Behavioral and contextual data for stress analysis

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Abstract. The spread of mobile phones in the world, increasing quantity and quality of sensors embedded in modern smartphones open up new opportunities for more individual and less obtrusive stress analysis in real-life situations. One of the aims of our research is to develop a real-life stress recognition method by measuring behavioral data and context, through gathering data from smartphones, and without the use of additional wearable sensors. The parameters collected from smartphones are audio, accelerometer, gyroscope, external lighting, screen light on/off, and self-reports (current stress level assessment). In a binary classification (stress or relax) we achieved over 81% accuracy using activity level information (accelerometer and gyroscope features) and decision tree algorithms. For a 3-class stress classification (low, medium, high) we achieved a 70% accuracy with the application of all features.

Keywords: Stress recognition; stress tracker; behavioral data; context; classification; smartphone.

1 Introduction

Due to the effects of stress, there are losses worth multibillions in the world economy [1]. Chronic, reoccurred and prolonged stress can induce problems with people's health [2], [3]. Stress can directly cause illness, through its physiological effects, or indirectly, through maladaptive health behaviors (smoking, poor eating habits or lack of sleep) [4]. Overabundance of stress in the modern world can cause all these problems.

Our aim was to explore the possibility of determining stress in real life by only using the data collected from smartphones. There have already been a number of studies where the smartphone was used as a tool for gathering contextual and behavioral data, as well as to analyze the stress and emotional state. In [5] authors used the smartphone data collected during the day and combined it with the heart-rate variability (HRV) data from a chest belt received during the night to predict the stress level. Picard et al. [6] analyzed the smartphone data and the data from a wrist sensor to find statistically significant features connected with the stress level, and to classify whether an individual was under stress or not. Smartphone usage patterns were applied to recognize

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users' daily happiness [7]. In another research contextual data and electrodermal activity (EDA) from a wristband sensor were used to recognize chronic stress situations on the basis of the user's context [8]. Authors in [9] also gathered contextual data (calendar events, phone calls, location, e-mail readings) to evaluate how the environment and events impact physiology. The main contribution of the presented work consists in selecting various properties from the behavioral pattern and the contextual information for analysis by using various algorithms. In addition, we set an aim to use mobile phones only for the purposes of stress measurement in real life without any additional external sensors, and this way we aimed at achievement of maximal noninvasiveness.

The remainder of the paper is organized as follows: Section 2 discusses a smartpnone as a stress recognition sensor. Stress level assessment methods are presented in Section 3. In section 4 the collected data description is given. Section 5 presents the results of the study. Finally, in Section 6 conclusions are given.

2 Smartphone as stress recognition sensor

According to the [10] 2.04 billions of smartphones will be in use by the end of 2015. Ericcson report claims that during 2014 alone, 800 million smartphone subscriptions were added worldwide [11]. This trend is continuing, and smartphone subscriptions set to more than double by 2020 [11]. A smartphone is an object that we carry with us. Modern smartphones can be called small computer centers due to their growing technical capabilities: an increase in CPU, RAM, the number of cores and performance. The smartphone is also a technical platform for various sensors: ranging from sensors that are regular for daily life and exist practically in every "normal" smartphone, like accelerometer (ACC), gyroscope (Gyro), GPS, Bluetooth 4.0 (BT4), light and proximity sensors, infrared sensors etc., to embedded sensors used for e-Health purposes: optical pulse and pulse oximetry (SpO2) sensors, gesture recognition, sensors for measuring environmental temperature and humidity, ultra red sensor and dosimeter. In this study, we used a "normal" smartphone Nexus 5 that does not have any e-Health sensors and does not require additional hardware.

A smartphone can capture and provide various types of data: (i) changes in our daily behavior (through the analysis of changes in the pattern of the way we use our phone, etc.), (ii) current type of activities (by analyzing the data from ACC and Gyro), (iii) context information (location, lighting, audio features, weather, etc.), (iv) and can be used for subjective self-assessment of current stress level.

