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A MINIMALLY-INVASIVE SYSTEM FOR FREE-LIVING ACTIVITY MONITORING IN HOME CARE

Fabrizio Clemente[1], *Carlo Manna*[2]

[1] Consiglio Nazionale delle Ricerche, Istituto di Ingegneria Biomedica, Roma, Italy, clemente@isib.cnr.it;
[2] Dipartimento di Ingegneria Elettrica, Università degli Studi di Napoli "Federico II", Napoli, Italy, massimo.manna@isib.cnr.it

Abstract – A minimal wearable system to monitoring remotely normal free-living activity (e.g. laying, sitting, standing, and slow walking) of patients in their home space is proposed. Owing to its wireless features, the system can represent a useful tool to be implemented in a long-time patient monitoring system. These systems are useful for the clinical out coming or for minor chronic pathologies not requiring hospitalization.

Keywords: Accelerometer, Biomedical Measurements, Medical Services.

1. INTRODUCTION

Home care allows patients to follow a therapeutic program at their home, while the care giver follows and monitors some biological parameters by the measurement of biomedical data trough instruments connected to the LAN and/or WAN network [1].

The International Classification of Functioning, Disability, and Health of the World Health Organization gives a central role to the identification and classification of the capability to have an adequate quality of life (i.e. what is actually executed in the current life contest). In such a context, monitoring and classifying abilities in performing functional motion task turns out to be crucial. Therefore techniques and methodologies for the assessment of mobility of the patient in his living space for a long time (>24 hours) are required [2].

Daily Physical Activity (PA) shows a large sets of behaviours of very heterogeneous nature (such as seating, standing, walking, cooking, watching television, sleeping, and so on). PA can be classified in light, moderate, hard, and very hard, according to the level of Energy Expenditure corresponding to target activities [3]. Main methods to monitor PA are based on individual recordings or on instrumental monitoring.

The former ones are based on both patient's report (self-compiled questionaries, diaries, logs, and so on) and recurrent exams by professionals or trained staff. As because they are based on patient fatigue perception These approaches are inaccurate [4]-[5].

Among instrumental methods, the use of accelerometric data is largely proposed [3], [6]-[8]. Instruments based on one, two, or tri-axial accelerometer (actigraphy) give information about the movement of the patient. Converting accelerometric data into a quantitative estimate of caloric expenditure or related to a categorical measure of time spent in light, moderate, or vigorous-intensity activity, makes the data more useful for PA monitoring applications [3].

Such approach in measuring PA level is a difficult and complex task [6]. There are different commercially available systems based on accelerometers [3], [7]-[8], such as IDEEA monitor, BodyMedia Armband, or MTI Actigraph, and many algorithms [9]-[11], performing this task from acquired data. The large part of them [12] are too complex to be proposed actually for home care monitoring (because patients have to wear many sensors on legs, arms, trunk etc.). Conversely, they have good performance in monitoring regular PA (such as running, walking, and so on). As a matter of fact, they show limits in evaluating free-living activity (standing, laying, watching TV, and so on), which are the normal tasks performed by patients requiring home monitoring [2]-[3],[7]-[8]. Therefore the problem remains open.

Using a three-axis accelerometer, the most performing algorithm has been proposed by Crouter et al [13]. The prediction equation is composed by two regression lines: one for walking and running (i.e. free living physical activity) and one for all other activity. However, it has been validated only on health young volunteers.

On this basis, in the present paper, a minimally invasive system, able to monitor and classify the main four free-living activities (laying, sitting, standing, and slow walking), is presented.

