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PII: S0263-2241(18)30285-9
DOI: https://doi.org/10.1016/j.measurement.2018.04.009
Reference: MEASUR 5410

To appear in: *Measurement*

Received Date: 31 July 2017
Accepted Date: 4 April 2018

Please cite this article as: P.V. Er, K.K. Tan, Non-Intrusive Fall Detection Monitoring for the Elderly Based on Fuzzy Logic, *Measurement* (2018), doi: https://doi.org/10.1016/j.measurement.2018.04.009

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Non-Intrusive Fall Detection Monitoring for the Elderly Based on Fuzzy Logic

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Abstract

This paper presents a health condition monitoring solution that detects an elderly accidental fall occurrence. The fall detection algorithm implements both accelerometer-based and sound-based detections for the possible occurrence of a valid fall. The accelerometer-based fall detection is instrumental in the detection of a valid fall occurrence. However, it has been shown that by using accelerometer alone is insufficient to accurately detect a fall, as the accelerometer also misinterprets some daily motion activities and classified them as valid falls. The sound sensor can be used to detect the sound pressure generated from a resultant fall, but sound pressure cannot by itself be used as a reliable indicator of a fall. Thus, a fuzzy logic-based fall detection algorithm is developed to process the output signals from the accelerometer and sound sensor, where a valid fall activity detected by the accelerometer, coupled with a detected sound pressure from the resultant fall can infer an occurrence of a valid fall. This paper demonstrates the fuzzy logic algorithm to improve the accuracy of detecting a valid fall as compared to the accelerometer only fall detection algorithm and it can be demonstrated that the algorithm is capable of minimizing false fall detections per day from high of 1.37 to low of 0.06.

Keywords: Fall Detection; Accelerometer; Sound Sensor; Fuzzy Logic; Sensor Fusion

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1. Introduction

Falls are the major cause of both fatal and non-fatal injuries among people and create a hindrance in living independently. The frequency of falls increases with age and frailty level. Between 2007 and 2011, in Singapore, at least 50 elderly persons have been found dead in their own homes from causes relating to falls and illnesses [1]. With the rapid technological advancements, various small and non-intrusive remote health condition monitoring solutions have been proposed and developed with the objectives to solve or mitigate problems encountered by elderly people living alone, and ultimately to save lives by providing them with timely assistance. Commercial product developments and active academic research on fall detection have been motivated by the considerable risks of falls and the substantial increase of the elderly people population. A typical fall detection system has two major functional components: (a) the detection component, which detects falls and (b) the communication component that communicates with emergency contact after fall detection.

In Singapore, the government takes initiative in making elderly-friendly public housing so as to facilitate aging in place [2]. In 2013, a pilot condition monitoring project called Elderly Monitoring System (EMS) was deployed to 500 public housing flats occupied by lone elderly residents. These in-home condition monitoring and alert system monitors round the clock activity levels of each resident in a non-intrusive way, and trigger an alert to a designated caregiver in the event of anomalies [2]. With the initial success of the pilot runs, several similar health condition monitoring systems [3][4] were also proposed and underwent trials by different competing solution providers aimed to solve or mitigate the same set of problems defined earlier.

The various health condition monitoring solutions proposed and demonstrated by different solutions providers, in many ways are similar to the condition monitoring idea where elderly people are monitored for motion activities. In most cases, optical camera and passive infrared (PIR) motion detectors are used for such purposes. The primary triggering criteria when a registered care-

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giver is alerted will be based on the abnormal lack of motion activities or from a manual trigger by an elderly person requesting for assistance.

Until now, an important monitoring criteria or feature is currently not automatically included in all the competing condition monitoring solutions. With the best efforts to understand the implementation of the various condition monitoring solutions, an automatic and reliable method of detecting an elderly person falling down is currently missing or not actively promoted. This feature lapse is intentional, as the various methods for reliable fall detections are currently still in active research, and the available fall detection algorithms and methods are not able to provide 100% human fall detection accuracy. A robust fall detection system is one that is able to classify the falls as "falls" and the non-falls as "non-falls" under real life conditions. If a fall event occurs and the system does not detect it, the consequences can be dramatic. In contrast, if the system reports an excessive number of false fall alerts, caregivers may perceive it as ineffective and useless, which may lead to device rejection.

There are commercially available systems that offer human fall detections, but these systems come with disclaimers stating that accuracy in detecting a valid human fall is not guaranteed. Several reviews [5, 6, 7, 8, 9] of the commercially available fall detection systems have shown that the commercially available systems are already available and deployed, but not in widespread use. The products are mainly offered as paid services for monitoring the safety of elderly people staying by themselves, and for eldercare centers. For the wearable products, they use either accelerometers or tilt sensors to detect a valid human fall.

To date, one of the most common implementation for detecting a fall requires an elderly person to wear a portable electronics wearable device with a built-in inertial sensor in the form of a tri-axial accelerometer, a wireless communication interface, and a battery. The accelerometer continuously detects motion accelerations in the three-dimensional vector space, and by analyzing the motion acceleration behavior, human fall occurrence can be ascertained or predicted. One of the well-known and practical accelerometer-based fall detec-

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tion algorithm is developed by Ning Jia [10] using an Analog Devices ADXL345 digital MEMs tri-axial accelerometer [11]. The well-known algorithm detects a sequence of known motion-based activities (e.g., free-fall, weightlessness, strike, motionless and long time motionless) that can be pieced together in order to approximate a valid fall. In yet another well-known implementation, Bourke *et al* [12] [13] developed a fall detection algorithm using a tri-axial accelerometer to detect fall impact and human posture. The algorithm, considered the sum of vectors of the accelerometer outputs and the detected posture to decide if a valid fall has occurred. Both algorithms are very highly accurate in detecting a real human fall process. However, both algorithms are also sensitive to human motion attributed to daily movements (sitting, standing, etc.) and each human motion is person dependent. In both approaches, a change in body orientation from upright to lying that occurs immediately after a large negative acceleration indicates a fall. However, generally despite all the research dedicated to fall detection, there still does not exist a 100% reliable algorithm that catches all falls with no false alarms. Hence, both algorithms also provide unwanted and false positive human fall results. In field implementations, both algorithms suffer substantial setbacks in terms of the relatively large amount of false positive fall detections.

For each elderly person, individual movement and physical reaction to the occurrence of a fall is not the same [14, 15, 16], thus it is difficult for the algorithms to cater to all forms of fall patterns, hence the incurred setbacks of false fall detections. In order to have an accurate detection, both algorithms require the elderly person to physically move or react to a fall in a certain way expected by the device manufacturers, which is neither logical not practical. Thus, using only accelerometer to detect a valid fall is insufficient when good accuracy with minimum false positives is desired.

In this paper, the authors propose an e-healthCM solution that automatically detects and predicts an elderly person accidental fall occurrence. The basic functionality of e-HealthCM is similar to the various health condition monitoring solutions for fall detection, where it monitors a senior citizen's home for

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accidental fall activity, and to automatically request for assistance when a valid fall is detected. With reference to the discussed shortfalls and known restrictions of an accelerometer only fall detector, the e-HealthCM improves on the overall fall detection accuracy by providing a second level of sound-based fall sensing as an enhancement to the accelerometer only fall detector.