3 Collecting self reports from user

Researchers use various methods for the purpose of current stress level assessment. Authors in [18] collected salivary cortisol, a hormone with important functions that participates in the development of stress reactions. Physiological parameters of the body like HRV in [19], EDA in [20], heart rate (HR) in [21], electromyography (EMG) in [22], blood volume pulse (BVP) in [23] etc. were used for the assessment

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of stress level. Self-reports about the current emotional state of participants were used in a large number of studies [8], [22], [5] as ground truth. In this study, we used subjective self-assessment by participants of their current stress level as ground truth in accordance with the study [8], in which authors claim that an average user is able to make a good assessment of own current stress or relax states. Based on this knowledge we used a 7-point scale questionnaire in our study, similar to NASA Task Load Index [24]. For this purpose application for Android, named "Stress Tracker", was developed. This application with a set time interval (in our case 1 hour) asked a participant to assess the current level of stress from Monday to Saturday from 09-00 to 20-00 with the possibility to leave a comment (Fig. 1). Self-reports should be triggered at least 30 minutes apart. Further, these self-reports were unloaded in a .csv format, and then imported into the MySQL database. Before importing the data into the database, time was converted into a Unix format as for all of the remaining parameters.

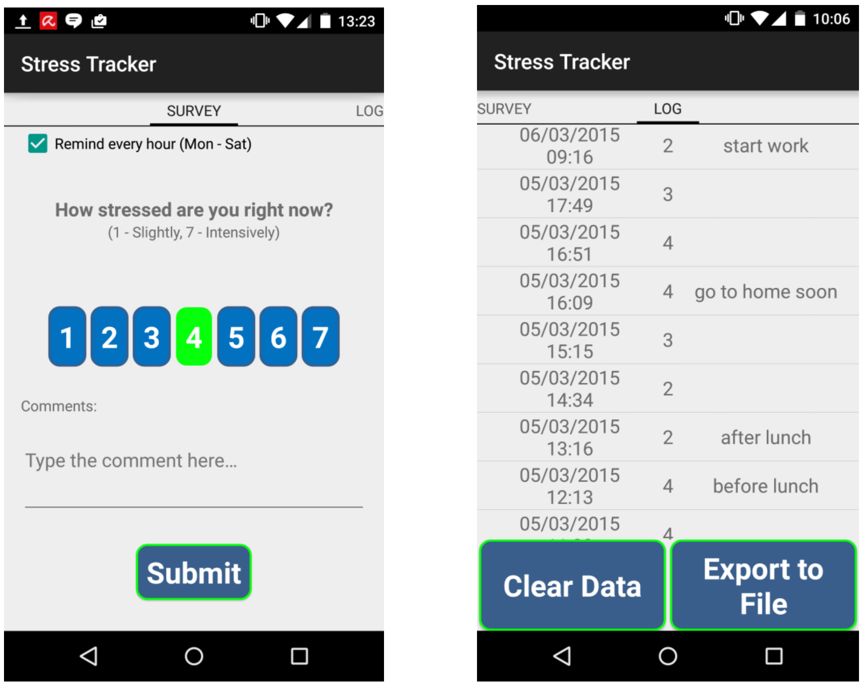

Fig. 1. Android application for assessment of current stress level. Left - main screen, right - log screen

4 Collected data

In [12] researchers made a classification of sensors which can be used in stress and emotion recognition systems, and figured out that behavioral and contextual data are the most interesting types to collect information noninvasively.

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There are solutions that provide low-level access to sensors built-in smartphones. The most popular of them are Funf [13], Sensor Data Collection Framework for Android (SCDF) [14] and MyExperience platform [15]. In our study application based on the framework Funf was used to gather the behavioral and contextual information, because Funf, in our opinion, provides the easiest way to get your data.

Table 1 presents the collected information and the time intervals when it was done.

Table 1. Gathering data from smartphone with time intervals.

Data type	Time interval between starts, sec.	Duration after start, sec.
Screen on/off	every change is counted	
Audio features	300	40
Light features	300	40
Gyroscope features	120	15
Assessment of stress level	1800-3600	
Accelerometer features	120	15

The frequency and duration of the information collection were selected based on: (i) minimization of the battery consumption, so that the phone can work without recharging for at least one day; (ii) minimization of the intervals when data is collected.

We counted every change of the screen off/on. Collected audio features include values of mel-frequency cepstral coefficients and power spectral density across frequency band. Light features describe ambient light. Gyroscope features are normalized values on axis X, Y and Z. By using accelerometer features, three activity levels were calculated: none, low and high.

