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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 from the value "Very Calm" to "Neutral" through to "Very Stressful". The survey also questioned the stress state of the individuals and how they felt before and after the role-play environment similar to the method reported in Singh, Conjeti, and Banerjee (2013). Reliability and validity of the experiment settings were evaluated based on the recommendations presented in Palmer and Hoffman (2001) and the analysis showed a reliable and valid rating – the average inter-rater reliability coefficient was 0.71 using Spearman's correlation and the survey responses showed no statistical significant differences across participants.

In total, there were 25 observers who had their stress signals recorded and 40 viewers. The participant cohort was made up of undergraduate and college students. There were 10 males and 15 females between the ages of 16 and 25 years. The mean age was 18.6 years old with a standard deviation of 2.1. There were 12 observers for the Interview experiment and 13 observers for the Meditation experiment. The participants had basic experience with Interview and Meditation environments.

2.1. Interview experiments

The Interview experiment had an interview setting with the aim of stimulating a stressful environment. The interview role-play had five Interviewers who interviewed one Interviewee for a hypothetical job position. The Interview Observer and the Interview Viewer watched the interview with the aim to determine which Interviewer was more confrontational towards the Interviewee. This was a way to make the Interview Observer and the Interview Viewer focus on the environment during the experiment. The setup of the Interview experiment is presented in Fig. 1.

The results from the survey completed by the Interview Viewers were used to define stress classes for the different stages of the role-play. This was also done to assess stress classes for the meditation role-play in the Meditation experiment. Analysis of survey responses is a common method used in the literature to validate stress classes for tasks (Hill & Boyle, 2007). The role-play was divided into seven stages of approximately equal time. Only the viewer knew about the stages so that they could fill in the questionnaire for the different stages. Viewers found that the earlier stages of the interview were more tense or stressful and as the interview progressed through the later stages, the interview environment became less stressful. The first stage was the most stressful and the last stage was the least stressful with $p < 0.01$ according to the Wilcoxon statistical test.

2.2. Meditation experiments

The environment for the Meditation experiment had the aim of stimulating a calm environment. For the meditation role-play, there was 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 experiment instructor provided tasks to the Meditation Observer and the Meditation 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. 2 shows the experiment setup.

Results from the survey that the Meditation Viewer did on the meditation environment were used to define stress classes for the different stages of the role-play. The approach for obtaining the results was the same as the approach taken to analyze the survey responses from the Interview experiment. Viewers found that the level of stress that the meditation created reduced as the meditation went into the later stages. The results showed that observing the last stage of the meditation was the least stressful. According to the Wilcoxon statistical test, the viewers found the first two stages of the meditation stressful and the last two stages as not stressful with $p < 0.01$.

3. Observer stress classification models

The stress classification models were built using features derived from the stress response signals of observers during the experiment. There were two types of classification models – a SVM model and a hybrid of a GA and SVM (GA-SVM). Features were provided as inputs to each of the classification models for stress recognition.

3.1. Model input

Features were derived from the stress sensor signals, which formed inputs to an observer stress classification model. The feature set included temporal features of the physiological signals and spatio-temporal features of faces captured by thermal video. Thermal videos of observers' faces were divided up into salient *volumes* where each volume had some section of facial regions (e.g. mid-forehead) in time series, which formed signals for feature extraction. The signals were segmented into 5 s intervals with an overlap of 50%. Statistic and measure values of the segments formed the stress feature set. These statistic values included the mean, standard deviation, kurtosis, skewness, interquartile range, minimum and maximum. Features derived from EEG signals also included statistics of signals in different frequency bands and measurements for Hjorth parameters and fractal dimensions. There were 1379 features in total.

For a thermal video of an observer's face during the course of the experiment, facial regions in the video were extracted and divided up into sections as in Fig. 3. A face detection method based on eye coordinates (Struc & Pavesic, 2009, 2010) and a template matching algorithm was used to extract a face region. A template of a facial region was developed from the first frame of a thermal video of the observer's face. The facial region was extracted using the Pretty Helpful Development Functions toolbox for Face Recognition (Struc & Pavesic, 2009, 2010; Struc, 2012), which calculated the intraocular displacement to detect a facial region in an image. This facial region formed a template for facial regions in each video frame of the thermal videos. Facial regions in each frame was extracted using MATLAB's Template Matcher system (Mathworks., 2012). The Template Matcher was set to search for the minimum difference pixel by pixel to find the area of the frame that best matched the template.

The facial regions extracted from a video were split into different sections. Grouped and arranged in order of time of appearance in a video, the sectioned face regions of video frames formed *volumes*. Statistics were calculated for each volume segmented into 5 s intervals like the other stress signals. An example of a thermal facial volume with a volume of a section of the facial region is shown in Fig. 3.

