Fall Detection on the Road

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***Abstract*—While for an automatic and autonomous indoor fall detection an enormous amount of different sensors is conceivable, for an outdoor fall detection only wearable sensors are applicable. For practical uses cases, it would be very beneficial if after a detected fall a medical alert is initiated. In indoor environments, a base station connected to a telephone line can handle these calls. On the road, this can be achieved by mobile phones or smartphones.**

In this paper we first estimate the suitability of several systems for an outdoor fall detection. Then, we propose a system for a *mobile and stationary* fall detection and alerting system. We implemented and evaluated this system, which is consisting of a smartphone and a wireless sensor node.

***Index Terms*—Outdoor Fall Detection; Wireless Sensor Node; Smartphone; Accelerometer**

I. Introduction & Related Work

The automatic detection of a person's fall is a much-debated topic and there are several different approaches, algorithms, sensors and systems [1]. In practical use cases, these systems should come along with an autonomous alarm signaling which transmits the event of a detected fall to some kind of emergency response infrastructure. Elderly people – living at home alone – represent a large target group for such systems. In the GAL project [2], we focus on such a setting. In case a person tumbles and nobody is around to help, an independent fall detection and alarming system could automatically call for help, even if the person is unable to trigger an alarm by his-/herself. This may additionally increase the personal feeling of security.

A. Fall Detection

An automatic fall detection in general can be performed by many different sensors and systems. One or more video sensors (cameras) are often and reliably used [3] in home environments. Arrays of infrared sensors [4], laser scanners [5] and even floor vibration and sound [6] are possible candidates for a fall detection. But, as these are stationary sensors, it is obvious that these sensors only work within a certain area which most likely will be located indoors.

However, most publications regarding fall detection consider wearable sensors. Accelerometers [7][8], gyroscopes [9] or even barometric pressure sensors [10] are attached on a person's body and allow a precise assessment of the body's motion. Whereas in most cases, these systems also only work within a certain area, as the raw data is just gathered by the wearable sensors and not processed in place. In most publications, these systems transmit raw sensor data to a powerful computer which is analyzing the data and performing fall detecting algorithms. Thus, most approaches that use wearable sensor nodes for fall detection are also only working indoors.

B. Personal Emergency Response System

The idea of a Personal Emergency Response System (PERS) [11] has come up a long time ago and nowadays these systems are widely used. Traditional PERS or medical alert systems usually consist of a wearable device and a base station. Whenever the user needs to call for help, he or she just has to press a button on the wearable mobile device. The mobile device then radios a message to the base station which is connected to a stationary phone line and initiates an emergency call to a certain service provider. Talking to health-care professionals and system operators, many different behaviors of elderly people equipped with a PERS can be observed:

1) Normal usage: The desired use case for a PERS is a person wearing an emergency wireless transmitter like a wristwatch, a necklace or a pendant permanently during the whole daytime.

2) Non-usage: During a normal maintenance interval, a service technician drops by for changing the batteries of the wireless transmitter. Not rarely, some elderly persons have to grope around for the device in various drawers, obviously never wearing it.

3) Refused usage: Even if a fall occurs and the respective person is unable to get up again on its own, some people tend to "not wanting to bother" other persons with their accident. Especially if the home care service is expected to appear within the next few hours, some elderly people prefer to wait helpless on the floor, rather than to put somebody out and call for help.

4) Anxious usage: Anxious or confused persons may tend to wear the transmitter additionally during bedtime. This can lead to a higher amount of false alarms, because of inadvertently triggering the alarm by a turnover or in the consequence of a bad dream.

5) Avoidance behavior: Besides that, anxious people may avoid to leave the residence, because the PERS only works inside the range of the base station ($\sim 30 - 100\,$meter).

The case of *non-usage* (I-B2) can only be handled by a non-invasive and non-worn autonomous system with deployed sensors like cameras, light barriers, laser scanners or other suitable sets for an indoor fall detection (see I-A). Nevertheless, these will never work outside the residence.

The case of *refused usage* (I-B3) can be addressed by an automatic fall detection without the need of an interaction of the user. The *anxious usage* (I-B4 could be handled by a system that only works automatically, without the opportunity of a manual trigger; but this would probably also lead to a lower acceptance rate of the system.

