Detecting Human Motion: Introducing Step, Fall and ADL Algorithms

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Abstract. Telecare is the term given to offering remote care to elderly and vulnerable people, providing them with the care and reassurance needed to allow them to keep living at home. As telecare is gaining research interests, we'll introduce a system which can be used to monitor the steps, falls and daily activities of high risk populations in this paper. Using this system it is possible for a patient to rehabilitate at home or for elderly to keep living independently in their own house while they are still monitored. This leads to a huge cost reduction in health services and moreover it will make patients satisfied for being able to live at home as long as possible and in all comfort.

Keywords: MEMS, Step Detection, Fall Detection, ADL, Freescale.

1 Introduction

Elderly people are the fastest growing segment of the population. Due to Europe's population pyramid, aging people are becoming a point of interest even faster than in the rest of the world. In 2035, one third of the Europeans will be more than over 65 years old, which will result in huge strains on health care services [5]. This will also cause a serious social and financial problem. Care centers will have to deal with a lack of rooms and cost reduction will become one of the most important objectives in public health services [5]. One of the possible solutions is to comply with the wish of elderly to keep living at home independently as long as possible. As we do this, an increasing number of high risk populations will be living alone at home. Therefore new advanced monitoring systems are gathering more research popularity. Not only for the elderly, but also for other high risk populations (people su_ering from illnesses such as epilepsy or Alzheimer or in the case of recent surgical intervention) will long-term monitoring become an issue.

In this paper we will describe a system based on 2 tri-axial accelerometers to detect the Activities of Daily Living (ADL) of a patient and to detect its steps and falls. In the first part we will focus on the most appropriate position of the sensor on the patient's body in order to receive clear signals of their movements. Furthermore we will describe different methods for detecting steps with techniques based on simple filters and thresholds or templates. Next to this we will also study the different methods to detect falls and a very basic ADL detection method is proposed. Subsequently we will

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go further into the methodology we used. After which the results which could be derived from our experiments are discussed and in the end we will draw some conclusions.

2 Research and Methodology

2.1 Equipment

The equipment consists of two accelerometer sensors, two data receivers and a data logging unit. The software for monitoring, logging and analyzing of the data is custom made. The MMA7260Q sensors used in the research are tri-axial accelerometers from Freescale. These sensors are mounted on a demo board called the Zstar 1 (represented in Fig. 1) which contains the accelerometer itself, a wireless radio module and an 8-bit MCU which can be re-programmed through a BDM (Background Debug Interface). The radio module creates a wireless link with the 2.4 GHz Zigbee protocol to a USB data receiver plugged in the computer.

Thanks to its wireless characteristics the board allows the sensor to be positioned at many different places on the body. Self-made Velcro straps are used (see Fig. 1) to easily mount the sensors around the upper body and legs. It is important for the reliability of the signal that the sensor cannot move freely and that the straps are as tight as possible. Concerning the study of fall events during the experimental phase of our research, it has to be noticed that every event is recorded on tape. Also the software which analyses the sensor activity is screen captured. Thanks to these recordings every fall event could be studied extensively and because of this possible misdetections could be evaluated more easily.