Data from various frequency bands were extracted from EEG signals and used to define some EEG features. There are four main frequency band categories used to analyze EEG signals and they are presented in Table 1. The band categories are Beta, Alpha, Theta and Delta. Each band category represents some state for a person. Beta and alpha waves represent conscious states of a person whereas theta and delta waves signify unconscious states. Rapid beta wave frequencies (and concomitant decrease in alpha wave frequencies) have been found to indicate stress (Lin & John, 2006; Novák et al., 2004; Hoffmann, 2005).

Measurements for Hjorth parameters (Hjorth, 1970) and fractal dimensions (Katz, 1988) are other measures used in analyzing EEG signals. Hjorth parameters are time-based characteristics of an EEG

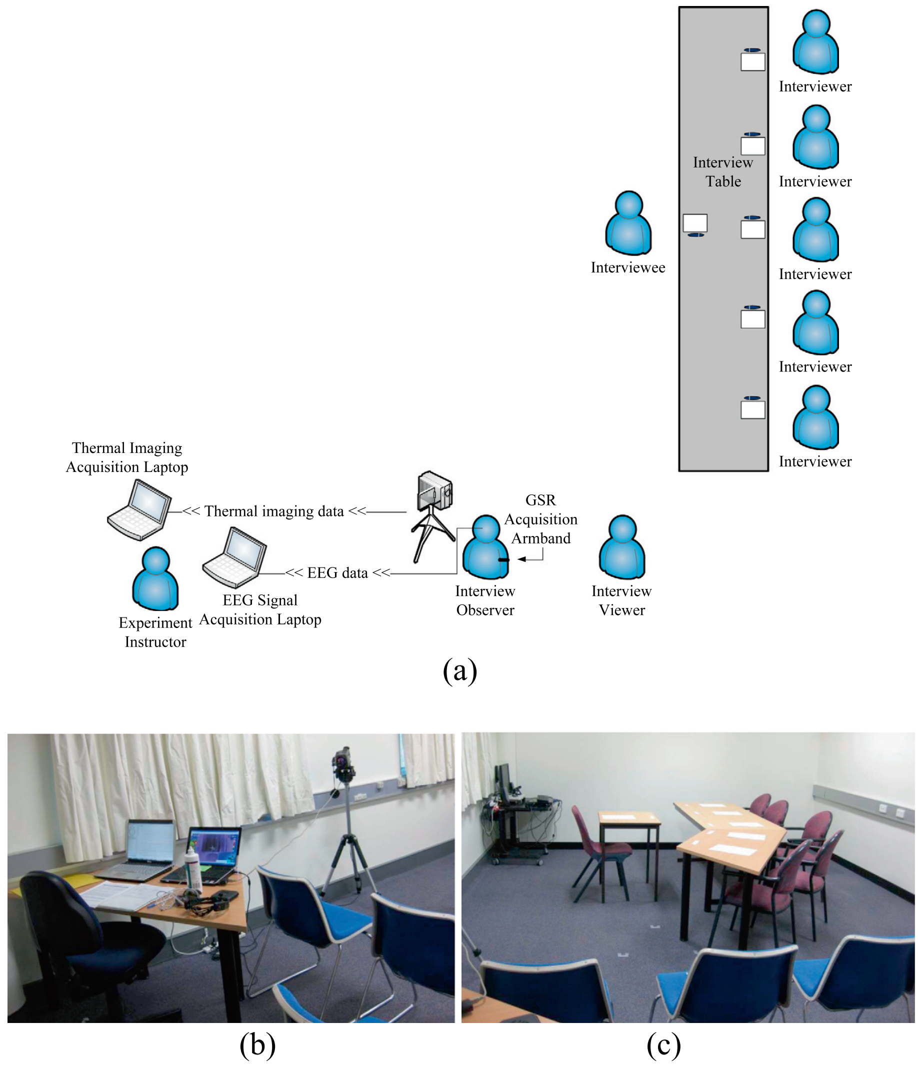

Fig. 1. Setup for the Interview experiment. The interview environment had Interviewers and an Interviewee. The Interview Observer and Interview Viewer watched the interview. The observer had their physiological and physical signals recorded and the viewer took notes of the interview. (a) A schematic diagram of the interview experiment setup. (b) A photograph of the data acquisition system. (c) A photograph of the interview setting setup.

