A Survey on Stress Detection using Machine Learning with Human-Computer Interaction

Dércio Anselmo Bobo[1], Ankita Gandhi[2], Jay Gandhi[3]
Department of Computer Science and Engineering
Parul Institute of Technology, Parul University, Gujarat, India
Email: *190303201006@paruluniversity.ac.in[1], jay.gandhi2881@paruluniversity.ac.in[2], ankita.gandhi@paruluniversity.ac.in[3]*
DOI:- https://doi.org/10.47531/SC.2022.03

Abstract

On a daily basis, people can experience a moment of stress for different reasons. It can become dangerous to mental health when this moment of stress is too frequent. Previous papers have indicated that we can use physiological signals to detect if a person is under stress or not. However, researchers have conducted experiments in the traditional method in a laboratory environment, which can lead to bias output because of the ground truth. This paper studies the possibility of detecting if a person is under stress or no, using machine learning classification algorithms and an unobtrusive wearable device where the person will use it on a daily basis, and the data will be collected and sent to our system. We can use various physiological signals to detect stress, such as Electrocardiogram (ECG), Galvanic Skin Response (GSR), and Blood Volume (BV). This physiological signal is used as input in different machine learning techniques to measure a person's stress. Most papers show that support vector machines have the best average classification. Applying the support vector machine, KNN and random forest were able to compare the three algorithms, and the SVM recorded the highest accuracy.

Keywords: *- Stress Detection, Machine Learning (ML), Human-computer Interaction (HCI), Wearable Devices, Physiological Signals*

INTRODUCTION

Stress is a sensation of physical or emotional tension. Stress is usually impersonated while the imaginative and physiological resources available could not match the analogous demands. For example, a person is challenged over a fascinating situation that is not usual in daily life. Numerous circumstances and states cause the appearance of stress that are not easily solvable such as family problems, work problems (not having the dream job, work overload or being unemployed), social issues, relationship issues etc. [1].In the modern lifestyle, people face numerous challenging situations that lead to stress. Stress can appear from any occasion or thoughts because of frustrated, angry, or nervous life event.

Being under stress for continued period leads to several consequences that wreck the individual's health and increase long-term problems and diseases such as high blood pressure, lack of sleep, obesity, diabetes, cardiovascular disease, and mental diseases. Hospital is the most suitable solution for monitoring and predicting stress level. Although it is expensive to do a routine check-up, most people do not prefer the hospital for a conventional check-up.

The alternate approach utilises devices like mobiles, smartwatches, or other wearable sensing devices to collect physiological signals such as an electrocardiogram (ECG) and electrodermal activity (EDA). These devices collect various signals that help to obtain valuable features to identify stressed and non-stressed states. Machine Learning technique assists in recognising stress features, which benefits people to detect stress level at an early stage. Also, it supports doctors to interpret the signals efficiently and provide appropriate treatment to patience [1].

Types of Stress

There are mainly two types of stress: Acute Stress and Chronic Stress.

A. Acute Stress

An acute stress reaction happens while manifestations occur due to an exceptionally stressful event. The pressure faced in daily life can trigger acute stress for a condensed period. Emotional distress, tension, muscular ache, and digestive tract problems are common acute stress symptoms. The acute state transpires from specific events or situations that involve traumatic events such as getting into a car accident or giving a speech in front of people. Once the event ends, the level of stress hormones returns to its normal state.

B. Chronic Stress

Chronic stress is the effect of emotional pressure experienced for a continued duration in which a person recognises they have little or no control. When the nervous system does not have adequate time to return to its natural state, it overpowers a biological change in remarkable parts of the brain, responsible for controlling the strength level, mood, memory, and behaviour. Chronic stress has similar effects to acute stress. However, it causes more harm to the physical health of a person.

OBJECTIVES AND SCOPE OF THE STUDY

Stress has been measured using a formal assessment based on human ratings, like some questionnaire or survey regarding a specific situation or event. The traditional evaluation of stress requires the intervention of the human, especially the manually recognising.

The purpose of this report is to support the objectives of this study, which are:

To study and identify the gaps and limitations in existing stress detection methods, also determine the most physiological signals used to detect stress and its advantages and disadvantages to purpose a way to classify and detect stress with better

RELATED WORK

This section will be about the summarise of some researchers conducted to detect the stress. The method or approach varies for each study. It can change in ways, and physiological signals used, the environment of study and classification technique. The measurement used in most researchers includes biological signs, skin temperature, blood volume, and more.

