

Towards Enhancing the Performance of a Stress Detection System

S.Arun Kumar, S.Sasikala

Abstract: Stress has now become a ubiquitous part of the fast-moving life, due to which many people are affected. Stress, is identified by physical signs of tension, like irritation, anger, nervousness and sadness at an exceeding level. A stressed individual has an abnormal heart rate, blood pressure and breathing. This may cause major variations in mood, productive lifestyle, and quality of life. This work concentrates on detecting the stress of a person by using the time series analysis of Electromyogram (EMG), Galvanic Skin Response (GSR hand and foot), Electrocardiogram (ECG) levels collected from physionet database. The obtained data is analysed and a dataset with healthy and stressed population is prepared. This work concentrates on improving the performance of a stress detection system using Support Vector Machine classifier. The Performance of the proposed system is measured using metrics like accuracy, sensitivity and specificity. A significant improvement in the metrics of the proposed system claims that this method will aid in diagnosing the stress rate of a person and aftermath necessary steps required to reduce the stress of the being.

Key Words: Stress, Physiological signals, time-series analysis, feature transformation, feature reduction, intelligent system, wear-ables

I. INTRODUCTION

Stress is inevitable part in the present fast-paced modern world. Stress is considered as epidemic of twenty-first century. The latter-day problems which are faced by the people in our society direct us to evolve methodologies to release stress. Statistics report that nearly 75% of people visit clinicians for stress related illness. A person confronting multiple challenges every day gets affected by stress. Stress is merely a physical response produced by our body. But if there is an increase in level, leads to assortment of health problems such as headaches, fatigue, sleeping disorders, digestive problems, high blood pressure, heart diseases, aging and obesity. Reducing one's stress level cannot make anyone feel better, but it will obviously increase the health on the long-term.

A study [1] in 'The Hindu' claims that, stress is one of the major reason for disorders like myocardial infarction, broken heart syndrome and sudden death.

Further, stress increases frustration, depression and anxiety. An article [2] in 'Times now' says that 'One student kills self every hour in India' Recent statistics of ministry of home affairs reports that 9,474 students committed suicide in 2016 in India. An article [3] in 'The Hindu' news reports that 'Stress among medicos goes undiagnosed'. In this case, many medical students committed suicide because of their inability to handle work related and academic stress.

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Adjustment disorders and general anxiety disorders were the most common problems found among students. Thus stress starts off as a trivial disturbance, but if left unattended it results in severe ramifications to a person's life. Irrespective of the age group stress affect all population risking their life.

Considering the importance of stress detection, many works in literature focused on developing stress detection system. In [4] a non invasive method of stress recognition based on behavioural and contextual data collected from smartphone was analysed. Stress level was determined based on physiological parameters for drivers and computer users. Stress detection system resulted in an improved accuracy of 97.4% and 90.01% was obtained for driver and computer users respectively.

Real time stress detection was performed on drivers while they followed a common route in city streets, highways and open roads in Boston area [5]. In that study, data collected from physiological sensors viz. Electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR) and respiratory rate are used to detect stress. The results claim that stress levels could be detected with an average accuracy of 97.4%. Physiological and behavioral markers of stress were determined in [6]. Sensor data, surveys and mobile phone usage behavior were used for data collection. Statistically correlated features extracted from the data were applied to machine learning classifier to classify the stress level of the person.

The stress level of computer users was analysed in [7]. A stress detection system was designed using physiological signals such as Blood Volume Pulse (BVP), Galvanic Skin Response (GSR), Pupil Diameter (PD) and Skin Temperature (ST). A significant improvement in results indicates that physiological signals are effective in determining the emotional states of subjects.

Bakker et.al [8] used GSR sensor data to detect stress level in human. The use of wearable devices in a non-lab setting to measure symptoms related to stress level was analysed in the work. Stress may be caused due to peer pressure, family crisis, low social support, role ambiguity and conflict, ergonomics of the work environment, work patterns with work schedule and shift work. The proposed idea of stress detection system will result in protecting one's health for a long term thus resulting in healthy life style and longevity. Stress must be reduced because it is important to promote more autonomy and activities to give more clarified roles and responsibilities. Therefore our work focuses on developing a system that uses physiological signals like heart rate, respiration rate,

and skin conductance to detect stress level of humans.

