Real-time Stress Evaluation using Wireless Body Sensor Networks

Maroun Koussaifi, Carol Habib, Abdallah Makhoul
FEMTO-ST Laboratory, University of Bourgogne Franche-Comté, Belfort, France, e-mail: firstname.lastname@univ-fcomte.fr.

***Abstract*—Stress is a physical, mental or emotional factor that causes bodily or mental tension. It is generally recognized as one of the major factors leading to a spectrum of health problems. Therefore, people with high risks of getting stressed should be continuously monitored in order to detect any stress signs before it causes health problems. Wireless body sensor networks(WBSNs) provide opportunities to monitor stress and can provide initial treatment. In this paper, we propose an energy-efficient stress detection and evaluation framework. A WBSN deployed on the patient's body collects stress-correlated physiological signals. First, the skin conductance (SC) is analyzed. Then, if any stress signs are detected, its level is calculated via a Fuzzy Inference System (FIS) using the following vital signs: Heart Rate (HR), Respiration Rate (RR) and Systolic Blood Pressure (ABPSys). The results show that the stress evaluation was coherent with the different experimental stages the monitored person has gone through.**

I. Introduction

Stress is your body's way of responding to any kind of demand. It can be caused by emotional, mental or physical situations. It is a common problem that affects almost all of us at some point in our lives.Stress detection and monitoring technology have the potential to help people better understand and release stress by increasing their awareness of higher levels of stress that would otherwise go undetected. Stress can be monitored by using a Wireless Body Sensor Network (WBSN) which is a self-configuring network composed of small biosensor nodes, communicating using radio signals.

Many existing approaches have been proposed to detect stress levels using the human being's physiological signals. In these approaches, authors have used neural networks (NN), which firstly need to be trained, to determine the stress level using as input the captured physiological signals. Another challenge directly related to WBSNs is the energy consumption due to the continuously transmission of data. In a WBSN, data transmission consumes the most power, consequently the sensors' lifetime is reduced. Therefore, data transmission should be then taken into consideration.

In this paper, we propose a real-time stress detection framework using a wireless biosensor node and a fuzzy inference system (FIS). First, the skin conductance (SC) is analyzed. If stress signs are detected, then stress level is evaluated via the FIS based on the monitored person's vital signs. These vital signs are: the Heart Rate (HR), the Respiration Rate (RR) and the Systolic Blood Pressure (ABPSys). The chosen vital signs are the most affected by stress when it occurs. In our proposed approach, the stress level evaluation process is only triggered when the coordinator detects stress signs, therefore data transmission is reduced and the biosensor nodes' energy resources last longer.

The remainder of this paper consists of a state of the art in relation with stress detection presented in Section II. The stress detection system is described in detail in Section III. An evaluation of the system is provided in Section IV. Section V shows and discusses the experimental results. Finally, Section VI concludes the paper and presents future works.

II. Related work

Different existing approaches and techniques have been proposed and developed to study a subject's stress level. In [1], a real-time personalized stress detection algorithm using the heart rate and the body temperature as inputs to a fuzzy logic system is proposed. In [2], the authors have developed a fuzzy logic system to detect stress in real-time. However, only two physiological signs have been used and no further analysis or assessment of the stress level is provided. Nonetheless, it is not common to focus only on one or two physiological signals but to focus on many of them in order to obtain further and more precise information about the stress level. Most of these approaches use deep learning or SVM to determine the stress level of an individual. However, no explanation about the used data in the training phase of these intelligent systems is provided. In modern days, there exists no medically verified data for stress that can be used to train a deep learning system to correctly calculate the stress level. Therefore, the existing approaches have been trained using proprietary stress related data making the algorithms unprecise and not generalized. Most of the previously mentioned approaches do not operate in real-time, first the data is collected then it is analyzed offline to get the results. To the best of our knowledge, none of the stress detection approaches in the literature have given any concern about the energy consumption that reduces the sensors' lifetime.

In this paper, a real-time stress detection and evaluation approach is proposed. It uses multiple vital signs as input and determines the stress level using a FIS. It also takes into consideration the data transmission to maximize the sensor nodes' lifetime. We develop a system composed of a Shimmer3 GSR+ sensor node and by extracting the HR, the ABPSys and the RR, the stress level is calculated.

