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Conference Paper · June 2015

DOI: 10.1007/978-3-319-19312-0_16

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Smart Fall: Accelerometer-based Fall Detection in a Smart Home Environment

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Abstract. The detection of falls in an elderly society is an active field of research because of the the enormous costs caused by falls. In this paper, Smart Fall is presented. It is a new accelerometer-based fall detection system integrated into an intelligent building. The developed system consists of two main components. Fall detection is realized inside a small customized wearable device that is characterized by low costs and low-energy consumption. Additionally, a receiver component is implemented which serves as mediator between the wearable device and a Smart Home environment. The wireless connection between the wearable and the receiver is performed by Bluetooth Low Energy (BLE) protocol. OpenHAB is used as platform-independent integration platform that connects home appliances vendor- and protocol-neutral. The integration of the fall detection system into an intelligent home environment offers quick reactions to falls and urgent support for fallen people.

1 Introduction

The World Health Organization [1] states in its global report that 28-35% of the 65+ year old people fall each year with an increasing rate for older people. 40% of injury deaths are caused by fatal falls. Falls are major health problems that cause enormous costs to health systems. Due to the aging society, both, the total amount of falls and the costs will increase in the future. The medical consequences of a fall highly depend on the rescue time [2]. This statement encourages the development of automatic fall detection systems to reduce the reaction time. A reliable fall detection system can provide urgent support and reduce the consequences of the fall.

Such a detection system is only of value if it is accepted by the concerned people. A major point is the intrusion of the fall detection system because people want to stay independent and undisturbed. Another important aspect of acceptance is the useability of the system that should be easy to install and use. Additionally, a low-cost system is preferable.

In this paper, a new accelerometer-based fall detection system with integration into a Smart Home environment is proposed. The integration into an intelligent building via Bluetooth Low Energy permits urgent support for fallen people with high battery lifetime. The system is characterized by its low costs and energy efficiency. Because of the small size of the customized wearable device, the system ensures minimal intrusion into the live of the concerned people.

The remainder of the paper is structured as follows: the next section gives an overview over existing fall detection algorithms and applications. In the following section, the Smart Fall system is described in detail considering the hardware, the fall detection algorithm and the integration into a Smart Home. The main section is followed by an evaluation of the system and conclusions.

2 Related Work

Due to the high importance of fall detection, it is an intensive field of research. There are several methods of detecting falls that can be categorized by their approach. Mubashir et al. [2] build an hierarchy of fall detection methods with three classes on top of the categorization. The top-layer consists of wearable sensors, vision system and ambient/fusion approaches. Wearable sensors are characterized by its cost-efficiency and easy installation. Camera-based methods feature low intrusion and high robustness but also higher costs and a more expensive installation than wearable sensors. The last category, ambient/fusion fall detection methods, mostly utilize pressure sensors for the detection of high vibrations. The intrusion is low, but the accuracy is stated to be not as good.

For reasons of low costs and easy useability of the device, a tri-axial accelerometer as basis of fall detection is used in this paper. Thus, approaches using accelerometers are summarized in the following section.

Igual et al. [3] distinguish between two fall detection techniques: TBM (threshold-based methods) and MLM (machine learning methods). TBM use predefined thresholds to distinguish between falls and ADL (activities of daily living). This technique is characterized by its simplicity and low computational costs. On the other hand, MLM apply supervised learning methods for fall detection. These methods are more computational intensive, and a dataset containing samples of falls and ADL is necessary to train a classifier.

Kangas et al. [4] determine thresholds for simple fall detection algorithms using a tri-axial accelerometer attached to either the waist, wrist and head. The results show that the waist and the head are the most suitable locations for placing the sensor. A fall is detected by comparing the vector sum of all three acceleration directions with a threshold and checking the body posture after fall. The authors claim that such a simple method can achieve high sensitivity and specificity up to 100%. The popular waist location is confirmed by Howcroft et al. [5] in a comprehensive literature review.

Another TBM approach is proposed by Ren et al. [6]. They developed an energy-efficient prototype that detects falls by considering the vector sum of the three acceleration axes and the BTA (Body Tilt Angle) after the fall. The fall sensor is connected to a home server using ZigBee protocol. An accuracy rate of 96% is achieved by the detection algorithm.

A location-independent fall detection algorithm is implemented by Mehner et al. [7]. They utilize a smartphone with integrated accelerometer and apply an energy-efficient detection method. It considers different phases of a fall: free fall, impact, post impact, stability and orientation check.

