Article

EEG-metric based mental stress detection

Gaurav[1], **R. S. Anand**[1], **Vinod Kumar**[2]
[1]Department of Electrical Engineering, Indian Institute of Technology Roorkee, Roorkee 247667, India
[2]Jaypee University of Information Technology, Waknaghat 712100, India
E-mail: gsbmi.dee2014@iitr.ac.in, anandfee@iitr.ac.in, vinodfee@iitr.ac.in

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Abstract
Mental stress level is a vital parameter affecting physical well-being, cognition, emotions, and professional efficiency. With growing adversities in modern living standards, causing abnormal mental stress, it is necessary to measure to cure it. Regular personal stress profile generated can be used as neurofeedback for the clinical as well as personal assessment. This paper describes a method to detect mental stress level based on physiological parameters. In this method, an electroencephalogram (EEG)-metric parameters based binary and ternary stress classifier is developed. This is validated through probabilistic stress profiler of differential stress inventory (a questionnaire based evaluation). Nine channel EEG is used to extract physiological signal. EEG-metric based cognitive state and workload outputs are generated for 41 healthy volunteers (37 males and 4 females, age; 24±5 years). All subjects were guided to perform three simple tasks of closed eye, focusing vision on a red dot on center of dark screen and focusing on a white screen. Central tendencies (mean, median and mode) and standard deviation were extracted of EEG-metric (sleep onset, distraction, low engagement, high engagement and cognitive states) as features. Either of the two or three classes of stress are evaluated from probabilistic stress profiler of differential stress inventory and used as training output classes. A supervisory training of multiple layer perceptron based binary support vector machine classifier was used to detect stress class one by one. 40 subject’s samples were used for training and interchanging one-by one 41th subjects stress class is determined from the designed classifier. Out of 41 subjects, stress level of 30 subjects is correctly identified by binary classifier and stress level of 26 subjects is correctly identified by ternary classifier, using multi-layer perceptron kernel based SVM.

Keywords EEG-metric; differential stress inventory questionnaire; SVM-MLP.

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1 Introduction

Psychological stress is a phenomenon related to thoughts, emotion, physiological changes and everyday social activities. High level of psychological stress can become cause of mental or physiological illness, or other health related problems. It has been observed in recent researches that high level of mental stress adversely affects cardiovascular, endocrine and immune system health, etc. and psychological health (Cohen et al., 2007). Stress is surveyed to be an unavoidable aspect of college student's life. A survey conducted by Nightline Association reported about 65% of university students observe some kind of mental or psychological stress in their daily academic and other activities (Zheng et al., 2016). Cognitive as well as physical performance can also be affected due to daily stress conditions. High risk professions, such as defense services, industrial process plants, vehicle, locomotives and flight operation and control are more prone to get affected due to high stress condition and can be highly dangerous (Driskell et al., 2013). Diagnose and measurement of stress level profiles; quantitatively and qualitatively with abnormality spotting can be achieved by majorly three methods: task oriented, questionnaire based and physiological parameters assessment based evaluations. Psychological questionnaire based methods are widely used to examine the stress profile, but this is mostly only empirical to subject's response and is prone to misrepresentation or manipulation, and it can result to incorrect measurement. Also, evaluation requires an extensive training and expertise.

Physiological and psychological parameters have been proposed to comparatively identify anxiety or stress level (Sharma et al., 2012; Glenn et al., 2014; Hermens et al., 2014). Also, questionnaire based stress evaluation methods have been developed, such as; Cohens Perceived Stress Scale (PSS), Stress Response Inventory (SRI) and Hamilton Depression Rating Scale (HDRS) (Cohen et al., 1983; Koh et al., 2000; Williams, 1988). Few of the methods to induce mental stress in lab settings are as mentioned (Skoluda et al., 2015). Changes in autonomic nervous system responses can be induced by anxiety, this can be observed through changes in physiological factors such as heart rate, blood pressure and respiratory rhythm (Jung et al., 2013). In previous studies, power spectrum density of electroencephalogram (EEG) is observed to changes in specific way with change in emotion or mental states (Alonso et al., 2015; Dogra et al., 2018; Zhang, 2018). Different EEG patterns are seen to be changed with increasing level of stress (Hsieh et al., 2013). Stress evaluation is also possible with examination of electrocardiogram (ECG) based factors, such as heart rate and heart rate variability (Xu et al., 2015).

