An automatic approach to continuous stress assessment during driving based on fuzzy c-means clustering

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Abstract

This paper presents a novel approach for driving stress assessment by fuzzy clustering. In previous researches, stress during real-world driving tasks has been detected in discrete levels, but in this study, we demonstrated that considering fixed-levels for stress in long periods is not authentic. Without employing discrete levels of stress, data remains unlabeled. So a clustering method has been proposed to compensate for the lack of the feasibility of classification. Due to uncertainties, the clusters can be defined in terms of fuzzy sets. Furthermore, using fuzzy clustering methods, data overlap is considered. In the proposed algorithm, utilizing membership values generated by fuzzy c-means, and weights assigned by fuzzy inference system (FIS), we present automatic continuous criteria for stress in the short time intervals. The continuous scale is defined between 0and100, where higher values represent higher stress levels. Our findings not only confirm rough results of previous studies, but also indicate improvements in precision and accuracy of stress assessment.

Keywords: Fuzzy c-means Clustering, Continuous stress criteria, Automatic stress assessment.

1. Introduction

There is a drastic relationship between stress and human being's health. Although stress has negative effects on health and well-being, urgent actions cannot be applied to effectively prevent or manage it even in patients. Fast and practical specification of stress level could help different groups of people considerably preventing illness, increased stress and social problems.

Existing studies have shown that mental stress can be recognized by the physiological information of humans, which is available through physiological signals such as electroencephalogram (EEG) [1,2], electrocardiogram (ECG), blood volume pressure (BVP) [3-7], galvanic skin response (GSR) [8-10], electromyogram (EMG) [4, 8-9] and respiration (RESP) [10].

The common approach in stress evaluation methods based on physiological signals is to extract the features followed by pattern recognition and machine learning algorithm to identify the relationship between stress and physiological information [12-15]. Zhai and Barreto [16] proposed a stress detection method based on automatic monitoring of four physiological signals including GSR, BVP, pupil diameter (PD) and skin temperature (ST). They utilized three classifiers consisting of Naïve Bayes, decision tree and support vector machine (SVM), and found that the physiological signals have a strong correlation with mental stress. In their study, stress has been classified as either "stressed" or "relaxed" [16].Setz et al. [17] focused on the electrodermal activity (EDA) for detecting stress. Several classifiers were evaluated; one of them achieved the accuracy of 82.2%. Also the performance of classifiers was compared for distinguishing between the "stress" and the "cognitive load". In another study [2] the stress in computer game players was labeled in three levels ("no stress", "average" and "high stress"), and over 90% accuracy was obtained using EEG signal. Also in [8], emotional states in car-racing drivers were classified into "high stress", "low stress", "disappointment" and "euphoria" levels. For that, SVM and ANFIS classifiers were used and overall classification rates of 79.3% and 76.7% were achieved respectively. Kumar et al. [18] suggested a stochastic fuzzy analysis method to continuously quantify stress levels based on short-time series of R-R intervals. Their experiment performed a 24 hours monitoring of 50 subjects in e-health setting. The subjects were ask at different times of the day during monitoring to report the subjective rating scores of stress felt by them during last five minutes on the scale from 0 to 100. Then the results are analyzed and compared with the subjective rating score. Finally, the estimation performance of R= 0.8198 is achieved.

Among different stressful situations, driving stress is considered as a drastic factor that affects awareness and performance of drivers which in turn can result in aggressive and dangerous behavior on roads. In a comprehensive research, Healey[19]used ECG, EMG, GSR and respiration

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signals to recognize three driving stress levels including "low stress", "medium stress" and "high stress", which respectively correspond to "rest", "highway driving" and "city driving". The biological signals recorded at MIT Media Lab. are now available as a dataset in Physionet [20]. This dataset has been used by many researchers to study stress [21-25]. For instance, Wang et al. [25] classified stress levels using ECG signals and a K-nearest neighbor classifier into two levels: "low stress" and "medium/high stress" [25].

In earlier studies, stress in drivers has been classified into discrete levels. However this type of classification is not capable of taking real-world variables such as individual differences, unpredictable events and behavioral details into account. For example, in a long driving experiment [19] how can the stress be considered as high in all participants with different genders, personalities, experience and ethnic background? Or how could it be claimed that a subject with 30 minutes driving has a fixed stress level? To answer these and other similar questions, defining continuous criteria for stress assessment is required.

