Age

Age Classification	Age Range (Years)
CLASS 1	10-19
CLASS 2	20-29
CLASS 3	30-39
CLASS 4	40-49
CLASS 5	50-59

Next, the raw ECG signal will go through preprocessing stage to remove external noise which are shown in Figures 4 and 5 (b) consisting of filtered ECG signals for both subjects.

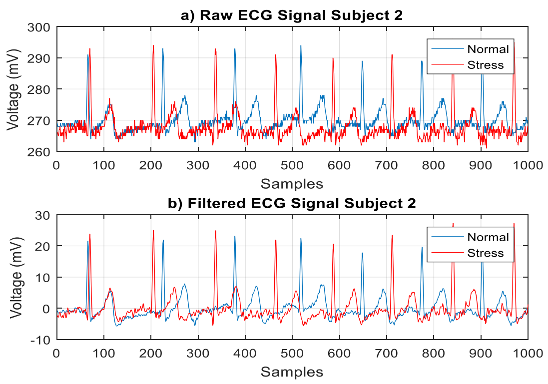

Figure 3. a) Raw and b) Filtered ECG signals subject 2 (class 1)

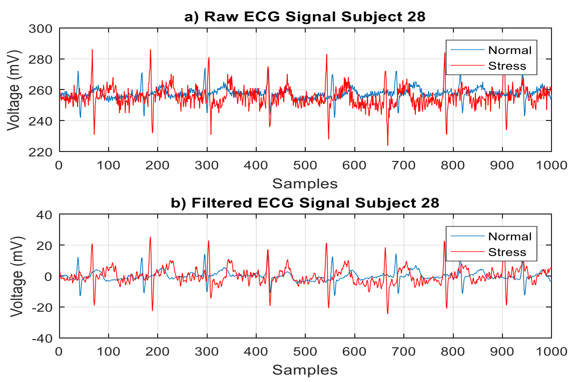

Figure 4. a) Raw and b) Filtered ECG signals subject 28 (class 5)

Then, QRS complexes are extracted from the filtered ECG signal. As can be seen in Figures 5 and 6, QRS rhythm for classes 1 and 5 were affected by stress situation when R peaks amplified.

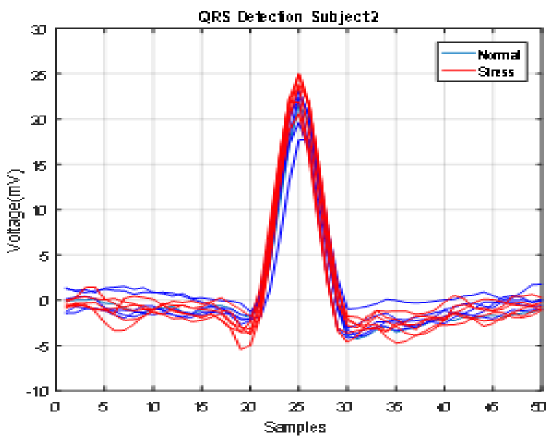

Figure 5. QRS complex subject 2 (class 1)

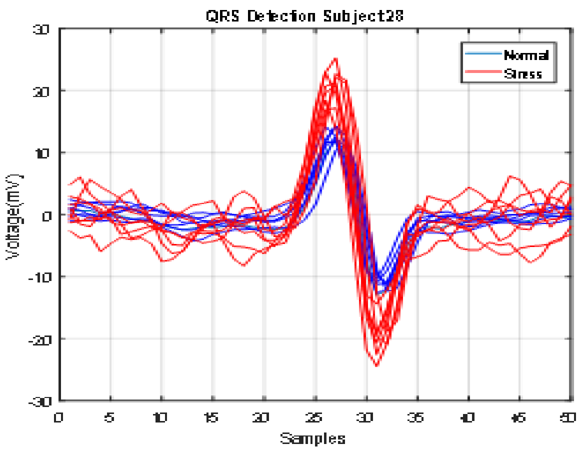

Figure 6. QRS complex subject 28 (class 5)

Finally, the data of the QRS complexes were used as the input in the classification stage. The classifier analyzes the affected amount of stress for each class of age. Figures 7 and 8 shows different Cardioid respond towards both classes between normal and stress states.