The *avoidance behavior* (I-B5 can be addressed by a mobile PERS, which is able to utilize other channels than just the local phone line to make an emergency call.

C. Mobile PERS

A mobile PERS has been considered in several smartphone applications. Apps like *PerFallD* [12] or *iFall* [13] are some examples that utilize the accelerometer of an Android smartphone for the realization of a fall detection. As they all additionally use the GSM/UMTS radio for sending messages or emergency calls, such system – consisting of just one mobile phone – could already be called a *mobile PERS*.

PerFallD is the only one of the previously referred mobile PERS that mentions the power consumption of the system. The authors claim that their system is able to run for ~ 33.5 hours on a HTC Dream (T-Mobile G1) smartphone. Referring to the datasheet, the maximum battery lifetime of this particular phone in idle state is ~ 402 hours. Thus, the lifetime decreases by more than a factor of 10 – if the manufacturer can be trusted regarding the achievable runtime. Nevertheless, it is a matter of common knowledge that the batteries of today's smartphones – of any manufacturer and any kind – will not last for a longer period of time, if the smartphone is actually used. In a heavy usage scenario [14], none of the up-to-date smartphones will last more than a few hours.

In the next section, we will state some design decisions for our approach of a *mobile PERS*, which consists of more than just a mobile phone and is presented in Section III. In Section IV we will give a short insight in the implementation which is then evaluated in Section V. Finally, in Section VI we conclude the paper.

II. Design Decisions

At a first glance, today's smartphones offer anything that is needed for a mobile fall detection and automated emergency calls. Most devices include an accelerometer, some even include a gyroscope. The computational power of smartphones is comparable to former workstations [15] and, thus, even complex algorithms for fall detection and gait analysis can easily be implement – in a common programming language like JAVA. Also, several mobile networks, like G2/3/4 networks or WiFi enable to make emergency calls from almost everywhere in the urban, suburban and rural areas. But, the tempting story of "one device fits all needs" is worth a second glance.

Table I
Fall detection capabilities of different systems

	Fixed Installation[1]	Smartphone	Sensor Node
Computing Power	very high	high	very limited
Available Memory	very high	high	very limited
Power Limitation	none[2]	very high	normal
Available Sensors	all	few	some[3]

A. Limitations of Smartphones

Unlike the processing capabilities of modern devices that more or less follow Moore's Law, only moderate progress can be observed for nowadays batteries. Thus, the normal usage of a smartphone is to carry it while outdoors and to charge it while indoors. In other words, a smartphone can never be the only sensor for a fall detection, as one normally immediately takes it out of the pocket and plugs it in a charging station when returning home. Another aspect to be considered when utilizing a smartphone for fall detection is the unspecified position and alignment at the body. As it is still a smartphone in the first place, some people put it in a pocket of the trousers, or in the jacket, or handbag or belt bag. While the correct alignment can be calculated by special algorithms [16], some of these locations are more tight, others are more loosely bound to the body, which may lead to huge inconsistencies in the fall detection.

B. Single Device for In- and Outdoor Fall Detection

If a "single-device-solution" for combined mobile and stationary PERS is wanted, this single device cannot be a smartphone, just because of it's power consumption. But, having one system for monitoring falls at home and another system for monitoring falls on the road does also not sound like the cleverest idea ever. In fact, such a diversity would rather lead to confusion than to a raised feeling of security.

C. Benefits and Limitations of Sensor Nodes

As mentioned in Section I-A, a wireless sensor node with a dedicated set of sensors is frequently used for performing a fall detection. In contrast to a smartphone, the usage of dedicated wireless sensor nodes allows a more or less exact placement on the person's body (e.g. by a belt or wrist mounted device). A wireless sensor node can also have a known and determined set of sensors, whereas the specific types of sensors in smartphones differ from unit type to unit type. Additionally, the configuration of theses sensors (range and resolution) can be directly controlled, whereas most smartphones only provide a high level abstraction for sensor data). Furthermore the implemented "intelligence" in nowadays digital sensors – e.g. an interrupt request at a certain acceleration threshold or at a detected predefined pattern – allows for more energy and computation efficient algorithms.