Accordingly, instead of already different classification and labeling methods, in the present study, we used fuzzy c- means clustering to specify levels of stress with higher resolutions. Due to uncertainties the cluster could be specified in terms of fuzzy sets [26]. Using of fuzzy concept whereas clusters have overlap leads to better results. Finally, quantitative criteria for subject's stress will be presented using fuzzy inference system (FIS).

The remaining of this paper is organized as follows. In section 2, first, the proposed algorithm is described. Then, detailed description of the experimental data, feature extraction, fuzzy clustering and fuzzy inference system for driving stress evaluation are introduced. In section 3, the experimental results and discussion are presented. Finally, conclusion is presented in section 4.

2. Methods

2.1. Algorithm

The block diagram of the proposed method for quantifying the stress levels is shown in Fig.1. In the procedure, first, HR, EMG, hand and foot GSR signals from the driving dataset [20] are used to extract the features. These features are fed into fuzzy c-means clustering method which in turn results the clusters with membership values. Then each cluster is divided to seven driving periods (SDPs) consisting of first rest, first city, first highway, second city, second highway, third city and second rest. These SDPs are determined by available markers in the dataset. The mean of cluster curve (MCC) for each segment is calculated and used as an input for FIS. The FIS input is denoted as a SDP-MCC matrix in the block diagram of Fig. 1. Using efficient if-then rules in FIS, the label of each cluster is obtained. Then proper weights are assigned to labeled clusters. Combining the membership values and weights already assigned to the clusters, along with scaling the results leads to the final continuous stress criteria. In the following subsections, each of the mentioned components is described in detail.

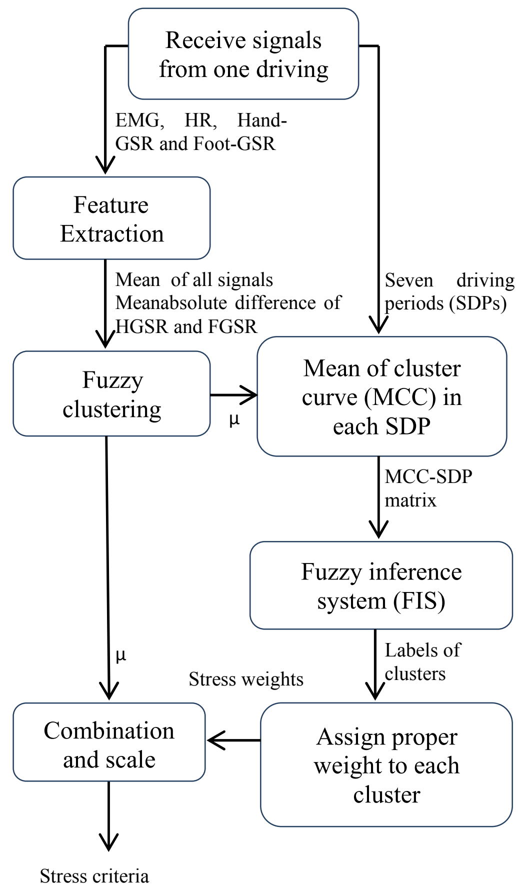

Fig 1. Block diagram of proposed algorithm

2.2. Experimental data

Providing stressful conditions and recording the physiological signals during real driving are costly and time-consuming. Fortunately, such a dataset produced by Healy in MIT Media Lab [19], is available at Physionet [20]. The experiments were performed on a specific route of open roads and where drivers traverse were limited to on daily commutes. The experiments were done in the real-world so that the physiological reactions of the drivers could be excited in a natural manner which in turn leads to more practical results. Among all participants, three drivers repeated the task several times and six drivers completed the task just once. For each drive, ECG, EMG, foot and hand GSR, respiration and marker signals were acquired from the sensors worn by the driver. Among all sixteen recordings of the dataset, [20] only ten drives consisting of #5, 6, 7, 8, 9, 10, 11, 12, 15 and 16arealmost complete for being used [21-26]. In drive #5, the first highway period lacks the heart rate data. Also in drives#9 and #16, the last rest periods lack clear marks. Therefore just seven drives consisting of #6, 7, 8, 10, 11, 12 and 15 which include all the sensors data are perfect and suitable to be used in the present study.

Obviously, the more number of physiological signals are used, the more computational cost must be paid. So in our study, heart rate, EMG, foot and hand GSR from dataset are used.

