The Usage of Body Area Networks for Fall-Detection

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***Abstract*—This paper presents an ongoing research analyzing existing fall-detection systems and developing a fully automated fall-detection system. The system is based on a Body Area Network (BAN), which is worn in form of a belt on the hip. To provide an accurate fall-detection five nodes continuously acquire data and the data exchange with the coordinator is done by ZigBee protocol. A sensor fusion algorithm on the coordinator determines the fall type sending a flag to an Android smart phone attached via Bluetooth. The Android Application contacts the emergency services. This architecture provides redundancy that is an important aspect of safety critical systems.**

Keywords: Body Area Network, fall-detection, threshold-based method, reliability, safety, ZigBee

I. Introduction

The progress of medical care increases life expectancy leading to an ageing population. The probability of multiple falls rises for persons because of growing age and diseases (e.g. Dementia & Parkinson). Falls cause severe injuries that require long convalescence or restriction of mobility.

In accordance with the study “Das Unfallgeschehen bei Erwachsenen in Deutschland” of Robert Koch Institute [1] 53.7 % of accidents in the age group over 60 are caused by falls. Additionally elderly people are scared to fall again and this leads to reluctance to move, which causes decrease of muscle strength and uncertainty of movement. Another reason that causes falls of elderly people are diseases e.g. Parkinson and Dementia. Research has shown that Dementia-patients have a 20 times higher risk and Parkinson-patients a 10 times higher risk of falling than healthy people of the same age. Other main reasons for falls are gait disturbances, reduced sight and disturbance of equilibrium [2].

Jean-Eric-Lundy, founder of Vigilio TeleMedical [3], reported that annually more than 20 million people over the age of 65 in Europe fall and that is the main reason for traumatic based cases of death [4]. A fast assistance is in this case very important to save life, because after a fall the person may not be able to call for help because of unconsciousness.

A. Statement of the problem

In the case of a fall situation or unconsciousness a prompt and fully automated assistance is needed. A solution to guarantee this could be continuous monitoring of vital signs via a wearable sensor network that is called a Body Area Network (BAN). The Wireless Smart Sensor Network (WSN) consists of wearable medical sensors, which communicate with computer systems and is worn on the body so that the mobility of the person is not restricted (Figure 1: Principle of Body Area Networks).

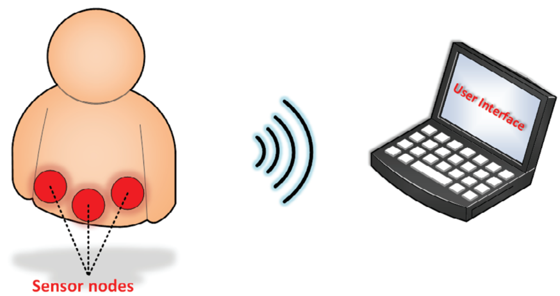

Fig. 1. Principle of Body Area Networks

A special challenge for the realization of this kind of assistance system is a reliable fall recognition. The fall-detection system should be able to distinguish between activities of daily life (e.g. running, walking, jump), fall-like activities(e.g. quick sit-down upright/reclined) and real falls (e.g. forward fall, left/right fall). Another aspect that should be considered is the purchase price of the system, that means it should be affordable for medical insurance so that patients can be supported to get this assistance. Because of the importance regarding the fast support of fall victims the European Union promoted a project called Fallwatch and one result of this is the fall-detection system “VigiFall” developed by the company Vigilio TeleMedical [3] [4]. The problem of this solution is the high purchase price so that one important requirement for the thesis will be the development of a cheap and efficient solution.

II. Current state of research

A. Vigi Fall [3] [4]

There are several approaches for fall-recognition which are available on the market. A solution which is already available is the above mentioned VigiFall system [3] [4], that consists of a sensor node that is worn by the person. This system should be able to detect a fall and contact fully automated the emergency services. The node communicates with infraredmotion sensors which are placed in the area and a central control unit. In the case that the person falls, the node sends a signal out. Thereby the motion sensors detect that there are no motions and they send a flag to the central control unit. With this incoming signal the control unit contacts fully automated the emergency services.

B. Igual et al. [5]

The scientific article of Igual et al. [5] is about fall-recognition and it gives an overview of several fall-detection systems. The paper presents context-aware systems and wearable systems that are used to detect falls.

Context-aware systems are placed in the environment, which means that sensors and actuators should be fixed in the area where the person is, so that falls can be detected. A context-aware system can be a video-based solution, which has the advantage that a person can have a reliable fall-detection with a prompt support. In spite of the accurate detection this solution has a disadvantage regarding privacy. People are monitored by camera and this is not well accepted by many. Additionally the high purchase price makes this not affordable for everyone and the system is not working outside the networked area, which is essential for detection.

