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Fall Detection Using Multi-sensory Accelerometer Sensor Network

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Abstract – **In this study we developed a measurement setup consisting of a sensor network to detect falls. A fall is characterized by a large peak in the magnitude of the acceleration vector. In contrast to the commonly used single sensor, we use a network of two sensors in order to increase accuracy and decrease false positives. The measurement setup consists of an acceleration sensor at the hip and one at the wrist. After gathering the acceleration data, the norm is calculated and we used Kaiser-Teager Energy Operator to detect sharp peaks. By setting the threshold on both the Kaiser-Teager Energy Operator peaks of the acceleration data of hip and the wrist, we can more accurately detect a fall.**

Keywords – **Biomedical Engineering, signal processing, acceleration sensor, sensor networks**

I. INTRODUCTION

The last twenty years, the number of persons above 65 years has grown extensively. Prospections on the future predict that this number will still continue to grow while the persons below 50 years will remain status quo. Elderly people require more aid than younger persons. This aging of the population is putting a lot of stress on our health care. A fall incident from a person above 65 years can cause serious injuries, such as hip fracture, head traumas and increases the morbidity.

One out of three persons above 65 years old experiences at least one fall incident per year [1]. A serious side-effect of a fall incident is the so-called 'long-lie', where the person remains immobile after a fall and doesn't succeed in getting up [2].

The injuries caused from a fall incident can be severely reduced by the quick response of other people or care givers. Therefore there is a need for an alarm system, which signals the next-of-kin or care-givers. This response of the alarm system is greatly dependent on the reliability and accuracy of the sensors, incorporated in the alarm system, which detects the fall incident and triggers the alarm.
In this study we present a proof-of-concept system that consists of a wireless sensor network, existing of several nodes. Each node contains programmable logic, a wireless transceiver and sensors.

Accelerometer data are a common way to detect falls. In contrast to video and audio, they do not require high performance demands and do not suffer from privacy issues [3].

Many studies have used accelerometer signals in order to detect falls, however most of them are limited to detection based on a single sensor [4]. Detection based on one sensor are prone to false positives. In this study; we want to use multiple sensors to detect falls in order to increase fall detection. This study used test persons, as our aim is to design the system, prior to using the system for a large scale data gathering.

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II. METHODS

In this section we describe the methodology, the acquisition and the processing of the signals and the measurement setup.

A. Sensor network

The sensor networks consists of commercially available sensor nodes [5] (Shimmer, Shimmer sensing, Ireland). A sensor network consists of nodes which have one or more sensors, a microcontroller/processor and a wireless transmission devices. An example of the sensor network used in this study is shown in Figure 1. Each shimmer node has a microprocessor (Texas Instruments MSP430), a triaxial accelerometer sensor and a Bluetooth telecommunication system. The sensor node is well suited for wearable applications. Moreover, the device is capable of long term monitoring (order of days) without intermittent recharging, both by streaming data through a Bluetooth communication or by writing data on an embedded SD card.

The sensor network of this study consists of 2 sensors: one placed at the hip and one placed at the wrist. It is our aim to improve the accuracy of the fall detection if more than one sensor is used. Both sensors will send data to the hub where the signals are analyzed and stored.

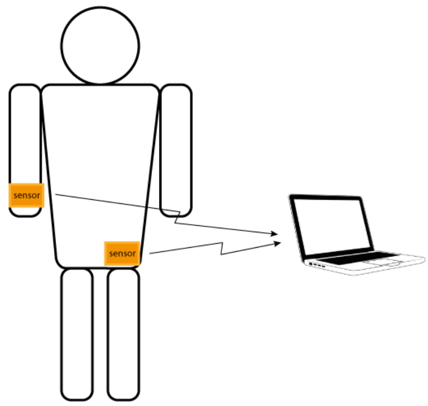

Fig. 1. The sensor network where a sensor is placed at the hip and the wrist. The accelerometer data is sent wirelessly to the hub

B. Labview front-end

In order to start the network and capture data from the sensor node, a computer interacts with the sensor network through a Labview interface [6]. The Labview program is able to connect to the devices and to stream the data. A screenshot of the Labview interface is illustrated in Fig. 2.