The remaining part of the paper is organized as follow: Section 2 presents the proposed hardware development. Section 3 presents the Fall detection Algorithm. Section 4 discusses the experiment and verification results and Section 5 concludes the paper.

2. Hardware Development

e-HealthCM consists of: (a) an e-HealthCM Base Station (e-BS) where detected fall alerts and caregivers notification are being handled, (b) wireless e-HealthCM Sound Sensor Modules (e-SS) for continuous monitoring of potential falls based on detected sound, and (c) wireless e-HealthCM Wearable Module (e-WM) that monitors accelerometer-based motion activity.

Having established the fact that using only e-WM motion activity monitoring feature to detect a valid fall is insufficient and prone to false fall detection due to the unpredictable nature of human movements [14, 15, 16], e-SS modules installed at various spots within a senior citizen's home are used to verify if a valid fall has occurred by measuring the localized sound pressure level for potential occurrence of a fall. Figures 1, 2 and 3 depict the respective hardware block diagrams for e-BS, e-SS and e-WM.

The e-BS module depicted in Figure 1 contains the various sub-blocks: (a) Wi-Fi Wireless Communication interface, (b) Microcontroller Unit (MCU), (c) Non-Volatile Memory, (d) GSM Modem, (e) Alert and (f) Power Supply. The Wi-Fi Wireless Communication interface receives Valid Fall Alert (VFA) message from the e-SS modules. The MCU processes the information, activates the Alert function which is a local audible sound alert to notify anyone in the vicinity that a fall has occurred, and notifies the designated caregivers of the

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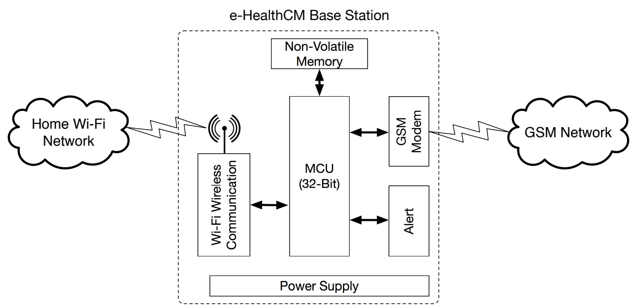

Figure 1: e-HealthCM Base Station Hardware Block Diagram.

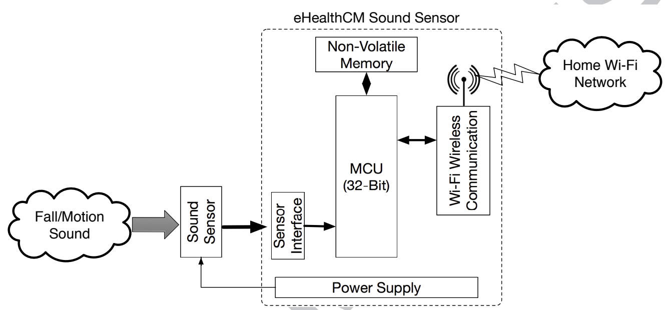

Figure 2: e-HealthCM Sound Sensor Hardware Block Diagram.

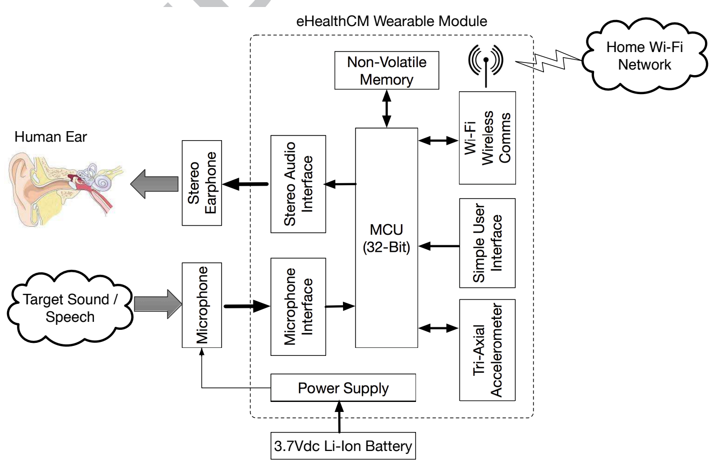

Figure 3: e-HealthCM Wearable Module Hardware Block Diagram.

fall occurrence via the attached GSM Modem. The Non-Volatile Memory stores the caregivers contact information.

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In Figure 2, the e-SS consists of a microphone-based Sound Sensor Interface, Non-Volatile Memory, MCU, Wi-Fi Wireless Communication interface and Power Supply sub-blocks. The Sound Sensor Interface provides the necessary biasing and signal conditioning to a connected uni-directional microphone (sound sensor). The microphone has a sensitivity of -46 dB/Pa, and a detection angle of 60°. The MCU continuously samples and processes the sound signal picked up from the microphone in-order to determine the current sound pressure level (SPL) [17] while waiting for an Inertial Fall Alert (IFA) Wi-Fi broadcast message from the nearby e-WM. If a valid IFA message is received, the SPL and IFA messages (or information) are processed by a fuzzy logic-based fall detection algorithm in order to determine if a valid fall has occurred. In the event of a valid fall, e-SS sends VFA message to the e-BS via Wi-Fi. Coefficients required for the sound pressure measurement and fuzzy logic are stored in the Non-Volatile Memory. Power Supply provides regulated and DC supply for the e-SS. Each e-SS is positioned perpendicularly on the wall surface of the senior citizen's apartment with an overlapped detection range as depicted in Figure 4. In-order to potentially maximize the e-HealthCM monitoring capability, e-HealthCM is mainly targeted to be deployed in single storey apartments where Wi-Fi coverage is good and easy to manage.

In Figure 3, the e-WM depicts a hardware block diagram of an accelerometer-based fall detector with an additional functionality of a pseudo-binaural hearing aid. e-WM consists of a Stereo Audio (Driver) Interface, Microphone Interface, Non-Volatile Memory, MCU, Wi-Fi Wireless Communication. Simple User Interface, Tri-Axial Accelerometer and Power Supply with Li-Ion Battery sub-blocks. The Stereo Audio (Driver) Interface to which an external stereo earphone can be attached and a Microphone Interface with an attached omni-directional microphone are the extra functionalities added to provide e-WM with a hearing aid capability. The hearing aid feature is enabled only if an elderly person benefits from it. However, in this paper, the authors are focused on the fall detection system.

