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Modeling a stress signal

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ABSTRACT

Stress is a major health problem in our world today. For this reason, it is important to gain an objective understanding of how average individuals respond to real-life events they observe in environments they encounter. Our aim is to estimate an objective stress signal for an observer of a real-world environment stimulated by meditation. A computational stress signal predictor system is proposed which was developed based on a support vector machine, genetic algorithm and an artificial neural network to predict the stress signal from a real-world data set. The data set comprised of physiological and physical sensor response signals for stress over the time of the meditation activity. A support vector machine based individual-independent classification model was developed to determine the overall shape of the stress signal and results suggested that it matched the curves formed by a linear function, a symmetric saturating linear function and a hyperbolic tangent function. Using this information of the shape of the stress signal, an artificial neural network based stress signal predictor was developed. Compared to the curves formed from a linear function, symmetric saturating linear function and hyperbolic tangent function, the stress signal produced by the stress signal predictor for the observers was the most similar to the curve formed by a hyperbolic tangent function with $p < 0.01$ according to statistical analysis. The research presented in this paper is a new dimension in stress research – it investigates developing an objective stress measure that is dependent on time.

1. Introduction

Stress is part of everyday life and it is widely accepted that stress which leads to less favorable states (such as anxiety, fear or anger) is a growing concern for people and society. The term, *stress*, was coined by Hans Selye and he defined it as “the non-specific response of the body to any demand for change” [1]. Stress is the body’s reaction or response to the imbalance caused between demands and resources available to a person. It is seen as a natural alarm, resistance and exhaustion [2] system for the body to prepare for a fight or flight response to protect the body from threats and changes. When experienced for longer periods without being managed, stress has been widely recognized as a major growing concern because it has the potential to cause chronic illnesses (e.g. cardiovascular diseases, diabetes and some forms of cancer) and increase economic costs in societies, especially in developed countries [3–5]. Benefits of stress research range from improving day-to-day activities, through increasing work productivity to benefitting the wider society motivating interest, making it a beneficial area of research and posing some difficult technical challenges for computer science.

There are various forms of *stressors* i.e. demands or stimuli that cause stress [6–9]. Some situations where stressors emerge are when playing video (action) games [10,11], solving difficult mathematical/logical problems [12], listening to energetic music [10], conducting a surgical operation [13], driving cars [9,14,15] and flying airplanes [16,17]. Under all these circumstances, the literature has reported the effect of stressors on individuals who interacted with stressors directly or were directly involved in the situation and in the environment. The work in this paper investigates the effect of a real-life environment on an *observer*. The observer sees a real-life setting that has a stressor caused by individuals in the setting and other individuals in the environment who interact with the stressor. This means that the observer does not have any influence on the environment, but is likely to engage emotionally and intellectually with the events in which they are present albeit passively.

Stressful events or emergency situations cause dynamic changes in the human body and they can be observed by changes in the body’s response signals, that is, the externally measurable reactions. These response signals are involuntarily caused by the autonomic nervous system, which is made up of the sympathetic

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nervous system (SNS) and the parasympathetic nervous system (PNS). When the body is under stress, activity in the SNS increases and dominates the activities produced by the PNS, which changes the body's response signals. The response signals obtained from non-invasive methods that reflect reactions of individuals and their bodies to stressful situations have been used to interpret stress. These measures have provided a basis for defining stress objectively.

Stress response signals used in this paper fall into two categories – physiological and physical signals. Physiological signals that have been used for stress analysis include electroencephalogram (EEG) [10,18–21], galvanic skin response (GSR) [22,23], electrocardiogram (ECG) [24] and blood pressure (BP) [25]. We define physical signals as signals where changes by the human body can be seen by humans without the need for equipment or tools that need to be attached to individuals to detect general fluctuations. Sophisticated equipment and sensors using vision technologies are still needed to obtain physical signals at sampling rates sufficient for data analysis and modeling as used in this paper. Physical signals include video recordings of a person and eye movement behavior [26].

In this work, EEG signals were used to capture neural activity in the brain of an observer of an environment. An EEG signal records complex electrical waveforms at the scalp formed by action electrical potentials during synaptic excitations and inhibitions of dendrites in the brain. Previous research shows that relationships exist between brain activity and stress [10,18–21].