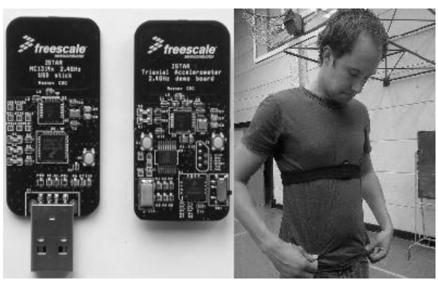

Fig. 1. Freescale Zstar sensor board and receiver

2.2 Sensor Placement

In order to create a comfortable system for patients and elderly, we wanted to use as less sensors as possible. Whether or not the information drawn from the sensor signal will be useful depends on the position of the sensor on the human body. In the literature a couple of places on the human body that are suitable for our purpose are described. In the end, we ended up with 2 interesting possibilities: a thigh sensor because this results in similar data as a foot-mounted sensor but with smaller signal peak fluctuations and secondly a sensor attached to the torso because this results in very reliable signals thanks to the torso's relatively constant orientation with respect to the user's heading [8]. During the tests we diagnosed that the thigh sensor returns a fluctuating signal because the accelerations are disturbed by the movement of the other leg, the torso sensor on the other hand returns a clean harmonized signal. Because of this we chose to use the torso sensor for our step and fall detection algorithm. Only for our ADL algorithm we used both sensors because by combining the data of these two sensors we we're able to create a basic ADL algorithm that makes it possible to detect the position of the user in real-time. Also during our experiments we found out that the Z-axis data as well as the Y-axis data are sufficient to detect steps, but the Y-axis data show the best recognizable peaks in the signal because the Y-axis represents accelerations up- and downwards. The Z-axis data is less accurate during the process of making turns.

2.3 Step Detection

Step detection is the process of determining steps from a dataflow, in our case a dataflow produced by accelerometers. These accelerometers are placed on a person's body to monitor its movements accurately. The basic model of human motion during a walk is a repeated cyclical movement that is remarkably consistent. Yet we can divide this cyclical movement in 2 parts: the so called stance phase when the foot is placed on the ground, and the swing phase when the foot is lifted off the ground and brought forward/backward to begin the next stride [6]. These 2 phases can be recognized in the accelerometer signal where 2 corresponding peaks can be noticed. The first peak occurs when the foot is lifted(swing phase)and the next peak corresponds to the movement in which the heel strikes the ground(stance phase). There are different possibilities available to determine steps from the accelerometer signal. 3 of the most important and widely known algorithms are named by Ying et al [9]:

* Pan-Tompkins Method
* Template-Matching Method
* Peak-Detection method based on combined dual-axial signals

Each algorithm has its own benefits and drawbacks, therefore we've created our own step detection algorithms that tries to combine these several methods into one algorithm that has only minor disadvantages.

Filters. For detecting steps we created an algorithm based on filters and peak detection. The filters are used to reduce unwanted high frequency elements and noise in order to properly process the signal data. The first filter is the discrete Kalman filter which reduces the influences of artifacts in the signal. The filter also brings the signals of the three axes at 0g no matter how they are orientated, which makes it easier to use thresholds, detecting zero crossings and calculating min and max values. The second filter is an Average filter to create a smoother signal. It calculates the average value of the last 50 input samples and produces a single output sample. It also removes the high frequency components present in the signal as you can see by

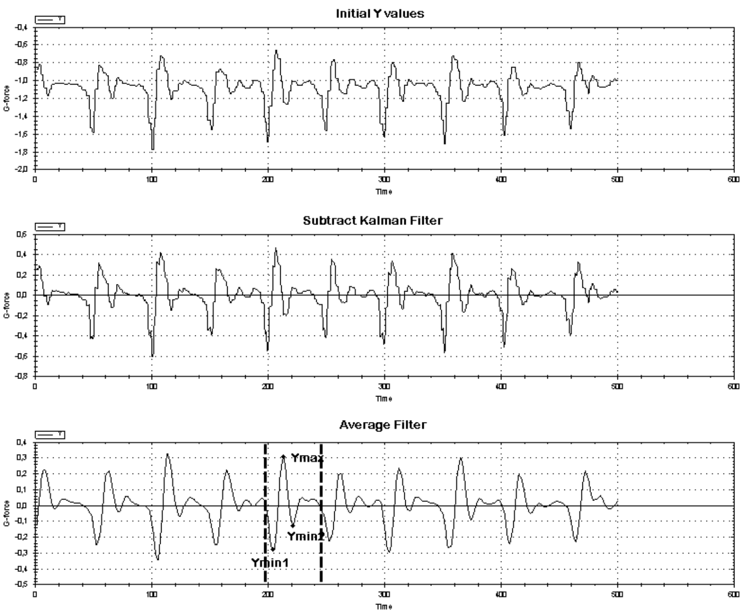

Fig. 2. Filters applied to the step signal

observing the sample demonstrated in Fig 2. The result is a clear signal with a recognizable pattern for each step taken.

