Optimal Time Segments for Stress Detection

Nandita Sharma and Tom Gedeon

Research School of Computer Science
Australian National University, Canberra, Australia
{Nandita.Sharma,Tom.Gedeon}@anu.edu.au

Abstract. Some response signals being modeled for humans over some time segments may not be relevant for analysis and modeling. These signals could contribute to reducing the quality of patterns captured by models, inefficient processing and may impose huge demands on storage resources. This work proposes an approach to search for relevant time segments from human response signals particularly, physiological and physical signals to recognize stress. The paper proposes an approach to determine time segments that were critical to differentiate the types of text based on stress. A support vector machine (SVM) was used to classify the different types of text based on the features of the response signals. A SVM and genetic algorithm (GA) hybrid approach is developed to determine optimal time segments for stress detection (OTSSD). As well as optimizing time segments, the GA also dealt with hundreds of stress features that may have included redundant and irrelevant features. Optimal time segments for stress in reading were successfully found and the GA and SVM hybrid classifier showed an improvement in stress recognition when optimized features from the critical time segments were used.

Keywords: time segments, genetic algorithms, support vector machines, physiological signals, physical signals, stress modeling.

1 Introduction

Human response signals can be used to objectively determine the state of a person in terms of how they feel and react to stimuli at certain points in time or over certain time periods. The main types of response signals to determine the *states* of a human are physiological (e.g. heart rate [1-3] and galvanic skin response [4, 5]) and physical (e.g. facial expression [6-9]) signals. To determine the state of a person under some given circumstance, these signals are captured over some time period to include the data for analyzing the state of the human. However, the signals over the total time period may not be necessary for processing to extract patterns for detecting the state and it may be possible that a smaller segment of the total time period may contain the data sufficient for analysis and modeling. Analysis of the smaller segment could result in significant improvement in efficiency because the effect of irrelevant or redundant data on the analysis will be reduced.

Several computational techniques already reported in literature can be used to select relevant and optimal time segments, but they are not useful for cases when

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relationship between the characteristics of signals and their features characterizing the human state that needs to be identified are not known. Visual inspection could be used to support selection of a more optimal time segment as reported in literature [10]. The visual analysis could be difficult and prone to errors. Previous research in literature has developed techniques to detect events from time series data and modeled the problems statistically e.g. change point detection problem using maximum likelihood methods [11]. These methods have been applied to traffic data [11] and electrical brain signals (EEG) [12]. For a problem like stress recognition defined in this paper, multiple response signals need sourcing and analysis. This poses a major technical challenge as little information is available on how the various signal combinations can be decoded and how the features affect stress recognition. Feature extraction methods including clustering analysis provide amenable methods to extract and use optimal patterns from time segments. These time segments have to be optimally selected though. Some human intervention may still be required in the process.

Stress is the body's reaction or response to the imbalance caused between demands and resources available to a person. Stress is seen as a natural alarm, resistance and exhaustion [13] 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 and left unmanaged, stress has been recognized as a growing concern in our age adversely impacting society due to its potential to cause chronic illnesses (e.g. cardiovascular diseases, diabetes and some forms of cancer) and high economic costs (especially in developed countries [14, 15]). Benefits of stress research range from improving personal operations, through increasing work productivity to benefitting society - motivating interest, making it a socially beneficial area of research and posing technical challenges in Computer Science. Various computational methods have been used to objectively classify stress to differentiate conditions causing stress from other conditions. The methods developed have used simplistic models formed from techniques like Bayesian networks [16], decision trees [17] and support vector machines [18]. These models have been built from a relatively smaller set of stress features than the sets used in the models in this paper. Further, this work contributes to stress research in the understanding of when individuals respond to stress during a typical activity like reading using a computational approach.

An experiment was conducted where an experiment participant read *stressed* and *non-stressed* text while their physiological and physical response signals were captured. Text was displayed to a participant for a specific time period and of this time period possibly a portion is needed to determine the stress state of participants. It may be that participants showed stress in their response signals while they were reading or they may have showed stress after they finished reading and digested what they read. This paper proposes approaches for selecting the critical time segments during the reading time.

