Fatigue Detection in Office Work using Electrocardiography and Electrodermal Activity

Eric Alvarez	Nicolo Mega	Dave Pleteau
Electrical Engineering	*Bioengineering*	*Electrical/Computer Engineering*
Hardware, Programming	*Product Development*	*Hardware, Programming*
alvarez.e@northeastern.edu	mega.n@northeastern.edu	pleteau.d@northeastern.edu

Abstract - **The purpose of this project was to make use of the BITalino's electrocardiography (ECG) and electrodermal activity (EDA) sensors to detect early signs of fatigue in the workplace. This was realized by having three test subjects record their signals in the morning and at the end of the day while taking a standardized test. After performing a time and frequency domain analysis on extracted features from the ECG and EDA signals for the three test subjects, a decrease in the low to high frequency power ratio and an increase in the skin conductance level and response were linked to an increased state of fatigue. These findings could be implemented into a wearable that could inform the user of early signs of fatigue.**

I. Introduction

Fatigue can create a range of different physical, mental, or emotional symptoms, such as nausea, depression, and a general reduction in mental or physical productivity [1]. Given its widespread physiological effects, fatigue can severely hinder one's performance at their job. Some of the causes of fatigue can be overworking, sleep deprivation, or even lack of physical activity [1]. Since its effects are so common, a portable device capable of analysing and detecting fatigue in workplace settings could be incredibly useful. Our project strives to realize this goal by making use of BITalino's electrocardiography (ECG) and electrodermal (EDA) sensors to recognize signs of fatigue for an individual. With these, workers can actively circumvent or plan around potential periods of mental exhaustion.

In the scope of this semester, we aimed to collect three sets of ECG and EDA data for three subjects and discover a correlation between these biomarkers and early signs of fatigue. This was determined by looking at discrepancies between these signals when taken in the morning versus at the end of the day while taking a standardized test. We hope to, in the future, implement these findings into a mobile sensor that shines an LED light when fatigue is detected.

TABLE I
HOMD FOR PROPOSED BITALINO ECG/EDA SENSOR

Device	Harm	Obtrusive	Monetary Cost	Data Quality	Overall
BITalino ECG/EDA Sensor	1	5	4	9	1
Fitbit Sense [4]	1	3	7	6	5

We aim to directly compete with current trackers such as the Fitbit Sense, which possesses an EDA and ECG tracking feature, by providing the EDA and ECG sensing at a lower, more accessible price. This surface sensor would be considered a Class I medical device by the Food and Drug Administration (FDA), given that it would only pose a low to moderate risk for the patient and/or user.

II. Methodology

Materials. Our goal was to use the data collected by the ECG and EDA sensors such as the changes in skin conductivity (SC) in response to an increase of sweat gland activity as well as the heart rate variability (HRV) of three test subjects. ECG was selected as a biomarker in this study because HRV has been suggested to provide adequate assessment of fatigue-sensitive psychological operations [2]. Moreover, EDA was chosen due to previous studies suggesting its tonic and phasic components are dependent on fatigue state [3]. Each test subject first took the same standardized test consisting of a writing/language portion and a mathematics section. The standardized test questions used were obtained from the College Board's Paper Practice SAT Tests website. From these practice tests, only the Writing and Language and Math (No Calculator) sections were selected, giving each subject 1 hour to complete a test comprised of 64 questions. With this, we obtained a baseline test score for each subject which we could compare with subsequent test scores once external factors to induce fatigue were added. For the EDA sensing, a total of (2) electrodes were placed on the anterior side of the hand on the middle and index finger. For the ECG, a total of (3) electrodes were used: the positive and negative on the left and right collarbones, respectively, and a third, reference electrode on the iliac crest (see Figure I). These electrodes were connected to the BITalino board's A2 (ECG) and A3 (EDA) channels. The BITalino data was recorded using the Open Signals (r)evolution software at a frequency of 1kHz.

