Mirosław ŁAZORYSZCZAK, Sebastian PERYT
WEST POMERANIAN UNIVERSITY OF TECHNOLOGY SZCZECIN, FACULTY OF COMPUTER SCIENCE AND INFORMATION TECHNOLOGY
52 Żołnierska Str., 71-210 Szczecin

A low-cost embedded inertial measurement system for the monitoring of human movement

Abstract

The paper presents a part of a prototype system for the monitoring of selected vital functions of humans and some preliminary results obtained from the device using implemented algorithm. The system consists of such essential modules like a microcontroller board, an inertial measurement unit and additional sensors. The main task of the device is human movement monitoring and detecting selected anomalies, e.g. fall or fainting. At the first stage, the movement classification was considered. The main movement type are walking, running and selected variants of transitions between different phases like standing up or going downstairs. The determining of the movement is based on the intuitive algorithm using raw data from accelerometers complemented by sensors like barometer and heart rate monitor. The algorithm utilizes automated multiscale-based peak detection and wavelet transform energy calculations. Finally, some further work directions and development possibilities are discussed.

Keywords: inertial measurement unit, embedded systems, human movement monitoring, sensor networks.

1. Introduction

The human movement monitoring is an issue gaining still in importance in an increasing number of cases. There are many researches that take a particular topic and commercial solutions used for different activities monitoring. However, there is still an area for further explorations. In this paper, the authors present a solution with the Inertial Measurement Unit (IMU) as a part of an embedded system.

IMU is an integrated system consisting of accelerometers and gyroscopes being capable of executing three dimensional measurements of both angular rate and specific force. Specific force is combined gravity force and acceleration measured by the accelerometer during its operation. This is why it is required to have in such a system another set of data from a gyroscope. This kind of a sensor is immune to acceleration and returns only gravitational force which is then subtracted from the accelerometer data resulting actual coordinate acceleration. The second measurement made by IMU called angular rate is a measure of rotation rate.

While in the last few years the term IMU has been used for many inertial systems such as Altitude Heading Reference System or Inertial Navigation System, the classical IMU provides only raw data from a 3-axis accelerometer and a 3-axis gyroscope without any additional navigation.

Due to the rapid development of MEMS systems, an older analog accelerometers and gyroscopes are replaced now by digital ones. This results in much smaller form-factor and lower price. However, the old analog systems provide still much better performance and reliability making them more useful in some areas where a great precision is required.

Inertial measurement systems vary depending on the performance whose meaning can be different for different purposes. In this paper, only consumer grade devices are considered because of acceptable cost to performance ratio.

The main task of the proposed system is the monitoring of several human activities including different types of movement in order to detecting for example abnormal behavior.

2. The human movement monitoring

The complete monitoring of human body requires the tracking of a large number of parameters. The total number of degrees of freedom (DOF) of human body is about 244 [4]. However, only a small subset is needed for the further analysis in case of movement classification. One of the most important issues is to determine where the inertial sensors should be fixed on human's body. The approaches vary in the matter of the device placement, or the methodology of data classification. In [3] the authors explain how the placement of an accelerometer influences the movement and static postures classification. During tests with placing tri-axial accelerometers on waist, thigh and ankle the authors found that the movement could be accurately classified with a sensor placed in any of those positions, although there were some differences in the accuracy. The posture detection requires two sensors – one on the waist and another on the thigh. In general, for human movement detection and classification researchers tend to place measurement units on the user's chest. Some of the examples are [6] and [7]. While researchers still use specially created measurement units from ground up, some are starting to utilize smartphones for this reasons. In [5] or [7] the whole data acquisition is done using those devices. While in [7] the device was placed securely on the subject's back, in [5] the participants were only told to carry their phones in their pants' leg front pocket during various activities. Because of such methodology there is serious possibility of some noises in readings caused only by phone movement in the pocket.

After collecting data, various approaches are used. There are approaches like [2], where the authors tend to use FFT for various movement classification. Others, like [6] or [7], use wavelets. In this paper, wavelets are used only for features extraction for the proposed algorithm of movement classification and anomalies detection. However, the same techniques are used with a wide range of artificial intelligence algorithms for achieving similar results.

3. The prototype system

One of the main goals during design of a measurement unit used for research was its low-cost and high availability of parts. Because it should be worn daily by human it also needs to be small, light and powered by battery.

