# Literature Review

## Background

A fall can be a very serious occurrence for an elderly patient, affecting not only their physical health, but also confidence and psychological well being. According to the World Health Organisation falls account for 40% of all injury related deaths (World Health Organization, 2007). Older people in particular are more likely to experience a fall. The aforementioned study found that approximately 28-35% of people aged over 65 fall at least once per year, this figure increases to 32-42% when considering those aged over 70. Furthermore, falls accounted for more than 50% of injury related hospital admissions for people over 65.

In addition to the obvious physical risks associated with a fall is the psychological impact. The study conducted by Bailey (Bailey, 2011) found that people who have experienced a fall have had negative experiences arising from the fact that they have been labelled a ‘faller’, by themselves and others. This labelling can have a severely detrimental effect on the quality of life of the individual, with typical advice to ‘fallers’ reported as being to ‘slow down’, or to ‘take care’ – this advice can cause a loss of confidence in the individual as they become acutely aware of their status as a ‘faller’.

A survey conducted by Demiris et al. (Demiris et al., 2004) of older adults (over 65) and their attitudes to smart homes identified a number of areas where the respondents felt that technology could be beneficial to them – these areas included emergency help and fall detection and prevention.

The figures outlined above clearly highlight that falls in the home are a significant problem, particularly for older or more vulnerable people. In order to deal with this problem a number of methods of using technology to detect when a fall event occurs have been developed and investigated.

## Fall detection system Approaches

The approaches taken tend to fall into one of two categories:

* Wearable systems: this approach employs a device which must be worn on the body of the user. It could feature sensors to automatically detect a fall event, or it could simply be a device featuring a button which is pressed in the event of a fall.
* Context aware systems: these are devices which require no active participation from the user. They make use of sensors in their environment to determine when a fall has occurred. These systems could use a camera to track the user’s movements, acoustic sensors to ‘listen’ for a fall, pressure sensors built into floors etc.

### Wearable Based Systems

There have been a number of solutions to the problem of fall detection based on the user wearing a sensor which will detect a fall. One such proposal was put forward by Wu et al (Ge Wu & Shuwan Xue, 2008). Their solution was a waist-worn device comprising a pocket PC and an accelerometer. The system monitors the user’s acceleration and if it exceeds a certain threshold (based on the user’s baseline movements) a fall event would be detected. The authors stated aim with this system was to detect a fall before the user hit the ground.

Wearable systems are problematic in that they require the user to alter their daily routine and wear a specialised piece of equipment, which may in itself be detrimental to their quality of life. Demiris et al. (Demiris et al., 2004)found that many older adults did not want to wear such a device all of the time.

Kochera (“In Brief: Falls Among Older Persons and the Role of the Home: An Analysis of Cost, Incidence, and Potential Savings From Home Modification - inb49\_falls.pdf,” n.d.) found that for older adults (over 65 years of age) 22% of falls occur away from the home – he also found that 55% occur inside the home with the remaining 23% happening outside, but near the home. These figures were significantly different for younger age groups, for example in the 35 - 64 group 48% of falls happened away from the home, so the target audience for a system will largely dictate its zone of operation. The advantage of wearable systems over camera based systems is that they are not limited to a specific location, and can travel with the user, making them able to detect falls both inside and outside the home, the disadvantage is that they can only work if the user is willing to wear them.

One widely used commercial fall detections system is the Lifeline range by Philips. This encompasses a suite of products and services centred on pendant based systems. The range starts with an in-home only pendant system which connects to a landline must be manually triggered in order to alert a responder, this can be extended with a pendant which features sensors and can automatically detect a fall, and the most sophisticated solution is a pendant with a mobile internet connection which can automatically detect falls both in and out of the home (Philips Lifeline, 2010).

A slightly different approach to wearable fall detection is taken in the 2015 paper “Fully Wireless Sensor Insole as Non-invasive Tool for Collecting Gait Data”(Talavera et al., 2015). The system proposed here is worn as an insole, rather than on the waist as in the previously discussed paper. The insoles communicate their data wirelessly using Bluetooth to a smartphone, this then uploads the data using WiFi or mobile data connection to a server where the gait data is analysed and the other data is processed according to a predefined scheme.

