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Continuous mental stress level assessment using electrocardiogram and electromyogram signals

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A R T I C L E I N F O

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A B S T R A C T

Stress endangers the mental and physical health of individuals and also has a major impact on society. Accurate, reliable and quantitative measurement of stress leads to detect the person's stress level in earlier stages and reduce the intervention time to manage it. Individuals' stress gradually changes from one level to another. That's why traditional stress recognition approaches are not useful in real-life. Besides, the physiological stress response is subject-dependent. We proposed a continuous personalized stress assessment method. For this purpose, a fuzzy-based model was employed which uses the electrocardiogram and electromyogram signals together to achieve a highly reliable and accurate mental stress index. A total of 34 healthy participants were recruited during a pre-designed stress-inducing protocol. The results of the experiments illustrated the feasibility of the proposed approach. The perceived stress score showed a high correlation (more than 0.9) with the mental stress index. Moreover, the average stress classification accuracy across all subjects for two-level and three-level achieved as 96.7 % and 75.6 %, respectively. The acceptable accuracy of multi-level stress detection, along with the obtained personalized stress index and high correlation between the perceived and estimated stress, emphasize the proposed methodology as an innovative approach, in line with state-of-the-art research.

1. Introduction

Mental stress can be defined as the human's body response to pressure from a special situation or life events [1]. Stress triggers a person's fight-or-flight response to fight the stressor or run away from it. How far everyone can handle the stress is individual [2]. Work stress, privacy, lifestyle and age all influence this tolerance. Briefly, stress brings a massive increase in energy of the whole body and hence, can have many different effects such as anxiety, depression, insomnia, memory impairment, difficulty concentrating, anger and aggression, as well as digestive and joint pain problems. The adverse effects of stress are apparent, physical illnesses and mental disorders where cause many personal and social issues [3]. If stress could be reliably and automatically identified, this could directly help individuals to manage it.

On the other hand, there is a complicated relationship between stress and human physiology [4]. A common method to deal with this issue is to detect the stress in two (stress/no stress) or three (low, medium and high) levels with conventional machine learning methods [5–8]. But the transition from no-stress (relaxation) state to stress state (e.g., moderate or high level) is a gradual process and feeling of a person from relaxation state to stress state do not change suddenly in real life [9]. So, these states must not treat as classical (e.g., binary) sets, which wholly include or exclude the given state. Subsequently, discrete stress level recognition which is known as multi-level stress recognition is not adequately precise due to neglecting a continuous nature of stress [10].

The relationship between multi-level stress recognition and continuous stress assessment is compared with the ground truth in Fig. 1A. The ground truth is drawn synthetically based on the stress response of the heart rate under stressful conditions [11]. The stress response is shown in four stages included baseline, hard and moderate tasks and recovery. In the two-level stress detection scheme (red line in Fig. 1A), "baseline" period and "tasks" periods are labeled as "no-stress" and "stress", respectively. In the multi-level stress recognition scheme (blue line in Fig. 1A), low-stress is assigned to the baseline period and moderate and high stress levels are assigned to the second and first tasks, respectively. In the continuous stress level assessment method, continuous quantitative values are assigned to the individual's stress. In this case, the amount of stress does not depend on the label of a specific period of time. For instance, if a person experiences moderate stress at baseline stage or low-stress at tasks, it will be evident in the continuous stress assessment

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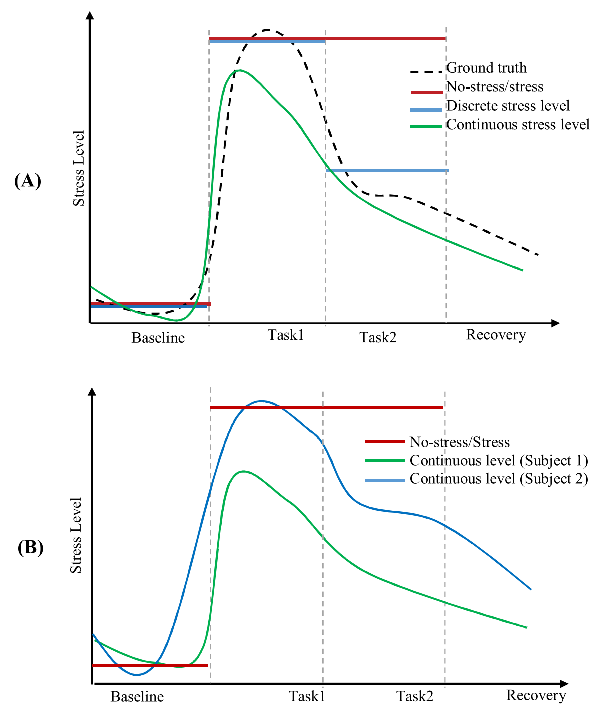

Fig. 1. A) Discrete/multi-level stress recognition and continuous stress level assessment approaches against synthetical ground truth. Comparing two-level stress recognition (red) and three-level recognition (blue) shows that as the number of levels increases, the representation of ground truth improves. The extreme improvement is provided using continuous stress assessment (black dashed line). B) Demonstrating Inter-subject differences by stress curve. continuous stress assessment considers inter-subject differences (blue and green lines), but two-level stress detection (red line) does not take into account inter-subject differences.