Fig. 2. A screenshot of the adapted front-end for reading and modifying sensor nodes

C. Acquisition of accelerometer data

An accelerometer sensor measures the acceleration vector along 3 orthogonal axes. Hence, the sampled data consists of 3 values per timestamp. Each value denotes the component of the acceleration vector along the 3 orthogonal axis. The acceleration data was sampled using a sampling frequency of 51.2 Hz. This frequency was chosen as it was the lowest standard values of the sensor node. Using this frequency, we aim to increase autonomy the data throughput will be lower than using higher sampling frequencies.

We acquired data from 3 test persons by letting them fall on a mattress in the lab. Although this is a controlled fall, our aim is to design and test the sensor network.

Both sensors were calibrated and the timing was synchronized prior to the measurement. This was done using the software accompanied with sensor (Shimmer, Shimmer Research, Ireland) [5].

D. Processing of the accelerometer signals

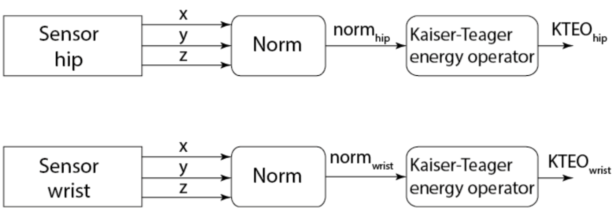

Fig. 3. Schematic overview of the processing of the sensor data

The processing of the accelerometer data is visualized in Figure 3.The accelerometer data was processed in Scilab (Scilab 5.5.0, Scilab Enterprises). First, the magnitude of the instantaneous acceleration vector at one sensor is calculated using the L_2-norm:

$$norm[i] = \sqrt{x[i]^2 + y[i]^2 + z[i]^2}$$

where $x[i]$, $y[i]$ and $z[i]$ denotes the i-th sample of the X, Y and Z-component of the acceleration.

After the calculation of the norm, the Kaiser-Teager Energy Operator (KTEO) is calculated of the norm. This energy operator is a non-linear operator that can detect high variations in a signal. It has been successfully used to detect onset in other biomedical signals and works especially well in signals where there is a sudden jump of a large amplitude [7]. One way of writing the result of the KTEO, $y[i]$, is:

$$KTEO[i] = norm[i]^2 - norm[i-1] * norm[i+1],$$

where norm[i] is the total acceleration at sample i.

E. Measurement setup

The setup was used to measure simultaneous accelerometer values from sensors at the hip and the wrist. We performed measurements with 3 test persons where each did 10 falls. The data from this dataset was stored and processed using the aforementioned methodology.

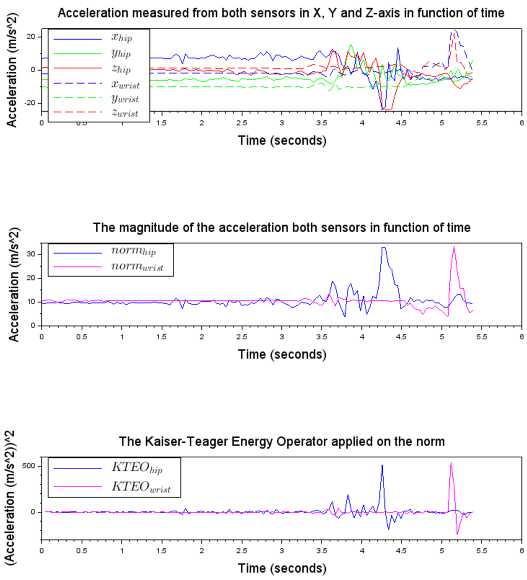

Fig. 4. (Top) the accelerometer signals measured from the sensor at the hip (solid) and the wrist (dashed) from patient 1. (Middle) The magnitude of the acceleration of both sensor. (Bottom) the energy signal calculated by the Kaiser-Teager Energy Operator of the norm.

III. Results

The results of the signal acquisition and processing of falls of two different test persons can be seen in Figure 3 and 4. The accelerometer signals consist of an X, Y and Z component for each sensor, illustrated at Figure 4 and 5 (top). In Figure 4 and 5 (middle) the total acceleration is shown. Note the distinct pattern of the fall and the delay of the accelerometer data of the wrist sensor. The result of the Kaiser-Teager operator can be seen in Figure 4 and 5 (bottom).

