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Embedded Sensors in Monitoring of Human Daily Activities

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Abstract The aim of the paper is to describe some results from experiments with embedded sensors using inertial sensors as wearable sensors. Authors were involved in last years in the development of ICT services for monitoring of elderly persons daily activities monitoring, and their home environment status monitoring and control as well.Main goal of the current research interest is to add embedded sensors to mentioned services for monitoring of the critical physiological parameters to get more information about users' behavior and critical situations.

Keywords: *wearable sensors, social service, inertial sensor, experiments*

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1. Introduction

Wearable sensors are continuously emerging over last decade and they are presenting important innovation tool for services associated with healthcare. There are several typical applications of wearable devices such as fall detection [1,2], distance walked and indoor positioning [3,4] or physiological parameters, e.g. blood pressure or ECG [5]. Ageing population [6] in developed countries opens an important topic, how to enable suitable and economically feasible health and social care using new unobtrusive technology for new type of social/health care services.

In our laboratory, we are trying different technology, preferably a wireless technology to assist in services for elderly and other vulnerable persons too. The key parameters for long-term monitoring of user's states based on measurements provided by wearable sensors were proposed to innovate existing laboratory system equipped with stationary sensors and actuators. For selected parameters, the framework for processing and evaluation of measurements was developed and its usability was examined in living lab – lab that simulates household's conditions. Emphasis was on the robustness of the solution as well as on its applicability in various conditions. The attention was paid to complementary data procession from several sensors with intention of minimization of divert distortive effects or with intention of undesirable sensors' properties.

Our research approach follows the rules for an effective work aiming in fast implementation of the applied research into real life. Therefore, we concentrated on existing technology on the market and related services [6,7].

Current situation on the market with embedded technology and services offers several partial solutions based on the implementation of new functions into smart watches, mobile phones or tablets. There are quite complex solutions between them like PAMSys, PLUXbiosignal, Simmer, Sensoplex, etc. (Karchnak 2015) [8].

However, there is still a space for the development of more complex services with affordable prices for the group of vulnerable persons.

2. MEMS Sensor Development and Trials

Our research group developed a sensor based on MEMS technology originally intended for tracking of a remote controlled car model. Later, we have been looking for other applications like assessment of a person's mobility and her/his range of motion [6,7,8]. As we had already used optical methods for human motion analysis in our laboratory, we decided to use MEMS sensor for a persons' motion abilities evaluation because we expected more simple measurement and data evaluation too. The further step after measurements of biomechanical and kinesiological parameters was to include such sensor into technology for monitoring of a person's physical activities and states.

2.1. Design of the Sensor

A small circuit board was developed aiming in minimizing of sensor size (PCB). Our functional sample was double-sided board PCB, and after adding other units our prototype got a cover too as shown in Figure 1.

Figure 1. IMU prototype

As sensor of acceleration, we used 3-axial accelerometer MMA7431 from FreeScale and gyroscope ITG3200 from InvenSense for angular velocity sensing. As control unit, we used microcontroller ATMEGA32L.

Communication of prototype with PC via USB is provided by FT232RL chip. Device communicates with PC via USB that is serving also as power supply. For implementation of wireless technology, UART pins RX and TX are ready. [9]

Implemented accelerometer MMA7431 is analog device, so MCU has to convert data to digital form utilizing its 10bit ADC. Gyroscope ITG3200 has 16-bit ADC on-chip, so the digital output can be send to MCU using I2C. As mentioned above, UART is employed for communication – FT232RL for USB or XBee, etc. Data is coded into a communication chain that is designed according to the following form:

$, x, y, z, T, 255, XX, YY, ZZ, 13, 10

Where:

$ - is the beginning of the chain,

x, y, z – are incoming raw acceleration data

T - is output of temperature sensor on gyroscope

255 – is separator character

XX, YY, ZZ – is gyroscope data

13, 10 – is end of the chain

Each of incoming sensor data are encoded by two bytes – high and low. These data need to be compiled and converted into one number and processed after that. Testing of device was performed using USB for communication as well as using wireless technology.

