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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.

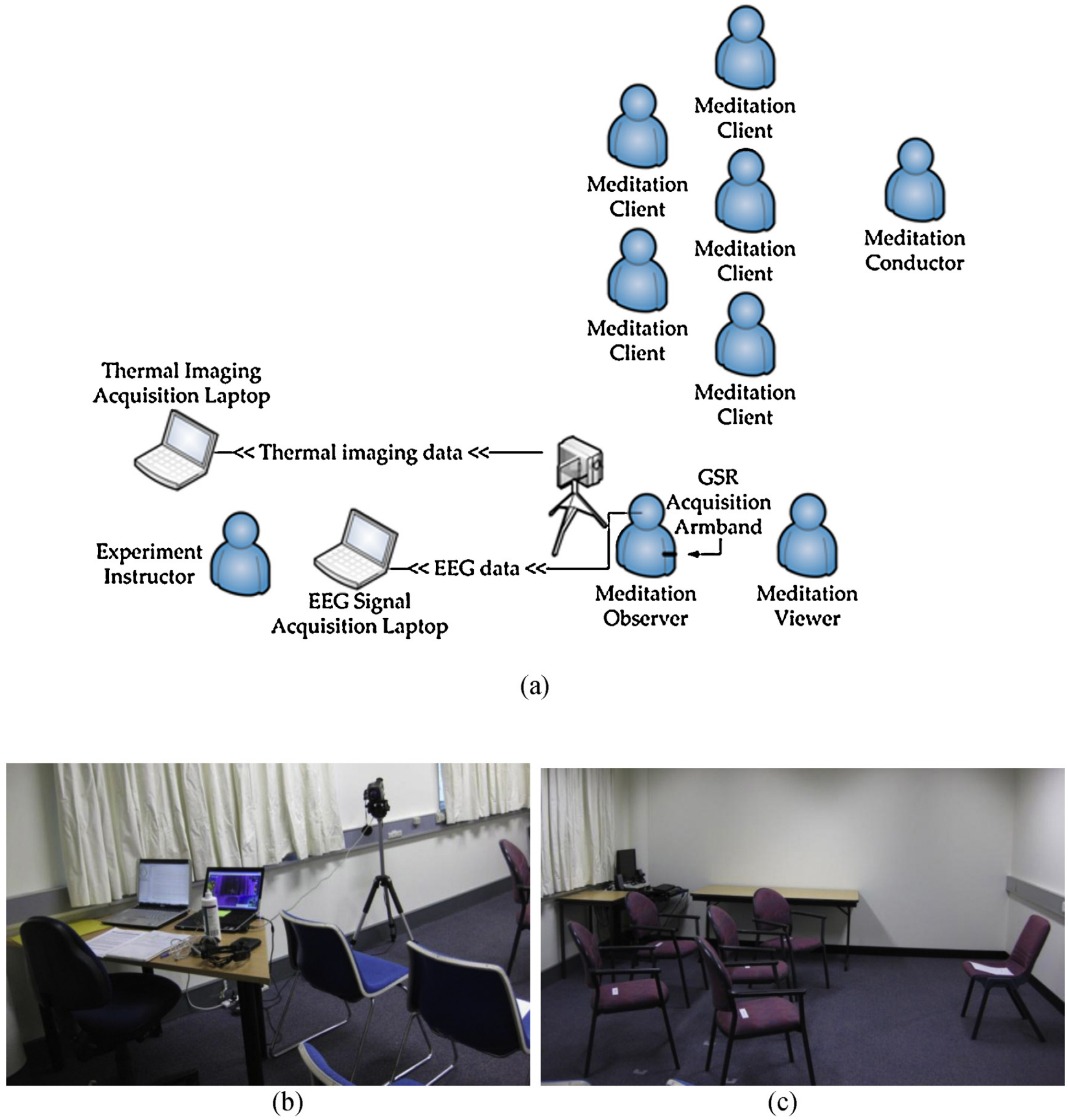

Fig. 1. Setup for the meditation experiment. The meditation environment used a meditation conductor and meditation clients. The meditation observer and meditation viewer watched the meditation. The observer had their physiological and physical signals recorded and the viewer took notes of the meditation. (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.

