Stress Estimation Using Biological Signals: A Simple and Efficient Method

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***Abstract*-- Stress is the physiological and psychological response of the body to external or internal pressures that the brain perceives as a threat, affecting both physical and mental performance. Low stress levels can enhance performance, but high stress levels can cause psychological and bodily harm. One effective method for estimating stress is mapping the features of biological signals to quantitative values for stress. In recent years, efforts have been made to continuously detect stress using biological signals and applying complex methods to estimate stress. This article introduces a simple and effective method for estimating stress. The existence of a monotonic increasing relationship between stress and biological signal features is an assumption of this study. Accordingly, EMG and ECG signals recorded under stressful conditions were preprocessed. Then, features were extracted and normalized from each time window. Subsequently, by calculating the 2-norm of the features and applying a scaling factor based on the individual's relative heart rate, a continuous value termed estimated stress was obtained. The qualitative evaluation of the results with self-reported values and stress levels at different stages of the experiment confirms the effectiveness of this method. The simplicity, understandability, and low computational cost are characteristics of the proposed method. The proposed method can be implemented in low-cost gadgets and can transfer stress estimation from the laboratory to daily life.**

***Index Terms*-- continuous stress, electrocardiogram signal, electromyogram signal, 2-norm**

I. Introduction

Stress can be defined as a physiological and psychological response to challenges, pressures, or unpleasant situations experienced by the brain and nervous system. This response involves changes in hormone levels and various brain regions, aimed at coping with the stressful situation and maintaining internal physiological balance [1]. However, stress always brings with it a hidden opportunity. When faced with stress, one can utilize their inner strengths to manage and achieve balance, improving efficiency [2]. But if the level of stress and the time when a person is under stress increases, it causes physical and psychological damage [3], [4]. Therefore, it is essential to recognize stress for its management and prevention.

One of the traditional ways to diagnose stress is to use questionnaires [5]. In this method, experts try to obtain a qualitative estimate of stress by asking questions in a questionnaire. But this method has limitations and the results cannot be trusted [6], [7]. Therefore, it is necessary to go towards methods such as the use of biological signals to eliminate human intervention in decisions. Stress detection is done using biological signals in both discrete and continuous ways [8]. In discrete methods, efforts are made to separate people's stress into qualitative levels (low stress, medium stress, and high stress) [9] while, in continuous methods, due to the continuous nature of stress, efforts are made to quantify the value of stress by mapping it to numerical values [8]. In continuous stress assessment methods, techniques such as fuzzy clustering and fuzzy inference systems [10], linear and nonlinear regression [11], and artificial intelligence [12] have been used to estimate stress, aiming to continuously estimate stress. However, due to not having the ground truth and great uncertainty in stress, it is another attractive research area for researchers [8].

Pourmohammadi and Maleki [8] attempted to achieve a continuous estimate of the stress of participants in an experiment with various stress levels using fuzzy clustering and weighting each cluster with a fuzzy inference system. Although they obtained good results, this method has two limitations. The first limitation is that the fuzzy inference system is not automated and depends on expert knowledge. The second limitation is that the basis for weighting each cluster is the stressor. This means that low stress was considered for all individuals in the initial resting state, even though some individuals experienced high stress due to being in a laboratory setting. Additionally, this method has high computational complexity due to the use of the fuzzy inference system.

In another study, Jiang and Wang [13] reported a continuous estimate of drivers' stress levels while driving using fuzzy c-means clustering and considering the size of the cluster centers.

First, biological features were extracted from the signals and these features were fuzzy clustered. Then, the cluster coefficients were calculated using the size of each cluster center. In the final step, by combining the membership values obtained from fuzzy clustering and the weight of each cluster, they achieved a continuous value referred to as drivers' stress. In this paper, reasonable justifications for the steps of the proposed method were not provided, and some of the steps are unreasonable.

Weijsman et al. [11] have also estimated stress continuously by using biological signals from 30 participants in a stressful experiment for 40 minutes and using logistic regression and linear regression techniques.

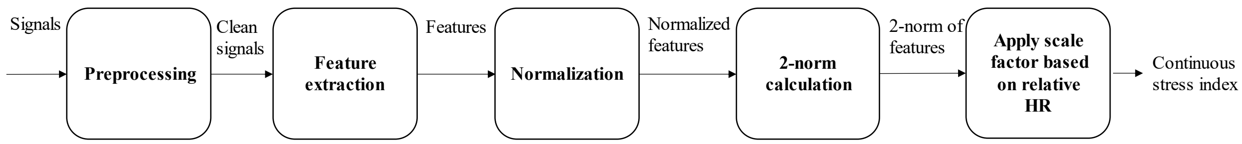

Fig. 1. Block diagram of the proposed method.

Although efforts have been made to continuously estimate stress using biological signals, the need for a reasonable and effective method that can be used for everyday practical applications and inexpensive equipment is strongly felt. In this article, an effective and simple method for continuously estimating stress using electrocardiogram (ECG) and electromyogram (EMG) signals is introduced.