The main part is a readymade module with 3 MEMS sensors on it known as AltIMU-10 v4 module manufactured by Pololu [1]. The 3 sensors are:

- LSM303D – 3-axis accelerometer and 3-axis magnetometer,
- L3GD20H – 3-axis gyroscope,
- LPS25H – barometer.

The second part of the measurement unit is a microcontroller gathering the whole data and preparing it for sending to an analytical device. The Teensy 3.1 board with ARM Cortex M4 core by Freescale (MK20DX256VLH7) [9] was chosen for this task. The main reasons for selecting this board are small dimensions, low price and relatively fast clock – 72 MHz.

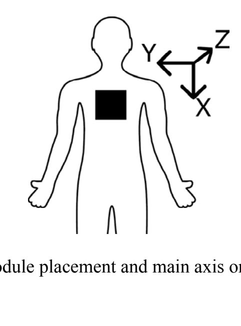

Fig. 1. The embedded module placement and main axis orientation

The last component is a communication module for Bluetooth communication – HC-05. It is a very simple component converting board serial communication to Bluetooth one.

All the modules are placed on a PCB adapter including required connections and a battery. The device dimensions are approximately 8×8 cm with weight below 100 g. These dimensions could be significantly reduced using more compact mount technology instead of standard 2.54” pin headers for easier assembly of the system.

For a user convenience, the measurement device was mounted on the user’s chest as shown in Figure 1. In this position, it should be secured firmly, so that some noise caused by self-movement of the unit during the user’s movement is reduced significantly. Axis description in Figure 1 represents the axis of the mounted accelerometer.

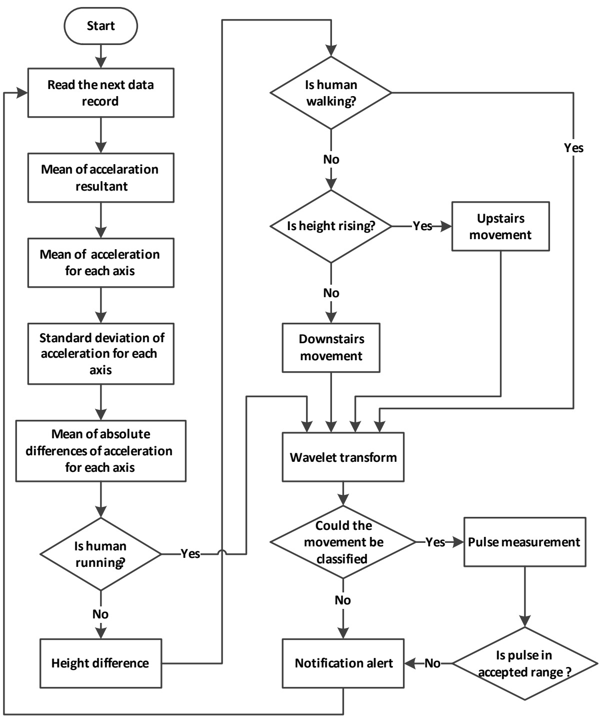

Fig. 2. The proposed algorithm for movement type determining

The main algorithm used for movement classification is presented in Figure 2. One of the features utilized for movement classification task was wavelet transform and wavelet energy. This technique is widely used in research of movement classification as it can be seen e.g. in [7] or [6].

Using equation from [7] it is possible to calculate total wavelet energy at a decomposition level i with A for approximation and D for the detail coefficient:

$$E_T = A_i A_i^T + \sum_{j=1}^{i} D_j D_j^T \qquad (1)$$

Next, the resulting value can be used to calculate two differentiating parameters describing the signal – EDR_A and EDR_{Dj}. They are calculated using the equations:

$$EDR_A = \frac{A_i A_i^T}{E_T} \qquad (2)$$

$$EDR_{D_j} = \frac{D_i D_j^T}{E_T}\ for\ j = 1, \ldots, i \qquad (3)$$

In [7] it has been proved that the normalized variance of DWT decomposition components as well as the normalized values of EDR components are very good parameters for distinguishing similar signals.