III. Stress Detection

In our proposed method, the coordinator continuously receives SC measurements from the GSR sensor node. In order to reduce the transmission of data, we propose to use the lowest sampling frequency possible (1 Hz [3]) indicated by the constructor of the sensor node. The Stress Detection Algorithm $StressD$ operates as follows (cf. Algorithm 1). A window size of 10 minutes is required to detect stress, thus the coordinator must record the received SC measurements. Stress detection can be made by calculating the average of the SC measurements over a time window of 10 minutes. If the average is above the normal range (greater than 1 MOhm [3]), then the person is going through a stress episode and stress should be evaluated to determine its level. If the average is within the normal range, then the person has not reached a stress episode yet. In both cases, we use a sliding time window of 10 minutes to recalculate the SC average after a time period T of two minutes.T is a time period that allows the coordinator to calculate the stress level frequently. Its value is updated depending on the evaluated stress level.

Algorithm 1 Stress Detection Algorithm

Require: Time period T, SC Threshold $threshold = 1M\Omega$
  repeat
    Store the received SC data
  until $ReceivingTime > 600000$ ms
  Initialize T to 5 mins
  Set $calcStress = True$
  Calculate $avgSC$ average of received SC data
  repeat
    if $avgSC > threshold$ **then**
      Evaluate $StressLevel$
      if $StressLevel > 3$ **then**
        repeat
          Re-Evaluate $StressLevel$ after time period T
          Update T
        until $StressLevel <= 3$
        $calcStress = false$
      else
        $calcStress = false$
      end if
    else
      Re-calculate $avgSC$ each $T = 2$ mins over a sliding window of 10 mins.
    end if
  until $calcStress = false$

IV. Stress Evaluation

Stress evaluation is done using a FIS and the following vital signs: the HR, the RR and the ABPSys. In the following, we show the correlation between each of the vital signs and stress and we explain the methods used to extract them from physiogical signals. Then, we present the components of the FIS. Vital signs and stress are highly correlated. Indeed the HR, RR and ABPSys vary and exceed the normal range when a person is experiencing acute stress due to an increase of the amounts of hormones in his/her body.

- *The Heart Rate*:

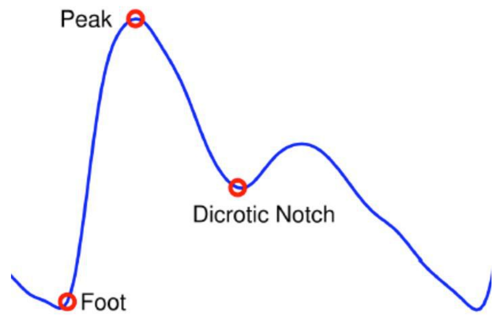

Fig. 1: PPG Waveform

The HR can be calculated from the PPG signal (shown in figure 1) using the following equation:

$$\frac{60 * x}{TimeToDetect(s)} \tag{1}$$

x (number of peaks) is specified in the setup phase of the coordinator. The higher x is, the more accurate the HR value is. However, the extraction will require more processing time. In this paper, we set x to a default value of 3.

- *The Blood Pressure*: According to [4], ABPSys, for an adult aged 18 and above, is calculated using the following equation:

$$ABPSys(mmHg) = (-0.6881 * PTT) + 210.94 \tag{2}$$

where PTT represents the pulse transit time in milliseconds (ms). To calculate PTT, the time interval between a waves peak of the PPG signal and the Dicrotic notch of the same waveform is determined (c.f. Figure 1).

- *The Respiration Rate*: To calculate the RR, there exists an algorithm called ”Multiparameter Respiratory Rate Estimation From the Photoplethysmogram” [5] which consists of studying the variations of the PPG signal values (frequency, intensity, and amplitude) over a fixed time window to calculate the RR.

We have chosen to use a FIS because it is an intelligent decision system that uses several variables as input to determine the output and it is easy to implement and configure in a mobile application. Also, in a FIS the training phase can be skipped, as long as we know the domain we are modelling and its reaction/behaviour rules. According to the universal pain assessment tool [6], stress is measured in a scale of 1 to 10, 10 being the highest level. Table I shows the average range of each vital sign with its corresponding stress level.