While the observer viewed the meditation environment, 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.

Results from the survey that the viewer completed on the meditation environment were used to define stress classes for the different stages of the role-play. Analysis of survey responses is a common method used in the literature to validate stress classes for tasks [38]. The role-play was divided into 7 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 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. Computational models for stress classification

Stress classification models were built using features derived from the stress response signals of observers during the experiment to provide information on the overall trend of the stress signal for observers. 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.

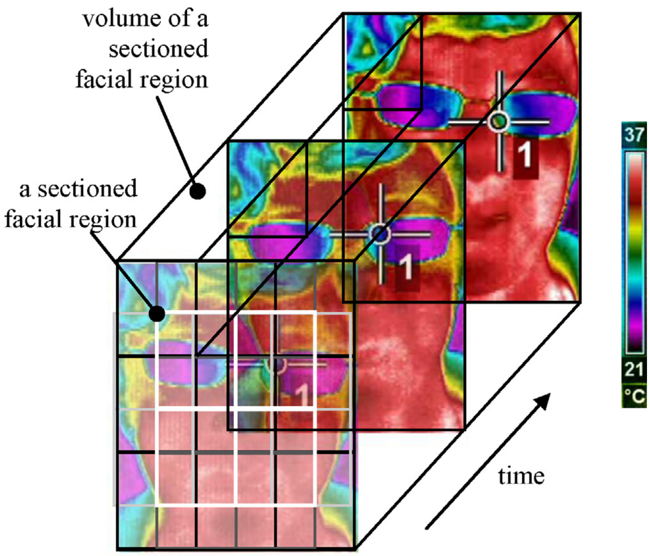

Fig. 2. A thermal facial volume of an observer.

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 time 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 shown in Fig. 2. A face detection method based on eye coordinates [39,40] 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 [39–41], 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 [42]. 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 time 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. 2.

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

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, which 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 [10,20,21].

Measurements for Hjorth parameters [43] and fractal dimensions [44] are other measures usually used in analyzing EEG signals and were calculated and added to the set of stress features. Hjorth parameters are time-based characteristics of an EEG 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

$$\mathrm{activity}(x) = \frac{\sum_{n=1}^{N}(x_n = \bar{x})^2}{N} \tag{1}$$

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

$$\mathrm{mobility}(x) = \sqrt{\frac{\mathrm{activity}(x')}{\mathrm{activity}(x)}} \tag{2}$$

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

$$\mathrm{complexity}(x) = \frac{\mathrm{mobility}(x')}{\mathrm{mobility}(x)} \tag{3}$$

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

$$\mathrm{fractal\ dimension}(x) = 1 + \frac{\log(L)}{\log(2(N-1))} \tag{4}$$

where

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

and

$$x^* = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{6}$$

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

3.2. Support vector machine model

An SVM model was developed to classify stress using the stress features. SVMs have been widely used in the literature for classification problems, including classifications based on physiological data [45,46]. Provided a set of training samples, an SVM transforms the data samples using a nonlinear mapping to a higher dimension with 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 [47] 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 help SVM based models to better capture patterns in the data [48–50]. In this work, a hybrid of an SVM and a GA was used to reduce the redundant and irrelevant features in the high-dimensional 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 classification, and obtain optimized features for predicting a stress signal.

GAs are global search algorithms, and have been commonly used to solve optimization problems [51]. They have been successfully used to select features from high-dimensional feature sets [52,53] and features derived from physiological signals [36,37]. The GA 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* operators 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.