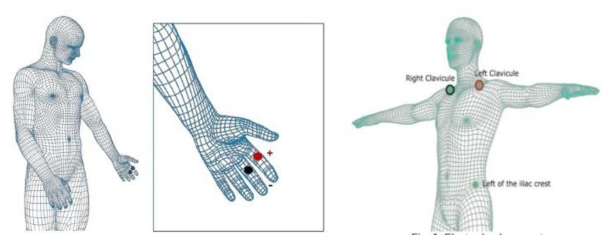

FIGURE I
ELECTRODE PLACEMENT FOR BITALINO EDA (LEFT) AND ECG (RIGHT) SENSOR

Data Acquisition Procedure. For data collection, we followed the 3 test subjects as their days progress for a total of

3 days for each subject. The day began by having the test subject collect 2 minutes of ECG and EDA data in the morning, during which the subject was not engaging in any mentally taxing activity. After this, the test subject would continue their day until around 6pm, at which point they were tasked with taking another 1-hour standardized test. This time, however, their ECG and EDA signals were measured before and as they were taking the test. ECG and EDA measurements were taken every 10 minutes for 30 seconds throughout the span of the 1 hour the test subject had to complete the test. This resulted in a total of 3 minutes and 30 seconds of data for a given subject taking the standardized test.

With this procedure, we aimed to induce mental fatigue in each test subject by both controlling the time of day which they take the test and the type of test that is being taken. By having the test subjects take the test at around 6pm, we were adding an additional stressor in their day after already having a full day of mental exertion. Moreover, by having SAT-based Writing and Language and Math questions, we were presenting each test subject with a multidisciplinary and mentally taxing task that simulates a similar degree of fatigue to that of a typical workday. Additionally, through the comparison of data collected in the morning versus data collected during examination, we aimed to observe abnormalities in both the R waves of the ECG QRS complex signals as well as the SC data using the *Bio-SP* MATLAB tool and Ledalab EDA Tonic and Phasic analyzer [5][6]. The specific feature extraction and filtering methodology and reasoning will be further explained in the *Experimental Results* section. Utilizing the mapping of each physiological data (SC and HRV), a threshold value for fatigue was empirically determined. After establishing distinguishable fatigue levels with our collected data, an algorithm to detect fatigue on a personal level can be developed on MATLAB.

As an additional component, we aim to interface this ECG/EDA data and fatigue detection algorithm with an Arduino-powered LED that will light up if the fatigue crosses the experimentally determined threshold value.

