Hotei: Stress Detection Component

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***Abstract*—The Hotei app aims to help manage a students stress levels. This report outlines the stress recognition element of the app which triggers prompts and notifications for the system. The requirements, background and initial design for this components supervised stress learning algorithm, along with the preliminary implementation and future development plans are outlined in this report.**

I. Introduction

The app Hotei is being developed with the aim to help manage a student's mental state by providing recommendations for activities in order to alleviate stress. This is an important issue for students, where surveys have shown that 27% of students suffer from a mental health problem, and 63% of students report suffering from stress levels that interfere with their day to day lives [1].

This component report focuses on the stress detection aspect of the application. The aim is to apply machine learning (ML) techniques to binary classify whether the user is currently stressed and provide real time notifications to the system. There are currently a variety of ML algorithms that have been implemented to detect stress, using features such as heart rate, blood pressure, skin conductivity and audio data. The key features of interest to this component are heart rate, heart rate variation and accelerometer data.

The following sections of this report outlines: the background research, providing a brief overview of related projects; a brief overview of the hardware for the Hotei app; the current design and implementation of the supervised stress learning algorithm; the methods for gathering the initial training data; and finally, the future work to be completed.

II. Background

The most widely used methods for measuring a subjects heart activity is through Electrocardiography (ECG) and Photoplethysmography (PPG). ECG is the process of recording the electrical activity of the heart, for a given subject, over a period of time with electrodes placed on the skin. PPG reads the subjects heart rate using a pulse oximeter which illuminates the skin and detects the changing levels in light absorption in order to measure the rate of blood flow. In recent years, this method has become more widely featured in wearable technology, such as the Apple Smart Watch. An overview of the history of PPG and recent developments in wearable pulse rate sensors is reviewed in [2].

There has shown to be a correlation between psychological stress and an increase in heart rate (HR). An example of such a paper is [3] where participants are tested for psychological stress, with the general findings that HR consistently increased among the different test groups. Similarly, in a trier social stress test, a moderate psychological stress test was conducted in a laboratory setting [4], subjects were found to significantly increase in heart rate throughout the experiment which shows the correlation between HR and stress. Hence, HR would be an ideal feature for measuring the users response to stress with the Hotei app.

A similar quantity is heart rate variability (HRV) which can be measured as the average deviation from the mean R-R, where R corresponds the the peak of an ECG or PPG wave, and is commonly done over a 5 minute period. The change in beat-to-beat variation is determined mainly by the current activity of the cardiovascular system. A link has been shown between high HRV values to overall good health and fitness, while low HRV values are associated with fatigue [5], stress [6] [7] and poor health. HRV has also been shown to have a positive correlation with a persons subjective well-being [8], and is indicative of positive habitual mood and overall satisfaction with life. Links have also been shown between low HRV and severe time pressure, emotional strain [9] and an elevated state of anxiety [10]. All these are common factors that are capable of affecting a students mental state and this hence makes HRV an important feature to measure.

Machine learning algorithms have been applied in a variety of ways to measure and detect stress in individuals. An example of such a method is featured in [11], where personalised stress detection is developed using a number of different extracted features, such as, the mean heart rate, heart rate deviation and respiration rate. This paper proposes a support vector machine (SVM) model to binary classify whether the user is stressed, mapping the inputs to a feature space and seeking a separating hyperplane. SVMs are a state of the art machine learning technique and have been shown to provide great performance for a variety of different applications. An issue highlighted is that their generalization can be poor if there is a large variation between different subjects results, hence this should be considered within the ML algorithm design.

Another ML technique, artificial neural networks (ANN), has also been used for analysing drivers stress levels [12]. This work is of interest since it goes further than similar papers on this topic by multi-classifying stress. Other work, such as in [**?**] only use ML to classify a subjects state into binary categories. Here stress is identified on a scale from 1 to 6 in order to categorize whether the drive currently has a low, moderate or high stress level. This would be an ideal goal for the Hotei application, allowing for a finer grain approach to measuring the users stress and therefore providing a more specific activity recommendation in response. The investigation of this area will be outlined in the section on further work.

To summarize, from the background research gathered we have found that the important features to measure in relation to stress is the users HR and HRV, which can be measured with ECG and PPG. ML methods that have been used for stress detection include SVM for binary and ANN models for multi-classification. For our purposes we shall focus first on binary classification of stress and look to further extend the model for multi-classification in the future.

