Real time data acquisition system for activity recognition using motion and physiological sensors

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Abstract—**In this paper we present the implementation of an activity recognition system based on a data acquisition system with sensors for acceleration and physiological parameters. In order to recognize more complex activities we need data acquisition from multiple sensors. Based on our previous experience gained in designing acquisition systems for activity recognition, we have designed and developed a system with three sensors. We developed two possible configurations: one using three acceleration sensors, and one with two acceleration sensors and one heart rate sensor. In the experimental phase we found that the third accelerometer that we've placed on the waist does not provide relevant data to improve the rate of recognition significantly. Thus we opted for the second option, considering that the integration of a physiological sensor provides additional information regarding activities, health status and detecting abnormal states. Starting from the experimental phase, we designed and developed a module integrating the three sensors, with additional functionalities such as an SD card to store the acquired data, and a Bluetooth module for connect to portable devices. In addition, we have integrated a RTC (Real Time Clock) module in order to add time label.**

Keywords: activity recognition, acceleration sensors, heart rate sensor, data acquisition, neural network.

I. INTRODUCTION

Taking into account the references studied, the requirements of such systems, we designed and implemented several data acquisition systems. In designing of these systems, we considered the following issues [11]:

- The number and type of sensors used
- Sensors placement on the body
- The minimum required level of usability
- Power consumption of wearable system
- Further data processing possibilities
- User interfacing

In data acquisition systems for activity recognition two categories of sensors are being used: wearable sensors and environmental sensors. Wearable sensors can be divided into inertial sensors and vital sign sensors (or biosensors). These sensors can be attached to the human body either directly or indirectly and usually provide a continuous flow of information. Environmental sensors may be deployed on a range of objects in smart home environments for monitoring user's movements and location and can be [1]: simple binary sensors, state-change sensors, motion sensors, contact switches and pressure sensors. A variety of other sensors such as: temperature sensors, light sensors, humidity sensors or power sensors have been also used in smart home environments to help in the detection of activities

In real-world scenarios using a single sensor type normally cannot provide enough information for detecting activities, especially for some complex ones, thus multiple sensors are needed to provide more accurate information related to activity monitoring. Accelerometers are the most frequently used sensors for ambulatory activity monitoring [2-11]. Data collected from accelerometers has four attributes: time, acceleration from x-axis, acceleration from y-axis and acceleration from z-axis.

In our experiment, presented in this work, we use two three-axis accelerometer built into a eZ430 Chronos smart watch produced by Texas Instruments and one heart rate sensor built in a chest belt. The accelerometer is used to measure the acceleration of the body in reference to axes x, y and z. Studying a large part of published works addressing this issue [14-20], we placed three sensors, as follows: first one on the right hand (acc1), second one on the right thigh (acc2) and third one on the chest (rc). Our work consist of two main parts: the data acquisition system and the activity recognition system

II. DATA ACQUISITION SYSTEM

In our research the main goal was to design and implement a data acquisition systems capable of acquiring different types of data in real time and to ensure local storage and the possibility of wireless transmission.

A. Hardware description

Our data acquisition system integrates two motion sensors (acceleration sensors) and a heart rate sensor. In Fig. 1 is presented our data acquisition interface which integrates on the same circuit board: the sensors interface, the real-time circuit, a micro SD card and a Bluetooth module. Interface circuit is provided with pins for simple connection to a microcontroller platform by overlapping.

The integration of data acquisition interface module in our data acquisition system is shown in Fig. 2, which presents full system structure. We tested various configurations for our data acquisition system in order to design an optimal system based on hardware resources usage.

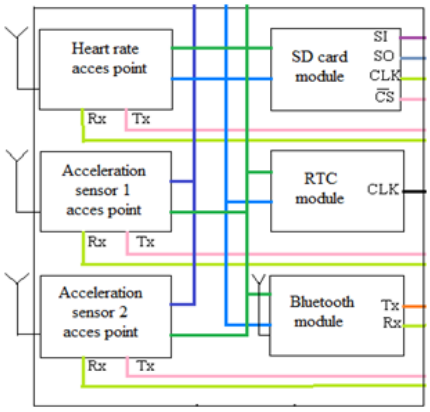

Fig. 1. Data acquisition interface

A first task of our research was to determine the optimum number of sensors and their optimal placement. As we presented in [12] we acquired 600 samples for each activity, from the three acceleration sensors placed on different parts of the body. After several experiments it was obvious that the third accelerometer, besides the fact that it is difficult to wear, it does not improve significantly the results. This is why we haven't used it in further experiments. Removing the third accelerometer enables the further integration of a heart rate sensor. The heart rate data were acquired but have not been used in activity recognition because their use did not increase the recognition rate of the activities. However the usefulness of heart rate data can be seen in a more complex system which enables not only recognition of activities but also health monitoring.

A second task of research has been the design and test of several models in Matlab for recognition of activities in order to find the best architecture and best performance. Using a FF-BP (Feed Forward Back Propagation) neural network architecture with two layers we have obtained recognition rates over 90%.