signal and the three Hjorth parameters are the Activity, Mobility and Complexity parameters. Suppose x is an EEG signal with values for N equally spaced timestamps. Then the Activity parameter is the variance of an EEG signal and is defined by

$$Activity(x) = \frac{\sum_{n=1}^{N}(x_n - \bar{x})^2}{N} \quad (1)$$

The Mobility parameter is a measure of the signal mean frequency. Given that x' is the derivative of x, then the Mobility parameter is defined by

$$Mobility(x) = \sqrt{\frac{Activity(x')}{Activity(x)}} \quad (2)$$

The Complexity parameter is a measure of the deviation of the EEG signal from the shape of the sine signal and is defined by

$$Complexity(x) = \frac{Mobility(x')}{Mobility(x)} \quad (3)$$

Fractal dimension measures of an EEG signal provides information of the space filling and self-similarity and can be approximated using the following definition

$$Fractal\ Dimension(x) = 1 + \frac{\log(L)}{\log(2(N-1))} \quad (4)$$

where

$$L = \sum_{n=2}^{N}\sqrt{(x_n^* - x_{n-1}^*)^2 + \left(\frac{n}{N} - \frac{(n-1)}{N-1}\right)} \quad (5)$$

and

$$x^* = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (6)$$

The feature values were normalized by individual to reduce the effect of individual bias in generating an individual-independent observer stress recognition model.

3.2. Support vector machine model

SVMs have been widely used in the literature for classification problems, including classifications based on physiological data (Cheng, 2012; Paul, Leung, Peterson, Sejnowski, & Poizner, 2010). Provided a set of training samples, an SVM transforms the data samples using a nonlinear mapping to a higher dimension with

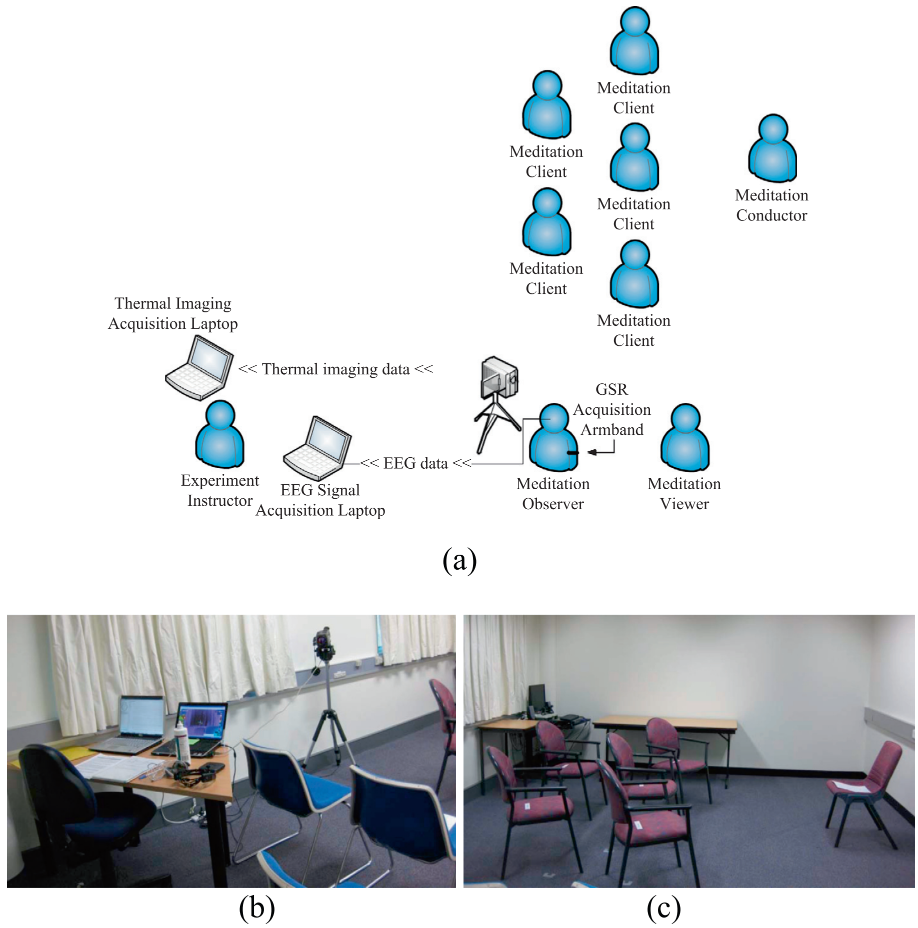

Fig. 2. Setup for the Meditation experiment. The meditation environment used a Meditation Conductor and Meditation Clients. The Meditation Observer and Meditation Viewer watched the meditation. The observer had their physiological and physical signals recorded and the viewer took notes of the meditation. (a) A schematic diagram of the Meditation experiment setup. (b) A photograph of the data acquisition system. (c) A photograph of the meditation setting setup.