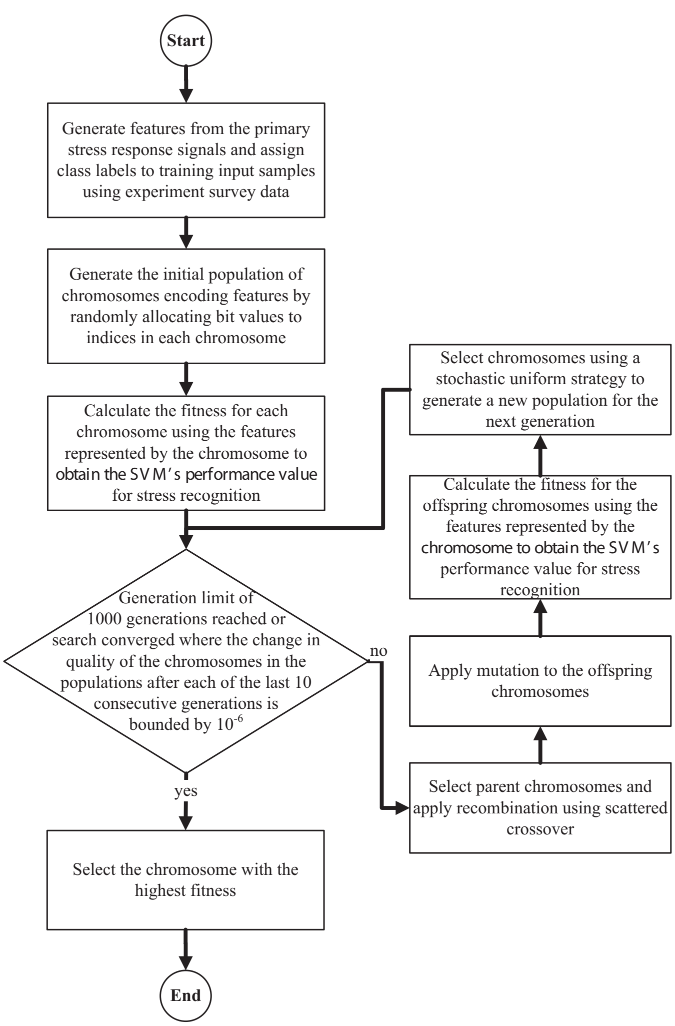

Fig. 3. The GA-SVM observer stress classification system.

Table 2
Implementation settings for the genetic algorithm in the genetic algorithm and support vector machine hybrid model.

GA parameter	Value/setting
Population size	100
Number of generations	2000
Crossover rate	0.80
Mutation rate	1/(length of the chromosome)
Crossover type	Scattered crossover
Mutation type	Uniform mutation
Selection type	Stochastic uniform selection

The initial population for the GA-SVM in this work used all the stress features available–primary and derived. The number of features used by each chromosome varied but the chromosome length was fixed to be 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 correct classification 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

As shown in Fig. 3, the system was implemented with the parameter settings for the GA given in Table 2. The parameter values were chosen experimentally. The computational model systems were implemented in MATLAB [54].

4. A computational model for estimating a stress signal

In this section, we propose a computational system based on an artificial neural network (ANN) to estimate a stress signal for observers of the meditation environment. ANNs are inspired by biological neural networks and have the capability to learn patterns or mathematical relationships that exist between characteristics in input tuples and the output. An ANN is made up of interconnected processing elements known as *artificial neurons*, which are connected by weighted links that pass signals between neurons. Feed-forward ANNs were used in this paper. A feed-forward ANN has an input layer, may have multiple hidden layers and an output layer where each layer is made up of neurons. Input tuples for the ANN are passed through the neurons in the input layer. Then the weighted links pass the signals to the neurons in the hidden layers which apply a nonlinear activation or transfer function to process the signals further and then in a similar fashion the signals progress through the following layers. Until the signals reach neurons in the output layer which causes the ANN to produce output.

The results from the stress classification models, which are discussed in detail in Section 5, mirrored the experiment survey responses in that the earlier stages of the environment were found to be more stressful than the later stages. As a result, we envisaged the overall trend of the stress signal for an observer for the duration of the environment to have stress decreasing over time. Thus, curves formed by a linear function, symmetric saturating linear function or hyperbolic tangent function are some examples of the functions that the stress signal could resemble. The various basic forms that the stress signal could take are presented in Fig. 4. The values on the vertical axes of the graphs in the figure provide a relative stress measure where a value of 1 means *most-stressed* and a value of −1 means *least-stressed*.