Like many other accelerometer-based fall detectors, e-WM relies on the built-

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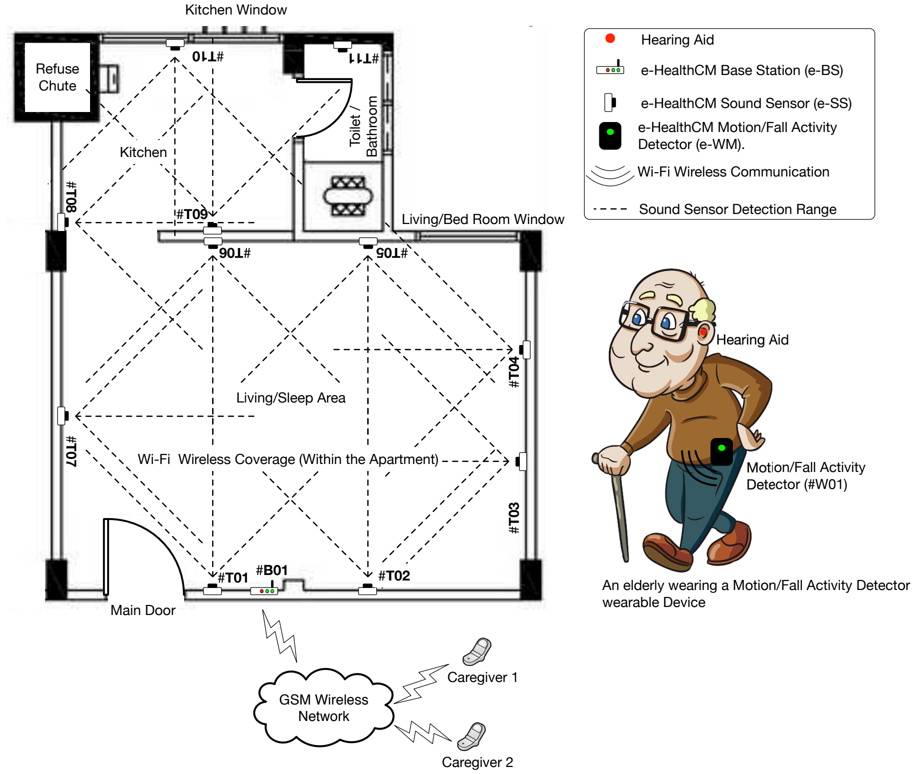

Figure 4: Healthcare-based e-HealthCM System Implemented in an apartment for the elderly

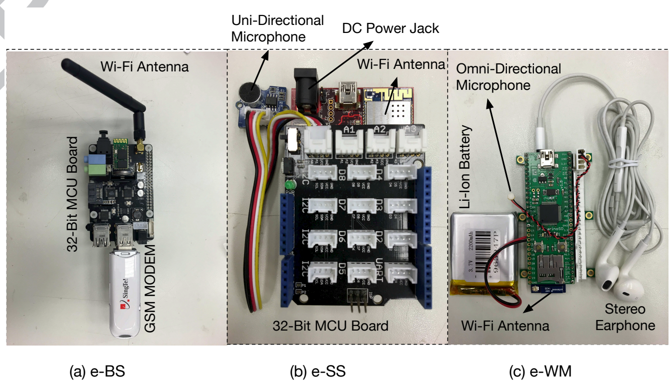

Figure 5: e-HealthCM Hardware Prototypes depicting (a) e-BS, (b) e-SS, and (c) e-WM.

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in digital tri-axial accelerometer to sample the elderly person's motion information, and the MCU processes the information using an accelerometer-based fall detection algorithm (with coefficients stored in the Non-Volatile Memory) to determine if a possible fall has occurred. If a fall is detected, e-WM broadcasts an IFA message via Wi-Fi to all the nearby e-SS modules. e-WM contains a Simple User Interface where an elderly person can manually request for assistance or configure its various device features, and it is powered via a small 3.7 VDC Li-Ion rechargeable battery. e-WM is either worn on the waist (clipped to the belt) or attached to a lanyard and hanged around the neck. e-WM is designed to be small and light so as to minimally invade into the daily activities of an elderly person.

The respective hardware prototypes of e-BS, e-SS and e-WM are depicted in Figure 5, (a), (b) and (c).

3. Algorithms for Human Fall Detection

e-HealthCM is designed to automatically detect an elderly person's accidental fall occurrence. e-HealthCM implements both accelerometer-based and sound-based detections for possible occurrence of human fall. e-WM implements the accelerometer-based fall detection algorithm, e-SS implements the fuzzy logic-based fall detection algorithm that takes in IFA message and SPL information, and e-BS implements the local alert and caregiver alerts.

3.1. Accelerometer-based Fall Detection

The inertial fall detection sensor embedded in the e-WM is the ADXL345 digital tri-axial MEMs accelerometer [11]; a small, low-power accelerometer with a 13-bit high resolution measurement of ±2 g, ±4 g, ±8 g, ±16 g acceleration. The built-in free fall detection feature makes it a very suitable detector for e-HealthCM. The digital output data is formatted to a 16-bit length, and is accessible through an I2C digital interface. As part of the power saving feature, the accelerometer can signal the MCU when to wake up and when to go back

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to sleep again by configuring a predefined interruption threshold through the MCU firmware.

The measured accelerations along the directions of x, y and z axis of the accelerometer are represented by vectors A_x, A_y and A_z, respectively. Let A_c denote the composition of accelerations in the three directions, with an amplitude which can be computed by Equation 1.

$$|A_c| = \sqrt{|A_x|^2 + |A_y|^2 + |A_z|^2}. \tag{1}$$

During the algorithm development process, daily human motion activities and fall detections procedure demonstrated by Ning Jia [10] is used. This procedure has been widely known to be highly reliable in detecting a valid fall, but also known to falsely detect falls from various normal (non-fall) motion activities. A volunteer emulating an elderly tested the ADXL345 on the e-WM by hanging it around the neck and performed the following daily motion activities: (a) Walking up a flight of stairs, (b) Walking down a flight of stairs, (c) Sitting down, and (d) Standing up.

Figure 6 - 9 depict the acceleration data plots of the motion activities.

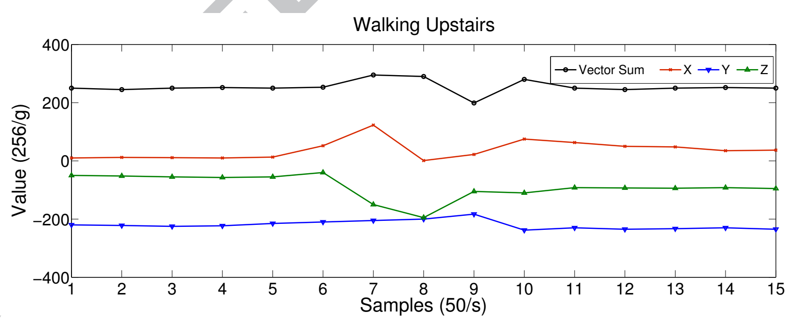

Figure 6: Volunteer walking up a flight of stairs

Movement of an elderly person is comparatively slow [10], so the acceleration change will not be very conspicuous during the walking motions. The most obvious acceleration change is a spike in Y (and the vector sum) at the instant of sitting down (Figure 8). The volunteer conducted emulated falls on a well cushioned floor (overlaid with a 1.5" thick foam rubber mat). The emulated falls

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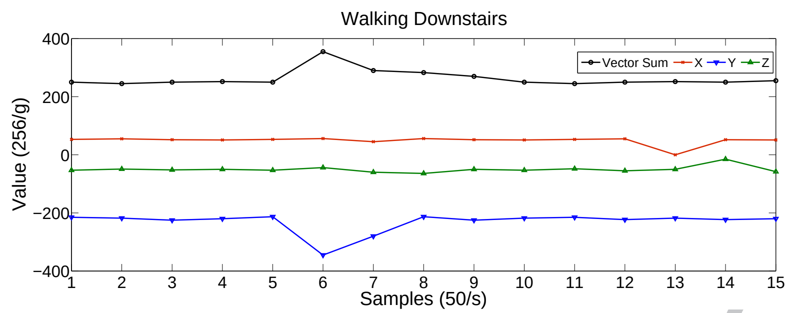