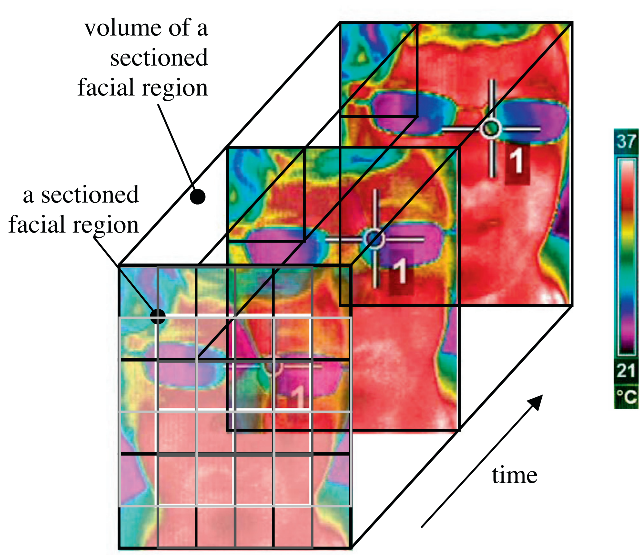

Fig. 3. A thermal facial volume of an observer.

the aim to determine a *hyperplane* that partitions data by class or labels. A hyperplane is chosen based on *support vectors*, which are training data samples that define maximum margins from the support vectors to the hyperplane to form the best decision boundary. This attempts to address the issue of data overfitting (Han, Kamber, & Pei, 2012) and helps to generalize classifications well.

3.3. A genetic algorithm and support vector machine hybrid model

SVMs are not robust to feature sets with redundant and irrelevant features for classification, so feature selection methods have been developed that helps SVM based models to better capture patterns in the data (Nguyen & De la Torre, 2010; Zhao, Fu, Ji, Tang, & Zhou, 2011; Lee & Yu, 2012). In this work, a hybrid of an SVM and a GA were used to reduce the redundant and irrelevant features in the input feature set for the SVM model. The hybrid was used to determine whether a feature selection component in the stress classification system improved the quality of the observer stress recognition.

GAs are global search algorithms, and have been commonly used to solve optimization problems (Goldberg, 1989). The search algorithm is based on the concept of natural evolution. It evolves a population of candidate solutions, represented by *chromosomes*, using *crossover*, *mutation* and *selection* operations in search for a better quality population based on some fitness measure. Crossover and mutation operations are applied to chromosomes to achieve diversity in the population and reduce the risk of the search being stuck with a local optimal population. After each generation during the search, the GA selects chromosomes, probabilistically mostly made up of better quality chromosomes, for the population in the next generation to direct the search to more favorable chromosomes.

Table 1
EEG frequency band categories.

Band category	Frequency range	Person's state
Beta	13–30	Alertness or anxiety
Alpha	8–13	Relaxation
Theta	4–8	Dream sleep or phase between consciousness and drowsiness
Delta	0.5–4	Coma or deep sleep

The initial population for the GA-SVM in this work had all the features. The number of features used by the chromosomes varied but the chromosome length was fixed. The length of a chromosome was equal to the total number of features in the feature space. A chromosome was a binary string where the index for a bit represented a feature and the bit value indicated whether the feature was used in the SVM classification. The fitness measure for a chromosome was the recognition rate of stress produced by a SVM model calculated using 10-fold cross validation. The architecture for the GA-SVM classification system is provided in Fig. 4. The system was implemented with the parameter settings for the GA given in Table 2.

4. Results and discussion

SVM and GA-SVM were implemented and tested on the data sets obtained from the Interview and Meditation experiments. The primary stress signals for observers were provided as input to the classification systems and the stress classes for Interview and Meditation environments were validated using the survey responses, which is the usual method reported in literature for validating stress classes (Hill & Boyle, 2007). A classification system generated a feature set and built a classification model using the feature set and the ground truth provided by the survey responses. The performance of the model was evaluated using the accuracy and F-score based on 10-fold cross-validation in recognizing two stress classes – *stressed* and *not-stressed* classes – from the test input data. The first two stages of the environments were labeled as *stressed* and the last two stages were labeled as *not-stressed* in

