Fall Detection with Distributed Floor-mounted Accelerometers

An overview of the development and evaluation of a fall detection system within the project eHome

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Abstract—**Within the project "eHome" a prototype of an assistive home system was developed, aiming to prolong the independent life of elderly people at home. Besides communication, e-access and safety relevant features, a core part of this system is an automatic fall detection, which utilizes floor-mounted accelerometers to gather body-sound signals that typically occur during a human fall. This approach targets to avoid acceptance, usability and reliability issues of available body-mounted fall detectors. The system was developed with focus on practical applicability, reliability and exploitability. The prototype was evaluated successfully in laboratory and during 507 days in real-life at homes of persons from the target group. During the laboratory trials a sensitivity of 87% and a specificity of 97.7% could be achieved for a defined fall scenario and across four tested floors. Further research is suggested to investigate floor dependencies of the fall detection performance.**

Keywords: fall detection, AAL, accelerometers, independent living, older people, floor vibrations

I. Introduction

Literature shows that approximately 30% of older people above 65 years fall once a year, whereas 70% of these falls occur at home. In the group of people over 80, the number of people falling at least once per year even rises up to 50% [14][15]. The consequences of a fall can be severe especially if first aid is supplied late; the life expectancy of people that suffered a fall and lay on the ground for one hour or more is less than six months in most cases [16].

Although fall detection research was undertaken by many institutions so far and a range of commercial products is widely available by now, literature research and interviews with experts from social care showed that existing body-worn devices are hardly used in Austria for social and reliability reasons and because of usability problems [10].

Advantages of wearable products generally are to be small, light-weight, easy-to-use at relatively low costs and are easily being installed as add-on to existing senior alarm telephones [18]. A limitation of wearable fall detectors obviously is that they have to be worn 24 hours and, depending on their design, might stigmatize the user.

Other research approaches use vision based surveillance to monitor user's behavior and to recognize abnormal situations like a fall. This image based approach has the disadvantage to be considered as highly intrusive by users and other involved persons [18].

To alleviate these issues the aim of the described fall detection research was to develop a prototype system which is using only minimal invasive environmental sensors mounted on the floor of the user's home. The system should be able to recognize possible fall events and to discriminate it from other types of floor vibration with a reasonable performance and reliability. The prototype should be evaluated in laboratory trials and real-life tests together with individuals from the target group of older persons and caring relatives.

After a short introduction of the eHome prototype, the methodology used to develop and test the fall detection solution and the results achieved during laboratory and real-life tests will be presented.

A. *The eHome system*

Within the project eHome an Ambient Assisted Living (AAL) system that aims at giving elderly people a feeling of security and contributes to an autonomous life at home was developed. eHome is based on the idea to equip the user's home with a set of minimally intrusive wireless sensors that allow the system to gather information about the user's behavior and react in defined potentially critical situation such as a fall. In such a case the system first asks the user visually and acoustically via a local touch screen terminal if he/she is alright. In case the user does not respond to this internal alert, the system forwards this information to relatives, care centers or other persons of trust by triggering an alarm chain, which uses VoIP telephony to contact one of the predefined persons.

The eHome system consists of a network of several multi-sensor-boxes. These boxes were developed specifically for the eHome project and include a high sensitivity microelectromechanical accelerometer (MEMS) to pick up structure-borne body sounds when attached to a floor. The sensitivity and signal-to-noise ratio of the accelerometer were important selection criteria since they limit the fall detection

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range a single sensor can cover. The device LIS344ALH from STMicroelectronics with a sensitivity of 600mV/g and a rms noise of 0.05mg/√Hz fulfilled these and other requirements such as low energy consumption and low cost and was hence integrated into the multi-sensor-boxes.

The boxes are wirelessly connected to one central server where further sensor-data based reasoning and decision-making is performed. The central server is further connected to a local, touch screen based user interface, which is used to inform about detected critical situations and also provides the user with convenience functions such as video-telephony and easy-to-use Internet access. These three main components of the eHome system are depicted in Figure 1 below. The multi-sensor-box was developed with a size constraint to ease the integration into existing living environments; the size of the final and depicted box is 7x5x3cm.