Figure 7: Volunteer walking down a flight of stairs

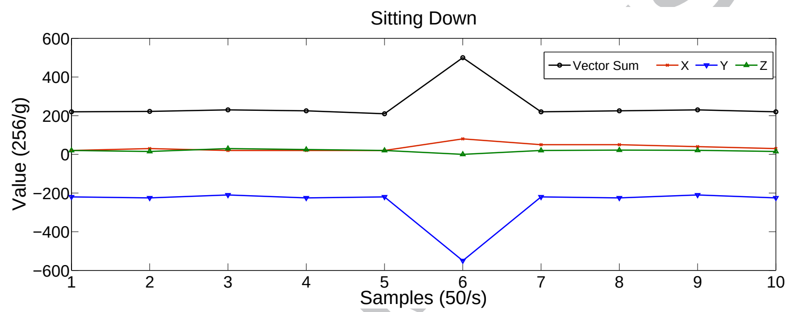

Figure 8: Volunteer sitting down

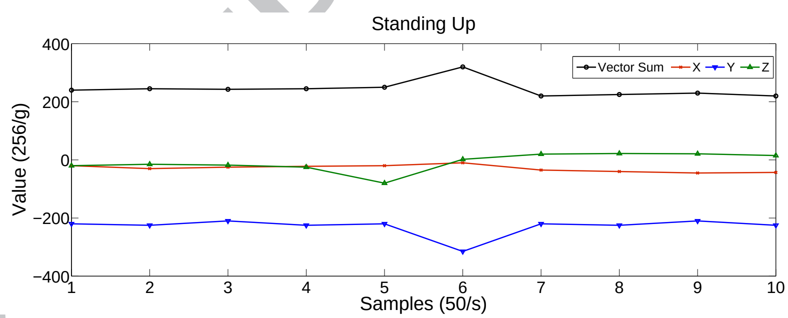

Figure 9: Volunteer standing up

mimic possible falls encountered by an elderly person based on some studies conducted [18][19]. The volunteer emulated several types of falls commonly encountered in the elderly ranging from falling from the side while sitting down, falling due to slippery surfaces etc. The acceleration profiles during falling in each of these scenarios are completely different. Figure 10 shows a recorded fall

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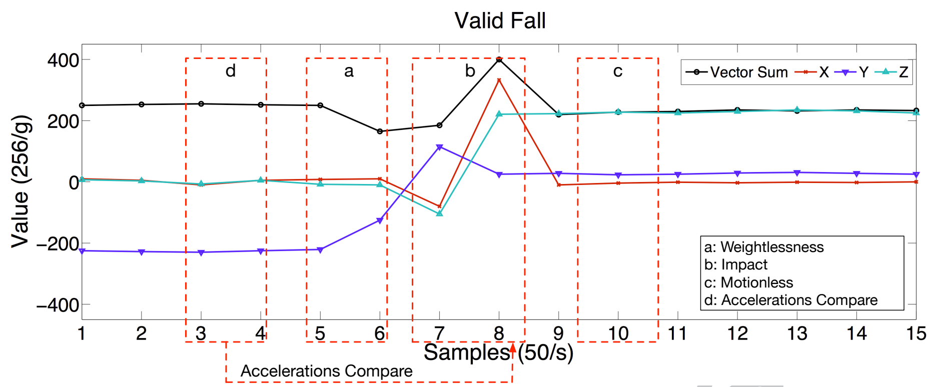

Figure 10: Volunteer emulates a fall

due to slippery surface, the respective change in acceleration during an emulated accidental fall.

By comparing Figure 10 with Figure 6 - 9, four critical characteristics of an emulated human fall event are observed that can be used as the major criteria for fall detection [10]. The characteristics are marked in the red boxes (Figure 10) and explained in detail:

1. **Weightlessness**: The weightlessness phenomenon always occur at the start of an elderly person (volunteer) fall event. It will become more significant during free fall, and the resultant vector sum of acceleration values will be towards 0g. The duration of the condition depends on the height of free fall. Even though weightlessness during an ordinary fall is not as significant as that during a free fall, the vector sum of acceleration is still substantially less than 1 g (under normal condition, it is generally greater than 1 g as depicted in Figure 6 - 9). Thus, the first basis of fall detection is to examine the fall status and that is easily done by the ADXL345 FREE_FALL interrupt.
2. **Impact**: After experiencing weightlessness, the elderly person's body will impact the ground or other objects. This is manifested on the acceleration curve as a large transient shock. This transient shock is detected by the ACTIVITY interrupt of ADXL345. Thus, the second basis of fall detec-

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tion is to determine the ACTIVITY interrupt right after the FREE_FALL interrupt.

3. **Motionless**: The elderly person, after a fall and an impact, will remain in a motionless position for a short period (or longer period as a possible sign of unconsciousness). On the acceleration curve, this shows as an interval of flat line, and is detected by the ADXL345 INACTIVITY interrupt. Thus, the third basis of fall detection is to determine the INACTIVITY interrupt after the ACTIVITY interrupt.

4. **Acceleration Comparison (before Weightlessness and during Motionless)**: After a fall, the elderly person's body will be in a completely different orientation than before a fall, hence the static acceleration in the three axes will be different from before the fall (before Weightlessness). In Figure 10, it is clear that the elderly person (volunteer) falls on the side, since the static acceleration has changed from 1 g on the Y axis to +1 g on the Z-axis. Thus, the fourth basis to determining a valid fall is to compare the difference between an initial acceleration value (at a time before Weightlessness) and a final acceleration value (at a time during Motionless). When the difference in acceleration exceeds a certain threshold, a valid fall can be ascertained.

The combination of the four characteristics will realize an inertial-based fall-detection algorithm that is able to generate an IFA event when a fall has occurred. The various timing parameters and the related acceleration thresholds have to be properly fine tuned in order to realize an effective algorithm with minimal false fall detections. The proposed fall detection algorithm takes full advantage of the internal function registers of the ADXL345, thus minimizing the complexity of the algorithm due to minimum access to the actual acceleration value (calculated using Equation 1). Figure 11 depicts the flowchart of the accelerometer-based fall detection algorithm.

From the algorithm flowchart in Figure 11, the algorithm functions as follows:

1. After an Initialization procedure, the algorithm waits for the FREE_FALL

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interrupt to occur (Weightlessness). Free Fall vector sum acceleration threshold (THRESH_FF) is set empirically to 0.8 g and Free Fall Acceleration Timeout (TIME_FF) is set empirically to 30 ms. The acceleration and timeout thresholds are determined from a series of fall occurrences (emulated by volunteers). Based on the acceleration data in Figure 10, acceleration threshold of 0.8 g is selected as a higher value generates false free fall occurrence, and a lower value reduces the free fall detection sensitivity. Based on the conducted experiment, the minimum time required for an elderly experiencing a free fall is typically < 30 ms. The timeout is set to 30 ms to detect false occurrence of free fall, where any detected free fall of ≥ 30 ms is not valid and the detection algorithm restarts.