2.3. Feature extraction

So far, no comprehensive study that considers determination of the best features of physiological signals for stress detection is not available [26]. Accordingly, mean value has been selected as an efficient feature with minimal calculations. The mean value for the signal X_n containing N samples, $X_n = \{x_1, x_2, \dots, x_N\}$is calculated by Eq.1.

$$mean\ of\ X_n = \frac{1}{N}\sum_{n=1}^{N} x_n \tag{1}$$

Among different features already extracted from GSR signals [9-12], the mean absolute difference (Eq.2)is a suitable feature.

$$\delta_X = \frac{1}{N-1}\sum_{n=1}^{N-1} |X_{n+1} - X_n| \tag{2}$$

Altogether, six features consisting of mean values of the four signals (heart rate, EMG, hand and foot GSR) in addition to mean absolute differences for hand and foot GSR are extracted for each ten-second window of signals.

2.4. Fuzzy c-means clustering

This algorithm works by assigning membership to each data point corresponding to each cluster center on the basis of distance between the cluster center and the data point. More the data is near to the cluster center more is its membership towards the particular cluster center. Clearly, summation of membership of each data point should be equal to one. In this algorithm the number of clusters must be predefined. After each iteration, membership and cluster centers are updated according to Eq. 3 and Eq.4.

$$\mu_{ij} = 1/\sum_{k=1}^{c}(d_{ij} - d_{ik})^{2/(m-1)} \tag{3}$$

$$v_j = \frac{\sum_{i=1}^{n}(\mu_{ij})^m x_i}{\sum_{i=1}^{n}(\mu_{ij})^m}, \forall j = 1,2,\dots,c \tag{4}$$

where μ_{ij} represents the membership of i^{th} data to j^{th} cluster center, d_{ij} represents the Euclidean distance between i^{th} data and j^{th} cluster center and c represents the number of cluster centers. m is the fuzziness index $m \in [1, \infty]$, n is the number of data points and v_j represents the j^{th} cluster center.

Main objective of fuzzy c-means algorithm is to minimize Eq. 5.

$$J = \sum_{i=1}^{n}\sum_{j=1}^{c}(\mu_{ij})^m \|x_i - v_j\|^2 \tag{5}$$

Where $||x_i - v_j||$is the Euclidean distance between i^{th} data and j^{th} cluster center. Algorithmic steps for Fuzzy c-means clustering are as follow.

Let $X=\{x_1,x_2,\dots,x_n\}$ be the set of data points and $v=\{v_1,v_2,\dots,v_c\}$be the set of centers.

1. Randomly select *'c'* cluster centers.
2. Calculate the fuzzy membership *'µij'* using Eq. 3
3. Compute the fuzzy centers *'vj'* using Eq. 4
4) Repeat step 2 and 3 until the minimum *'J'* value is achieved (Eq. 5) [27]

2.5. Fuzzy inference system

A fuzzy inference system (FIS) is a system that uses fuzzy set theory to map inputs (SDP-MCC matrix*)* to outputs (labels of clusters) [28]. Our version of FIS is Mamdani inference system and including the seven inputs (SDPs)and an output (cluster labels).

Fig. 2(a) shows the membership functions of inputs which are trapezoidal and are associated with three linguistic values (low, medium and high). Fig. 2(b) shows the membership functions of output which are triangular and are associated with five linguistic variables (very low, low, medium, high, and very high).

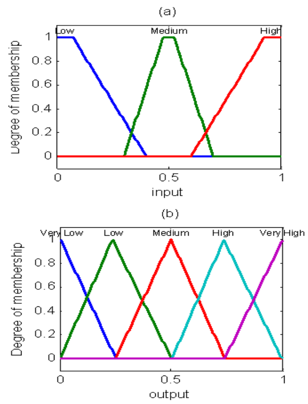

Fig. 2. Membership function of designed FIS for a) inputs, b) output.

Fuzzy rules are a collection of the linguistic statements that describe how the FIS should make a decision regarding labeling the output. Fuzzy rules are written based on scrutiny on signals and as a replacement for expert, must be covered all drives and leading to proper results in specific terms or unpredictable events. Table 1 show five rules which are determined in our implementation.