The system uses this data to create a detailed analysis of the user’s gait, and thus assesses their risk of falling. Additionally, the system can detect a fall event should one occur. The paper states that the fall detection is carried out on the smartphone, with the more detailed gait analysis carried out by the remote server.

The insoles are battery powered and wirelessly recharged using a docking station, the system will alert the user of any issues with the insoles, i.e., low battery, low signal or other errors via the mobile phone application.

The limitations of wearable systems pointed out in the system put forward by Wu & Xue (Ge Wu & Shuwan Xue, 2008) are present here too, most prominently that the system obviously will only function when actually worn by the user, and that the system will not function should the battery not be charged.

Another potential issue with this system is its dependence on the user owning a smartphone. A study by the Pew Research Centre (Smith, 2015) found that smartphone usage within adults over 65 is at only 27% (more recent statistics on this?). The same age group, those over 65 years of age, was found by the World Health Organisation to have a 28-35% risk of a having a fall event each year, with this risk rising exponentially with advancing age.

This means that the majority of the ‘at-risk’ group are precluded from using this system due to not owning a smart phone. Additionally, the system is limited by the range of the Bluetooth Low Energy system used to transmit to the smart phone. Townsend et al. (Townsend, Davidson, Akiba, & Cufí, 2014) state that range could theoretically extend to a maximum range of 30m, in practice a range of 2-5m was more typical. Taking this typical range, it’s possible that a user could move out of range of the system if they were to walk across a room without bringing their phone.

### Context Aware Systems

Context aware systems are those which are ‘built into’ the user’s environment and do not require any active participation from the user, such as wearing a sensor, as the previously presented systems do.

A number of systems have also been documented at both research and commercial stages that use various types of sensors embedded within the floor of a living environment to detect the movement of the user, including any fall events. One such commercial system, SensFloor, consists of a textile underlay containing proximity sensors. This underlay is cut to fit the floor dimensions of the room and is placed under the floor covering (linoleum, carpet, tiles etc.). The sensor network communicates wirelessly with a control box and offers a wide range of features, including fall detection, gait analysis and spill detection.

A separate, different floor based system is suggested by Alwan et al. (Alwan et al., 2006). This system detects the vibration in a concrete floor caused by a falling person (or in the case of the trial a human analogue dummy). A piezo-electric sensor is used to detect the vibration resulting from the fall, with the system proving to detect 100% of falls in testing., with 0% false alarms.

Both of these system show a lot of promise in terms of fall detection, the first system SensFloor needs to be fitted underneath the floor covering which adds considerably to the cost of fitting. The second vibration system also has shown very high accuracy figures and it can be retro fitted although it has only been tested with concrete floors which are typically found in a care home environment. There was no testing available for wooden floors which would be more typically found in a domestic setting.

Methods making use of audio cues have also been investigated, Popescu (Popescu & Mahnot, 2009) and Li et al. (Li, Zeng, Popescu, & Ho, 2010) both propose methods using arrays of microphones to detect falls. These systems make use of signal processing to isolate likely fall events. The solution put forward in both these papers also uses a motion detector, and in the event that motion is detected after a fall-like event, it is classified as a false alarm and used to retrain the system to improve future detection. The authors here have not conducted testing to determine the accuracy of their proposed system, additionally they acknowledge that the presence of background noise such as televisions or radios could also pose a significant challenge to the efficacy of the system.

Several solutions for fall detection have been put forward using RGB based cameras. Nait-Charif et all (Nait-Charif & McKenna, 2004), suggest a method using a ceiling mounted wide-angle camera looking downwards over the room. The use of camera based systems was discussed by Demiris et al.(Demiris et al., 2004), with the respondents to a survey (adults over 65), stating that they felt the use of a camera would be an unacceptable violation of privacy unless the image contained only shadows or outlines to preserve anonymity.

The study reported that these concerns would be exacerbated if the system was monitored, even if the purpose of the monitoring was to provide assistance should it be needed. The issue of privacy, combined with the rapid drop in price of other methods such as infra red or time of flight based systems mean that RGB may no longer be the most appropriate method of fall detection.