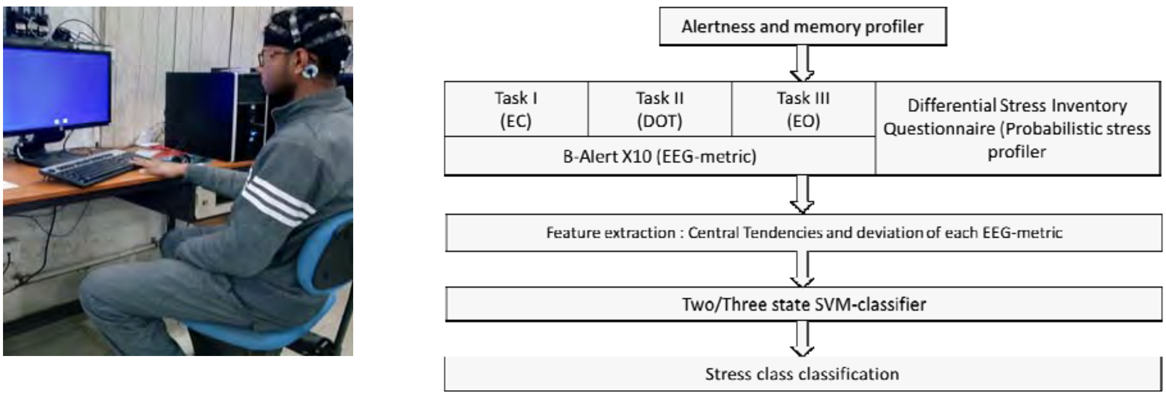
Cardiac and respiration activity was found to offer better stress assessment biomarkers than speech, galvanic skin response or skin temperature when recorded with wearable biomedical measurement systems (Seoane et al., 2014). For evaluation of anxiety in daily life scenarios, wearable systems which work on physiological parameters have been developed (Wu et al., 2012). A non-invasive EEG sensor for chronic stress evaluation was proposed to be worked in everyday social or professional environments (Hu et al., 2015). Multimodal physiological parameters based mental fatigue prediction methods are developed (Laurentet al., 2013). More studies are needed to validate their efficacy in case of mental stress evaluation.

Present method is an attempt to develop a method to measure overall psychological stress advent through physiological signals and it's parameters, visually EEG. EEG signal is an electrical impression of bioelectric potential from brain, during regular stimulus and triggering of neuronal activity, due to neuronal cell-dendrite current dipole dynamic change. Using EEG as a signature of regular brain neuronal activity, discrete stress levels can be evaluated. In this method, metrics generated from B-Alert X10 based EEG system and questionnaire based; differential stress inventory (DSI), are together used for discrete level stress profile assessment. Features processed and generated through EEG-based metrics and discrete levels of stress profile evaluated from DSI are incorporated on a support vector machine (SVM) based supervisory learning system, which is further used to assess discrete class of stress profile of particular subject.