Kerdegari et al. [8] evaluate different machine learning classification algorithms. A sliding window technique is used to split the continuous acceleration data into overlapping, fixed-size windows and extract certain features. Data are recorded by a waist worn device, and the evaluation shows that Multilayer Perceptron is the best option with its high accuracy of 90%.

3 Smart Fall System

As stated in the previous section, there are already various robust fall detection approaches and algorithms, but in most cases there is a focus on the algorithmic realization instead of integration into a wider context. In this paper, a novel fall detection system with integration into an intelligent building is presented. This allows further processing of a fall event by the Smart Home. Another advantage is the indirect localization of the fallen person inside the house which permits fast support. The detection of a fall is based on an accelerometer integrated into a wearable device. It is focused on energy efficiency, low costs as well as easy usage. A small size of the customized wearable targets to enhance the acceptance.

This section describes the fall detection system. First, a high-level overview of the application is given and described in detail. The next subsection focuses on the hardware needed for realization, and the customized wearable device is presented. The following subsection considers the fall detection algorithm that utilizes the acceleration data. Finally, the integration into a Smart Home environment is explained.

3.1 System Description

The system consists of two main components: the wearable device that is attached to the user and a component that receives signals from the wearable and serves as connection to the home automation bus. Figure 1 illustrates the situation. The user is depicted in the bottom right of the draft with the Smart Fall device. If the wearable detects a fall, a signal is send to the receiver via BLE (Bluetooth Low Energy). In this case, a small low-cost computer board called Raspberry Pi with a BLE dongle is chosen as receiver. The Raspberry Pi is connected to the home automation bus and is able to forward the fall event. As reaction to the fall, urgent support for the fallen person can be provided. Both components are shaded in red in the figure.

The central unit of the Smart Fall system is the wearable device which mainly consists of an accelerometer, a microprocessor and a wireless communication module. The decision for a wearable device incorporating an accelerometer is made because of several reasons: (1) high accuracy can be achieved, (2) low costs and (3) small footprint yield to higher acceptance.

Another advantage over vision-based methods is the protection of the privacy because people do not feel comfortable if they are observed by cameras [9]. Due

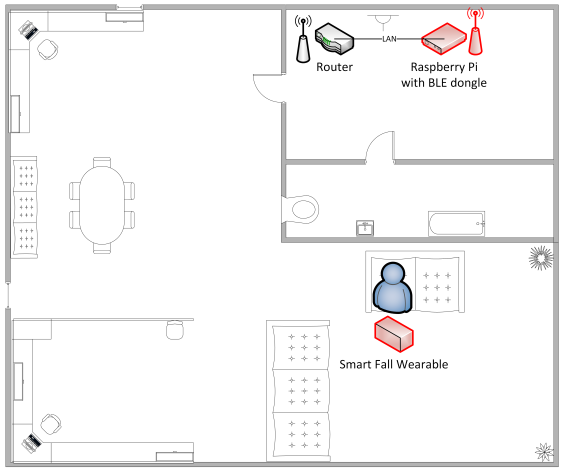


Fig. 1: Smart Fall environment

to this, accelerometers are more likely to be accepted by the user. The position of the attached device significantly influences the performance of the system. As a result of the literature research, the waist is chosen as position for the wearable because it is supposed to be the optimal position for fall detection.

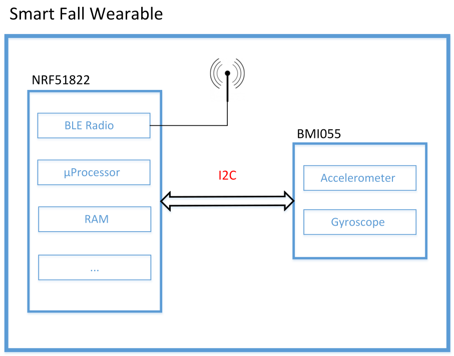
The second component is an embedded system, a small computer. It serves as receiver for fall events emitted by the wearable and as binding to the Smart Home. This small computer is cost-effective and can be installed in the home unobtrusively.

3.2 Hardware

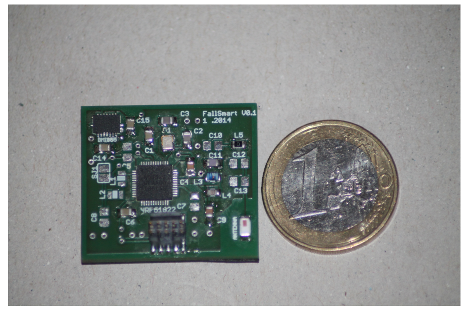
This section describes the newly developed hardware that is used for the system and explains the decision for several components. Figure 2 gives an overview over the structure of the device and the first prototype.