2. After FREE_FALL interrupt is asserted, the algorithm waits for the ACTIVITY interrupt (Impact). Based on Figure 10, any large vector sum acceleration of ≥ 1.5 g can be safely classified as an abnormal activity. Thus, vector sum for Activity Acceleration threshold (THRESH_ACT) is set empirically to 1.5 g.
3. From a series of fall occurrences (emulated by volunteers), the maximum time required for an elderly experiencing a fall to hit the floor is typically < 200 ms. The time interval threshold between FREE_FALL interrupt (Weightlessness) and ACTIVITY interrupt (Impact) is set empirically to 200 ms. The time interval threshold is set to detect false occurrence of a free fall, where any detected free fall duration of ≥ 200 ms is not valid and the detection algorithm restarts.
4. After the ACTIVITY interrupt is asserted, the algorithm waits for the INACTIVITY interrupt (Motionless After Impact). Inactivity Acceleration threshold (THRESH_INACT) is set empirically to 0.2 g. Based on an observation (Figure 10), any small changes in vector sum acceleration ≤ 0.2 g after an ACTIVITY interrupt is considered an inactivity. This value is optimal as any higher or lower values cause inaccurate inactivity detection.
5. The INACTIVITY interrupt (Motionless After Impact) must be asserted

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within 3.5 seconds after the ACTIVITY interrupt (Impact). Otherwise, it is not a valid condition and the algorithm restarts. From the conducted fall experiments, when a valid fall occurs, an ACTIVITY interrupt is asserted followed by an INACTIVITY interrupt within a short time duration. This time duration is dependent on the physical health of the elderly being monitored, thus the timeout also vary according, and here, the timeout is set to 3.5 seconds.

6. The stable acceleration value after INACTIVITY interrupt (STABLE_STAT) is compared against the initial acceleration value (INITIAL_STAT, recorded after Initialization), and if the difference exceeds the 0.7 g threshold, a Valid Fall is detected, and the algorithm generates an IFA event. This threshold value is determined from the vector sum acceleration data captured in Figure 10.
7. After detecting a fall, the ACTIVITY interrupt is continuously being monitored to determine if the elderly moves after a fall. The delta sum THRESH_ACT is set empirically to 0.5 g, Once the elderly moves, the ACTIVITY interrupt is generated to complete the entire fall detection sequence, and the algorithm restarts. The threshold value is used to restart the fall detection algorithm, and is a value that does not easily triggers a restart of the fall detection algorithm. Typically after a fall, the elderly may recovers from the fall and gets up unaided or being aided by a third party. In both cases, the algorithm must restart. Thus, based on Figure 10, the delta sum activity threshold is set to 0.5 g, and this value is highly dependent upon the elderly's physical health.

3.2. Fuzzy Logic-based Fall Detection

In the earlier sections, an accelerometer-based fall detection algorithm is proposed and developed and the known limitations pertaining to the accelerometer-based fall detector are also highlighted. In this section, a new algorithm to further improve on the fall detection accuracy is proposed with the use of fuzzy

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logic. This new algorithm does not replaces the accelerometer-based fall detection algorithm discussed earlier as it provides an overall fall detection accuracy enhancement by introducing a sound-based fall detection methodology. Each e-SS module continuously measures SPL in its vicinity, and receives IFA information broadcast via Wi-Fi if an inertial-based fall has been detected. The idea is to fuse the IFA message from the e-WM with the SPL sound-based fall information from the e-SS using fuzzy logic. This fuzzy logic-based algorithm resides within all the e-SS modules and if a valid fall has been detected by one or more e-SS modules, each respective module notifies the e-BS of a valid fall occurrence.

In a quiet residential environment, the typical indoor SPL is measured to be in the range of 30 dB - 50 dB SPL. 30 dB is a typical bedroom SPL, 40 dB typically represents a person whispering, and 50 dB represents a typical person talking SPL. A group of people doing an intense discussion can have a moderate SPL of 60 dB. 70 dB SPL represents a noisy office, restaurant or street noise, and 80 dB SPL is very loud, representing the sound of a heavy street noise and an average factory floor [20].

Sound signal sampled by the uni-directional microphone is directly processed by the MCU within the e-SS to determine its SPL value and its duration of occurrence. Microphone sensitivity (in dB) is defined in Equation (2), where $20 \cdot log_{10}(Sensitivity(mV/Pa)) = -46$ dB/Pa is the specification of the microphone sensitivity in dB/Pa and $20 \cdot log_{10}(1000mV/Pa) = -94$ dB/Pa is the microphone's reference output ratio. The SPL (in dB) is calculated by using Equation (3) [21] [22] and $V_{ref} = 10^{-\frac{46}{20}}$. V_{MIC} is the RMS sound signal voltage level.

$$\begin{aligned} Sensitivity\ (dB) = \ & 20 \cdot log_{10}(Sensitivity(mV/Pa)) - \\ & 20 \cdot log_{10}(1000mV/Pa) \end{aligned} \tag{2}$$

$$SPL(dB) = Sensitivity\ (dB) + 20 \cdot log_{10}(\frac{V_{MIC}}{V_{ref}}) \tag{3}$$

Sound generated from a fall usually emits from an elderly body impacting

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the floor or a hard object. An experiment was conducted where a volunteer emulates several occurrences of falls (front fall, back fall, side fall, and fall from a chair) on a hard floor overlayed with soft rubber foam. The recorded SPL for each fall is within the range of 50 dB to 70 dB with a sound duration of $\leq$ 500 ms. A short burst sound with SPL of $>$ 70 dB and duration of $\leq$ 500 ms can also be associated with an occurrence of a fall, where the large SPL can be associated with the elderly person's body shattering a glass object during impact. Based on this conducted experiment, sound can be used as an indicator to detect or estimate an elderly person's fall occurrence.

Having established a possible scenario where sound can be used to identify a valid fall, the next step is to use fuzzy logic to fuse together the IFA message and sound information. The proposed fuzzy logic-based fall detection algorithm has three inputs and a single output. The defined fuzzy logic function inputs are:

1. IFAINFO: IFA message received when an inertial fall is detected by an e-WM resulting in IFA message being broadcasted (by e-WM) and received by an e-SS. e-SS sets IFAINFO = HIGH when it receives an IFA message from e-WM, otherwise e-SS clears IFAINFO = LOW.
2. DURATION: signal represents the length of a sound event sampled by the e-SS, where DURATION = LOW if the length of the sound event is $\leq$ 500 ms, and DURATION = HIGH if the length is $>$ 500 ms
3. SPLVALUE: signal represents the SPL of the sampled sound event, where SPLVALUE = LOW if SPLVALUE $\leq$ 30 dB, SPLVALUE = MID if 30 dB $<$ SPL $\leq$ 50 dB, and SPLVALUE = HIGH if SPL $>$ 50 dB.

The fuzzy logic function has only a single output FOUTPUT where it produces FALL for a valid fall occurrence, and NOFALL for otherwise. Thus, the Mamdani fuzzy rule system [23] for detecting a valid fall has five rules:

1. IF **IFAINFO** is LOW then **FOUTPUT** is NOFALL
2. IF **IFAINFO** is HIGH and **DURATION** is LONG then **FOUTPUT** is NOFALL

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3. IF **IFAINFO** is HIGH and **DURATION** is SHORT and **SPLVALUE** is LOW then **FOUTPUT** is NOFALL
4. IF **IFAINFO** is HIGH and **DURATION** is SHORT and **SPLVALUE** is MID then **FOUTPUT** is FALL
5. IF **IFAINFO** is HIGH and **DURATION** is SHORT and **SPLVALUE** is HIGH then **FOUTPUT** is FALL

The constructed membership functions for IFAINFO, DURATION and S-PLVALUE inputs are respectively depicted in Figure 12 to 14, and the membership function for FOUTPUT is depicted in Figure 15.