The human body's physiological and physical response signals obtained from non-invasive methods that reflect reactions of individuals to stressful situations have been used to interpret stress levels. Physiological signals include the galvanic skin response (GSR), electrocardiogram (ECG) and blood pressure (BP). Unlike physiological signals, we define physical signals as a time-varying characteristic where changes 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 capturing stress patterns. Examples of physical signals are eye fixation and pupil dilation signals. GSR, ECG, BP, eye fixation and pupil dilation signals are the primary stress response signals used in this paper.

The aim of this paper is to determine whether time segments for stress exist that are more relevant to recognize stress in reading. We coin the term *stress episode* to mean a time segment that gives stress patterns in stress response signals required for stress recognition and critical to classify stress. As a consequence of this definition, without stress episodes, two different types of stimuli cannot be differentiated based on stress provided that one stimulus causes stress and the other stimulus does not cause stress. A computational approach is proposed to obtain stress episodes based on a support vector machine (SVM) and a genetic algorithm (GA). The approach also deals with redundant and irrelevant features from stress response signals for stress classification.

The paper presents the reading experiment that was implemented to collect physiological and physical data from which stress features were derived. Then it proposes a hybrid method to search for stress episodes in the features using a GA and a SVM. The GA was implemented to optimize time segments encoded in various forms. The optimization was based on the features and stress classification quality obtained from a SVM. Results of the optimization of the time segments encoded in various forms are presented and discussed. A summary of this work and suggestions for future work are provided as conclusion.

2 Data Collection: Reading Experiment

A reading experiment was done to collect various physiological and physical data from individuals while they read text. Thirty-five undergraduate Computer Science students, compromising 25 males and 10 females, over the age range of 18 to 24 years old were recruited as experiment participants. Each participant had to understand the requirements of the experiment from written experiment instructions with the guidance of the experiment instructor before they filled in the experiment consent form. 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 excerpts. After finishing the reading, participants had to do an assessment. To summarize, the process of the experiment for an experiment participant was:

1. Study experiment requirements
2. Provide consent
3. Calibrate sensors
4. Read text
5. Answer survey questions related to the reading

Every participant had their physiological and physical measurements taken over the twelve minutes reading time period. During the reading period, a participant read the experiment instruction text and then read the main text, which was made up of *stressed* and *non-stressed* types of text validated by participants. The instruction text was in the style of the main text for participants to get trial runs of the reading tasks. Stressed text had stressful content in the direction towards distress (e.g. an excerpt about war victims and an excerpt about a ghost in a bedroom), whereas the non-stressed text had content that created an illusion of meditation or soothing environments (e.g. an excerpt about a drive through a scenic terrain and an excerpt about a flower festival) and was not stressful or at least was relatively less stressful compared with the text labeled as stressed. Results from the experiment survey validated the text classes. This is a common method used in literature to validate stress classes for tasks [19]. Participants found the text that were labeled stressed stressful and text labeled non-stressed as not stressful with a statistical significance of $p < 0.001$ according to the T-test.

Each type of text had the same number of text excerpts and each text excerpt was displayed on a computer monitor for participants to read. For consistency, each text excerpt had approximately 120 words. It 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 text had 70 characters including spaces.