The proposed work aims at developing a system to detect the stress of a person by using the time-series analysis of Electromyogram (EMG), Galvanic Skin Response (GSR hand and foot), Electrocardiogram signals collected from the Physionet. Feature extraction is followed by a back end SVM classifier with linear and nonlinear kernel functions. Furthermore, the features are reduced using the techniques like Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). The performance of the stress detection system is assessed in terms of metrics like accuracy, sensitivity and specificity.

The paper is organized as follows: Section II describes the database used; Section III discusses the methodology employed. Section IV evaluates the performance of the proposed system. Section V concludes the paper.

II. DATA BASE USED

Jennifer Healey and Picard RW [5], contributed a database to Physionet [9] that contains multiparameter recordings collected from 17 healthy volunteers, taken while they were driving on a pre determined path that includes city streets and highways in and around Boston area. The stress level is determined by the physiological sensors which include ECG, EMG (right trapezius), GSR (galvanic skin resistance) measured on the hand and foot, and respiration. Five physiological sensors were placed on the subject. ECG on the chest, EMG on the left shoulder, respiration sensor around the diaphragm and two skin conductivity sensors (SC), on the left hand and the left foot. The sensors were connected to a computer to collect data. The physiological signals of ECG, EMG, GSR and respiratory sensor were sampled at 496Hz, 15.5Hz, 31Hz and 31Hz respectively. The objective of the study for which these data were collected was to analyse the possibility of automatic stress recognition. The duration of the recording ranges from 65 to 93 minutes.

III. METHODOLOGY

A. System architecture

The architecture of the proposed stress detection system is depicted in Fig 1. A stress detection system was designed using time series analysis of physiological signals such as ECG, EMG, hand GSR and foot GSR. The signals are reduced and classified using a Support Vector machine classifier. The performance of the stress detection system is assessed in terms of accuracy, sensitivity and specificity.

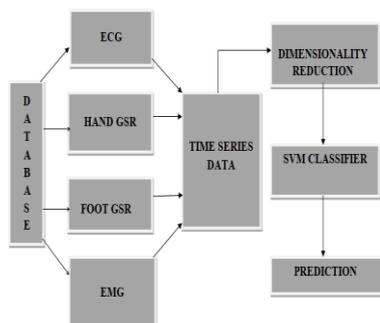


Fig. 1: System architecture of proposed stress detection system

B. Time Series Analysis

Majority of the studies in literature enhances the performance of a stress detection system using physiological signals [5] [6]. In [10] an anomaly detection system was built using time series analysis of ECG signals. Wireless sensor network based system that monitors a person's vitals was built and collected sensor data was analyzed for anomalies. Different measures of chaos in time series data was analyzed from an electrocardiogram RR-Interval time series in a patient for anomaly identification [11]. The commonly used physiological signals are ECG, EMG, EEG, GSR and heart rate. Time series data is prepared from ECG, EMG, foot GSR and Hand GSR physiological signals for about 5 minute duration from stressed and non-stressed subjects of Physionet database. The time series of a stressed individual for a 10 sec and 1 hour duration is shown in Fig 2 and Fig 3 respectively. The graph includes the waveform of different features such as ECG, EMG, EEG, GSR and heart rate values.

ECG: Electrocardiogram measures the electrical activity of heart. ECG electrodes placed over the subject's skin are used to extract the electrical signals. ECG gives accurate estimate about heart rate and rhythm. ECG signal is widely used in stress analysis because the pattern of resting ECG varies from a stressed or exercise ECG.

EMG: Electromyogram measures the electrical activity of skeletal muscles and nerves that control them. Stress results in induced musculo skeletal complaints resulting in increased muscle tension. Stress levels can be determined from EMG Signals placed on upper trapezius muscle [12].

GSR: Galvanic skin response is a sensitive marker in measure of skin conductance or electro dermal activity.

