Hybrid Genetic Algorithms for Stress Recognition in Reading

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Abstract. Stress is a major problem facing our world today and affects everyday lives providing motivation to develop an objective understanding of stress during typical activities. Physiological and physical response signals showing symptoms for stress can be used to provide hundreds of features. This encounters the problem of selecting appropriate features for stress recognition from a set of features that may include irrelevant, redundant or corrupted features. In addition, there is also a problem for selecting an appropriate computational classification model with optimal parameters to capture general stress patterns. The aim of this paper is to determine whether stress can be detected from individual-independent computational classification models with a genetic algorithm (GA) optimization scheme from sensor sourced stress response signals induced by reading text. The GA was used to select stress features, select a type of classifier and optimize the classifier's parameters for stress recognition. The classification models used were artificial neural networks (ANNs) and support vector machines (SVMs). Stress recognition rates obtained from an ANN and a SVM without a GA were 68% and 67% respectively. With a GA hybrid, the stress recognition rate improved to 89%. The improvement shows that a GA has the capacity to select salient stress features and define an optimal classification model with optimized parameter settings for stress recognition.

Keywords: stress classification, artificial neural networks, genetic algorithms, support vector machines, reading.

1 Introduction

Stress is part of everyday life and it has been widely accepted that stress, which can lead to less favorable emotional states, such as anxiety, fear or anger, is a growing concern for people and society. Stress has been defined as "the non-specific response of the body to any demand for change" [1]. It is the body's response to the imbalance caused between demands and resources available to a person. Stress 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 of time without being managed, stress has been widely recognized as a major growing concern. It has the potential to cause chronic illnesses (e.g. cardiovascular

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diseases, diabetes and some forms of cancer) and increase economic costs in societies, especially in developed countries [3, 4]. 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 technical challenges in Computer Science.

Objectively, stress has been interpreted from the human body's hormonal imbalances and response signals obtained from non-invasive methods. When a person is under stress, increased amounts of stress hormones (e.g. cortisol or catecholamine levels) are released and measures for these hormones are obtained via invasive methods (e.g. taking blood, saliva or urine samples) performed by qualified practitioners, and require lengthy analysis procedures conducted by qualified scientists [5-8]. On the other hand, the response signals that can be captured by non-invasive methods are easier to acquire, relatively cheaper and analysis time periods are relatively shorter. These are some of the reasons why non-invasive methods for objective stress detection are popular in literature [9-14]. Response signals are known to reflect reactions of individuals and their bodies to stressful situations [15, 16]. Stress response signals used in this paper fall into two categories – physiological and physical signals. Physiological signals include the galvanic skin response (GSR), electrocardiogram (ECG) and blood pressure (BP). Unlike these signals, 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 eye gaze and pupil dilation signals. GSR, ECG, BP, eye gaze and pupil dilation signals have been used to detect stress in literature [13, 17, 18] but this combination has not been reported in literature so far. We use this combination of sensor signals in this paper and refer to them as primary signals for stress.

Various computational methods have been used to objectively classify stress to differentiate conditions causing stress from other conditions. The methods developed have used somewhat simplistic models based on techniques like Bayesian networks [18], decision trees [19] and support vector machines [20]. The parameters for the stress models in literature were chosen using a trial-and-error process. In this paper, models based on support vector machines (SVMs) and artificial neural networks (ANNs) are used and a genetic algorithm (GA) method is proposed for optimizing parameters for the models and selecting the better model for stress classification.

Further, computational models for stress recognition developed in literature have used a relatively smaller set of stress features than the sets used for the models in this paper [18-20]. Hundreds of stress features can be derived from primary signals for stress detection. However, this set of features may include redundant and irrelevant features which may outweigh the more effective features showing stress patterns. This could cause a stress classifier to produce lower quality classifications. Since this paper is dealing with sensor data, some features may suffer from corruption as well. In order to achieve a good classification model that is robust to such features that may reduce the performance of classifications, appropriate feature selection methods must be developed and adopted by classifiers. A GA could be used to select subsets of features for optimizing stress classifications. It is a global search algorithm and has been commonly used to solve optimization problems [21] including feature selection problems to select features derived from physiological signals [22, 23]. Approaches used in this paper use a GA to select appropriate stress features with the goal to improve the quality for stress classification.