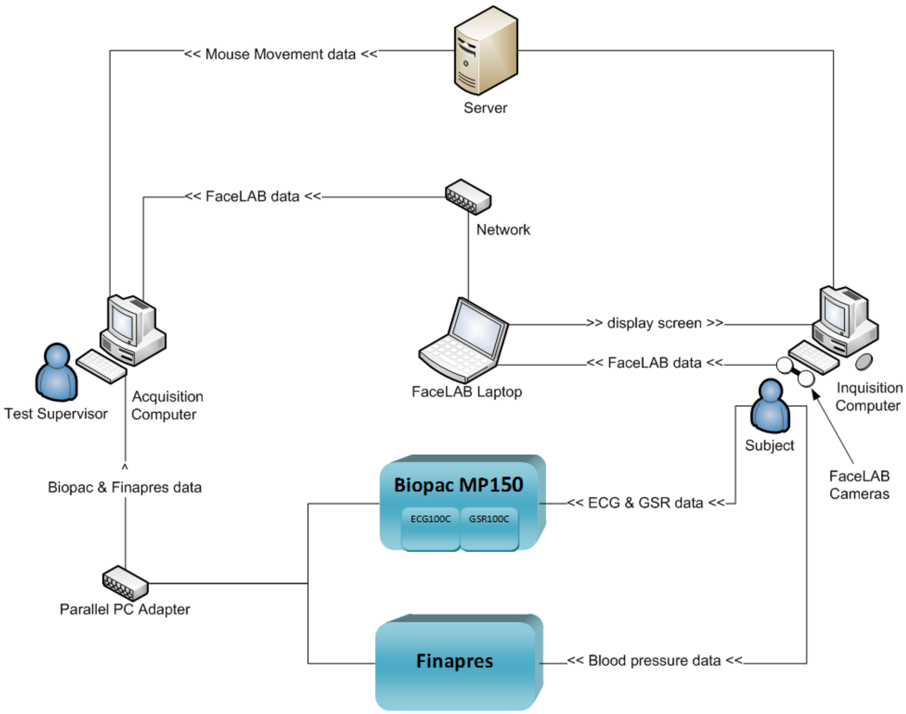


Fig. 1. Equipment setup for the reading experiment

Feature values were derived from physiological and physical 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. The equipment setup for the reading experiment is shown in Fig. 1. Other stress symptom signals were derived from primary signals such as, heart rate variability, which was calculated from consecutive ECG peaks and another popular signal used for stress detection [20, 21]. Statistics (e.g. 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. Regions of the computer screen are shown in Fig. 2. The statistic and measure values formed the stress feature set. There were 215 features in total. Feature vectors for each participant were normalized by the participant's baseline before they were provided to the classifier.

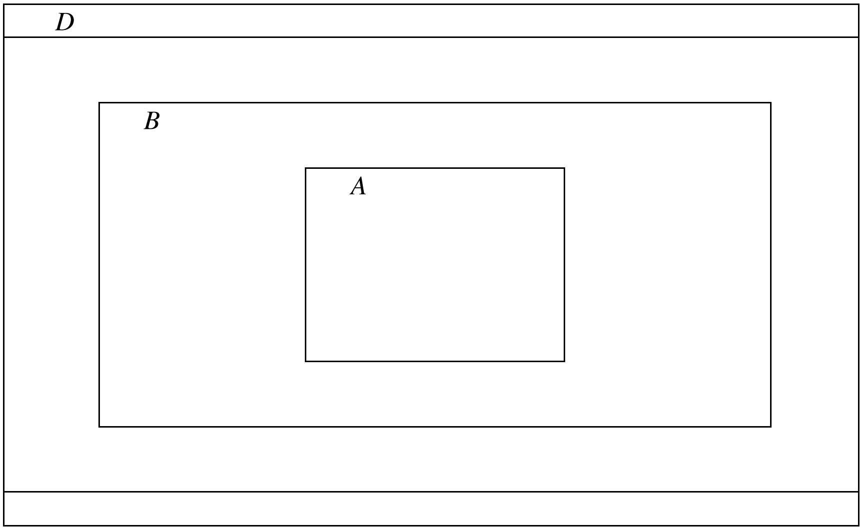


Fig. 2. Bounding rectangles define the different regions of the computer screen to determine a subset of eye gaze features. The bounding rectangles show regions A, B, C and D. Region A contains the text area where text was displayed to a participant. Region B is the region without A and regions C and D are defined similarly. Region D had the application menu and the toolbar. Note that the diagram is not drawn to scale.

