MultiSense: A Highly Reliable Wearable-free Human Fall Detection Systems

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Abstract: A reliable fall detection system has tremendous value to the well-being of seniors living alone. We design and implement MultiSense, a novel fall detection system, which has the following desirable features. First, it does not require the human to wear any device, therefore it is convenient to seniors. Second, it has been tested in typical settings including living room and bathroom, and has shown very good accuracy. Third, it is built with inexpensive components, with expected hardware cost around $150 to cover a typical room. Therefore, it has a key advantage over the current commercial fall detection systems which all require the human to wear some device, as well as over academic research prototypes which have various limitations such as lower accuracy. The high accuracy is achieved mainly by combining senses from multiple types of sensors that complement each other, which includes a motion sensor, a heat sensor, and a floor vibration sensor. As the activities that are difficult to classify for some sensors are often not difficult for others, combining the strength of multiple types of sensors brings the performance to a level that can meet the requirements in practice.

1 INTRODUCTION

A reliable fall detection system has tremendous value to the well-being of seniors living alone. Studies show that "one out of five falls causes a serious injury such as broken bones or a head injury (CDC, 2013)." We design and implement MultiSense, a novel fall detection system, which has the following main desirable features:

- It is wearable-free, i.e., does not require the human to wear any device, therefore it is very convenient to seniors.
- It has shown excellent performance, e.g., it detected all falls and raised no false alarms in a daily use test, outperforming all existing systems to the best of our knowledge.
- It is inexpensive. The hardware cost is expected to be $150 or less to cover a typical room.

Currently, there are many companies offering fall detection services with monthly charges around $40. However, to the best of our knowledge, all commercial systems, such as those listed as the top 10 fall detection systems at (Preece, 2019), require the human to wear some device, which can be inconvenient (Skubic et al., 2016; Lipsitz et al., 2016). Many attempts have been made in the academia on wearable-free fall detection, including using depth camera (Mastorakis and Makris, 2012; Planinc and Kampel, 2012; Ma et al., 2014), vision (Debard et al., 2015; Anderson et al., 2009), sound (Li et al., 2014; Li et al., 2012), radar and RF signals (et al., 2015; Gadde et al., 2014; Amin et al., 2015; Wang et al., 2017), floor vibration (Alwan et al., 2006; Zigel et al., 2009), etc. However, to date, the academia prototypes suffer various kinds of limitations. For example, some may have low accuracy in certain cases, some may have high cost, and some may be intrusive to users with privacy concerns. Therefore, academic wearable-free solutions are yet to be adopted by the industry.

MultiSense achieves good performance mainly by *combining senses from multiple types of sensors, which complement each other and enable simple and robust rules to detect falls*. The sensors include a motion sensor, a body heat sensor, and a floor vibration sensor. For example, upon a fall, the motion sensor always reports a *motion-to-stationary transition*, i.e., a motion period followed by a stationary period, corresponding to the action during the fall and the inactivity after the fall (Sposaro and Tyson, 2009). However, similar observations can be made during many other events, such as a sit event. With the help of the vi-

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bration sensor, however, the fall and sit event can be very easily distinguished, because the latter produces much smaller floor vibration than the former.

One of the most notable features of MultiSense is that it does not depend on the availability of large training data set. Instead, it makes decisions according to simple logic and well-understood facts about falls, such as a motion-to-stationary transition, the floor vibration, which should hold for all falls. Therefore, MultiSense is in sharp contrast with other fall detection technologies, which typically involve machine learning and training data. This, we believe, is an advantage for the particular problem of fall detection for seniors, because good training data may be difficult to obtain, as the fall actions of seniors can be very different from those of the healthy younger persons who perform falls during the data collection (Khan and Hoey, 2017; Kangas et al., 2012).

In the rest of the paper, Section 2 discusses related work. Section 3 gives an overview of MultiSense. Section 4 explains the details of MultiSense. Section 5 explains how MultiSense classifies activities other than fall. Section 6 evaluates MultiSense. Section 7 compares MultiSense with other systems. Section 8 concludes the chapter.

2 RELATED WORK

The limitations of existing fall detection systems that depend on wearable devices has led to a vast body of academic research work on wearable-free fall detection. Ambient sensors that have been studied for fall detection include vibration, sound, Wi-Fi, infrared, Doppler radar, embedded sensors in the flooring materials, thermal, and certain combinations of the sensors. Vibration sensors in combination with a microphone was studied in (Alwan et al., 2006)(Zigel et al., 2009); however, a number of issues in practice, such as the difference in the intensity between the test object and real human, as well as the effect of human activities that may cause high floor vibration, such as jumping and stomping, were not considered. MultiSense on the other hand is evaluated with simulated human falls and common human activities. Fall detection with only sound signal was studied in (Li et al., 2012; Li et al., 2014) based on signal processing techniques to locate the source of the sound signal; however, it may generate 0.4 false alarms per hour based on the reported performance. Wi-Fall (Wang et al., 2017) is a system that detects human falls based on Wi-Fi Channel State Information (CSI); however, the reported accuracy is around 90%, which may not meet the accuracy in some fall detection application scenarios. MultiSense also has an RF module, but also has other sensors for activity classification to achieve high accuracy. Thermal data has been used for human tracking or activity recognition (Portmann et al., 2014; Malpani et al., 2016). MultiSense is different mainly because it also relies on other types of sensors, while using simple logic for fall detection, without attempting to solve typical image processing problems, such as human shape reconstruction.