Table 1. FIS rules with objective of labeling fuzzy clusters

No	Rules
1	*If* (Rest1 is not High) and (City1 is not Low) and (HW1 is not Low) and (City2 is not Low) and (HW2 is not Low) and (City3 is not Low) *then* (Label is High)
2	*If* (City1 is not High) and (HW1 is not Medium) and (City2 is not High) and (HW2 is Medium) and (City3 is not High) and (Rest2 is not Low) *then* (Label is Low)
3	*If* (Rest1 is High) and (City1 is Low) and (City2 is Low) *then* (Label is VeryLow)
4	*If* (Rest1 is not High) and (City1 is High) *then* (Label is VeryHigh)
5	*If* (Rest1 is Low) and (HW1 is not Low) and (HW2 is Medium) *then* (Label is Medium)

3. Results and discussion

In total of available signals from dataset, HR, EMG, hand GSR and foot GSR are selected. Each of signals segment into a series of 100 second window with 90% overlap. For each window, six features including mean and mean absolute difference are extracted. Fig. 3 shows a biosignal diagram of drive #8 achieved from stress in driving dataset as an example, indicating whole driving procedure. Fig. 4 shows six mentioned features and their performance to trace signal variations.

In the next step, features are given to fuzzy c-means clustering with predefined number of clusters (c=5). After clustering, there are the membership values corresponding to each cluster center for every 10 seconds of signals that can be determined the efficient criteria for stress in subjects. Each cluster is divided to seven driving periods (rest1, city1, highway1, city2, highway2, city3, rest2) by marker identification available from dataset. Mean of cluster curve (MCC) in SDPs is calculated as an agent for membership values. With repetition of above step for 5 clusters, the SDP-MCC matrix is obtained. A normalized SDP-MCC matrix of drive #8 is given in Table 2 as an example.

Table 2. SDP- MCC matrix for drive #8

SDPs / clusters	R1	C1	H1	C2	H2	C3	R2
1	0.17	0.84	0.63	0.61	0.45	0.00	0.19
2	0.00	0.05	0.04	0.02	0.05	0.04	0.96
3	0.19	0.00	0.34	0.00	0.10	0.64	0.13
4	0.15	0.21	0.02	0.04	0.02	0.00	0.05
5	0.44	0.48	0.39	0.26	0.00	0.60	0.37

This matrix is applied to FIS. Then predefined weights are assigned to labeled clusters. That's mean if labels of five clusters determine as very low, low, medium, high and very high, the assigned weights will be 0.01, 0.25, 0.5, 0.75 and 1, respectively. The output of FIS and the assigned weights for drive #8 are given in Table 3 as an example.

Table 3. The output of FIS and assigned weight

Fuzzy output	0.5719	0.081	0.882	0.3	0.7474
Assigned weight	0.5	0.01	1	0.25	0.75

After assigning weights to the clusters, for each 100 seconds window with 90% overlap, the determined membership values calculated from fuzzy c-means, are multiplied to the corresponding weights of the clusters. Then, sum of the multiplication results is scaled to the range 0-100, in order to quantify stress. For better representation, a collection of 100 different colors in the range of dark blue to dark red of the visible spectra was defined using "colormap" command of MATLAB. Thus, for any quantified value of stress in the range 0-100, one of the mentioned colors is chosen. In other words, the color is associated to the stress value of the corresponding window.