A participant was shown a segment of text for a set period of time for reading. According to the reading rate for an average person and considering the number of words per line and character size, sufficient time was given to participants to read the text [22]. This was validated by the participants' eye movement data patterns and survey responses. In addition, results from the survey responses showed that participants easily understood the text. However, the reading time provided may have been longer than necessary to show stress. Using stress response signals over the total reading time may bury the critical time segments that have stress symptoms. As a result, the data over the irrelevant time segments may be irrelevant and could outweigh the data that has stress symptoms. This may have a negative impact on stress classification.

3 A Genetic Algorithm for Feature and Time Segment Selection

GAs have been widely used for optimization problems. A GA is a global search method and it has been successfully used for feature selection from physiological signals for human state classification [23]. This work uses a GA for feature selection from various stress response signals and proposes a GA based approach to find stress episodes in the reading data.

A GA is based on the concept of natural evolution. It evolves a population of candidate solutions, represented by *chromosomes*, in search for better quality chromosomes. The approach applies *crossover* and *mutation* operations to the chromosomes to achieve diversity in the population and reduce risk of the search to reach a local optimal population. After each iteration during the search, the GA *selects* chromosomes, mostly made up of better quality solutions, for the population in the next iteration to direct the search to more favorable chromosomes. In this work, the quality for a chromosome is based on the accuracy, sensitivity, specificity and the F-score values of the stress classifications using the information represented by the chromosome.

A chromosome for the problem for stress recognition in reading either represented time segments as candidate stress episodes, a subset of features from the set of all stress features or a combination of both. Conventionally, a chromosome has encoding for one type of a solution e.g. features [23]. In the case for this work, the goal was to find stress episodes and features over the stress episodes that produced better stress recognition results. Hybrid chromosomes have been developed and used in literature [24, 25] but to the best of our knowledge, it has not been used for this kind of work particularly, for encoding signal and time segment data.

Each chromosome was a binary string of fixed length. For the chromosome that encoded features, which we denote as C_F, the chromosome contained information for all the features in the space of all stress features. The index of the chromosome represented a feature and its value indicated whether the feature was used in the classification to define the corresponding model. The length of the chromosome was equal to the number of stress features. On the other hand, there were three different ways in which time segments were encoded. A time segment chromosome had one of the following definitions:

- C_{TS}. An index of the chromosome represented a time segment of the total reading time. The value for the index represented whether the feature values over the corresponding time segment was used in the classification.
- C_{OTS}. A chromosome that had overlapping time segments where an index of the chromosome represented a time segment of the total reading time. Similar to C-TS, the value for the index represented whether the feature values over the time segment was used in the classification.

- C_{TTS}. A chromosome that had the start and end times of a time segment where the first half of the chromosome had the start time of the time segment and the second half had the end time. Stress feature values over the time segment used in the classification.

Another type of chromosome was developed that had encodings for both features and time segments. The classification model was defined by the feature values during the time segments depicted in the time segment encoding component of the chromosome. There were three variations for this type of chromosome and they differed on the time segment encoding component:

- $C_{F\text{-}TS}$. A composite structure with encodings for features and time segments of the total reading time. An index of time segment encoding component of the chromosome represented a time segment in the total reading time and its value represented whether the feature values in the feature encoding component was used in the classification.
- $C_{F\text{-}OTS}$. A composite structure with encodings for features and overlapping time segments of the total reading time. An index of time segment encoding component of the chromosome represented a time segment in the total reading time and its value represented whether the feature values in the feature encoding component was used in the classification.
- $C_{F\text{-}TTS}$. A composite structure with encodings for features and start and end times of a time segment. The definition for time segment encoding component was based on C_{TTS}. Feature values depicted by the feature encoding component over the time segment was used in the classification.

4 A Genetic Algorithm and Support Vector Machine Hybrid Stress Classifier

A stress recognition approach consisting of a hybrid of a GA and SVM was used to determine OTSSD. The GA searched for stress episodes based on the quality of the stress classifications produced by the SVM given subsets of stress features and time segments over the reading time.