Figure 1. eHome system: multi-sensor-box, central server and local user interface (illustration not to scale)

The eHome system was evaluated in a field study within the framework of the "Living Lab Schwechat" [17] for a total duration of 20 months and together with 11 seniors in their private homes. [12]

II. METHODS

A. Working principle

The idea behind the fall detection method is based on the assumption that the impact of a human fall on the ground generates measureable vibrations that are propagating through the floor and can be measured by acceleration sensors in a distance of several meters. Furthermore it was assumed that the characteristics of the so gathered signal differ significantly between the fall of a human being and other sources of structure-borne body sounds such as impacting objects, steps, or earthquakes.

This underlying idea was already proposed earlier by Alwan et al. [7], the same authors as of this work [19][20] and by Litvak, D., Gannot, I. & Zigel, Y. [8]. Alwan et al. used one large piezo based sensor at one spot of a floor and Litvak et al. used sound data gathered by a microphone in addition to floor mounted accelerometers for classification. In comparison the solution proposed in this approach uses several distributed accelerometers to pick up floor vibrations on several spots to enhance the fall detection performance but does omit sensors that could be perceived as intrusive by the user such as cameras and microphones.

In this work focus was laid upon evaluation of the practical applicability of the approach as well as further validation and development of the proposed technique.

B. Defining a fall scenario

A study, which researched the fall situations in Vienna, found that 72% of falls from elderly over 60 occur on one floor-level (i.e. not from a higher point down), 17% from stairs and 16% from higher positions such as a ladder or a chair [13]. Furthermore, one of three accidents at home happens during walking, 13% during cleaning, 12% during cooking and 12 % from a lying position. [13]

Older people are less likely to be able to protect themselves during the fall by using their hands [1]. Especially the "oldest old" are hardly able to get up by themselves after a fall and might remain lying on the floor for longer times as reported by Jane Fleming et al. [11] who found that in more than half of the accidents in the age group 90+ the person was found lying on the floor and in 30% of the cases had lain there for an hour or more.

Based on these findings our further project work focused primarily on falls from an upright or sitting position where the user falls in a forward direction without dampening the fall with the hands.

The following considerations led to this decision

- As mentioned above these are the most common types of falls, including falls with severe medical consequences (such as a femoral neck fracture) that happen typically after stumbling or slipping
- In contrary to falls from lower plains such as slowly slipping off a chair or the bed, these types of falls typically show a high impact, strong enough to cause serious injuries including femoral neck fracture, which is one of the leading causes of long-term rehabilitation for elderly people [13]
- The evaluation of real life data gathered in flats of elderly people going along with assumptions about impacting objects in everyday life suggest to lay emphasis on the energy a falling object transfers to the floor. Since the impact energy is related to the weight of the impacting object, it is unlikely that during everyday life falling objects will produce impacts comparable to a fall of a human.
- During simulations of falls with a dummy puppet it could be shown that even when only using one fall scenario, the gathered body sound characteristics vary in a high degree. One reason for this irreproducibility can be found in the complex mechanics of the human like dummy, which narrows the possibilities to control its fall. These simulation constraints are welcome and go along with expectations about the real model as falls of a human being also vary a lot in their characteristics. For a robust fall detection, parameters must be calculated being common denominators for different kinds of falls. This leads to the assumption that a system that is capable of recognizing one kind of fall has to be tolerant and might also be able to perform in similar fall scenarios
- The variability of falls is nearly unlimited, to achieve sound performance statistics within the projects

lifetime the limitation to certain fall scenarios is needed also from an economic perspective

C. Selected fall scenario

Based on fall statistics the following scenario was built and used for development and evaluation of the eHome fall detection system.

The user falls down to the ground from a standing or sitting position in a forward direction and because of the impact and possible injuries is not able to stand up any more, thus generating less activity in the sensor equipped flat. This fall happens anywhere within the sensor-equipped room and transmits energy in form of vibrations directly onto the floor. The eHome system recognizes the event, reacts within minutes and offers the user help (optically and acoustically) via the user interface. In case the user does not respond within a certain timeframe, the system triggers an alarm chain automatically that calls predefined telephone numbers until a person answers and establishes a video/audio call. The called person, who also finally decides whether further help is needed and might call the emergency or look after the user by himself/herself, does the further alarm handling.