The structure of the article is such that in the method section, the database is introduced and pre-processing and feature extraction are performed. Thereafter, by calculating the 2-norm and applying a scaling factor based on the individual's relative heart rate, a quantitative measure of stress is determined. In the results section, the stress curve of participants estimated using electrocardiogram and electromyogram signals is presented. In the Discussion and Conclusion section, the effectiveness of the method is evaluated according to the self-reported values of participants and stressful conditions in the testing stages.

II. METHOD

Fig 1 illustrates the block diagram of the proposed method, which includes the steps of preprocessing, feature extraction, normalization, calculation of 2-norm, and application of a scaling factor based on the individual's relative heart rate. EMG and ECG signals recorded under stress conditions from the SBSL database were used. In the preprocessing stage, in addition to filtering the signals, the electromyogram signals were normalized based on maximum voluntary contraction (MVC). Next, features with a monotonically increasing relationship with stress were extracted from these signals, and the feature values were normalized to ensure equal influence of the features on the final result. In the last stage, the 2-norm of the normalized features was calculated, and a scaling factor based on the individual's relative heart rate was applied to determine the continuous stress index.

A. Database

In this paper, the SBSL database [8] is utilized, which includes ECG and EMG signals from the right and left trapezius and the right and left erector spinae muscles. This database comprises data from 34 healthy participants aged between 20 and 37 years. The signals were recorded over five stages: initial rest, Task 1, Task 2, Task 3, and final rest (recovery), which will be introduced in detail. The experiment is designed such that the stressors increase from Task 1 to Task 3 (tasks become more challenging).

During the initial rest phase, 30 neutral images of nature accompanied by calming music were presented. In Task 1, congruent Stroop tasks and Simple math calculations were used to induce stress. In Task 2, incongruent Stroop tasks and moderate-level math calculations were employed. In Task 3, incongruent Stroop tasks and difficult-level math calculations were used, accompanied by radio sound as environmental noise. In the final rest phase, 30 neutral images of nature accompanied by calming music were presented to allow participants to recover. After each phase, participants reported their Perceived stress on a scale from 1 to 5, with 1 indicating very low stress and 5 indicating very high stress.

B. Preprocessing

EMG and ECG signals may be contaminated by motion artifacts, movements due to breathing, high voltage line inducted interference, and other biological interferences. To reduce these noises and artifacts, ECG signals were filtered using a third-order bandpass filter with cutoff frequencies of 5 and 15 Hz to facilitate the identification of R-peaks. Additionally, muscle signals were filtered using a fourth-order Butterworth high-pass filter with a cutoff frequency of 30 Hz [14].

On the other hand, inter-individual differences such as age, gender, and fitness level, and intra-individual differences such as fatigue and motivation make comparing EMG signals across individuals and conditions difficult [15]. To address this issue, EMG signals were normalized using a reference value obtained from the EMG signal recorded under maximum voluntary contraction (MVC) conditions. Specifically, the absolute value of the EMG signals recorded during MVC was computed, then windowed using a 100-millisecond window, and the average value of each window was calculated. Finally, the maximum of these average values was taken as the reference value, and each EMG signal was divided by this reference value for normalization [16].

C. Feature extraction

The proposed method is based on the assumption that the features used have a monotonically increasing relationship with stress. Fig 2 shows hypothetical examples of the monotonic increasing relationship between stress and features. Fig 2, the relationship between the feature and stress can be either linear or nonlinear.

Fig. 2. Hypothetical examples of a monotonically increasing relationship between stress and features of biological signals.

Since stress causes an increase in heart rate as well as increased muscle activity [17], the features listed in Table I were used for EMG and ECG signals. These features have been normalized such that their values increase with increasing stress.

TABLE I

Extracted features for stress estimation from a window of EMG and ECG signals. For EMG signal features, N denotes the number of samples in a window and A_i denotes the i-th sample. For ECG signal features, T represents the duration of the window in seconds, n denotes the number of R-peaks in a window, R_i denotes the i-th peak, and RR_i denotes the i-th interval between two consecutive R-peaks.