III. EXPERIMENTAL RESULTS

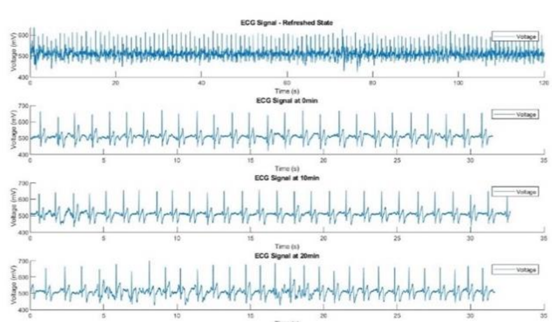

FIGURE III
SAMPLE RAW OUTPUT ECG SENSOR DATA FROM TEST SUBJECT IN MORNING, BEFORE TEST, AND DURING TEST

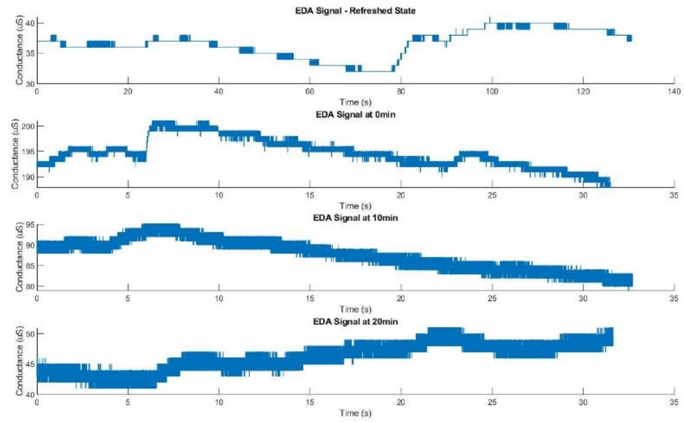

FIGURE IV
SAMPLE RAW OUTPUT EDA SENSOR DATA FROM TEST SUBJECT IN MORNING, BEFORE TEST, AND DURING TEST

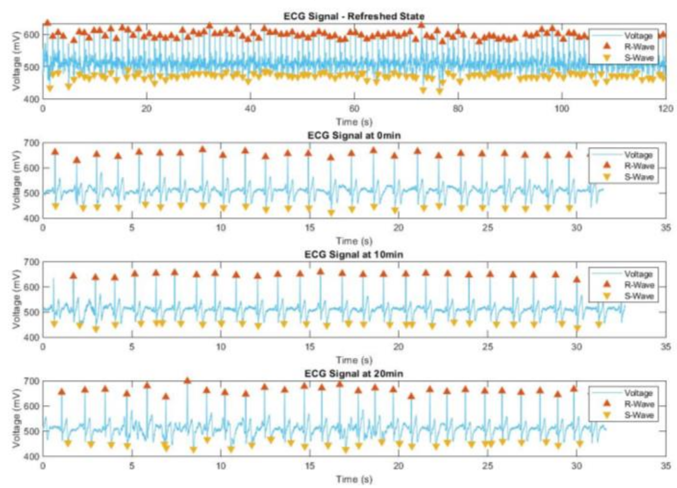

FIGURE V
SAMPLE FILTERED OUTPUT ECG SENSOR DATA FROM TEST SUBJECT IN MORNING, BEFORE TEST, AND DURING TEST

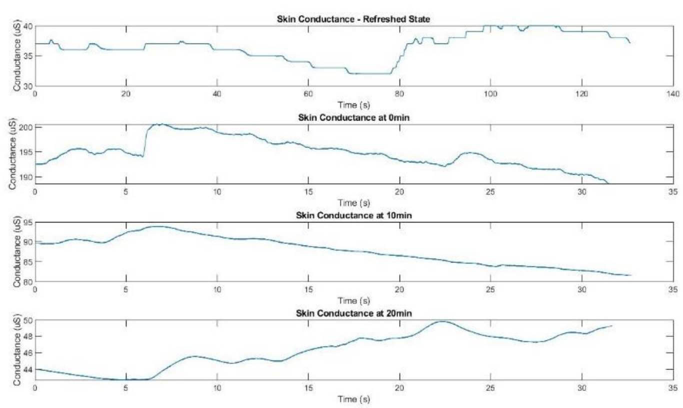

FIGURE VI
SAMPLE FILTERED OUTPUT EDA SENSOR DATA FROM TEST SUBJECT IN MORNING, BEFORE TEST, AND DURING TEST

Pre-Processing and Filtering Steps. Data recorded over the period of testing, in addition to that collected as a baseline for individual ECG and EDA values, was imported into

MATLAB. Raw data was then parsed based upon ECG and EDA data, while time steps were generated for each data point accordingly. Time steps utilized the recording frequency of 1kHz and were then converted to seconds. Plots for each set of raw data were created and sub-plotted prior to any processing.

Each set of ECG sensor data was then analyzed to find local extrema in the form of minimum and maximum values, which represent the location of R-waves and S-waves. After having confirmed the location of these extrema, they were plotted on the graph in addition to the original data. Doing so would facilitate the identification of these points as well as calculating intervals between extrema.

Additionally, each set of EDA sensor data was then plotted utilizing an averaging filter to alleviate the rough nature of the raw EDA data. This filtering allowed for a clearer visual representation of the signals themselves, facilitating interpretation to be completed later.

Feature Extraction. The ECG and EDA data were analyzed in both the time and frequency domain to extract the features listed in Table II and III. Many of these features have been used to detect stress in working environments [7] and mental fatigue in people, like drivers [8].