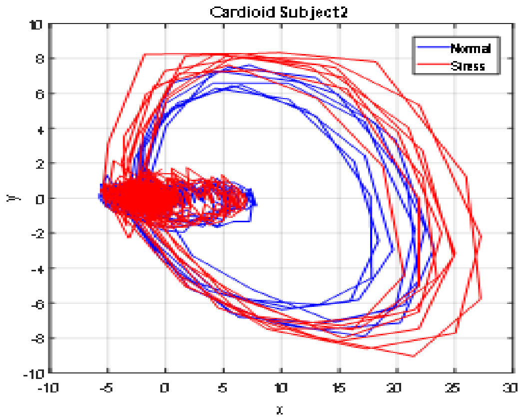

Figure 7. Cardioid subject 2 (class 1)

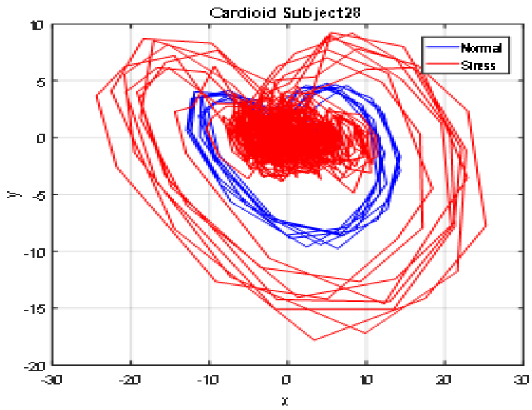

Figure 8. Cardioid subject 28 (class 5)

Overall data were taken, and it shows that RRI from all subjects were decreased, amplitude of R peak increase and Cardioid shows larger area during stress state. Thus, in order to clarify the most affected stress based on age variabilities, this study measure the percentage changes of all classifications between normal and stress states in for all participants.

Then, calculation on the average percentage changes for age varieties in normal and stress conditions are done and classify it using RRI, different amplitudes of R and Cardioid area as shown in equations 1, 2 and 3. The results of the experimentation were illustrated in Figure 9.

$$\%\,Changes\ RRI\ = \frac{RRI\ normal - RRI\ stress}{RRI\ normal}\ X\ 100\% \tag{1}$$

$$\%\,Changes\ of\ R\ peak\ = \frac{R\ peak\ stress - R\ peak\ normal}{R\ peak\ stress}\ X\ 100\% \tag{2}$$

$$\%\,Changes\ in\ Cardioid = \frac{Cardioid\ stress - Cardioid\ normal}{Cardioid\ Stress}\ X\ 100\% \tag{3}$$

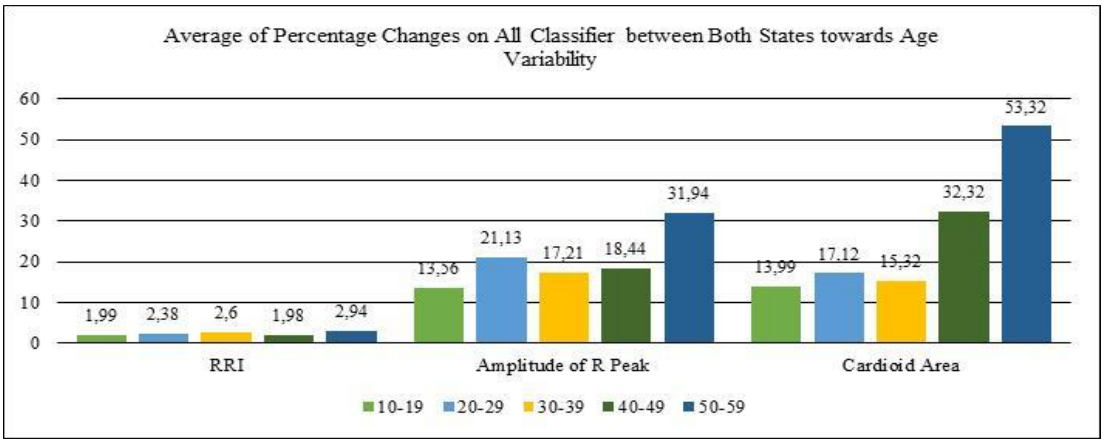

Figure 9. Average of percentage changes on all classifier between both states towards age variability