SVMs have been widely used in literature for classification problems based on physiological data [26]. A SVM constructs a maximum margin separator, to separate data into classes. It transforms the data to a higher dimensional space where it constructs a linear separating hyperplane. The hyperplane is a decision boundary with the largest possible distance to example points. This helps to generalize classifications well and have been claimed to be resistant to overfitting the data. However, the classification performance of a SVM is subject to the features provided as input. The GA provided a set of features over GA selected time segments to the SVM to determine the quality of stress classifications and evolved the set of features and time segments in search for stress episodes.

To obtain stress classification results from a SVM, the stress reading data set was divided up into 3 subsets – training, validation and test sets – where 50% of the data samples were used for training the SVM model and the rest of the data set was divided up equally to validate and test the model. MATLAB was used to implement and test the models.

The parameters for the GA implemented were set as provided in Table 1.

Table 1. Parameter settings for GAs that used to find optimal time segments and feature selection

GA Parameter	Value/Setting
population size	100
number of generations	2000
crossover rate	0.8
mutation rate	0.01
crossover type	scattered crossover
mutation type	uniform mutation
selection type	stochastic uniform selection

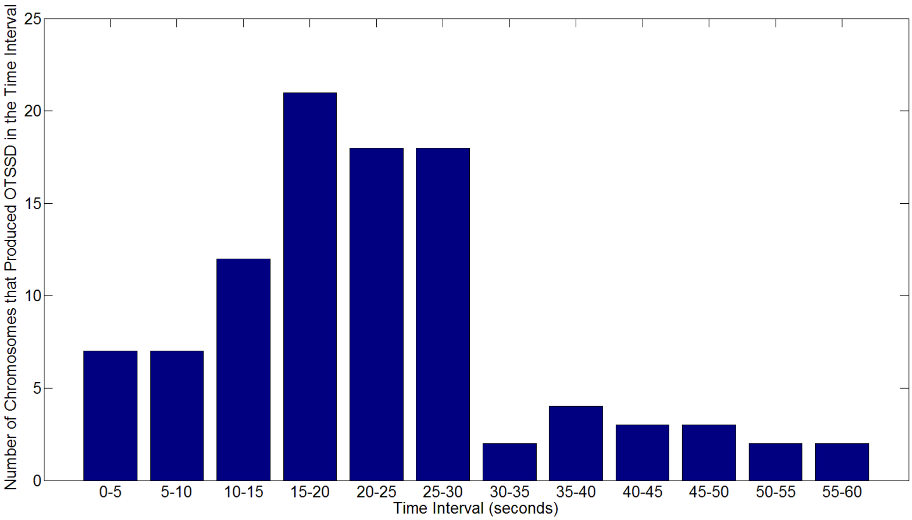
5 Results and Discussion

The GA-SVM hybrid approach was implemented using each of the different chromosomes to search for stress episodes in reading. GA-SVMs with C_{TS}, C_{OTS}, $C_{F\text{-}TS}$ and $C_{F\text{-}OTS}$ were implemented with different time segment intervals. The interval sizes were chosen based on the time segment size for feature extraction, which was 5 seconds and detailed earlier in section 2. The GA provided multiple time segments at the end of the GA search from which the longest time segment that was defined by the multiple consecutive time segment intervals was chosen as a stress episode. Results of the GA and SVM approach using the different types of chromosomes to search for OTSSD are presented in Table 2. The interval length for a time segment in each of the chromosomes C_{TS}, C_{OTS}, $C_{F\text{-}TS}$ and $C_{F\text{-}OTS}$ is depicted by *i* seconds in C_{TS_i}, C_{OTS_i}, $C_{F\text{-}TS\_i}$ and $C_{F\text{-}OTS\_i}$ respectively.