ANNs were developed that took the optimized stress features found from the model in Section 3 as input with the aim to produce a signal that took the form of either a linear function, symmetric saturating linear function or a hyperbolic tangent function. Three different types of ANNs were developed and they differed on the type of desired output estimator function as provided below:

- **ANN_Linear:** the ANN had a linear desired output estimator function.
- **ANN_SLin:** the ANN had a symmetric saturating linear desired output estimator function.
- **ANN_Tanh:** the ANN had a hyperbolic tangent desired output estimator function.

The MATLAB adapt function was used to train the ANNs on an incremental basis. Each network was trained using the Levenberg–Marquardt algorithm for 1000 epochs or until the magnitude of the gradient for the mean square error (MSE) was less than 10^{-5} during the validation phase. The MSE is the average squared error determined from the actual output of the network and the expected output. The number of neurons in the input layer for each ANN was equal to the number of optimized features obtained from the GA-SVM system and each ANN had 7 hidden neurons and one neuron in the output layer. If all the stress features had been provided as input to the ANN, then the network would have become unnecessarily large requiring longer times for executing ANN training and testing phases and contribute to capturing poorer stress patterns to predict a stress signal. During the training phase, an ANN was presented with a data sample which had stress feature values as input and an estimate value on the curve of the function for a particular time segment. The point of training using this desired output estimator is that we do not know the 'time' values of instantaneous stress as we have only a few human provided labels which relate to many stress feature values. Training to the different curves enables us to determine if a representation can be formed which well relates the data to the curve. This is more complex and adaptive than finding a curve of best fit to the data.

5. Results and discussion

SVM and GA-SVM systems were implemented and tested on the data sets obtained from the meditation experiment. The primary stress signals for observers were provided as input to the classification systems. A classification system generated a feature set and used it to build a classification model for stress. The performance of the model was evaluated using the accuracy and *F*-score based on 10-fold cross-validation in recognizing two stress classes – *most-stressed* and *least-stressed* classes – from the test input data. The first two stages of the environments were labeled as *most-stressed* and the last two stages were labeled as *least-stressed* in accordance with the results of the survey responses. A visualization of the model input data is given in Fig. 5. Stress classification results produced by the SVM and GA-SVM systems are presented in Table 3.

Feature sets selected by the GA in the GA-SVM classification systems showed that the EEG band power features made up most of the optimized feature set (Fig. 6). This suggests that the band power feature had a stronger relationship with stress classes than