D. Simulation of Falls

To evaluate body sound parameters originating from human falls, it was necessary to develop a method to simulate the fall scenario described above.

After the first test phase in a laboratory setting, where young human volunteers helped to create fall data, research on test dummies was done to be able to conduct larger scale studies on different kinds of floors. The following properties were considered significant for an adequate dummy to produce realistic falls reliably:

- The dummy should have moveable limbs to generate human like impacts on the floor since early fall studies showed that limbs often fall on the floor shortly before or after the rest of the body creating fuzzy structure-borne sound signals
- The texture and density of the skin should follow a bio-mechanical model being adequate for fall simulations. The head for example should be harder than the thigh
- The weight of the dummy should be close to the typical weight of older women (i.e. about 60kg), since this is the group primarily suffering from falls. Based on the system design it is assumed that a system that is capable of detecting falls of women will also be able to detect falls of typically heavier men

Based on the above points and on market availability, two commercially available dummies were selected and evaluated. The model "Rescue Randy" from "Simulaids" showed the closest features to human falls and was hence used for further research.

During the fall studies the dummy was borrowed for the time of the trials from the "Austrian Red Cross" and was then dressed like a human as the dampening properties of the worn fabric were considered to influence the fall induced body sound. Figure 2 shows the selected fall dummy.

Figure 2. Selected fall dummy (© simulaids.com)

III. THE FALL DETECTION SYSTEM

A. Number and placement of sensors

Literature and early experiments showed that reliably detecting a fall based on one floor-mounted sensor only is difficult since small impacts very close to the sensor can hardly be discriminated from stronger impacts further away [2,3]. To avoid this issue eHome uses at least three sensors for each room and operates on a virtually aggregated data set from all sensors placed within the same room.

According to interviews with experts on building acoustics, the ideal place for picking up the vibration signal is located in the middle of the room since ceiling constructions can be considered basically as a two dimensional "guitar string" model that exposes the highest amplitude in the middle between the mounting points after excitation. For practical reasons it would be best to mount the sensors in the corners of a room where they least interfere with user activities and do not pose a potential risk of falling over them. For the project it was decided to mount the sensors in the middle of the room's edges such as shown in Fig. 1 below, which is a compromise between the two points above.

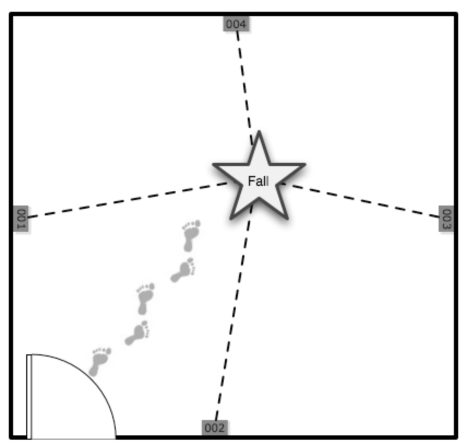

Figure 3. Placement of sensors in example room

B. Steps of the fall detection process

Vibration event detection, data gathering and segmentation of data are done on the multi-sensor-boxes of the sensor network. Data are gathered via these boxes by sampling the amplified and filtered accelerometer signal with a sampling rate of 2kHz. Feature extraction algorithms including a Fast Fourier Transform calculate a defined set of 36 fall-relevant parameters that are further being sent to a central server. The energy transduced to a floor due to a fall is seen as a major indicator, thus besides its frequency spectrum amplitude parameters are calculated and further qualified. The following parameters are calculated by the sensor boxes.