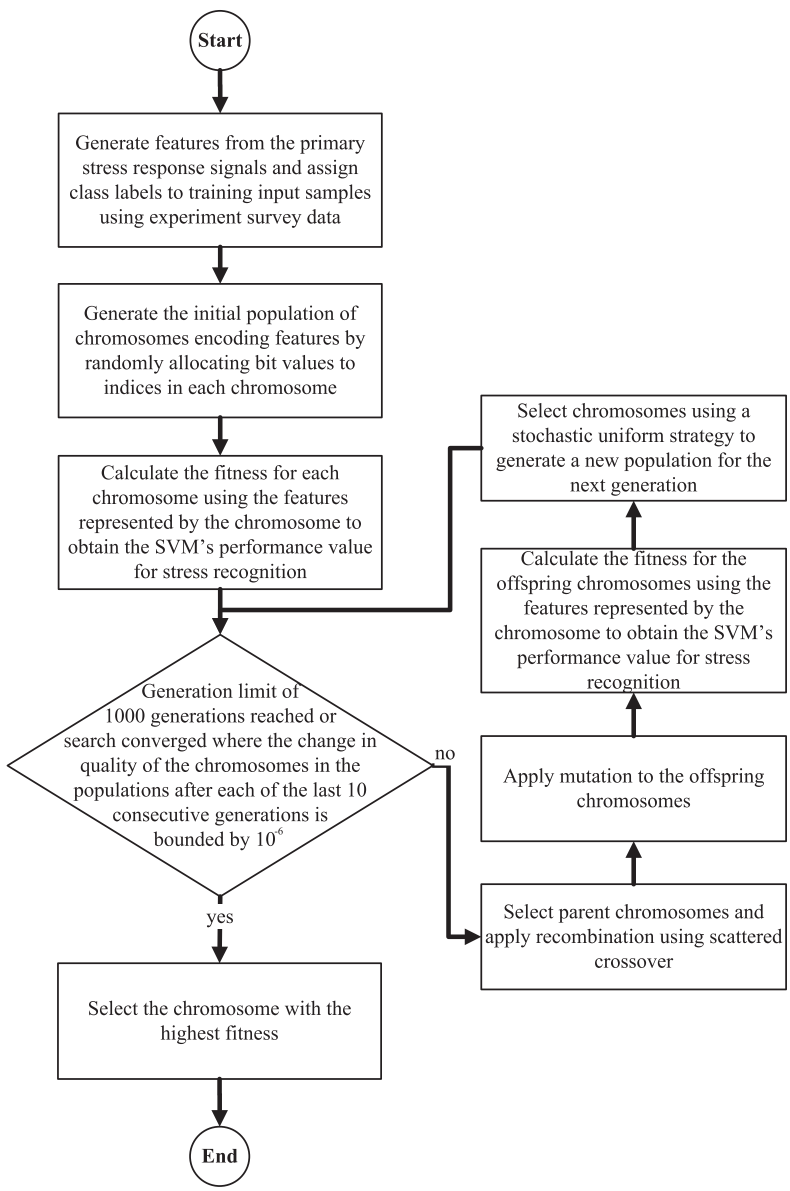

Fig. 4. The GA-SVM observer stress recognition system.

Table 2
Implementation settings for the genetic algorithm.

GA parameter	Value/setting
Population size	100
Number of generations	2000
Crossover rate	0.8
Mutation rate	1/(length of the chromosome)
Crossover type	scattered crossover
Mutation type	uniform mutation
Selection type	stochastic uniform selection

Table 3
Performance measures for the observer stress computational models using 10-fold cross validation.

Stress recognition measure	SVM	SVM with optimized stress features
Accuracy	0.87	0.98
F-score	0.89	0.96

Table 4
Performance measures for the stress computational models using 10-fold cross validation for observers for environment classification.

Stress recognition measure	SVM	SVM with optimized stress features
Accuracy	0.79	0.95
F-score	0.82	0.96

Table 5
Performance measures for the stress computational models using 10-fold cross validation for observers of the interview environment.

Stress recognition measure	SVM	SVM with optimized stress features
Accuracy	0.84	0.90
F-score	0.80	0.89

Table 6
Performance measures for the stress computational models using 10-fold cross validation for observers of the meditation environment.

Stress recognition measure	SVM	SVM with optimized stress features
Accuracy	0.92	0.99
F-score	0.92	0.98

accordance with the results of the survey responses. Stress recognition results produced by the SVM and GA-SVM systems are presented in Table 3.

Stress recognition rates were significantly better when feature selection was incorporated in stress classification system according to the Student's *T*-test ($p < 0.01$). In addition, results for the classification systems show that observers showed characteristics in their physiological and physical response signals that were different during the different times of the environment. The patterns in the response signals in the earlier stages of the environments were different to the patterns in the later stages.