Signal	Formula	Description
EMG	$Energy = \sum_{i=1}^{N}(\lvert A_i\rvert^2)$	Energy
EMG	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {A_i}^2}$	Root Mean Square
EMG	$MAD = \frac{1}{N-1}\sum_{i=2}^{N}\lvert A_i - A_{i-1}\rvert$	Mean absolute difference
ECG	$MRR = \frac{1}{n-1}\sum_{i=1}^{n-1} RR_i$	Mean of RR intervals
ECG	$RMSSD = \sqrt{\frac{1}{n-2}\sum_{i=1}^{n-2}(RR_{i+1} - RR_i)^2}$	Root mean square of successive differences of RR intervals
ECG	$MHR = \frac{60\,n}{T}$	Mean HR

D. Normalization

In the normalization process, two main objectives were considered. First, to ensure that differences due to data scale do not affect the values obtained for the features. Second, to ensure that the normalized features exhibit a monotonically increasing behavior with stress [18]. For those features whose variations with stress are monotonically increasing, normalization was performed using (1), where a_k represents the feature value in the k-th window, a_{min} and a_{max} represent the minimum and maximum values in the feature vector for each participant, respectively, and y_k denotes the scaled feature [19].

$$y_k = \frac{(a_k - a_{min})}{(a_{max} - a_{min})} \tag{1}$$

Additionally, for those features whose variations with stress are monotonically decreasing (such as the mean of R-peak intervals and root mean square of R-peak intervals), normalization was performed using (2). It is important to emphasize that all normalized features will be monotonically increasing.

$$y_k = \frac{(a_k - a_{max})}{(a_{min} - a_{max})} \tag{2}$$

E. Calculate 2-norm

2-norm is a method for calculating distance in an n-dimensional space [20]. To calculate the distance between features, (3) was used, where d represents the Euclidean distance, y_l denotes the value of the l-th feature, and l is the number of features.

$$d = \sqrt{y_1^2 + y_2^2 + \cdots + y_l^2} \tag{3}$$

F. Scale factor based on relative heart rate

In experimental conditions, maximum stress is not necessarily perceived by all individuals, and perceived stress can vary among individuals for the same stressor. Moreover, the ECG signal and heart rate feature demonstrate more robust behavior in representing stress compared to other features. Therefore, a scaling factor based on heart rate was applied to the 2-norm of the normalized features to obtain a continuous stress index. The stress scaling factor is shown in (4). In this equation, MHR_j denotes the average heart rate of the j-th participant, and MHR_{min} and MHR_{max} represent the minimum and maximum average heart rates of all participants, respectively.

$$Stress\ factor = \frac{MHR_j - MHR_{min}}{MHR_{max} - MHR_{min}} \tag{4}$$

The stress factors and the values obtained from (3) were multiplied to derive the continuous stress index for each time window, as in (5).

$$Stress\ index = stress\ factor \times d \tag{5}$$

G. Quantitative Evaluation Criterion

To evaluate the stress estimated by the proposed method, the correlation between the estimated stress and the self-reported data of the participants was used based on (6), where $corr(x, y)$ indicates the correlation of the estimated stress with self-reports, E(.) represents the mean, and V(.) denotes the variance.

$$corr(x,y) = \frac{E\left[\left(x - E(x)\left(y - E(y)\right)\right)\right]}{\sqrt{V(x)V(y)}} \tag{6}$$

III. Results

The proposed method was implemented using the EMG and ECG signals from the [8] database. Stress estimation was performed once using only the ECG signal and again using both the ECG and EMG signals to allow for a comparison of the performance of these two modalities. For ECG-based estimations, the three ECG features listed in Table I were used, and for EMG-ECG-based estimations, all six features listed in Table I were used. A rectangular sliding window with a length of 60 seconds and a 50-second overlap was used for signal segmentation.