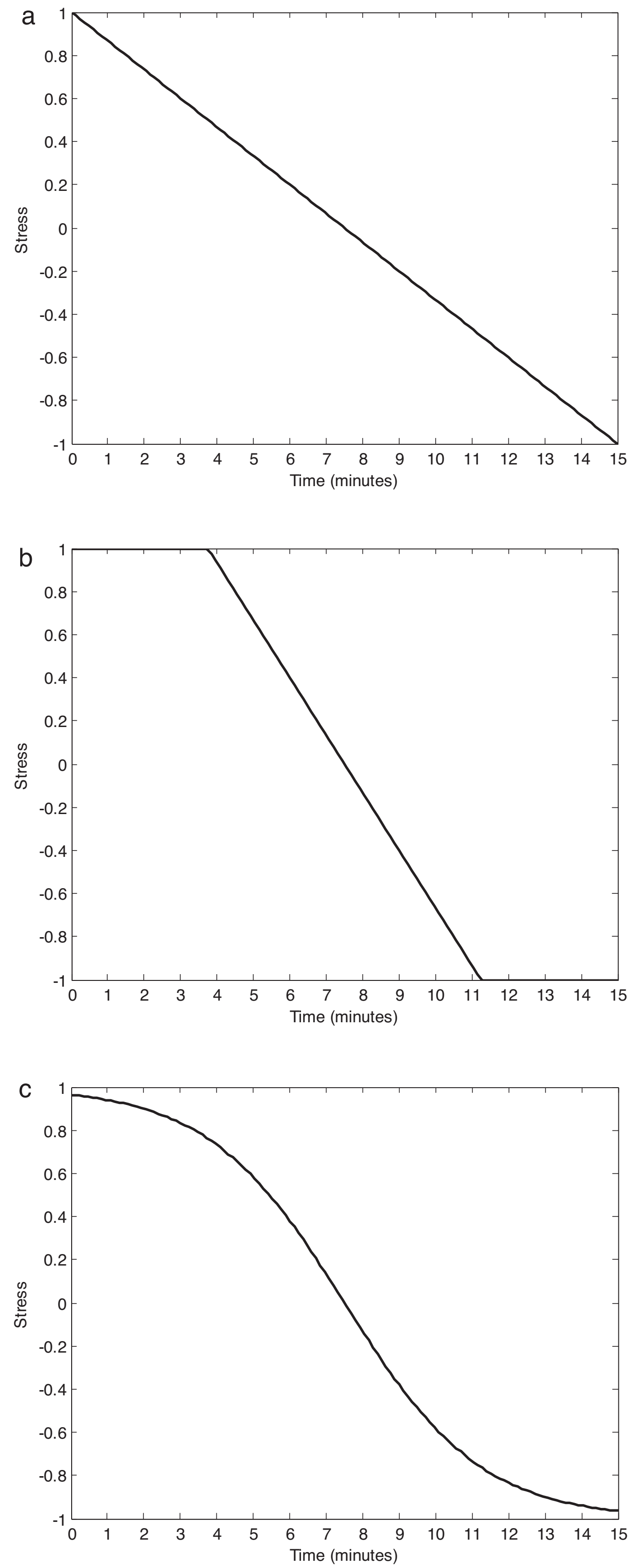

Fig. 4. Forms of the stress signal (a) linear (b) symmetric saturating linear (c) hyperbolic tangent.

Feature Index

Experiment Stage	F$_1$	F$_2$	F$_3$	…	F$_{1379}$
S$_1$	x_F$_1$S$_1$	x_F$_2$S$_1$	x_F$_3$S$_1$	…	x_F$_{1379}$S$_1$
S$_2$	x_F$_1$S$_2$	x_F$_2$S$_2$	x_F$_3$S$_2$	…	x_F$_{1379}$S$_2$
S$_6$	x_F$_1$S$_6$	x_F$_2$S$_6$	x_F$_3$S$_6$	…	x_F$_{1379}$S$_6$
S$_7$	x_F$_1$S$_7$	x_F$_2$S$_7$	x_F$_3$S$_7$	…	x_F$_{1379}$S$_7$

Fig. 5. The form of the classification model input data for an observer.

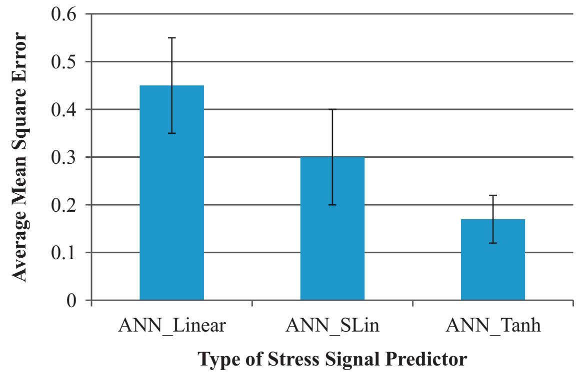

Fig. 7. Average mean square error of the outputs produced by the stress signal predictors in relation to their corresponding curve forms presented in Fig. 4.

Table 3
Performance measures for the stress computational models using 10-fold cross validation for observers of the meditation environment.

Stress classification measure	SVM	SVM with optimized stress features	SVM with EEG band power features only as input
Correct classification rate	0.92	0.99	0.95
F-score	0.92	0.98	0.95

other types of features used in this paper. The SVM system was modeled with the EEG band power features only and its performance results for observer stress classification are given in Table 3. The stress classification results of the SVM that had EEG band power features provided as input could not be differentiated from the results obtained from the GA-SVM classification system on all stress features i.e. SVM with stress features optimized by a GA ($p > 0.1$).