Fig. 1: System hardware.

III. Hardware

The hardware for this project consists of three main components: an Apple Watch, iPhone and Polar H7 heart rate monitor. The diagram in figure 1 shows the hardware components used and how the devices communicate within the system via Bluetooth.

The application is split across the system with a separate iOS app on the iPhone and watch app on the Apple Watch, which communicate via the watch connectivity framework. As outlined in the initial design report, the main app for user interaction is found on the iPhone device.

The Apple watch is able to measure the users heart rate, by using PPG. An advantage of using this hardware it that is features a graphical interface which can be used to provide additional information to the user, such as notifications and feedback. An issue with this device is, when using PPG, the accuracy of the heart rate readings can be effected by movement.

Polar H7 chest strap heart rate monitor is used for extracting the R-R intervals which are used to calculate the users HRV. This is used because of the current state of the functionality provided by Apple for the watchOS. Currently, it is not possible to receive the raw PPG signal or the R-R intervals with the Apple Watch. The only information available from the sensors related to the heart is the heart rate, hence why we have opted to include the Polar H7 in our system.

IV. Implementation

For the Hotei application's stress detection component the core measurements taken are the users heart rate (HR), heart rate variation (HRV) and accelerometer readings. The features are outlined in table I.

Feature	Description	Sensor
HR	avg. heart rate	ECG
HRV	avg. heart rate variation	ECG
SDHRV	standard deviation HRV	ECG
Acceleration	avg. acceleration	accelerometer
SD Acceleration	standard deviation acceleration	accelerometer

TABLE I: Features extracted from the time domain HR, HRV and accelerometer signals.

These features will be used to train the SVM model to classify the binary state of whether the user is stressed or not stressed, using +1 -1 labels. The ECG signals are gathered from the Polar H7 heart rate monitor, which is described in section III, and the accelerometer readings are gathered from the Apple Watch. The accelerometer readings are required to take account for the change in HR and HRV due to strenuous activity, rather than mental stress, which would effect the results.

The HRV calculation will be extracted from the ECG signal and classified. The features can be analysed in either the time domain, calculating the average R-R intervals, or the frequency domain, calculating the power of the normal sinus to normal sinus (NN) interval of the ECG signal. For this project the analysis will be done in the time domain.

The ML element of the app will be done using the Torch framework for iOS, which is able to create neural networks and SVM models. Torch provides a Matlab like environment for machine learning development, making it simple to rapidly prototype algorithms. The ML model will be calculated on the iPhone, using the data sent from the Apple Watch and Polar H7 devices. We foresee that the computational cost of training the models may be too much for the given platform and if so it will be moved to a cloud based service such as AWS (amazon web services).

The initial implementation for this component has been carried out in Matlab, for prototyping purposes, and the experimentation and findings with different types of data sets is outlined in the following sections.

A. Data sets

Firstly, different data sets relating to HR, HRV using PPG and ECG signal types were investigated to form a basis for the design of this component. This was done specifically to experiment with processing these signal types and to estimate the required sampling rates to accurately extract the features required.

There are a large selection of HR data sets that are publicly available. Initial experimentation was performed on a synthetic data set for PPG and ECG signal [13], used for verify algorithms estimating respiratory rate. This was done to calculate the current HR and HRV on idealised data, which is not subjected to distortion or noise. Figure 2 shows the plot of the ECG and PPG in Matlab for a particular sample, captured over a 10 second period. The peaks, marked in the diagram, were used to get the R-R interval and calculate the samples HRV and BPM.

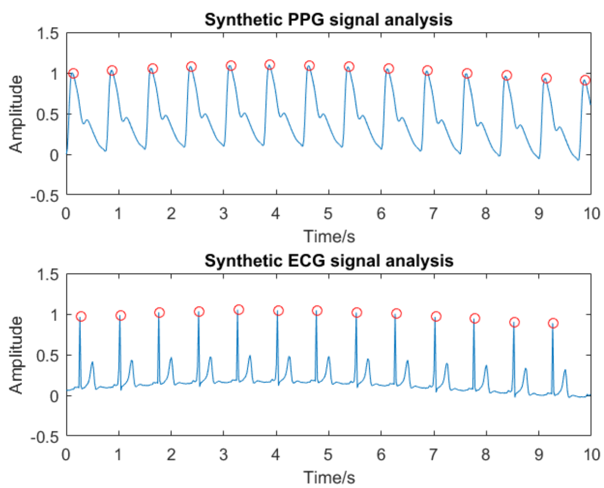

Fig. 2: Plot for the synthetic ECG and PPG signals in the time domain.