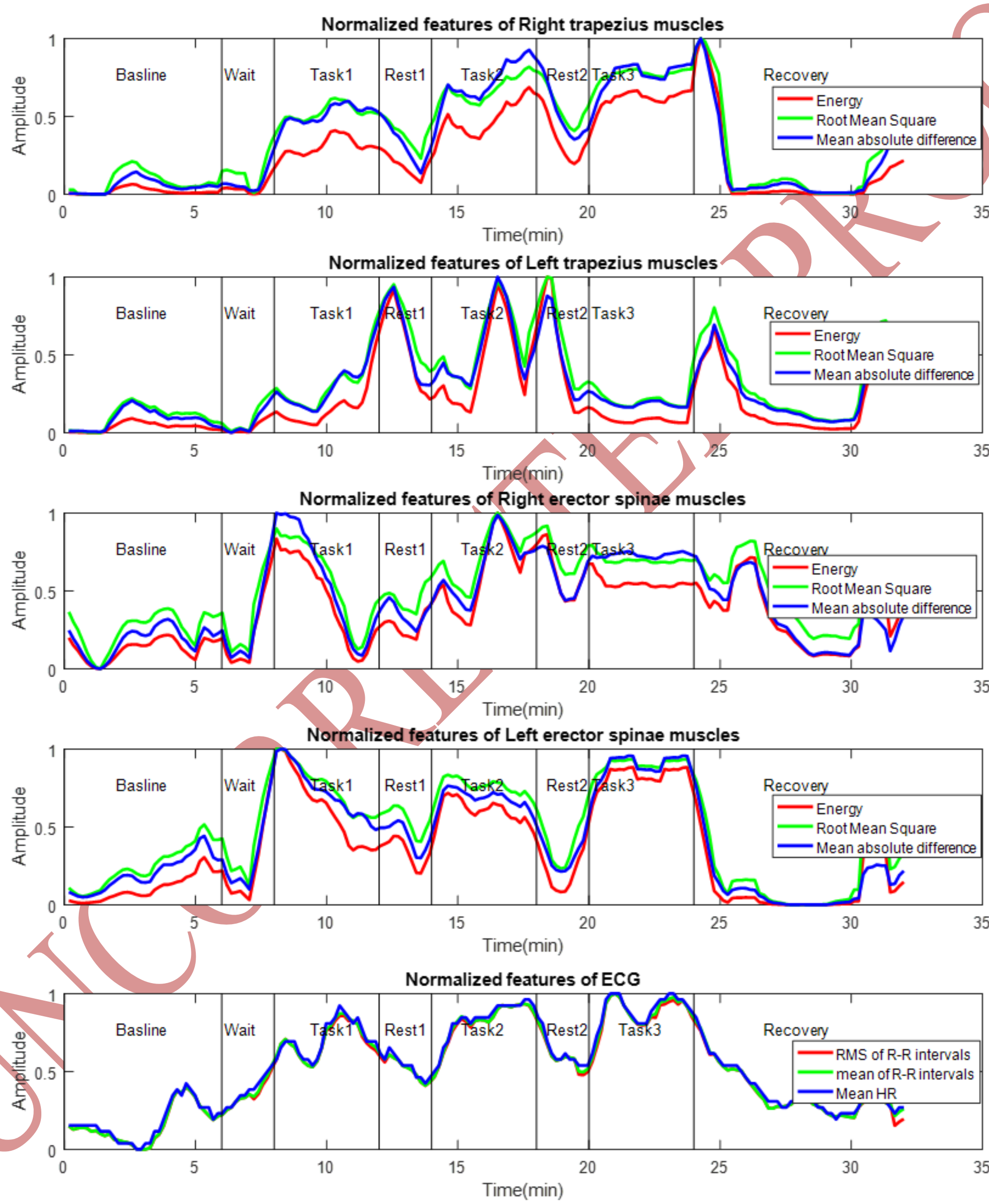

Fig. 3. Display of normalized features for participant twelve. Each condition of the experiment is separated by vertical lines, and each feature is depicted with a distinct color.

Fig 3 illustrates the behavior of normalized features for Participant twelve. Based on this plot, the monotonically increasing behavior of the features with stress can be validated. As expected, the values of normalized features in tasks one through three are higher compared to their counterparts in the resting state.

Fig 4 depicts the stress estimation curve using the proposed method and utilizing both ECG and EMG signals for four participants.