The performance for classification models not only depends on the inputs provided but also on model parameter settings. Hybrid GAs have been presented in literature that selected features for SVM based classification and optimized SVM parameters for various applications such as bankruptcy prediction [24], microarray analysis [25], intrusion detection [26]. GA and ANN hybrid methods with feature selection and parameter optimization has also been developed (e.g. weight optimization [27]) including applications in gear fault detection [28] and retail credit risk assessment [29]. The methods used in literature used different applications, different parameters for optimization and different features for selection from the ones presented in this work. Moreover, these forms of hybrid GAs are novel to the area of stress research.

This paper details the reading experiment done for stress data acquisition. It proposes hybrid GA methods to select an appropriate stress classification model, optimize parameter settings for the model to best capture stress patterns and select an appropriate subset of features as inputs for the model for stress recognition. Results for the performance of the hybrid GA methods are presented and discussed in regards to the aim for this work, which is to determine whether GA hybrid methods can develop stress classification models that improve the quality for recognizing stress patterns. The paper concludes with a summary of the findings and some suggestions for future work.

2 Stress Data Acquisition from Reading Experiment

Stress data was collected from a reading experiment where experiment participants read various types of text. Thirty-five undergraduate students were recruited as experiment participants. The participant cohort was made up of 25 males and 10 females over the age of 18 years old. Each participant had to understand the requirements of the experiment from a written set of experiment instructions with the guidance of the experiment instructor before they provided their consent to take part in the experiment. Afterwards, physiological stress sensors were attached to the participant and physical stress sensors were calibrated. The instructor notified the participant to start reading, which triggered a sequence of text paragraphs. After finishing the reading, participants had to do an assessment based on the reading. An outline of the process of the experiment for an experiment participant is shown in Fig. 1.

Each participant had physiological and physical measurements taken over the 12 minutes reading time period. During the reading period, a participant read *stressed* and *non-stressed* types of text. Stressed text had stressful content in the direction towards distress, fear and tension whereas the non-stressed text had content that created an illusion of meditation or soothing environments validated by participants. Each

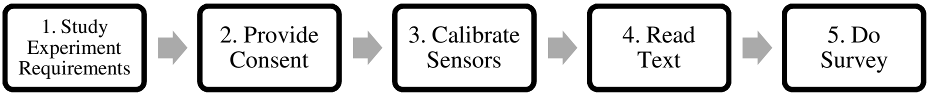

Fig. 1. Process followed by an experiment participant during the reading experiment

type of text had the same number of paragraphs and each paragraph was displayed on a computer monitor for participants to read one at a time. A participant read three stressed and three non-stressed paragraphs in some order. For consistency, each paragraph was displayed on a 1050 x 1680 pixel Dell monitor, displayed for 60 seconds and positioned at the same location of the computer screen for each participant. Each line of the paragraph had 70 characters including spaces.

Results from the experiment survey validated the text classes. This is a common method used in literature to validate stress classes for tasks [30]. Participants found the paragraphs that were labeled stressed as stressful and text labeled non-stressed as not stressful with a statistical significance of $p < 0.001$ according to the Wilcoxon test.

Physiological and physical sensor signals (which we refer to as primary stress signals) captured during the experiment were GSR, ECG, BP, eye gaze and pupil diameter signals. Biopac ECG100C, Biopac GSR100C and Finapres Finger Cuff systems were used to take ECG, GSR and blood pressure recordings at a sampling rate of 1000 Hz. Eye gaze and pupil dilation signals were obtained using Seeing Machines FaceLAB system with a pair of infrared cameras at 60 Hz. A schematic diagram of the experiment setup is shown in Fig. 2.

There were other stress signals that were derived from the primary stress signals to form other stress response signals. These signals included the heart rate variability signal, which was calculated from consecutive ECG peaks. The heart rate variability signal is another popular signal used for stress detection [9, 31].

Features were derived from stress signals. Statistics (including mean and standard deviation) were calculated for the signal measurements for each 5 second interval during the stressed and non-stressed reading. Measures such as the number of peaks for periodic signals, the distance an eye covered, the number of forward and backward tracking fixations, and the proportion of the time the eye fixated on different regions of the computer screen over 5 second intervals were also obtained. The statistic and measure values formed the stress feature set. There were 215 features in total.