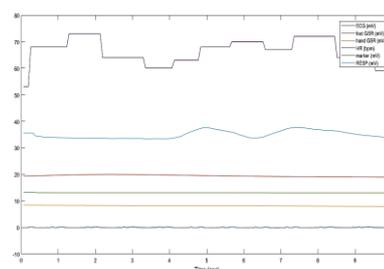


Fig. 2: Time series of physiological signals for 10 sec Duration

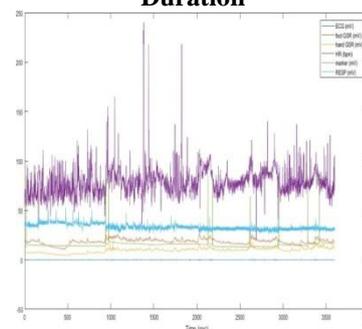


Fig. 3: Time series of physiological signals for 1 hour duration

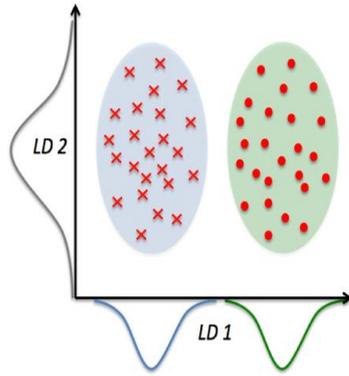


Fig.4:PCA in dimensionality reduction

It modulates the sweat secretion from sweat glands. The glands are highest in the hand and foot region of human body. Abrupt changes in sweat secretion in hand and foot are observed under stressed conditions. Thus there is a strong correlation between stress and GSR[13][14].

C. Time series dimensionality reduction

The amount of data generated in time series analysis is huge and observations are highly correlated. Further in high dimensional data, not all the parameters measured are useful in understanding the desired objective. This limits the analysis and increases the computational complexity associated with classification. Therefore the high dimensionality of time series data can be reduced using dimensionality reduction techniques like PCA and LDA resulting in improved performance. PCA: Principal Component analysis (PCA) is a linear mean square based dimensionality reduction technique [15]. In PCA, the dimension is reduced by determining orthogonal linear combinations called principal components with largest variance. The first several principal components contain most of the information and this results in discarding remaining components without loss of information.

LDA: Linear Discriminant Analysis (LDA) is also a linear dimensionality reduction technique [16]. PCA as a technique determines the directions of maximal variance. When compared to PCA, LDA tries to find a feature subspace that maximizes the separability of classes. In LDA, between class variance is maximized and within class variances are minimized. LDA models the difference between the classes of data. Whereas, PCA is independent on difference in classes.

TP-True Positive, FP-False Positive TN-True Negative, FN-False Negative

The concept of PCA and LDA is explained in Fig 4 and Fig 5 respectively.

D. Classification

Support Vector Machine (SVM) is a supervised learning algorithm used for binary and multiclass classification problems. After performing feature extraction, the Support Vector Machine (SVM) classifier [17] [18] [22] is used to differentiate stressed and non-stressed subjects. SVM creates an optimal separating hyper plane between the two classes by using the training data and maximizes the margins between two classes of the hyperplane. SVM uses linear or nonlinear

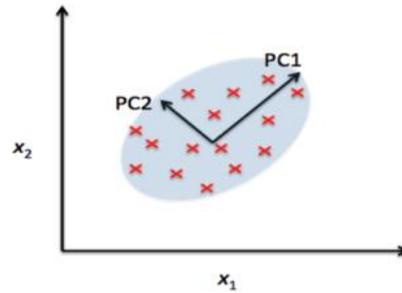


Fig. 5: LDA in dimensionality reduction

kernels to classify the data. Linearly separable data is classified using a linear SVM. If the data is highly non-linear, kernel transformation is used to transform a non-linear separable data to linearly separable in higher dimensions. In this work, SVM with linear and non-linear (polynomial, quadratic and Radial Basis Function (RBF) kernels) are used in classifying stressed and non-stressed individuals. The concept of linear and non-linear SVM is illustrated in Fig6 and Fig7 respectively.

		Predicted class	
		P	N
Actual Class	P	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)

Fig. 6: Linear SVM in classification

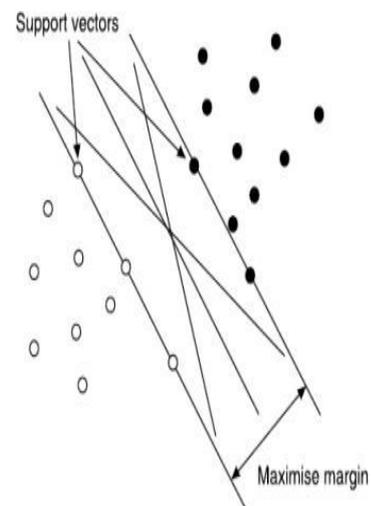


Fig. 8: Confusion matrix
Sensitivity = Specificity = Precision =

TP FN + TP
TN FP + TN (3)
TP TP + FP (2) (4)