1. Peak to peak value of the amplitude as a parameter for the highest measured energy of the impact
2. Average rectified value of the amplitude as a parameter for the average energy of the impact
3. Weighted average rectified value, which is similar to parameter 2 but prioritizes the data of the first seconds of the vibration with 1/n which in most cases contains the characteristic oscillation
4. Duration of the signal
5. 32 discrete values of the frequency spectrum up to 1kHz calculated by a fast Fourier transform

Algorithms on the central server use aggregation methods to fuse the multi-sensor-data to one set of parameters by means of timestamps generated by the sensor network to identify signals of the same origin. A fall is expected to transduce enough energy to the floor that all boxes in its near ambience are able to measure the vibrations. At least three boxes are needed during sensor data fusion to estimate the impact energy transmitted to the floor by averaging the single picked-up energy signals. More sensor boxes are needed on larger floors because of the limited range a box can cover. This number obviously depends on the size of the room as well as the floor type, as a rule of thumb rooms larger than 25m^2 were equipped with an additional sensor during the trials. As a consequence 3 measured events with the origin of different sensor boxes must be recognized within a certain timeframe.

Based on the combined sensor data, pattern recognition algorithms are used to identify a potential fall event. The implemented algorithm uses a weighted threshold based evaluation of the most significant parameters. These are the first four parameters listed above. The frequency spectrum was not evaluated in user trials so far but various lab tests suggest further research in this issue having the potential of a significant improvement of the algorithms' specificity and sensitivity.

After such a potential fall event is detected, an activity indicator is evaluated for a configurable period of time to identify whether or not the user was able to get up on his/her own. In case a certain activity threshold was not exceeded, an alarm is generated and handled by higher layers. This activity indicator is generated out of multimodal sensor and user events which comprise of vibration, infrared movement and door contact sensors as well as button presses on the local user interface of the system. Fig. 4 shows the single steps of the detection algorithm on the left side together with an example of how the data diminishes when propagating through the abstraction layers on the right side.

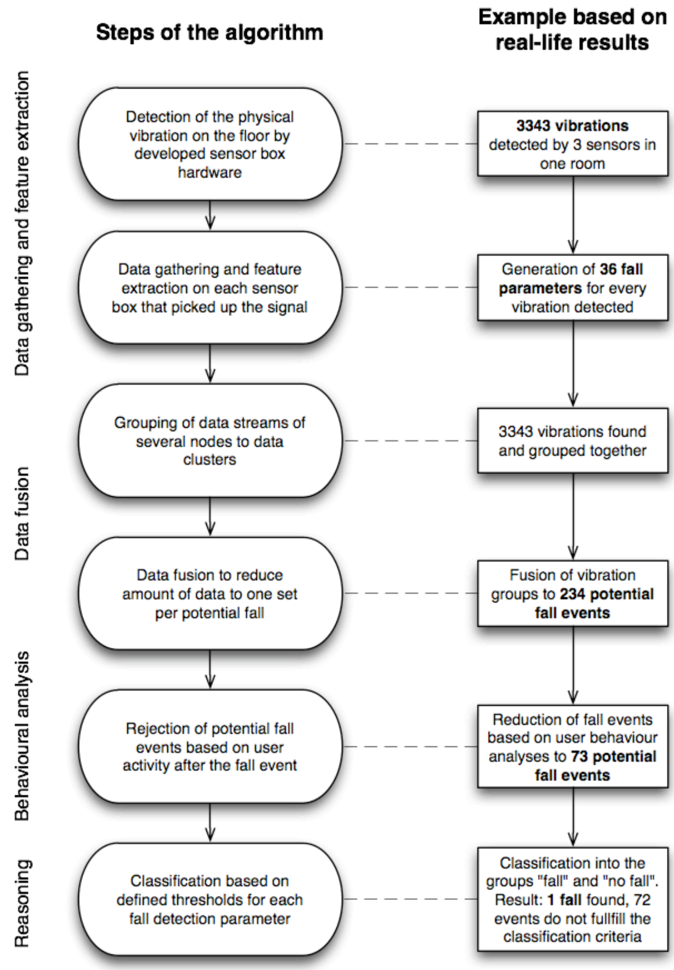

Figure 4. Steps of the fall detection process

IV. Evaluation of the Fall Detection System

A. *Laboratory evaluation*

A trial was conducted in eight rooms of different buildings with different floor types. Altogether 183 tests were carried out with the final prototype hardware that was also used in the field trials. Impact sound measurements of predefined objects and the test dummy were carried out to investigate the influence of different floor and fall characteristics.