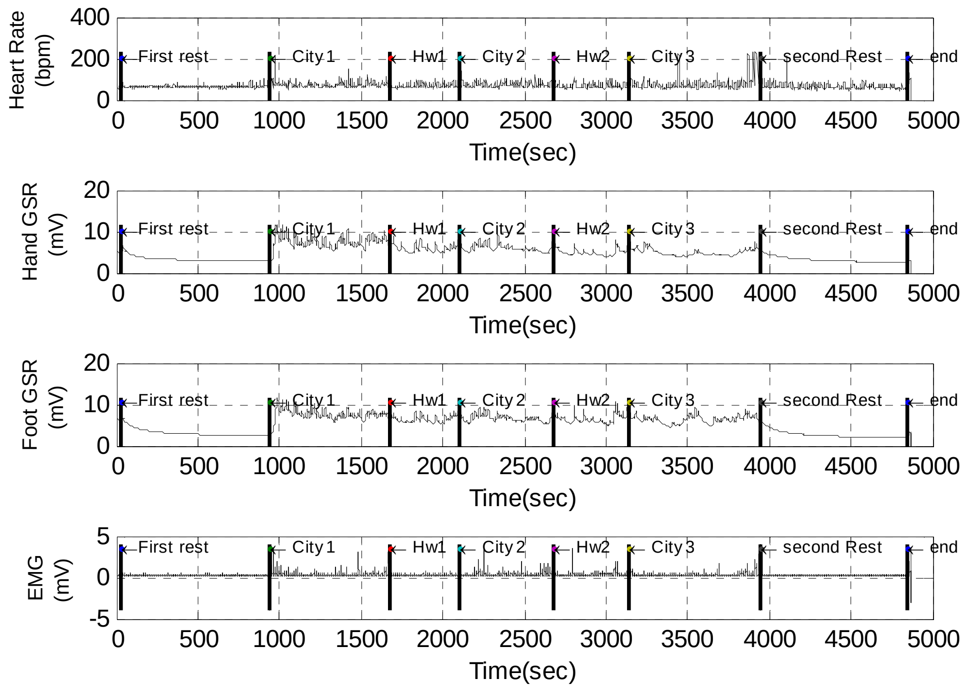

Fig. 3. Selected signals from dataset for drive #8 as an example

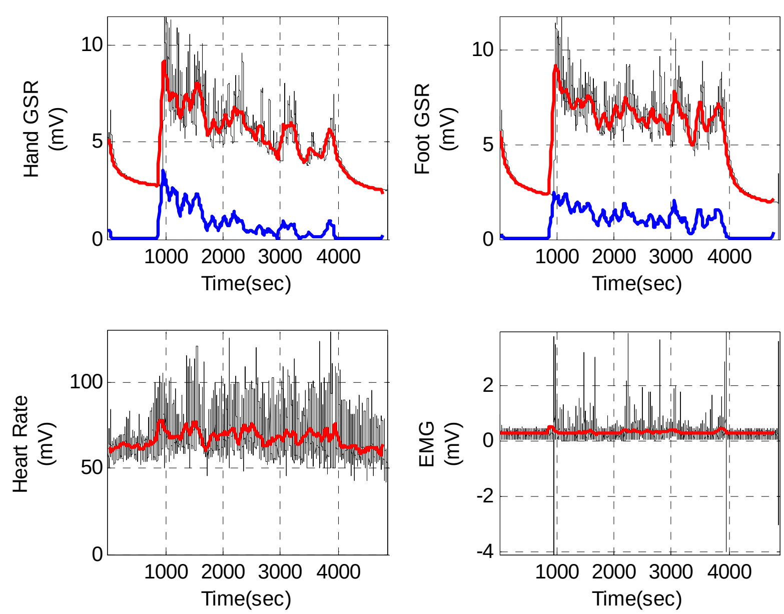

Fig. 4. The appearance of the six features. Mean feature is shown by red color for all signals and mean absolute deference is shown by blue color for hand and foot GSR.

As mentioned, the lower values are related to the lower levels of stress which are represented with lower wavelength of the visible spectra (such as blue, cyan).In contrast, higher values which were assigned to the higher stress are represented with higher wavelengths of visible spectra (red, yellow). Similarly, middle values are related to the average levels of stress which are represented with the color range of green. Fig. 5 shows the stress criteria for drive #8 which is achieved using described procedure. Seven driving period's indicator and the five confines of stress criteria are also shown in Fig. 5.

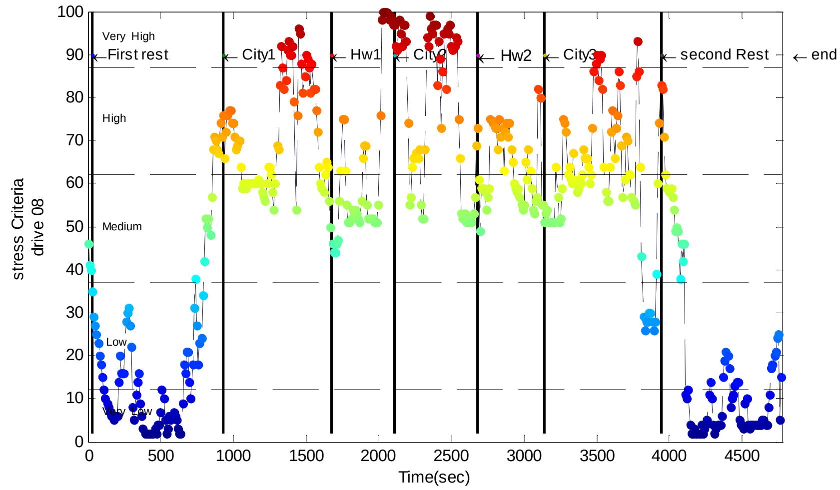

Fig. 5. Stress criteria for drive #8

The colors improve the perception of stress in every moment. Stress is evaluated from very low to very high, 0 to 100 and the dark blue to dark red. With more scrutiny in stress criteria in Fig. 5, it is understood that stress of participant during rest1 is almost very low, but near to the end of this period, it gradually increases. Because of the approaching to the start of experiment, the stress increasing is natural.