A depth based system for fall detection is put forward by Stone & Skubic (Stone & Skubic, 2015). The system developed makes use of a Microsoft Kinect camera. The authors have chosen not to use the available software packages to abstract the Kinect’s functionality, and instead have developed their own custom method of tracking the user. This system only looks at data from the infrared camera, rendering the user as a silhouette and so addressing the privacy concerns previously mentioned. A reasonably high level of accuracy was demonstrated for falls occurring within 4 metres of the camera, with fall detection rates of 90% for falls from a standing position, 70% for those from a seated position and 71% for those occurring from a lying positon with these accuracy figures dropping off for falls occurring more than 4 metres from the system. These accuracy levels demonstrate the promise held by the Kinect for these types of applications, although the system put forward here was somewhat limited in the fact that it was running offline, i.e. the video was recorded and analysed after the fact (the authors state that running online with a PC should be possible, but the results presented are for the offline system). Another, obvious, limitation of the system is that it can only detect a fall in the area that it is monitoring.

### Multi-modal systems

There has also been research into the use of multiple methods of detection. Chen et al (Chen, Jafari, & Kehtarnavaz, 2015) suggest a method of using a Kinect along with accelerometers. The aim in their research was general human pose recognition, rather than just fall recognition as discussed here. Their findings show that augmenting the Kinect sensor with an accelerometer greatly increases its accuracy in detecting actions, with the authors reaching accuracy rates approaching 98% for certain poses. It is also worth pointing out that the algorithms used to detect the poses here were reasonably complex, leading to a slight delay in pose recognition, as well as necessitating a powerful computer to run the program (a PC with an Intel i7 processor).

Kwolek and Kepski (Kwolek & Kepski, 2016) put forward a similar approach using a Kinect camera along with an accelerometer to detect a fall using fuzzy logic. The system uses both the depth information from the camera to relate the position of the body, along with the velocity provided by the accelerometer to determine if a fall event was taking place with a higher degree of certainty than either sensor alone could provide.

In the commercial sector Philip have also launched a connected home system specifically aimed at elder care, and allowing people to continue living independently in their own home for as long as possible. This system, CareSensus, leverages advances made in the Internet of Things and is made up of a number of sensors monitoring a users movement throughout their home, opening and closing of doors, time spent in bed and even time spent in the the toilet. The data from these sensors is collected by a centralised hub and uploaded via data connection for further analysis. A caregiver can then log on and view the users statistics to see if there is cause for concern. This system doesn’t explicitly detect a fall, but can be used with Philips’ other pendant based systems in order to do so.

### Comparing Systems

A brief comparison of the pros and cons of a number of the fall detection methods are outlined below.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Wearable** | **Camera** | **3D Camera** | **Auditory** | **Floor/built in** |
| **+**accurate  **+**cheap  **+**Low cost  -must be worn  **-**dependant on batteries,must be recharged | **+**doesn’t need to be worn  **+**not battery dependant  **+**High accuracy  **+**Low cost  **-**privacy concerns as user clearly visible | **+**doesn’t need to be worn  **+**not battery dependant  **+**High accuracy  **+**Low cost  **+**3D cameras track users as shapes, preserving privacy | **+**Doesn’t need to be worn  **+**not battery dependant  **-**difficult to test  **-**potential difficulties with background noise, tv/radio etc. | **+**Doesn’t need to be worn by user  **+**Using multiple built in sensors can achieve advanced analytics  **+**not battery dependant  **+**High accuracy  **-**High fitting cost: must be built into environment |

## Adoption of Fall Detection Systems

There are a number of reasons why a fall detection system may not be adopted by a user. These reasons are outlined below.

### System Accuracy

Noury et al. (Noury et al., 2007)highlight that one of the major barriers to the widespread adoption of fall detection systems is their level of accuracy. A fall detection system needs to accurately detect any real falls, but also needs to be able to distinguish between real falls and normal movements. A system which registers false positives will quickly become an annoyance to both the user and any person responding to the false positives. The authors highlight that there is no consensus on how to measure the accuracy of fall detection systems and because of this it is very difficult to compare systems against one another or to determine how the tests carried out compare to real life situations. Igual et al (Igual, Medrano, & Plaza, 2013) also point out that typically when fall detection systems are tested, the test subjects used are very rarely the group at which they are aimed, due to the inherent danger of a fall to a vulnerable or elderly person. Tests are carried out using younger people simulating falls, and as such there may be a difference in the nature of these falls and the real falls as experienced by a vulnerable person.