TABLE I: Stress categories

	Low Stress	Medium Stress	High Stress
HR (Bpm)	40-70	70-90	>90
RR (Rpm)	8-16	16-20	>20
ABPSys (mmHg)	80-120	120-139	139
Stress Level	0-3	3-7	7-10

The FIS has three inputs: the HR, the RR and the ABPSys and has one output: the stress level. For this purpose, membership functions are defined for the three inputs as well as for the output. The membership are in a ramp shapes which are built according to Table I. In the proposed approach, the FIS rules are defined manually based on national health organization reports on stress and its effect on a persons vital signs.

When the coordinator detects stress signs based on the SC values, it orders the sensor node to stop streaming SC data and to start sending the PPG signal, and then it orders the sensor to stop when the vital signs are extracted. We propose to adapt the time period T at which the stress level is evaluated according to the evolution of the stress level value as follows:

- If the stress level is high, T decreases in order to evaluate the stress level more frequently.
- If the stress level is low, T increases in order to reduce the frequency at which the coordinator requests the PPG signal and evaluates the stress level and then it preserves its processing and energy resources.

When the stress level reaches the normal range (below 3), the stress detection process repeats from the beginning, where the system detects stress from the SC data.

V. Experimental results

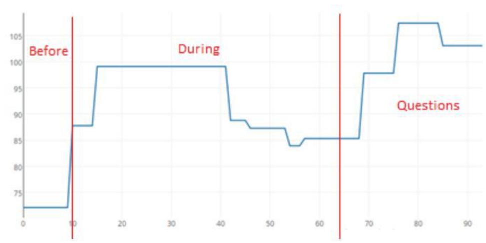

Fig. 2: HR Variation

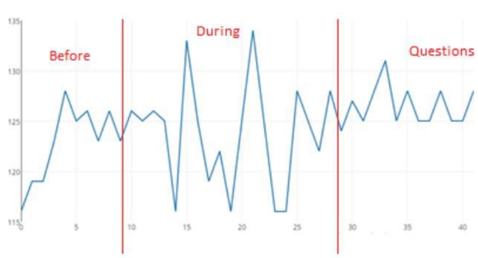

Fig. 3: ABPSys Variation

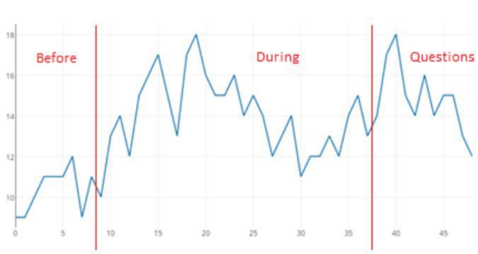

Fig. 4: RR Variation

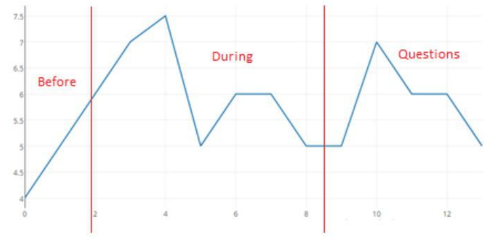

Fig. 5: Stress level Variation

The coordinator is a smartphone running an Android application implementing the proposed stress detection and evaluation approach. It uses Bluetooth to communicate with the Shimmer3 GSR+ sensor node. The experiment was made on a person doing an oral presentation. The main outcome of the experiment is to test the coherence and accuracy of the proposed FIS and minor interest was given to the stress detection phase. The sensor node was configured to send the PPG signal to the coordinator for the vital signs extraction. Figures 2, 3 and 4 show the variation of HR, ABPSys and RR respectively over time during the three following stages: before the presentation, during the presentation and after the presentation (during question time). Figure 5 shows the stress level variation during the three stages of the experiment.

VI. Conclusion

In this work, we have proposed a real-time stress detection and evaluation framework using WBSN. Our method consists of analyzing the SC signal transmitted by the GSR sensor node to the coordinator. When stress signs are detected the coordinator requests the PPG signal from the PPG sensor node to extract the vital signs and evaluate the stress level using the FIS. The results show that the proposed approach gave a good prediction of the stress level.

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