Mental Stress Detection Using Multimodal Sensing in a Wireless Body Area Network

Marina Rodríguez Aliberas

Technische Universität Berlin
Telecommunication Networks Group (TKN)

Universitat Ramon Llull
Dept. d'Electrònica i Comunicacions de Enginyeria i Arquitectura La Salle

rodriguez@tkn.tu-berlin.de, marinara@gmail.com

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Supervisors: Dipl.Inf. Jan-Hinrich Hauer, M.Sc. Rosa Maria Alsina Pagès,
Prof. Dr.-Ing. Adam Wolisz

Abstract: This thesis presents the design and implementation of a software framework that allows to collect and store physiological data on small sensor devices attached to a human being (forming a Wireless Body Area Network). It describes how sensor data from two biosensors (GSR and ECG) is collected in a number of field experiments, where subjects are exposed to different emotional situations. The experiments are done together with a group of researchers from the department of psychology at Freie Universität Berlin, FUB. The collected data is then used to (post factum) extract a set of features, which are used as input for existing machine learning algorithms to study how mental stress of human beings can be detected automatically. The evaluation of the algorithms shows that multimodal sensing can improve the stress detection accuracy.

1 Background

Mental stress is an emotion which has become frequent in world's population, to the point of affecting health and causing diseases. However, often people do not recognize or underestimate the level of stress they suffer. Consequently, the interest for monitoring body responses to better understand the level of stress people are experiencing in every day life has increased considerably [LWB07]. Stress and emotions have complex body responses and one single sensor is likely not enough to detect stress [HNS10]; it is more promising to analyse signals from several sources of the body to understand better the reaction to a specific emotion [P00].

The goal of this Master thesis was to develop a low-cost distributed platform for measurement of different biological signals and demonstrate that results, processed by properly selected machine learning algorithms (MLA), deliver correct results. For this purpose a software framework was developed, allowing to collect sensor data on sensor devices attached to a human body. A wireless Body Area Network (BAN, [LBM11]) was used to synchronize the data from the sensor nodes. The platform was used to perform experiments with subjects exposed to different emotional situations.

Major contributions of the thesis are the design and implementation of a software framework in the TinyOS 2 [LG09] operating system to collect human bio-signals; the design and implementation of a wireless time synchronization protocol to synchronize data from all components of a BAN; characterization of bio-signals using feature extraction; and the study of machine learning algorithms for stress recognition.

2 System Development and Experiments

Some components needed for this project were already available: an operating system (TinyOS 2), wireless body sensors (Shimmer2R, [BGMOKASC10]), and some device drivers were given. ECG (electrocardiogram) and GSR (galvanic skin response) sensors were chosen for their good results showed in other research works focused on physiological responses related to emotions ([HCA11] , [HRB04] , [HNS10]).

The first step of the development was to analyse the hardware and given software. Afterwards a software framework for collecting the bio-signal data was designed and implemented according to the possibilities and limitations of the hardware. The software framework was structured in three main functional parts: a component to sample and get the data from the sensors, a component to store that data on an SD card and a component to synchronize the devices of the BAN; all those parts were coordinated by an application written in nesC [LG09].

There were some synchronization issues to be solved: how to have the same time reference in all devices, how to make this times accurate enough and how to remove the effect of '*clock drift*' (provoked by slightly differences on the oscillation frequency of a clock, compared to its theoretical work frequency). To solve those problems a time synchronization algorithm was designed and implemented in TinyOS 2. The solution proposed is based on a global time reference provided by a device with an accurate local oscillator which is broadcast by a base station to the rest of the BAN nodes in order to