3 Hybrid Genetic Algorithm, Artificial Neural Network and Support Vector Machine Stress Classification Models

GAs have been widely used as a search algorithm for a wide range of optimization problems [23]. A GA is a global search algorithm and is inspired by the concept of natural evolution. It evolves a population of candidate solutions, represented by *chromosomes*, in search for better quality chromosomes. The search evolves a

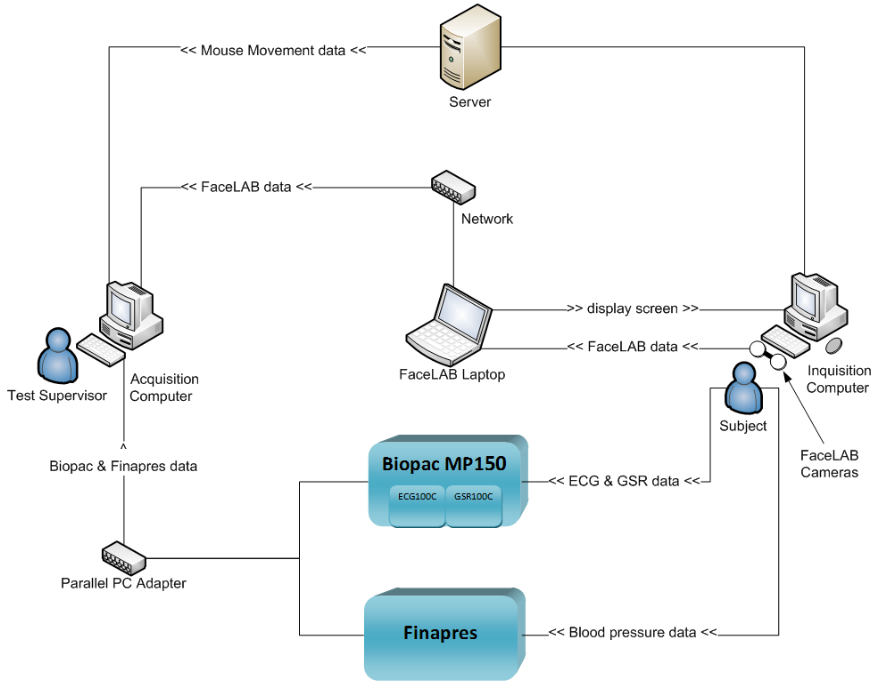

Fig. 2. Equipment setup for the reading experiment

population of chromosomes using *crossover*, *mutation* and *selection* methods. 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, mostly made up of better quality chromosomes, for the population in the next generation to direct the search to more favorable chromosomes. In this paper, the quality of a chromosome is based on the accuracy, sensitivity, specificity and the F-score values of the stress classifications derived from the classifier, its parameters and a subset of stress features encoded by the chromosome. The classifiers used for stress classification were ANNs and SVMs.

An ANN, inspired by biological neural networks, has the capability to learn patterns to recognize characteristics in input tuples by classes. It 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 trained with the Levenberg-Marquardt learning algorithm were used in this paper.

The layers and neurons in each layer define the *topology* of a feed-forward ANN. An ANN has an input layer, may have multiple hidden layers and an output layer. Input tuples for the ANN are passed through the input layer. Then the weighted links pass the weighted signals to the neurons in the hidden layers which process the signals further and then in a similar fashion the signals progress through the following layers. The processed signals are propagated through the ANN in this fashion for the signals to reach neurons in the output layer which causes the ANN to produce the output for the ANN. Essentially, a signal is propagated through the ANN layer after layer. In addition, the topology of the ANN can be designed to include a *time-delay* to exploit the time-varying nature of the stress features. Choosing the appropriate number of points in time for stress classification is another task that forms part of the process for designing the topology. The topology is usually designed by a trial and error process. Further, the topology may have an impact on the performance for classification. The approach proposed in this paper aims to optimize the topology for stress classification.

A SVM is another type of classification model that is used for stress classification in this paper. SVMs have been widely used in literature for classification problems including classifications based on physiological data [32]. Unlike an ANN, it is known to produce a global solution. Provided a set of training samples, a 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. The optimal 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 contributes to the resistance to data overfitting and helps to generalize classifications well. Further, there is a range of parameters that need to be chosen to define a SVM but this paper focuses on selecting and tuning the *kernel* function and the method for selecting the optimal hyperplane.

With the hundreds of stress features and the numerous options for settings for the stress classification models, a GA was used to find an optimal subset of features and search for a classifier that could best capture stress patterns in the features. Three different GAs, GA-ANN, GA-SVM and GA-ANN-SVM, were developed for stress classification. They differed in the type of classification model used to define stress recognition in the search and the type of chromosome. The chromosomes had components for features and parameters for classification models. Each type of chromosome was a binary string and represented the features and the parameters for the classification model. In the component of the chromosome that encoded the features, the index for a bit represented a feature and the bit value indicated whether the feature was used in the classification. For the components that encoded the parameter value, the binary string was treated as a binary number which was converted to its equivalent decimal number to extract the value for the component. The hybrid GAs are defined as follows:

