# Fall Prediction Amongst the Elderly Using Data from an Ambient Assisted Living System

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Abstract: Falls amongst the elderly are life threatening. Being able to predict falls means steps could be taken to reduce fall likelihood or severity. In this paper we report on our work using data generated by HalleyAssist, an advanced Ambient Assisted Living System, to predict falls amongst the elderly. HalleyAssist unobtrusively monitors older people using sensors to provide services to help them with their day-to-day activities. We conducted a three-month trial of the HalleyAssist system with six households of older people primarily to gauge acceptance and utility of the system. During the trial we also asked participants to keep a 'falls diary' in which they recorded the date, time and location of any falls. After the initial trial we continued monitoring one of the participants (with her consent) who was susceptible to falls, for an additional seven months. Over the ten months of the trial she fell 32 times on 28 days. None of the other participants fell during the trial. We analysed data from the sensors and correlated it with whether she fell later in the day. Using techniques from machine learning we were able to identify features that enabled a fall to be predicted with 64.9 % accuracy.

## 1 INTRODUCTION

A consequence of people living longer, smaller families, the difficulties of finding enough aged care support staff, and families that are geographically dispersed means that older people who might otherwise be able to live comfortably in their own home with only a small amount of assistance are more likely to be institutionalised if there is no support.

Consequently, there has been interest in how the Internet of Things (IoT) might be used to provide support to older people living alone. The Internet of Things comprises sensors and actuators connected to the Internet with sensors generating data that is processed by cloud or fog computing and then generating actions for actuators to carry out.

A particularly significant development of the Internet of Things are ambient Assisted Living Systems (AAL). These are unobtrusive systems that that operate in the background of a home, helping with day to day actions that may be difficult for an older or disabled person. In an AAL motion sensors can turn on lights, heat sensors can turn on air heating or cooling, medication reminders can be scheduled, security can be automated and a care giver can be informed if there is an unusual event requiring attention such as a fall or an unusual change in behaviour such as the older person becoming bed-ridden.

We have over the past five years developed and commercialised the HalleyAssist System, an advanced Ambient Assisted Living system developed by SP Tech Solutions Pty Ltd with contributions from Swinburne University of Technology. One of the features of HalleyAssist that distinguishes it from other Ambient Assisted Living systems is that it incorporates Artificial Intelligence features to identify both acute and chronic conditions that require assistance or other form of response from a carer. HalleyAssist Artificial Intelligence is based on using sensors deployed as part of the system in order to detect unusual events (anomalies) when they happen and to act upon them. Usually the action is to report the anomaly to a care giver via the HalleyAssist App.

HalleyAssist detects anomalies in two broad ways. It includes both statistical learning where it detects what sensor activations are normal for this person, and rule based anomaly detection where specific sensor activations are interpreted as having a particular

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meaning, such as a fall.

For example, the system detect falls based on the location and activation of motion sensors. Falls are particularly dangerous for elderly people and rapid detection of them is important in minimising the damage caused by them. The system is also able to detect significant changes in behaviour. For example, if a person usually leaves his or her bed fewer than two times a night but starts leaving it much more than that, that may be indicative of an acute condition, for example a urinary tract infection requiring them to visit the bathroom multiple times. Of course there may be any number of other explanations but unusual changes in behaviour may well be significant and require some form of intervention by a carer.

One of the areas of research we have been exploring is predicting falls based on sensor activations. Are there patterns of sensor activation, such as might be generated by broken or restless sleep, that are predictive of falls the following day? Being able to determine that a fall is more likely than normal could be particularly useful in preventing them or in making them less likely. For example if the system suggested that a fall was quite likely on a particular day, the person might modify their schedule so that they are less likely to have a fall, or make the consequences of a fall less damaging.

However, research in this area is very difficult because there are many obstacles to obtaining any useful data. Trials of AALs during which falls are likely are difficult to arrange, have ethical implications and require a reasonable length of time and number of participants. Correlating any falls with sensor activations requires the participant to recall accurately when the fall occured. Also, although the consequences of falls can be devastating, they are, fortunately, quite rare amongst people living alone.

Consequently, when we ran an ethically approved major trial of HalleyAssist we took the opportunity to ask participants to record the date, time and location of any falls. The primary purpose of the trial was to assess the acceptance of the system. We certainly were not hoping for falls. However, if falls occurred we wanted to be in a position to analyse the data associated with them. To that end we asked participants of the trial to keep a 'falls diary' where they recorded when and where any falls happened.

The trial ran for ten months starting 28th February 2020 till 31st December 2020.