(Fig. 1B). The curve of the continuous stress level assessment was called "stress curve" [12].

The stress curve reflects the changes (magnitude and direction) of the individual's stress in the face of stressful conditions. Fig. 1B shows the stress curve for two individuals facing the same stressors. The 2-level stress detection is assigned "no-stress" and "stress" labels in the baseline and tasks, respectively. In this case, regardless of the difference between the individuals, the assigned label is the same for both of them. But continuous stress level assessment method is constantly personalized and consider individual differences in the stress curve.

The main challenge of continuous stress level assessment is the lack of equipment to measure the stress and therefore, lack of ground truth of the stress curve, which makes regression and mapping methods inapplicable for continuous stress level determination.

Among the numerous researches in the field of stress detection, few studies have paid attention to the continuous assessment of stress with the mentioned characteristics [12–15]. The regression methods [14,15] and Fuzzy approaches [12,13] are the most popular methods to assessed stress continuously. Jiang and Wang [12] have continuously estimated driving stress using fuzzy clustering and non-linear mapping. They didn't provide quantitative evaluation, such as the correlation coefficient for their results [12]. Wijsman et al. [14] used linear regression to obtain the continuous estimation of stress levels. They employed several physiological signals such as the EMG of the upper trapezius muscle, ECG, respiration rate and skin conductance. The results of linear regression were evaluated in comparison with the accuracy of stress level classification for stress and rest situations. The classification accuracy and correlation were obtained as 86.4 % and 0.302, respectively [14].

Kumar et al. [13] quantified the stress value using the heartbeat intervals and stochastic fuzzy analysis approach. The correlation coefficient between the rating scores of subjects and the predicted stress values have been obtained about 0.8198 [13]. Arza et al. [15] estimated the stress levels in a continuous way for both stress and relaxation stages in the range of 0–100. The correlation coefficient between the estimated stress and stress level reference was obtained at about 0.67 [15].

While some researches tried to develop a continuous and quantitative stress level assessment model, there is a lack of reliable and effective methods adopted by researchers. The objective of this research is to assess stress continuously, quantitatively, and precisely based on the physiological response of an individual. Physiological biomarkers were chosen due to their being involuntary and independent from the external factors. Data were collected in a laboratory where subjects were under pre-designed stressful conditions. The State-trait anxiety inventory questionnaire [16] was adopted to annotate stress. After signal preprocessing and feature extraction, the fuzzy model was employed to assess individuals' stress using the EMG and ECG signals continuously. Finally, stress levels were quantized to a continuous scale of 0–100.

The novelty of this research lies in the simplicity and reliability of the proposed method and considering inter-subject differences where the overall accuracy of stress evaluation is improved. Briefly, our main contributions can be summarized as follows:

- Stress is estimated continuously and quantitatively based on the physiological biomarkers of an individual
- The inter-subject differences are considered in response to the stressful events using the fuzzy model
- The continuous nature of mental stress is considered

The paper has been organized as follows: The proposed continuous stress level assessment approach will be described in Section 2. Section 3 explains the findings of this research and represents the numerical results. Section 4 discusses the achieved results and compares them with the conventional stress detection methods, followed by Section 5 which summarizes the paper.

2. Method

The proposed stress assessment method can be divided into four main blocks: data acquisition, preprocessing, feature extraction and stress assessment model which is based on the fuzzy approach. Briefly, the ECG signal and EMG signals of the right and left trapezius and the right and left erector spinae muscles were acquired in the laboratory where subjects experienced several simulated stress states. The EMG signal of the erector spinae muscle introduced as an effective stress indicator in previous studies [8,17]. Then, all the recorded signals were filtered to reduce the effect of noise and artifacts. In the feature extraction step, several features were obtained from the filtered signals in time and frequency domains. Finally, a fuzzy clustering and fuzzy inference system were employed to assess the stress levels continuously. Fig. 2 shows the block diagram of the proposed method.