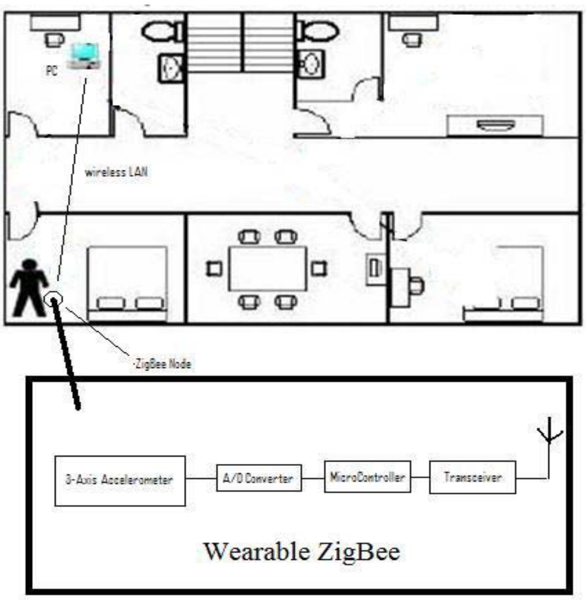


Fig. 1. The use of an actigraph for patient PA monitoring in his living space.

2. BACKGROUND

As said, wireless accelerometry systems have been largely proposed to measure functional activities and performances [14]-[16]. In a free living context, movements are generally not known and unexpected, thus PA must be identified from accelerometric signals.

An accelerometer is a device that produces an electrical output (i.e. charge, voltage, current or change of resistance) proportional to the acceleration to which it is exposed, typically expressed in m/s^2 or in G-values. Piezo-resistive and variable capacitance accelerometers, very frequently used in human movement applications, respond to accelerations due to movements, as well as to gravitational acceleration.

Actigraphs are small, portable electronic devices, based on accelerometers, generating an internal signal each time they are moved. Patients have on the wrist of the dominant arm, or on the waist, devices recording ‘activity’ data for long periods, and summing it over time windows (‘epochs’) to be considered by dedicated algorithms to identify funcional performances.

There are different approaches to classify actigrafy data. The most common are based on threshold crossing, time above the threshold and integrated activity [14] .

Other methods based on reference–pattern classification or pattern recognition have been proposed [9]-[11], [17]

However, as far as the estimate of normal free living activity (sitting, standing and so on) is concerned, many of the current approaches have strong limitation [12].

3. MATERIALS AND METHODS

In the following (i) the *actigraph unit*, and (ii) the *algorithm* of the proposed minimally invasive system for monitoring and classifying up to four free-living activities are described.

3.1 Actigraph unit

The unit is composed of three main components and has been designed for home monitoring of heart failure, such as reported in Fig. 1. The patient has the unit on the belt, and data are locally acquired and sent to home computer unit.

In the following, the main unit characteristics for achieving the required performance are described.

Sensor

Tri-axial sensors must measure acceleration in the range 0.05-2 G, have a band limited frequency of 0.25- 2.5 Hz. These parameters detect normal body motion and filter out high frequency movements such as vibrations The chosen component, LIS3V02DQ from ST, has also an on-board ADC low consumption (0.5 mA), and implements an HW interrupt to switch the system in sleeping mode if not mechanically elicited. Last but not least, the package is small (less than 8x8 mm) and has light weight.

Micro processor

Micro processor based technology offers processors with good performance to be inserted in these systems having low consumption, low cost, and small dimensions. For the present application it has been used a Texas Instrument MSP 430 micro processor, that includes all the hardware and software capabilities required to develop an entire wireless communication protocol.

Transceiver

In biomedical applications, the most used technology is Bluetooth, but it shows some limits, overcome by other technology. ZigBee offers low consumption, is NLOS (No Light of Site) and can be inserted in a network up to 64 nodes to realize a larger monitoring system.

In the present application it has been adopted a Texas Instrument CC2500 multi-channel RF transceiver designed for low-power wireless applications.

3.2 Algorithm

The task of the present paper is to evaluate free living activity (as previously defined) and the classification of the body movements in the different physical position.

Data from tri-axial accelerometer are acquired at frequency of 20 Hz and elaborated by an algorithm based on three step procedure:

i) The recognition of physical position (sitting, etc.)
ii) Classification of body motion
iii) Integration of data

i) The recognition of physical position

In order to recognize the physical position of a patient, the proposed algorithm analyze the following quantity:

$$A = a_x + a_y + a_z \qquad (1)$$

Where a_x, a_y and a_z, are the accelerometer signals.