By using the constructed membership functions that define the fuzzy logic rules, the IFA message and sound information can be fused for an effective detection of an elderly person's fall occurrence. The accuracy of the fall detection algorithm will be verified in Section 4 in the later part of the chapter.

4. Experiment and Verification

4.1. Fall Detection Algorithm Verification

In this section, the developed accelerometer-based algorithm and the fuzzy logic-based algorithm are tested for false human fall occurrence detection. Five volunteers are engaged to emulate elderly physical behaviors in performing common daily motion activities such as: (a) Walking and using stairs, (b) Sitting down, (c) Standing up, and (d) squatting. Each of the volunteers hangs an e-WM around the neck and is required to perform all the defined motion activities, and each activity requires 10 repeats. For each volunteer, the occurrence of false fall detection (in %) from known motion activity is determined as: $Error(\%) = \frac{x}{40} \times 100$, where x is the number of detected false fall occurrences.

Table 1 depicts the false fall occurrence detection results using only the accelerometer-based algorithm in the e-WM, and Table 2 depicts the detection results using the fuzzy logic-based algorithm in the e-SS. Based on the results, without fuzzy logic, the accelerometer-based algorithm has the maximum false

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fall detection of 20%. With fuzzy logic, the false fall detection is further reduced to $\leq 2.5\%$, thus greatly improving in the false fall detection problem.

Table 1: Accelerometer-based algorithm in detecting false fall occurrences.

Volunteer	Motion Type				Error
	Walking	Sitting Down	Standing Up	Squatting	(%)
1	2	3	0	0	12.5
2	3	3	0	1	12.5
3	3	4	0	1	20
4	2	3	1	0	15
5	3	3	0	0	15

Table 2: Fuzzy logic-based algorithm in detecting false fall occurrences.

Volunteer	Motion Type				Error
	Walking	Sitting Down	Standing Up	Squatting	(%)
1	1	0	0	0	2.5
2	0	0	0	0	0
3	1	0	0	0	2.5
4	1	0	0	0	2.5
5	0	0	0	0	0

The same volunteers are tasked to emulate four types of falls namely: (a) Front fall, (b) Back fall, (c) Side fall, and (d) Fall from a chair. The experiment was conducted in a lab with a tiled floor overlaid with a 1.5" thick soft rubber foam mat to cushion the emulated falls. Each fall is executed 10 times by each volunteer. For each volunteer, the fall detection accuracy (in %) from known fall activity is determined as: $Accuracy(\%) = \frac{y}{40} \times 100$, where y is the number of detected valid fall occurrences.

Table 3 depicts the detection results using only the accelerometer-based algorithm (e-WM), and Table 4 depicts the detection results using the fuzzy logic-based algorithm (e-SS). To detect a valid fall, the accelerometer-based al-

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gorithm is sufficient as it presents at least 95% accuracy in detecting the various emulated falls scenarios. Thus, the accelerometer-based algorithm is sufficiently accurate in detecting a valid fall but is prone to false falls detections. The fuzzy logic algorithm is very effective in reducing the false falls detections but does not improve the overall accuracy of the valid fall detection.

Table 3: Accelerometer-based algorithm in detecting valid fall occurrences.

Volunteer	Fall Type				Accuracy
	Front	Back	Side	From a Chair	(%)
1	10	10	10	10	100
2	10	10	10	10	100
3	10	10	9	10	97.5
4	10	10	9	9	95
5	10	10	10	9	97.5

Table 4: Fuzzy logic-based algorithm in detecting valid fall occurrences.

Volunteer	Fall Type				Accuracy
	Front	Back	Side	From a Chair	(%)
1	10	10	10	10	100
2	10	10	10	10	100
3	10	10	9	10	97.5
4	10	10	9	9	95
5	10	10	10	9	97.5

4.2. e-HealthCM Trial Deployments

e-HealthCM systems have been tested in selected homes of lone senior citizens. Several conditions must be met before an elderly person is selected for the trial:

1. ≥ 70 years of age and lives alone in a studio apartment.

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2. With mild to moderate hearing difficulty on one of both ears.
3. Have access to caregivers who are family members or friends.
4. Able body, healthy and without any known chronic and mental illness.
5. Allows motion activity data to be collected during the trial period.

The trial was conducted on four lone elderly persons households (S1 - S4) meeting the requirements, located in various parts of Singapore, for a period of 30 days. Two caregivers were assigned to each household. e-HealthCM system consisting of an e-BS and several e-SS modules installed in each of the elderly person's apartment and adjusted to ensure maximum area coverage within the apartment. Each elderly person is also assigned an e-WM attached to a lanyard and worn around the neck during daytime within the apartment. Each elderly person was informed to remove the e-WM only when leaving the apartment and during sleeping.

The e-WM hearing aid feature was tailored to each elderly person's hearing level by performing on the spot simple hearing loss calibrations for the elderly persons. During the period of the trial, the elderly persons were advised to press on the alert button on the e-WM if help was required, and in the event of false fall detection alarm, they were to note down the date, time, frequency of the motion activity (Walk, Sit Down, Stand Up or Squat) they were performing that caused the false fall alerts on the provided log books. They were also briefed on the simple way to reset e-HealthCM after each false fall detection, and designated care givers will call and check on them when fall alerts were triggered. During the trial, the four elderly volunteers did not experience any form of valid fall, hence the collected results reflected only the occurrences of false fall occurrences from the performed daily activities. Figure 16 - 19 depict the false fall detections data (from daily motion activities) for the 30 days trial period for the respective elderly volunteers. The number of false fall detections for the elderly volunteers range from 0.06 - 0.1 (6% - 10%) false fall per day for 30 days trial. The detailed data is tabulated and depicted in Tables 1 - 4.

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In order to benchmark the effectiveness of the e-HealthCM fuzzy logic algorithm in minimizing false fall detection, an able bodied volunteer (V1) was designated as a reference and tasked to wear a specially modified e-WM that operated in a stand-alone mode and retro-fitted with a small audible speaker. This modified e-WM uses only the accelerometer-based algorithm to detect an occurrence of a fall. This volunteer was tasked to wear the modified e-WM for the same 30 days trial duration. During the trial, the volunteer wore the modified e-WM throughout the day and only removed it while sleeping. The modified e-WM generated a low audible sound once a fall was detected, and the volunteer was tasked to record down the date, time, frequency of the motion activity (Walk, Sit Down, Stand Up or Squat) he was performing that caused the false fall alerts on the provided log book. This trial was executed concurrently with the trial involving the four elderly volunteers.