During this time, one of the participants, an elderly woman who had a history of falls, fell 31 times during the trial. We have used her records of when falls occured and records from HalleyAssist to see if it is possible to see if there is any predictive power in sensor activations. In this initial trial we explored the association between a poor night's sleep and the likelihood of a fall the following day. Poor sleep has been associated with falls (Noh et al., 2017). We were interested in whether sensors indicating a poor night's sleep could be used to predict an increased likelihood of a fall the following day.

Based on the sensor activations we can successfully predict days when a fall will occur 61% of the time and days when a fall will not occur 65% of the time.

We think these results are interesting but acknowledge that they are hardly conclusive. There are many caveats associated with these results which we discuss later in the paper. Nevertheless, they are encouraging and we plan to continue with further collection and analysis of data.

The remainder of this paper is structured as follows. Section 2 discusses related research in this area. Section 3 describes the trials and their outcomes. Section 4 provides an analysis of the sensor and fall data. Finally, Section 5 is our conclusion where we summarise our work and discuss future research.

## 2 RELATED RESEARCH

Ambient Assisted Living Systems (AALs) have attracted a great deal of research attention over the past ten years (Forkan et al., 2019a; Demiris and Hensel, 2008; Forkan et al., 2019b). These systems are an application of the Internet of Things where data from sensors is processed by a central hub or a cloud process which then issues commands to actuators to control the living environment in an unobtrusive manner. HalleyAssist is a AAL system that helps older people remain living in their own home or in a minimal supported accommodation by providing unobtrusive assistance and monitoring (Forkan et al., 2019b).

As well as supporting day to day activities such as providing lighting, heating and cooling AALs can also provide reminders of appointments, notification of the weather as well as reminders to take medication, eat sufficient food and drink sufficient water (Demiris and Hensel, 2008).

However, they can also be used to identify events and trends that a carer should be notified of. So for example, long term trends such as isolation, wandering or sleeplessness might be detected and the carer informed. Such changes might be due to chronic or acute illnesses such as dementia or infection or they might report on some particular event requiring immediate response, the most common of which is a fall (Forkan et al., 2019b).

A fall by an older person can have devastating consequences (Berg and Cassells, 1992). Reduced reaction times, weaker muscles and more fragile bones mean a fall can result in serious injury. It is also possible that the older person may be unable to get back up after a fall leading to further serious consequences. Consequently, rooms need to be designed so as to make falls less likely but if they do happen, make the consequences less damaging than they might be if they occurred in another environment (Bianco et al., 2015).

Ideally it would be best to prevent a fall from happening in the first place (Tinetti, 2003). If it were known that on a certain day a person was more likely to fall than on other days then it might be possible to take preemptive steps to prevent a fall or minimize its consequences.

AALs have potential in fall detection and possibly in fall prevention. Camera based systems have been trialed and provide useful information for researchers about the nature of a fall, but camera based AALs are strongly resisted by older people (De Miguel et al., 2017). Wearables have also been trialed but also face resistance from older people. There is also the difficulty of people, particularly those with dementia forgetting to wear the device. Sensor based systems where sensors such as motion based sensors, bed sensors, temperature sensors are located throughout the living space are much better accepted and have been trialed with some success (Liu et al., 2014).

There has been very little research into the potential of AALs to predict falls. Yet there may well be behaviourial factors that can be detected by sensors that are associated with falls. In particular, a poor night's sleep has been associated with falls the following day (Noh et al., 2017). If an AAL can detect that a person has slept poorly then it may be that the system could issue a warning to them to take extra care or to inform their carer.

In section 4 we demonstrate that for the data we collected during our trials a fall was associated with a poor night's sleep as detected by a bed sensor attached to the system. This in turn, can be used to predict when a person has a heightened risk of falling the following day.

## 3 HalleyAssist TRIAL

HalleyAssist Pty Ltd was formed to develop the HalleyAssist product. It is an AAL intended to enable older people to live independently with with assistance from sensors and actuators to control warming and cooling, provide medication, food and liquid reminders, manage security, and monitor the elderly person for events that might require the attention of a carer.

HalleyAssist comprises five modules (Forkan et al., 2019b):

- Ambient Assisted Living Subsystem
- Learning Module
- Anomaly Detection Module
- Caregiver Module
- Reporting Module

The Ambient Assisted Living Subsystem controls heating, cooling, lighting, security and other activities to help the user in their day-to-day lviing. The Learning Module and the Anomaly Detection Module are AI based subsystems that learn what is normal for the person and detects whether or not data observed over the past reporting interval (which is configurable) is anomalous. The Reporting Module and the Caregiver Module enable a carer to monitor the user in an unobtrusive manner. The Caregiver Module is a smart phone App that displays data generated by the Reporting Module.