For experimenting with real data, the CaponoBase Respiratory Rate Benchmark data set [14] was used. This set contains raw PPG signals for 42 different cases over 8 minute periods, along with reference ECG signals. These were again experimented with in Matlab to calculate the HRV and HR of the ECG and PPG signals.

These data sets have been useful for initial experimentation purposes, but they do not meet the required needs of this project. There were few suitable data sets that were publicly available that featured heart rate data along with specific labels for the participants mental state, hence why, a prototype app has been developed to gather the initial training data. The first version of the test app for data gathering collects HR and accelerometer reading using the Apple Watch, with the chest strap monitor to be added in the future to gather HRV readings.

B. *Test app*

Currently, the test app gathers HR and accelerometer data for training the machine learning algorithm to classify the users stress level. Figure 3 shows the design of the test apps interface for the Apple Watch where it displays the users current heart rate and allows the user to submit feedback on a 1 to 5 scale of how stressed they currently feel. Notifications also appear if the users heart rate appears elevated, prompting them again to submit feedback on their current stress levels. This is done in order to create a labelled training set, which is required for the supervised learning algorithm.

The rating system is based on a 1 to 5 scale in order to future proof the data, as explained in section II, so that it can be used for training a multi-class model for stress. This multi-class model is described in the extended work for this project. For binary classification purposes with a SVM the samples for different ratings can be collapsed into the labels 0 and 1, e.g. if the rating is ≤ 2 classify as 0, if > 2 classify as 1.

The heart rate data is gathered by querying the Apple HealthKit, in normal operation this is only sampled once every 10 minutes. To bypass this problem a workout can be started, allowing for the heart rate to be sampled once every 5 seconds. This meets the requirements of the app by providing close to real time data. The HealthKit does not feature any functionality for querying HRV, hence why this particular feature is not gathered from this device.

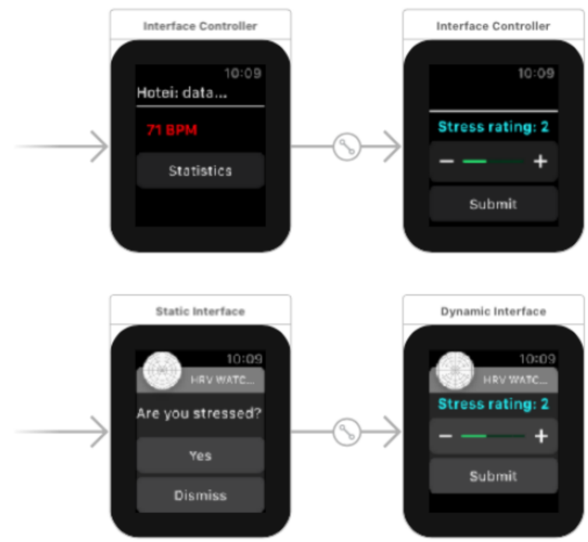

Fig. 3: Application for gathering the initial heart rate variability data for testing.

C. *Data gathering*

The initial data gathering procedure will require 5 students to use the application over a 4 day period, where the users will be prompted throughout the day to rate their current stress levels. This data will just be gathered with the users experience their normal daily routine, to emulate the expected data we would see with the final app. The data will be uploaded daily from the device to cloud services where all the users data will be aggregated together. The key elements stored for each sample of data will be the users id, the time the sample was taken, the users heart rate, the accelerometer reading and the associated stress label.

V. Further Work

The main work to be carried out is to extend the current implementation of the stress detection component to incorporate the Polar H7 into the test application, so that HRV data can be gathered. This is a straight forward process, with the API between the Polar H7 and iOS being well-documented.

The SVM will be implemented using the Torch framework and trained on the current data gathered. This will be implemented on the iPhone device as part of the main application.

Finally, if time allows, the stress detection model will be extended to perform multi-classification with a artificial neural network model, using the features previously described.

VI. Conclusion

This report has outlined the initial planning and design of the stress detection component for our application, Hotei. The key elements are the HR, HRV and accelerometer readings which are used to train the SVM model. An app has been developed for data gathering and initial testing purposes and further work is to be carried out developing this component, looking at incorporating HRV and multi-classification models.

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