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MSAS: An M-mental health care System for Automatic Stress detection

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Abstract

The negative signs of stress can be reduced or even eliminated if they are recognized early. Hence, the level of stress needs to be continuously measured and reported especially if the stressors are frequent or continuous. M-health is a new technology to provide mobile healthcare services including mental and behavioral. It allows the healthcare specialists and patients to be linked beyond their mobility and physical location while the system is connected. This paper presents the system model for an M-mental healthcare system which automatically detects stress. This system, which is called MSAS, continuously measures the stress level using wearable sensors connected to a mobile phone. The consumer gets alarm and/or the mental healthcare team receives a call if the stress level is recognized above a particular threshold. MathLab is used to simulate and evaluate MSAS. The results show that MSAS offers benefits to detect stress with an acceptable level of accuracy.

Keywords: Stress, Mental Disorder, M-health, Sensory System,Artificial Intelligence

Introduction

Stress is an organism reaction to the internal or external factors such as work overload, task complexity, high responsibility, job insecurity and inconvenient environmental conditions. Stress arises when arousal increases. This is caused by surging hormones such as adrenaline and cortisol through body when a stressful event arises (Sioni, 2014). Stress occurs in three forms: 1) Acute: stress caused by short-term stress factor, 2) Episodic acute: acute stress which frequently and/or periodically arises, 3) Chronic: stress caused by long-term stress

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factors (Bakker et al., 2011). Among all the forms, chronic stress is more harmful and can subject to mental disorders, disabilities and/or bad habits such as headache, heart disease, stomach upset, sadness, depression, restlessness, irritability, drug abuse, and nervous habit if runs for long periods.

Early stress recognition or awareness of being under stress aims to manage stress. This offers a high impact on reduction of health risks and disorders. For example, a student may concentrate on finishing up and submitting his/her homework earlier when s/he gets stress due to close deadline. However, sometime stress cannot be simply recognized as people may be less likely to notice whether they are under high stress or not. In such this case, stress detection technologies are required to understand and relieve stress.

Mobile health technology (M-health) has the potential to offer healthcare benefits (Poh et al., 2004). This technology utilizes digital process and communication to deal with diseases and disorders depending on the application. M-health allows healthcare team to repeatedly monitor the patients health status using reported sensory information such as heart rate, skin conductivity and respiration rate. This technology offers resource utilization, time management, accuracy and quality of service benefits (Chan et al., 2014).

The rest of this paper is organized as follow: Section 2 provides a literature review in this field of research. Section 3 proposes an M-health system to detect the level of stress using physiological markers. Section 4 introduces the test results of MSAS. The last section concludes the paper and presents some plans for future work.

Stress can subject to sympathetic responses from automatic nervous system (ANS). This influences physiological markers such as voice, heart rate, galvanic skin response (GSR) and facial expressions (Sandulescu et al., 2015). Considering vocal and facial parameters cannot provide an acceptable level of accuracy in stress recognition due to the effects of either internal or external factors. For example, facial expression might be influenced by environmental conditions, disabilities, makeup and subjective control (Busso et al., 2004) On the other hand, the effect of external factors and subjective control on physiological parameters is limited or even addressed as negligible. This results in increasing the accuracy of stress measurement.

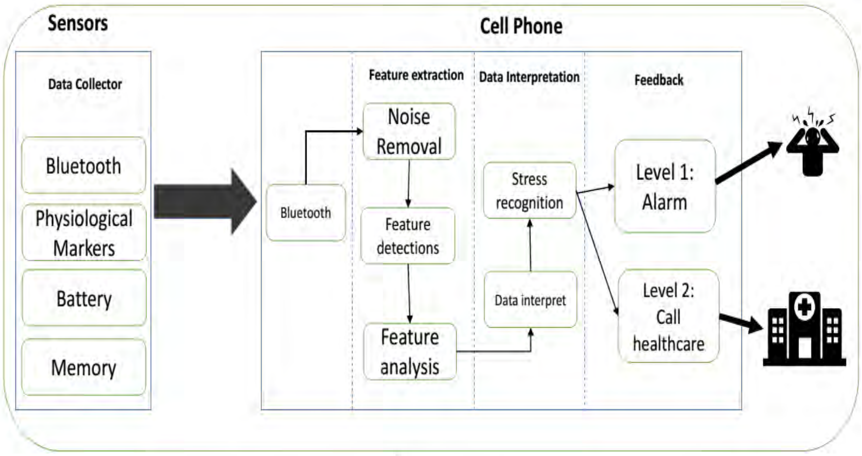
Jacobs et al. (1994) considers the effects of stress on skin conductivity, heart-rate and blood pressure to see how stress is correlated to the level of arousal. According to this research, stress influences the level of arousal and increases skin conductivity and heart-rate when the patients do not use cardiac drugs.