After the first rest period drivers exited through a narrow, winding ramp and drove through busy Main Street in the city [10]. Our results (e.g. Fig. 5) show that exiting from the garage and interring to the city causes to increase the stress criteria.

The city period expected to generate high stress, that the drivers encountered traffic and unexpected hazards such as cyclists and pedestrians [10]. As shown in Fig. 5, city periods almost have high and very high stress. Effect of the unpredictable events is recognizable in the stress criteria.

The route then led drivers away from the city and onto a highway. Between two tolls, drivers performed uninterrupted highway driving [10]. In the highway periods, stress criteria are changed between high and medium regions. It can be related to the subject's skill and experience in driving. Stress in the beginning of the last rest gradually decrease to the very low region. As described, the proposed algorithm creates more details about driver's stress, increases precise and considers individual differs. Obtained results are consistent with previous studies; however, they reject the assumption of constant stress during each driving period.

In total 27 driving runs were attempted, some drives were not used due to lost data and deviation proscribed driving rout [19]. Also several drives in published dataset [20] did not contain all the sensors information and the mark of different driving period did not clear. Moreover few and unclear information exist about details of events during trials and author's effort did not result to access more information.

Conducting experiment in the natural environment allows many unexpected events occur. For example, one of drivers, during the first of two highway driving segments took an unexpected exit and had to get back on the highway. Additionally, during the second rest period the subject was agitated due to needed to the restroom and had difficulty resting. Another subject had a minor accident during the city driving. Hence, participants had different age, gender, skill and experience for driving. In stance first subject was a male undergraduate with three years of driving experience who had not driving regularly for the past three years. The second subject was an undergraduate male student with over four years of driving experience. He had not driven a month previous to the experiment and stress in driving experiment was his second driving experiment in this city. The third subject was a female undergraduate with eight years of driving experience [19].

Due to these individual differs and unpredictable events during driving in [10, 19] were confirmed to avoid misclassification, their simulation has a relatively long time window such that a data period that is partially inconsistent with the assumption still had enough data in line with that assumption to make the correct classification. According to this theory, several studies were classified stress with the long time window.

But our results clearly represent valid and efficient criteria for driving stress in each moment without using long time window. Result is demonstrated in Fig. 5 represent continuous stress from the start of experiment till the end of it, furthermore demonstrate individual differs and unexpected hazards during experiment.

Despite these advantages, our suggested algorithm is automatic, fully practical and applicable for the other stressful scenarios. Fig. 6 shows an implementation of the proposed method with assigning colors to stress criteria, on four selective signals (HR, EMG, hand GSR and foot GSR) for drive #8 as an example. Colors clearly demonstrate the stress variations during driving on recorded signals.

As mentioned, the stress variation from very low to very high is illustrated by blue wavelength spectra to red wavelength spectra.

