

## **Analysis of Automobile Drivers Stress By Using Physiological Signals**

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### **Abstract—**

This paper gives an analysis of variation of the physiological signals of a person with respect to the stress developed within him/her. Normally automobile drivers feel tired (more stress) during long travel. Many accidents occur due to the tiredness of the driver. Due to over tired, the driver may sleep during driving. To overcome this difficulties, we propose a new concept using Electro Encyclogram Signal (EEG) of the driver. The analysis was done using EEG to get different stress levels. The EEG for normal persons and abnormal persons and stressed persons are stored in a database. The EEG of the driver is frequently monitored and supposed for feature extraction. This process is done using Machine learning algorithm. The feature is compared with the existing data using Artificial Neural Networks (ANN). The result shows whether the driver is normal or in tired. The analysis points out the fact that the physiological signals can be used as a metric for monitoring the stress of a person.

**Keywords—**Stress, QRS power, ECG, breathing rate, respiratory signal, correlation coefficient.

### **I. INTRODUCTION**

American Psychological Association defines stress as “any uncomfortable emotional experience accompanied by predictable biochemical, physiological and behavioral changes”. Reaction of a person from a normal state to an excited state in order to preserve his/her integrity can also be defined as stress. An extreme amount of stress can produce extreme health issues and it can affect the cardiovascular and central nervous system. Modern automobiles incorporate an intelligent

system to monitor the stress level of the driver inside it to ensure the safety [6]. According to the US census bureau, 10% of the total road accidents in 2005 were caused due to the distraction of the drivers during driving. The number rose to 16% in 2009. Another statistics given by the Network of Employers for Traffic Safety (NETS) say that 20-50% of the accidents are caused due driver's distraction. These statistical results show the importance of analysis of stress in a person. Stressful mind does not produce a constructive result.

In Earlier days analysis of the stress is done using the ECG and the respiratory signals acquired from the automobile drivers. Stress of an automobile driver is highly correlated to heart rate and Galvanic Skin Response (GSR) [2]. We intend to analyze the stress in a different way using different feature signals extracted from the ECG

and the respiratory signal. This study can pave the way for more options of physiological signal features that reflect the stress of a person. It is proved that the heart rate and the galvanic skin resistance are the two features that are highly correlated with the stress of a person. Using this result, the analysis was done in this paper by taking heart rate as the marker signal.

In previous method QRS power was the feature signal extracted from the ECG signal of the driver [1]. This feature signal was further correlated with the marker signal. It was able to see a clear variation in the correlation when the stress varies. Breathing rate was the feature signal extracted from the respiratory signals. This was also correlated with the stress marker signal. Both feature signals showed a direct relation with the stress marker signal. The analysis is finally tabulated to check the change in the correlation coefficients of the feature signals. . The analysis

Jennifer A. Healy, Rosalind W. Picard et al in their paper of Detection Stress During Real-World Driving Tasks Using Physiological Sensors suggested that methods for collecting and analyzing physiological data during real world driving tasks to determine a driver's relative stress level. Electrocardiogram, electromyogram, skin conductance and respiration were recorded

continuously while drivers followed a set route through open roads in the greater Boston area[2]. Data from twenty-four drives of at least fifty minute duration were collected for analysis. The data were analyzed in two ways.

Analysis I used features from five minute intervals of data during the rest, highway and city driving conditions to distinguish three levels of driver stress with an accuracy of over 97% across multiple drivers and driving days.

Analysis II compared continuous features, calculated at one second intervals throughout the entire drive, with a metric of observable stressors created by independent coders from video tapes. The results show that for most drivers studied, skin conductivity and heart rate metrics are most closely correlated with driver stress level. These recordings indicate that physiological signals can provide a metric of driver stress in future cars capable of physiological monitoring. Such a metric could be used to help manage non-critical in-vehicle Information systems and could also provide a continuous measure of how different road and traffic conditions affect drivers. This experiment was designed to monitor drivers' physiologic reactions during real-world driving.

## II. PHYSIOLOGICAL SIGNALS FEATURE EXTRACTION

### A. ECG FEATURE EXTRACTION

Electro Cardio Gram is the graphical plot of electrical activity of the heart. The important parts of an ECG are P wave, QRS complex and T wave. Each wave has its own biological importance. P wave corresponds to the atrial depolarization. And QRS complex corresponds to the ventricular Depolarization along with atrial repolarization and finally T wave represents ventricular repolarization. Since pumping of the heart to all parts of the body via aorta takes place during ventricular depolarization, QRS complex has got the maximum amplitude. Hence QRS complex is a good feature that can be extracted from the ECG for the studies of pumping of heart. QRS detection is done by using Pan Tompkins Algorithm[3]. After the QRS detection, the next stage is to extract the QRS complex from the ECG signal by taking the index of the pulses in the output of the Pan Tompkins algorithm after giving the time delay compensation. The power estimation is done by using the Welch method. . Hamming window of length 6 is used for the PSD calculation[5]. Window equation is:  
$$W(n) = 0.5(1 - \cos(2\pi(n/N))), 0 < n < N$$

The power equation using Welch method is:

$$PQRS(f_n) = 1/K \sum_{k=1}^K I_k(f_n)$$

$$I_k(f_n) = L/U |A_k(n)|^2$$

L is the length of the window.