There are two main components that build the functional unit of the wearable. The NRF51822 by Nordic Semiconductor [10] is a ultra-low-power system on a chip that is build around a 32-bit ARM Cortex M0 with 256 KB flash and 16 KB memory. It incorporates a BLE transceiver which permits sending and receiving in 2.4 GHz frequency.

The second component is the sensor of the system, the Bosch BMI055 triaxial accelerometer [11] which provides linear acceleration in three orthogonal directions. Its accelerometer is stated as ultra-low-power IC (Integrated Circuit) with a current consumption of 130 μA. This yields to an increasing lifetime of the battery power supply. The accelerometer is capable of a bandwidth up to 1 kHz and measures acceleration in a range up to $\pm$ 16 g with a resolution of 12 bit. For the fall detection algorithm a range of $\pm$ 4 g is chosen because it is sufficient to separate falls from ADL.



(a) Block diagram



(b) Hardware

Fig. 2: Smart Fall wearable

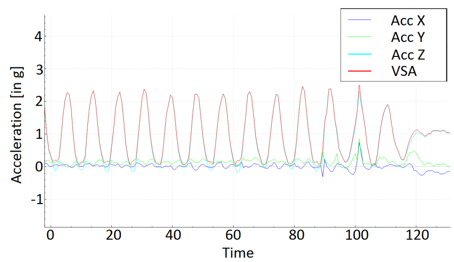
The fall detection is performed inside the wearable. NRF51822's microprocessor gets the acceleration values of the BMI055 using I^{2}C communication protocol. The values are processed, and fall events are transmitted by BLE transceiver and antenna to the receiver station. It is obvious from the hardware description that the selection of the hardware components targets to low costs and energy efficiency.

3.3 Fall Detection Algorithm

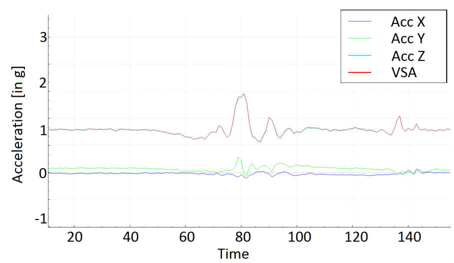
The task of the fall detection algorithm is to distinguish between falls and ADL robustly. In this section, the algorithm for fall detection is presented. It is a TBM considering several states of a fall similar like in [7] or [4]. The decision is fallen onto a TBM to support the low-power requirements because TBM are less computational intensive than MLM. The method is based on acceleration data provided by a tri-axial accelerometer. An acceleration value measured in g is given for each dimension in space. These values are further referred to x-, y- and z- acceleration. The VSA (vector sum of acceleration data) is a scalar representing the total acceleration in all three directions. It is calculated as follows:

$$VSA = \sqrt{x^2 + y^2 + z^2} \ . \tag{1}$$

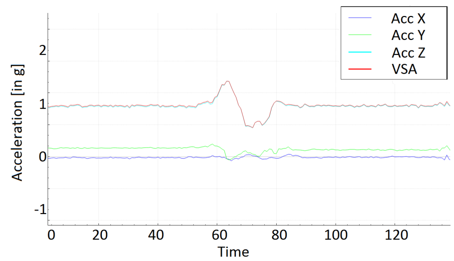
The first three graphs in Figure 3 give an overview over some ADL situations where x-, y-, z- acceleration and the VSA are visualized dependent on the time. Note that the time values are indices and no time unit. The most important graph is the VSA colored in red. In a situation with no acceleration, the axis parallel to the gravitation vector measures ± 1 g, while the other axes are close to 0 g. Therefore, the VSA is 1 g in such a situation. In the setup for the example figures, the z-axis is positioned parallel to the gravitation which leads to the similarity of the z-axis graph and the VSA graph. Figure 3a shows acceleration values for faster walking. The VSA is characterized by a periodic oscillation with peaks at



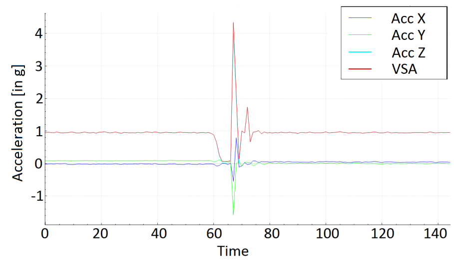
(a) Walking



(b) Sitting



(c) Standing up



(d) Fall

Fig. 3: Acceleration data during several ADL and a fall

about 2.3 g. Sitting down on a chair results in a different acceleration graph. The situation is featured by a decreasing VSA followed by a strong acceleration increase. This happens because of the movement towards the ground followed by the impact on the chair that yields to a higher VSA. The opposite action, standing up, leads to an increasing VSA followed by an acceleration decrease down to 0.6 g. These figures show that each action is characterized by its own graph.