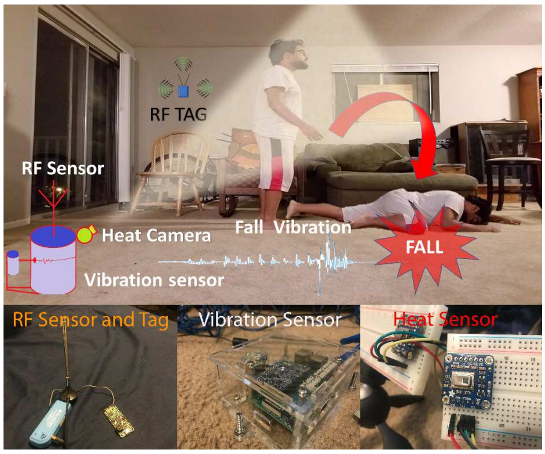


Figure 1: MultiSense system and sensors.

A recent multi-year testing in senior homes was reported in (Skubic et al., 2016), which uses a combination of Doppler radar, Kinect, and webcam for fall detection. It was admitted that the solution is susceptible to sudden light changes and has difficulty detecting falls occurring at such moments, such as a fall occurred while opening the curtain. It is also more expensive and may be less acceptable to users with higher privacy concerns.

3 OVERVIEW OF MultiSense

This section gives an overview of MultiSense.

3.1 Features for Fall Detection

MultiSense is illustrated in Fig. 1. It is expected that one MultiSense *device* will be needed in a room of size around 16 square meters. Larger rooms will need more devices proportionally. A device collects 3 types of signals: the motion signal, the heat signal, and the floor vibration signal. Roughly speaking, MultiSense uses three simple facts as features that are likely to be true for all falls:

- A *motion-to-stationary transition* in the motion signal: A fall will begin with an motion period,

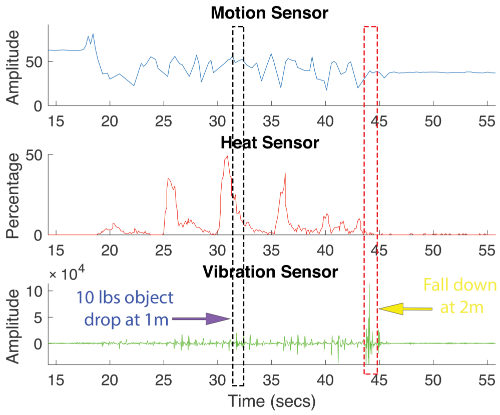


Figure 2: Typical signals.

followed by a stationary period when the person lays on the floor.

- The heat sensor cannot detect the human after the fall: the heat sensor measures temperatures. A person in its view can be detected because the body has higher temperatures than the environment. As the sensor points upwards, after the fall when the person lays on the floor, the sensor can detect no or very small area of the body.
- Large vibrations: A fall generates larger vibrations than typical activities at the same spot.

For example, Fig. 2 shows the output of the sensors when a person walked into the room, got close to the device at about 1 m, dropped a 10-pound object, walked away, then fell at about 2 m to the device. It can be seen that:

- The motion-to-stationary transition occurs in the motion signal at around 44 sec, the time the fall occurred.
- The heat sensor reading is close to 0 after the person has fallen, therefore can determine the person is not standing. Additionally, the heat sensor reading is higher if the person is closer to the sensor, and therefore can be used to estimate the distance to the person.
- The vibration of the fall is much higher than walking steps and the object drop, even when the object was 10 lbs and was dropped at a closer distance.

3.2 Outline of The Detection Algorithm

The detection algorithm is designed around the features of falls explained earlier. It constantly checks the motion sensor for the motion-to-stationary transition. Once a transition is found, the algorithm estimates the distance of the person to the device with the heat sensor reading. Currently, the possible distances are: within 0.5 m, within 1 m, in the view, or not in the view. The distance is used to select a threshold of the vibration; higher thresholds are used for smaller distances. If the vibration reading is higher than the selected threshold and the heat sensor does not detect the person after the transition, the algorithm declares a fall. If the vibration reading is higher than the threshold but the heat sensor still detects a standing person after the transition, the algorithm waits for 30 seconds, and still declares a fall is no movement has been detected in the 30 seconds. This is because if it is an actual fall, the heat sensor has likely detected some heat source but not an actual person. However, after the fall, the person will likely be stationary; therefore the algorithm can still detect the fall after 30 seconds. If it is not a fall but some activity such as jumping or stomping, it is extremely unlikely that the person will remain stationary for 30 seconds. It is clear that the algorithm should detect falls; in Section 5, it is explained why it will not misclassify non-fall activities as falls.