GA-ANN. The GA used an ANN for stress classification. The chromosome encoded the following components:

- Stress features
- Number of hidden layers (ANN)
- Number of neurons in the first hidden layer (ANN)
- Number of neurons in the second hidden layer (ANN)
- Number of neurons in the third hidden layer (ANN)
- Time-delay (ANN)

GA-SVM. The GA used a SVM for stress classification. The chromosome encoded the following components:

- Stress features
- Type of kernel function: The bit value represented polynomial or Gaussian radial basis function. (SVM)
- Type of method: The bit value represented quadratic programming or sequential minimal optimization method. (SVM)
- Degree for the polynomial kernel function (SVM)
- Sigma value for the Gaussian radial basis function (SVM)

GA-ANN-SVM. The GA used an ANN or a SVM for stress classification depending on the value for chromosome component that encoded the type of classification model. The chromosome in this search is essentially made up of the chromosomes in GA-ANN and GA-SVM and encoded the following components:

- Stress features
- Type of classification model: The bit value represented ANN or SVM.
- Number of hidden layers (ANN)
- Number of neurons in the first hidden layer (ANN)
- Number of neurons in the second hidden layer (ANN)
- Number of neurons in the third hidden layer (ANN)
- Time-delay (ANN)
- Type of kernel function: The bit value represented polynomial or Gaussian radial basis function. (SVM)
- Type of method: The bit value represented quadratic programming or sequential minimal optimization method. (SVM)
- Degree for the polynomial kernel function (SVM)
- Sigma value for the Gaussian radial basis function (SVM)

Some components in the chromosomes for the GA hybrids are analogous to recessive genes in the biological domain. For GA-ANN, the chromosome component that provided the value for the number of hidden layers was used to determine whether the chromosome components that encoded the number of hidden neurons for each of the hidden layers were needed to be interpreted. For instance, if the number of hidden layers was interpreted to be 2, then the components that encoded the number of neurons in the first and second hidden layers were interpreted to define the ANN for classification and the component that encoded the number of neurons for the third hidden layer was not used. Likewise for GA-SVM, the component for the degree for the polynomial function was interpreted only if the polynomial function was selected as the kernel function i.e. the value for component that encoded the type of the kernel function was the polynomial function. Alternatively if the Gaussian radial basis function was selected, the sigma value for the Gaussian radial basis function was interpreted to define the SVM. GA-ANN-SVM was implemented in a similar fashion with the addition of the chromosome component that provided which type of classifier to use. If ANN was selected, then only the components that encoded the settings for ANN were