2 Experiment and Methods

2.1 EEG-based metrics for cognitive states

B-Alert X10® is a wireless hardware system for EEG and ECG acquisition with 9 channel EEG and single channel ECG (B-Alert.com, 2011). B-Alert X-10 system follows 10-20 system of EEG electrodes placement. The nine electrodes are fixed at Fz, F3 and F4 i.e. at center, left and right position of frontal region scalp; Cz, C3 and C4 at center, left and right position of central region of scalp; Poz, P3 and P4 at center of parieto-occipital, and left and right region of parietal region of scalp. ECG electrodes are placed in lead-I region according to Einthoven triangle. Each EEG electrode to scalp impedance is checked before recording and kept below 30KΩ. The sampling frequency for acquisition is kept at 265 samples per second and 16 bit resolution. Before acquisition, an alertness and memory profiler test (AMP) is conducted on each subject which comprises of 3-choice vigilance task (3CVT), visual psychomotor vigilance Task (VPVT) and auditory psychomotor vigilance task (APVT), this takes approximately 20 minutes. After AMP test, the acquisition can be started to get 9 channel raw EEG signal and 1 channel raw ECG signal. Along with EEG and ECG signal, EEG-based metrics including cognitive state and workload outputs is also produced each epoch of second. These EEG-metrics are probability of sleep onset, distraction, low engagement, high engagement, cognitive states (sleep Onset, distraction, low engagement, high engagement), and 2-class model of workload (high workload, low workload) (Berka et al. , 2007). The EEG-metrics are generated as discriminant function analysis of spectral powers of EEG signals in different ranges of frequencies. EEG-metrics is generated from every second as epoch by epoch outputs from ABM model. In this study, probability of sleep onset, distraction, low engagement, high engagement, cognitive states were taken as features to train. For acquisition and analysis, Acknowledge 4.2 software of Biopac™ is used. Acknowledge 4.2 is equipped with filtering, mathematical and analysis tools.



(a) (b)

Fig. 1 (a). A participant fixed with B-Alert X10 system on scalp, perform AMP test. (b) Flowchart of task operation, data acquisition and stress classification.

2.2 Questionnaire based stress profiler evaluation

DSI is a questionnaire based psychological battery test provided by Vienna test system to analyze and differentiate behavioral stress and distribute to the specific category of stress experiences (Rost et al., 1989). The stress questionnaire consists of 52 questions of causes, 21 questions on symptoms, 30 questions on coping and 20 questions on stabilization. The subject has to choose the amount of accordance of themselves, with the condition mentioned in the questionnaire. According to the responses of the subject's, raw score of the evaluation for stress causes, symptoms, coping and stress stability is evaluated. Final evaluation result consists of probabilistic profile classification of the subject in describable classes as Type-I: Normal type, Type-II: Overstressed, Type-III: Stress resistant, Type-IV: Low-stress-successful coping, Type-V: High stress-successful coping, with values between 0 and 1, sum of all profiler is equal to 1. This profiler is used for the training the classes of stress detection system.

2.3 Data acquisition, cognitive tasks and evaluation method

For stress classification study, B-Alert X10 system's EEG and ECG electrodes were attached to the subject's head scalp and chest. Before starting physiological signal acquisition, 15 minutes of baseline, AMP test, is guided to perform by the subject, which generates a learnt, ready to use, definition system for cognitive state and workload outputs. Three tasks are to be performed by all subjects in physically rest condition sitting on a chair. The tasks are, first is 5 minutes of eyes closed (EC), then 5 minutes of eyes open focusing vision on a red color dot on a dark screen (DOT) and 5 minutes of eyes open with focus on a bright screen (EO). First two tasks were performed in a dark environment and third one in a bright environment. During the task, simultaneously the EEG, ECG, cognitive state and workload outputs are acquired and recorded. After the completion of physiological parameters acquisition, a psychological questionnaire of differential stress inventory is conducted on the subjects and stress probabilistic profiling is done. Profiling of 41 subjects (37 males and 4 females) was done with their consent. All the subjects are healthy students from IIT Roorkee with clean medical records, no chronic diseases and age range of 24±5 years. In Fig.1 (a) is shown, a subject is performing AMP task while EEG profile getting recorded.

