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Detection and Prevention of Seniors Falls

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Abstract: The paper deals with the issue of seniors' security and safety, namely the security problems related to falls of independently living elderly citizens. The number of elderly people is growing very fast worldwide and very often they live unattended in their house or flat. In case of accidently falling down, they are often unable help themselves and stay on the floor for hours or even longer. This may lead even to the death if no help comes. Various possibilities of their fall detection are studied. We analyze the historical development, current capabilities and efficiency of different approaches and methods. We address the willingness and ability of seniors to actively use technology, detection limits, privacy, personal data security and other important factors. In addition, we discuss the challenges, current shortcomings, issues and trends in fall detection or operation reliability in real-life conditions. The main future goal would be to maintain the personal privacy and security of irrelevant information in modern fall detection systems.

Keywords: Assistive technology, Emergency response, Fall detection, Security, Smart phones, Senior inspect, Witrack.

1. Introduction

Worldwide, the number of persons over 60 years is growing faster than any other age group. According to the World Health Organization (WHO) study [1] approximately 28-35 % of people aged 65 and over fall each year. This number is even increasing to 32-42 % for those over 70 years of age. In fact, the number of falls increases exponentially with age-related biological changes. Falls are defined here as "inadvertently coming to rest on the ground, floor or other lower level, excluding intentional change in position to rest on furniture, leaning on the walls or other objects". Falls and consequent injuries are major public health problems that often require medical attention. They lead to 20-30 % of mild to severe injuries, and are underlying cause of 10-15 % of all emergency department visits and account for 40 % of all injury deaths. If preventive measures are not taken in immediate future, the numbers of injuries caused by falls is projected to double in the year 2030.

In addition, falls may also result in post-fall syndrome that includes dependence, loss of autonomy, confusion, immobilization and depression, which will lead to a further restriction in daily activities. Such dependence is shown, for example, in a study by S. M. Friedman et al. [2], where authors state that each syndrome may lead to the other. Namely, an individual who falls may subsequently develop fear of further falls. This distinction underlies the concept of primary prevention, in which the onset of fear of falling is prevented, versus secondary prevention, in which fear of falling is prevented from progressing. Falls consequences can significantly mitigate their early detection combined with an effective emergency system.

The effect of automatic fall detection units on the fear of falling was studied by S. Brownsell et al. [3] on the group of participants, who had experienced a fall in the previous six months. Most users who wore their fall detectors at least occasionally felt more confident and independent and considered that the detector improved their safety.

One of determining factors influencing the severity of fall consequences in older people is the amount of time spent lying on the floor or ground [4]. This is particularly critical when a person cannot call for help, for instance when she/he has lost consciousness or is alone when the fall occurs. Even when uninjured, 47 % of people who have experienced a fall were unable to get back up without help. Lying on the floor due to a fall event for one hour or more is defined as a "long-lie". Experiencing a "long-lie" event is associated with serious injuries, higher mortality rates and hospital admissions, as well as consequent care home admissions.

Therefore, calling for help systems and other technological equipment for detecting, preventing, and mitigating falls consequences have become a social necessity and it is very important to use reliable and sufficiently sensitive systems.

A fall detection system could be defined as a system which detects falls and alerts a designated person or emergency services in order to facilitate rapid assistance. A system causing too many false alarms is inconvenient for the system supervisor while the not responding system can result in injuries or even in death.

For these and other reasons, some fall detection studies originated a few years ago, for example Noury and collective [5] in 2008 or a similar analysis [6] published in 2012 by Mubashir and other co-authors. In recent years, there has been rapid development in the field of fall detection and so some systems are missing in the above studies, such as those based on the use of smart phones and the like. These missing trends are described in this work, which builds on our publication [7].

In Section 2, individual systems are described. Starting with "The first call for help system", continuing with the "Automatic fall detection" and, at the end, the "Mobile personal airbag" system. In Section 3, more recent and some complex projects are mentioned. Also the possibility of using smartphones in the area of fall detection can be found here. Section 4, concludes the article and suggests future possible developments in the area.

2. Individual Systems

2.1. The First Call for Help System

The first call for help system, in English often called Medical Alarm or Personal Emergency Response System (PERS) was developed in Germany in the early 70s of the 20th century by Wilhem Hormann [8]. The system was programmed to send messages after pressing a button. The button (transmitter) was designed to be worn by a senior living alone. The cost was 795 USD and was offered through Popular Science magazine in October 1975 (Fig. 1).