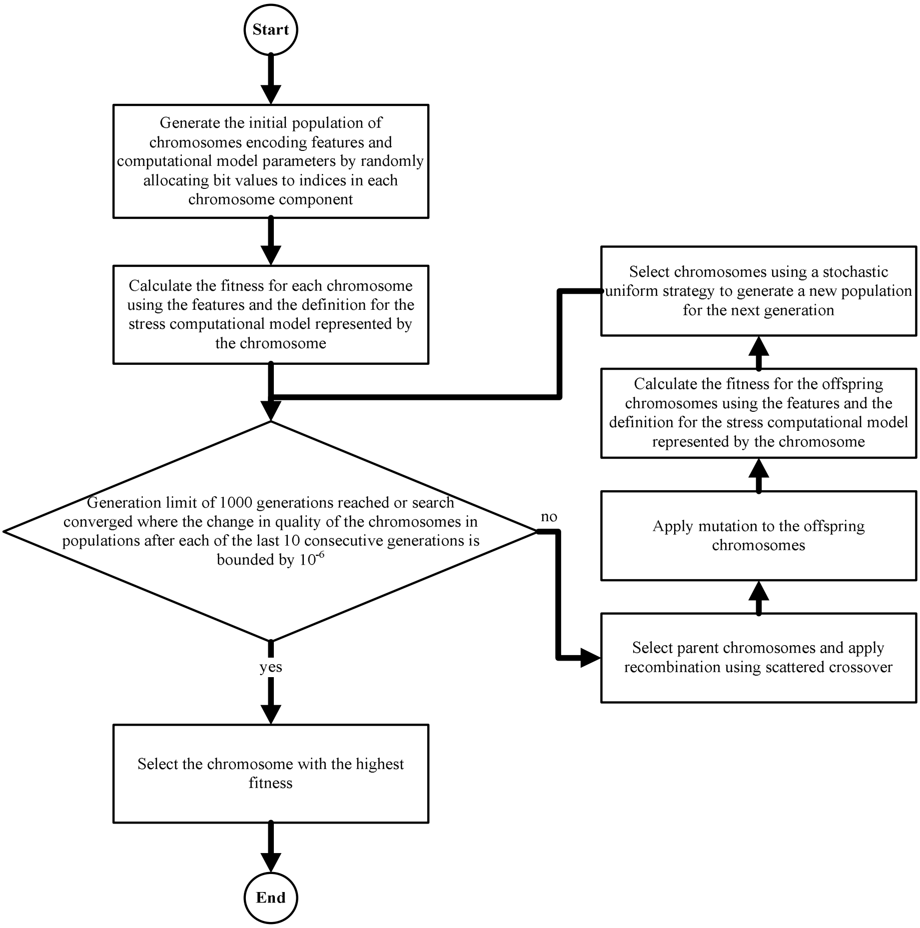

Fig. 3. The architecture for a GA hybrid algorithm for stress classification

Table 1. Parameter settings for the GA

GA Parameter	Value/Setting
population size	100
number of generations	2000
crossover rate	0.8
mutation rate	0.01
crossover type	MATLAB's Scattered Crossover
mutation type	MATLAB's Uniform Mutation
selection type	MATLAB's Stochastic Uniform Selection

interpreted and the components for SVM settings were not interpreted and similarly if SVM was selected then the SVM setting components were interpreted and ANN setting components were not interpreted.

The architecture for the GA hybrid algorithms is shown in Fig. 3 and Table 1 gives the parameter settings for the GA used in the search implementation.

4 Results and Discussion

Hybrid GAs were developed and tested on the reading data set for stress classification. The stress classification results achieved by an ANN, SVM and the different GA hybrids based on ANNs and SVMs are presented in Table 2. Ten-fold cross-validation was used to calculate the performance for the classifications. Overall, the GA hybrids produced better classification results than methods that did not use a GA to select appropriate stress features and optimize parameter settings for classification models to capture stress patterns. GA-ANN, GA-SVM and GA-ANN-SVM produced the best classification results with recognition rates of 89% based on two significant figures. It suggests that this recognition rate is the best result achievable for stress classification in reading based on an ANN or SVM. The recognition rates for GA hybrids were at least 21% greater than the rates produced by classification methods without a GA.

Table 2. Performance for the stress classification methods using ten-fold cross-validation

Classification Performance Measure	ANN	SVM	GA-ANN	GA-SVM	GA-ANN-SVM
Recognition rate	0.68	0.67	**0.89**	**0.89**	**0.89**
F-score	0.67	0.67	0.87	**0.89**	0.88

Table 3. Execution times for the stress classification methods

	ANN	SVM	GA-ANN	GA-SVM	GA-ANN-SVM
Execution time (hours)	0.05	0.01	96.03	5.12	45.82

Performance measures for the classification methods show that it was beneficial to use the feature selection and classifier parameter optimization methods in order to develop a classification model that captured stress patterns in reading. Using all the features for stress classification, like for the ANN and the SVM methods, would have included redundant and irrelevant features which may have outweighed the important features for stress recognition. The GA hybrids reduced the redundant and irrelevant features to develop stress classifiers.

Execution times were recorded for the methods while they were tested on the reading data set. The execution times for each method are shown in Table 3. GA-ANN and GA-ANN-SVM took several days to produce a result, which was a lot longer than the other methods. The execution time for GA-SVM was in the order of hours.

In terms of quality of stress classifications produced and the amount of time taken to produce a result, GA-SVM performed the best out of all the other classification methods with the highest stress recognition rate and relatively low search execution time.

5 Conclusion and Future Work

GA hybrids that selected appropriate stress features and optimized classification model parameters were developed and tested for stress recognition. There were three different GAs proposed and they differed in the classification models which were used to define quality of stress classification in the search. One of the GAs used an ANN and incorporated an optimization strategy for the ANN to classify stress using features selected by the search (GA-ANN). Another GA hybrid was defined similarly but an SVM classifier was used instead of the ANN classifier (GA-SVM). The other GA hybrid was defined to select the type of classifier out of ANN and SVM to determine the quality of stress classification as well as select appropriate stress features and optimize classifier parameter settings (GA-ANN-SVM). The GA hybrids were tested on the reading data set to recognize stress patterns. Results showed that the quality for stress classification based on the ANN and SVM classifications improved with their GA hybrid counterparts – GA-SVM and GA-ANN produced better classification results than SVM and ANN respectively. In future, this work could be extended to incorporate a mechanism to select salient time segments in reading to determine critical time segments that are needed to differentiate the different reading classes in terms of stress measures. This approach could improve the performance for recognizing stress in reading.

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