The classification systems were provided stress response signals categorized by the type of environment setting – interview or meditation setting. Classification results for the environment setting based on the response signals of observers are provided in Table 4.

The classification systems captured better observer stress patterns to distinguish whether the observer was stressed during a particular stage of an environment (performance results in Table 3) than classification systems that distinguished whether the observer was viewing an Interview or Meditation environment (performance results in Table 4). Statistical analysis showed that observer stress recognition rates were better for classification systems that classified stress classes based on the stage of the environment ($p < 0.05$). Results from Tables 3 and 4 also show that stress patterns of observers were common for a particular stage of the environment irrespective of the environment setting. For future work, stress signals could be modeled for more than two environments and investigation can be done to determine whether stress patterns captured in some of the environments can be used to recognize stress in other environments. Future work could also investigate developing models that provide better classification rates to recognize environments that observers viewed using stress response signals from observers.

Stress response signals obtained from the Interview experiment was modeled using the SVM and GA-SVM classification systems with the first two stages of the interview environment labeled as stressed and the last two stages labeled as not-stressed. Results for the performance of the classification systems are given in Table 5.

Similarly, the stress response signals for the observers of the Meditation experiment were modeled using the SVM and GA-SVM classification systems. Stress recognition results for the systems are presented in Table 6.

For the different environment stages, the classification systems captured better stress patterns for the meditation environment than the interview environment ($p < 0.01$). This is the case because the meditation environment might have influenced the stress levels for observers more over the course of the environment than the interview environment. The results correlate with the experiment survey responses, which show that the change in stress for the meditation environment was greater than the interview environment.

Feature sets selected by the GAs in the GA-SVM classification systems showed that the EEG band power feature was common to all the feature sets. This suggests that the band power feature had a stronger relationship with stress classes than other types of features used in this paper. SVM and GA-SVM were modeled with the EEG band power features only and their performance results for observer stress recognition are given in Table 7. The stress recognition results could not be differentiated from the results obtained from the GA-SVM classification systems for the investigations done to report results in Tables 3–6 ($p > 0.1$).

5. Conclusion and future work

Computational models of stress for observers of real-life environments were developed based on a SVM using real-world stress data sets formed from the Interview and Meditation experiments. The data sets were made up of physiological and physical sensor signals, which were provided to individual-independent observer

Table 7
Performance measures for the stress computational models using 10-fold cross validation for observers using EEG band power features as input.

Stress recognition measure	Stress recognition by stages	Stress recognition by environments	Stress recognition by stages for interview environment	Stress recognition by stages for meditation environment
Accuracy	0.96	0.92	0.86	0.95
F-score	0.95	0.9	0.88	0.95

stress recognition systems to capture stress patterns in the data for the interview and meditation environments. Observer stress patterns were successfully captured by the computational models for the different environments. In addition, relative stress patterns were successfully captured by the models irrespective of the environment. This work provides a method to recognize observer stress and determine whether an environment is stressful or not stressful. Our future work will extend on the stress recognition model, which we developed in this work, to provide a measure for multiple stress levels to show the different degrees of stress shown by individuals over particular moments in an environment. Other future work will include investigating methods for stress analysis for observers of other types of environments and modeling online observer stress analysis, which would provide real-time feedback on stress.

References

Ashton, H., Savage, R., Thompson, J., & Watson, D. (2012). A method for measuring human behavioural and physiological responses at different stress levels in a driving simulator. *British Journal of Pharmacology, 45*, 532–545.

Bakker, J., Pechenizkiy, M., & Sidorova, N. (2011). What's your current stress level? Detection of stress patterns from GSR sensor data. In *International conference on data mining workshops (ICDMW)* (pp. 573–580). Vancouver, BC.

Cheng, B. (2012). Emotion recognition from physiological signals using support vector machine. In Y. Wu (Ed.). *Software engineering and knowledge engineering: Theory and practice* (Vol. 114, pp. 49–52). Berlin/Heidelberg: Springer.

de Santos Sierra, A., Avila, C. S., Guerra Casanova, J., Bailador del Pozo, G., & Jara Vera, V. (2010). Two stress detection schemes based on physiological signals for real-time applications. In *International conference on intelligent information hiding and multimedia signal processing* (pp. 364–367). Darmstadt.

Dharmawan, Z. (2007). Analysis of computer games player stress level using EEG data. Master of Science Thesis Report, Faculty of Electrical Engineering, Mathematics and Computer Science, Delft University of Technology, Netherlands.

Dishman, R. K., Nakamura, Y., Garcia, M. E., Thompson, R. W., Dunn, A. L., & Blair, S. N. (2000). Heart rate variability, trait anxiety, and perceived stress among physically fit men and women. *International Journal of Psychophysiology, 37*, 121–133.