TABLE II
TIME AND FREQUENCY DOMAIN HRV FEATURES TO BE EXTRACTED FROM ECG SIGNAL

Domain	Feature	Unit
Time	Mean Heart Rate	BPM
	Root-Mean Square of R-to-R interval (Heart Rate Variability)	s
Frequency	Total Power Spectral Density	ms^2/Hz
	High Frequency Power (HF)	ms^2
	Low Frequency Power (LF)	ms^2
	Low Frequency Power/High Frequency (LF/HF) Power Ratio	%

TABLE III
TIME AND FREQUENCY DOMAIN FEATURES TO BE EXTRACTED FROM EDA SIGNAL

Domain	Feature	Unit
Time	Mean of SCL (tonic value)	uS
	Mean of SCR (phasic value)	uS

Data Analysis. The ECG and EDA data was analyzed in either the time and frequency domain (or both) to extract the features listed in Table II and III. The goal was to identify which features, in either domain, that show an identifiable pattern to indicate mental fatigue. For the ECG data, the time domain features measured were the mean heart rate and root mean square of the R-R interval. In the frequency domain, only the low-frequency (LF) and high-frequency (HF) bands were investigated. A bandpass filter was used to filter the signal into the LF band (0.04-0.15Hz) and HF band (0.15–0.4 Hz) [10]. Afterwards, trends in the energy in both those bands were observed by plotting its power spectral density.

Using Ledalab EDA Tonic and Phasic analyzer [6], our EDA signal was decomposed into its tonic and phasic components. The tonic component of the EDA provided insight on the slow changing skin conductance in absence of any stimuli. While the phasic component gave details on the skin conductance response to a stimulus (in our case, this is the SAT taken at the end of the day). The tonic component of EDA was captured by the skin conductance level (SCL), while the phasic component could be modeled by the skin conductance response (SCR). From Němcová et al.'s [8] literature review on multimodal features used to detect stress and fatigue [in drivers], we expected that as the subject becomes more stressed, their heart rate, skin conductance, and LF/HF ratio will increase. On the other hand, heart rate variability will decrease with increasing stress.

Results. After following the data acquisition procedure outline above, the three test subjects accumulated four standardized test scores—three of which were taken at the end of the day and one taken at the beginning of the day for a baseline score:

TABLE IV
STANDARDIZED TEST SCORES FOR EACH SUBJECT

Subject	Day	Test Score
A	Baseline	36/64
	1	24/64
	2	46/64
	3	49/64
B	Baseline	49/64
	1	55/64
	2	56/64
	3	53/64
C	Baseline	53/64
	1	50/64
	2	57/64
	3	59/64

Each subject did better with each proceeding exam, and many of them did better than their baseline. This result counters our hypothesis that the subject would do worse on the exam at the end of the day (due to fatigue). That said, all subjects expressed they felt mentally fatigued during and after the exam. The high scores under these conditions emphasizes the individuality of fatigue—some individuals will performance better under stress and fatigue than while others.

Given the subjects felt mentally exhausted during the test, it is possible to identify emotional fatigue indicators in their bio-signals. Table V-VIII contains the average heart rate, HRV, LF/HF, SCL, and SCR for each day (separated by subject, day, and morning/afternoon test):

TABLE V

AVERAGE ELECTROCARDIOGRAPHY FEATURE VALUES FOR EACH SUBJECT TAKEN IN THE MORNING WITHOUT STANDARDIZED TEST

Subject	Day	Heart Rate (bpm)	Heart Rate Variability (ms)	LF/HF Ratio
A	1	55.5	1.105	1.021
	2	54.0	1.138	1.148
	3	53.5	1.125	1.124
B	1	52.0	1.214	1.021
	2	56.5	1.093	2.793
	3	56.5	1.087	1.087
C	1	51.0	1.228	0.988
	2	41.0	1.464	0.982
	3	62.5	1.003	0.942