The system is designed to be flexible in most of its functions. In particular new sensors and actuators can be easily added to the system, anomaly detection can be fine tuned and adapted to detect new situations and monitoring and reporting periods and sensor thresholds can be adjusted.

A diagram showing the key components and their interactions is shown in Figure 1.

New sensors can be readily added using a variety of communications protocols. The system supports ZigBee, WiFi and cellular communications. All the sensors are connected to the central hub via WiFi or ZigBee. The system is able to support large numbers of sensors but in the installations used in the trials of it each household has had less than ten sensors attached. These are usually motion detection, bed activity and door closing and opening sensors.

A major trial of the system was carried out from March to December 2020 primarily to determine acceptance and to field test the system for reliability and effectiveness. The purpose of this paper is not to discuss those trials, but to discuss the prediction of falls based on data generated by the system. Nevertheless a brief summary of the project is appropriate. The project received ethical approval from Swinburne University of Technology. The system was installed in six households. These households comprised single people living alone with some limited support from family member carers who did not live with the person. The participants and carers were surveyed before and after the trial. Feedback from the

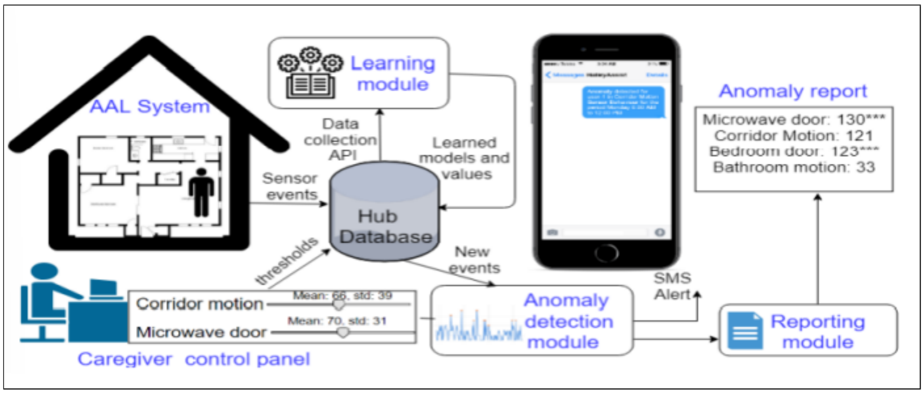


Figure 1: HalleyAssist Architecture (Forkan et al., 2019b).

participants was excellent. The system was well accepted and proved very reliable and useful for carers and the elderly participants.

# 4 ANALYSIS

## 4.1 Data Attributes Used to Predict Falls

As noted in (Noh et al., 2017) falls amongst the elderly are often associated with poor sleep. We made use of sensor activations that indicated that the user had probably slept poorly. We made use of a sensor on the bed that detected excessive movement when compared with usual sleep patterns, number of absences from the bed and total duration of absences from the bed. The rationale behind choosing these features as a proxy for a poor night's sleep was that they were readily collected and seems to capture a prolonged and interrupted night's sleep. Data captured between the hours of midnight and 6 a.m. were used in the training and testing of the classifier.

We developed two metrics that captured the magnituded of these features and so acted as proxies for a poor night's sleep. The first was the number of sleep cycles based on tossing and turning during the night. The second was the number of absences from the bed. Both of these were obtained from a bed sensor installed beneath the mattress.

The sleep cycles metric was based on the number of episodes of 'tossing and turning' and their duration during the night. A period of restful sleep would typically be broken with a period of tossing and turning. The duration of the tossing and turning episodes was averaged over the number of the episodes to give a metric for sleep disturbance. The bed sensor was able to detect the absence of the person from the bed.

We used the WEKA system with the above features to train a Naive Baye's classifier using the data from the falls diary which said whether or not a fall occurred in the following day (Hall et al., 2009).

## 4.2 Results

Amongst elderly people living alone falls are, fortunately, rare. Only one participant of the trial experienced falls. However, she fell frequently. Of a total of 308 days of the trial, she fell at least once, occasionally more, on 28 days.

Using the Naive Baye's classifier trained on the sleep data and using k-fold testing we were able to predict whether or not a fall would occur with an Accuracy of 64.9%. We were able to predict days when a fall occured 60.7% of the time and days when a fall will not occur 64.9% of the time. We obtained an overall Accuracy of 64.9%. The overall F-Score was 0.73. The Accuracy is shown in Table 1 while the confusion matrix is in Table 2 and the accuracy by class is in Table 3.