But, on the other hand, a "normal" (wireless) sensor node is surely an additional device, as it is not capable of making emergency calls outside the radio range of it's base station.

[1] See first paragraph of Section I-A.
[2] Excluding wireless wearable sensors.
[3] Dependent on the used sensor node.

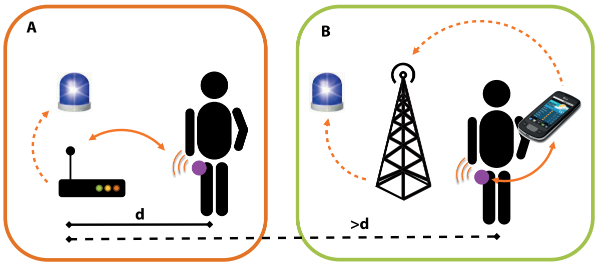

Figure 1. Fall detection system, indoors (A) and outdoors (B).

In Table I we summarized our assessment of the different systems for an autonomous fall detection.

III. System Overview

As a consequence of the arguments presented in Section II, we propose an autonomous fall detection and emergency call system consisting of 3 parts. We consider one and the same system for detecting the falls and different systems – according to the location of the user – for making emergency calls. In Figure 1 the components and the basic functionality is presented. In an indoor environment (A) and within the communication range (d) of the base station, a worn wireless sensor node directly communicates via a wireless link with a base station, like in a "normal" PERS scenario. As an enhancement to the normal PERS setting, this node is not just a mobile alarm button. With the onboard sensors an automatic fall detection can be performed, whereas the computation of the algorithms could be performed either directly on the node or the raw data is transmitted to the (presumably more powerful) base station and processed there.

In an outdoor environment (B) the same worn wireless sensor node collects data. But, in this particular case, it communicates with a mobile phone, which again is responsible for making emergency calls. These emergency calls could be enriched by localization data derived from the cellular network or a built-in GPS receiver. Here, too, the computation of the fall detection algorithms can either be performed on the wireless sensor node or on the mobile phone, which again only in the latter case would have to be a smartphone. When just acting as a gateway for emergency calls, even an already present legacy phone can be utilized for this purpose. For that

Figure 2. INGA sensor node, extended by a Bluetooth shield.

case, we expect only little additional battery drain at the mobile phone.

For the indoor and the outdoor scenario, we assume that the constant transmission of raw data to another device (be it base station or smartphone), will lead to an increased power consumption of the system.

IV. Implementation

The implementation covers three different use cases:

1) Sensor sampling and fall detection performed by sensor node; emergency alarm performed by smartphone.
2) Sensor sampling performed by sensor node; fall detection and emergency alarm performed by smartphone.
3) Sensor sampling, fall detection, and emergency alarm performed by a smartphone.

For our implementation, we used an INGA [17] wireless sensor node. This node is equipped with an accelereometer, a gyroscope and a barometric pressure sensor, but, for a proof-of-concept implementation, we only utilized the accelerometer for the fall detection.

The wireless sensor node is equipped with an IEEE 802.15.4 compatible radio transceiver, which is widely used in the area of Wireless Sensor Networks (WSNs) and Wireless Body Area Networks (WBANs). Unfortunately, most of the existing mobile phones do not offer such a radio interface. To still enable a communication between a WBAN and a mobile phone (or smartphone), we developed a Bluetooth shield which can be mounted below INGA (see Figure 2) and allows a connection to any Bluetooth capable phone. We also developed a respective hardware driver for the Contiki Operating System [18], which runs on INGA. We implemented a fall detection algorithm that takes advantage of the "intelligence" of INGAs concerning accelerometer [19]. Besides the automatic fall detection, the push button can be used to manually trigger the transmission of an emergency call.

We used a common Android smartphone as counterpart and implemented the three different applications. All applications are able to initiate emergency calls, using the hands-free mode of the phone or send a text message with a predefined text to a predefined phone number (see Figure 3).

In the first application, the fall detection takes place on the wireless sensor node and only alarm requests are send via the Bluetooth link.