Based on Figure 9, Cardioid represent the highest changes (normal to stress conditions) in classification technique towards age variability. Class 5 which represents the age range between 50-59 years old were the most affected age level when facing stress conditions which is 2.94% as compared to all classes.

The value of RRI is decrease due to the slower beat to beat that reflects to the increasing heart rate. However, the amount of stress affected were quite similar to the other classes of age.

Besides, a dominant change in average value of percentage changes in amplitude of R peak (31.94%) and Cardiod area (53.32%) for Class 5 supports the RRI statement as an alternative which these classifications manage to clearly differentiate changes of stress affected rather than other classes of age. Amplitude of R peak increase during stress states is due to the activation of SNS which occur when the body feels treated in a stress condition.

In another point, Cardioid graph shows larger area due to the internal signal of a body starts to response with the stress situation by increasing the heart rate. The result reflects to the report which been discussed in previous section that states age range between 50-59 years old were the highest number of victims who commit suicide which majority comes from stress issues [2]. Thus, our proposed method supports the hypothesis that Class 5 is mostly affected by emotional response due to stress.

4.2. ECG Based Stress Recognition Integrating with Gender Variability

The first two stages which are signal acquisition and preprocessing were performed. During data acquisition stage, four examples out of 20 subject's raw ECG signal were collected from subjects 19 and 30 were shown as in Figures 10 until 13 (a).

It is noted that subjects 19are female participant, while subject 30 are male participant. Next, the raw ECG signals were filtered in preprocessing stage. Figures 10 until 13 (b) represents the filtered ECG signals for each subject.