In Fig 2 the course of the target parameter during the transition from standing to sit position (sit down) (Fig. 2.a) and from sit to stand position (stand up) (Fig. 2.b) are reported. Stand up movement (*transition1* in the following) and sit down movement (*transition2* in the following*)* shows very different shapes.

Hence, defining empirically thresholds, the proposed algorithm distinguish between the two transition (stand up and sit down movement).

ii) Classification of body motion

In order to classify the activity level of a patient, coefficient of variations (CVs), as defined in [13], are computed from accelerometer data in time windows considering an entire single movement. According to [13], values of CV <10 indicate a moderate activity (e.g. slow walking), whereas CV>10 indicate light activities (i.e. laying, standing, sitting).

iii) Integration of data

The overall procedure for classifying the activity is the following:

$$1)\ if \quad (transition1)$$
$$if\ CV < 10\ then \quad (\text{walking activity})$$
$$otherwise\ (\text{stand up})$$
$$2)\ if \quad (transition2)\ then\ (\text{sit})$$

However, the thresholds to identify *transition1* and *transition2* must be tuned according to the age and anthropometric patient data [20]. Thus, in the proposed approach, these levels are patient related.

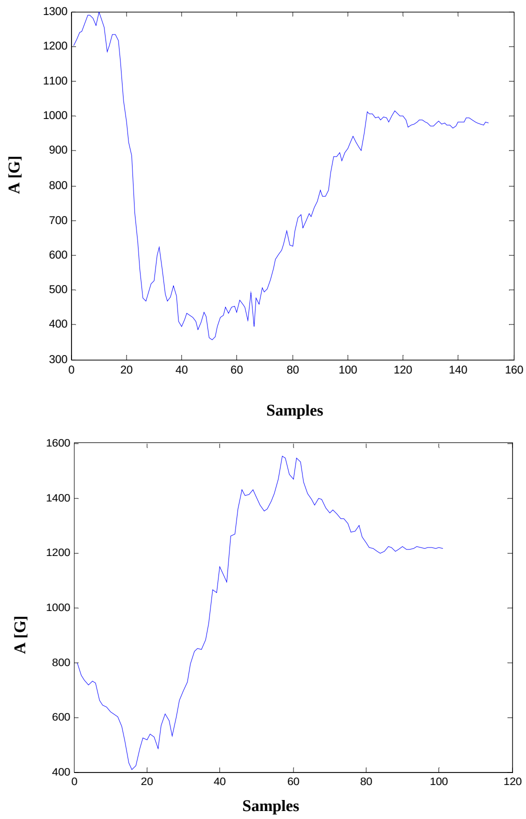
4. EXPERIMENTAL RESULTS

The system has been tested in the framework for a larger project of heart failure home monitoring [22].

A healthy subject (22 years old) performs 10 sequences of movements and activities (laying, standing, sitting, slow walking). Data acquired from the sensor are processed and sent via ZigBee to the PC desktop to be store for further computations.

Results show encouraging performance to detect the considered physical activity.

The validation of the results is currently ongoing.



a) b)

Fig. 2. The computed parameter A vs. Samples (f_c=20 Hz) during (a) stand up movement, *transition1*; (b) sit down movement, *transition2*.

5. CONCLUSIONS

In the present paper, a monitoring PA system able to assess normal free living activity (as sitting, standing and so on), has been proposed. The system is based on wearable low cost, low energy consumption device able to be inserted in a home LAN ZigBee based. A two step procedure to derive from measured data information on the on going PA has been proposed. Preliminary experimental results show encouraging performance.

Finally, such as reported in [18]-[19], for each of the four target activities (laying, sitting, standing, and slow walking), it is possible to get different levels of Energy Expenditure. Therefore future work can be conducted in order to improve the procedure for the Energy Expenditure measurements.

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