One can notice the delay of the peak in the wrist sensor compared to the sensor at the hip. This can be explained by the fact that the impact first occurs at the hip. An impact of the wrist is then seen afterwards. This can be used to develop an algorithm to detect a fall using a wrist and hip sensor. A similar behavior was seen in most datasets. However, we did not notice this behavior in every dataset.

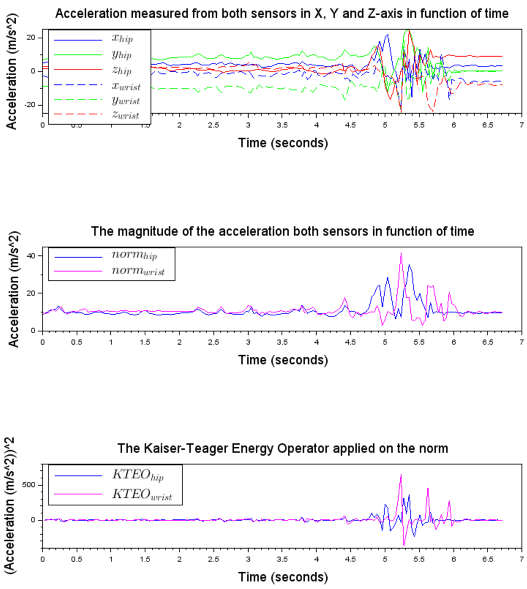

Fig. 5. (Top) the accelerometer signals measured from the sensor at the hip (solid) and the wrist (dashed) from patient 2. (Middle) The magnitude of the acceleration of both sensor. (Bottom) the energy signal calculated by the Kaiser-Teager Energy Operator of the norm.

IV. Discussion

In this study we demonstrated the possibility of detecting a fall using a multi-sensory approach. We used a sensor at the hip and the wrist. In practice this can be associated with devices like a smartphone at the hip and a smartwatch at the wrist. We can use the measured signals to develop an algorithm to detect falls. However, in order to determine the performance of such an algorithm a large scale study has to be performed and data has to be acquired. This will be our future work.

Furthermore, we used test persons to measure accelerometer data during a fall. In a large scale study we would use realistic data measured from elderly. This study was a feasibility study, whether the use of two sensors would be of added value. In order to not overburden the elder person, we have to make sure the system can operate as autonomous as possible in order to gather data. With this system, we are able to measure the data continuously for approximately 5 days if the data is stored locally on a micro-SD card. Using a continuous stream of data using Bluetooth the system can transmit data for on average 14 hours till a recharging of the battery has to take place.

It is our aim to implement the detection algorithm in the sensor nodes itself. The low-complexity of the Kaiser-Teager operator increases the autonomy of the sensor, as calculations are simple. This also enables us to develop a real-time implementation of the algorithm as the KTEO operator only creates a delay of 2 samples which is 0.039 seconds. Furhtermore, as the orientation of the sensor is not known a priori, the algorithm can work orientation independently as we calculate the total acceleration.

V. Conclusion

We can conclude that we can use the multi-sensory approach to gather data in an automatic way. Hence, a large dataset will enable us to design a fall detection algorithm to detect falls using a multiple sensors.

In this study we used two sensors, in future work we tend to explore the use of more than two sensors. Also, here the sensors are placed at hip and wrist. We want to investigate if sensors can also be placed at other locations of the human body.

References

[1] Hausdorff JM, Rios DA, Edelber HK. Gait variability and fall risk in community–living older adults: a 1–year prospective study. Archives of Physical Medicine and Rehabilitation 2001, vol. 82(8), pp. 1050–6.

[2] Lord S.R., Sherrington C.,Menz H.B., “Falls in older people: riskfactors and strategies for prevention”, Cambridge: Cambridge University 2001

[3] Nyan M.N., Tay F.E.H., Tan A.W.Y. and Seah K.H.W., Distinguishing fall activities from normal activities by angular rate characteristics and high-speed camera characterization, 2006, Medical Engineering and Physics, Vol. 28, pp. 842-849.

[4] Igual R., Medrano C. and Plaza I, Challenges, issues and trends in fall detection systems, Biomedical Engineering Online, 2013, Vol. 12(66), pp. 1-24

[5] http://www.shimmersensing.com

[6] http://www.ni.com/labview/

[7] Li X., Zhou P., Aruin A.S., Teager-Kaiser energy operation of suface EMG improves muscle activity onset detection, Annals of Biomedical Engineering, 2007, vol. 35(7), pp. 1532-8