2.1. Signal acquisition

34 subjects (11 males and 23 females) were selected for this study among university students. All the subjects were healthy without cardiopathy, heart disorders, musculoskeletal disorders and mental diseases and with ages between 20–37 years. The subjects were first informed about the process of experiment and provided their consent. Signal recording is sensitive to the place of sensors, sudden body movement and the subjects' mood during the experiment. These considerations must be taken into account. Both signals were recorded continuously during the whole experiment. The ECG and The EMG signals were acquired using the ECG v.12 device manufactured by Bayamed [18] and the Datalog device by Biometrics [19], respectively. Also, besides the SX230 surface electrode and Skintact F-55 electrode

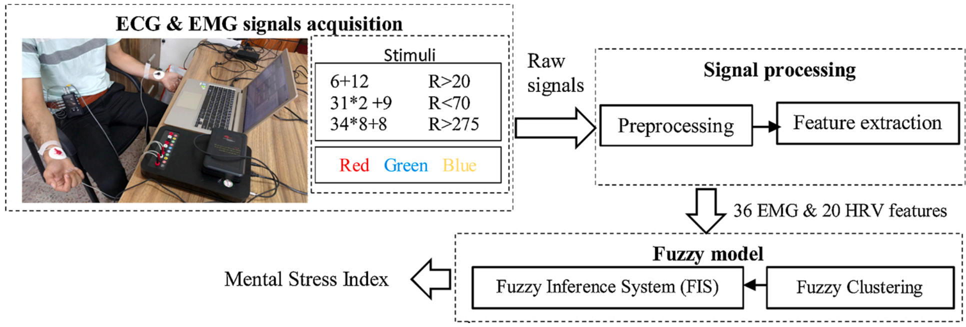

Fig. 2. Block diagram of the proposed continuous stress level assessment framework.

were utilized to record EMG and ECG signals, respectively. The electrodes were placed on the body according to the SENIAM standard [20]. The sampling rate of both devices is 1000 sample/sec.

In order to design an experiment that efficiently induces the mental stress in an individual, considerable insight into human psychology is needed. At first, participants signed the consent form and fill out the trait anxiety questionnaire (STAI-Y2). The maximum voluntary contraction (MVC) from muscles was recorded according to methods described in [21,22]. In the main stress-inducing procedure, the EMG and ECG signals were recorded simultaneously and continuously for 32 min. Fig. 3 demonstrates the stress induction procedure. The experiment consisted of three stress task phases of four minutes length: a Stroop color-word test and a math test. The tasks were separated by filling questionnaire (Y1) phases of two minutes length. The first rest and last rest (recovery) phases relaxed the subject for four minutes. In anticipation (A) stage, tasks described to the subject.

In this study, we select the most validated methods to simulate stressful conditions [23,24]. In the first rest stage, neutral pictures were displayed with relaxing music. The same process was repeated in the recovery stage. The mental arithmetic with three levels of difficulty and the Stroop color-word tasks were developed to induce the stress in subjects. For each task stage, a Stroop color-word test [25] was presented as a first task. Four color words included blue, green, red and yellow were written in incongruous ink color, e.g., the word green was written in the color red. The subjects' correct answer should be the color of the real ink, e.g., red in the previous example. A mathematical test was performed as the second task that each math expression was presented for a maximum time of 5 s. To avoid no-thinking responses, no response was received during the first 2 s. All three tasks have a fixed duration (four minutes). The harder mathematical questions, limitation of time and noisy environment makes the tasks 3 more difficult than tasks 1 and 2. At the end of each stage of the stress-inducing protocol, the subjects were rated their perceived stress on a scale of 1–5 (no stress to very high stress) and filled out the state anxiety questionnaire (STAI-Y1).

2.2. Signal processing

2.2.1. Preprocessing

All the EMG and ECG signals being recorded are influenced by various noise sources: baseline wander caused by breathing, movement artifacts, high voltage line's inducted interference, high frequency noise and other biological signals as pollution. In order to reduce the noise and artifacts, a preprocessing block was developed to efficiently filter the recorded signals.

The EMG signals were contaminated by the ECG signal. Therefore, EMGs were filtered using a fourth-order zero-phase Butterworth high-pass filter with a cut-off frequency of 30 Hz. Such a cut-off frequency was chosen to eliminate the effect of ECG acquisition. This technique for removal of ECG contamination was applied in the literature [26–29]. On the other hand, and in order to clean the ECG signal and precisely extract the R peaks, a 3th-order zero-phase Butterworth band-pass filter with cut-off frequencies of 5 and 15 Hz was applied. The band-pass filter reduces the effects of perturbations caused by muscle movements, 50 Hz power-line interference, baseline deviation, and T-wave interference. Subsequently, RR intervals were obtained using the Pan-Tompkins peak detection algorithm [30].

2.2.2. Feature extraction

RR interval is the time gap between two consecutive normal R peaks of the ECG signal. The RR interval is the main feature for analyzing the Heart Rate Variability (HRV). HRV has been extensively applied to understand the function of the Autonomic Nerves System (ANS). The sympathetic nervous system (SNS) and parasympathetic nervous system (PNS) are two parts of ANS that control the emergency – "fight or flight" – situations and relaxed activity, respectively. However, under mental stress, the normal balance between SNS and PNS systems will be altered [31]. The sympathetic activity of the heart increases with the stress level. When the stress increases, heart rate arises and more blood is pumped to the muscle, which leads to muscle tension. Therefore, the EMG signal recorded during stress has higher muscle activity than the EMG signal of the rest [32].