Fig. 1. Emergency Dialer.

2.2. Automatic Fall Detection

Research on automatic fall detection progressed through the nineties of the twentieth century. Lord and Colvin [9] studied the causes and consequences of falls in the elderly, they tried to prevent falls and suggested the use of an accelerometer to detect a fall. The first detector prototype was developed in the fall of 1998. It used a piezoelectric shock sensor for detecting abnormal peaks caused by the fall and a mercury tilt switch for detecting the orientation of the falling user.

One of the first attempts to detect the fall based on video cameras was described by Wu [10] in 2000. Results showed that the horizontal and vertical speed can be utilized to distinguish a fall from normal activities.

In 2002, Prado et al. [11] developed a prototype system for detecting fall based on two dual-axis accelerometers placed in a patch worn on the user back at his cross level. The same year, Norbert Noury [12] developed a smart sensor with evaluation algorithm. The prototype contained a piezoelectric accelerometer, vibration sensor and a switch responsive to the position. Unfortunately, it turned out that the vibration sensor is too sensitive.

T. Degen et al. [13] introduced a fall detector for elderly people in the form of a wristband in 2003. The device was comfortable to wear, but its reliability was only 65 %.

Some of the acceleration based fall detectors can be seen in Table 1.

Table 1. Comparison of acceleration based fall detectors.

Study	Year	Objective	Detection technique	Tested	SP/SE	Detector location
Kangas et al. [14]	2009	prototype verification	exceeding the threshold value; min.2 phase	20 persons	100 % / 97 %	wrists, head, waist
Shan et al. [15]	2010	investigation of a pre-impact fall detector	support vector machines (SVM)	5 persons	100 % / 97.5 %	waist
Bourke et al. [16]	2010	comparision of novel fall detection algorithms	considering the fall impact, the velocity and the person posture	20 persons	SP: 100 %	waist
Lai et al. [17]	2011	several acceleration sensors for joint sensing fall events	exceeding the threshold value; compared acceleration in 3 axes	9 persons	Accuracy 92.92 %	neck, hand, waist, foot
Yuwono et al. [18]	2012	verification of a sophisticated fall detection method	machine learning method (MLM), perceptron network structure adaptation	8 persons	99 % / 98,6 %	waist
Kerdagari et al. [19]	2012	investigation of the performance of different classification algorithms	machine learning method (MLM); combination of several methods	50 persons	SE: 90.15 %	waist
Cheng et al. [20]	2013	daily activity monitoring and fall detection	exceeding the threshold value; using a decision tree	14 persons	95 % / 97.6 %	chest, thigh

In 2004, Sixsmith et al. [21] used a variety of cheap infrared cameras mounted on the wall. The alarm started when there was no observed activity over long period of time or during the detection of a fall. Attempts (20 falls + 10 attempts without falling) unfortunately showed that only 30 % of falls were properly detected.

Several groups around the world were engaged in the new devices development in 2006. Kang et al. [22] have developed a bracelet, in which the fall monitoring and modules for measurement of the single-channel electrocardiogram (ECG), blood pressure, pulse oximetry, breathing, and temperature were merged. Nyan et al. [23] have conducted fall detection experiments based on a high-speed camera and three gyroscopes installed in the undershirt. The gyroscopes were concretely placed on the chest, arm and at the waist. The camera was used to study the position of the body during the fall, while the angular velocity was the guideline for the fall detection. Miaou et al. [24] reported fall detection based on the panoramic camera and information about the user (the height to width ratio and Body Mass Index (BMI)). This system brought a 70% accuracy without user information and 81% accuracy with this information. Alwan et al. [25] suggested a fall detection system based on floor shocks sensing by a piezoelectric sensor. It showed 100% detection rate, but falls simulations were carried out with dummies.

Srinivasan et al. [26] studied the automatic detection of the fall based on triaxial accelerometer and passive infrared detectors (PIR) in 2007. The triaxial accelerometer worn by the user was placed at the waist for fall detection while the PIR detectors were mounted on the wall to provide information about the horizontal movement. The same year Almeida et al. [27] presented the stick with a gyroscope, which helped detect the downfall and measured the number of steps. The fall detection was based on the angular velocity evaluation.

In 2008, Doukas and Maglogiannis suggested a combination of accelerometer and a microphone placed on a leg [28]. Based on the short-time Fourier transformation it was described that during the impact the low-frequency sound signals with high amplitude are formed and can be used to detect falls. The same year, Bourke et al. [29] introduced a fall detection system and algorithm that were incorporated into a custom designed garment.