A third task of research has been related to the need of preprocessing the raw data in order to achieve better recognition rates. As is shown in the literature, data can be preprocessed to get new features such as: mean, variance, energy, correlation coefficients, entropy domain frequency bands Log FFT, etc. After performing several simulations we found that the standard deviation can be used with good results as additional input data for the neural network.

As is presented in Fig. 2 our system has two main parts: a wearable system and a data acquisition system. The wearable system contains two acceleration sensors integrated in smart watches and a heart rate sensor integrated in a chest belt. Data acquisition system contains access points to connect three sensors, a SD card for storing data, a RTC module in order to introduce time label for the data acquired and a Bluetooth module, creating the possibility for connecting portable devices with our system. As we can see the serial ports of the microcontroller are entirely used: Serial 1 for the access point of heart rate sensor, Serial 2 and 3 for accelerometer 1 and accelerometer 2. Bluetooth module is connected on Serial port 0 which is used also as an interface with the PC. System power is provided by an external battery in order to be wearable. SD card module is connected via SPI interface and RTC module is connected through SOSCI pin to microcontroller platform.

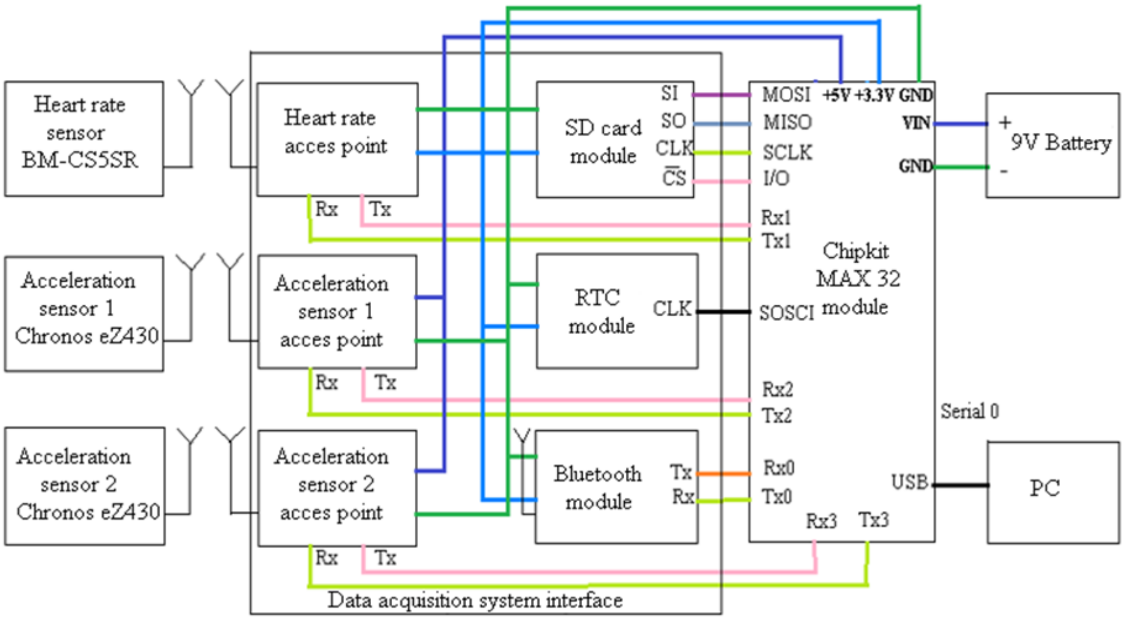

Fig.2. Data acquisition system using two acceleration sensors and one heart rate sensor

The practical implementation of the acquisition system with multiple sensors is shown in Fig. 3.

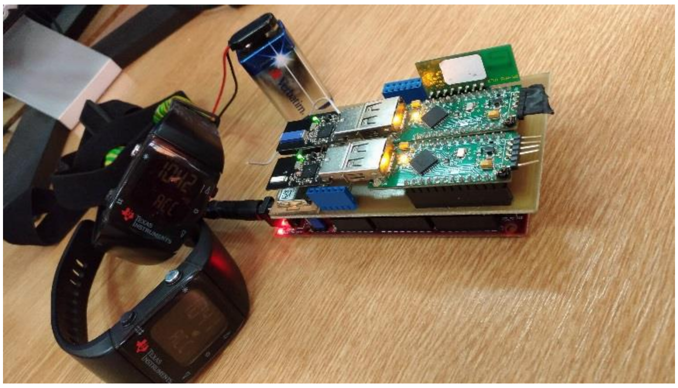

Fig. 3. Experimental platform of data acquisition system using acceleration sensors

B. *Software description*

The software component of this work consists of two main parts: the data acquisition and processing software and the data analysis software. The first part handles data acquisition from the wearable system and its transmission to a PC through a serial port or to an SD card for storing. Data acquisition software was developed using the MPIDE environment. Fig. 4 presents a code sequence for data acquisition from two acceleration sensors.