Twenty HRV features -as listed in Table 1- were extracted from each 60 s window of the ECG signal. The extraction of significant features for all signals was the purpose of the selection of 60-second window. Although, to show that ultra-short-term HRV features (e.g., 60 s) were valid surrogates for the short-term HRV feature (normally 5 min), statistical analyses based on prior works [33] were conducted.

The Spearman's correlation between ultra-short HRV features against equivalent short one for the rest (first rest) and stress (Task3) phases were calculated and presented in Table 2. As Table 2 is shown, all features of 1 min window are significant for rest and stress phases (*p*-value$<$0.05) and have correlations above 0.7 (rho$>$0.7). Therefore, the features of our study are valid surrogate for short term HRV features. Accordingly, we set the window lengths to 60 s.

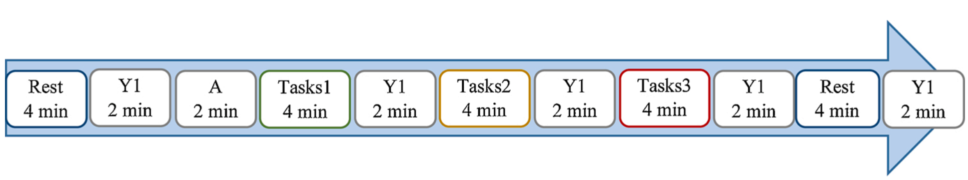

Fig. 3. The timeline of the stress-inducing experiment.

Table 1
HRV features employed in this work and their descriptions.

No	Feature	unit	description
1	mRR	ms	Mean of RR intervals
2	SDRR	ms	Standard deviation of RR intervals
3	RMSSD	ms	Root mean square of successive differences of RR intervals
4	SDSD	ms	Standard deviation of successive differences of RR intervals
5	CVRR	%	The coefficient of variance of RR intervals
6	PNN50	%	Corresponding percentage of NN50 (number of interval differences of successive RR intervals greater than 50 ms)
7	PNN20	%	Corresponding percentage of NN20 (number of interval differences of successive RR intervals greater than 20 ms)
8	mHR	bpm	Average heart rate
9	minRR	ms	Minimum value among RR intervals
10	maxRR	ms	Maximum value among RR intervals
11	δRRI	n.u.	Mean of absolute values of the first difference of RR intervals
12	QD	n.u.	Quartile deviation of RR intervals
13	CSI	n.u.	Cardiac sympathetic index
14	CVI	n.u.	Cardiac vagal index
15	SD1	ms	Standard deviation for T direction in Poincare plot
16	SD2	ms	Standard deviation for L direction in Poincare plot
17	LF	ms^2	Total energy of RR intervals in the low frequency band (0.04–0.15 Hz)
18	HF	ms^2	Total energy of RR intervals in the high frequency band (0.15–0.4 Hz)
19	LFHF	n.u.	Ratio of LF power to HF power
20	TP	ms^2	Total energy of RR intervals

Table 2
Spearman's Correlation analysis of HRV features.

HRV features	Rest phase	Stress phase
mRR	0.99	0.99
SDRR	0.92	0.86
CVRR	0.90	0.77
SDSD	0.95	0.84
RMSSD	0.95	0.84
SD1	0.95	0.84
SD2	0.88	0.82
PNN50	0.98	0.97
PNN20	0.96	0.97
LF	0.84	0.89
HF	0.98	0.89
LFHF	0.93	0.79
TP	0.89	0.93
mHR	0.99	0.99
minRR	0.93	0.78
maxRR	0.97	0.97
CSI	0.96	0.85
CVI	0.96	0.91
QD	0.92	0.86
δRRI	0.96	0.93

Nine time and frequency features were extracted from each EMG signal. The muscle activity was calculated by rectifying and filtering the preprocessed EMGs with a fourth-order low-pass Butterworth filter with the cut-off frequency of 6 Hz. Moreover, as the Power Spectral Density (PSD) of all the preprocessed EMG was extracted by applying the Fast Fourier Transform (FFT). The list of extracted features along with their descriptions is shown in Table 3. For more details on the features equation, see [32,34,35].

2.3. *Fuzzy model*

The aim of employing the fuzzy model is to identify various levels of stress and to represent the mental stress index (MSI) on a continuous scale of 0–100. The transition from one stress level to another is the gradual process [36]. Forasmuch as stress is classified to the few separated (e.g., two or three) levels, such a real gradual transition is neglected. Since the mapping of biomarker parameters to different stress

Table 3
The EMG features employed in this work and their descriptions.

No	Feature	unit	description
1	RMSE	mV	Root Mean Square of EMG
2	RMSA	mV	Root Mean Square of muscle activity
3	MAV	mV	Mean Absolute Value
4	Variance	mV	Variance
5	Energy	W	Energy
6	MNF	Hz	Mean Frequency
7	MDF	Hz	Median Frequency
8	ZC	–	Zero crossing
9	FR	–	Frequency Ratio

levels is a difficult task [4], the fuzzy model is employed for stress classification because of its capability to handle the uncertainties of data [34]. Defining appropriate parameters for the fuzzy model helps to handle the vagueness of the physiological inputs and stress levels as output. The implementation of the fuzzy model consists of 2 steps: fuzzy clustering and fuzzy inference system that considered in the following.