2.1.1.Monitoring of critical situations - monitoring scenario

A very important issue for a successful monitoring is an optimal selection of a scenario. Variety of wearable sensors and their functions enable different innovative solutions adjusted to specific type of persons and their environments. Monitoring of daily activities is now commonly integrated with functionalities oriented on long time monitoring of physiological parameters served for the health care aims. Clients then may stay at home and in the same time their basic functions are under supervision. In such way, wearable sensors offer important information about health conditions, activities of clients, and their behavior.

Analysis of the long time collected data enables identification and even prediction of a critical health situation. For example, changes in gait speed, and hip extension may indicate a negative changes in health conditions related to a person's mobility. Such data may play an important role in the health and social care systems, especially for vulnerable persons, elderly including.

The main goal for implementing of wearable sensors is to enable identification of dangerous behavior, or health status of vulnerable persons without creating an obstructive home environment. In the same time such service will improve safety, self-confidence, and well-being of users. Such complex goal may be reached by the integration of wearable sensors into the intelligent environments, where stationary sensors network exists, and control system provides supervisory tasks and actions.

2.2. Complex Supervising System

The general structure of a complex supervising system consists of:

1. Stationary sensors of environment.
2. Wearable sensors for motion activities and physiological parameters.
3. Communication interfaces.
4. Techniques for data processing and evaluation.
5. Models of user's behavior and actual behavioral analysis to discover significant changes.

Monitoring of users living in a supported environment is a subject of many research projects. Many of them are focusing on the design of complex supervising system. However, many of them stress a specific role of such system like saving energy [10,11,12], recognition of individual users, and monitoring of users health status [13,14,15,16,17]. For example, the system may identify possible Parkinson's disease in behavioral changes of a person like slowing medium walking speed, and changes in hip extension [18]. Above mentioned researchers apply different methods for data analysis. Basically, the system may work in the following structure shown in Figure 2.

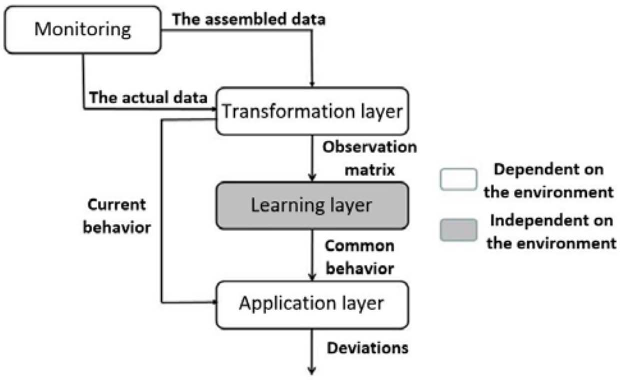

Figure 2. System architecture for detection of changes in user's behavior (adapted from [15])

2.2.1.Wearable sensors role in the monitoring scenario

Stationary sensors play an important role in monitoring of the environmental data like temperature, lighting, energy consumption, but also for identification of daily activities of users. Embedded wearable sensors add more personal information dealing with health status or critical situations during physical activities – fall, etc. Therefore both kinds of sensors are important for identification of critical situations, and behavioral changes too.

Wearable sensors usually offer the following data:

- Numbers of steps per day n(i).
- Medium walk speed v(i).

- Medium step lengths l(i)
- Energy consumption e(i)
- Percentage of time spent in static and dynamic activities a(i).
- Total time of dynamic activities t(i).
- Extension in hip joint r(i).
- Numbers of activations of the panic button p(i).
- Part of the room space where user spends majority of time during day q(i).

Wearable sensors must be warned all the day. In the case of a critical accidental situation, a signal is generated and sent to supervising system (social centre with 24 hours service, or a member of family, etc.). Potential dangerous situations and necessary actions are described in the next chapter.