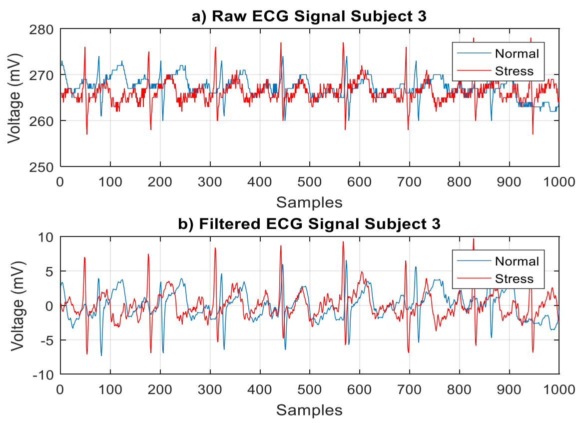

Figure 10. a) Raw and b) Filtered ECG signal female subject 3

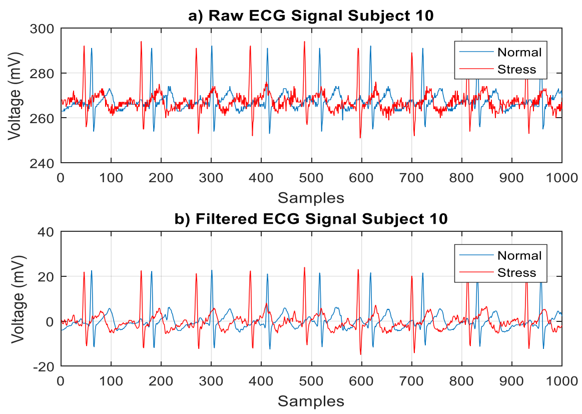

Figure 11. a) Raw and b) Filtered ECG signal male subject 10

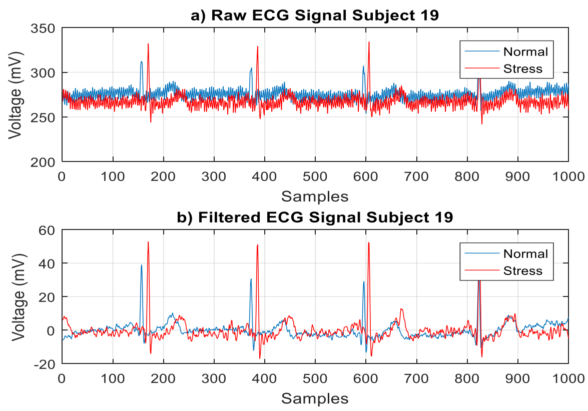

Figure 12. a) Raw and b) Filtered ECG signal female subject 19

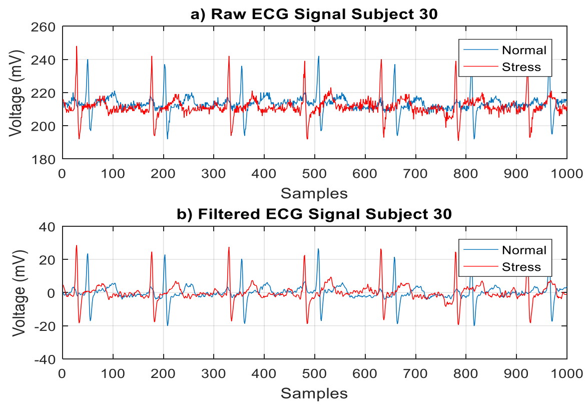

Figure 13. a) Raw and b) Filtered ECG signal male subject 30

Generally, the graph shows changes of ECG signal from normal state to stress state. As can be seen, Sgolay filter tends to preserve the characteristics of ECG signal. Then, the study continued with the feature extraction stage by extracting QRS complexes using Pan Tompkins algorithm from each ECG cycle. The illustration of this stage from all subjects are shown as Figures 14 until 17.