K is the number of segments of the input.

A<sub>k</sub> is the Fourier transform of the kth segment.

I<sub>k</sub> is the modified period gram of the kth segment.

PQRS is the average of the period grams of all K

### B. FEATURE SIGNAL FORMATION

The estimated power of the QRS complex from a single cycle is averaged so that such averaged power of the QRS complex formed the feature signal for the analysis. The feature signal thus formed is classified based on the mean value of the QRS power. Those powers above the mean value are taken as high power and the other as low power. Heart rate reflects the stress of the person. Hence heart rate was taken as the marker signal which reflected the stress of the driver. Heart rate and the stress showed a direct relation i.e. as the stress of the person increases the heart rate also increases.

Hence the heart rate signal was classified based on a threshold value of 80 in such a way that those heart beat above the threshold were classified as high stress marker signal and the other as the low stress marker signal. Comparison is made between the QRS power, both high and low power, to high stress and low stress marker signals for 10 drivers. Comparison is made by calculating the correlation coefficients between the corresponding QRS power and the stress marker signals. The equation for the correlation coefficient is,

$$C(x, y) = E \{ (x(n) - \mu_x) (y(n+k) - \mu_y) \}$$

Where, r = correlation coefficient

$$C(x, y) = \text{Cross Covariance of } x \text{ and } y$$

$\mu$  = Standard deviation.

E { } = Expectation value

The correlation coefficients were tabulated. The comparison between the correlation coefficients pointed out the fact that the high stress condition of a person is more correlated to high QRS power than low power and low stress condition is more correlated to low QRS power. The list of correlation coefficients corresponding to the stress and power.

### C. RESPIRATION SIGNAL FEATURE EXTRACTION

Respiratory signals are the reflections of breathing of person. Here, the respiratory signals were acquired in response to the expansion of the chest using a Hall Effect transducer tied on the diaphragm area of the person. The feature signal extracted from the respiratory signal was the number of breaths per minute or the breathing rate of the person. The feature extraction from the respiratory signal is conducted by detecting the peaks in the signal per minute. This feature signal is divided in to high breathing rate and low breathing rate by giving a threshold value. Here, mean of the breathing rate in 30 min is taken as the threshold. The two respiratory feature signals are then compared with the same stress marker signals used in ECG analysis by calculating the correlation coefficients for 10 different drivers.

### III. EEG SIGNAL FEATURE EXTRACTION

#### A. DISCRIMINATIVE VERSUS GENERATIVE FRAMEWORKS

Broadly, two categories of machine-learning frameworks exist: discriminative and generative. The key difference is that, by observing a signal, discriminative frameworks attempt to model a specific target variable associated with a process, whereas generative frameworks attempt to model the underlying process more broadly, potentially making numerous variables accessible within an algorithm. The challenge with generative frameworks is that substantial training data can be needed to create adequate models; this is of particular concern when models are being dynamically constructed and rapid convergence is desired (as in the clinical applications considered in this work). Limited medical data, especially for rare patio physiologic events, thus makes embedded generative models potentially less viable. On the other hand, the focus on specific variables makes algorithms using and constructing discriminative models potentially more robust. In fact, many medical devices being considered today are interested in decoding targeted states for specific actuation-control and prosthetic functions; these can be well addressed by dis- criminative frameworks. This work thus focuses on enabling various discriminative algorithms along with algorithms for adaptive model construction.

#### B. ACTIVE LEARNING FOR MODEL ADAPTATION

A key benefit of an efficient data driven modeling framework for medical sensor applications is that with patient-specific data being acquired continuously by the sensors, patient customization of the embedded models is possible. The challenge is that in a supervised-

learning frame work, patient-by-patient customization requires effort from experts, limiting its scalability. Active learning is an approach wherein the most informative instances are chosen from a training pool to reduce the labeling effort. Active learning has recently shown to enable efficient model customization with minimal labeling effort from human experts in clinical applications including arrhythmia detection and seizure detection. Block diagram of EEG feature signal extraction is shown in fig 1. In the processor presented, we incorporate support for a modified active-learning framework where in data can instead be continuously assessed as it is being sensed to down select to a highly reduced set of optimal instances which can then be sent to clinical experts to enable scalable customization over a network.