In contrast to the graphs of ADL, Figure 3d illustrates a typical flow of a fall. The first indication for a fall is a decrease of the VSA. Compared to sitting down on a chair, this decrease is higher and deceeds a minimal value. This is caused by the free fall which tends to 0 g in an optimal situation. After reaching the local minimum, the VSA strongly increases with a peak up to 4 g. In comparison to a walking situation or sitting down, the peak has a higher value. This high peak is the result from the transition from a free fall to the impact on the ground which yields to high acceleration values. Finally, there is a stabilization after the fall that *can* differ from the situation before the fall if people fall from an upright posture into lying posture. If falls out of beds are considered, the acceleration values before and after the fall can be similar because of the similar body orientation.

From these observations, a fall detection algorithm and its features can be derived. The most discriminative characteristics are the free fall before the impact and the impact itself giving information about the intensity of the fall.

These characteristics can be recognized by analyzing the VSA. Additionally, an orientation check after the fall makes the algorithm more robust.

The threshold-based fall detection algorithm can be represented by a state chart where each state corresponds to a well-defined state of a fall. Figure 4 gives an overview over the state machine. It consists of several states and transitions between states. A transition happens if the attached condition is satisfied. The default and starting state is called *Before Fall*. For each acceleration sample and VSA value, the state machine is updated according to the current state, the input and the transition. Each state, its meaning and transitions are described in the following paragraphs.

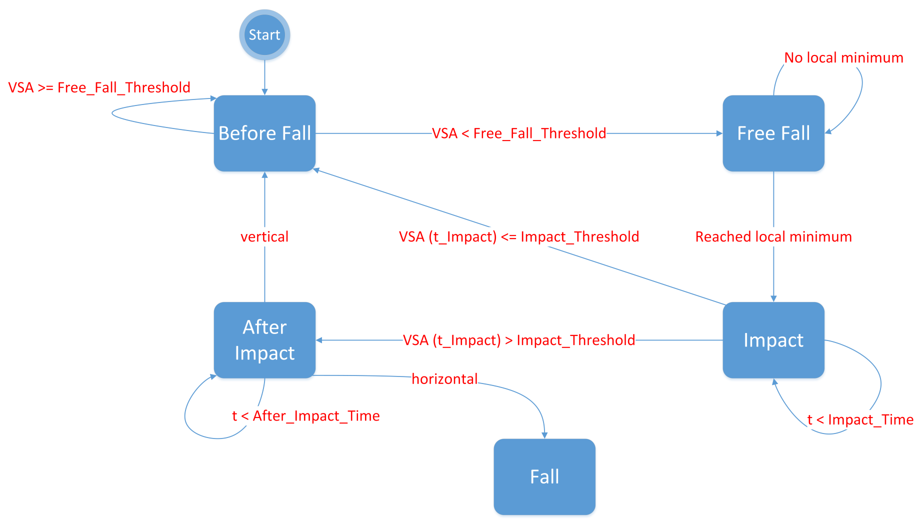


Fig. 4: Fall detection algorithm's state chart

Before Fall The first indicator for a fall is the free fall before the impact. A steady situation is characterized by a VSA that tends to 1 g because of the gravitation that effects the accelerometer. A free fall has a VSA close to 0 g. To determine a free fall, a threshold *Free_Fall_Threshold* is needed. Each VSA is compared against this value. If the VSA deceeds the threshold, the current state is updated to *Free Fall* state. Otherwise the current state remains the same. In the current implementation *Free_Fall_Threshold* is set to 0.7 g.

Free Fall This state represents the falling of the person. The VSA decreases until it reaches a local minimum which is the end of the falling process and the beginning of the impact. If the local minimum is reached, the current state is changed to *Impact* state.