For training of SVM system, each subject's total 60 features are taken. From the 5 minutes of EC, DOT and EC; five EEG-metrics; sleep onset, distraction, low engagement, high engagement and cognitive state values were used for feature formation. Mean, sum of mean and variance, median and mode of each EEG-based metric for each task was taken as feature. This way total 60 features were accounted for each subjects for training purpose. For output classification, DSI outputs are used. Probabilistic profiler of DSI is combined to form two classes. Profiling is created by adding Type-II: Overstressed and Type-V: High stress to get 'High Stress'. Sum of Type-I: Normal type, Type-III: Stress resistant and Type-IV: Low-stress is to get 'Low Stress'. Similar way a three state stress profile was also created. These 60 features along with stress class of 40 subjects is fed to a multilayer perceptron based SVM classifier. Once the learning is complete, the 60 features of 41st subject are fed to the classifier system to get stress class. Fig. 1 (b) depicts the experimental flow of task performance, DSI evaluation, feature formation and supervised learning based classifier development.

2.4 Linear support vector machine based binary classifier

For classification of the stress profile based on EEG-metrics, support vector machine (SVM) is used. SVM is a supervised learning scheme for classification and regression (Vapnik et al., 1998; Zhao and Hasan, 2013). The principle behind SVM algorithm is theory of structural risk minimization. The hyperplane function of classification is decided based on minimizing of generalization error for decision boundaries. Also SVM is resistant to over-training, and performance increases with generalization. Simplest form of SVM does binary classification, in which few points in the data space is identified to construct a hyperplane which separates two classes of points.

The training data *x* consists of *n* data samples each of *m* dimensions and belonging to class *y*, is expressed as:

$$(x_1, y_1),...,(x_i, y_i),...,(x_n, y_n),\ \ x \in \Re^m, y \in \{+1,-1\}$$

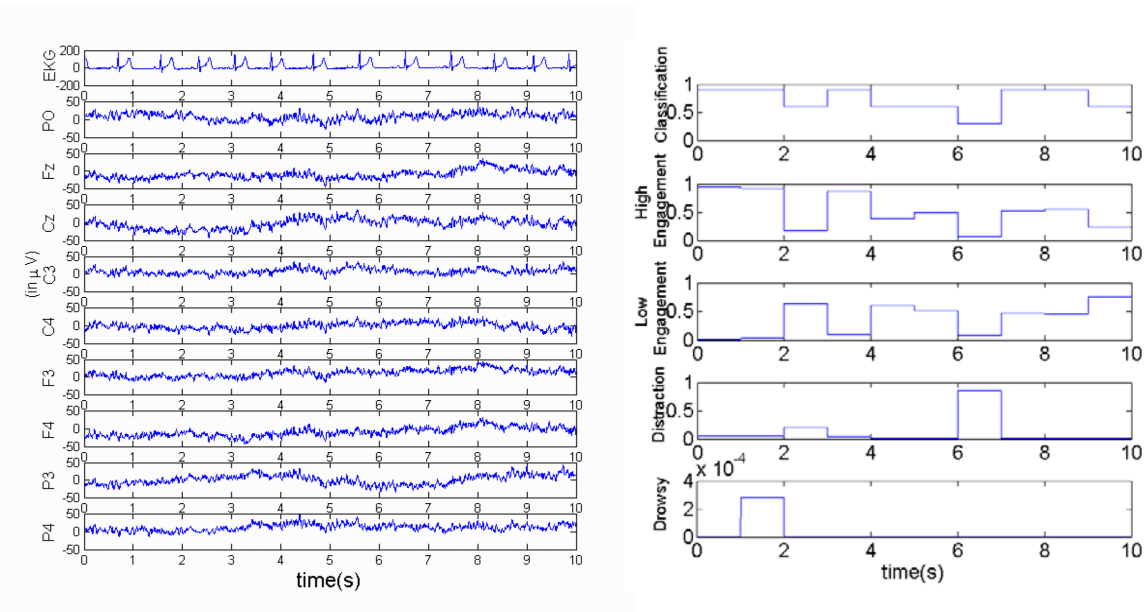
SVM projects data (x_i , y_i) into an infinite dimensional hyperplane (x_i , y_i) by using dedicated normalized kernel function and defines its decision rule as sign($f(x)$). The discriminant function $f(x)$ creates the optimum hyperplane decision boundary by using weight vector w^* and bias b^*.