Algorithm. The algorithm that we created is based on a combination of thresholding and peak searching. To easily process the signal we created an array that consists of the last hundred samples of the accelerometer signal. When a new sample is added to the array all other samples shift one place further until the oldest sample is overwritten, also known as the 'first in first out' (FIFO) principle. For every new sample the array is evaluated by the step detection algorithm. If the last one passes a threshold value, the algorithm is triggered. Observe from the third image from Fig. 2 that one step consists of a small negative peak, which occurs when the foot is lifted o_ the ground, followed by a positive peak and again a large negative one when the heel strikes the ground. The peaks vary in amplitude and in time domain. When the last and also largest negative peak is detected by a threshold value, the other (earlier) peaks are already stored in the array and the algorithm can do a checkup. When the next large positive and small negative peaks are detected, the algorithm checks the time span between the two negative peaks. If this time span is small enough, the signal is marked as a step.

Experiments and Results. The experiments to validate our step detection algorithm include two parts: an objective validation part and an experimentation part. The experiments are all done on a terrain with various obstacles and different underground. A pedometer was used as a reference. The subjects being monitored were three young adults and two elderly. They were advised to step as naturally as possible.

Part 1: Three human observers monitored the events of the subject and counted its steps taken after which the observers their results we're compared to become inter-observer reliability. In case they obtained a different step count result, the experiment was re-executed. Next to this, another observer who could not see any of the events made a note for every step he could distinguish from the accelerometer signal. These notes were then being compared to the results of the algorithm and the pedometer. The subject did 5 ranges of tests with various step lengths and speed. If we compute the average accuracy of these 5 ranges we should take false positives and negatives into account, resulting into an overall accuracy of 92.40% for the observer. The software on the other hand achieved an overall accuracy of 92,20%. So the pedometer has registered almost the same number of steps as the algorithm did.

Part 2: In our experiment we did several ranges of hundred steps. Some of them included fast walking, other rather slowly or even stumbling. A part of the ranges were done by elderly, others by young adults with or without carrying an object. During our experiments we used the pedometer as a reference. We use the pedometer as a reference because it is a well-known step count device and has a high accuracy although not perfect [7]. The results of our experiment are represented in Table. 1,as you can see the overall accuracy for the pedometer was 97.80% and 97.78% for the algorithm.

2.4 Fall Detection

The second part of our research concerns fall detection. Because the end of a fall may be characterized by an impact and horizontal orientation [1], fall detectors have to be able to detect at least one or even better both of these events. Most fall detection systems are based on the shock received by the body when it hits the ground. Detecting the shock can be accomplished by analyzing the sensor data with a threshold technique.

Different Systems. As already mentioned before, fall detection is a crucial method to extend the lives of a great group of elderly people. To put this technology into practice, a number of different approaches are proposed.

Fall detection systems can be divided in two main groups: namely the primary fall detection systems that instantaneously detect falls and the secondary fall detection systems which detect falls by the absence of normal activities [1]. These two main groups can again be split up into different subgroups, namely systems based on worn devices and on the other hand Environment sensing systems which require an infrastructure at the patient's location. This final subgroup has major drawbacks such as its cost and intrusiveness. [5]

Algorithm. The data from the sensor attached to the torso is as well as it is used to detect steps, now used to detect falls. We know by experiments and research that a fall event is characterized by a large acceleration peak in one or more directions which is followed by a horizontal position. A typical fall event signal is represented in Fig. 3 For the detection of a large acceleration the magnitude vector $r = \sqrt{(x^2 + y^2 + z^2)}$ of the three axes is calculated. If this value passes a certain threshold, the algorithm is triggered. We then wait for the signal to return to a relative normal acceleration. Next, after another small delay of 40 samples the position of the

Table 1. Step Detection Statistics

#	Steps Taken	Pedometer	Algorithm	Type
1	100	101	101	Normal walking
2	102	101	102	Normal walking
3	101	99	107	Normal walking
4	99	100	100	Normal walking
5	100	102	102	Normal walking
6	100	100	102	Fast walking
7	100	99	96	Stumbling
8	100	100	102	Normal walking
9	100	98	104	Doing activities
10	100	89	103	With charge
11	100	89	101	With charge
12	100	100	98	With charge
13	100	100	98	With charge
14	100	99	102	With charge
15	100	98	105	With charge
16	100	100	103	With charge
17	9	/	9	Elder subject
18	16	/	16	Elder subject
	100%	97.80%	97.78%	