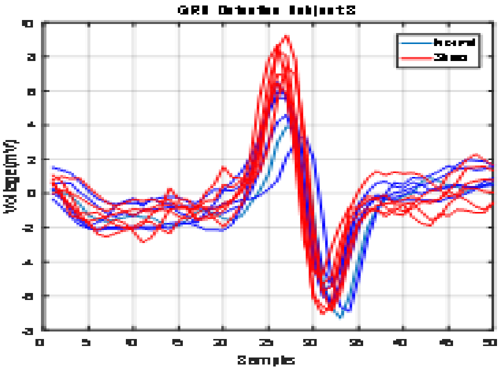

Figure 14. QRS complex female subject 3

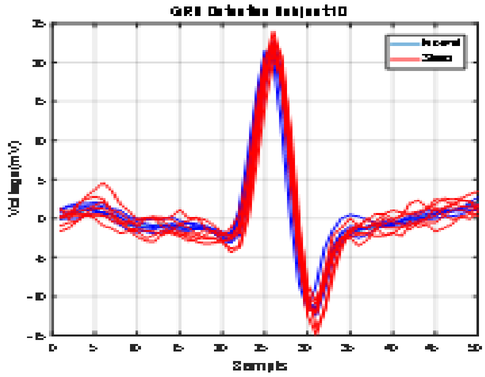

Figure 15. QRS complex male subject 10

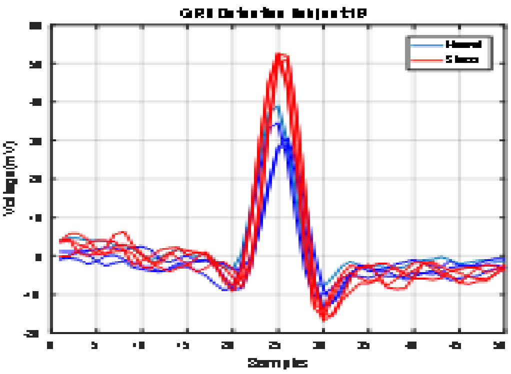

Figure 16. QRS complex female subject 3

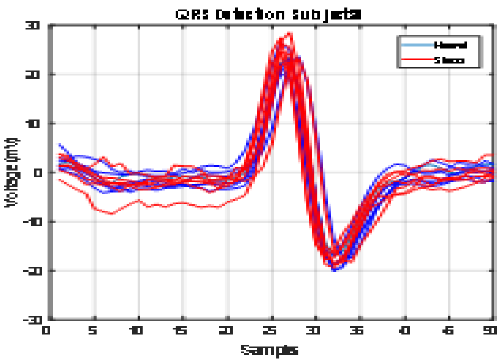

Figure 17. QRS complex male subject 10

After obtaining QRS complexes, this study used the R peak as an indicator to proceed for the proposed classification which is calculating the different amplitudes of R peak and average of RRI to verify changes of any heart activity during both states.

Figures 18 until 21, Cardioid illustrates that both gender was affected during stress state. In addition, as stress change the heart activity of a person, Cardiod graph shows that female subject was the most affected changes of heart activity rather than male.

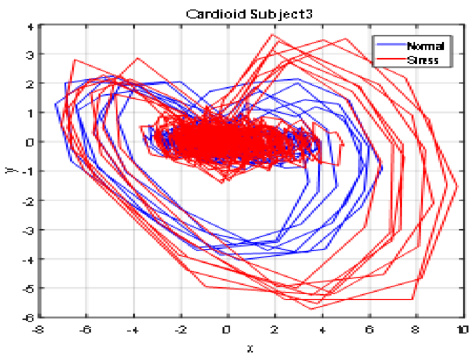

Figure 18. Cardioid Female Subject 3

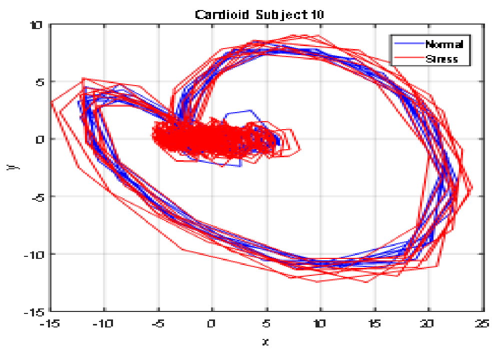

Figure 19. Cardioid Male Subject 10

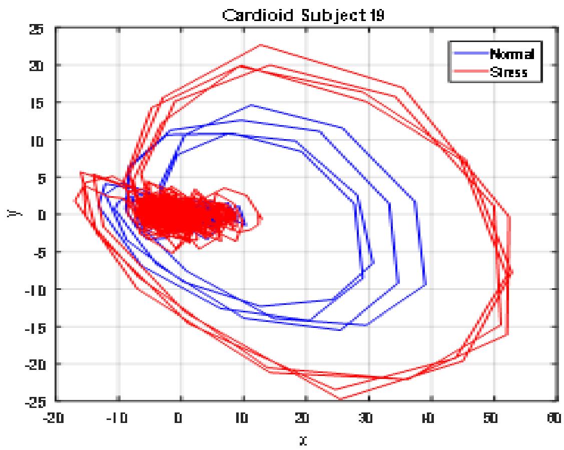

Figure 20. Cardioid female subject 19

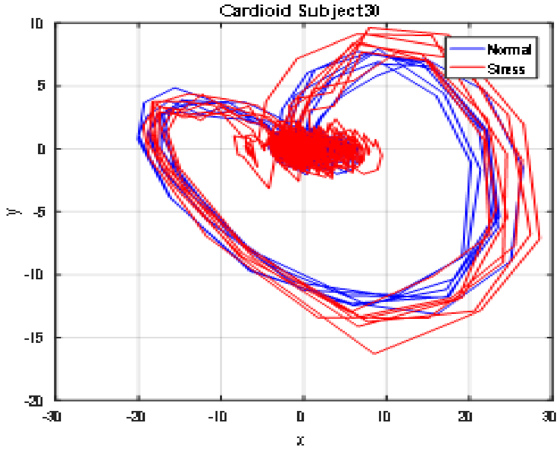

Figure 21. Cardioid male subject 30

Overall data were taken, and it shows that RRI from all subjects were decreased, amplitude of R peak increase and Cardioid shows larger area during stress state. Thus, in order to clarify the most affected stress in both gender, calculation on the average percentage changes for both gender in normal and stress conditions are done and classify it using RRI, different amplitudes of R and Cardioid area as in equations 4, 5 and 6 been illustrated in Figure 22.