Tzeng et al. [30] used in 2010 a pressure sensor in the floor to identify fall strength combined with infrared camera to detect the movement of a person. Bianchi et al. [31] developed a fall detection system based on barometric pressure sensor and a triaxial accelerometer located at the waist. On the basis of the barometric pressure difference between the waistline and the earth, the experimental results showed that the obtained sensor information was useful for the fall detection.

2.3. Mobile Personal Airbag

It is a 2009 pilot project for the protection against injuries from falls [32]. Behind this project stands a Japanese scientist Toshiyjo Tamura and his team. The researchers designed a wearable device containing a fall detector directly connected to the airbag. The signal containing information about the acceleration and angular velocity was used for the airbag activation. Sixteen people were monitored during a fall simulation. Based on the data an algorithm was designed so that the downfall was evaluated 300 ms before the actual impact of people on the ground. This signal was then used to start the 2.4 liter airbag. Although this system can help to prevent injuries due to falling, other research/development is required to miniaturize the inflation system.

3. More Recent Projects

3.1. Fallwatch Project

The French company Vigilio S.A. launched a project FallWatch [33] funded by the FP7-SME program with the timeframe 2009 - 2012. The challenge was to develop a new generation of fall detection devices, including call for help system, which would be effective in minimizing the consequences of falls. FallWatch is a miniature radio communicating wearable device in the form of an adhesive patch. The project deals with the fall from the moment it occurs, i.e., from its detection through the cause investigation to desired action. Fall-Watch may be regarded as a context-aware system. The user wears a "patch" and FallWatch constantly monitors the kinematic variables and classifies the situation according to three degrees of state activity: low, medium and high. Another component is the home central unit that monitors activity using signals from PIR detectors and classifies the situation according to three-level scale (no activity, normal activity, exceptional activity), see Fig. 2. Detail comparison of compare-aware systems was done for example by Igual and his colleagues in [34]. Some of them can be seen in Table 2.

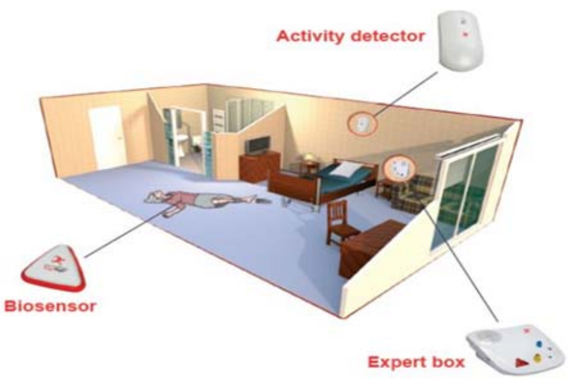

Fig. 2. FallWatch Vigifall.

3.2. Smartphones as a Fall Detection System

Developers are trying to detect the fall using smart phones since 2010. Dai et al. [35] introduced the fall detection based on mobile phones in 2010 and recently the detection based on triaxial accelerometers becomes more and more popular.

In 2012, Fang et al. [36] compared the accuracy of fall detection for smart phones placed on the waist, chest and thigh, and found that its chest location is the most appropriate. The advantage of using a smartphone to detect the fall is the possibility of simultaneous use for sending warning messages and / or tracking the person who needs help.

Koshmak et al. [37] experimented with detection of a fall with 7 skiers. They had with them a smart phone when skying downhill and the pulse and blood oxygen saturation were measured. The measured values were unexpectedly variable in critical situations.

Also, Kau and Chan [38] conducted a study with smartphones. Fall was detected using a triaxial accelerometer and electronic compass.

3.3. Senior Inspect Project

A purely Czech product in the fall detection area is the Senior Inspect project. The project was developed by The CleverTech spin-off company.

The spin-off company allows the important process called technology transfer in academic environment to take place and is usually founded by university staff with contribution from external specialists or companies. The CleverTech is a spin-off company consisting of Faculty of Biomedical Engineering at Czech Technical University (CTU) in Prague, First faculty of medicine at Charles University in Prague and some external entities. The first testing of the product began in 2010, the commercial use in 2013 [39].