$$f(x) = w^* \phi(x) + b^*$$

The optimum values of w^* and b^* are estimated by solving following optimization problem where, C is regularization parameter and ξ_i s are slack variables allowing inseparable data.

$$\min_{w,\xi} \left\{ \frac{1}{2} w^2 + C \sum_{i=1}^{n} \xi_i \right\}; \qquad y_i(w.\phi(x_i) + b) \geq 1 - \xi_i, \qquad \xi_i \geq 0$$

This problem is solved using Lagrange optimization through dual formation, which finally yields optimum value for weight vector w^* and bias b^*. Since SVM estimates an infinite dimensional optimum hyper plane, usually it performs better than the other supervised learning algorithms while solving classification problems even on higher dimensional input features. Other optimal decision boundaries, such as polynomial, radial basis function based and multi-layer perceptron based kernels can also be used in place of linear decision boundary for better classification results.



(a) (b)

Fig. 2 (a). Plot of raw ECG and EEG signal sample acquired from B-Alert X10, (b) EEG-metric acquired from B-Alert X10.

3 Results

Fig. 2 (a) shows 10s raw signal sample of one channel ECG and nine channel EEG, acquired through B-Alert X10 system, Fig. 2 (b) shows five of the eight EEG-metric based cognitive states chosen for feature selection, with respect time. As shown in Fig. 2 (b) EEG-metric are generated every second epoch by epoch. The EEG-metrics lies between 0 and 1. Fig. 3 shows boxplot of all EEG-metrics features (mean and median) of all samples of ‘High Stress’ and ‘Low Stress’ taken together. Fig. 3 (a) and (b) are box plot of mean and median of metrics: high engagement, low engagement, distraction and drowsy metrics for the task of eyes closed. Similarly, in Fig. 3 (c) and (d), features are for the task of open eyes with vision focused on red dot on dark screen, and Fig. 3 (e) and (d), features are for task of open eyes with vision focused on white screen. Fig. 3 (g) and (h) are Box plot of means and medians of cognitive state classification of less stress and high stress group for three tasks of dot focus, eyes closed and eyes open.

Table 1 is the representation of maximum, minimum, median and mode of all the features, visually, cognitive state classification, high engagement, low engagement, distraction and drowsiness for three task conditions, for two stress classes (Less stress and High stress). Table 1(a) are observation for task of open eyes focusing on a bright dot on dark screen, Table 1(b) are observation for task of closed eyes focusing in a dark room, Table 1(c) are observation for task of open eyes focusing on a bright screen. It is observed that central tendencies (mean and median) for high engagement and low engagement metrics are higher for high stress class than less stress class, whereas distraction and drowsy metrics are lesser for high stress than low stress. Cognitive state classification metric for DOT and EO tasks is seen at ‘Low Engagement’ for both less and high stress class. Whereas for EC task, less stress class is seen in ‘Distraction’ state and ‘Low Engagement’ for high stress class. Binary class SVM with various decision boundaries: linear, quadratic, polynomial, radial-basis function (RBF) and multi-layer perceptron (MLP), were used to develop classifiers using 60 features of each of 40 subjects on two and three class of stresses. Similarly, by interchanging training and prediction matrix of all 41 subjects, the efficacy of the SVM based system is to be checked.