EEG band power features were used to predict the stress signal for observers of the meditation environment. The features were provided as input to the three ANN stress signal predictors – ANN_Linear, ANN_SLin and ANN_Tanh. The form of the input data is provided in each type of ANN was trained and tested on experiment subject data on a leave-one-out basis so the ANN would predict a stress signal for one subject after being trained on data for the other subjects. The average MSE calculated for each of the ANNs based on the values on the corresponding curve, which was provided in Fig. 4, is presented in Fig. 7.

ANN_Tanh produced the best estimation of the stress signal as shown by the lowest MSE value compared to ANN_Linear and ANN_SLin, and results from the statistical Student's *T*-test of the MSE values, which provided $p < 0.01$. According to the MSE values for ANN_Linear and ANN_SLin, ANN_SLin produced a better estimate of the stress signal compared to ANN_Linear with $0.01 < p < 0.01$. Examples of the outputs from the three ANNs in relation to the form of the curve of the corresponding functions are shown in Fig. 8. The curves produced by the ANNs show that the overall rate of change in stress is negative, which is consistent with the results produced by the classification systems, but there were certain times in the meditation experiment when the curves had a positive rate of change as shown by slight increases in stress values over the time periods. This observation could not be deduced by the survey responses from the experiment. Future work could extend the ANN stress signal predictor with desired output estimator functions that could form curves with rate of change that has a positive rate of change for certain time periods and survey responses could be captured at a higher level of granularity to validate the slight increases in the stress signal.

Feature Index

Experiment Time Segment (seconds)	F$_1$	F$_2$	F$_3$	…	F$_{1379}$
T$_{0-5}$	x_F$_1$T$_{0-5}$	x_F$_2$T$_{0-5}$	x_F$_3$T$_{0-5}$	…	x_F$_{1379}$ T$_{0-5}$
T$_{2.5-7.5}$	x_F$_1$T$_{2.5-7.5}$	x_F$_2$T$_{2.5-7.5}$	x_F$_3$T$_{2.5-7.5}$	…	x_F$_{1379}$T$_{2.5-7.5}$
T$_{5-10}$	x_F$_1$T$_{5-10}$	x_F$_2$T$_{5-10}$	x_F$_3$T$_{5-10}$	…	x_F$_{1379}$T$_{5-10}$
T$_{7.5-12.5}$	x_F$_1$T$_{7.5-12.5}$	x_F$_2$T$_{7.5-12.5}$	x_F$_3$T$_{7.5-12.5}$	…	x_F$_{1379}$T$_{7.5-12.5}$
T$_{10-15}$	x_F$_1$T$_{10-15}$	x_F$_2$T$_{10-15}$	x_F$_3$T$_{10-15}$	…	x_F$_{1379}$T$_{10-15}$
	⋮	⋮	⋮	⋮	⋮
T$_{892.5-897.5}$	x_F$_1$T$_{892.5-897.5}$	x_F$_2$T$_{892.5-897.5}$	x_F$_3$T$_{892.5-897.5}$	…	x_F$_{1379}$T$_{892.5-897.5}$
T$_{989.5-900}$	x_F$_1$T$_{989.5-900}$	x_F$_2$T$_{989.5-900}$	x_F$_3$T$_{989.5-900}$	…	x_F$_{137}$T$_{989.5-900}$

Fig. 6. A visualization of the input data for the stress signal estimator model for an observer.