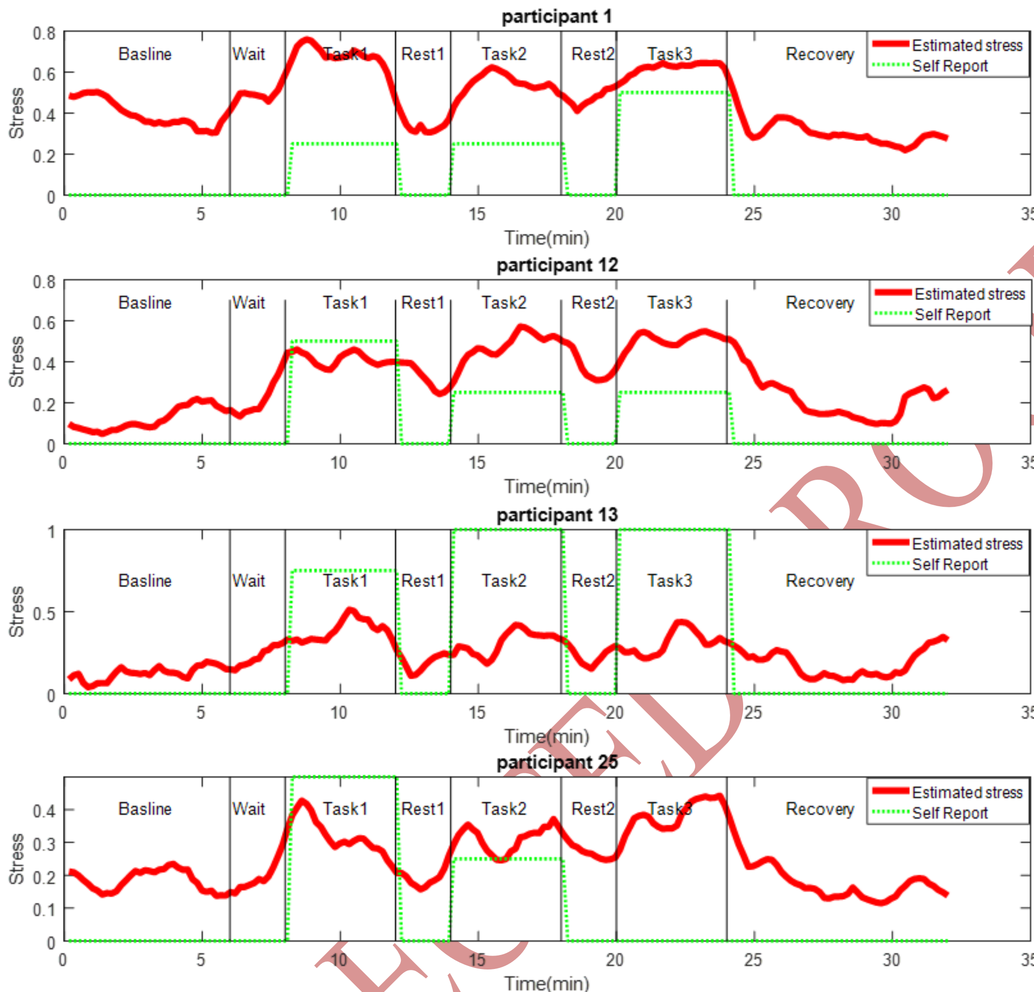

Fig. 4. The stress estimation curve using the proposed method with ECG and EMG signals for participants 1, 12, 13, and 25. The red curve represents the estimated stress, while the green curve represents the self-reported by the participants

Based on the estimated stress, it is observed that during the initial rest period, the participants' stress levels are low. As Task 1 begins, the stress levels increase, and the stress curves change according to each task, with these changes varying for each individual. The stress levels in Task 1 are often higher than in the other tasks. This is likely because the new experience and unfamiliarity with the experimental procedure cause participants to experience more stress in the early stages of the experiment [21]. While the stressor is designed to increase from Task 1 to Task 3.

The following section focuses on stress estimation using only ECG signals. Fig 5 shows the estimated stress using ECG signals.

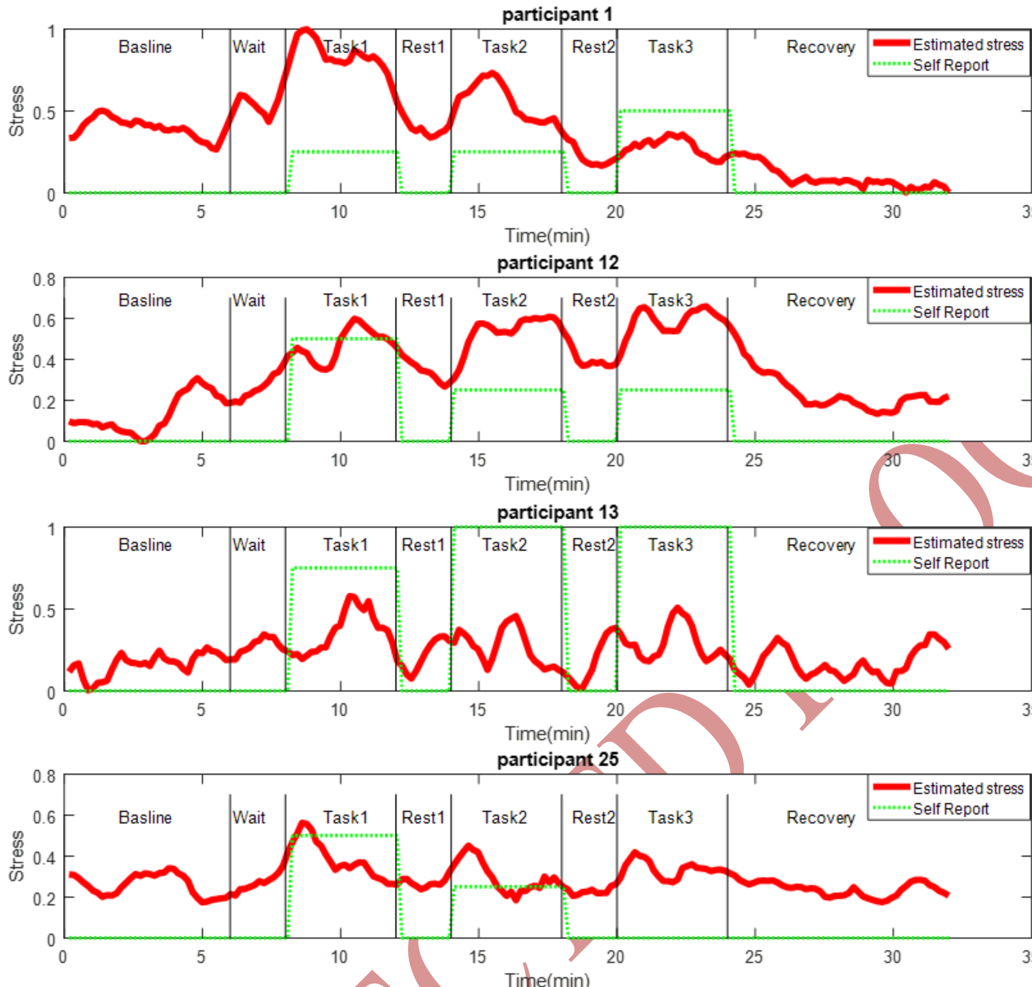

Fig. 5. Estimated stress using ECG signals for participants 1, 12, 13, and 25. The red line represents the stress curve, while the green line represents the participants' self-reported stress.