The following research questions were elaborated:

1. How do human falls compare to common sources of solid-borne sounds such as objects falling to the floor or vibrations caused by activities of daily living? Is it possible to find a discrimination function between them in order to classify between falls and objects?
2. How do the placement of the sensors in the room and the location of the falls (e.g. in the middle of the room or at the rooms edges) influence the measurement?
3. What influence does the floor type have on the performance of the fall classification?

1) Human falls and other sources of solid-borne sounds

In order to simulate vibration noise on the floor three different types of objects were used in the trials. As shown in Fig. 5 the impact sounds of a ball, a wastepaper basket and a chair were used in comparison to the impact sounds produced by the dummy to evaluate research question 1. These objects were selected because they cover a wide spectrum of different impact properties (strong vs weak impact, low vs high frequency spectrum of the impact, rebouncing after the first impact vs not rebouncing) and their impact is reproducible.

Figure 5. selected objects: ball, basket, chair and dummy

Based on the measured data a discrimination function between dummy falls and the impacts of the used objects was developed. Using this function the fall detection algorithm showed the following performance, which is given in Table I.

TABLE I. RESULTS OF FIRST LABORATORY EVALUATION

# of impacts	dummy	objects
Fall detected	38	11
No fall detected	6	128
Total	**44**	**139**

Out of 44 dummy falls 38 were classified correctly, 11 out of 139 impacts of objects were misclassified as falls, in 8 cases the chair and in 3 cases the basket. The sensitivity of the fall detection algorithm at this stage could be calculated as 86% at a specificity of 92%.

This result was achieved with an algorithm that was optimized to detect falls on all eight tested floors, algorithms that were parameterized for one floor only had a higher performance. Four of the six false negatives origin on the same floor, which suggests a high relevance of floor characteristics for the fall detection performance.

2) Activities of daily living compared to human falls

To evaluate the question whether the chosen objects are representative for typical sources of heavy impacts during real life as well as to determine the occurrence probability of heavy impacts in real life, a further lab trial was conducted on four of the eight previously tested floors. During an evaluation period of approx. three weeks the eHome system was installed into the homes of three volunteers of the project team for a total duration of 69 days (all together) and gathered real-life vibration measurements. The volunteers were instructed to behave as usual during the test phase in their home. Table II gives a summary of test durations and data gathered during the trial.

TABLE II. SUMMARY OF DATA GATHERED DURING SECOND LAB TRIAL

Testfloors	Total no. Vibrations	Events found	Evaluation time (days)
TF1	11566	187	15
TF2	12986	27	20
TF3	8322	379	17
TF4	5703	91	17
Total	**38577**	**684**	**69**

During this time the systems picked up a total of 38577 vibrations caused by movement on the floor and occasionally falling objects. Of the gathered data the fall detection algorithm identified 684 events having an impact strong enough to trigger at least three sensors on the floor in the same room. These 684 events were analyzed by the system and classified by the pattern recognition algorithms into 668 negatives and 16 potential falls

On the same floors 24 dummy falls were performed, of which 23 (n=23) were found to be valid; in one case data was missing because only two sensors detected the event. The fall detection algorithm was used to classify the 23 remaining falls and detected 20 falls correctly.

By combining the results of dummy tests and results gained during the long-term lab trials at the homes of project members, the performance characteristics of the fall detection system could be calculated and are shown in Table III.

TABLE III. RESULT OF SECOND LAB TRIAL

Tested floors 1-4	Fall	No fall
Test positive	20	16
Test negative	3	668
Total	**23**	**684**

In comparison to common sources of body sounds in real life situations the fall detection showed a sensitivity of 87% and a specificity of 97.7% when combining the results of four floors.

3) Position of sensors and falling objects

Due to inhomogeneous floor structures the position of sensors can have a significant influence on the fall detection rate. Positions in the corner of a room or above a steel beam within the floor's construction showed a higher attenuation, which in some cases prevented the sensor from picking up the vibration signal even during the dummy falls. During the field trials and laboratory tests it was hence taken care that all sensors are responding to a stomp with the feet from a distance of one meter.