Algorithm 1: MultiSense Fall Detection Algorithm.

```
if the motion sensor detects a motion-to-stationary transition then
    if the vibration reading is larger than a threshold based on the estimated distance then
        if the heat sensor does not detect the human to be standing after the transition then
            Declare a Fall
        else
            Declare Fall if no movement is detected by the motion sensor in the next 30 seconds
        end if
    end if
end if
```

3.3 Installation and Cost Breakdown

The motion signal is based on the changes of the electromagnetic field due to human movements. It is collected by an RF receiver inside the device, which monitors the RF signal emitted by small ultra-low power RF transmitters placed in the same room. For each RF receiver, 1-2 transmitters are needed. The heat sensor and the vibration sensor are inside the device. The heat sensor detects humans based on the temperature, and should be positioned at least half a meter above the floor, pointing upwards at an angle, with no obstacles within one meter to block its view. It is also suggested to keep the heat sensor away from heat sources, such as a stove or the air conditioner. The vibration sensor should have contact with the floor to monitor vibration. The overall cost is estimated at \$150 based on the parts used in the prototype, including: \$40 for the processing unit which can be a Raspberry Pi, \$30 for the RF unit, \$40 for the heat sensor, \$15 for the vibration sensor, and \$25 for other circuits.

3.4 Discussions on More than One Person

MultiSense is designed for seniors living alone, and the algorithm assumes that there is only one person in the room. When there are more than one person, if one person falls, the other can provide help. As a result, even if MultiSense fails to detect an actual fall, it will not be an issue in practice. The other type of error, i.e., misclassifying non-fall activities as falls, is less critical but still annoying. However, note that: 1) if the second person is moving, the motion-to-stationary transition cannot be observed, 2) if the second person is in the view of the heat sensor, MultiSense should usually find a person standing. Therefore, the second person can help causing errors, only when the person stays motionless and out of the view of the heat sensor, but somehow helps generating some large vibration, which is an unlikely scenario.

4 DETAILS OF MultiSense

In this section, we explain our solutions to many practical challenges in MultiSense, such as determining the existence of the motion, estimating the human distance even in the presence of a heat source, etc.

4.1 Motion Detection (MD) Module

The MD module is based on the RF signal. It consists of a receiver and simple transmitters called *tags* operating in the 433 MHz band, where the receiver is currently implemented with inexpensive low bandwidth software defined radios (RFS,), and the tags are implemented with programmable wireless modules (RFT,). Basically, the tags periodically transmit their IDs and the receiver demodulates the RF signal and considers there is motion if the fluctuation of the wireless channel is above a level, and otherwise stationary.

4.1.1 Implementation

In practice, the main challenge is to extend the battery life of the tags, because at least some of them may have to be placed in locations with no power outlet, such as a shower room. Therefore, an ultra-low power design based on *pulse interval modulation* is adopted for the tags, which has been used in some active RFIDs, allowing the RFID to last on a single coin cell battery for 2-3 years (RFC,). To be more specific, in the current design, a tag transmits its ID on average every 200 ms, with some random offset every time to avoid consistently colliding with another tag. The tag ID is basically a *burst* of 10 *pulses*, where each pulse is very short for about 40 μs. The tag identity is represented by the intervals between the pulses, called the *signature*, which are preselected pseudo random numbers, ranging from 1.5 to 2.5 ms. For example, Fig. 3(a) shows the burst from one tag. With the pulse interval modulation, the tag is idle for most of the times, except when it needs to transmit its ID, which is less than 0.2% of the time with the current design.

As there could be multiple tags in the vicinity, the receiver adopts a simple algorithm to separate the signals from the tags, which can also tolerate some low level of collision, where a collision occurs when the pluses from two tags overlaps in time. For example, Fig. 3(b) shows the bursts from two tags. The algorithm assumes that the number of tags is small and the tag signatures are known to the receiver, which are true in the current implementation. The receiver scans the signal for pulses. When it finds a pulse, it assumes the pulse to be the first pulse of a burst of some tag and starts checking the tags. For a particular tag, the receiver aligns the first pulse of the tag with the identified pulse, and checks if the *matching condition* is satisfied, i.e., at least 9 pulses are found at the time the tag is supposed to transmit pulses according to its signature. The receiver checks all tags and outputs any tag that satisfies the matching condition. The complexity is further reduced, i.e., not all detected pulses are considered as the first pulse and trigger the check, by exploiting one feature in the current design. That is, the first and the last pulses of a burst are separated by a constant time. Therefore, a pulse is considered a first pulse only if a pulse also appears at exactly the time when the last pulse is supposed to appear.

4.1.2 Extracting the Wireless Channel Condition

The condition of the wireless channel from a tag to a receiver can be easily learned from the amplitude of the pulses. It was found that the measured amplitude is stationary when there is no human movement; however, with human movement, which changes the electromagnetic field, the measured amplitude will show significant variations. Therefore, MultiSense uses the amplitude of the pulses as the decision variable to es-

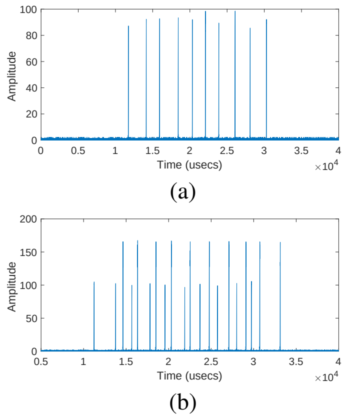


Figure 3: Bursts from tags.