Participant 1 and Participant 13 show a significant increase in estimated stress during Task 1 and Task 2 periods, which corresponds well with their self-reported stress. Similarly, Participant 12 and Participant 25 also show an increase in stress during Task 1 and Task 2, but the intensity of this increase is less compared to Participants 1 and 13. For Participant 12, a slight decrease in estimated stress is observed during Rest1, but there is a slight increase during Rest2. In Participant 25, a noticeable decrease in stress is seen during Rest1, while stress remains relatively constant during Rest2. The estimated stress for all participants decreases during the Recovery period, indicating a return to the baseline state after the stress-inducing tasks. In all participants, the estimated stress increases with the onset of tasks and decreases with rest, indicating the accuracy of the proposed method in detecting stress changes in response to tasks and rest periods. The reduction in stress during the Recovery period for all participants shows that the proposed method effectively identifies the return to baseline after stress-inducing tasks.

The observed differences in the intensity and pattern of stress changes among participants highlight individual differences in perceiving stress from the same stressor. For example, Participant 1 experienced higher stress levels, while Participant 25 experienced lower stress.

In Fig 6, the estimated stress using only the ECG signal is compared with the estimated stress using both ECG and EMG signals.

Based on the estimated stress, it appears that both EMG and ECG signals are useful for stress estimation. However, the stress curve estimated using both ECG and EMG signals aligns better with the participants' self-reports. For instance, in Participant 1, there is greater coherence between the self-reported stress and the estimated stress using both ECG and EMG signals in Task 2 and Task 3. For participant 1, the estimated stress using only the ECG signal reached its peak in Task 1 because this participant had the highest heart rate among all participants during this period, resulting in a stress coefficient of 1.

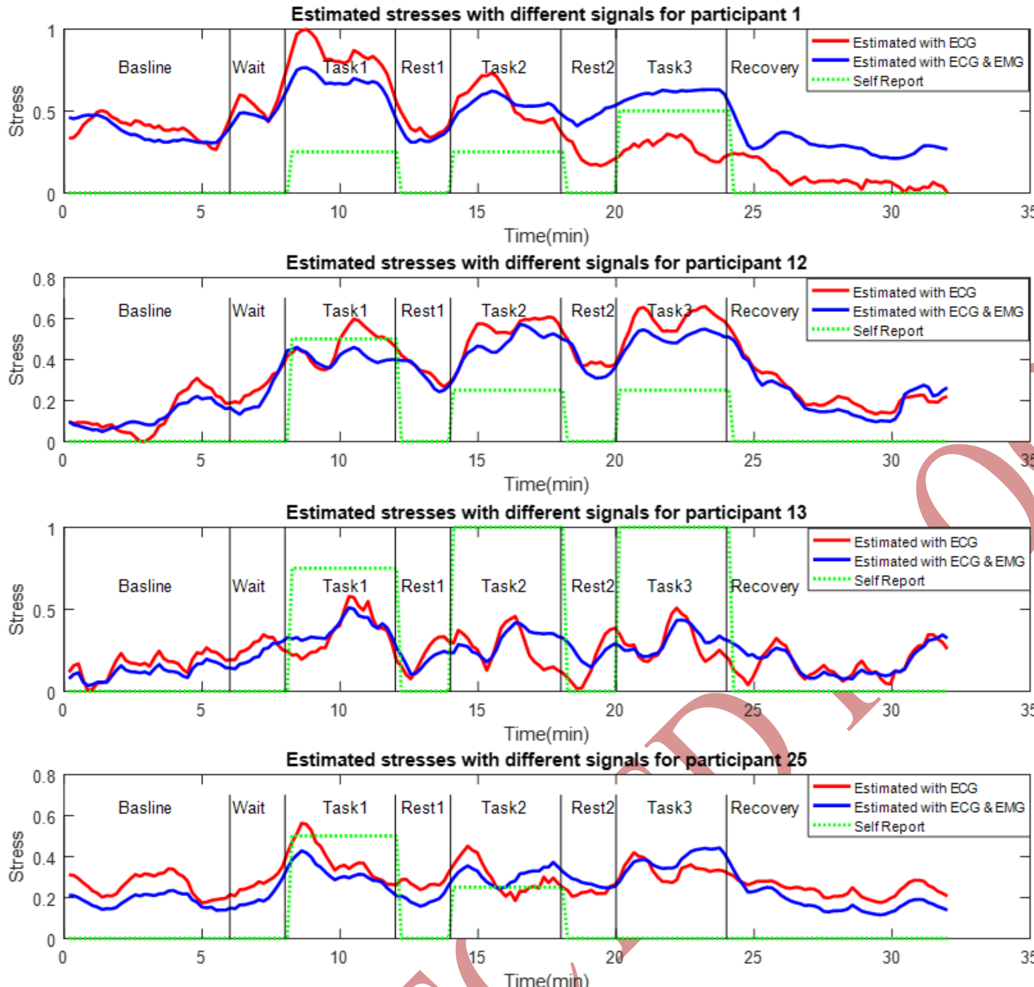

Fig. 6. Comparison of estimated stress using only the ECG signal versus estimated stress using both ECG and EMG signals.