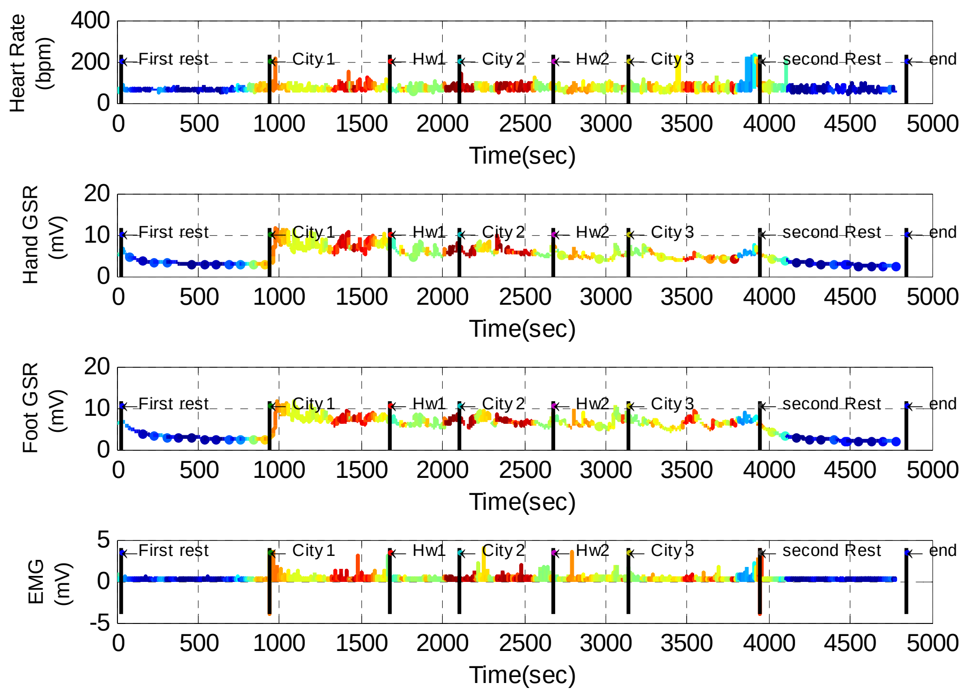

Fig. 6. Implementation of the stress criteria via colors

In fact any of previous works in the driving stress detection field, do not study stress in the continuous manner. Stress in drivers always was classified in discrete levels (low, medium and high) and the stress recognition accuracy was reported as an output. But some previous studies evaluated stress in the non-driving situations utilizing complex techniques instead of simple classification methods [18, 29], same as our proposed approach.

It is shown that the stress criteria (achieved by our automatic approach) are positively correlated with the dataset information and the previous work results (Fig. 5). In the stress driving dataset, the participants were ask to rate their stress during the driving periods in range of 1 to 5. In order to comparison between the subjective rating scores and the results of the proposed algorithm, the averaging in each driving period is needed. Calculation of the averaged stress criteria in SDPs of all drives, provide another representation of the stress variations during driving (Fig. 7).

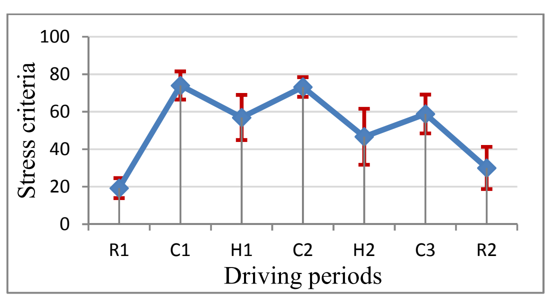

Fig. 7. Mean and standard deviation of averaged stress criteria in SDPs.

Fig. 7 confirms the results of the previous studies including low stress in rest, medium stress in highway and high stress in city. Also standard deviation demonstrates individual differences during driving. Fig. 8 compares average of the stress criteria in SDPs and the subjective rating scores. We obtain a correlation of R=0.9223 between the subjective rating scores and the proposed method output. The suggested technique shows better performance than R=0.8198 and R=0.71 in [18] and [29], respectively.

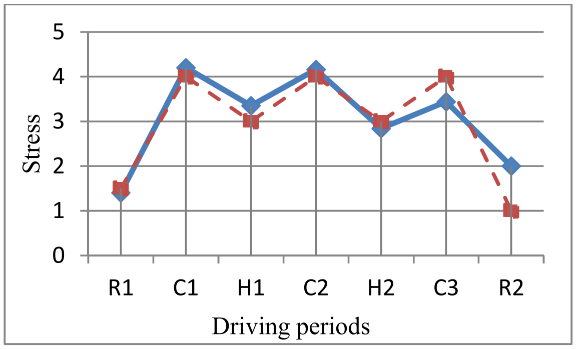

Fig. 8. The comparison between the average of the stress in SDPs (blue solid line) and the subjective rating scores (red dashed line)

4. Conclusion

In this paper, an automatic approach to continuous stress assessment during driving using physiological signals is proposed. Whereas most of the event details during driving are neglected by discrete assumption of the stress levels, continuous stress assessment is presented. Also fuzzy c-means clustering is considered to be suitable for data that do not have proper labels and the clusters that have overlap. The experimental results confirm this assertion. Lack of sufficient details about dataset is compensated by fuzzy if-then rules and finally results demonstrate that the stress variations from one driving period to another are smoothed in lieu of fluctuation. Moreover, with presenting averaged stress in SDPs, previous studies are confirmed. Proposed method is extendable to other stressful scenarios. In the future work, optimization methods such as Genetic algorithm are used to optimize number of clusters and to assign proper weights to clusters.

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