Bakker et al. (2011) utilizes Galvanic Skin Response (GSR) sensor to detect stress. According to the experiments, GSR signals change when the experiment participants cope with stressful events. The GSR signals are measured in 72 time series each of which for 5 participants. Then, an aggregation algorithm is used to collect and combine the signals to get a big view from GSR signals over the time series. Finally, Adaptive Windowing (ADWIN) algorithm is used to recognize the signal change and detect stress.

Healey and Picard, (2005) detects stress using a sensory system which collects physiological data while driving. The system comprises of an electrocardiogram (EKG) on chest, an electromyogram (EMG) on the left shoulder, a respiration sensor (Resp.) on the back around the diaphragm, and two skin conductivity sensors (SC) one on left hand and one on left foot. Under the experiments, 24 participants drive for 50 minutes (including five minutes rest) on a highway. According to the results, three levels of stress are recognized with %97 of accuracy.

Ojha and Subashini, (2014) focuses on analyzing Electrocardiograph records (ECG) to study the behavior of cardiac signals in stressful situations. ECG signals addresses abnormal waveforms in response to stress. By this, the meaningful features of ECG is extracted and analyzed then to find out the signal changes. However, external (i.e. thermal and environmental) and internal (i.e. frequent re-connections between ECG device and body) noises may influence ECG signals. This reduces the quality of signal processing and consequently subjects to inaccurate stress recognition. MathLab is used to filter signals and remove noises. The results show an accuracy of %75 in stress recognition.

Figure 1. The System Model of MSAS



Method

The proposed approach

MSAS is an M-mental healthcare system which is proposed to automatically detect the level of stress. The key duty of this system is to collect and interpret the physiological symptoms that are caused by stress. MSAS alarms healthcare team if the stress level is recognized above a particular threshold.

In fact, acute stress is avoided, the patients are alarmed in the case of episode acute stress and the healthcare system or specialists are called when chronic stress is recognized. Figure 1 shows the system model of MSAS which comprises of four connected components. These components are explained as below:

1) Data collection: this uses wearable sensors to collect the physiological markers such skin conductivity (SC) or heart rate which are correlated to stress. Under MSAS, the sensor returns SC data as electronic signals. SC slightly is increased if the level of stress increases for normal consumers who do not use mental drugs (Jacobs et al., 1994). The collected data is transmitted to the mobile phone via Bluetooth.

2) Feature extraction: this is the responsible of detecting meaningful features of SC signals that show the impacts of stress. As Figure 2 shows, stress is detected when SC signal gets peak (Sano and Picard, 2013). MSAS aims to recognize the level of stress by considering the signal peaks. However, SC signals can be influenced

by noises caused by sweat or frequent disconnections between skin and the sensory device. Hence, a noise removal algorithm is required to remove noises and return then clear signals for data feature extraction and interpretation.

3) Data interpretation: this analyzes and interprets the collected data to understand how the physiological signal changes due to stress. MSAS detects stress when SC signals matches the stress recognition pattern. According to the literatures, a number of patterns is proposed for stress recognition according to the physiological symptoms (Sharma and Kapoor, 2013) and (Sioni, 2014).

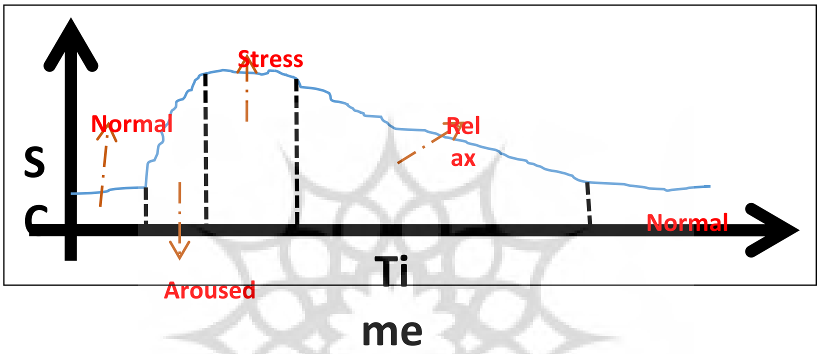


Figure 2. the stress signal pattern for normal people.