Table II presents the correlation between the stress estimated by the proposed method and the self-reports of the participants. The average correlation for all participants in the case of stress estimation using the ECG signal and in the case of stress estimation using both ECG and EMG signals were found to be 0.31 and 0.49, respectively.

Table II

Correlation of stress estimated by the proposed method with participants' self-report in two modes of stress estimation using ECG signal and stress estimation using ECG and EMG signals.

correlation		
With ECG and EMG	**With ECG**	**Participant number**
0.77	0.20	1
0.14	0.11	2
0.70	0.47	3
0.08	0.17	4
0.45	0.61	5
0.21	-0.09	6
0.50	0.48	7
0.59	0.63	8
0.91	0.76	9
0.65	0.53	10
0.35	0.20	11
0.76	0.73	12
0.79	0.55	13
0.47	0.63	14
0.30	0.22	15
0.57	0.43	16
0.54	0.21	17
0.46	0.39	18
0.60	0.17	19
0.77	0.70	20
0.71	0.66	21
0.54	0.48	22
0.86	0.80	23
0.72	0.63	24
0.31	0.49	25
0.29	0.04	26
0.70	0.42	27
0.52	0.68	28
-0.18	-0.26	29
0.09	0.05	30
0.49	0.54	31
0.80	0.46	32
0.23	0.14	33
0.27	0.08	34
0.49	0.31	Average

Table III shows the task accuracy for participants 1, 12, 13, and 25 in each of the tasks. Task accuracy indicates that participants 1 and 12 have higher accuracy compared to participants 13 and 25. This suggests that participants 1 and 12 paid more attention to the pre-designed stress-inducing tasks and naturally experienced more stress. This is evident in the estimated stress using the proposed method, where the range of estimated stress for participants 1 and 12 is higher than for participants 13 and 25.

TABLE III
Task accuracy for participants as a percentage.

	Participant 1	Participant 12	Participant 13	Participant 25
Task 1	٪60	٪61	٪52	٪48
Task 2	٪59	٪52	٪35	٪26
Task 3	٪43	٪30	٪28	٪40

IV. Discussion and Conclusion

In this study, a simple and efficient method for continuous stress estimation using biological signals was proposed. The analysis of the results indicates that the estimated stress follows a reasonable pattern in response to the stressor. Additionally, individual differences in the estimated stress levels were observable.

The stress estimation method using only the ECG signal was able to identify overall stress changes and performed well in distinguishing between task and rest periods. Adding the EMG signal to the ECG improved the alignment of the estimated stress with self-reported stress levels. This combination provided a more comprehensive view of the individual's physiological state and significantly enhanced stress assessment.

One limitation of the proposed method was the assumption of a linear relationship between stress and features. For future research, it is recommended to consider the nonlinear dynamics of each feature to achieve more accurate stress estimation curves.

The results of this study indicate that the proposed method is capable of accurately detecting stress over long periods. Due to its simplicity of implementation and applicability to individuals in various conditions, this method can serve as an effective tool for stress prevention and management. This research has shown that by leveraging biological signals, stress can be effectively identified. Using small, inexpensive gadgets that operate based on biological signals, stress can be estimated efficiently and easily, enabling users to better manage stress in their daily lives.

References

[1] Chen, B., Wang, L., Li, B., & Liu, W. (2022). Work stress, mental health, and employee performance. Frontiers in Psychology, 13, 1006580. https://doi.org/10.3389/fpsyg.2022.1006580

[2] I. H. Robertson. (2017).“The stress test: Can stress ever be beneficial?” Journal of the British Academy, volume 5, pp. 163-176, doi: 10.5871/jba/005.163.

[3] J. N. Morey, I. A. Boggero, A. B. Scott, and S. C. Segerstrom. (2015). “Current directions in stress and human immune function,” Current Opinion in Psychology, vol. 5. doi: 10.1016/j.copsyc.2015.03.007.

[4] Rosenbaum, D. L., & White, K. S. (2015). The relation of anxiety, depression, and stress to binge eating behavior. Journal of Health Psychology, 20(6), 887–898. https://doi.org/10.1177/1359105315580212.