Table 1: Overall Accuracy.

| | | |
|---|---|---|
| Correctly Classified Instances | 200 | 64.9% |
| Incorrectly Classified Instances | 108 | 35.1% |
| Total Number of Instances | 308 | |

Table 2: Confusion Matrix for Fall Data.

| a | b | classified as |
|---|---|---|
| 183 | 97 | a = No fall |
| 11 | 17 | b = Fall |

The confusion matrix tells us that the system was able to predict a fall 17 of the 28 days when a fall did not occur and 183 of the 210 days when one did occur.

The accuracy by class table gives us the True Positive (TP) and False Positive (FP) probabilities. Other frequently used metrics are also included which also use False Negative (FN) and True Negative (TN).

Table 3: Accuracy by Class.

| | TP | FP | Precision | Recall | F-Measure |
|---|---|---|---|---|---|
| Days without a fall | 0.65 | 0.39 | 0.65 | 0.65 | 0.77 |
| Days with a fall | 0.61 | 0.35 | 0.15 | 0.61 | 0.24 |
| Weighted Average | 0.65 | 0.39 | 0.87 | 0.65 | 0.73 |

These are Accuracy, Precision, Recall and F-Measure. These are defined below:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}. \quad (1)$$

$$Precision = \frac{TP}{TP+FP}. \quad (2)$$

$$Recall = \frac{TP}{TP+FN}. \quad (3)$$

$$F-measure = 2.\frac{precision.recall}{precision+recall}. \quad (4)$$

Accuracy is the simplest measure. It tells us how many times the system made the correct prediction. However for datasets such as this where there are many more days without a fall than with a fall it can be misleading. Consequently, other metrics need to be considered. Precision is a measure of consistency and Recall measures the number of True Positives compared with the number of Predicted Positives. Recall is sometimes referred to as the True Positive Rate. The F-measure is the harmonic mean of Accuracy and Precision.

For our data all metrics apart from one Precision measure are 0.6 or above. However, the Precision for Days with a fall is 0.15, caused by the large number of False Positives which is a consequence of there being many more days without a fall than days with a fall.

### 4.3 Discussion

Using only one general concept, that of a poor night's sleep, as a predictor of falls we can correctly determine whether or not a fall is likely to occur approximately 65 % of the time. Of course there are many limitations to this study. Only one person fell, the number of days on which she fell was only 28 and the only behaviour used was an indication of a poor night's sleep. Nevertheless, given how scarce behavioural data before a fall is, the results are very encouraging. It may be that other behavioural data may also be indicative of a fall. It is known that multiple factors affect the probability of a fall. For example, low blood sugar and dehydration have also been noted as precursors to a fall. Perhaps sensor data that can act as proxy for these biological markers may also help improve the accuracy of the fall prediction. For example, a sensor on the kitchen tap that is activated less than usual may indicate potential dehydration. Perhaps the refrigerator not being opened may be an indicator of low blood sugar. We are not claiming that this is the case but that if other factors are associated with falls, sensors installed at strategic locations in the home may be able to be used as proxies for these markers and used to predict whether a fall is likely the next day.

## 5 CONCLUSION

We have taken a simple to state behaviour (a poor night's sleep), used sensor data that acts as a proxy to identify that behaviour and demonstrated that using that it is possible to predict an increased likelihood of a fall the following day. While the results are interesting and potentially significant, it is important not to overstate the significance of the result. Only one person fell and she fell on only 28 days. Nevertheless the results are promising. As far as we can determine there has been no comparable collection of such data before this work.

Perhaps more sophisticated behaviours such as dehydration, hunger and stress which are implicated in falls can also be detected using sensors that act as proxies for these biological markers. Perhaps tap, cupboard and refrigerator door opening sensors can be used as proxies for dehydration and low blood sugar which have also been implicated in falls.

Our interest in this research is in developing techniques for predicting an increased likelihood of a fall. However, another perspective is that it gives researchers into falls amongst the elderly data to explore what the factors are that contribute to a fall. It may be useful for researchers into falls to know what are and are not factors that contribute to a fall.

This is very much a report of work in progress. We believe there is evidence that systems such as HalleyAssist can not only help people live more independent lives than might otherwise be possible but also enable prediction of health threats of which falling is just one example. Are there sensor activations that can be used as proxies that suggest increased likelihood of illnesses? We intend continuing research into this area in the hope of making life for the elderly more independent and safer.

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