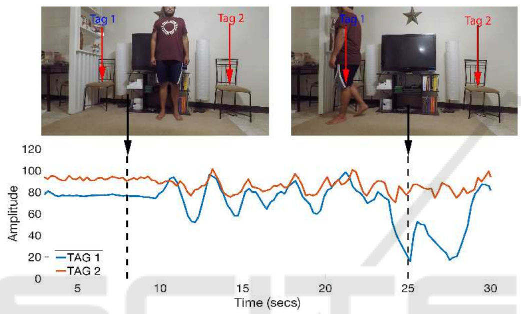


Figure 4: Motion sensor reading examples.

timate whether or not the person is moving. An example is shown in Fig. 4, where the amplitude of 2 tags are shown. The person was stationary up to 10 seconds, and started moving afterwards. Correspondingly, the tags signals were stationary in the first 10 seconds and started to fluctuate in various ways afterwards. To determine whether the person is stationary or moving, MultiSense calculates the standard deviation of the pulse amplitudes, and considers human movement detected if the standard deviation is more than 3 times the standard deviation of the signal when the person is not present. As a receiver may receive the signal from multiple tags, the tag with the largest fluctuation is used, because motion exists if fluctuation can be detected by any tag. The fluctuation threshold is calibrated at regular intervals when the person is determined not in the room.

4.1.3 Discussion

The RF-base motion detection is more sensitive to movements near the tag or the receiver. One concern is that after a fall near the tag or the receiver, the person may make some small movements, causing the system to believe there is still motion. However, in practice, the tags should be mounted at a certain height above the floor, and is therefore naturally a certain distance away from the person after the fall as the person is on the floor. Further testing was conducted to uncover the response of the system to human small movements at 25 cm from the receiver, which show that micro movements made by a person after a fall does not affect the receiver enough to falsely classify as in motion. Another concern was that human movement in other rooms; however it was also found that the fluctuation is also too small to cause any error.

4.2 Heat Sensing (HS) Module

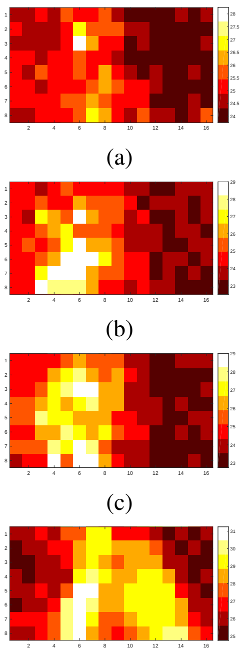
The Heat Sensing (HS) module is implemented with Adafruit AMG8833 IR Thermal Camera due to its low cost, which has 64 pixels, each spanning angle of roughly 7.5 degrees (hea,). The heat sensor outputs the temperature values based on the infrared signals it receives on each pixel. With proper calibration, it can be used to both estimate the distance of the person to the device, as well as determining whether or not the person is standing.

4.2.1 Estimation of Human Distance

The human distance can be estimated, because the closer the person is, the more pixels in the sensor report high values. For example, Fig. 5 shows the heat maps of different distances. To estimate the distance, the algorithm selects a lower and upper temperature threshold, and considers any pixel within this range to be occupied by a human body, and refers to them as *human pixels*. The details for establishing these thresholds are discussed in Section 4.2.4. The algorithm uses the percentage of human pixels as the decision variable. Based on empirical data, when the percentage are at least 3%, 25%, and 50%, the distance are within the view, 1 meter, and half meter, respectively.

4.2.2 Standing Human Detection

The heat sensor can determine if a person is standing or not, because after the person has fallen down, the person should be outside the view of the heat sensor, which points upwards. However, it could happen that the sensor can still detect the person, for example, when the person falls very close to the sensor, or when the person lands on the hip in a sitting pose. Nevertheless, even in these cases, the person should only appear in the bottom part of the sensor. Therefore, the algorithm looks for human pixels only in the *inspected area*, which is the top 50% of the sensor if the estimated human distance is 0.5 meters or less,



(a) (b) (c) (d)

Figure 5: Heat sensor raw reading. (a) Not in the view. (b) Inside the view. (c) Within 1 m. (d) Within 0.5 m.

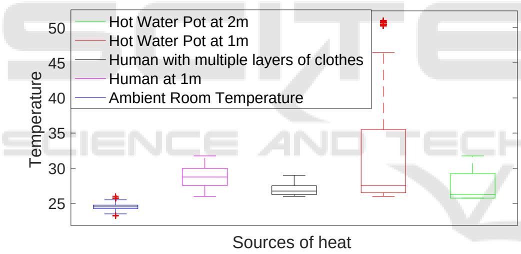


Figure 6: Temperature readings on the heat sensor.

and the top 75% of the sensor for all other distances. The algorithm checks the bottom row of the inspected area for human pixels. As a standing person should always appear on this row, the algorithm considers the person to be standing if at least 2 human pixels are found in this row. The bottom row may be redefined if heat sources are present, which is explained in Section 4.2.3.