Figure 20 depicts the trial results for the number of false falls detected using the modified e-WM. The number of detected false falls is at 1.37 per day for 30 days trial. This figure indicates that false fall activity is detected each day. By comparing the results against Figure 16 - 19 of the elderly volunteers, it is obvious that the fuzzy logic algorithm in the e-HealthCM (deployed to the elderly volunteers) is capable of minimizing false fall detections (false fall detection per day decreases from high of 1.37 to low of 0.06). The figure for false fall detection per day for each elderly volunteer is consistently ≤ 0.1, indicating very minimal detection of false fall activity. The trials were considered successful with the fuzzy logic-based algorithm verified to be effective in reducing false fall alerts.

4.3. Comparisons of e-HealthCM with Other Fall Detection Systems

The work of Noury *et al.* [24] can be considered as the first to conduct survey and comparisons of systems, algorithms and sensors, for the automatic detection of the fall of elderly persons. It points out the difficulty to compare the performances of the different systems due to the lack of a common framework. Mubashir *et al.* [16] also published similar comparisons results based on

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the recent works. From the conducted surveys[24] [16], any fall detection systems utilizing tri-axial accelerometer for fall detection can easily achieve 100% in detecting a valid fall. However, the number of false fall detections due to daily motion activities is also very high at 50% or more. Thus, accelerometer based system are always perceived to be unreliable due to the difficulties in minimizing the false fall detections. In attempts to reduce the number of false fall detection, many researchers also incorporate secondary verification procedures with varying degree of successes. The secondary verification procedures can be in the form of additional sensors or processing methods. Khan *et al.* [25] demonstrated the feasibility of using sound for fall detection and Hsieh *et al.* [26] demonstrated the feasibility of using machine learning approach to enhance an existing fall detection algorithm. These secondary verification techniques are important towards realizing a reliable fall detection systems.

From the conducted field trial, the proposed fall detection algorithm in the e-HealthCM hardware prototype are verified to be operational with good accuracy of rejecting false fall activities. It is of great interest to compare the performance of e-HealthCM with other similar fall detection systems, and trial results have indicated an improved performance over the various system proposed in [16, 25, 26] with only 6% - 10% of false fall detection registered over the 30 days trial. This performance improvement is attributed to the accelerometer and sound sensor fusion with fuzzy inference algorithm.

5. Conclusion

In this paper, a non-intrusive fall detection monitoring system (e-HealthCM) for the elderly based on fuzzy logic has been proposed, designed and successfully implemented. The proposed fall detection monitoring system consists of three main components i.e., a base station module (e-BS) where fall alerts and caregiver notification are being handled when a fall is detected, sound sensor modules (e-SS) for continuous monitoring of potential falls based on detected sound, and finally an accelerometer-based wearable module (e-WM) for real-

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time motion activities monitoring. Extensive research have shown that using accelerometer alone for fall detection monitoring is insufficient to provide a reliable system, as the accelerometer itself is easily prone to false fall detections resulted from daily motion activities. In order to increase the valid fall detection accuracy, a microphone-based sound sensor module is introduced into this proposed monitoring system. These e-SS modules are installed at strategic locations within a senior citizen's home to provide an additional sound based fall detection function. Fuzzy logic algorithm is developed to fuse and process the accelerometer and sound data, resulting in a highly accurate fall detection solution. Experiments are carried out to verify the effectiveness of the proposed fall detection solution and comparison between the purely accelerometer-based and fuzzy logic-based algorithm are documented in this paper. Five volunteers are engaged to emulate elderly physical behaviors in performing common daily activities in the experiment. Based on the experiment results, the purely accelerometer-based fall detection system has the maximum false fall detection of 20%, whereas the proposed fuzzy logic-based algorithm has the false fall detection rate reduced to $\leq 2.5\%$. The e-HealthCM is also trialed in lone elderly household for a period of 30 days, and the number of false fall detection rate is as low as 0.06 per day. In order to benchmark the effectiveness of the fuzzy logic-based algorithm detection, purely accelerometer-based system is used in this trial on the same elderly over a 30 days trial duration and the recorded false fall detection rate is as high as 1.37 per day. The trial is considered successful with the fuzzy logic-based algorithm verified to be effective in reducing the number false fall alert.

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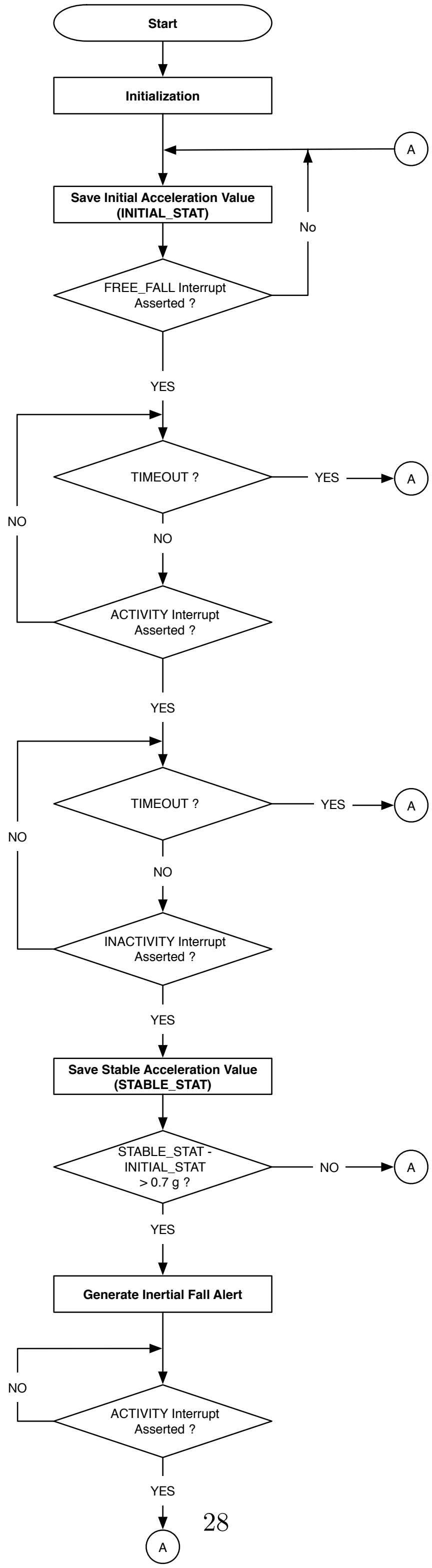

Figure 11: ADXL345-based Fall Detection Algorithm

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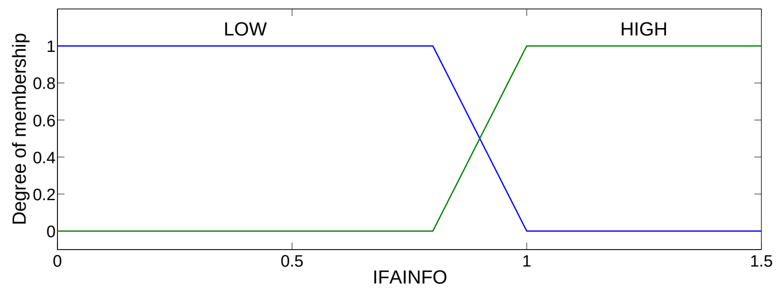

Figure 12: Membership Function for IFAINFO input.