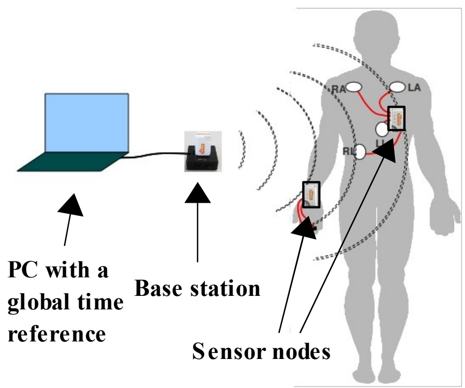

Figure 2. Platform schematic

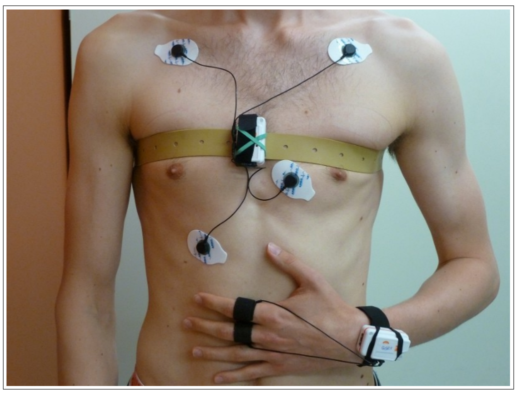

Figure 1.Participant with sensors/electrodes

have a global time equivalence to the node's local time. In the process of sending a timestamp periodically, time delay errors where minimized to the order of milliseconds, which resulted to be an acceptable accuracy for our application.

The platform (see Figure 1) is composed by a synchronization device (a PC), a base station that broadcasts the synchronization packets (Shimmer2R node connected to the PC), and two sensor nodes attached to the body of the participant (one placed in the chest, ECG, and the other one in the wrist, GSR, see Figure 2). After validating and testing the platform's performance, a serial of experiments with 20 participants were done along with experts on emotion recognition (a group of researchers from the Cluster of Excellence '*Languages of Emotion*' from the Freie Universität Berlin). Each participant did two consecutive sessions (of approximately 20 minutes each) with a computer software used by the psychologists. For the period of a session the participant (wearing the body sensors) sat alone in front of a computer which showed a sequence of standardized pictures with emotional content (IAPS, [CBL96]). In the meantime the platform was extracting bio-signals of the participant, so later on the all data fragments (GSR and ECG signals) were assigned to a user and an standardized rating.

3 Stress Detection with Learning Algorithms and Conclusions

Once the data was collected, it was processed by different MLA to analyse their ability to automatically detect stress. MLAs do not use the raw signals to classify entries, but just some properties of the signal, so-called features. Examples of MLA used for emotion detection are [G09], [SKC10], [HCA11], [HCC06]. Before evaluating the algorithms a selection of the features that best characterize the signals was (e.g. RMSSD or SCL) was done. This process was carried out in Matlab along with existing feature extraction and classification libraries. Four steps summarize this process: Parsing and pre-processing the raw data from all participants, feature extraction of the parsed data, training of the algorithms and selection of the most suitable MLA for stress detection (through the analysis of the results). Four MLA were analysed: Bayesian Network, Random Decision Tree, K Nearest Neighbour using No-nested Generalized Examples (NNge) and Lazy IB1 instance based learning algorithm, [DHS01]. In order to train and compare the algorithms a software called Weka [DCS11] was used.

Instance-based algorithms (Lazy IB1) obtained the best results of classification, using a multimodal combinations of features (4 features: two GSR and two ECG features) to classify the data, with an accuracy of 69%. Better accuracies were obtained but with a worse performance in detecting stressed situations (instead they had a better detection of non-stress situations). Percentages of detection (slightly lower than in other experiments related to emotions) are considered to be improved by having a more even amount of stress and non-stress situations (50%-50%), normalizing the features extracted and having a bigger amount of experiment's data (just 75% of ECG and 40% of GSR experiment's data could be used for classification).

Although the system has limitations and further research needs to be done to perform a more precise emotional features classification, this project and its experimental results show that physiological signals (ECG and GSR) provide a promising basis for detecting emotions. It also confirms that multimodal systems improve the accuracy of the detection, in response to the high complexity of emotions themselves. Future lines of work are suggested to improve the flexibility and accuracy of the platform (for example the design of a GUI for the platform, the replacement of the PC with a smartphone or the use of a more interactive psychological test).

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