4.2.3 Presence of Heat Sources

Heat sources, like a fireplace or a cup of hot water, when introduced into the environment, may sometimes be confused as human pixels. Fig. 6 shows the temperature readings of some heat sources compared to the human body temperature. It was found that:

- Smaller heat sources, like a cup of hot tea, when placed near the sensor, some areas surrounding the heat source can sometimes be classified as human pixels. Fortunately, when placed at distances further than 1 m, they are much smaller than the area mapped to a single pixel and usually does not register anything significantly higher than the ambient room temperature.
- Larger heat sources, like a fireplace or a large hot pot of water, when placed near the sensor, the outer edges of the heat source may have a lower temperature than the middle, and may fall within the thresholds of a human pixel. When placed further away, the decay in infrared signal strength causes the sensor to register a temperature that is lower than the actual temperature of the heat source, and also may be classified as human pixels.

There are two main issues that arise when heat sources are introduced into the environment. First, the human distance estimation algorithm may mistake some of the heat source pixels as human pixels. This leads MultiSense to believe that the person is closer than the person actually is, and apply a larger vibration threshold. Second, the standing human detection is also affected, as MultiSense might detect a standing person if a heat source present in the top part of the sensor.

To overcome this, a simple algorithm is run first to remove heat source pixels before running the distance and standing estimation modules, based on the fact the most heat sources will lead to some very hot pixels. To elaborate, the algorithm first checks if any pixel exceeds the upper human temperature threshold. If such pixels are found, the algorithm discards them, as well as any adjacent pixels, as these may also be affected by the heat source. The higher the temperature reading, the more adjacent pixels are removed. In the current implementation, if a pixel has a reading of more than 40, then pixels with a distance of 3 or less are removed; otherwise, pixels with a distance 2 are removed. After some pixels are removed, the bottom row needed in standing human detection is redefined as the lowest pixel that has not been removed in each column of the inspected area. If more than 50% of the pixels are estimated to be some heat source, the heat sensor data is rendered useless, and the situation is treated the same as when the human is not in the view of the sensor.

4.2.4 Threshold Values

To establish the lower threshold, a simple clustering algorithm is used to cluster the sensor readings in to two clusters. The cluster with lower values is assumed to be the ambient temperature, and the lower threshold is the mean temperature of this cluster plus 8 times the standard deviation of all temperature readings in this cluster. The upper threshold is calibrated only once per sensor, by recording the maximum temperature reported by the heat sensor pixels when the human is standing close to the sensor, and remains constant thereafter. One may concern that the human body temperature may go lower if the human is wearing multiple layers of clothing as shown in Fig. 6. However, this will usually only happen in colder temperatures, when the overall ambient temperature of the room is also lower, and so it will still be higher than the lower threshold. The heat sensor is calibrated at regular intervals as long as no movement is detected in the room, i.e. the human may be present in the room, but is not mobile.

4.3 Floor Vibration Detection (FVD) Module

The Floor Vibration Detection (FVD) module reports the vibration of the floor. Currently, it is implemented with RaspberryShake (vib,), a seismograph device for Raspberry Pi, which constantly reports the vibration reading every 20 ms that reflects the amount of vibration felt by the sensor. Typically, the maximum observed vibration reading reflects the intensity of the vibration, and is therefore used as the decision variable. The vibration reading is compared with certain threshold values to help determine if a fall has occurred. Clearly, even for exactly the same person or object falling in exactly the same manner, many factors can lead to changes in the reading, including, the distance to the sensor, the floor type, i.e., concrete or wood, etc. Therefore, the threshold values must be learned for each deployment, which fortunately can be achieved by a simple process. That is, during installation of the system, simulated falling events should be created in the room on a number of calibration locations to record the signal amplitude to determine the threshold value at variant distances to the device, where the number of distances depends on the room size.

5 COPING WITH NON-FALL ACTIVITIES

In this section, we explain how the internal logic of MultiSense copes with typical non-fall activities and makes the correct decisions except for only some rare activities.

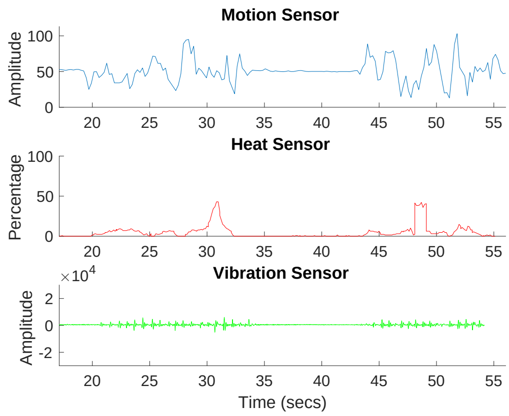


Figure 7: Sitting down and standing up.