The second application utilizes the sensors of the via Bluetooth connected INGA wireless sensor node. In this case, all raw data is transmitted to the smartphone and processed there. We implemented a fall detection and a depitch algorithm [16].

The third application works as a standalone fall detection and alerting system which uses the same algorithms as the second application, but only utilizes the acceleration sensor of the smartphone.

V. Evaluation

For the evaluation of our previously described implementation we used a Motorola Milestone, running Android 2.3.7 and Cyanogen Mod 7.1.5 ROM. First of all, we concentrate on the battery drain of the smartphone, which we consider most

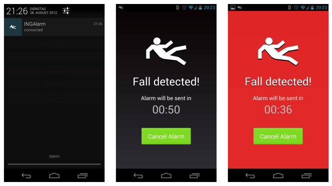

Figure 3. Android application for WBAN connection and alarm notifications.

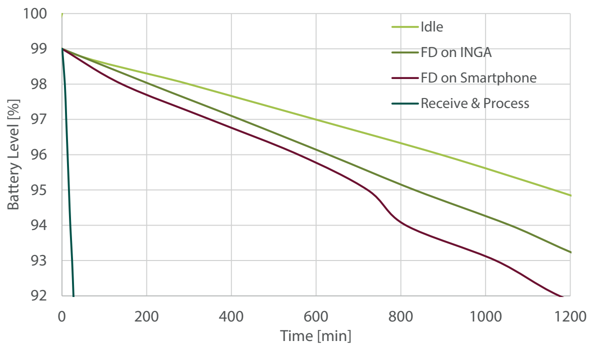

Figure 4. Battery drain of the smartphone for the different use cases. The "Receive & Process" curves are plotted in detail in Figure 5.

important for a mobile fall detection system. Our systems also uses the modified INGA [17] sensor node, running Contiki 2.5; and we also measured it's energy consumption in the implemented use cases. As mentioned in the abstract, we are not willing and able to give an estimation of the actual *quality* of the different algorithms. But, we can estimate the actual costs in terms of energy consumption and asses whether to implement an algorithm on either one device or another.

A. *Baseline for Smartphone*

As already mentioned in Section I, the baseline for the smartphone in a realistic use case is hard to tell. The manufacturer of the used phone claims a standby time of 380 hours in UMTS mode – but this surely only applies for an completely "unused" phone, if ever. During our evaluation no phone calls occurred and most of the unused system processes have been shut down. We constantly monitored the state of the battery with a self-developed application. The "Idle"-curve in Figure 4 shows the results of these measurements.

B. *Sensor sampling on node, fall detection on smartphone*

The data acquisition by the wireless sensor node has the advantage that the data can be gathered at one or more defined positions on the body. Additionally, the advantages of a fully controllable and programmable sensor, like the freedom to chose different ranges, speeds and resolutions, can be used. When just sampling this data and transferring it to a powerful computer – like a smartphone – complex calculations can be performed on accurately gathered data. Unfortunately, this consumes the most energy – by far. We sampled and transmitted the data of INGAs accelerometer at three different data rates. As the "Receive & Process"-curves in Figure 4 are very close to each other and are decreasing very fast, we

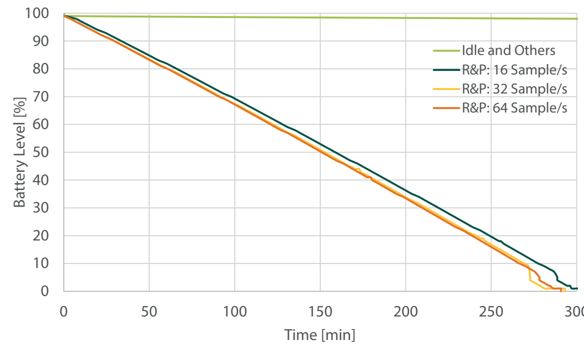

Figure 5. Battery drain of the smartphone for receiving and processing (R&P) raw data from a wireless sensor node at different data rates. The "Idle and Others"-curves are plotted in detail in Figure 4.