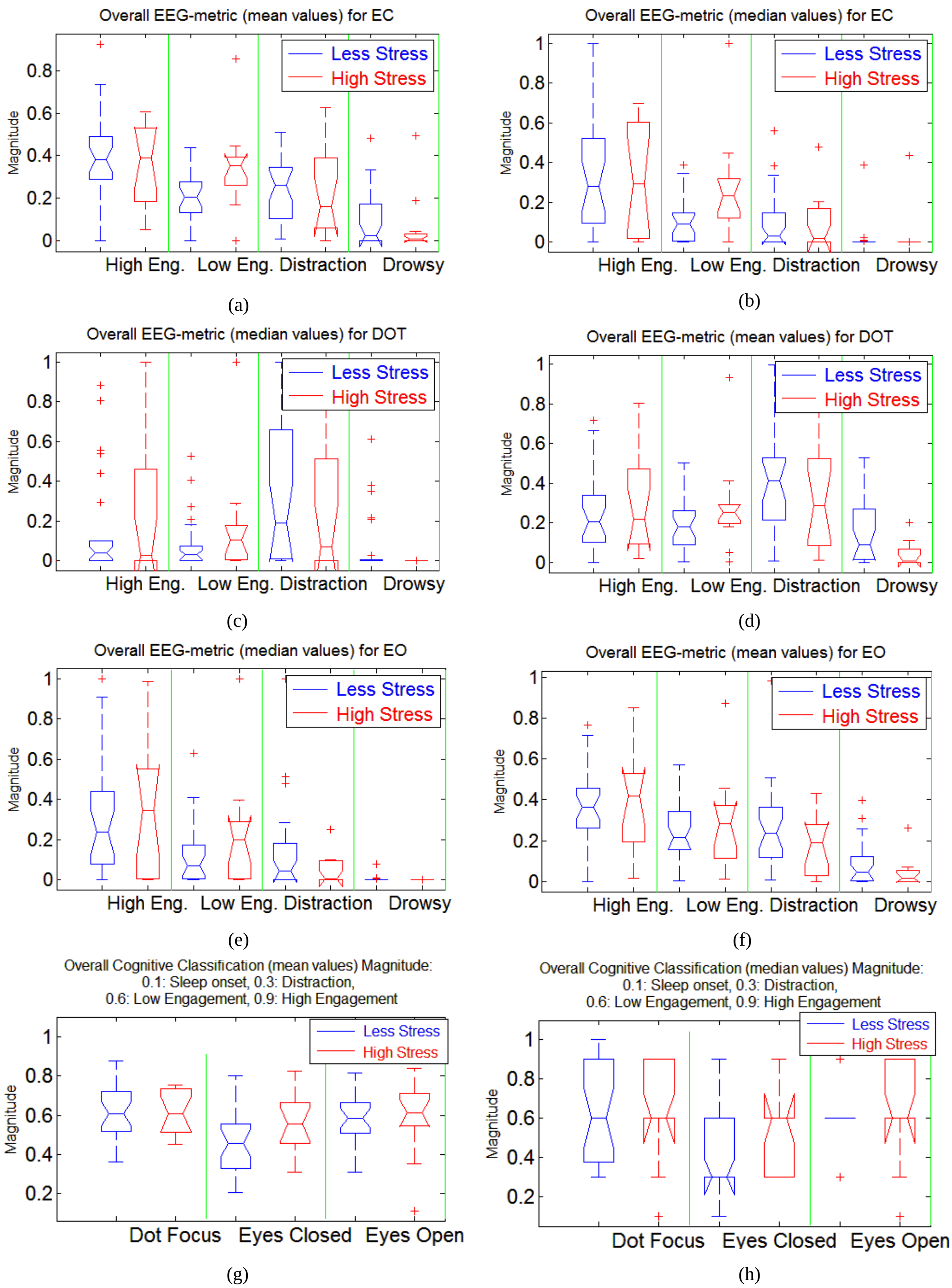


Fig. 3 Box plot showing contrast out of 41 subjects of either 'Less stress' or 'High Stress' EEG-metrics features of (high engagement, low engagement, Distraction, Drowsy) for the tasks of (a) mean while closed eyes (b) median while closed eyes (c) mean while focusing on a dot on dark screen, (d) median while focusing on a dot on dark screen (e) mean while open eyes (f) median while open eyes, (g) mean of cognitive state classification of less stress and high stress group for three tasks of dot focus, eyes closed and eyes open, (h) medians cognitive state classification.