5.1 Everyday Activities

Everyday activities include: 1) entering the room, 2) walking in the room, possibly making a stop in the middle, 3) sitting down for a while, 4) getting up, and 5) leaving the room, possibly slamming the door on the way out. In such activities, the motion sensor may detect a motion-to-stationary transition, for example, when the person sits down, leaves the room, or makes a stop during walking. Also, the heat sensor may be blocked, for example, by the chair. However, MultiSense can easily determine no fall has occurred, because none of such activities will generate large vibrations exceeding the vibration threshold. Note that even for door slamming, as its vibration is mainly on the walls, while the vibration sensor is on the floor, the vibration reading is low. An example is shown in Fig. 7, where the person sat down at around 32 sec, after which the heat sensor was blocked, then got up at around 43 sec. It can be seen that the vibration sensor readings are small.

5.2 Object Drop

Dropping an object may also occur in everyday lives, although it should be much less often than other everyday activities discussed earlier. It may need a separate discussion, because it will lead to larger vibration sensor readings.

5.2.1 Normal Object Drop

In a typical scenario, after a person drops an object, the person will bend over to pick it up. In this case, the motion sensor will not find a motion-to-stationary transition at the time when large vibration was recorded, therefore no fall will be declared. Fig. 8 shows an example, where the person dropped

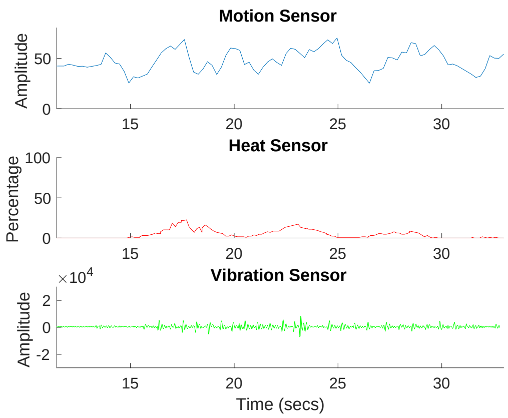


Figure 8: Normal object drop.

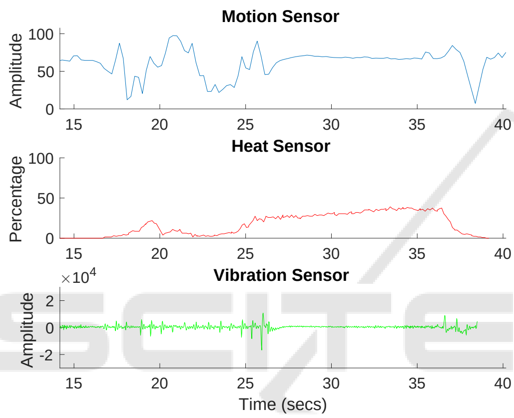


Figure 9: Freeze large object drop within 1 meter.

a 20-lb object while walking, then picked it up, then continued waling. It can be seen that no motion-to-stationary transition occurred.

5.2.2 Freeze Object Drop

In some very rare cases, a person may drop an object while walking, and then stop walking, therefore the word "freeze." In this case, the motion sensor will detect a motion-to-stationary transition. Fortunately, it was found that even 20-lb objects will not cause as large a vibration as a human fall at the same distance to the sensor. As a result, MultiSense will still not declare a fall, because it can select the correct vibration threshold, which will be higher than the vibration cased by the drop. In addition, in many cases, the person is still within the view of the heat sensor after the drop, further preventing a fall to be declared, as long as the freezing period is not longer than 30 sec. An example is shown in Fig. 9, where a 20-lb object was dropped at around 26 sec.

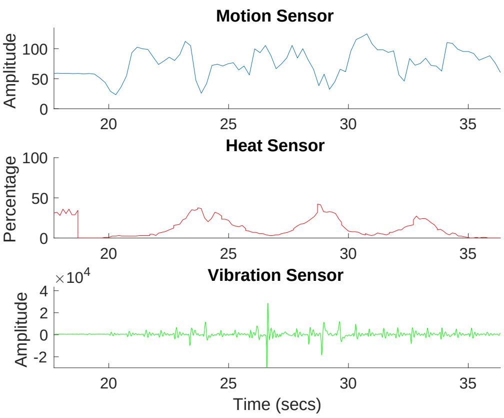


Figure 10: Normal jump.

5.3 Jumping and Hard Stomping

It could happen that a person jumps or stomps hard, although it could be less often for seniors. These activities are most challenging to a fall detection system, because they may generate the motion-to-stationary transition, as well as large vibrations. Note that the stomping has to be hard because soft stomping will not generate large vibrations.

5.3.1 Normal Jumping and Hard Stomping

In a normal scenario, a person, while walking, may jump or stomp, and then continue walking. MultiSense will not declare a fall, because the person is moving continuously and there will be no motion-to-stationary transition. An example is shown in Fig. 10, where the jump occurs at around 26 sec, but the motion sensor records large variations throughout the period.

5.3.2 Close Freeze Jumping or Hard Stomping

To further challenge MultiSense, consider a scenario where the person is initially walking, then jumps or stomps hard at a location that is still in the view of the heat sensor, and then stands still. MultiSense will not consider it a fall, because although a motion-to-stationary transition does occur and the vibration sensor will likely register a large vibration value, the heat sensor should still detect the person as standing. An example is shown in Fig. 11, where the person jumps at around 30 sec, however the heat sensor detects the person to be standing. MultiSense may declare a fall, only if the person stays still after the jump or stomp for over 30 seconds, which can be argued to be an extremely unlikely scenario.

