Unveiling Markers of Stress Via Smartphone Usage

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Abstract

Numerous Android apps leverage from the information provided by embedded sensors of the smartphones. The prime objective of this work is to conduct a state-of-the-art short survey of stress-related research and determine which inbuilt sensors and features of smartphone applications can help in determining stress among students. The study focused on three factors, physical activities, sociability, and ambiance, and it shows how smartphones can take advantage of these aspects to determine stress.

1 Introduction

Stress is, any uncomfortable "emotional experience accompanied by predictable biochemical, physiological and behavioral changes" [3]. Factors of Stress are omnipresent that can influence anyone irrespective of their gender, age, living conditions, etc., and can trigger physical issues (like muscle pain, high blood pressure, and a weakened immune system) and psychological problems (such as depression and anxiety). Besides physiological symptoms, over-consumption of junk food, alcoholism, drugs, and smoking are a few behavioral indicators of stress [9]. Although stress is a psychological phenomenon, it has physiological impacts such as variation in skin conductance, neck pain, blood pressure, heart rate, catecholamine, and cortisol secretions [18]. All of these phenomena can be used to evaluate stress level either clinically or technologically, and with high credibility, but are not very practical due to cost, test durations, user biasedness and truthfulness in case of surveys. The idea of this work, i.e., detecting stress through smartphones, was conceived while investigation inactivity and activity among the students via smartphone usage in the project SOCIALITE[1] [2], Section 2 puts forward the motivation of behind work. Further, state of the art related to three markers of stress (i.e., Physical Activities, Sociability, and Ambiance) are proposed, along with the probable features and evaluators that can be captured via smartphones. In Section 3 concluding remarks are made.

2 Survey over Markers of Stress

This section describes the motivation of our contribution. The probable three factors that influence the stress levels in humans are also inspected in this section, along with the three types of data collection via a smartphone app as shown in Figure 2.

•**Elemental Work with Smartphone** dentification of stress-related

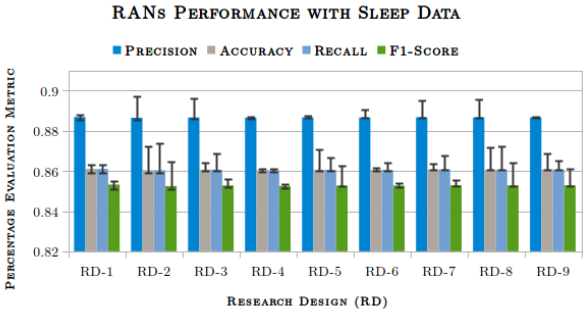

Figure 1: Evaluation of Modeling of SOCIALITE data with RANs

attributes via smartphone has its motivation from an experiment of project SOCIALITE. The project SOCIALITE is an attempt to address some aspects related to IoTs, by considering the existing IoT framework (such as FIWARE) in conjunction with people-centric technologies (like smartphones, sensor-boxes, and other IoT source), and proposing a solution consisting WSNs, mobility, and ubiquity, along with cognitive services and context-awareness, for supporting People-2-People interaction. Nowadays, smartphones are omnipresent and have been an invaluable source of data. To benefit from this smartphone data, in project SOCIALITE, smartphone app ISABELA[2] [2] was used to capture data pertaining to the attributes such as *Activity, Day, Luminescence, Sound, Alarm, and Phone-lock-state*. The data was then utilized to model the "Active-State", and "Inactive-State" of the recipients using a computational modeling approach Regulated Activation Networks [15]. The generated model was evaluated with Precision= 89.02% (ca.), Recall= 86.13% (ca.), F1-score= 85.53% (ca.), and Accuracy= 86.13% (ca.) (see Figure 1 for the research design with varying train data for 90% -to- 10%, and vice versa for test data). Further, statistical analysis of observations of data (specific to three students individually) with the generated model depicted that one student was mostly "Inactive" all the time, which does not commensurate with the assumed normal behavior of the student [15]. Consequently, it indicates the reasons (such as personal problems, illness, or stress) that leads to such behavior of that student.