Altogether, for two states stress classifiers, out of 41 binary outputs, 23 were correct for linear and quadratic, 22 for polynomial, 27 for RBF and 30 for MLP. So accuracy of 56.09% for linear and quadratic, 53.66% for polynomial, 65.85% for RBF and 73.1% for MLP based decision boundary was observed. This evaluates multi-layer perceptron based SVM as the best classifier for two state stress classes.

For three states stress classifiers, out of 41 binary outputs, 16 were correct for linear and quadratic, 17 for polynomial, 23 for RBF and 26 for MLP. So accuracy of 39.02% for linear and quadratic, 41.46% for polynomial, 56.10% for RBF and 63.41% for MLP based decision boundary was observed. This evaluates multi-layer perceptron based SVM as the best classifier for both: two state as well as three stress classes.

Table 1 (a) Comparison of maximum, minimum, median and mode of EEG-metric features for two stress classes (Less stress and High stress) while focusing on a dot on a screen.

Less Stress Class	CC (Mean)*	CC (Median)	CC (Mode)	HE (Mean)	HE (Median)	HE (Mode)	LE (Mean)	LE (Median)	LE (Mode)	Dist (Mean)	Dist (Median)	Dist (Mode)	Dro (Mean)	Dro (Median)	Dro (Mode)
Minimum	0.36	0.3	0.1	0	0	0	0	0	0	0.01	0	0	0	0	0
Maximum	0.88	1	1	0.92	1	1	0.44	0.39	0.62	0.51	0.56	0.19	0.48	0.39	1
Median	0.61	0.6	0.9	0.38	0.28	0	0.2	0.09	0	0.26	0.03	0	0.02	0	0
Mode	0.61	0.6	0.9	0.29	0	0	0.27	0	0	0.01	0	0	0	0	0

High Stress Class	CC (Mean)	CC (Median)	CC (Mode)	HE (Mean)	HE (Median)	HE (Mode)	LE (Mean)	LE (Median)	LE (Mode)	Dist (Mean)	Dist (Median)	Dist (Mode)	Dro (Mean)	Dro (Median)	Dro (Mode)
Minimum	0.45	0.1	0.1	0.05	0	0	0	0	0	0	0	0	0	0	0
Maximum	0.76	0.9	0.9	0.6	0.7	1	0.85	1	1	0.63	0.87	1	0.5	0.43	1
Median	0.605	0.6	0.75	0.395	0.29	0	0.355	0.24	0	0.16	0.015	0	0.005	0	0
Mode	0.58	0.6	0.9	0.55	0.01	0	0.36	0.24	0	0.06	0	0	0	0	0

Table 1 (b) Comparison of maximum, minimum, median and mode of EEG-metric features for two stress classes (Less stress and High stress) while eyes closed.

Less Stress Class	CC (Mean)	CC (Median)	CC (Mode)	HE (Mean)	HE (Median)	HE (Mode)	LE (Mean)	LE (Median)	LE (Mode)	Dist (Mean)	Dist (Median)	Dist (Mode)	Dro (Mean)	Dro (Median)	Dro (Mode)
Minimum	0.21	0.1	0.1	0	0	0	0.01	0	0	0.01	0	0	0	0	0
Maximum	0.8	0.9	0.9	0.72	0.88	0.15	0.5	0.52	0.82	1	1	1	0.53	0.61	1
Median	0.46	0.3	0.3	0.21	0.04	0	0.18	0.03	0	0.41	0.19	0	0.09	0	0
Mode	0.56	0.3	0.3	0.03	0	0	0.02	0	0	0.41	0	0	0	0	0