Fig.4. MPIDE software interface for data acquisition

The structure of the data acquired from our wearable system can include a number of maximum seven data vectors in case of two acceleration sensors and one heart rate sensor. The matrix of data obtained contains on its columns data vectors from: heart rate sensor, V (rc), and the two accelerometers, V(a1x), V(a1y), V(a1z), V(a2x), V(a2y) and V(a2z). Its form is:

$$\text{data} = \begin{bmatrix} rc_1 & a_{1x1} & a_{1y1} & a_{1z1} & a_{2x1} & a_{2y1} & a_{2z1} \\ rc_2 & a_{1x2} & a_{1y2} & a_{1z2} & a_{2x2} & a_{2y2} & a_{2z2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ rc_n & a_{1xn} & a_{1yn} & a_{1zn} & a_{2xn} & a_{2zn} & a_{2zn} \end{bmatrix} \qquad (1)$$

Where *rc* are heart rate values, *a* is the acceleration for three axes, and n is the number of samples acquired (in our case n=600).

III. ACTIVITY RECOGNITION SYSTEM

Same as in our system presented in [12], [13] we have proposed to recognize seventeen activities or postures as follows: standing, sitting, supine, prone, left lateral recumbent, right lateral recumbent, walking, running, left bending, right bending, squats, settlements and lifting the chair, falls, turns left and right, upstairs, down stairs. In Fig. 5 is presented the recognition system structure modeled in System Generator.

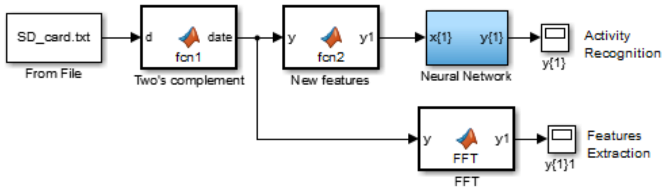

Fig. 5. Recognition system structure modeled in System Generator [13]

The recognition system includes the following functional blocks: Two's complement, New features, Neural network and FFT (Fast Fourier Transform). Two's complement and New features blocks are used for primary data processing and extraction of new features such as media acceleration on three axes and its standard deviation. The most important block of our system is the neural network block, and its configuration was one of the challenges we faced in order to obtain better recognition with low hardware costs. One of the possible structures of the neural network, if we use all data vectors from two inertial sensors, the mean and standard deviation (a total of 11 vectors), is presented in Fig. 6.

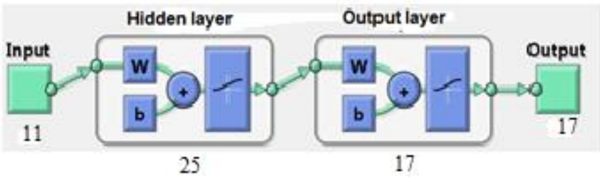

Fig. 6. A possible structure of neural network

For performance evaluation of the neural network several performance functions can be used, the most used being MSE (Mean Square Error). It is also possible to calculate the total number of recognition errors for each activity, which is a relevant parameter for the performance of neural network recognition

IV. EXPERIMENTAL RESULT

After several experimental measurements, we intend to create a database with acquired data. This database will include data from 20 subjects for a total of 20 predefined activities. We aim to be able to compare our database with other similar existing databases. Fig. 7 presents our activity to acquiring data from two subjects.

Fig. 7. Acquiring data from two subjects

A graphical representation of the acquired data for 17 activities is presented in Fig. 8.

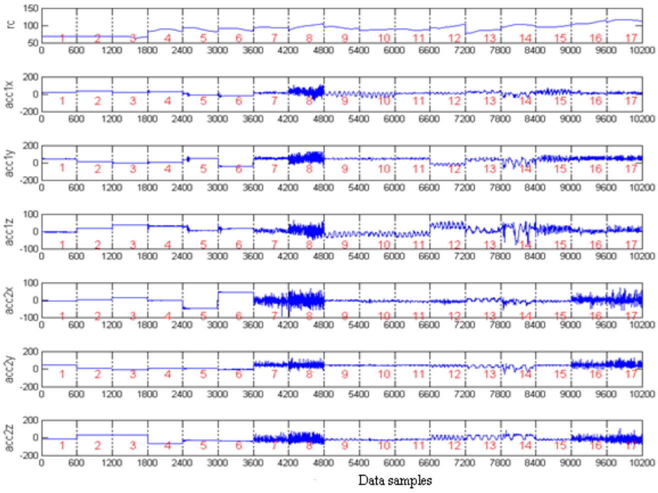

Fig. 8. Graphical representation of the acquired data for 17 activities

V. CONCLUSIONS

In this paper we present a data acquisition system using motion and physiological sensors, for acquiring data related to body position, simple movements and health status.

The presented system allows sensors data to be recorded from a wearable system containing two acceleration sensors and one heart rate sensor in files (for storage and further processing) or real-time tracking of the parameters provided by sensors. This type of system allowed us to create a database for activity recognition.

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