Impact The impact of the falling person onto the ground is characterized by a strong increase of the VSA. Its value gives information about the intensity of the fall. This feature is the second import characteristic for distinguishing falls from ADL. In general, falls have greater impact intensities than ADL which can be seen comparing diagrams in Figure 3. The state machine remains in the current state for a time of *Impact_Time*, which is set to 300 ms. *t_Impact* is the time of the maximum in the time window and *VSA(t_Impact)* its acceleration value. A second threshold *Impact_Threshold* is used to distinguish falls from ADL. In the current implementation its value is set to 2.5 g. If the intensity of the impact maximum is smaller than the threshold, the current state is updated to *Before Fall*. This is the case in a walking situation as stated in Figure 3a where VSA undercuts the *Free_Fall_Threshold* and the following maximum does not reach the *Impact_Threshold*. If the impact maximum exceeds the threshold, it is assumed to be fall relevant. The current state is updated accordingly.

After Impact If a free fall is followed by a strong impact, the acceleration data are analyzed for a lying posture of the person. This is done in a time interval of the length *After_Impact_Time* after the impact. Three seconds for the time interval are chosen for the algorithm. Formula 2 calculates the absolute tilt angle with respect to the x-axis. $tilt = 0°$ corresponds to a horizontal posture, while $tilt = 90°$ is a vertical posture:

$$tilt = abs\left(arcsin\left(\frac{x}{VSA}\right)\right) \ . \tag{2}$$

A sample is considered as horizontal if its tilt value is smaller or equal than 45°. In the current implementation, the tilt angles of all acceleration samples in the time interval are checked against its tilt value. If most of the samples (here: 70%) are horizontal, the posture is considered horizontal, otherwise vertical. A horizontal posture after the impact is classified as a fall. The transitions in the state diagram are visualized accordingly.

Fall This is the situation when a free fall is followed by a strong impact and a horizontal posture. In this case, a fall is detected. Because of the orientation check in the previous phase, only falls that end in a horizontal posture are considered.

3.4 Home Integration

A major contribution of this work is the integration of the fall detection system into a Smart Home environment. This environment is characterized by a high degree of interconnection between home appliances and entertainment devices. Its aims are an increasing quality of living, better security and energy efficiency due to the automatic and remote control of the connected devices. The Smart Fall system aims to increase the quality of living for elderly people in their home environment.

This section describes the chosen wireless technology and justifies the decision with regard to the requirements. Afterwards, the integration into the Smart Home is explained.

Bluetooth Low Energy The integration of the Smart Fall system into an intelligent building is realized by a wireless connection between the wearable device and the receiver that serves as a binding to the home automation bus. The low-cost and energy efficiency demands of the system require a low-energy wireless communication protocol. Siekkinen et al. [12] compare BLE protocol with ZigBee/802.15.4 which is popular in home automation. It is concluded that BLE is very energy efficient compared to ZigBee. Also, Dementyev et al. [13] analyze the power consumption of three low-power standards in a cyclic sleep scenario. The results show that BLE achieved the best results followed by ZigBee and ANT. Therefore, BLE is chosen as wireless technology to connect the wearable device with the receiver in the home.

BLE [14] was introduced in 2010 as part of the new Bluetooth Core Specification Version 4.0. It is a short range wireless standard that enables BLE devices to run from a coin cell battery due to its low-power consumption. The specification uses a service-based architecture, called GATT (Generic Attribute Profile), to treat communication between server and client. In the case of the Smart Fall system, the receiver component acts as client and the wearable as server. A server provides data in form of characteristics representing one logical value respectively. Several related characteristics can be summarized to a service. The developed BLE server provides a service containing four characteristics: one characteristic for each acceleration direction and a characteristic indicating the detection of a fall. Additionally, GATT protocol offers notifications. It is possible to register a client at the server to receive notifications on a certain characteristic. This avoids the continuous polling of data and saves resources. The characteristic that indicates a fall supports notifications. The receiver component is able to observe the state of seven connected wearable devices which leads to easy scalability of the system.

OpenHAB OpenHAB [15] provides an integration platform to connect several devices vendor- and protocol-neutral to the home automation bus. It is an open source Java software solution which is platform-independent and is able to run on low-cost targets like a Raspberry Pi. A powerful rule engine is integrated to accomplish automation tasks. The integration of the devices is realized by an event-based architecture which is illustrated in Figure 5. An asynchronous event bus is the base of OpenHAB's architecture. All devices are connected to each other via the bus, and information are transported from and to the devices. The different devices are linked to the event bus by specific protocol bindings. There are already a lot of bindings integrated into OpenHAB that allow an easy integration of devices into the system. An item repository is directly connect to the bus and keeps track of all devices' states. These states are used to represent the devices on the user interface and to inform the automation logic execution engine about current states.