The other category of fall-detection systems that was presented in this paper are wearable systems, which are worn on the body and are based on a Body Area Network (BAN, see Figure 1: Principle of Body Area Networks). This solution is able to detect falls independent from the environment compared to context-aware systems. Igual et al. [5] present systems that use the sensor combination of accelerometer and gyroscope and built-in systems, which represent the usage of the internal sensors of smart phones. The investigations of Igual et al. [5] illustrate that for context-aware systems the following techniques were used:

- Image processing + threshold based recognition
- Image processing + classification models

For wearable systems these techniques were used:

- Threshold based recognition
- Fall-detection based on machine learning

C. Li et al. [6]

Li et al. [6] demonstrate a solution regarding fall-detection based on Body Area Networks. The system consists of two nodes (Figure 2: System according to Li et al. [6]). These nodes are wearable microcontrollers, which have integrated the sensor combination of accelerometer and gyroscope and are placed on the chest (Node A) and on the thigh (Node B).

Li et al. [6] distinguish between two categories of motion sequences:

Fig. 2. System according to Li et al. [6]

- Static postures
  - standing, sitting, lying & bending
- Dynamic postures
  - Activities of daily life → walking, walk on stairs, sit, jump, lay down, run
  - Fall-like motions → quick sit-down upright, quick sit-down reclined
  - Flat surface falls → fall forward, fall backward, fall right, fall left
  - Inclined falls → fall on stairs

The following diagram illustrates the difference between static & dynamic postures. To avoid huge computational effort for the microcontroller a 3-Phases-Algorithm was developed to detect falls and is composed as follows:

- 1.Phase - Activity analysis → monitoring if person is in a static or dynamic position.
- 2.Phase - Position analysis → If static posture, check whether the actual position is lying position.
- 3.Phase - State transition analysis → If lying position, check whether this was intentional or unintentional. For this the previous 5 seconds of data are used to analyze it. Is this position unintentional the algorithm categorizes it as a fall.

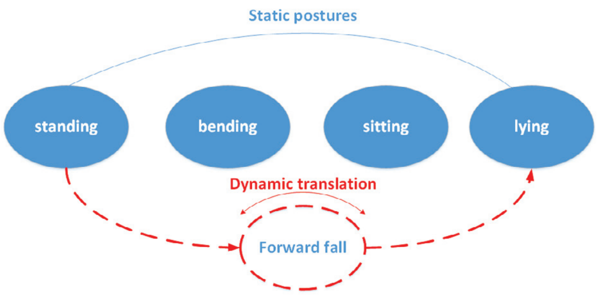

Fig. 3. Static & Dynamic postures by Li et al. [6]

The algorithm is a threshold-based solution, that means thresholds from the sensors are used in the different phases of the algorithm for classification. The test result shows a positive result with 91% of sensitivity on 70 measurements and 92% of accuracy on 72 measurements. The challenge of this proposed solution is that the algorithm has the difficulty in differentiating jumping into bed and falling against a wall with seated posture.

III. Further research

In this chapter we present the actual ongoing research and development regarding our fall-detection solution. The target of our research is to develop an fully automated fall-detection system in form of a belt that is able to allow a reliable detection of falls and in case of falls to contact the emergency services (Figure 4: Fall event escalation scheme). The following subsections describe the development path that includes the reproduction of the algorithm used by Li et al. [6], our proposed system architecture and the hardware that is used to realize the fall-detection belt.

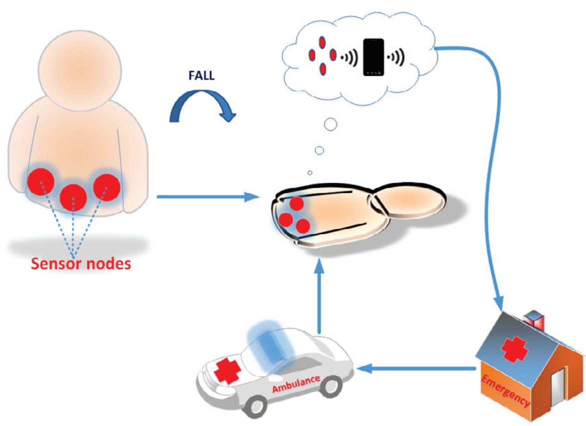

Fig. 4. Fall event escalation scheme

A. Reproduction of Li et al. - Architecture [6]

The first step of the development path is the reproduction of the fall-detection system proposed by Li et al. [6] which is based on a Body Area Network (BAN) that is composed of two wearable sensor nodes (see Figure 2: System according to Li et al. [6]). This BAN comprises two nodes which acquire continuously sensor data and send it via the ZigBee protocol to the coordinator (see Figure 5: BAN according to Li et al. [6]). After the development of this system a test protocol that