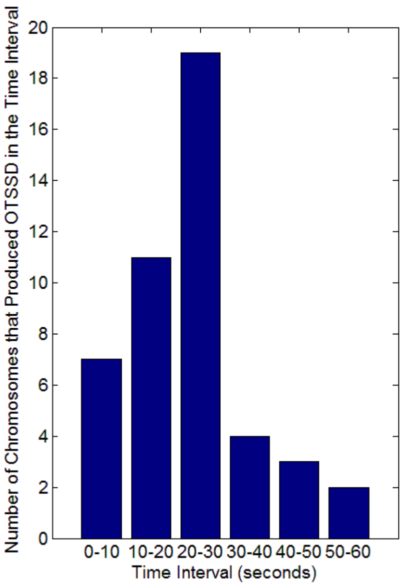
Participants of the reading experiment were given 60 seconds to read a text excerpt. Results in Table 2 show that stress episodes in the reading data appeared within a smaller segment of the total reading time in particular, they appeared around 15-30 seconds. During this time interval, the SVM produced the highest stress recognition rates. Fig. 3 shows the number OTSSD searches that produced stress episodes during various time intervals of the total reading time. Each OTSSD search used one type of chromosome listed in Table 2. The distribution of the number of OTSSD searches show that most of the searches produced stress episodes between 15-30 seconds.

Table 2. Summary of the results obtained for different types of chromosomes used to find stress episodes in the reading data set. The table shows stress episodes obtained from the different types of chromosomes and their performances in stress recognition based on 10-fold cross-validation are provided.

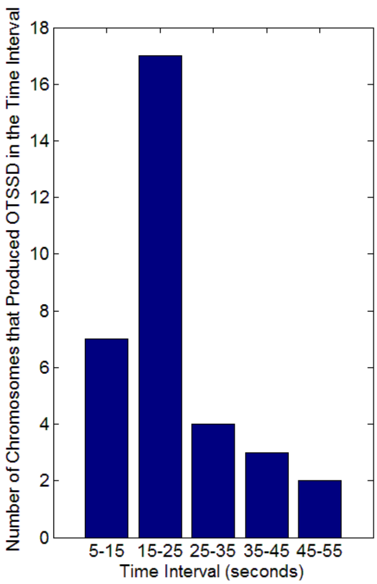
Chromosome	Stress episode interval (seconds)	Recognition rate	F-score
C_{TS}			
C_{TS_60}	0-60	0.67	0.67
C_{TS_30}	0-30	0.75	0.72
C_{TS_20}	0-20	0.85	0.86
C_{TS_15}	15-30	0.89	0.88
C_{TS_10}	10-20	0.90	0.89
C_{TS_5}	15-30	0.92	0.90
C_{OTS}			
C_{OTS_30}	0-30	0.75	0.72
C_{OTS_20}	10-30	0.85	0.86
C_{OTS_15}	15-30	0.89	0.88
C_{OTS_10}	15-30	0.89	0.90
C_{OTS_5}	15-30	0.92	0.90
C_{TTS}			
C_{TTS}	15-30	0.92	0.90
$C_{F\text{-}TS}$			
$C_{F\text{-}TS\_60}$	0-60	0.76	0.74
$C_{F\text{-}TS\_30}$	0-30	0.88	0.90
$C_{F\text{-}TS\_20}$	0-20	0.93	0.91
$C_{F\text{-}TS\_15}$	15-30	0.99	0.98
$C_{F\text{-}TS\_10}$	10-20	0.93	0.91
$C_{F\text{-}TS\_5}$	15-30	**0.99**	**0.98**
$C_{F\text{-}OTS}$			
$C_{F\text{-}OTS\_30}$	20-50	0.80	0.82
$C_{F\text{-}OTS\_20}$	20-40	0.87	0.86
$C_{F\text{-}OTS\_15}$	15-30	0.99	0.98
$C_{F\text{-}OTS\_10}$	10-20	0.93	0.91
$C_{F\text{-}OTS\_5}$	15-30	**0.99**	**0.98**
$C_{F\text{-}TTS}$			
$C_{F\text{-}TTS}$	15-30	**0.99**	**0.98**



(a)



(b)



(c)

Fig. 3. Distribution for the stress episodes produced by OTSSD searches where each search used one type of chromosome in Table 2 over the reading time. Frequency of the OTSSD searches that produced stress episodes within various time intervals: (a) 5 seconds (b) 10 seconds starting from 0 seconds and (c) 10 seconds starting from 5 second.