2.3.1. *Fuzzy clustering*

Briefly, Fuzzy clustering implements clusters of data which have not the sharp boundaries, exactly similar to boundaries of stress and rest states. Fuzzy clusters contain membership values between 0 and 1 that empower the fuzzy model to create flexibility in capturing various aspects of uncertainties in the data [13,37]. After clustering the data with the fuzzy c-means clustering method, "*c*" clusters contained membership values were obtained. In other words, each experiment's stages (rests, tasks and questionnaires) had "*c*" clusters. Fig. 4 demonstrates the five clusters in stress-inducing experiment stages such that area under each cluster show with a unique color. The blue color cluster has the most membership values in the first rest and the last rest (recovery) stages; the yellow color cluster has the most membership values in the task1 and the task2 stages, also task3 belongs to the orange cluster. In each experiment stage, the average of the area under clusters was calculated and prepared as fuzzy model input.

Based on the practical analysis, the more the number of clusters, the more details of the MSI can be obtained. If the number of clusters was low (e.g., 2), the stress index has been displayed in fewer details. On the other hand, when the number of clusters arises, the computational complexity of the proposed model increases dramatically. Therefore, the optimum number of clusters (c) should be determined based on the input by a trade-off between the details of the mental stress index and computational load. Further details are only valuable as long as they provide useful information. Considering the mentioned factors, the number of clusters was chosen as $c = 5$ and accordingly, the membership values (U) were achieved in the range of [0,1] by using the fuzzy *c*-means clustering algorithm.

2.3.2. *Fuzzy inference system*

We can implement the fuzzy inference system in 5 stages:

1) Specifying the input and output variable: The model has four inputs included the area under clusters in first rest and three stages of tasks (i.e., Task1, Task2, and Task3) that calculated according to the previous section and stress weight as an output.
2) fuzzification: By applying the membership functions, the belonging degree of variables to each appropriate fuzzy set was determined [38]. We adopted the triangular membership functions with three fuzzy linguistic variables (*low*, *medium*, and *high*) in this study.
3) Rules Definition: Several rules were defined to arrange an analytical relationship between the input variables and system output. Rules were established on the expert knowledge and background knowledge of data.
4) Output aggregations: In the aggregation process, all rule outputs for each output variable were merged to a unique fuzzy set using

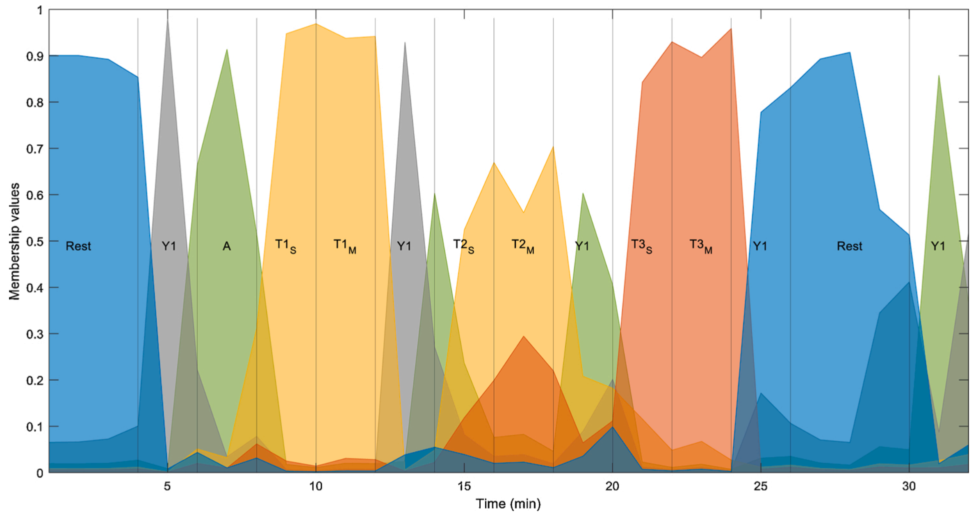

Fig. 4. The membership values of five clusters in experiment stages with unique colors for each cluster. The first rest and the last rest stages are four minutes. Y1 stages include two minutes to complete the state anxiety questionnaire (STAI-Y1) and A is two minutes anticipation stage. Tx_S and Tx_M (x: 1, 2 and 3) are Stroop and mathematical tasks, respectively.

"maximum" method. Output linguistic variables include *very low*, *low*, *medium*, *high*, and *very high*. Each output fuzzy set assigns a special weight to each output value utilizing the triangular membership function.

5) Output variable defuzzification: This step transformed fuzzy output values into numerical weights (*W*) with "centroid" method.