Jennifer A. Healey and Rosalind W. Picard [2][3] conducted the research and recorded and analysed the physiological signals such as ECC, EMG, Galvanic Skin Response for foot and hand and respiration in real world environment while users were driving, they detect stress level in three different areas. To classify the stress level, they used 22 features from five signals and used the linear discriminant function (LDF)

Researchers as K. Soman et al. [4], Yong Deng et al. [5], Yong Deng et al. [6], Zhai and Barreto [7], A. Ghaderi et al. [8] have used the MIT-BIH Physio Net Multi-parameter Database that is used for drivers stress level. This database consists of ECG, EMG, foot GSR, hand GSR, heart rate (HR), and respiration signals collected by Healey and Piccard [2] from wearable sensors on 17 automobile drivers while driving from MIT's East Garage to River Street Bridge and back through three cities and two highways between an initial rest and a final rest states. In paper [4], the authors used ECG and respiration signals and extracted QRS power spectrum and breathing as features to measure the stress level. In the paper [5], the authors used different features dataset. They applied machine learning classification techniques like Naïve Bayes, Support Vector Machine, Decision tree, linear discriminant function (LDF) and K-nearest neighbour to classify the stress level. In paper [6], they have selected appropriate features and reduce from 22 to 5 applying principal component analysis (PCA). They got an accuracy of 78.94%. In paper [7] was used four physiological signals, GSR, Blood Volume Pulse (BVP), Pupil Diameter (PD), and ST for detect computer users stress and used three machine learning techniques, NB, SVM and Decision Tree, to classify stress level. In paper [8], the authors used time segmented physiological signals (GSR, foot GSR, EMG, HR and Respiration) for the 17 drivers from the database to extract 78 features ranked by SVM and classifier. Finally, the best features were selected out of these, and SVM and KNN machine learning classifiers were applied to classify the stress level of the drivers.

P. Karthikeyan et al. [9] applied mental arithmetic tasks to induce stress in 40 subjects, and they were able to obtain ECG, EMG, Heart rate Variability, GSR and ST signals. Higher-order spectra (HOS) of HRV were 93.75% accurate and decreased to 75% without HOS. H. Kurniawan, et al. [10] used Speech and GSR as a physiological signal to achieve the best accuracy for used Speech, and GSR Signals employing the Stroop Color test, Trier Social Stress test and Trier Mental Challenge test for stress-inducing stimuli were collected. B. G. Lee and W. Y. Chung, [11] the authors in this paper used driver self-report and skin conductance to detect stress levels. A camera was used to record facial images of the driver, and a wearable glove with signal processing and sensor module units collected GSR signals. The accuracy of detecting stress levels by using motion sensors and an SVM classifier is 94.78%. A. Anderson et al. [12] collected physiological data from EEG, ECG, GSR, photoplethysmography (PPG) and electrooculography (EOG). The authors applied machine learning algorithms to detect emotional arousal and identify stimulus type (e.g., games, music, videos).In paper [13], the authors presented WESAD, a multimodal dataset for wearable stress and affect detection. In contrast to other available datasets, WESAD features all physiological modalities commonly integrated into commercial and medical devices. The results suggest that a chest-based device leads to the overall best classification results, and by adding data of a wrist-based device, no further improvement is achieved.

However, the results obtained using only wrist-based devices are promising. In [14], the main goal of this study was to determine whether activity information can compensate for the interactive effects of mental stress and physical activity, which affect the accuracy of mental stress detection.

This paper presented a multimodal approach to model the mental stress activation affected by physical activities using accelerometers, ECG, and GSR sensors.

DISCUSSION

Researchers have been trying to develop new systems to detect stress automatically. It is stated that to identify if a person is under stress or not, there are some stress indicators. These indicators may vary according to the nature of the experiments being applied. As described in the literature survey section, many physical changes and emotions have been associated with stress, such as eye position and blinking, facial expressions and gestures. The difference in heartbeat peaks can be verified during stress state.