The user wears a small communications unit and in a critical situation presses the SOS button. The system also enables a range of advanced automatic features in case the user is unable to press the button by himself/herself. When setting off an alarm in the surveillance center the position is determined and the voice call is established directly with the user through the communication unit. On the base of the individual assistance profile and the user agreement the next procedure is selected (the family, professional associations, integrated rescue system etc. are contacted). Key benefits include:

- Simplicity of use;
- Possibility of the communication, localization;
- Panic button;
- The support for proper use;
- Automatic detection of emergency situations (including the fall).

3.4. FATE Solution

The Polytechnic University of Catalonia project Fall Detector for the Elderly (FATE), which was launched in 2012 with EU funding, should soon bring results. The FATE system is being developed to be an affordable and reliable system capable of detecting falls both inside and outside home [40]. The system consists of two main elements plus a series of secondary elements. The main elements are:

• Highly sensitive fall detector incorporating accelerometers, capable of running a complex, specific fall detection algorithm in order to provide accurate fall detection.

Table 2. Comparison of some context-aware systems [34].

Study	Year	Basis	Features used for fall detection	Tested	SP/SE	Type of sensor
Miaou et al.	2006	Customized fall detection system using omnicamera images	The ratio of people's height and weight	20 persons	With personal information: SP: 86 % SE: 90 %	Camera
Vishwakarma et al.	2007	Automatic detection of human fall in video	Aspect ratio, horizontal and vertical gradient distribution of object in XY plane and fall angle	1 person	SP: 100 % SE: 100 %	Camera
Fu et al.	2008	Contrast vision systém designed to detect accidental falls	Change in illumination	3 persons	3 possible scenarios evaluated with positive results	Contrast vision sensor
Anderson et al.	2009	3D representation of humans (voxels) using multiple cameras. Two levels of fuzzy logic determines first a state and then activities (f.i. a fall)	At low level: silhouettes from each camera, to build a set of voxels. At an intermediate level: centroid, height, major orientation of the body and similarity of the major orientation with the ground plane normal.	Not specified	SE: 100 % SP: 93.75 %	Camera
Lie et al.	2010	Vision fall detection system considering privacy issues	The ratio and difference of human body silhouette bounding box height and width	15 persons (age 24–60)	Accuracy 84.44 %	Camera
Tzeng et al.	2010	A system that adjusts the detection sensitivity on a case-by-case basis to reduce unnecessary alarms	Floor pressure signal Image features: standard deviation of vertical projection histogram, standard deviation of horizontal projection histogram, and aspect ratio	Not specified	SP: 96.7 % SE: 100 %	Pressure/ infrared sensors
Rougier et al.	2011	A vision system based on analyzing human shape deformation	Some edge points from the silhouette of the person	Not specified	Accuracy (falls and ADL correctly classified): 98 %	Camera
Mastorakis et al.	2012	Real-time fall detection system based on the Kinect sensor	The width, height and depth of the human posture, which define a 3D bounding box	8 persons	All falls were accurately detected	Infrared Sensor
Zhang et al.	2012	Privacy Preserving Automatic Fall Detection	Deformation and person's height	5 persons	Accuracy 94 %	RGBD cameras

• Telecommunications layer based on wireless technologies. It consists of an indoors telecommunications network based on Zigbee, a central computer (with or without Internet connection) and a mobile phone communication with the central computer and the fall sensor via Bluetooth. All incidences and measures are stored in the server, so that they can be used as a monitoring data for the carers/doctors thus improving subject fall prevention and treatment. Once detected and confirmed, fall events are communicated by the mobile phone (or Internet, if this service is available) to relatives or health service providers.

Secondary elements are:

• Bed presence sensor to dismiss false falls (if the person lies on the bad in a sudden way while wearing the fall detector) to control the time the person spends in bed (to detect potential health problems or behavior anomalies) and to detect falls from the bed (as the user may decide not to wear the fall sensor during sleeping hours).

• i-Walker to detect fall risk for elders with significant gait difficulties, i.e., walker with integrated automatic brake, tilt sensors and with pressure sensors placed in the handle.

3.4. Personal Motion Sensor with the Fall Detection IMSAFE

Individual Mobility Sensor for Automatic Fall Evaluation (IMSAFE) [41] is based on a combination of the power converter placed in shoe soles with accelerometer located in the belt measuring stroke, orientation and deviation from the pattern posture (Fig. 3). The device was developed in the form of 2 different prototypes in 2012 at the University of San Diego. The declared detection accuracy of this project is high, 97.14 %.

Table 3. Smartphone based fall detectors [34].