Once all the data has been collected, it was imported from a cloud storage to a separate database table in MySQL. Each data type was put in a separate table with the key field "timestamp" (Unix format), which corresponds to the time of occurrence of the event.

5 Results

The data was analyzed with the WEKA software package [16]. WEKA is a collection of algorithms for machine learning to solve data mining tasks. The system allows applying algorithms to the data samples, as well as running the algorithms in Java programs.

Values of self-assessment of the current stress level for a binary classification were divided into two classes. Values 1, 2, 3 correspond to the "relax" class and values 4, 5, 6, 7 correspond to the "stress" class. Next, all data from the MySQL database was

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processed and converted to the WEKA format (ARFF - Attribute-Relation File Format) and then uploaded into the program. ARFF format is a simple format, which organizes as .csv file with headers that describe the variables. After normalization of the data, there was classification made as follows: 4 algorithms were used for the classification with different sets of features to get a better understanding of the significance of certain properties for the purpose of stress recognition.

Results of a 3-class classification are presented in Table 2. For this task self-assessments were divided into 3 classes: values 1,2 correspond to "low" stress, values 3, 4, 5 correspond to "moderate" stress and values 6, 7 correspond to "high" class.

A 10-fold cross validation was applied to estimate how good prediction results will be in practice. We randomly divided the data into 10 parts, and each part was used as a control set whereas others were used as a training set. Four algorithms were used for data classification: k-nearest neighbors (kNN), decision tree (J48 and REPTree), and simple logic. We will not describe how these algorithms work, but note that in our case REPTree algorithm was the best and kNN algorithm was the worst for 2-class classification. The computation results are presented in Table 2.

Table 2. Analysis results.

Algorithms / Set of features	kNN	J48	Simple logic	REP Tree
all features (3-class classification)	62.50%	63.75%	70.00 %	61.25%
all features (2-class classification)	65.00%	73.75%	73.75%	76.25%
without Gyro and ACC data (2-class)	53.75%	71.25%	70.00%	72.50%
without screen off/on data (2-class)	57.50%	72.50%	75.00%	76.25%
without lux data (2-class)	68.75%	75.00%	77.50%	76.25%
without audio data (2-class)	57.50%	75.00%	75.00%	80.00%
only Gyro and ACC data (2-class)	73.75%	81.25%	75.00%	81.25%

As shown in Table 2, the accuracy of binary classification with the exclusion of the data from Gyro and ACC is 2.5% to 11.25% lower (the average value is 5.31%) compared to the use of all features for the analysis. On the other hand, by using the data only from Gyro and ACC the accuracy of 2-class classification is 1.25% to 8.75% higher (the average value is 5.63%) compared to the use of all parameters.

Thus, according to the results presented above, it is possible to conclude that the Gyro and ACC data are significant parameters for stress analysis, the consideration of which increase the accuracy of classification.

As we can see in Table 2, the contribution of various sets of features for the classification accuracy can be both: positive and negative, except for the variant without the

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lux data, in which accuracy of classification is up to 3.75% higher (the average value is 2.19%) compared to the use of all parameters.

Therefore, it is important to choose the significant sets of parameters that could lead to an increase in the accuracy of classification. It is possible to find optimal features with the highest correlation to stress level (or emotions) using a combination of different algorithms for this. In [17] the authors used the genetic algorithm to select the significant parameters to optimize stress classifications and got a better result compared to the classification without using a genetic algorithm.

6 Discussion and conclusion

Our results showed over 81% accuracy in a binary classification (stress and relax) and over 71% accuracy in a 3-class classification (low, medium and high stress) using the data from a smartphone only. ACC and Gyro features, and external lighting data were correlated with the stress level more than other features (audio, screen light on/off).

Although our results are preliminary, it is possible to conclude that a smartphone can be used as an instrument of stress determination. Moreover, we believe that a smartphone can provide a real-time feedback to individuals about their stress level and help them to reduce or even avoid stressful situations by providing prompts on how to change their behavior, but this assumption should be checked on practice.

We plan to collect many various types of data in real life from smartphones and then to choose optimal parameters which are strongly correlated with stress. In addition, we want to gather physiological data from wearable sensors (HRV, EDA, SpO_2, etc.) to get robust results.

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