4) System feedback: MSAS contacts the patients or healthcare teams via mobile phone when the level of stress is recognized. This system alarms the patients if stress is recognized as episodic acute (low-level), whereas it calls the healthcare teams or specialist when chronic stress (high-level) is detected.

To test and evaluate MSAS, simulation is used as real wearable sensors are expensive for laboratory experiments. Mathlab Ledalab is a software program that generates SC signal samples according to manual or random pattern. To enhance the reliability of results, MSAS was tested in 100 experiments each of which runs for 300 seconds. Each experiment uses a random generated SC signal in terms of amplitude and peak count to simulate a different level of stress. The generated signals are filtered using low-pass Butterworth which cuts 5Hz due to the potential sweat noise between skin and the sensor. Then, the number of signal peak is counted during each 30 seconds. There is a normal situation if the peaks are rare. The level of stress is minor and the consumer is alarmed if the peaks are not are and they are not repeated during the next 30 seconds. The level of stress is high and should be reported to the specialist or healthcare system if the peaks are continuously repeated. Figure 3 shows an example of the simulated SC signals in Mathlab Ledalab.

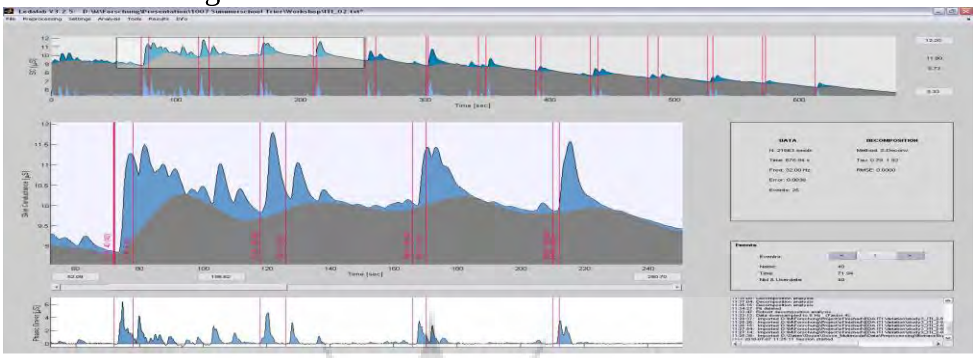


Figure 3. SC signals in Mathlab Ledalab.

Results

As Figure 4 shows, 26, 33 and 41 of the experiments (out of 100) respectively match acute, episodic acute and chronic classes of stress. According to the results, MSAS recognizes a correct level of stress with 80% of accuracy in the worst case.

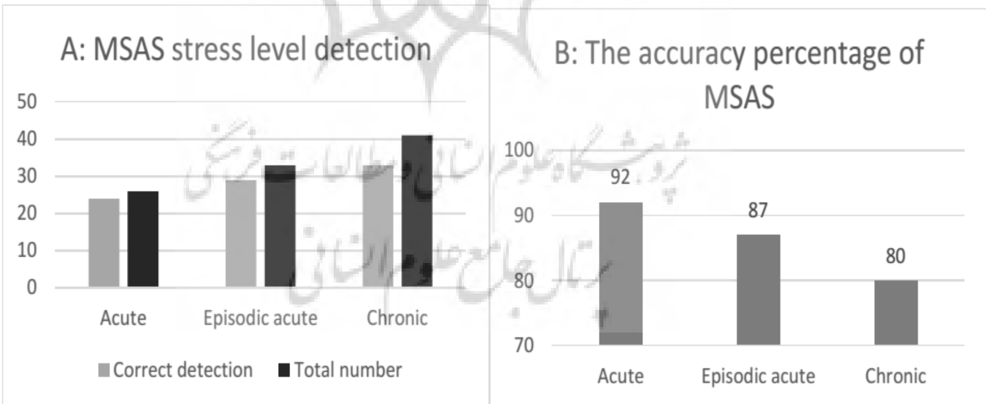


Figure 4. The simulation results of MSAS

Conclusion

The key duty of MSAS is to eliminate the harmful effects of stress by early detection. The empirical results show MSAS would be able to recognize correct level of stress in most circumstances. MSAS can be implemented using Q sensors and real mobile applications. However, the system security and the effect of external noises are the challenging issues that may result in reduction of reliability of system to deal with stress. This can be addressed as a further work.

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