Another type of physiological signal obtained from an observer of an environment in this work was GSR. GSR enables measurement of the flow of electricity through the skin of a person. When the person is under stress, the activity in the SNS causes an increase in the moisture on the skin, which increases the flow of electricity. As a result, it increases skin conductance [27]. Conversely, the skin conductance is reduced when the individual becomes less stressed. The fluctuations in skin conductance are recorded as changes in GSR.

A relatively new area of research is analyzing stress using facial data from videos in the thermal spectrum. Blood flow through superficial blood vessels, which are situated under the skin and above the bone and muscle layer of the human body allow thermal images to be captured. It has been reported in the literature that stress can be successfully detected from thermal imaging [7] due to changes in skin temperature under stress. Facial expressions have been analyzed [28] and classified [29–31] using thermal imaging but we can find no literature on computational models for stress analysis using the feature definitions and models we present in this work.

In this paper, we use EEG, GSR and video recordings of faces in the thermal spectrum. We will refer to these sensor signals as *primary stress signals*. Use of this set of sensor signals is novel to research in stress classification. The signals are used to develop computational models for modeling and recognizing stress and estimating a stress signal.

Various computational methods have been used to objectively define and classify stress to differentiate conditions causing stress from other conditions [32]. The methods developed have used models formed from Bayesian networks [27,33], decision trees [34] fuzzy models [35] and support vector machines [6]. Previous work has developed stress classification or stress recognition models for detecting stress for particular stress stimuli or environments. However, our work presents a stress measure of an observer of an environment over some period of time in that environment.

Large numbers of stress features can be derived from primary stress signals and presented as input to stress computational models. However besides useful features, this set of features can include redundant and irrelevant features which may swamp the more effective features showing stress patterns. As a consequence, this could cause a classifier to learn weaker stress patterns and produce lower quality classifications. Since this paper deals with sensor data, some features may suffer from corruption as well. In order to achieve a good classification model which is robust to such potential features that may reduce the performance of classifications, appropriate feature selection must take place. A genetic algorithm (GA), which is a global search algorithm, could be used to select subsets of features for optimizing stress classifications. GAs have been successfully used to select features derived from physiological signals [36,37]. In this work, a GA is used to determine whether a smaller subset of stress features exists that better capture observer stress patterns and the resulting feature set is used to estimate a stress signal.

This paper proposes a method for estimating a stress signal for an observer of a real-life environment. Firstly, it details the experiment that was conducted to obtain primary stress sensor signal data of an observer of an environment with a meditation setting. The paper describes the individual-independent computational models developed based on an SVM to classify stress to determine the overall trend of the stress signal i.e. whether stress was increased or decreased over time for individuals. It describes a hybrid of a GA and SVM model system to optimize features for stress classification. Then the paper presents a modeling method based on an ANN to model a stress signal informed by the overall trend given by the stress classification models and using the optimized features as input. Further, it presents the results and an analysis of the results. The paper concludes with a summary of the findings and suggests directions for future work.

2. Data collection

An experiment was done to acquire physiological and physical signals for stress analysis from 13 experiment subjects. The subject cohort comprised of 5 males and 8 females between the ages of 16 and 25 years. The experiment had an *observer*, who was the experiment subject. Their primary stress signals were recorded while they observed an environment with a meditation setting enacted by a scripted role-play. The role-play had a *Meditation Conductor* who led the meditation by reading out a meditation script that the five *Meditation Clients* had to listen to and follow. The meditation had the aim of creating an overall calm environment. There was a *viewer* of the setting who took notes and watched the role-play just like the observer. The viewers' reports provided the stress class labels for the data set.

The experiment instructor provided tasks to the observer and the viewer to watch the meditation and determine which client meditated the most. This was a way to draw their attention away from the meditation conductor and not act like one of the meditation clients. That is, to stay as either an observer or a viewer of the meditation instead of meditating themselves. Fig. 1 shows the experiment setup.

Before the start of each experiment, the observer and viewer had to understand the requirements of the experiment from a written set of experiment instructions and what was involved in the experiment with the guidance of the experiment instructor. After providing their consent to participate in the experiment, the experiment instructor attached EEG and GSR sensors to the observer and calibrated the thermal camera. The viewer was provided with a questionnaire that they filled in during the experiment to record their perception of the stressfulness of the setting and their stress state during the different stages of the role-play. The experiment instructor signaled the actors to start the role-play. In total, the experiment took approximately 30 min, which included the role-play that took 15 min.