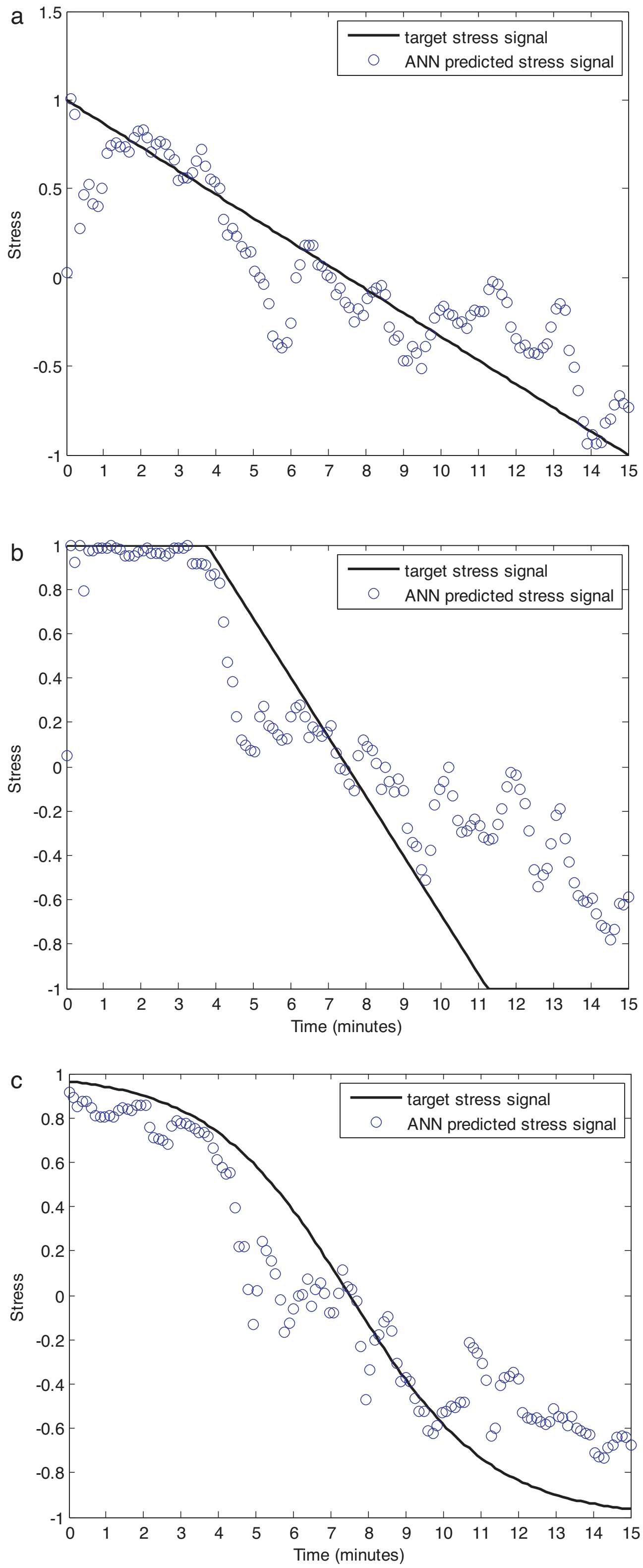

Fig. 8. Outputs of the ANN based stress signal predictors for an observer of the meditation environment: (a) ANN_Linear, (b) ANN_SLin, and (c) ANN_Tanh.

6. Conclusion and future work

A computational method to model a stress signal of an observer for an environment was successfully developed from a real-world data set of stress response signals. The data set was made up of physiological and physical sensor signals and survey responses, which were provided to an individual-independent observer stress classification system based on an SVM to determine the overall profile of the stress signal. A hybrid model of a GA and an SVM was developed to determine which types of stress feature are more relevant for stress detection. The optimized features were used to estimate a stress signal using the proposed stress signal predictor, which is based on an ANN. Results showed that the stress signal for observers was best represented using a curve that resembled to a hyperbolic tangent function rather than being similar to a linear function or a symmetric saturating linear function. Future work could extend the stress signal predictor system to include optimization of the derivative or rate of change of the transfer functions of the ANN to further generalize the process for estimating a stress signal. Other work could include estimating a stress signal for an observer and comparing their stress signal across multiple environments. Additionally, future work could include estimating a stress signal for an individual interacting with particular stress stimuli as opposed to estimating a stress signal of an observer who was not actively engaged in the environment, which was the focus in this paper. Our work in the future will include investigating a user interface system for our modeling system with appropriate sensors best suited to individuals to provide a stress measure in real time. Further, our models generated and used quite a large number of features. Future work will include investigating rule extraction techniques to make the models useful for decision support for users including health practitioners monitoring stress.

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