2.2.2.Classification of Critical Situations

Definition of dangerous and potentially dangerous situations depends on many factors. Analysis of human motion activities offers prediction of many dangerous health critical states. In Table 1, we summarized the most frequent acute statuses and raised actions:

Table 1. Classification of dangerous, potentially dangerous situations

Acute state, potentially dangerous	Action invoked
Lower number of steps comparing to the long-time average value	Inspection from a health centre and/or a carer, identification of a reason, motivation to increase physical activity
Larger angle in hip extension	Inspection from a health centre or a carer, identification of a reason, treatment/rehabilitation
Lowering walk speed	Examination by a medical doctor, assessment of a fall risk
Greater variability in the step length	Examination by a medical doctor, and neurological specialist
Lowering a ratio of time spent in dynamic activities	Inspection from a health centre and/or a carer, identification of a reason, motivation to increase physical activity
Permanently raising time of lying in the bed	Inspection from a health centre and/or a carer, identification of a reason, motivation to increase physical activity
Fall detection	Complementary inspection, sending an alarm message, inspection by a carer, when accident repeats examination by a medical doctor, and proper treatment/rehabilitation, removing barriers at home

There is a relation between less walking intensity - lowering number of steps, length of walk, and walk speed- and fall risk; variation in step length and in the same time increasing of hip extension may indicate the Parkinson disease. Increasing time spent in the bed may indicate a depression, or great mobility problems, etc. These are reasons to monitor above mentioned parameters, evaluate them in long time period, and provide actions when necessary.

3. Experimental Testing

Fall detection plays an important role in vulnerable person's life. Fall is the main reason of many injuries, even deaths, especially in elderly population. Fast reaction and contacting of caregivers or family can save life of injured person. There are many different ways how to recognize the fall, however utilizing MEMS sensors has following advantages:

- device is small and reliable,
- device can work remotely,
- capable of employing the smart algorithms,
- low cost device.

3.1. Fall Detection Device

Development of reliable and robust algorithm of fall detection is crucial. One of the possible ways of fall detection is comparison of absolute value of acceleration to the threshold and after passing this threshold follows computation of the tilt. For such sensing, one triaxial accelerometer is sufficient. Accelerometer senses gravitational vectors in each axis. Amplitude of measured gravity changes its value as sinus α between sensing axis and horizontal plane (Figure 3).

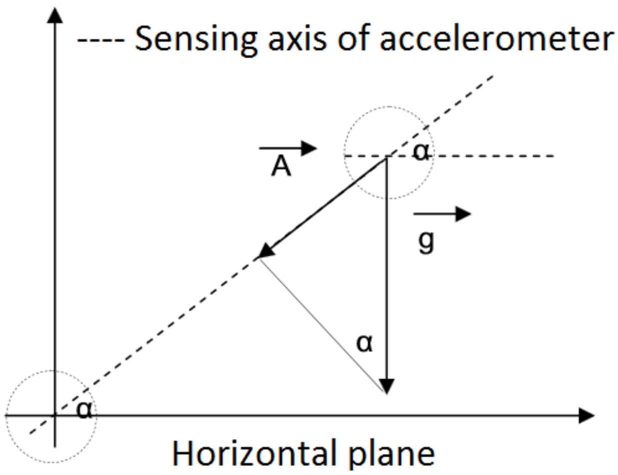

Figure 3. Sensing axis and horizontal plane

Our device contains 3-axial accelerometer and gyroscope. Accelerometer provides information about higher acceleration values that can indicate fall. But similar information gives also a jump, or stair climbing. Gyroscope provides us with angular velocity and we can derive tilt value from that too. By combining these data – acceleration, angular velocity and tilt, we obtain complex motion information. Setting the appropriate thresholds for each parameter is of utmost priority.

According to the possibility of obtaining information about acceleration, angular velocity and tilt, we proposed simple fall algorithm (Figure 4). Absolute value of acceleration with frequency of 20Hz is monitored, and if it passes threshold $|A_T|$ then the following 30 samples are monitored for passing two other thresholds – angular velocity threshold $|\omega_T|$ and tilt threshold $|\theta_T|$. If all conditions are true, then a fall has occurred with a high probability.