$$Average\ \%\ changes\ of\ RRI = \frac{\%\ changes\ of\ RRI}{10\ male\ or\ 10\ female}\ X\ 100\% \tag{4}$$

$$Average\ \%\ changes\ of\ R\ peak = \frac{\%\ changes\ of\ R\ peak}{10\ male\ or\ 10\ female}\ X\ 100\% \tag{5}$$

$$Average\ \%\ changes\ in\ Cardioid = \frac{\%\ changes\ in\ Cardioid}{10\ male\ or\ 10\ female}\ X\ 100\% \tag{6}$$

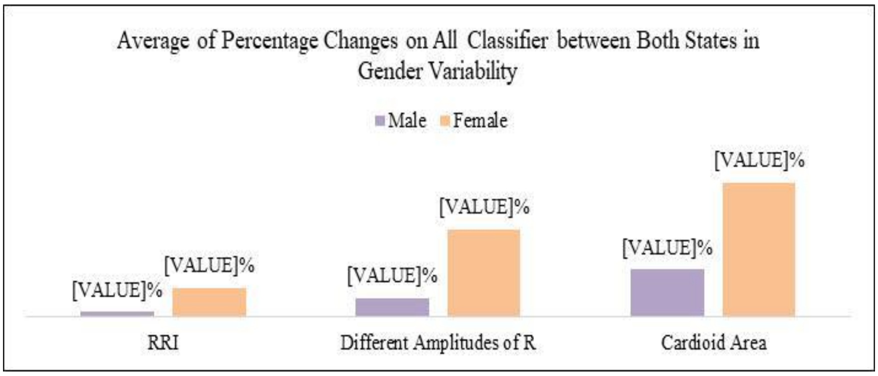

Figure 22. Average of percentage changes on all classifier between both states in gender variability

RRI value states the average of percentage changes from normal to stress condition is 11.59% for female participants, while average value for male participants is 2.17%. In terms of amplitude changes between both states (normal and stress), it is recorded that mean value for female participants reached 34.98% while mean value for male participants were smaller which is 7.50%. In addition, Cardioid area shows higher mean value for female participants rather than male participants which are 53.81% and 19.03% respectively. It can be concluded that higher average of percentage changes between normal and stress states remark that female was easily triggered by stress rather than male by the previous statement.

Overall, the data shows some similarities regarding male and female ECG signals. Female subject shows higher average of percentage changes between normal and stress state in all classification. The result reflects to the previous work which states that women are easily influenced by emotional situations that leads to stress rather than men who are susceptible in coronary heart disease [12].

5. CONCLUSION

As a conclusion, the objectives of this study have been successfully achieved. This study was established as an efficient method on stress recognition system using ECG incorporating different gender and age. This research has been conducted with the deep understanding of all the stages in this study which are data acquisition, pre-processing, feature extraction and classification. ECG signal is proven to contribute in differentiating between normal and stress states that reflects the first objective, which is to investigate a potential scheme in measuring stress level using human biological response. As a proof of concept with 30 participants included, the experimentation result showed that RR intervals will be narrower, amplitudes of R will be higher and Cardioid area graph will be larger during stress state. Thus, these outcomes reflect the second objective on developing stress recognition using ECG in consideration with different classification of age and gender.

Then, the capability of the proposed technique was identified and evaluated using potential classification methods for stress measurement incorporated with age and gender variabilities that reflects the third objective. In age variability test, Class 5 (age range of 50-59 years old) obtained the highest mean value of percentage changes to the stress response as compared to other classes that gives classification results of 2.94%, 31.94% and 53.32% in terms of RR interval, changes of R peak amplitudes and Cardioid graph area, correspondingly.