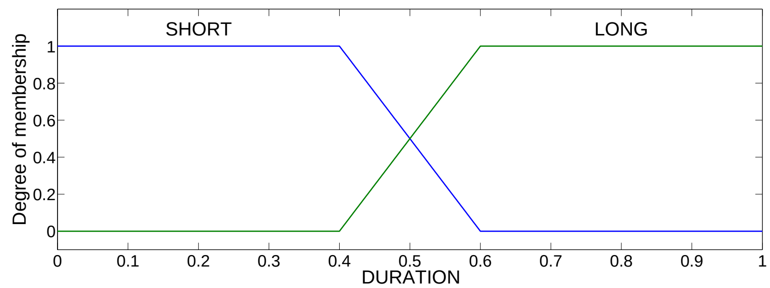

Figure 13: Membership Function for DURATION input.

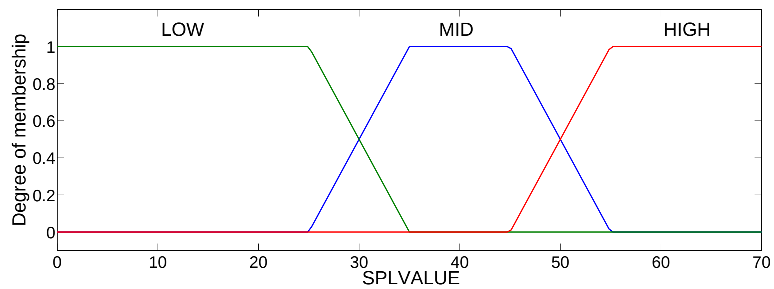

Figure 14: Membership Function for SPLVALUE input.

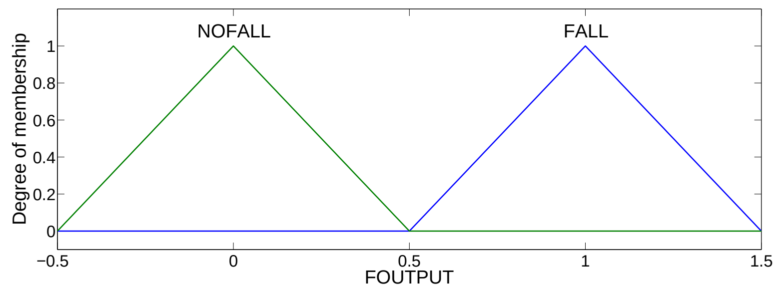

Figure 15: Membership Function for FOUTPUT.

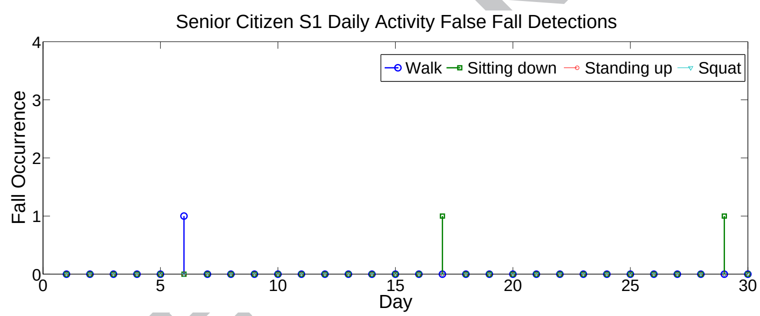

Figure 16: Senior Citizen S1 false fall occurrences from daily activities.

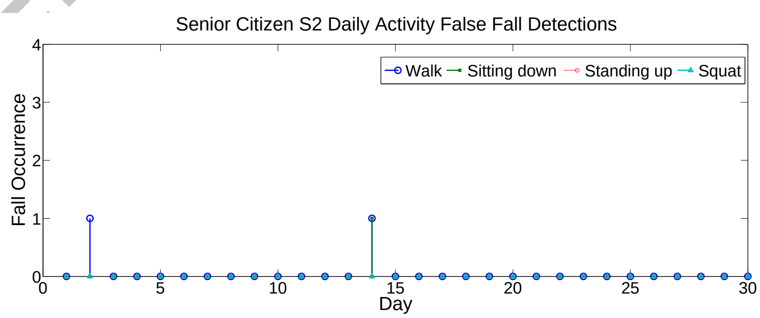

Figure 17: Senior Citizen S2 false fall occurrences from daily activities.

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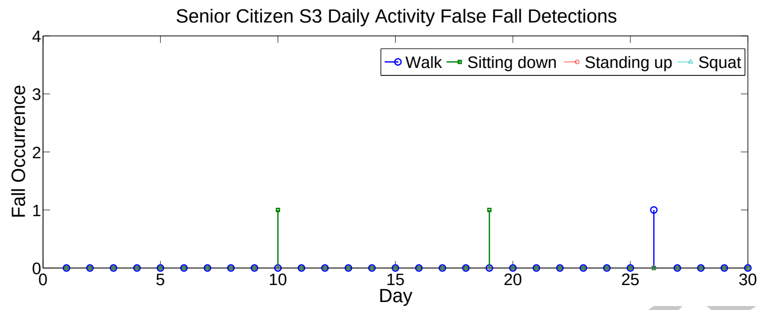

Figure 18: Senior Citizen S3 false fall occurrences from daily activities.

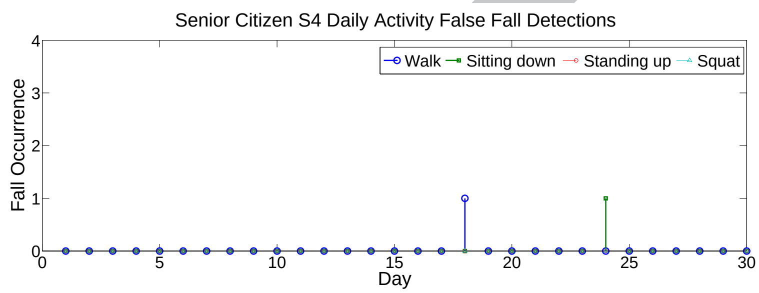

Figure 19: Senior Citizen S4 false fall occurrences from daily activities.

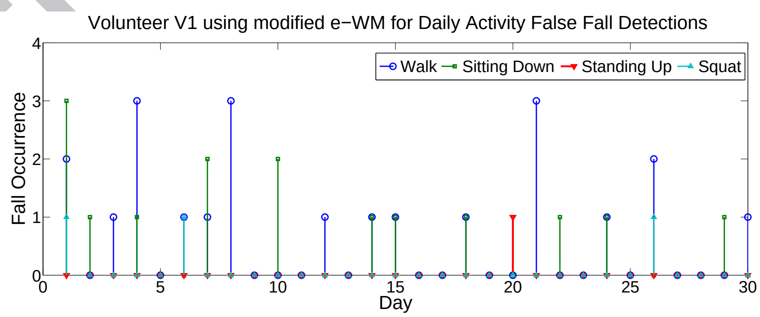

Figure 20: Volunteer V1 using a modified e-WM to detect false fall occurrences from daily activities.

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Highlights

- Accelerometer-based fall detection prompts to false fall detection.
- Fusion of sound sensor and accelerometer to increase the fall detection accuracy.
- A short burst sound in the range of 50 dB to 70 dB and duration less than 500 ms.
- Fuzzy logic-based fall detection algorithm.
- False fall detections per day decrease from high of 1.37 to low of 0.06.

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