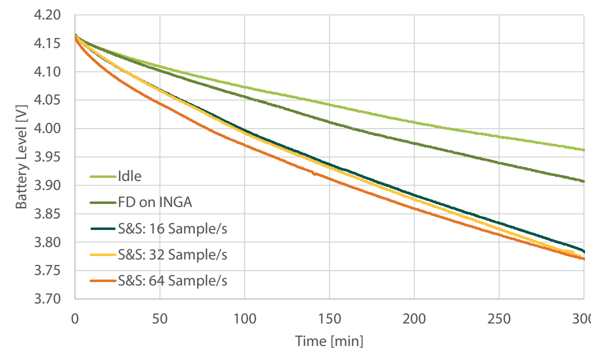

Figure 6. Battery drain of the INGA wireless sensor node. The "Sample & Send"-curves (S&S) appertain to the respective "Receive & Process"-curves (R&P) in Figures 4 and 5.

provided a more detailed view in Figure 5. After less than 5 hours of receiving and processing samples, the battery of the smartphone is completely empty. And this only applies for the unrealistic case that there are no other tasks running on the smartphone.

C. *Sensor sampling and fall detection on node*

Performing sensor sampling and fall detection on wireless sensor nodes and just sending alarm notifications via the Bluetooth link leads to the longest lifetime of the smartphone in all our use cases. Although the Bluetooth connection was constantly established, the "FD on INGA"-line in Figure 4 shows only a comparatively small additional battery drain. The advantages of being able to predetermine the position of the sensor(s) and to fully configure these sensors apply for this use case as well. The limited computational power of the 8 bit microcontroller could be compensated by the utilization of "intelligent" interrupt based detection algorithms.

D. *Sensor sampling and fall detection on smartphone*

As smartphones usually do not allow the use of the interrupts of the built-in accelerometers, these accelerometers have to be constantly polled, which leads to a significant higher energy consumption. On the other hand, no additional communication between the smartphone and another device is needed. Looking at the energy consumption, the pure smartphone based solution performs as expected. The "FD on Smartphone"-curve in Figure 4 shows, that this solution consumes up to twice as much energy, as a fall detection performed by a wireless sensor node.

E. Energy consumption of the wireless sensor node

As long as a wireless sensor node is involved in the fall detection, it surely consumes additional energy. This energy is usually provided by a battery and cannot be neglected. In Figure 6 the drain of the wireless sensor nodes battery ($950\,\mathrm{mAh}$) is presented. The energy consumption behaves similar to the smartphone. When the battery voltage level drops below $3\,\mathrm{V}$ the nodes stops working because INGA's internal low drop-out voltage regulator expects voltages higher than $3\,\mathrm{V}$ – in this specific use case this happens after ~ 8 hours when continuously sampling and sending 64 sample/s. Executing a fall detection on INGA and sending just emergency events performs much better than the continuous transmission of data to a smartphone.

VI. Summary and Conclusion

It was not the intention of this paper to give a qualitative analysis of different algorithms for fall detection, but where and how to implement these algorithms. So, performing a fall detection on a smartphone is not the worst thing to do. However, the additional power consumption evoked by constantly polling the accelerometer and performing calculations surely lowers the lifetime of the system, but, not in a critical way – if the smartphone is not used for any other purpose than detecting falls and if an additional fall detection system for indoor usage is persent.

A smartphone is usually only present at the body of a person – and by this only able to detect falls or act like an emergency button – when the person leaves the residence. When the person is at home, smartphones usually charge in some electrical outlet. Thus, a smartphone can never be the one and only solution for an integrated fall detection.

Implementing the fall detection algorithms on wireless sensor nodes and communicating these events to either a fixed base station (indoors) or a carried smartphone (outdoors), combines the benefits of both worlds. Admittedly, the wireless sensor nodes only have the limited computation power of an 8 bit microcontroller, but they can take advantage of the already available "intelligence" of the digital accelerometers, like interrupt based routines. The sensors can be placed at predefined sites – maybe attached to a belt or weaved in clothing – and the overall power consumption of the proposed combined indoor and outdoor fall detection system is comparable low. Thus, an accurate and secure fall detection can be achieved with the proposed system.

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