Furthermore the surface the object falls onto does have an influence to the measurement, as falls onto a carpet or firm place such as a doorsill will result in lower amplitude measurements than falls in the middle of the room.

4) Evaluation of different floor types

The floors were selected with respect to the actual living situation of the target group. Therefore tests were carried out in buildings of different construction/renovation years starting from the 1920s to 2000.

Due to their attenuation characteristics, measurements on different floors showed different results, which makes an algorithm specialized to one floor inappropriate for others. Although most tested floors showed similar attenuation properties, two floors in the laboratory trials showed a much higher / lower attenuation than the average. In particular the floor with the lowest attenuation (a light wooden structure of an attic) showed peak-to-peak amplitude measurements that were higher by a factor of 1.75 than the floor with the lowest tested excitability (a concrete floor in the ground floor without a room below)

A classification of floors based on their material and structural properties does not seem to be a feasible solution to increase the systems performance because of the high variety of floor materials and their compositions. Other solutions are suggested in chapter VI.

B. Field trials

The fall detection system was installed on 15 different floors during the eHome field trials [12]. The main goals were:

- Measure frequency of occurrence and type of common noise from falling objects and noise generated during user movement
- Measure real-life performance data of the fall detection algorithm

During the 507 days evaluation period no real fall occurred, hence no real-life sensitivity of the algorithm can be given. The fall detection algorithm developed during the laboratory trials was used for evaluation of the false positive rate. Table IV shows the performance results achieved during the field trials.

TABLE IV. SUMMARY OF DATA GATHERED IN FIELD TRIALS

Real life test floors	Total vibrations gathered	Events[a] found	Events after behavioral analysis	falls detected
TP1	3343	234	73	1
TP2_WZ[b]	70252	1476	217	7
TP2_SZ	16099	88	15	0
TP3	13914	748	401	3
TP4_KU	15369	132	44	0
TP4_SZ	7444	241	110	2
TP5_WZ	505	19	8	0
TP5_SZ	1251	11	6	0
TP6_KU	8692	51	26	0
TP6_SZ	16929	29	4	0
TP7	26064	321	46	1
TP8	15741	1384	108	1
TP9	6405	119	39	1
TP10	8251	317	73	2
TP11	12781	459	155	2
Total	**223040**	**5629**	**1325**	**20**

a. At least three vibration signals that refer to the same origin are referred to as "vibration event"

b. WZ=living room, SZ=bedroom, KU=kitchen

Out of 5629 detected events the system considered 1325 as potential falls based on the last filter stage (the 30 seconds post evaluation period) and reported 20 falls after considering the previously described fall parameters. The reported falls were all false positives. It is notable that seven false positives were reported at a site (Test Person TP2) where a small child was often playing on the floor the system was installed on.

The "total vibrations gathered" shown in Table IV vary strongly between the different test sites for the following reasons:

- The system was installed on the floors for approximately four weeks at each test-site except TP2, TP3 and TP4 where the system was installed for approximately four months
- The floors at the test-sites varied from concrete slab floors at the basement with high dampening properties to prestressed ceilings with lower attenuation. High dampening properties lead to less gathered vibration events since weak vibrations are less likely to be detected by the sensors
- Users behave differently and also the usage of the sensor equipped rooms varied between the test-sites

At all test-sites events consisting of at least three coinciding measured vibrations could be found, which states that the system was capable of detecting and analyzing heavy impacts on all floors.

V. DISCUSSION OF RESULTS

For humane reasons it could not be fully evaluated whether the used fall dummy produces realistic human like falls. Although a set of human falls was produced for comparison in the beginning of the project by volunteers and project members, it can not be stated that even the recorded body sounds of this set contain realistic falls since conscious healthy people cannot avoid the reflex to protect themselves with their hands when falling, which according to literature is often not the case when older people fall.