Finally, the MSI was calculated as the linear combination of the weighted membership:

$$MSI(k) = \sum_{c=1}^{5} (U(c,k) \times W(c)) \tag{1}$$

Where *U*, *W and k* denote the membership value, assigned weight, and the corresponding window number, respectively.

3. Results

We employed four different evaluation methods to validate the suggested methodology and compare the obtained results with the previous works, 4 different analysis methods were employed:

1. Analyzing the amount of continuous stress index versus time (stress curve)
2. Statistical analysis of findings
3. Calculating the correlation between the estimated stress and the stress reported by the subjects
4. Calculating the accuracy of stress detection.

The obtained results confirmed that the stress level of subjects is directly proportional to the difficulty of mathematical tasks. Fig. 5A shows the state anxiety inventory (Y1) results in five steps of the stress

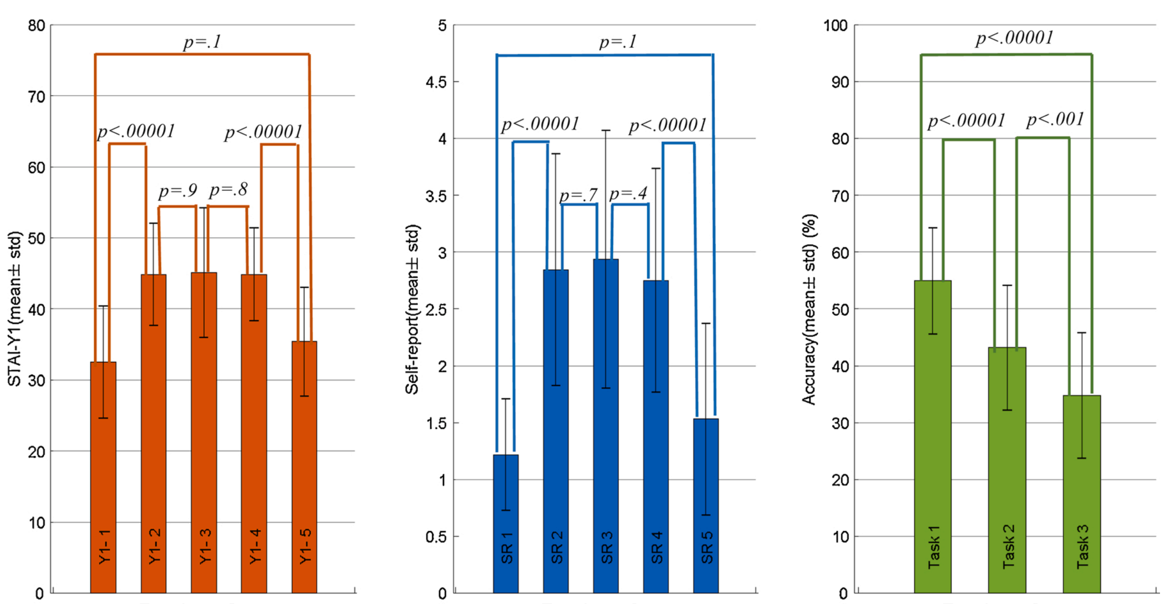

Fig. 5. A) State anxiety inventory (Y1) test results in five steps of the experimental procedure. B) Self-report (SR) of subjects in five steps of the experimental procedure. C) Performance (accuracy) in answering the mathematical questions under the three-level tasks. Task1 represents a simple level, Task2 represents medium difficulty level and Task3 represents a high difficulty level.

induction procedure. Results show a significant difference (*t*-test *p*-value < 0.00001) among perceived stress in rests (baseline, recovery) and Tasks (1–3) stages. Fig. 5B presents a rating score of the subjects. There is a significant difference between relaxation stages and tasks. The rating scores of subjects among tasks are not significantly different. Fig. 5C demonstrates the results of the performance (accuracy) of the subjects in answering the questions under the three-level tasks. Based on the results, there is a clear reduction in performance with increasing difficulty levels of tasks. Also, there is a remarkable difference between the accuracies of answering that confirm the effectiveness of stressors. Also, the average of the trait anxiety inventory (Y2) across all subjects was found to be 38.3 (according to the STAI manual [16] shows moderate stress).

3.1. Stress curve

After extracting features for every 60 s of the signals and choosing the optimum number of clusters as $c = 5$, by applying the proposed approach, the MSI could be plotted over time, which is called "*stress curve*." Fig. 6 shows the average stress index for all subjects in the whole experiment time. Stress curves are plotted for two randomly selected subjects in Fig. 7. The stress curve shows details of individual stress (individual differences) over the time of the experiment.

3.2. Statistical analysis

For statistical analysis of findings, *p*-values of each pair of experiment stages were determined. It is shown that if the *p*-value of two experiment periods is less than 0.05, there is a significant difference between the stress indices of these experiment stages. To obtain the *p*-values, paired *t*-test values are calculated for each pair of the stress indices derived for experiment stages [15] (Table 4).

Table 4 declares that the first rest stage is significantly different from the other stages. Task1 and Task2 have no significant difference ($p > 0.05$), but there is a significant difference between Task3 and other stages.