They propose two metrics:

* Sensitivity: whether the system can detect all real fall events.
* Specificity: whether the system can discern between real falls and actions which look like falls.

The authors also put forward a suite of tests to evaluate a fall detection system, which is shown below:

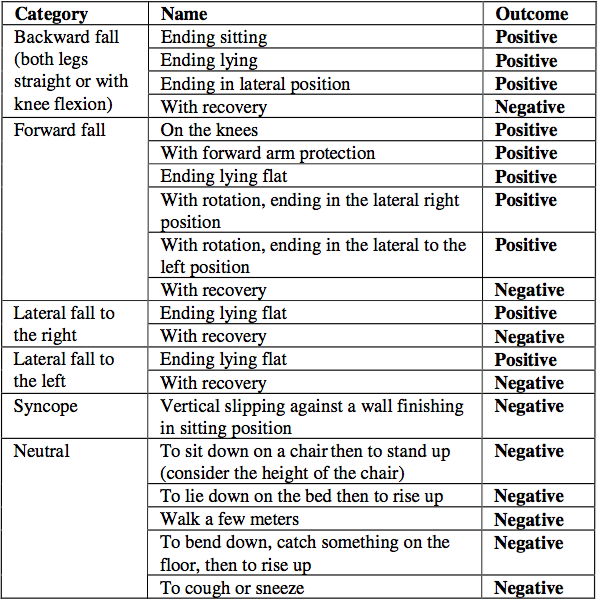


Figure 1 - Noury et al. Fall detection evaluation criteria. Figure from Noury et al., 2007

### Ethical Concerns

## There are several ethical concerns surrounding the use of fall detection systems. Ganyo (Ganyo, 2011), points out that when considering any fall detection system it is important to weigh up the implications both positive and negative according to a few criteria:

* Autonomy: does the user have the capacity to refuse aspects of the service, have they been fully informed of the information being captured and who has access to it. Does the user have control over how an event is responded to should one occur?
* Privacy: In what way does the proposed system impact the user’s privacy?
* Benefits: What are the short/long term benefits of using a system?

The use of any fall detection system involves tracking some aspect of a user’s movement and so will result in some level of compromise in terms of privacy, but the level of compromise will be determined by the type of system employed.

Some studies (Stewart & Stewart, 2012) have indicated that users of pendant style fall detection systems find them too conspicuous. They felt wearing the pendant labelled them as being at a high risk of falling and reported unwelcome attention whilst wearing it, feeling as if they had a disability. Another study (Brownswell, 2004) found that some wearers (those who did not wish to wear the pendant in the first place) of these alarms actually felt more vulnerable whilst wearing them, as it made them conscious of the likelihood of them experiencing a fall. The same study found that many of the other patients wearing the detector found that wearing it did make them feel less vulnerable and more confident.

Another risk which may arise from using fall detection systems is that their use will mean that the user has less contact with humans, be they caregivers or family members. The use of the system should serve only to bolster the independence and confidence of the individual, and not as an isolating factor.

## Conclusions & Primary Research Direction

From reviewing the current literature and evaluating the state of the art, a number of insights can be drawn.

Wearable type fall detection systems, whilst accurate, are significantly limited because if the user doesn’t wear the device then it cannot function. The user may choose not to wear the device for a number of reasons; because they make the wearer fell vulnerable, self conscious or simply because the user has forgotten to wear the device (Stewart & Stewart, 2012).

Context aware systems which co-exist in a more passive way in the users’ day to day environment do not require any active part to be taken by the user for them to be functional. In particular, three dimensional camera systems have shown promise. The method of operation means that the image captured of the user is merely an outline, this goes some way toward addressing the privacy concerns which had been expressed regarding RGB camera systems (Demiris et al., 2004). Additionally, the use of multiple sensors has proven to be beneficial in detecting a fall and in avoiding false positives (Chen et al., 2015; Kwolek & Kepski, 2016).

From the review of literature, it seems a sensible approach to a primary research area would be to investigate the possibilities offered for real time context aware fall detection systems by the Microsoft Kinect. Additionally, the majority of the systems researched require high powered, bulky and expensive PCs – research will also be undertaken into the possibility of using a lower powered, inexpensive computing solution, such as a Raspberry Pi.

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