Dou, Q. (2009). An SVM ranking approach to stress assignment. University of Alberta.

Goldberg, D. E. (1989). *Genetic algorithms in search, optimization, and machine learning*. Addison-Wesley.

Haak, M., Bos, S., Panic, S., & Rothkrantz, L. J. M. (2008). Detecting stress using eye blinks and brain activity from EEG signals. In *Proceeding of the 1st driver car interaction and interface (DCII 2008)* (p. 10). Chez Technical University, Prague.

Haddad, D., Walter, S., Ratley, R., & Smith, M. (2001). Investigation and evaluation of voice stress analysis technology, Air Force Research Lab Rome NY Information Directorate.

Han, J., Kamber, M., & Pei, J. (2012). *Data mining: Concepts and techniques* (3rd ed.). San Francisco: Morgan Kaufmann.

Healey, J., & Picard, R. (2000). Smartcar: Detecting driver stress. In *International conference on, pattern recognition* (pp. 218–221).

Healey, J. A., & Picard, R. W. (2005). Detecting stress during real-world driving tasks using physiological sensors. *IEEE Transactions on Intelligent Transportation Systems, 6*, 156–166.

Hennessy, D. A., & Wiesenthal, D. L. (1999). Traffic congestion, driver stress, and driver aggression. *Aggressive Behavior, 25*, 409–423.

Hernández, B., Olague, G., Hammoud, R., Trujillo, L., & Romero, E. (2007). Visual learning of texture descriptors for facial expression recognition in thermal imagery. *Computer Vision and Image Understanding, 106*, 258–269.

Hill, J. D., & Boyle, L. N. (2007). Driver stress as influenced by driving maneuvers and roadway conditions. *Transportation Research Part F: Traffic Psychology and Behaviour, 10*, 177–186.

Hjorth, B. (1970). EEG analysis based on time domain properties. *Electroencephalography and Clinical Neurophysiology, 29*, 306–310.

Hjortskov, N., Rissén, D., Blangsted, A., Fallentin, N., Lundberg, U., & Søgaard, K. (2004). The effect of mental stress on heart rate variability and blood pressure during computer work. *European Journal of Applied Physiology, 92*, 84–89.

Hoffman-Goetz, L., & Pedersen, B. K. (1994). Exercise and the immune system: A model of the stress response? *Immunology Today, 15*, 382–387.

Hoffmann, E. (2005). Brain training against stress: Theory, methods and results from an outcome study. *Stress Report, 4*, 24.

Hong, J. H., Ramos, J., & Dey, A. K. (2012). Understanding physiological responses to stressors during physical activity. In *Proceedings of the 2012 ACM conference on ubiquitous computing* (pp. 270–279).

Interactive-Productline. (2013, 10/02/2013). Interactive Productline IP AB – Mindball. Available: <http://www.mindball.se/index.html>.

Jarlier, S., Grandjean, D., Delplanque, S., N'Diaye, K., Cayeux, I., Velazco, M. I., et al. (2011). Thermal analysis of facial muscles contractions. *IEEE Transactions on Affective Computing, 2*, 2–9.

Katz, M. J. (1988). Fractals and the analysis of waveforms. *Computers in Biology and Medicine, 18*, 145–156.

Kumar, M., Weippert, M., Vilbrandt, R., Kreuzfeld, S., & Stoll, R. (2007). Fuzzy evaluation of heart rate signals for mental stress assessment. *IEEE Transactions on Fuzzy Systems, 15*, 791–808.

Lee, M.-Y., & Yu, S.-N. (2012). Selection of heart rate variability features for congestive heart failure recognition using support vector machine-based criteria. In *5th European conference of the international federation for, medical and biological engineering* (pp. 400–403).

Liao, W., Zhang, W., Zhu, Z., & Ji, Q. (2005). A real-time human stress monitoring system using dynamic Bayesian network. In *Computer vision and pattern recognition – Workshops* (p. 70).

Lifeline-Australia. (2009, 15/03/2013). Stress Costs Taxpayer $300K Every Day. Available: <www.lifeline.org.au>.

Lin, T., & John, L. (2006). Quantifying mental relaxation with EEG for use in computer games. In *International conference on internet computing* (pp. 409–415). Las Vegas, NV, USA.

Lin, T., Omata, M., Hu, W., & Imamiya, A. (2005). Do physiological data relate to traditional usability indexes?. In *Proceedings of the 17th Australia conference on computer–human interaction: Citizens online: Considerations for today and the, future* (pp. 1–10).