High Stress Class	CC (Mean)	CC (Median)	CC (Mode)	HE (Mean)	HE (Median)	HE (Mode)	LE (Mean)	LE (Median)	LE (Mode)	Dist (Mean)	Dist (Median)	Dist (Mode)	Dro (Mean)	Dro (Median)	Dro (Mode)
Minimum	0.31	0.3	0	0.02	0	0	0	0	0	0.01	0	0	0	0	0

Maximum	0.83	0.9	0.9	0.8	1	1	0.93	1	1	0.85	1	1	0.2	0	0
Median	0.55	0.6	0.45	0.22	0.025	0	0.255	0.105	0	0.29	0.07	0	0.01	0	0
Mode	0.55	0.3	0.3	0.22	0	0	0.2	0	0	0.01	0	0	0.01	0	0

Table 1 (c) Comparison of maximum, minimum, median and mode of EEG-metric features for two stress classes (Less stress and High stress) while looking at a bright screen.

Less Stress Class	CC (Mean)	CC (Median)	CC (Mode)	HE (Mean)	HE (Median)	HE (Mode)	LE (Mean)	LE (Median)	LE (Mode)	Dist (Mean)	Dist (Median)	Dist (Mode)	Dro (Mean)	Dro (Median)	Dro (Mode)
Minimum	0.31	0.3	0.1	0	0	0	0.01	0	0	0.01	0	0	0	0	0
Maximum	0.82	0.9	0.9	0.77	1	0.71	0.57	0.63	0.25	0.98	1	1	0.4	0.08	1
Median	0.59	0.6	0.6	0.36	0.24	0	0.21	0.07	0	0.24	0.04	0	0.04	0	0
Mode	0.55	0.6	0.9	0.26	0	0	0.13	0	0	0.24	0	0	0	0	0

High Stress Class	CC (Mean)	CC (Median)	CC (Mode)	HE (Mean)	HE (Median)	HE (Mode)	LE (Mean)	LE (Median)	LE (Mode)	Dist (Mean)	Dist (Median)	Dist (Mode)	Dro (Mean)	Dro (Median)	Dro (Mode)
Minimum	0.11	0.1	0.1	0.01	0	0	0.01	0	0	0	0	0	0	0	0
Maximum	0.84	0.9	0.9	0.85	0.99	1	0.87	1	1	0.84	1	1	0.97	1	1
Median	0.62	0.6	0.75	0.42	0.345	0	0.28	0.2	0	0.185	0.005	0	0.015	0	0
Mode	0.62	0.6	0.9	0.53	0	0	0.37	0	0	0.03	0	0	0	0	0

*CC: Cognitive classification state, HE: High engagement metric, LE: Low Engagement metric, Dist: Distraction metric and Dro: Drowsiness metric

4 Discussion

More development in the methods are possible, to detect multiple class and multiple level outputs and to get detailed stress profiler on the basis of physiological signals. Also scopes for better feature choice for classification and feature dimension reduction without affecting the classification mechanism can be further achieved. With mental stress emulator at lab setup, a real time stress or anxiety level detector is also possible. Other than questionnaire based stress profiler, other methods such as task based stress level can be used for training purpose. Further, the number of EEG can be reduced and validity of method with lesser electrodes is to be checked. With other possible EEG-metrics and reduced dimension, the predictor can be developed. The duration of task conduction can be minimized and real-time stress level detection methods can be possible.

5 Conclusion

A simple SVM based classification method for discrete stress level detection was developed using EEG-metrics and cognitive states as features for training and discrete classes generated from evaluation of differential stress inventory questionnaire based stress profiler as training outputs. The experimental study on 41 subjects successfully detected 30 subject’s stress level correctly for binary classifier and 26 subject’s for ternary classifier, which establishes the efficacy of the method. The method can be used for general purpose stress level detection.

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