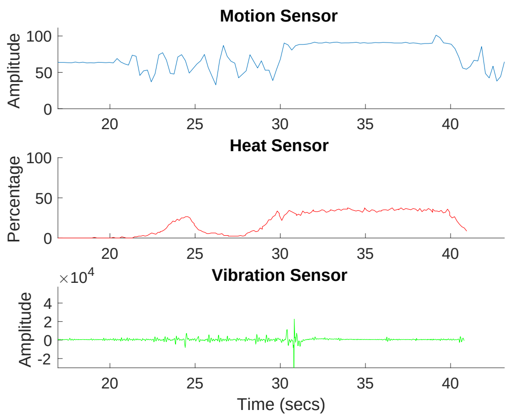


Figure 11: Freeze jumping at close distances.

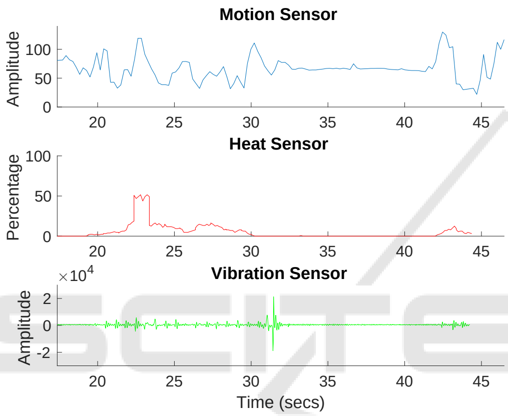


Figure 12: Freeze jumping far away.

5.3.3 Far Freeze Jumping or Hard Stomping

A misclassification may occur when a person jumps or stomps hard at a location outside the view of the heat sensor, and then stands still. Note that such activities should be very rare for seniors. The motion sensor will detect a motion-to-stationary transition. The heat sensor will not detect the person; therefore, MultiSense has to apply the smallest vibration threshold. As the vibration caused by a jump or a hard stomp is comparable to those caused by a fall, the vibration threshold may be exceeded. An example is shown in Fig. 12, where the jump occurred at around 31 sec, and the signal is similar to that from a fall. To avoid misclassification, the device should be placed such that the person is in the view of the heat sensor as much as possible.

6 EVALUATION

MultiSense is evaluated in realistic environments including a living room and a bathroom. The evaluation includes:

- False Negative (FN) stress tests: a person falls in different manners and locations, to check if MultiSense can correctly detect the falls.
- False Positive (FP) stress tests: the activities listed in Section 5 are repeated for a number of times, to check if MultiSense can correctly determine them not to be falls.
- Daily use tests: the system runs for 24 hours in a room with the person conducting normal activities, to check if the system makes any incorrect alarms of falls.

Overall, *MultiSense reports excellent performance, with **no errors in the FN stress tests and the daily use tests**, and errors in the FP stress tests only for 2 activities that should occur very rarely for the seniors.*

6.1 False Negative Stress Tests

The FN stress tests were conducted in a typical living room and a bathroom, and in the presence of a heat source. It was found that MultiSense correctly detected all falls.

6.1.1 Living Room Tests

A total of 100 experiments were conducted inside a typical living room of size around 16 square meters with carpet on concrete floor, as shown in the left of Fig. 13. Each experiment starts with a 5-second calibration period, after which the test subject starts some normal activities, such as walking, and then simulates a fall at a random time. The types of falls include hard falls, soft falls, forward falls, and backward falls, and occurred at various distances to the device. The locations of some of the falls are shown in the right of Fig. 13. To be more exact, in 37%, 53%, and 10% of the tests, the heat sensor could determine that the person at a distance of 1 meter or less, more than 1 m but still in the view, and not in the view, respectively.

Fig. 14 and Fig. 15 explains the main reasons why MultiSense was able to detect all falls correctly. Note that the first check of any potential fall is the motion-to-stationary transition. Fig. 14 is a scatter plot, where the x and y coordinates of a point are the threshold for detecting motion and the motion sensor reading, respectively. The readings before and after the fall are shown in different colors. It can be seen that the data before fall are all above the diagonal line, while the

Figure 13: The living room in the test.

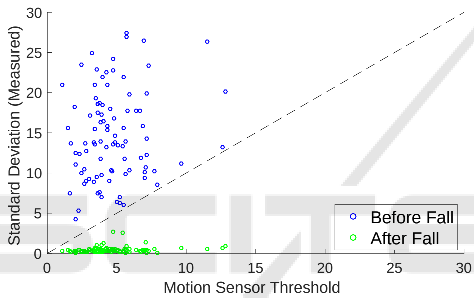


Figure 14: Motion-to-stationary transition detection in the living room.

data after fall are all below the line, which suggests that the motion was detected before the fall and not detected after the fall. The threshold values appear in a fairly large range, which is caused by a defect in the current tag implementation, as it sometimes transmits pulses at different magnitudes. Fig. 15 is also a scatter plot, where the x and y coordinates of a point are the selected vibration threshold and the vibration reading of the fall, respectively. It can be seen that the vibration threshold was exceeded in all cases shown in the figure, suggesting that MultiSense indeed picked the right threshold depending on the distances of the fall to the device. It may need to be mentioned that for the living room, based on its size, 3 vibration threshold values were learned. Therefore, the points would appear in three vertical lines. Only two lines are in the figure, because falls very close to the device lead to very large vibration readings and have to be cut off to show details in other cases.