Study	Year	Basis	Detection technique	Tested	SP/SE	Smartphone location
Sposaro et al.	2009	Alert system for fall detection using smart phones	TBM considering the impact, the difference in position before and after the fall and whether the fallen patient is able to regain the upright position	Not specified	Not specified	Thigh (pocket)
Dai et al.	2010	Mobile phones as a platform for developing fall detection systems	TBM considering the impact, the wearer's orientation and the common step mechanics during falling	15participants from 20 to 30 years old (2 females, 13 males)	Good detection Performance	Chest, waist, thigh
Lopes et al.	2011	Application to detect and report falls, sending SMS or locating the phone	TBM considering the impact	Not specified	Not specified	Thigh
Albert et al.	2012	Demonstrate techniques to not only reliably detect a fall but also to automatically classify the type	MLMs using a large timeseries feature set from the acceleration signal.	15 subjects (8 females, 7 males, ages 22–50)	Across an average week of everyday movements there are 2–3 non-falls misclassified as falls	Back
Fang et al.	2012	Fall detection prototype for the Android-based Platform	TBM considering the impact and the patient's orientation	4 persons	SP: 73.78 % SE: 77.22 %	Chest, waist thigh
Abbate et al	2012	A system to monitor the movements of patients, recognize a fall, and automatically send a request for help to the caregivers	MLM Eight acceleration properties of fall-like events are classified using multi-layer feed-forward neural network	7 volunteers (5 male, 2 female, ages 20–67	SP: 100 % SE: 100 %	waist

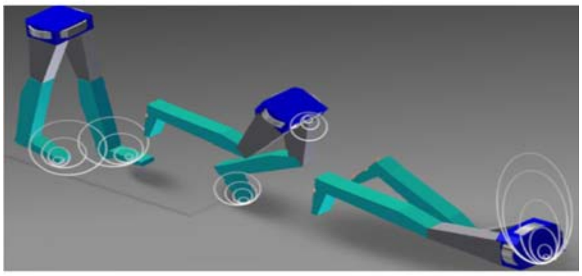

Fig. 3. IMSAFE - fall detection in the soles [41].

3.4. Czech Project ARTEMIS

Another Czech project monitoring the health condition comes from student Marek Novak. This student was awarded a prize in 2013 for his project Artemis [42], whose aim was to develop the concept of wireless modules for monitoring and processing of physiological parameters.

Here, the sensors wirelessly transmit data to a central unit in the form of a wristwatch (hereinafter referred to as watch), which performs filtering, processing and data displaying. The watch enables communication with similar devices, and network access. Miniature sensors are wearable on clothing or can be worn as bracelets. Such sensors are sensor for measuring an electrocardiogram (ECG), a motion sensor for detecting a fall, global positioning system (GPS) location sensor, temperature, transmissive pulse oximetry and several others. The watch is equipped with a 1.8-inch color display.

From a technological perspective, the application runs on inexpensive low-power communication modules Nordic nRF24L01+ and MRF49XA with low power consumption. For controlling STM32L microcontrollers are used. The whole implementation uses as a power supply ordinary Li Ion battery. Communication with the public networks is provided via Bluetooth and Global System for Mobile Communication (GSM).

From the application point of view, ARTEMIS provides an inexpensive and convenient all age groups monitoring, from newborns to seniors. The next version should be based on the platform Intel Quark, which allows with integrated Wi-Fi even better wireless options.

3.5. Kinect, Game Console

Putting Microsoft Kinect game console on the market aroused an interest for many researchers dealing with the camera fall detection. This console detects the motion using sensors and the response action is based on the player motion without the need of any control device touching. Stone et al. [43] introduced in 2013 two state detection techniques and verified the system using a relatively large set of data from thirteen households. The detection algorithm was based on the following measured variables: minimum and average vertical speed, the maximal vertical acceleration and the shading rate (which is evaluated for each of the pixels). This data set included 3339 days (i.e. 9 years) of continuous data, holding 454 falls, of which 445 were performed by actors and nine cases involved real falls in a normal situation.

Further study using the game console Kinect was elaborated at Lawrence Technological University [44]. The authors utilized three types of Kinect sensors: a standard camera, an infrared (IR) camera, and a microphone array. The IR camera detects points projected by a laser and automatically converts them into a depth map (Fig. 4.)

