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Modeling observer stress for typical real environments

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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. The aims of this paper are to introduce the concept of *observer stress* and investigate whether a computational model can be developed to recognize observer stress using physiological and physical response sensor signals. The paper discusses the motivations for the investigation and details the experiments for data collection for observers of real-life settings which used unobtrusive methods suited to real-life environments. It describes an individual-independent support vector machine based model classifier to recognize stress patterns from observer response signals. A genetic algorithm is used for feature selection to build a classifier. The classifier recognized observer stress with an accuracy of 98%. The outcomes of this research provide a new application area for knowledge discovery and data mining to predict human stress response to real-life environments and a possible future extension on managing stress objectively.

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" (Selye, 1965). 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 (Hoffman-Goetz & Pedersen, 1994) 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 (The American Institute of Stress, 2012, 2013; Lifeline-Australia, 2009). 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 (Sharma & Gedeon, 2012).

There are various forms of stressors i.e. demands or stimuli that cause stress (Zhai & Barreto, 2006; Yuen et al., 2009; Hjortskov et al., 2004; Healey & Picard, 2005). Some situations where stressors emerge are when playing video (action) games Lin & John, 2006; Lin, Omata, Hu, & Imamiya, 2005, solving difficult mathematical/logical problems (Lovallo, 2005), listening to energetic music (Lin & John, 2006), conducting a surgical operation (Sexton, Thomas, & Helmreich, 2000), driving cars (Healey & Picard, 2000, 2005; Hennessy & Wiesenthal, 1999) and flying airplanes (Haddad, Walter, Ratley, & Smith, 2001; Roscoe, 1992). 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 who observes the environment with a real-life setting that has a stressor stimulated by individuals in the environment – a novel area for stress analysis. We coin the term observer stress to mean the observer of such an environment.

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 (ANS). The ANS is made up of the Sympathetic 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

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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) (Lin & John, 2006; Dharmawan, 2007; Interactive Productline., 2013; Novák, Lhotská, Eck, & Sorf, 2004; Hoffmann, 2005, galvanic skin response (GSR) Bakker, Pechenizkiy, & Sidorova, 2011; de Santos Sierra, Avila, Guerra Casanova, Bailador del Pozo, & Jara Vera, 2010), electrocardiogram (ECG) (Dishman et al., 2000) and blood pressure (BP) (Ashton, Savage, Thompson, & Watson, 2012). We define physical signals as signals where changes by the human body can be seen by humans without the need for equipment and tools that need to be attached to individuals to detect general fluctuations. However, sophisticated equipment and sensors using vision technologies are still needed to obtain physical signals at sampling rates sufficient for data analysis and modeling like the ones used in this paper. Physical signals include video recordings of a person and eye behavior (Haak, Bos, Panic, & Rothkrantz, 2008).

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 (Lin & John, 2006; Dharmawan, 2007; Interactive Productline, 2013; Novák et al., 2004; Hoffmann, 2005).

Another type of physiological signal obtained from an observer of an environment for stress recognition 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 (Liao, Zhang, Zhu, & Ji, 2005). 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 recognition of 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 (Yuen et al., 2009) due to changes in skin temperature under stress. Facial expressions have been analyzed (Jarlier et al., 2011) and classified (Zhao & Pietikainen, 2007; Hernández, Olague, Hammoud, Trujillo, & Romero, 2007; Trujillo, Olague, Hammoud, & Hernandez, 2005) using thermal imaging but from our understanding, the literature has not developed computational models for stress recognition using the feature definitions 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 recognition. They are used to develop computational models for modeling and recognizing stress.

Various computational methods have been used to objectively define and classify stress to differentiate conditions causing stress from other conditions. The methods developed have used models formed from Bayesian networks (Liao et al., 2005; Hong, Ramos, & Dey, 2012), decision trees (Zhai & Barreto, 2006) fuzzy models (Kumar, Weippert, Vilbrandt, Kreuzfeld, & Stoll, 2007) and support vector machines (Dou, 2009). This work uses a novel set of stress features to model stress based on a support vector machine (SVM).

Large numbers of stress features can be derived from primary stress signals to classify stress. However, 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) could be used to select subsets of features for optimizing stress classifications. GAs have been successfully used to select features derived from physiological signals (Park, Jang, Kim, Huh, & Sohn, 2011; Niu, Chen, & Chen, 2011). In this work, a GA is used to determine whether a smaller subset of stress features exists that better capture observer stress patterns.

This paper presents a computational model of observer stress for an observer of a real-life environment. The paper describes the experiments that were conducted to acquire primary stress sensor signals and details the models of observer stress that were developed to capture stress patterns across observers of two different environment settings – interview and meditation settings. It presents a method for selecting features from thousands of features derived from the stress signals with an aim to improve the model performance to capture more general stress patterns for better stress recognition. 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

Two different experiments were conducted which differed on the type of real-life setting for the *observer*, who was the experiment subject. One experiment had an interview setting (Interview experiment) and the other experiment had a meditation setting (Meditation experiment). Each experiment had a scripted role-play to stimulate an environment that an observer viewed while they had their EEG signals, GSR signals and thermal videos recorded. EEG signals were sourced using the Emotiv system, GSR signals were sourced by the BodyBugg system developed by SenseWear and thermal videos were captured using the FLIR infrared camera model SC620. EEG signals were sourced at a sampling rate of 128 Hz, thermal videos were sampled at 32 Hz with the frame width and height of 640 and 480 pixels respectively and GSR signals were sourced with a sampling rate of 0.0167 Hz.

Each experiment took approximately 30 min which included a role-play that took 15 min. A role-play was acted out by six people. Consistent experiment room settings including sensor equipment and furniture locations, and temperature and lighting settings were used for the experiments. There were one or more viewers of the environment who took notes of the environment and watched the role-play just like the observer. The viewers' reports validated the stress classes for the environments.

Before the start of each experiment, the observer and viewer(s) 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 validate the stress state during the different stages of the role-play. The experiment instructor signaled the actors to start the role-play.

Surveys are a common tool used in the literature to validate stress states (Hill & Boyle, 2007). The responses provided ground truth for the classification models developed in this work. The questions in the survey asked participants to provide observations and a relative stress score for each stage of the role-play elicited by the environment on a seven-point Likert Semantic Scale ranging