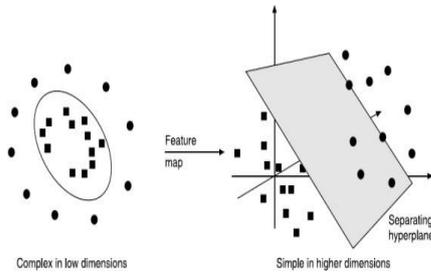


Fig. 7: Non linear SVM using Kernel transformation

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

StressDetectionssystemusingtimeseriesanalysisofphysiological signals collected from physionet database is developed. The baseline system describes the time series analysis of physiological signals from the physionet database and classified by a back-end SVM Classifier. Furthermore, dimensionality reduction is done using by varioustechniqueslikePCAandLDAfollowedbyaSVMclassifierandcompared with its baseline counterpart. From the classification results confusion matrix is obtained and performance metrics like accuracy, specificity, sensitivity and precision are calculated from the confusion matrix. The confusion matrix is shown in Fig8. Themathematicalexpressionstocalculatethemetrics[19] are given in equations 1 to 4.

$$Accuracy = \frac{TP + TN}{FP + FN + TP + TN} \quad (1)$$

Time series Data duration	Sensitivity	Specificity	Precision	Accuracy
10 seconds	1	0.9545	0.9568	0.9773
1 minute	1	0.9546	0.9568	0.9776
2 minutes	1	0.9563	0.9581	0.9681
3 minutes	1	0.9745	0.9751	0.9851
5 minutes	1	0.9717	0.9696	0.9872

TABLE I: Performance Metrics using linear SVM

Kernel Functions	Sensitivity	Specificity	Precision	Accuracy
Polynomial	0.9951	0.9887	0.9890	0.9919
Quadratic	0.9987	0.9866	0.9862	0.9925
RBF	1	0.9799	0.9807	0.9901

TABLE II: Performance Metrics using non linear SVM Reduction

Dimensionality Reduction Techniques	Sensitivity	Specificity	Precision	Accuracy
PCA	1	0.9467	0.9469	0.9727
LDA	0.7890	0.9592	0.9504	0.8745

TABLE III: Performance Metrics after dimensionality

A. Performance Metrics

A single performance metric is not sufficient to evaluate the overall performance of a system [20] [21]. In this work, apart from accuracy, sensitivity and specificity are also

calculated to evaluate the proposed technique. In the baseline system the time series extracted from ECG, EMG, foot GSR and Hand GSR physiological signals for about varying time duration is classified using a linear support vector machine classifier. Table I compares the performance metrics for varied duration of time series data ranging from 10 seconds to 5minutes.

An improved accuracy and other performance metric reveals the effectiveness of the proposed system. Kernel technique is employed to convert the non linear data to linear data using polynomial, quadratic and RBF kernels for a standard time duration of 5 minutes. From, Table II it is observed that non linear kernel further increases the system performance over the baseline system .

Dimensionality reduction is employed prior to classification to reduce the complexity of the proposed system. PCA and LDA are used as dimensionality reduction techniques. From Table III it is evident that PCA improves the system performance when compared toLDA .

B. Inference

The results from Table II, reveals that the nonlinear SVM is best in terms of improving the system performance because of the non-linearity in the data. For anydetectionsystemincreaseinspecificityimpliesreductionin false positive rate. The specificity is also improved in the kernel based transformation. Though there is accuracy andspecificitytradeoff,thepercentageofchangeinvariousmetricsisminimal.From the metrics of Table III, it is evident that dimensionality reduction using PCA improves the performance as it calculates the variation in data when compared with LDA. Reduced feature size and less complexity is achieved using dimensionality reduction techniques at the cost of less degradation in system performance.

V. CONCLUSION

In this work, Stress detection system is developed from time series physiological signals and relevant performance metrics are evaluated. A significant improvement in accuracy is obtained. This improvement claims that this method will aid in diagnosing the stress rate of a person and aftermath necessary steps required to reduce the stress of the being. The improved performance and simplicity makes it an ideal system for low cost stress detection. The future scope involves addition of a the controller based hardware module to display the results of the real time values based on the heart rate, GSR and respiratory sensors according to the state of the person. Furthermore, system performance can be improved by integrating the hardware and software modules and a low cost stress detecting wearable could also be developed.

The proposed system may help in predicting the stressed people, thereby helpful for the society in solving the serious existing problem of stress by knowing the rate of the stressed level and taking necessary steps and preventive measures to further decrease the stressed level.

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