3.3. Correlation analysis

The correlation between the estimated stress index and reported perceived stress (self-report and STAI) was identified to compare the findings of this work with other same studies. For two random variables x and y, the correlation coefficient r can be calculated by using the Eq. (2), where μ_m and σ_m denote the mean and standard deviation of random variable m, respectively, and N is the length of m.

$$r(x,y) = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{x_i-\mu_x}{\sigma_x}\right)\left(\frac{y_i-\mu_y}{\sigma_y}\right) \tag{2}$$

The mean of the correlation analysis across all subjects is 0.959 (*p*-value$<$0.0099).

3.4. Stress detection accuracy

The estimated MSI based on the information provided in Fig. 5C can be roughly segmented into three class labels: low, medium, and high as follows:

- If $0 \leq$ stress index ≤ 33 then a label is 'Low'
- If $33 <$ stress index < 66 then a label is 'Moderate'
- If $66 \leq$ stress index ≤ 100 then a label is 'High'

The mean of the stress index estimated by the proposed approach for all subjects has been calculated at the three stages of the experiment and then using the above labels, the accuracy of stress detection was calculated. The results are presented in Table 5. The average accuracy of three-level stress detection found to be 75.6 %. In the case of two-level, the accuracy of stress detection found to be 96.7 %.

4. Discussion

The objective of the present study is to detect stress relying on the continuous nature of mental stress states changes. We collected physiological data included EMG and ECG signals from subjects engaged in pre-designed stress induction tasks. Signal processing methods and fuzzy approaches were used. The fuzzy method copes with uncertainty and complicated relationships between physiological biomarkers and mental stress.

Although most of the ordinary stress detection methods were announced accuracy of detection [39–41], some continuous stress level evaluation approaches reported the correlation [14,15,42]. We reported both in this study. The correlation between output estimated stress and stress rating score by subjects is absolutely high (more than 0.9). Also, two-level and three-level stress recognition accuracies are 75.6 % and 96.7 %, respectively. Table 6 reviews previous studies in the case of the stress assessment methods and results.

In the meantime, the stress curve provides more details of changes in mental states, does not eliminate individual differences, and quantifies an individual's stress. The stress curves of Fig. 7 confirm these benefits well. Subject #1 was significantly under stress prior to starting the task (during responding to the questionnaire and anticipation stages), but

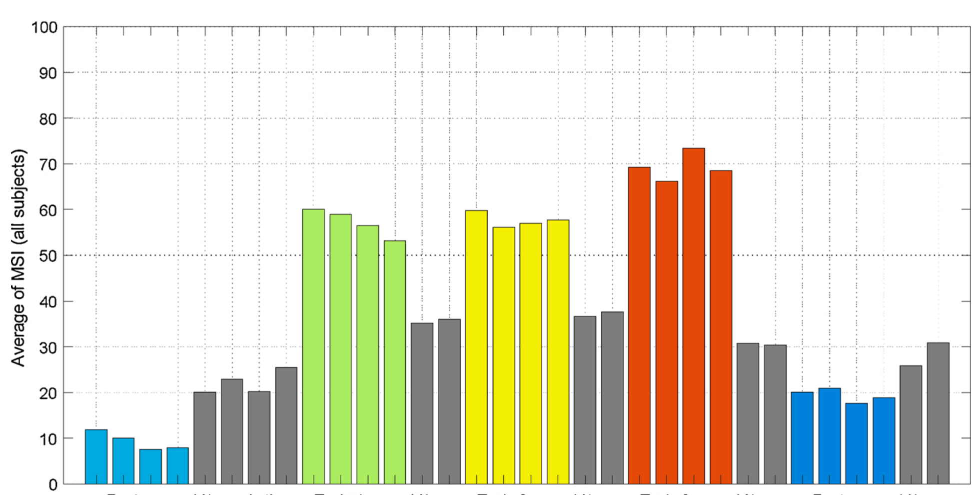

Fig. 6. Average stress curve of all subjects. Different colors separate experiment stages. Rest: 4 min, Y1: 2 min, Anti: 2 min, Tasks: 4 min.