On the other hand, gender analysis shows higher mean of percentage changes in female volunteers between both states illustrating RR interval, amplitude of R peak and Cardioid area of 11.59%, 34.98% and 53.81% consequently. Yet, the mean value of percentage changes in RR interval, amplitude changes in R peak and Cardioid graph area for male was only affected by 2.17%, 7.50%, 19.03% respectively. Therefore, the overall results obtained shows that ECG signal is a reliable technique to be used in recognizing stress integrating age and gender variability.

Even though the study was capable of recognizing stress using ECG signal integrating gender and age variabilities, there are still room for improvement such as including the influence of fusion method, consider surrounding condition in obtaining normal data and include different timing for data acquisition.

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REFERENCES

[1] The Star Online (2013). Regus: 70% M'sian workers see increase in stress-related illnesses - Business News | The Star Online. [online] Available at: https://www.thestar.com.my/business/business-news/2013/11/22/70-pct-of-malaysian-workers-see-increase-in-stress-related-illness-says-survey/ [Accessed 19 Jan. 2018].

[2] Tianjie, W. (2016). Teen suicides highest in 15 years but overall rate falls: SOS. [online] The Straits Times. Available at: http://www.straitstimes.com/singapore/teen-suicides-highest-in-15-years-but-overall-rate-falls [Accessed 18 Nov. 2017].

[3] Jackson, J. (2016). 3 out of 4 Doctor Visits are for Stress Related Ailments - Employee & Family Resources. [online] Employee & Family Resources. Available at: http://www.efr.org/3-4-doctor-visits-stress-related-ailments/ [Accessed 20 Mar. 2018].

[4] Osha.europa.eu. (2018). Work-related diseases - Safety and health at work - EU-OSHA. [online] Available at: https://osha.europa.eu/en/themes/work-related-diseases [Accessed 10 Mar. 2018].

[5] Scott, S., Sliwinski, M. and Blanchard-Fields, F. (2013). Age differences in emotional responses to daily stress: The role of timing, severity, and global perceived stress. *Psychology and Aging*, 28(4), pp.1076-1087.

[6] Stoney, C., Davis, M. and Matthews, K. (1987). Sex Differences in Physiological Responses to Stress and in Coronary Heart Disease: A Causal Link?. *Psychophysiology*, 24(2), pp.127-131.

[7] Boesch, M., Sefidan, S., Ehlert, U., Annen, H., Wyss, T., Steptoe, A. and La Marca, R. (2014). Mood and autonomic responses to repeated exposure to the Trier Social Stress Test for Groups (TSST-G). *Psychoneuroendocrinology*, 43, pp.41-51.

[8] Verkuil, B., Brosschot, J. and Thayer, J. (2014). Cardiac reactivity to and recovery from acute stress: Temporal associations with implicit anxiety. *International Journal of Psychophysiology*, 92(2), pp.85-91.