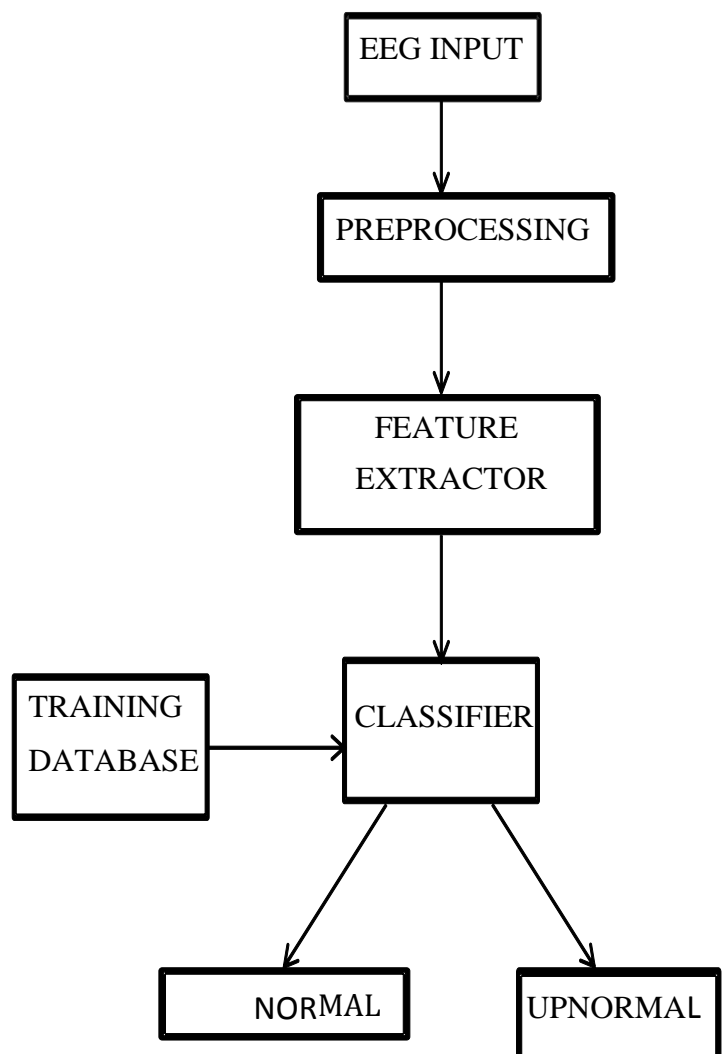


Fig.1: Block diagram of EEG feature signal extraction

### C. ACTIVE-LEARNING DATA SELECTION (ALDS)

Accelerator Active learning involves selecting the optimal data instances in a training pool in order to reduce the analysis and labeling effort required by an expert during supervised model construction. For medical sensor applications, we modify the concept to improve the scalability of model customization during dynamic model adaptation. Our approach enables algorithms wherein a seed model constructed offline from population-level patient-generic data is initially used by the processor. The processor then assess the sensed data to choose the optimal instances to send to clinical experts. In this process, a pool size is specified by a user-defined epoch of sensed data, and the batch size, which we aim to make much smaller, is defined as the number of selected instances from within the epoch. The batch data is transmitted to a clinical expert, who assigns training labels to construct a refined model.

## VI. CONCLUSION

Low-power physiological-signal recording technologies have emerged for advanced medical applications enabled by low-power devices. For many envisioned applications, however, it is critical to extract clinically valuable outputs from the acquired physiological signals. The challenge is that analyzing physiological signals requires high-order model due to the complex nature of the underlying processes. In this work, we propose a biomedical processor with configurable machine-learning accelerators for low-energy and real-time detection algorithms. Supporting various classification kernel functions, a configurable SVM module enables a wide tradeoff space for classification energy and memory.

The analysis done in this paper clearly proved the variation of physiological parameters with respect to the stress developed. It is a scientific explanation for the cardiac and respiratory problems occurring in the persons who are stressful. Persons with stressful minds are prone to heart diseases since their ventricles take an extra power to pump the blood and this will increase the blood pressure which will cause the problems of hypertension. In the present days most of the people are undergoing stress and it is good to perform practices which can reduce their stress which will make them healthy. As a part of future research, it is possible to analyze other physiological signals which can give a higher metric for stress analysis. In this paper only a single category of subject was taken i.e. automobile drivers. The comparison of stress between different categories of subjects also will help to study about the stress in a better way. That also can be taken as a future aspect of the research. From the light of the

research conducted for this paper the overall conclusion is that, how much stress we reduce, that much healthier we become.

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## REFERENCES

- [1] Karthik Soman, Varghese Alex, Chaithanya Srinivas. "Analysis of Physiological Signals in Response to Stress using ECG and Respiratory Signals of Automobile Drivers", IEEE
- [2] Jennifer A. Healy and Rosalind W. Picard, "Detecting Stress During Real-World Driving Tasks Using Physiological Sensors," IEEE Transactions on Intelligent Transportation systems, vol. 6, no. 2, June 2005.
- [3] Jiapu Pan and Willis J. Tompkins, "A Real Time QRS Detection Algorithm," IEEE Transactions on Bio Medical Engineering, vol. BME-32, no. 3, March 1985.
- [4] Rangaraj M. Rangayyan, "Bio Medical Signal Analysis – A Case Study Approach", 4th ed. IEEE press, 2009.
- [5] P.D. Welch, "A Direct Digital Method of Power Spectrum Estimation",IBM Journal, April 1961.
- [6] K.J.W Wilson, Anne Waugh, Janet S. Ross, "Ross and Wilson Anatomy and Physiology in Health and Illness", 8th ed. Churchill Livingston, 1996.