Figure 2: Data acquisition of markers of stress via a smartphone app

• **Physical Activities and their impact on stress**. Activities involving the physical movement of the human body has an immense effect in relieving stress [13]. There are pieces of evidence that exercises, frequent walks, swimming helps in increasing the production of feel-good endomorphins that help in treating mild forms of depression and anxiety [6]. Physiological movements are also found to alleviate hypertension, blood pressure, and obesity-related problems, which are among the critical symptoms of stress [10]. In the Internet of Things (IoT), Human Activity Recognition (HAR) is an essential domain of research with a notable contribution focusing upon identification of human activities such as walking, running, jumping, and sitting [1]. Since physical movement is an essential factor that correlates with the stress and attributes related to physical movements can be utilized in determining stress levels, see first row of Table 1 for probable features that can be observed via Smartphone.

• **Social communications and its relation with stress**. Being social is an essential part of a healthy lifestyle, however, it is not necessary to be very eloquent in order to be social, as communication is a crucial part of sociability, and highly correlated to loneliness and social isolation [14] can motivate people to adopt ill habits such as smoking, drinking, and drug usage [12]. Smartphones have been used to study the sociability of students by monitoring their physical activity and ambient noise [8]. Sociability is necessary, but there are shreds of evidence that it is related to the decline in the academic performance of students [7], this deterioration has been linked to stress among students [17]. With the aid of data from app usage of smartphones it's possible to study sociability of a person and determine how it is linked to stress, see second row of Table 1 for possible Sociability related attributes.

• **Effects of environment over stress**. As aforementioned, stress

[1] "Social-Oriented Internet of Things Architecture, Solutions and Environment"- https://www.cisuc.uc.pt/projects/show/215

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Table 1: Proposed Attributes for all 3 markers of stress

Marker	Atributes	Labels
Physical Activity	Walking, Running, Sitting, Laying, Jumping, Standing	Image Stress Meter, Stroop Color Test , Stress Questionnaire
Sociability	Facebook, Whatsapp, Twitter, Voice call, Text messages	Image Stress Meter, Stroop Color Test , Stress Questionnaire
Ambience	Noise, Temperature, Humidity, Pollutants	Image Stress Meter, Stroop Color Test , Stress Questionnaire

is a phenomenon that emanates from an individual's evaluation and response to its environment. The Ambiance is an important determinant that can influence the stress accumulation in an individual. Crowd, noise, climate, and pollution are a few such factors that have an impact on the psychological conditions of a person [5]. Smartphones embedded sensors can be used to determine all four, prior, mentioned stressors. The microphone can be used to determine the number of different speakers in the crowd [19], and the noise as in the environment [20]. Ambient pollutant and climate-related data can be obtained from global weather data APIs, see the third row of Table 1 that shows the Ambience related feature that can be collected.

The Table 1 lists the attributes and labels that can be collected via smartphone w.r.t three Markers. The data representing characteristics, logged in Table 1, can be gathered in an aggregated manner, i.e. average values of the attributes to be collected at a fixed interval of time. In the case of Physical Activity attributes, the average time spent in performing the activity should be recorded for the period. Whereas the Sociability attribute can log minutes spent on texting, talking, and browsing during the interval, and count of people connected with the user. For Ambiance related characteristics, average, minimum, and maximum values can be collected. To establish the relationship between the collected data for the three stressors mentioned above with stress levels of an individual, one of the following three stress tests are recommended for recording the stress levels of the subject as the label. Perceived Stress Scale (PSS) [4] is a classic stress assessment instrument and can be used as a reference to develop the questionnaire. Photographic Affect Meter [11] is a tool to associate emotion with images and identify stress in humans. Stroop's Effect [16] is also suitable for the stress evaluation purpose, as it has vast literature on evaluating criteria, and easy to implement as an app.

3 Conclusion

Stress is an important phenomenon and primarily studied through psychological, and biological methods. This article produces a shot survey of three important factors (Physical activities, sociability, and ambiance) that have been correlated with stress. Some contributions tend to determine attributes related to, previously mentioned, 3 aspects with the aid of smartphones. These attributes have been beneficial for research such as mobility detection, and environmental monitoring. In the scope of SOCIALITE project, an initial work shows how it is possible to reveal stress levels of a subject by modeling "Activity" and "Inactivity", and statistically analyzing them. Furthermore, as future work, the data obtained from smartphones about these characteristics will help not only in a learning system that determines personalized stress models, but also enables monitoring, and effectively manage stress among people.

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