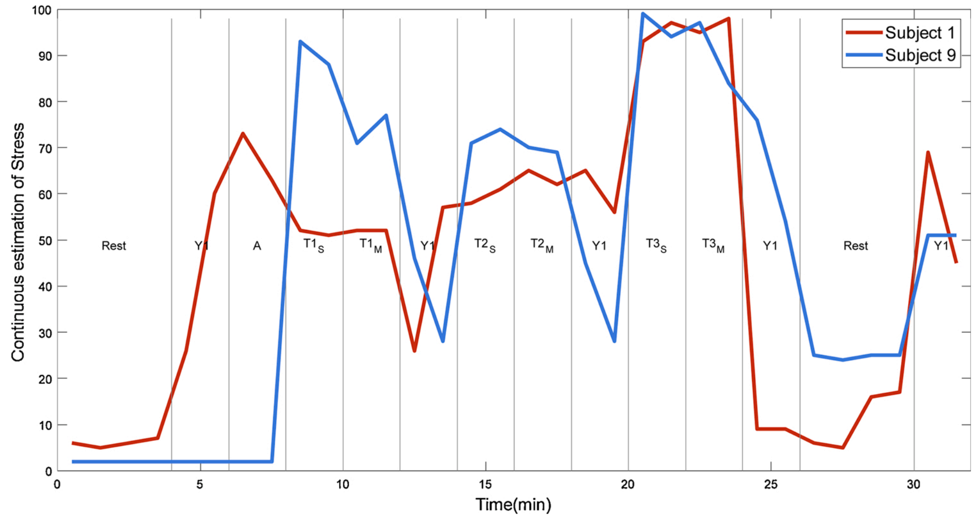

Fig. 7. Stress curves of the two subjects; subject #9 (sex: male, age: 20) and subject #1 (sex: female, age: 25). Y1: state anxiety questionnaire (STAI-Y1), A: anticipation, Tx_S and Tx_M (x: 1, 2 and 3): Stroop and mathematical tasks, respectively.

Table 4
p-values of each pair of experiment periods calculated using a paired *t*-test.

Experiment Period	Task1	Task2	Task3	Recovery
First rest	1.2×10^{-12}	1.5×10^{-14}	8.3×10^{-16}	0.0012
Task1		0.5221	8.4×10^{-4}	4.7×10^{-9}
Task2			7.7×10^{-5}	1.1×10^{-8}
Task3				1.7×10^{-10}

Table 5
The confusion matrix of the three-level stress detection.

		Predicted stress		
		Low	Moderate	High
Actual stress	Low	93.3	6.7	0
	Moderate	13.3	53.4	33.3
	High	3.3	16.7	80

subject #9 had no stress until task 1 began. This confirms that subject #1 is more affected by the stressful environment than subject #9. Interestingly, subject #9 is younger. Furthermore, according to stress curves, both subjects in Task 3 endured a great deal of stress, but their stress levels declined rapidly afterward and have been reported high perceived stress levels for this stage.

As can be seen, more details of the individual's states are identified, and along with evidence such as age, sex and personality traits, valuable information about persons' stress is obtained that can be effective in stress management.

5. Conclusion

The novel stress assessment methods must consider the continuous and subject-dependent nature of mental stress. Accordingly, we developed a methodology for fuzzy-based continuous stress level assessment using the ECG and EMG signals. The relationship between biological signals and stress levels are uncertain and complicated. The suggested fuzzy model included fuzzy clustering and fuzzy inference system algorithms that seem to be an efficient tool in the presence of uncertainties. Our method offers a personalized model that highly correlated with perceived stress. The correlation between estimated stress and perceived stress of subjects was yielded as 0.959.

If a body area network used to provide biological signals [46] for the proposed method, it is possible to employ assessed stress for different

Table 6
Comparison among the results of the proposed method and previous studies.

Ref	Physiological signal	Method	Correlation	Levels: Accuracy
[4]	ECG, EMG, EEG, GSR	General regression neural network	–	3-level: 85.2 %
[13]	ECG	Fuzzy model	0.8198	–
[14]	ECG, respiration, GSR, EMG	Linear regression	0.302	2-level: 86.4 %
[15]	PPG, HR, ST	Linear regression	0.67	–
[39]	ECG, GSR, respiration rate, blood pressure, and blood oximeter	Machine learning approach	–	2-level: 95.8 %
[40]	EDA	Machine learning approach	–	3-level: 97.83 %
[41]	ECG, GSR, Computer interaction, Facial expressions, Body posture	Linear regression & Machine learning approach	0.7105	2-level: 90 %
[43]	HRV	Machine learning approach	0.52	2-level: 72 %
[42]	ECG, Respiration	Hidden Markov Model	0.71	–
[44]	ECG, PCG	Machine learning approach	–	2-level: 96.67 %
[45]	HRV, smartphone	Logistic regression	–	3-level, 61 %
Proposed method	**HRV, EMG**	**Fuzzy model**	**0.959**	**2-level:** 96.7 % **3-level: 75.6%**

PCG: Phonocardiography, PPG: Pulse Photoplethysmogram, ST: Skin Temperature, GSR: Galvanic Skin Response, EDA: electrodermal activity.

practical applications. Monitoring student's stress during exams and monitoring drivers' stress while driving are examples of these applications. By combining this idea with features such as mobile phones, applets, the internet of things, and intelligent vehicles [47], it can be used in a variety of applications.

CRediT authorship contribution statement

Sara Pourmohammadi: Conceptualization, Methodology, Data curation, Software, Validation, Formal analysis, Writing - original draft, Visualization, Investigation. **Ali Maleki:** Conceptualization, Methodology, Validation, Writing - review & editing, Visualization, Investigation, Supervision, Project administration.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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