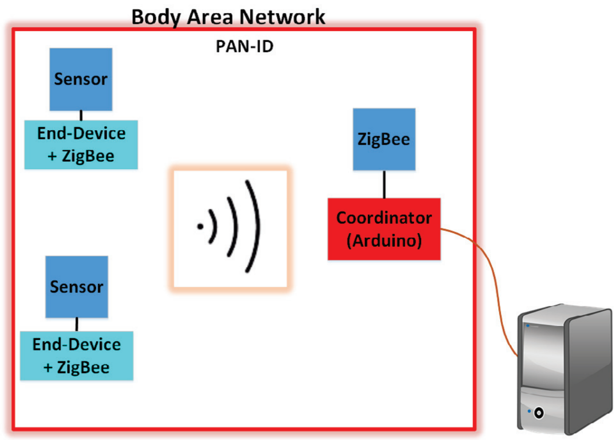

Fig. 5. BAN according to Li et al. [6]

is based on Li et al. [6] and Pannurat et al. [7] was created to reproduce several motions with test persons. The test protocol includes the movements that are stated in the chapter before. With this testing model we are able to detect the thresholds which categorize the different kind of motions. Important to know is, that the physical properties of a human e.g. body weight, body height and age can influence the measured values. For example when a person suffering from obesity is falling down, the impact value differs from the value of a thin body. Additionally it should be taken into consideration that simulated falls or other movements cannot correspond perfectly to a real fall, because persons form protective mechanisms to avoid injuries during the test. The tests are done with several test persons to have an overview about the different thresholds. The following measurements illustrate some motions from different persons that are represented from the acceleration and angular rate of both nodes (chest & thigh). From the measurements the different peak values are evident. When we consider the graph, which illustrates a long term measurement of the acceleration and angular rate magnitude of both nodes that are placed on the chest and thigh (see Figure 6: Person A - Rotation with fall-event) we can evaluate falls. For this we used the magnitude of the acceleration and angular rate how it is proposed by Li et al. [6] The magnitude is calculated by the formulae:

$$|\vec{a}| = \sqrt{a_x^2 + a_y^2 + a_z^2}$$
$$|\vec{\omega}| = \sqrt{\omega_x^2 + \omega_y^2 + \omega_z^2}$$

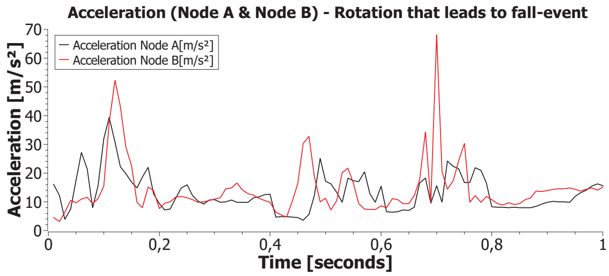

Fig. 6. Person A - Rotation with fall-event (Acceleration)

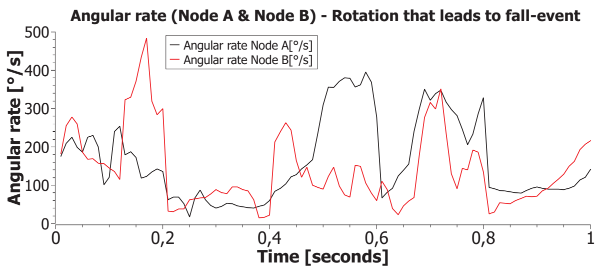

Fig. 7. Person A - Rotation with fall-event (Angular rate)

For example when we analyze the time window of 0.7 seconds a huge acceleration on the thigh (Node B) and a small acceleration on Node A is displayed. This means that the test person had the first impact with the thigh and because of this the acceleration of the chest was damped. The graph that displays the angular rate (see Figure 7: Person A - Rotation with fall-event (Angular rate)), shows at the same time, that the person did rotational move before and during the fall-event.