Lovallo, W. R (2005). *Stress & health: Biological and psychological interactions*. Sage Publications, Inc.

Mathworks. (2012, 08/09/2012). Vision TemplateMatcher System Object R2012a. Available: <http://www.mathworks.com.au/help/vision/ref/vision.templatematcherclass.html>.

Nguyen, M. H., & De la Torre, F. (2010). Optimal feature selection for support vector machines. *Pattern Recognition, 43*, 584–591.

Niu, X., Chen, L., & Chen, Q. (2011). Research on genetic algorithm based on emotion recognition using physiological signals. In *International conference on computational problem-solving* (pp. 614–618).

Novák, D., Lhotská, L., Eck, V., & Sorf, M. (2004). EEG and VEP signal processing. Technical Report, Czech Technical University in Prague, Department of Cybernetics.

Palmer, J. F., & Hoffman, R. E. (2001). Rating reliability and representation validity in scenic landscape assessments. *Landscape and Urban Planning, 54*, 149–161.

Park, B. J., Jang, E. H., Kim, S. H., Huh, C., & Sohn, J. H. (2011). Feature selection on multi-physiological signals for emotion recognition. In *2011 International conference on engineering and industries (ICEI)* (pp. 1–6). Korea.

Paul, P. P., Leung, H., Peterson, D. A., Sejnowski, T. J., & Poizner, H. (2010). Detecting Neural decision patterns using SVM-based EEG classification. In *International conference on bioinformatics and biomedical engineering* (pp. 1–4). Chengdu.

Roscoe, A. (1992). Assessing pilot workload. Why measure heart rate, HRV and respiration? *Biological Psychology, 34*, 259–287.

Selye, H. (1965). The stress syndrome. *The American Journal of Nursing, 65*, 97–99.

Sexton, J. B., Thomas, E. J., & Helmreich, R. L. (2000). Error, stress, and teamwork in medicine and aviation: Cross sectional surveys. *BMJ, 320*, 745.

Sharma, N., & Gedeon, T. (2012). Objective measures, sensors and computational techniques for stress recognition and classification: A survey. *Computer Methods and Programs in Biomedicine, 108*, 1287–1301.

Singh, R. R., Conjeti, S., & Banerjee, R. (2013). A comparative evaluation of neural network classifiers for stress level analysis of automotive drivers using physiological signals. *Biomedical Signal Processing and Control, 8*, 740–754.

Struc, V. (2012, 08/09/2012). The Ph.D. Toolbox: Pretty Helpful Development Functions for Face Recognition. Available: <http://luks.fe.uni-lj.si/sl/osebje/vitomir/face_tools/PhDface/>.

Struc, V., & Pavesic, N. (2009). Gabor-based kernel partial-least-squares discrimination features for face recognition. *Informatica (Vilnius), 20*, 115–138.

Struc, V., & Pavesic, N. (2010). The complete Gabor-fisher classifier for robust face recognition. *EURASIP Advances in Signal Processing*, 26.

The-American-Institute-of-Stress. (05/03/2012). America's No. 1 Health Problem – Why is there more stress today? Available: <http://www.stress.org/americas.htm>.

The-American-Institute-of-Stress. (20/02/2013). Workplace stress. Available: <http://www.stress.org/workplace-stress/>.

Trujillo, L., Olague, G., Hammoud, R., & Hernandez, B. (2005). Automatic feature localization in thermal images for facial expression recognition. In *IEEE computer society conference on computer vision and pattern recognition – Workshops, 2005. CVPR workshops* (p. 14). San Diego, CA, USA.

Yuen, P., Hong, K., Chen, T., Tsitiridis, A., Kam, F., & Jackman, J., et al. (2009). Emotional & physical stress detection and classification using thermal imaging technique. In *3rd International conference on crime detection and prevention (ICDP 2009)* (pp. 1–6). London.

Zhai, J., & Barreto, A. (2006). Stress recognition using non-invasive technology. In *Proceedings of the 19th international Florida artificial intelligence research society conference FLAIRS* (pp. 395–400).

Zhai, J., & Barreto, A. (2006). Stress detection in computer users based on digital signal processing of noninvasive physiological variables. In *Proceedings of the 28th IEEE EMBS annual international conference* (pp. 1355–1358).

Zhao, M., Fu, C., Ji, L., Tang, K., & Zhou, M. (2011). Feature selection and parameter optimization for support vector machines: A new approach based on genetic algorithm with feature chromosomes. *Expert Systems with Applications, 38*, 5197–5204.

Zhao, G., & Pietikainen, M. (2007). Dynamic texture recognition using local binary patterns with an application to facial expressions. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 29*, 915–928.