[5] Watanabe, K., Imamura, K., Eguchi, H., Hidaka, Y., Komase, Y., Sakuraya, A., Inoue, A., Kobayashi, Y., Sasaki, N., Tsuno, K., Ando, E., Arima, H., Asaoka, H., Hino, A., Iida, M., Iwanaga, M., Inoue, R., Otsuka, Y., Shimazu, A., Kawakami, N., … Tsutsumi, A. (2023). Usage of the Brief Job Stress Questionnaire: A Systematic Review of a Comprehensive Job Stress Questionnaire in Japan from 2003 to 2021. International journal of environmental research and public health, 20(3), 1814. https://doi.org/10.3390/ijerph20031814.

[6] Sudman, S., & Bradburn, N. M. (1973). Effects of Time and Memory Factors on Response in Surveys. Journal of the American Statistical Association, 68(344), 805–815. https://doi.org/10.1080/01621459.1973.10481428.

[7] Razavi, Tiffani (2001) Self-report measures: an overview of concerns and limitations of questionnaire use in occupational stress research (Discussion Papers in Accounting and Management Science, 01-175) Southampton, UK. University of Southampton 23pp.

[8] S. Pourmohammadi and A. Maleki. (2021). “Continuous mental stress level assessment using electrocardiogram and electromyogram signals,” Biomedical Signal Processing and Control, vol. 68, Jul, doi: 10.1016/j.bspc.2021.102694.

[9] S. Pourmohammadi and A. Maleki. (2020). “Stress detection using ECG and EMG signals: A comprehensive study,” Computer Methods and Programs in Biomedicine, vol. 193, doi: 10.1016/j.cmpb.2020.105482.

[10] S. Pourmohammadi and A. Maleki. (2015). “An automatic approach to continuous stress assessment during driving based on fuzzy c-means clustering,” MODARES JOURNAL OF ELECTRICAL ENGINEERING, vol. 15, no. 4.

[11] J. Wijsman, B. Grundlehner, H. Liu, J. Penders, and H. Hermens. (2012).“Towards continuous mental stress level estimation from physiological signals,” International Journal of Psychophysiology, vol. 85, no. 3, doi: 10.1016/j.ijpsycho.2012.07.158.

[12] M. Gjoreski, H. Gjoreski, M. Luštrek, and M. Gams. (2016). “Continuous stress detection using a wrist device - in laboratory and real life,” in UbiComp 2016 Adjunct - Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing. doi: 10.1145/2968219.2968306.

[13] M. Jiang and Z. Wang. (2009). "A Method for Stress Detection Based on FCM Algorithm," 2009 2nd International Congress on Image and Signal Processing, Tianjin, China, 2009, pp. 1-5, doi: 10.1109/CISP.5304150.

[14] S. Tivatansakul and M. Ohkura. (2015). “Improvement of the emotional healthcare system with stress detection from ECG signal,” in Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS, 2015. doi: 10.1109/EMBC.7319953.

[15] A. Burden. (2010). “How should we normalize electromyograms obtained from healthy participants? What we have learned from over 25 years of research,” Journal of Electromyography and Kinesiology, vol. 20, no. 6. doi: 10.1016/j.jelekin.2010.07.004.

[16] Knudson, Duane. (1993). Comparison of EMG normalization methods in a sit-to-stand movement. Journal of Human Movement Studies. 25. 39-50. https://www.researchgate.net/publication/240177110

[17] van Kraaij, A. W. J., Schiavone, G., Lutin, E., Claes, S., & Van Hoof, C. (2020). Relationship Between Chronic Stress and Heart Rate Over Time Modulated by Gender in a Cohort of Office Workers: Cross-Sectional Study Using Wearable Technologies. Journal of medical Internet research, 22(9), e18253. https://doi.org/10.2196/18253.

[18] K. S. Prathyusha and B. E. Reddy. (2021). “Normalization methods for multiple sources of data,” in Proceedings - 5th International Conference on Intelligent Computing and Control Systems, ICICCS 2021. doi: 10.1109/ICICCS51141.2021.9432142.

[19] A. Aytekin. (2021). “Comparative analysis of normalization techniques in the context of MCDM problems,” Decision Making: Applications in Management and Engineering, vol. 4, no. 2, pp. 1–25, doi: 10.31181/dmame210402001a.

[20] M. K. Hossain and S. Abufardeh. (2019). “A new method of calculating Squared Euclidean Distance (SED) using PTreE technology and its performance analysis,” in Proceedings of 34th International Conference on Computers and Their Applications, CATA 2019. doi: 10.29007/trrg.

[21] Ghazali, D. A., Breque, C., Sosner, P., Lesbordes, M., Chavagnat, J. J., Ragot, S., & Oriot, D. (2019). Stress response in the daily lives of simulation repeaters. A randomized controlled trial assessing stress evolution over one year of repetitive immersive simulations. PloS one, 14(7), e0220111. https://doi.org/10.1371/journal.pone.0220111.