B. Fall-detection belt

After several tests were made with the Li et al. - Architecture [6] (see Figure 2: System according to Li et al. [6]), we built up a prototype in form of a belt that is worn on the hip (see Figure 9: Fall-detection belt). The proposed solution has the requirements to be reliable and build in a way that the patient has no restriction of movement. For these reasons we came up with a fall-detection system in form of a belt, which is worn on the hip and is composed of a five sensor node BAN. Each node contains an accelerometer and a gyroscope and communicates via ZigBee (see Figure 8: Fall-detection Belt). In the BAN four of the nodes are acting as end-devices and the other node as the coordinator. All four nodes acquire data continuously, monitor thresholds for different fall types and exchange the data with the coordinator. The proposed positioning of sensors in the belt facilitates this recognition in contrast to the system architecture used by Li et al. [6] (Figure 10: Three axis reference draft).

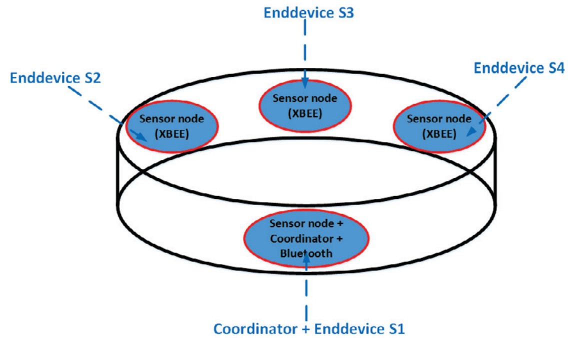

Fig. 8. Fall-detection belt

Fig. 9. Fall-detection belt

The idea is, that with this special positioning more precise fall characterization are achieved. The categorization is divided in two parts:

- Initial event → leads to subsequent event
- End event → end position which is a static posture e.g. lying on the floor

To have a comparison between the architecture of Li et al. [6] and our proposed solution we used the same test procedure used before to see how efficient the fall-detection belt can recognize falls.

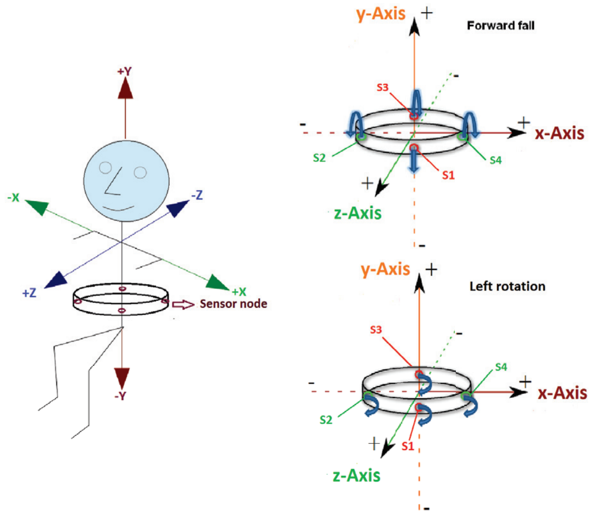

Fig. 10. Three axis reference draft

In this section some measurements of the belt-nodes are illustrated that represent a rotation that leads to a fall-event. Important to know is that for our solution we use the acceleration magnitude, that signalizes a fall and the single value of the axis x, y and z of the gyroscope to detect which kind of rotation was done by the person. How the following graphs display with this architecture we have more detailed information to rebuild the fall-event.

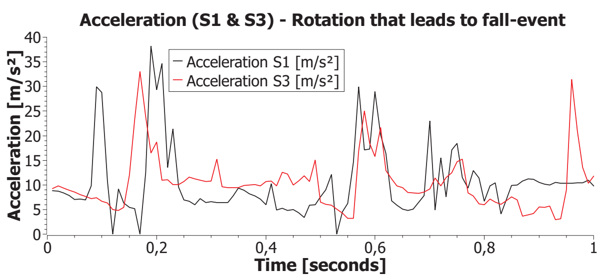

Fig. 11. Person A (S1+S3) - Rotation with fall-event (Acceleration)

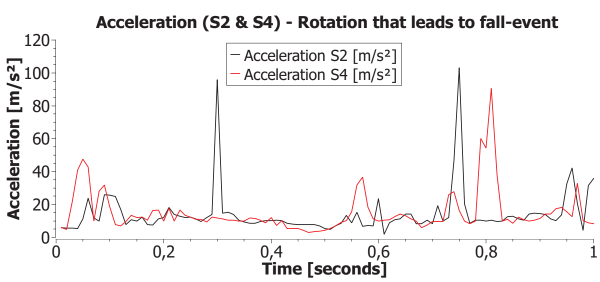

Fig. 12. Person A (S2+S4) - Rotation with fall-event (Acceleration)