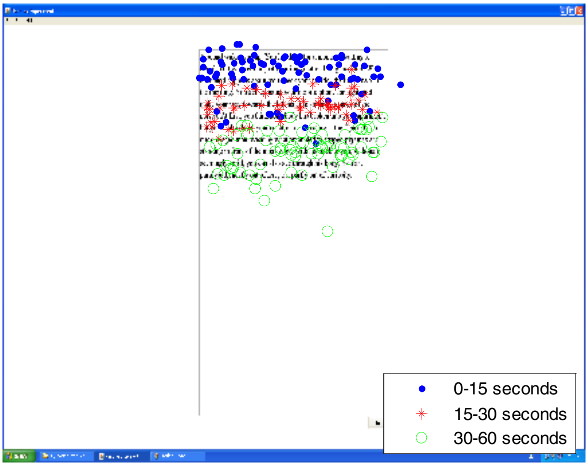


Fig. 4. Average eye fixation coordinates of experiment participants reading a text excerpt over different time intervals of the total reading time

Searches for OTSSD that optimized features produced better stress recognition rates than searches with chromosomes that only optimized time segments. The searches that optimized features had chromosomes that had a feature encoding component. The average stress recognition rate for searches that optimized features was 0.92 whereas the average stress recognition rate searches without feature optimization was 0.85. Without feature optimization, redundant features and features irrelevant to SVM based stress recognition may have existed. These features were reduced with the use of a GA in search for OTSSD, which produced a better stress recognition rate. The best recognition rate was 99% and it was produced by the OTSSD search that optimized features and found a stress episode between the 15-30 reading time interval.

OTSSD searches with chromosomes with time segment intervals that evolved the start and end times of the time segment interval and time segments with relatively short time intervals, in particular 5 seconds, found stress episodes with higher stress recognition rates. Using chromosomes C_{TTS} and $C_{F\text{-}TTS}$ in the search that evolved the start and end times for candidate stress episodes provided more flexibility in the search for OTSSD because the search space was less constrained. Chromosomes with time segments that had 5 second intervals also had a similar characteristic. On the other hand, the design for other chromosomes made it difficult or impossible for the OTSSD search to find stress episodes with higher stress recognition rates.

To relate the time interval for stress episodes found by the OTSSD searches to an average reading excerpt in the experiment, average eye fixations of participants in relation to the reading display during the reading time are presented in Fig. 4. In accordance to the stress episode for reading, participants approximately read a third of the text before the start of the stress episode. They read over half of the text in total by the end of the stress episode. Investigation of the content of a text excerpt with division of text by content and its relationship with stress was beyond the scope for this work. Future research could investigate what divisions of a text excerpt caused stress episodes.

6 Conclusion and Future Work

A computational approach for optimal time segments for stress detection (OTSSD) was developed to determine optimal time segments, or stress episodes, with optimized stress features to obtain necessary stress data and improve stress recognition in reading. A GA and SVM based hybrid technique was used where the GA searched for stress episodes based on the classification results produced by the SVM. The GA was extended to include stress feature optimization as well. Stress episodes were successfully found and results showed an improvement in SVM based stress recognition when a GA was used to select appropriate features and relevant time segments for stress during the reading period. The GA and SVM hybrid proposed could be extended to search for stress episodes or other types of critical time segments for other types of signal based classification for efficient storage, processing and analysis. There may be a possibility that certain feature signals correspond to stress levels more strongly than other feature signals during a particular time segment. To consider such a case and possibly different latency times for stress symptoms from the different response signals, future work could investigate developing classification models with time segment selection that are adaptable to features individually. Further, future research could extend statistical methods for event detection reported in literature for the multi-signal reading stress data.

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