Wearable sensors to detect seizures and attacks - challenges of data gathering

Pekka Siirtola *, Heli Koskimäki *, Henna Mönttinen *, and Juha Röning *

Abstract: The wearable sensor market is currently one of the most rapidly growing area in consumer electronics. One of the most interesting application field for wearable sensors is early detection of diseases, seizures and attacks as it would save a huge amount of money from society. In order to train reliable recognition models for these purposes, a high quality training data needs to be collected. This study concentrates on challenges on gathering such data set based on our own experiences when collecting data using wearable sensors to detect migraine attacks.

Key Words: Wearable sensors, early diagnosis, data gathering

1. Introduction

The wearable sensor market is currently one of the most rapidly growing area in consumer electronics. In research perspective, this has enabled that wearable sensors based recognition (activities, gestures, symptoms, diagnosis) to become one of the fastest developing areas of machine learning. The remarkable progress in the actual sensor development including improved memory and battery properties has made possible to measure human physiology 24/7, and more importantly with such accurate readings that have previously been possible only in laboratory settings.

One of the most interesting application field for wearable sensors is early detection of diseases, seizures and attacks. For instance, in [1] epileptic attacks were predicted based on heart rate variability which can be measured optically using wearable sensors. Heart rate variability has been used to recognize other disorders as well. In [2] it was used to screen sleep apnea.

Other wearable sensors have been used to early diagnosis as well. In [3] accelerometers, gyroscopes and magnetometers were used to detect Parkinson disease. In addition, migraine attacks have been recognized beforehand in [4]. This was done using data from finger-held SpO2 device and ECG patches attached to chest.

These kind of applications have a huge market potential. For instance, it is estimated that 15% of people in developed countries suffer from migraine and the yearly costs of these in Europe are 111 Billion Euros [5]. By helping just a fraction of those people, huge savings can be achieved to society not to mention the improvement of quality of life of the actual patients.

In this study, challenges related to data gathering are discussed when the aim is to collect the data using wearable sensors and use it to early detection of seizures and attacks.

* Biomimetics and Intelligent Systems Group, P.O. BOX 4500, FI-90014, University of Oulu
E-mail: pekka.siirtola@oulu.fi
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2. Sensors to measure biosignals

Wearable device can include a wide range of sensors. These include accelerometer, gyroscope, magnetometer, photoplethysmography (PPG), temperature and electrodermal activity sensors.

Photoplethysmography (PPG) sensor is used to measure blood volume pulse. Blood volume pulse can then be used to calculate heart rate and interbeat interval which is the time interval between individual beats of the heart.

Electrodermal activity (EDA) depicts skin's electrical changes caused by sweating. When sweat pores fill with sweat, the conductivity of skin increases. As the sweat secretion of skin is sympathetically controlled, sympathetic arousal can be detected as increasing skin conductance [6].

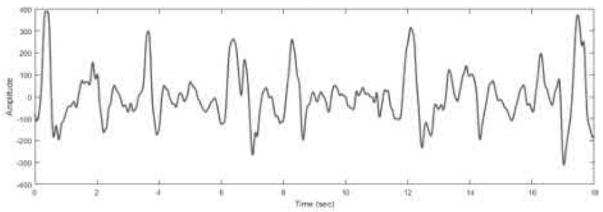
Skin temperature is measured with a infrared (IR) thermopile that detects the temperature difference between an IR absorber and a reference [7]. The skin temperature has a close connection with skin blood flow and changes in the skin temperature may affect to electrodermal activity [6].

With accelerometer, magnetometer and gyroscope the movement of the object / limb it is attached can be measured. These signals are highly dependable of the sensor location and the human in question, so their usage has to be handled carefully.