To connect the Smart Fall system to the OpenHAB event bus, a new Smart Fall binding is implemented. The modular structure allows an easy and flexible integration of the binding. It offers direct access to the characteristics of the

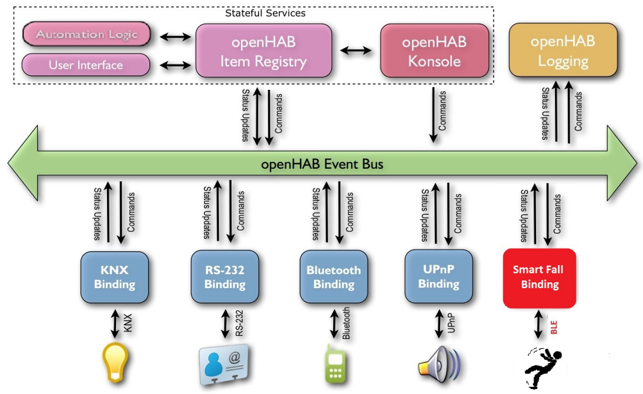


Fig. 5: OpenHAB architecture (Referring to [15])

BLE server on the wearable. Therefore, it is possible to view the provided data, like the detection of a fall, on OpenHAB's user interface.

OpenHAB's rule engine allows to react on incoming events easily. In the current implementation of Smart Fall, a smartphone notification is realized that informs a predefined person about the occurrence of a fall. The quick reaction to a fall in form of urgent support reduces the risks of serious consequences. Due to the high degree of networking in the home, lots of other reactions are imaginable. If a fall is detected, the home could automatically open the windows in the relevant room to provide fresh air for the fallen person. In another scenario, a service robot could be send to the fallen person to administer first aid. The utilization of OpenHAB as extensible integration platform allows fast development and effective interaction with the intelligent building.

4 Evaluation

The following section focuses on the evaluation of the fall detection algorithm. Ten healthy people were asked to wear a waist belt with the Smart Fall wearable device and perform ADL and falls. Falls were performed backwards, sidewards and forwards, each five times per participant. Walking, sitting, jumping and going stairs up and down were considered as ADL. Each action was performed five times by each person. While performing the activities, a supervisor monitored and documented the algorithm's results. Table 1 gives an overview over the evaluation results where the last row and column contain the sums of the corresponding column and row respectively. There are 136 (true positive classifications) out of 150 falls correctly classified, while 14 (false negative classifications) falls were classified as ADL and not detected. These misclassifications are mostly caused by the simulation of falls, especially by simulating forward falls. The participant intuitively absorbs the intensity of the fall by using his or her knees and hands. Therefore, the *Impact_Threshold* of 2.5 g is not exceeded, and no fall is detected.

Table 1: Fall detection confusion matrix

		Activity		
		Fall	ADL	
Algorithm's output	Fall	136 (TP)	0 (FP)	136
	ADL	14 (FN)	250 (TN)	264
		150	250	

On basis of the confusion matrix, the sensitivity and specificity can be calculated as follows:

$$Sensitivity = \frac{TP}{TP + FN} \ , \tag{3}$$

$$Specificity = \frac{TN}{FP + TN} \ . \tag{4}$$

These values result in a sensitivity of 91% and a specificity of 100%. This means that 91% of all falls are detected and all of the ADL are classified correctly. In comparison to other fall detection solutions, the results are reasonable. It shows that the Smart Fall system is a robust system for detecting falls. Especially, the specificity encourages a high acceptance by the user because there are no false alarms.

5 Conclusions & Future Work

In this paper, a new low-cost fall detection system inside a Smart Home environment has been presented. The system consists of two main components: a wearable device that is worn by people at the waist and a receiver component that acts as gateway to the home automation bus. The wearable device is able to measure linear acceleration in three axis and communicate over BLE protocol, which is stated to consume low energy. All components of the developed hardware system feature low-power consumption which yields to long lifetime. Additionally, a fall detection algorithm is implemented on the wearable device. The use of thresholds for fall detection results in low power consumption but still achieves high sensitivity and specificity. Finally, a software component that connects the wearable device with the Smart Home environment was developed. The combination of robust fall detection and intelligent building integration offers fast support for fallen people and lots of possibilities to react on falls.

Further work will focus on an improved interaction with the Smart Home, e.g. guiding a helping person through the house via programmable trail signs. Especially, this would be of great interest if the system is deployed in larger buildings like hospitals or nursing homes. Additionally, a more comprehensive evaluation with real falls is planned.

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