[9] Brindle, R., Ginty, A., Phillips, A., Fisher, J., McIntyre, D. and Carroll, D. (2015). Heart rate complexity: A novel approach to assessing cardiac stress reactivity. *Psychophysiology*, 53(4), pp.465-472.
[10] E. Shokr (2015), "Effect of Exam Stress on Heart Rate Variability Parameters in Healthy Students," *J. Nurs J India*, 84(3), p. 65.
[11] Kudielka, B. and Kirschbaum, C. (2005). Sex differences in HPA axis responses to stress: a review. Biological Psychology, 69(1), pp.113-132.
[12] Mccarty, D., Manzi, S., Medsger, T., Ramsey-Goldman, R., Laporte, R. and Kwoh, C. (1995). Incidence of systemic lupus erythematosus race and gender differences. *Arthritis & Rheumatism*, 38(9), pp.1260-1270.
[13] Selye, H. (1973). The Evolution of the Stress Concept: The originator of the concept traces its development from the discovery in 1936 of the alarm reaction to modern therapeutic applications of syntoxic and catatoxic hormones. *American scientist*, pp. 692-699.
[14] Mukhopadhyay, S. (2015). Wearable Sensors for Human Activity Monitoring: A Review. *IEEE Sensors Journal*, 15(3), pp.1321-1330.
[15] Hansen, F. (2018). "Fight or Flight" vs. "Rest and Digest" | Adrenal Fatigue Solution. [online] Adrenal Fatigue Solution. Available at: https://adrenalfatiguesolution.com/fight-or-flight-vs-rest-and-digest/ [Accessed 22 Dec. 2017].
[16] P. Karthikeyan, M. Murugappan and S. Yaacob, *"A review on stress inducement stimuli for assessing human stress using physiological signals,"* 2011 IEEE 7th International Colloquium on Signal Processing and its Applications, Penang, 2011, pp. 420-425.
[17] Hernando, A., Lazaro, J., Gil, E., Arza, A., Garzon, J., Lopez-Anton, R., De La Camara, C., Laguna, P., Aguilo, J., and Bailon, R. (2016). Inclusion of respiratory frequency information in heart rate variability analysis for stress assessment. *IEEE Journal of Biomedical and Health Informatics*, 20(4):1016 – 1025
[18] S. Banerjee, R. Bailón, J. Lazáro, V. Marozas, P. Laguna and E. Gil, *"A two-step Gaussian modelling to assess PPG morphological variability induced by psychological stress,"* 2017 Computing in Cardiology (CinC), Rennes, 2017, pp. 1-4.
[19] Luijcks, R., Vossen, C., Roggeveen, S., van Os, J., Hermens, H. and Lousberg, R. (2016). Impact of early life adversity on EMG stress reactivity of the trapezius muscle. *Medicine*, 95(39), p 4745.
[20] P. Gaikwad and A. N. Paithane, "*Novel approach for stress recognition using EEG signal by SVM classifier,"* 2017 International Conference on Computing Methodologies and Communication (ICCMC), Erode, 2017, pp. 967-971.
[21] J. Zhang, W. Wen, F. Huang and G. Liu, *"Recognition of Real-Scene Stress in Examination with Heart Rate Features,"* 2017 9th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), Hangzhou, 2017, pp. 26-29.
[22] R. P. Tripathi and G. R. Mishra, *"Design and implementation of a real time stress monitoring system with the help of ECG using Matlab tool,"* 2017 International Conference on Computer, Communications and Electronics (Comptelix), Jaipur, 2017, pp. 365-369.
[23] B. Hwang, J. W. Ryu, C. Park and B. Zhang, *"A novel method to monitor human stress states using ultra-short-term ECG spectral feature,"* 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Seogwipo, 2017, pp. 2381-2384.
[24] N. Munla, M. Khalil, A. Shahin and A. Mourad, *"Driver stress level detection using HRV analysis,"* 2015 International Conference on Advances in Biomedical Engineering (ICABME), Beirut, 2015, pp. 61-64.
[25] Goel, S., Kau, G., & Toma, P. (2017). A novel technique for stress recognition using ECG signal pattern. *Current Pediatric Research (2017)*, 21(4), pp. 674-679.
[26] W. Liang, S. Hu, Z. Shao and J. Tan, *"A real-time cardiac arrhythmia classification system with wearable electrocardiogram,"* 2011 IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems, Kunming, 2011, pp. 102-106.
[27] J. Fajardo, D. Astudillo, K. Palacio-Baus, L. Solano-Quinde and S. Wong, *"Evaluation of two QRS detection algorithm on ECG stress test database,"* 2016 IEEE ANDESCON, Arequipa, 2016, pp. 1-4.
[28] M. Karlsson, R. Hörnsten, A. Rydberg, and U. Wiklund (2012), "Automatic filtering of outliers in RR intervals before analysis of heart rate variability in Holter recordings: a comparison with carefully edited data," *BioMedical Engineering OnLine*, vol. 11, no. 1, p. 2.
[29] Azam, S.N.A.M. & Zainal, N.I. & Sidek, K.A.. (2015). Development of cardioid based graph ECG heart abnormalities classification technique. *ARPN Journal of Engineering and Applied Sciences*, vol. 10, no. 21, pp. 9759-9765

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