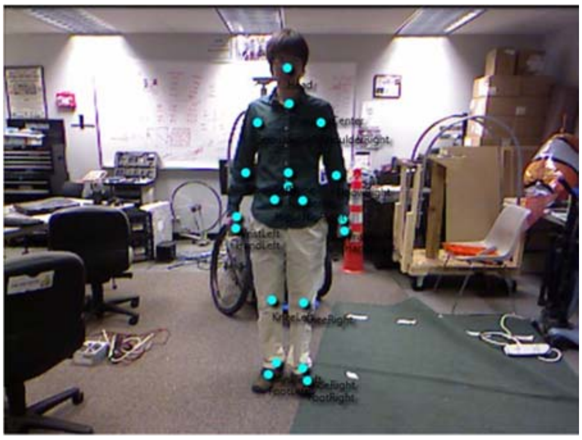

Fig. 4. Kinect fall detection.

The cameras are calibrated so that the depth map pixels correspond to the pixels in the standard camera images. They also use a Kinect software development kit (SDK) which is a free software package providing a variety of useful tools. The software automatically detects the 3D location. Additionally, the floor plane is automatically detected. Two algorithms to detect falls using the Kinect SDK were developed. The first algorithm uses only joint position data. This algorithm calculates the distance from the floor to each joint. If the maximum distance is less than some threshold value, a fall is detected. The second algorithm calculates the velocity of each joint in the direction normal to the floor plane. The velocities are averaged over all joints and many frames. If this average velocity is lower (downward velocities are defined as negative) than some threshold value, a fall is detected.

Voice recognition is used to reduce false positive reports. After a fall is detected, the event is validated using the Kinect microphone array and a voice recognition system. Once a fall is detected, a new thread is created to ask the user if he requires assistance. The thread waits for a response of yes or no. In the case of a yes, a fall is reported. In the case of a no, the report is canceled. A timer is also set. If the timer ends without receiving a yes or no response, a fall is reported.

Falls are reported through email or Multimedia Messaging Service (MMS) with attached pictures of the event.

The system has been tested quite extensively even with people using canes, crutches, and walkers and works reliably. It offers an affordable way of fall detection. One major concern is that a simulated fall may be significantly different from an actual fall.

3.6. WiTrack Project

Since 2013, the WiTrack project is in its prototype stage. It is a 3D monitoring which works even if the person is occluded from the WiTrack device or in a different room. This project originated at Massachusetts Institute of Technology (MIT). The system tracks the 3D motion of a user using the radio signals reflected from his body. WiTrack does not require the user to carry any wireless device, yet its accuracy exceeds current radio frequency (RF) localization systems, which require the user to hold a transceiver [45]. It operates at a fairly low-power, transmitting only 0.75 milliwatts. This signals strength is 100 times lower than the Wi-Fi and even 1000 times lower than the broadcast signal from a GSM phone. WiTrack can determine not only the center of the human body, but also monitors the movement of the limbs and head. The detection accuracy is 96.9 %. WiTrack may be part of the user electronics and has wide possibilities of usage, not just a fall detection, but also appliance control or playing games.

5. Conclusion

Although it may seem that, with all technological development nowadays, fall detection must be a simple matter, it is actually not. Currently, this complex problem does not have a standardized solution. Reliable, inexpensive and senior friendly devices for the fall detection are still not available on the market despite the fact that they become essential in order to provide a rapid assistance and to prevent fear of falling among seniors.

Most often, detection methods are based on signals from accelerometers and gyroscopes placed in the various types of equipment and on the video detection. Lately, efforts are being made towards the smart phones use and more free of charge applications are becoming available.

One of the shortcomings of current solutions is loss of privacy, mainly when using video detection but not only. The smart phone fall detection needs to solve the problems associated with limited battery capacity and the need for recharging. Also, the smart phones cannot compete with the complex solutions that sophisticate systems provide.

Helpful would be a public database of accelerometer signals and video signals of fall situations. Since it is not acceptable to subject older people to simulated falls, the data are severely limited. Most reported studies used young volunteers to simulate falls. Unfortunately, even if there was a public database the simulated data might not match those of the real seniors´ daily life situations.

Sharing source codes of the algorithms would also be helpful.

The future fall detection development will probably include using more sophisticated smart mobile phones because of their decreasing price and increasing hardware potential. In the commerce sphere, the extension of systems like the Senior Inspect with other health functions has huge potential. The combination of systems which are able to monitor the user without using wearable devices inside his home with some suitable device used outside will definitely succeed. The main goal will be to maintain the privacy and security of irrelevant information (the data obtained in the time during which falls do not occur), but simultaneously to monitor and capture sufficient data when it is crucial.

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