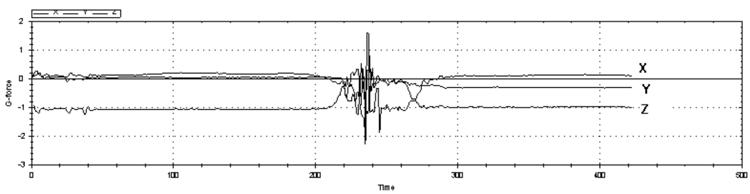

Fig. 3. Tri-axial data of a fall event

patient is analyzed. If this turns out to be horizontal, the event is categorized as a fall. To detect the horizontal position, the algorithm checks if the Y-axis is around 0g. Another fall can now not be detected unless the posture of the user has returned to normal and the Y-axis acceleration reverted to -1g. Currently we're working with a sample rate of 20ms which comes down to 50 samples a second In order to detect the large peaks from the impact with the ground we decided not to use filters while analyzing the data for fall events as they may cut off peaks which result in unusable data.

Experiments and Results Again the testing is divided in two parts: an objective validation part and an experimentation part.

Part 1: the objective validation was done by one human observer who monitored the events of the subject and noted when a fall had taken place. Another observer which could not see the subject, monitored the signal coming from the acceleration sensor and made a note with a timestamp for every fall event. The notes of these two observatories were then compared with the results of the algorithm. The subject did 6 ranges of tests with a total of 51 events. 35 events were categorized as a fall by the observer. The other events included movements like lying on a bed or bending. The data observer at his turn marked 37 of the events as a fall where the algorithm eventually registered 35 fall events. Two falls were detected as false positive and two as false negative. The results are represented in Table. 2.

Part 2: As we wanted some consistency in the detection schemes we simulated 3 different fall variations: forward falls, backward falls and lateral falls. These different types of falls were carried out by three subjects and were repeated 20 times so we could study 100 falls. Three of these falls were not detected by the algorithm: namely a forward fall with legs straight, one fall with knee flexion and one fall backward with obstruction. This resulted in an error-state of 3% miss-detected falls in this test.

Table 2. Fall Detection Statistics

#	Events	Falls Observed	Data Observer	Algorithm	False Pos.	False Neg.
1	10	5	6	5	0	0
2	21	10	12	12	2	0
3	5	5	5	4	0	1
4	5	5	5	5	0	0
5	5	5	4	4	0	1
6	5	5	5	5	0	0
		100%	93%	93%		

2.5 Detecting the Position of the User

So, the placement of two sensors creates the possibility to easily detect three different postures: sitting, lying and standing. These ADL's are detected by properly investigating the signal as done by Culhane et al [2]. The accelerometer sends data from three different axes to the computer. As we mount our sensor one way up, the vertical axis is the Y-axis. In normal position, the Y-axis value is always around -1g. If a user changes position to lying, both sensors at the thigh and torso are oriented horizontally. The Y-axis value of the two sensors is then changed to around 0g as the sensors are orientated horizontally, which can be indicated by using two threshold values. Also a sitting position can be detected. The sensor on the thigh is then orientated horizontally while the one attached to the torso is orientated vertically to the ground. In standing position, both sensors are orientated vertically to the ground.

3 Conclusion

The system described in this paper is able to monitor a patient real-time by detecting his posture, count his steps taken and register fall events over a certain time. The posture detection system is very reliable since it properly detects whether the subject is sitting, lying or standing. We call this the detection of the Activities of Daily Living. The tests of the step detection algorithm resulted in values that approached the pedometer results. Nevertheless the pedometer has more false negatives than false positives. This means that the majority of our system's miss-detected steps weren't actually steps. This could be improved by tweaking the algorithm a little by maximizing or minimizing the threshold value and shorten the distance between the negative peaks. As these values are patient dependent we're planning to include automatical thresholding in our future work by which we become a self learning algorithm. Next to this, the fall detection algorithm has also produced very pleasing results. In the test scenario of 5 different falls 97% of the fall events were effectively categorized as such.

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