4. Experimental results

The goal of this research was to classify six types of movement: standing up, sitting down, walking, running, going upstairs and downstairs as well as triggering alarm in case of anomaly detection. Measurements were made on people of different gender (male and female). The data used for illustration purposes was collected from the people of similar age and physique. All the data were gathered from the measurement device as a raw accelerometer and gyroscope readings by a mobile device and later analyzed using Matlab.

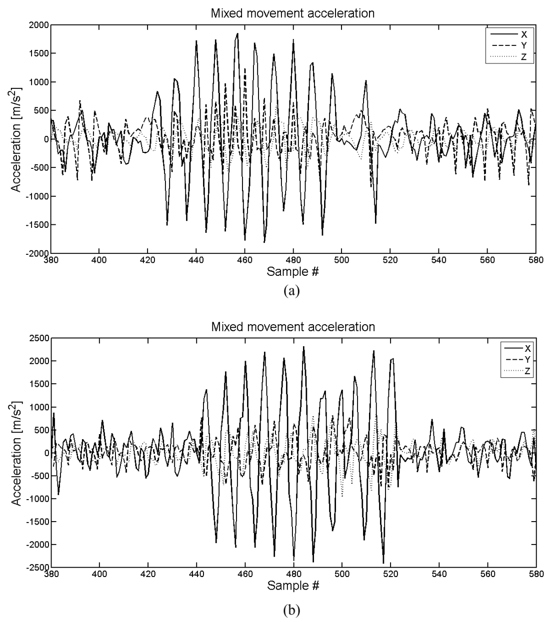

Fig. 3. The accelerometer data for three axes and selected male (a) and female (b) for different movement types

The first part of research was to gather and test all the movements separately. For this, each of the mentioned movements was repeated 50 times. On this data set an initial classification was made to distinguish the features of each movement type.

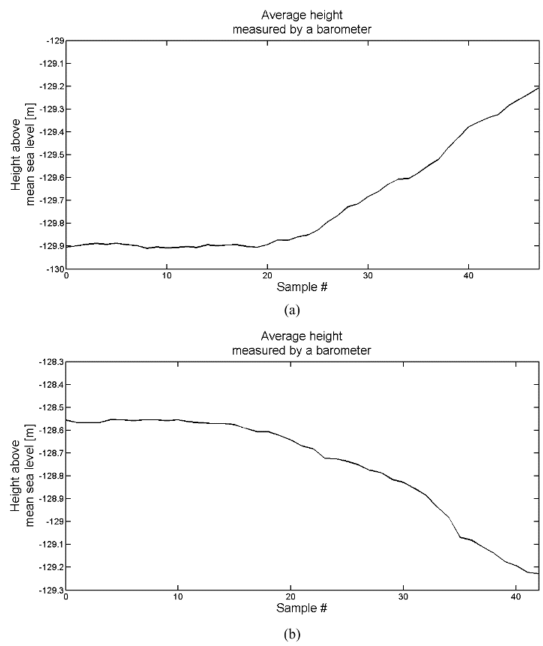

Fig. 4. Examples illustrating the results of height measurements using the barometer for going upstairs (a) and downstairs (b)

The next step was to record some mixed movements and analyze the results using the proposed algorithm.

To distinguish movement types in the evaluation phase, three different approaches were used. The first one was accelerometer data used to distinguish mostly running from other activity types. In Figure 3, the increased acceleration on all the axes around 440 – 500 sample is visible. This was the starting point when the users were asked to run. The especially high amplitude can be seen on X axis because it is the vertical axis of the device.

As the next classifier, the barometer measurements were used to classify ascending and descending based on the height above the sea level relative to the starting position. Due to the relativity of measurements taken, the whole system was protected from a possible reading error through a longer period of times due to ambient pressure changes. As opposed to the accelerometer and gyroscope reading, the barometer data was compared in two-second windows. The sample outcome plotted for going up and down the stairs are shown in Figure 4.

Tab. 1. Selected section of table used for best mother wavelet and decomposition level selection

	Daubechies 4	
Decomposition level	EDR_A	EDR_D
2	131.48%	115.64%
3	47.07%	106.04%
4	30.41%	88.50%
5	27.42%	71.67%
6	27.27%	63.04%

Key elements while using the technique mentioned in Section 3 is peaking the correct (that is giving best results) mother wavelet and decomposition level. The average value of the standard derivative from the average of all EDR_A and EDR_{Dj} for a given level was used as a grading criterion. To better see which result was the best, the percentage value of the standard derivative in the average value was used. The results for Daubechies 4 are collected in Table 1.