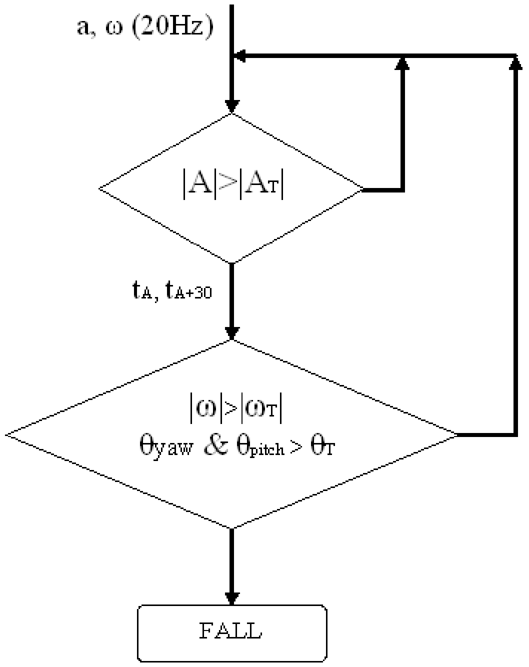

Figure 4. Fall detection algorithm

To verify proposed algorithm, we performed experiments. IMU was placed on the belt of the proband. During experiment, data was sent to PC with frequency of 20Hz. Person was walking on the floor, with little disturbing elements such as small stairs, and after more than 25 seconds asimulated fall occurred. Our threshold parameter settings were following: $|A_T|$=2,5g, $|\omega_T|$=300°/s, $|\theta_T|$=45°. These thresholds were set by empirical testing. Graphical interpretations of experimental data are shown in Figure 5.

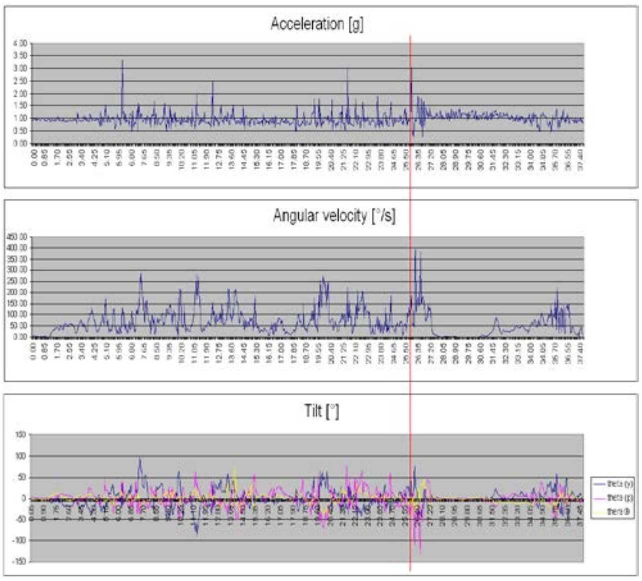

Figure 5. Visualized data from experiment

The device has to be reliable, it is essential to detect true alarm and neglect false ones. We decided to assess reliability of proposed algorithm as a ratio of false alarms to all alarms, as in (1):

$$r = 1 - \frac{A_F}{A_A} \quad (1)$$

where r – reliability, A_F – number of false alarms, A_A – number of all alarms

Results were satisfactory – reliability was r=0,91. We assessed feasibility of acceleration as determinant of fall detection using (1), but results were not satisfying at all (r < 0,6). It means that acceleration itself does not provide enough information for fall detection. Consequently, using of appropriate sensor combinations and data fusion as angular velocity and tilt are essential. Acceleration data as a trigger for further assessment of other movement elements (e.g. angular velocity) seem to be acceptable and suitable solution.

Proposed algorithm was created in C++ and implemented into PC application for fall detection. In our future work we plan to apply various wireless technologies, such as XBee for communication of fall detector with control system. System will run on Raspberry Pi due to its low cost and appropriate properties.

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