During the field trials no real fall happened, hence no sensitivity of the fall detection system in real life of older people can be given. This was expected since for a viable performance analysis a large set of real falls would be needed, that likely will not be gathered during a comparatively short evaluation period of 507 days [14][15]. The sensitivity of the fall detection algorithm was instead evaluated during the laboratory trials. From a scientific point of view specificity of the lab trials and sensitivity of the field trials must not be combined to provide full real-life performance statistics since they were generated using different floors.

The developed fall detection system uses a post evaluation period of 30 seconds. During this time the system analyses whether or not the user was able to get up by him/herself or not by measuring the number of activity events after the potential fall. This method greatly reduces the false positive rate as most vibrations occur in groups in real-life and is based on the assumption that the fallen user is not able to get up by him- / herself shortly after the fall. The used method for evaluating the post evaluation period did not differentiate between usual activity after an event and activity produced e.g. when crawling after having sustained a hip fracture. For the targeted scenario it was assumed that the person is not able to move from 5 seconds after the fall to at least 30 seconds after the fall.

The fall detection method used is likely to show a lower specificity in cases where more than one person lives in the same premises since it requires that vibrations occurring at the same time (+- 100ms) refer to the same origin, which might often not be the case if two persons move inside the same room. This case was not included in the scenarios since eHome was designed as a single user system.

VI. SUMMARY AND OUTLOOK

Based on research and previous experience in the field of fall recognition a fall scenario and the methodology to simulate this scenario by using a fall dummy were elaborated. Because of the complexity of sound propagation through inhomogeneous floor constructions and the high variety of different floor materials and composition, a practical approach was followed during development of the fall detection algorithm. Relevant time and frequency domain parameters of body sound signals were identified in laboratory tests and a detection algorithm was implemented on the target hardware.

During two main laboratory trials all together about 450 fall tests were performed on eight different floors in five different buildings. The impact sound characteristics of a dummy puppet, three different kinds of objects as well as randomly caused impact sounds during daily living of three volunteers of the project group for a total duration of 69 days were compared against each other. Using the so gained experience the fall detection system could be parameterized to distinguish about 80% of the impact sounds of the dummy puppet from impact sounds of other sources when combining the data from all tested floors. It has to be noted that the performance varies with the attenuation characteristics of the present floor.

Similar fall detection techniques suggested by Alwan et al. [7] and by Litvak, Gannot & Zigel [8] have shown better laboratory performances of 100% sensitivity and specificity in case of Alwan et al, and 97.5% sensitivity and 98.5% specificity in case of Litvak, Gannot & Zigel when comparing dummy impacts to impacts of other objects. The performance differences to this work are to most parts due to the fact that the reference systems were tested with a very limited number of floors (two floors and one floor respectively), which directly influences the performance of the classification algorithm. Complementary to this work our research focused on the practical applicability of the system under real-life conditions, not on optimizing the performance in one specific laboratory setting.

Using the fall detection system developed in laboratory 15 floors in flats of people being part of the target group were equipped for a total duration of 20 months during the eHome field trials. During this time no test participant fell down hence no real life performance data can be provided regarding the sensitivity of the fall detection system. Instead the false positive rate was evaluated retrospectively on the gathered data. The algorithm that showed a detection rate of about 80% during the laboratory trials, reported 20 false alarms based on 507 days of real-life data.

Research showed that there is a tendency that vibrations with high energy, long duration and comparatively low frequencies qualify for a human fall. However, the optimal classification thresholds for these parameters depend on the used floor. It could be shown that when customized to a room, it is possible to implement fall detection with high reliability. Due to complex frequency characteristics of floors and high differences between the measurements of different floors, one algorithm that fits all tested floors has a poorer performance.

Further work on this area should focus on methods to alleviate floor dependencies of the detection process. One approach could be to measure floor relevant characteristics of the floors in the user's premises prior to the installation of the system to be able to estimate the achievable fall detection performance and customize the system to the users home. Another possible solution that could achieve better performance especially across different floors would be a system that learns typical vibration events triggered by the user for each room and reacts on unusual "fall-like" vibrations.

The extension of the system to support multi user environments would be a promising next step that could reduce the burden of caring relatives that live together with the user. Further real-life tests are suggested to be able to validate the results and to pick up data of real falls.

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