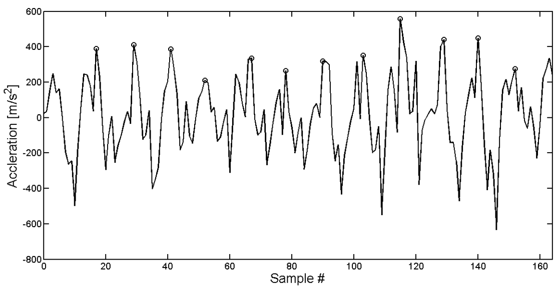

Fig. 5. The peaks detected by the AMPD algorithm

The best classification results can be obtained when combining the mentioned techniques and eventually adding the additional ones. Such additional parameters could be time between local maxima of a signal calculated by automated multiscale-based peak detection (AMPD) described in [8].

Knowing the repetitive movement tends to generate periodic signal, this algorithm allows detecting peaks and using additional information to better classify the results from the previous classifiers. A sample result from one of the axes with dots representing the detected maxima using AMPD is displayed in Figure 5.

5. Conclusion and further work

The presented paper describes selected aspects of human movement monitoring by embedded devices built from widely available development modules. The system is not very sophisticated, it is even less complex than contemporary smartphones. There are also potentially significant opportunities to optimize the device in terms of size and power consumption. However, the system was conceived mainly as a development platform for further research because its set of features could be easily extended including increase in the number and/or type of sensors. Such a solution allows selecting the type of communication between the host and sensors (e.g. a wired or wireless) depending on several requirements including medical indications. On the other hand, support for additional sensors enables closer monitoring of the human condition and better detecting of potential anomalies.

6. References

[1] AltIMU product page, https://www.pololu.com/product/2470.

[2] DeVaul R., Dunn S.: Real-Time Motion Classification for Wearable Computing Applications. Project paper, 2001, http://www.media.mit.edu/wearables/mithril/realtime.pdf

[3] Fortune E., Lugade V., Kaufman K.: Posture and movement classification: the comparison of tri-axial accelerometer numbers and anatomical placement. Journal of Biomechanical Engineering, Vol. 136, May, 2014, pp. 0510031–0510038, doi: 10.1115/1.4026230.

[4] Kou A. D.: A mechanical analysis of force distribution between redundant, multiple degree-of-freedom actuators in the human: Implications for the central nervous system, in Human Movement Science, No 13, pp. 635-663, Elsevier, 1994.

[5] Kwapisz J., Weiss G., Moore S.: Activity Recognition using Cell Phone Accelerometers. ACM SIGKDD Explorations Newsletter, Vol. 12, Issue 2, December 2010, pp. 74-82.

[6] Lockhart T., Soangra R., Zhang J., Wu X.: Wavelet based automated postural event detection and activity classification with single IMU (TEMPO). Biomed Sci Instrum. 2013, Vol. 49, pp. 224-233.

[7] Mitchell E., Mongahan D., O'Connor N.: Classification of Sporting Activities Using Smartphone Accelerometers. Sensors, Vol. 13(4), pp. 5317-5337, 2013, doi: 10.3390/s130405317.

[8] Scholkmann F., Boss J., Wolf M.: An Efficient Algorithm for Automatic Peak Detection in Noisy Periodic and Quasi-Periodic Signals, Algorithms, vol. 5, issue 4, pp. 588-603, doi:10.3390/a5040588,

[9] Teensy 3.1 product page, https://www.pjrc.com/teensy/teensy31.html.

Received: 25.09.2015 Paper reviewed Accepted: 03.11.2015

Mirosław ŁAZORYSZCZAK, PhD

Mirosław Łazoryszczak is an assistant professor at the West Pomeranian University of Technology Szczecin, Faculty of Computer Science and Information Technology. He received his PhD in 2006. His research interests include embedded systems, and application of programmable devices.

e-mail: mlazoryszczak@wi.zut.edu.pl

Sebastian PERYT, BSc

Sebastian Peryt is a 5th year student of Computer Science at the West Pomeranian University of Technology Szczecin, Faculty of Computer Science and Information Technology. His research interests include embedded systems and signal processing.

e-mail: speryt@wi.zut.edu.pl