Reference	Physiological Signal	Machine Learning Technique	Number of Features	Future Works
2013 [4]	ECG and Respiration	SVM	2	Comparison of stress between different categories of subjects
2013. [5]		Naïve Bayes, SVM, Decision tree, (LDF), KNN	11	Other kinds of feature selection and feature fusion methods
2012 [6]	HR, FGSR, HGSR, RESP	PCA, SVM, KNN	22	Increase number of datasets in-depth analysis on individual driver effect
2006 [7]	GSR BVP, Pupil Diameter (PD), and ST	NB, SVM and DTree,	11	Classify the stress under not controlled conditions
2015 [8]	GSR, foot GSR, EMG, HR, and Respiration	SVM and KNN	78	
2013 [9]	ECG, EMG, HRV, GSR and ST	KNN	148	Classification for individual signals and its feature performance;
2013 [10]	Speech and GSR	Means, GMM, SVM, Dtree	144	Collect data from real word environment;
2017 [11]	GSR	SVM	46	Make a relationship between the driver stress and driving events.
2017 [12]	EEG, ECG, GSR, PPG, EOG	KNN, SVM, Badge Trees, Complex Tree	98	Classify valence according to a minimum number of signals.
2018 [13]	ECG, BVP, GSR, RESP, HRV, ACC, EMG	KNN, DTree, LDA, RF	41	Create personalised models which can predict the affective state of a specific person.
2012[14]	ECG, GSR	Dtree, Bayesian Network, SVM	27	limited to three specific activities and a relatively short recording time
2019 [15]	HR, BVP, GSR, ST, RR, and accelerometer data.	Random Forest	63	Investigate the relation between labelled stress level, recognised stress level and cortisol levels.

The methodology that we found more efficient and precisely obey the following:

Data Collection

The step where we choose how we can obtain the data that will be used on the project. For years many researchers used the dataset from drivers [2]. Others conducted experiments in a laboratory or real life scenarios. This paper will evaluate the public dataset from the UCL Machine Learning repository WESAD [16]. WESAD is a publicly available dataset for wearable stress and affects detection. This multimodal dataset features physiological, and motion data were recorded from both a wrist- and a chest-worn device of 15 subjects during a lab study measured using an Empatica E4 wrist-worn device. The following sensor modalities are included: blood volume pulse (BVP), electrocardiogram (ECG), electrodermal activity (EDA), accelerometers (ACC), respiration (RESP), body temperature (ST), and three-axis acceleration. In addition, self-reports of the subjects, which were obtained using several established questionnaires, are contained in the dataset.

Pre-Processing Data

Data pre-processing is a step where the data will be cleansed, transformed, and prepared to be processed. Feature selection plays an essential role in predicting both accuracy and real time performance. Feature selection is about reducing the dimensionality of the input features and the number of sensors to wear, which can bring more friendliness to users around the globe.

Feature Extraction

Features can be divided into three classes: time domain, frequency domain and non-linear features. Time domain features are the mean of RR intervals, the standard deviation of RR intervals, the root mean square of RR intervals, the percentage of the number of successive RR intervals varying more than 50ms. Frequency domain features can be counted as Low-Frequency component, High-Frequency Component, LF/HF ratio. The most common non-linear features are entropy, complexity, Poincare Plots, recurrence, and fluctuation slopes [1]. A GSR increase for 2 to 5 consecutive seconds, in-between a local minimum and a local maximum GSR value, is the first indication to detect if the person is on stress moment or not. Using the same feature extraction result as [13] from the WESAD dataset, it's possible to extract all features. For the Empatica E4, we can extract features from the following physiological signal: ACC, BVP, EDA and TEMP. The heart rate (HR) and corresponding statistical features (mean, standard deviation) will be computed using the peaks. The heart rate variability (HRV) was derived from the location of the heartbeats, which is an important starting point for additional features.[13].The EDA is controlled by the sympathetic nervous system (SNS), and hence it is particularly sensitive to high arousal states. First, a 5 Hz lowpass filter will be applied to the raw EDA signal, similar to related work [13][17][18]. Then, statistical features will be computed (e.g. mean, standard deviation, dynamic range, etc.).The feature extraction from the respiratory signal is conducted by detecting the peaks within the signal per minute. This feature signal is split into high breathing rate and low breathing rate by giving a threshold value.

Classification Algorithm

Once the features are determined, the machine learning algorithms can then apply to build the classification model. Galvanic skin response, heart rate variability and skin temperature can reflect autonomic nervous system activity. Thus their features help predict the stress level of an individual. Random forest, support vector machine and decision trees are examples of effective classification algorithms for mental stress detection.

CONCLUSION

Most of the wearable available in the market enables the continuous stream of physiological data with high temporal resolution. One can be used for basic research, clinical application, or daily routines in real-life situations. They are "objective" in that they do not require individuals to report on their current state, and they are less interruptive because people can go about their regular routines.

It was observed that the detection of stress is essential for the mental health of a person. Many researchers have studied stress detection, but many performed in a laboratory environment or using a clinical trial. Also, many researchers used machine learning techniques to make an evaluation of stress on subjects more generalised as possible as conventional approaches may provide a biased result.

Approaches which include SVM, decision trees, Bayesian networks, and various other techniques have been applied by researchers, and these studies involve features engineering. The most crucial factor identified in machine learning techniques is features extraction, which is the core of the machine learning process. When the features are extracted in the wrong way, it will influence the learning capability of the algorithms.

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