TABLE VI
AVERAGE ELECTROCARDIOGRAPHY FEATURE VALUES FOR EACH SUBJECT TAKEN DURING STANDARDIZED TEST IN THE AFTERNOON

Subject	Day	Heart Rate (bpm)	Heart Rate Variability (s)	LF/HF Ratio
A	1	54.4	1.127	0.991
	2	54.5	1.122	0.963
	3	50.4	1.197	0.884
B	1	53.5	1.169	0.994
	2	56.1	1.096	1.223
	3	55.6	1.099	0.994
C	1	51.4	1.248	0.989
	2	54.1	1.121	0.969
	3	60.8	1.018	0.985

As seen in Tables V and VI, the heart rate and heart rate variability values between the morning set and afternoon set of data did not show a clear trend with regards to fatigue. This could have been due to a variance in the adhesion of the electrodes, which could have resulted in unexpected artifacts in the signals. However, in the frequency domain, it was important to note that the low to high frequency power ratio decreased between the test subjects' morning and afternoon values, indicating fatigue. This corroborated the claim made by Němcová et al.'s [8] literature review on multimodal features used to detect stress and fatigue, which stated that the low to high frequency power ratio decreased as physical fatigue was more prominent. Given the subjects took the test at the end of the day, it makes sense since the LF/HF indicates their physical tiredness.

TABLE VII
AVERAGE ELECTRODERMAL ACTIVITY FEATURE VALUES FOR EACH SUBJECT TAKEN IN THE MORNING WITHOUT STANDARDIZED TEST

Subject	Day	Mean SCR/Phasic Value (uS)	Mean SCL/Tonic Value (uS)
A	1	0.97	35.9
	2	1.89	49.7
	3	2.79	212
B	1	3.20	49.0
	2	1.85	63.5
	3	5.82	93.7
C	1	3.02	139
	2	1.77	117
	3	5.82	93.7

TABLE VIII
AVERAGE ELECTRODERMAL ACTIVITY FEATURE VALUES FOR EACH SUBJECT TAKEN DURING STANDARDIZED TEST IN THE AFTERNOON

Subject	Day	Mean SCR/Phasic Value (uS)	Mean SCL/Tonic Value (uS)
A	1	4.70	108
	2	3.51	177
	3	4.40	145
B	1	17.2	498
	2	14.6	251
	3	2.51	129
C	1	4.17	198
	2	11.1	566
	3	2.51	129

Regarding EDA results, the mean of the tonic and phasic values increased when a stressor was introduced. In other words, subjects felt more stressed during the test than in the morning. This result matches the expected behavior of the tonic and phasic components of the EDA data—increase in stressed leads to an increase in skin conductivity in both tonic and phasic will increase and, thus, their phasic and tonic component from their EDA readings will as well.

As an individual is stressed for a prolonged period, they will begin to experience cognitive fatigue. The data collected further supports this trend with an overall increase in the phasic and tonic values between the morning and afternoon sets of data for the three test subjects. In the future, we will use the average values found for each of these features as an indicator of stress. If a user remains at those feature values for an hour or more, then we will indicate to them they will begin to feel mentally exhausted. A huge cause of mental exhaustion of prolong stress, so it's vital to keep track of how long these biosignals remained at those mean values.

IV. CONCLUSION AND FUTURE WORK

This research presents the feasibility of detecting a correlation between electrocardiography and electrodermal activity signals and early signs of fatigue. The experimental results corroborate the ability to detect fatigue in each individual by extracting both time and frequency domain features from their ECG and EDA data. Moreover, we were able to prove already established trends such as the inversely proportional relationship between mental fatigue and the low to high frequency power ratio of the ECG signal [6].

Given limitations such as the restricted sample size of test subjects due to university guidelines and variance of adhesion for electrodes, in the future, the conceptual findings of this research can be scaled up to a larger sample size and electrodes can be configured to adhere consistently. It is our belief that the correlation deduced in this research between ECG and EDA features and early signs of fatigue can be implemented into a Class I wearable that can communicate psychological state to the user. With this information, the user could actively circumvent periods of fatigue to maximize productivity in the workplace.

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