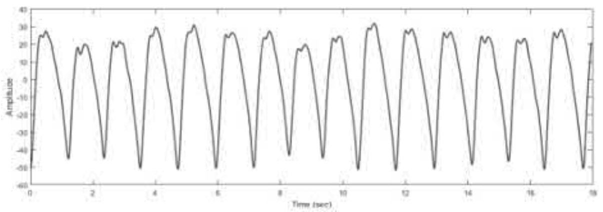
3. Challenges of data gathering

This section is based on experiences we had when gathering data using a wrist-worn device to recognize migraine attacks beforehand. However, the faced challenges are not tightly related to migraine as a disease, and therefore, the same challenges should be noted when data is gathered from any other disease as well.

Challenges can be divided into three categories. They were related to (1) usability of device, (2) amount of data, and (3) quality of data. Usability issues like poor battery life, and problems with uploading the data are not discussed here as they are related to the used device and when other devices are used the problems are not necessarily the same.



(a) Blood volume pulse while person moves.



(b) Blood volume pulse while person sleeps.

Fig. 1 Physical activity disturbes biosignal measurements.

3.1 Quality of the data

Without high quality training data there is no high quality, reliable, recognition models. The data is of high quality when it is accurate, correct and truthful. Unfortunately the data gathered during our data collection session did not always fulfill these requirements. When predictions are made about the status of human body using wearable sensors, biosignals such as heart rate, heart rate variability, temperature and galvanic skin response are often in more important role than inertial sensors such as accelerometer, magnetometer and gyroscope which can be instead used to measure movement. However, it wan noted that physical activity can cause a lot of disturbances to biosignals, measurements become unreliable or in the worst case they are totally missing. This was especially noticeable in the case of heart rate variability signal. In fact, there were long intervals where this data was not available at all because movement caused by physical activity had disturbed measurements. Heart rate variability is calculated from blood volume pulse, and Figure 1 shows examples of blood volume pulse signal while the person is moving and while he is sleeping, and therefore, not moving. It is clear that variability calculated from Figure 1(a) is not reliable and using it can cause false positive and false negative predictions. Because of these problems, it was not possible to use data from these intervals in the recognition process.

To overcome the data quality problems caused by physical activity, we pre-processed the data set so that it includes only sleep-time data. The advantage of using sleep-time data is that during sleep people are mostly still, and therefore, it does not include disturbances caused by movement which can be easily seen from Figure 1(b). This makes sleep-time data highly reliable and usable to detect early symptoms of seizures and attacks.

3.2 Amount of data

In addition to quality of data, also the amount of data is important. In order to train reliable models, a decent amount of data needs to be collected. In addition, when the aim is the early detection of seizures and attacks, data needs to be collected from healthy periods but similarly data is needed to gather during seizure and early symptoms of it. The problem from the data gathering point of view is that seizures and attacks do not occur often. For instance, in the case of migraine some patients have attacks only once a month. Therefore, the study subjects for the data gathering should be chosen so that they have attacks more frequently, for instance bimonthly, to get decent amount of data from both healthy and non-healthy days. Still this leads to very long data gathering session and highly imbalanced data set which needs to be considered in the model training phase.

Another factor that needs to be noted is that not all seizures and attacks are the same, in fact, symptoms can be highly personal. For instance, migraine types can be divided into 6 main categories, and each of these into several sub-categories. Therefore, in order to train user-independent recognition model, data needs to be collected from a huge number of study subjects. Other option is to train personal recognition model for each subject. This approach requires data gathering session from each new user which means that device the detect seizures and attacks beforehand would not be usable out-of-the-box.

4. Conclusion

Early diagnosis of seizures and attacks using wearable sensors has a huge market potential. To build reliable recognition models, we need an extensive and high quality training data set. This study concentrated on challenges of data gathering. It was noted that movement causes a lot of disturbances to biosignals making it unreliable. Therefore, we suggested to base the recognition to sleep-time data as people are mainly still while sleeping. Moreover, it was noted that the amount of data can be as issue. Seizures and attacks do not occur very often making data set imbalanced and data gathering session long. In addition, symptoms can be highly personal, and therefore, data should be collected from a huge number of study subjects or the models need to be user-independent.

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