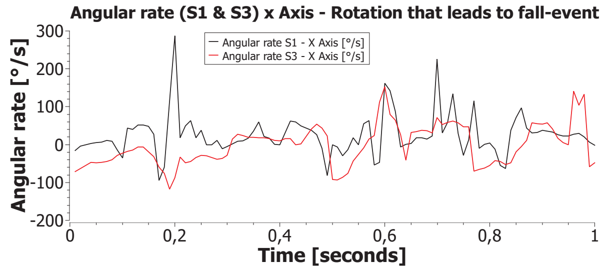

Fig. 13. Person A (S1+S3) - Rotation with fall-event x-Axis (Angular rate)

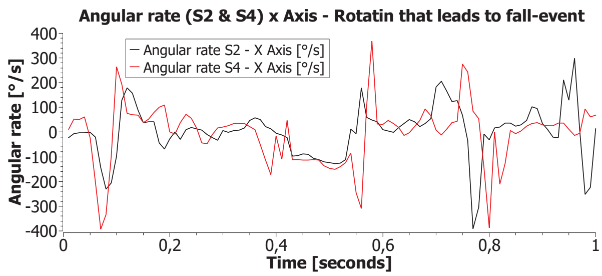

Fig. 14. Person A (S2+S4) - Rotation with fall-event x-Axis (Angular rate)

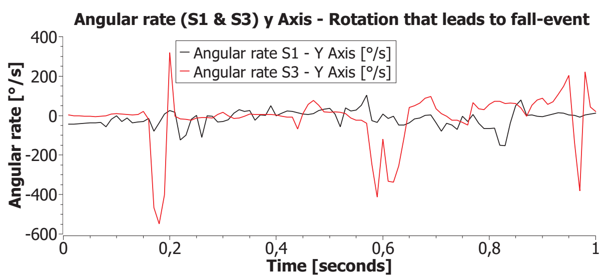

Fig. 15. Person A (S1+S3) - Rotation with fall-event y-Axis (Angular rate)

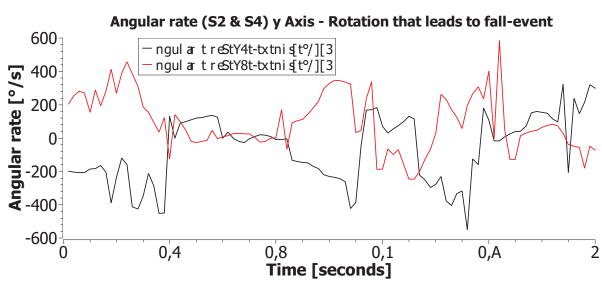

Fig. 16. Person A (S2+S4) - Rotation with fall-event y-Axis (Angular rate)

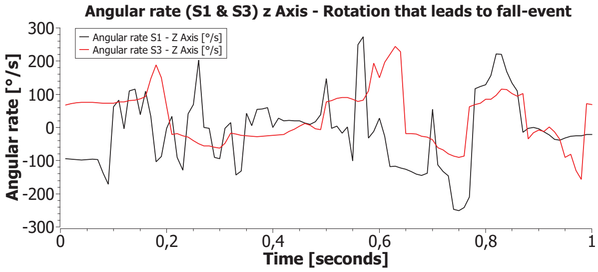

Fig. 17. Person A (S1+S3) - Rotation with fall-event z-Axis (Angular rate)

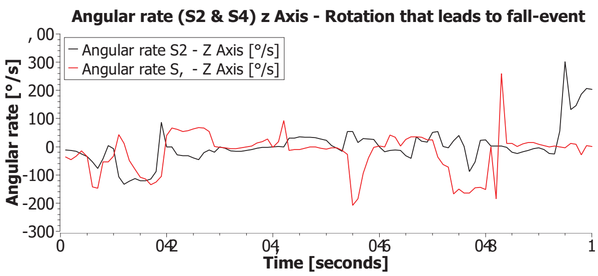

Fig. 18. Person A (S2+S4) - Rotation with fall-event z-Axis (Angular rate)

IV. Future Prospect

The target of this ongoing research is to continue the development of this prototype. Especially we intend to improve the architecture with more powerful hardware. An idea is to place tiny sensors inside the belt and hard-wire these with the main-node (coordinator). For algorithmic performance reasons the used coordinator board should be replaced with a microcontroller, which is able to handle parallel running tasks. Additionally to elaborate the threshold-based approach a Complex Event Processing (CEP) algorithm proposed by Boubeta-Puig et al. [8] is investigated.

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