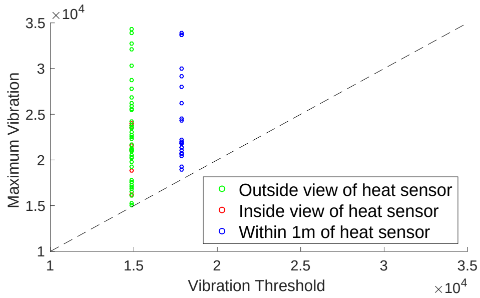


Figure 15: Vibration sensor reading and the threshold in the living room.

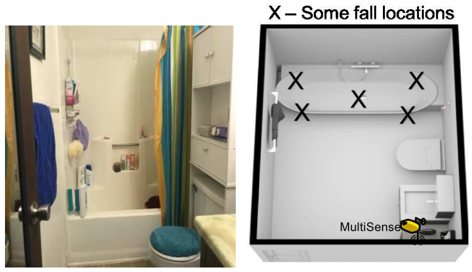


Figure 16: The bathroom in the test.

6.1.2 Bathroom Tests

A total of 50 experiments were conducted inside a bathroom shown in the left of Fig. 16, with similar calibration period at the beginning, and various kinds of falls at random times afterwards. Some of the fall locations are shown in the right of Fig. 16. As the bathroom is small, falls were simulated in the bathtub, noting that falls outside the bathtub are equivalent to falls near the device in the living room. In half of the cases, the shower curtain was open, and the other half closed, which simulate falls occurred when the person was trying to leave the bathtub, and falls inside the bathtub, respectively. Note that the heat sensor is outside the bathtub, and cannot detect the person when the shower curtain is closed.

Fig. 17 and Fig. 18 explains the main reasons why MultiSense was able to detected all falls correctly. Fig. 17 is a scatter plot, confirming that all fall events lead to detected motion-to-stationary transitions. Fig. 18 shows the Cumulative Density Function (CDF) plot of the vibration reading of the falls, in which the vertical line is the threshold. Note that only one threshold was used because the bathroom is small. It can be seen that the vibration threshold was exceeded in all cases.

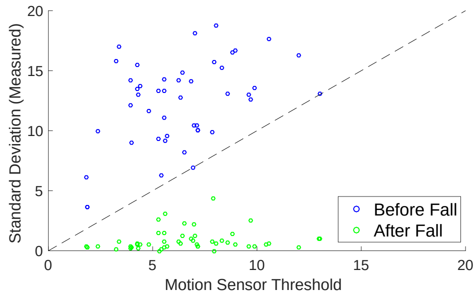


Figure 17: Motion-to-stationary transition detection in the bathroom.

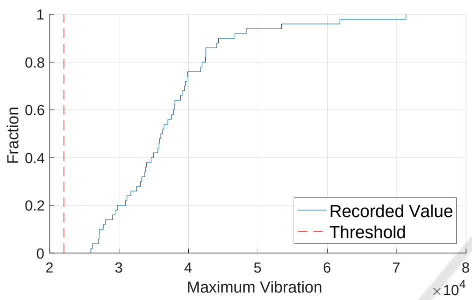


Figure 18: Vibration sensor reading and the threshold in the bathroom.

6.1.3 Heat Source Tests

MultiSense was also tested with heat sources placed close to the sensor. A total of 8 tests were conducted with a person simulating a fall next to the heat source, as well as behind the heat source. Additionally, a larger heat source was used in 2 tests, such that the heat source covered more than half of the sensor area. As mentioned in Section 4, this will cause MultiSense to ignore the heat sensor data, and rely only on the motion and the vibration sensors. Still, MultiSense detected the falls in all cases.

6.2 False Positive Stress Test

The activities listed in Section 5 also tested, and, as expected, MultiSense did not declare any falls, except for 80% and 20% cases for Far Freeze Jump and Far Freeze Hard Stomp, respectively. However, as explained earlier, these two activities are likely to be very rare for seniors.

6.3 Daily Use Test

MultiSense was also tested over a 24-hour period in a living room. During the test period, 7 human falls were simulated at random times, and MultiSense detected all falls correctly. In addition, usual day-to-day activities, such as leaving or entering the room, sitting down, standing up, walking around, etc., were conducted, and MultiSense did not report any falls for such activities.

7 COMPARISON

Table 1 is a comparison between MultiSense and some existing wearable-free fall detection systems, where the performance numbers are those reported in the papers and the costs are estimated based on the cost of sensors used in MultiSense. It can be seen that MuliSense has superior performance, and is not susceptible to privacy breaches or the imperfection of the training data, while keeping the cost modest.

Table 1: Comparison with other systems.

Name	FN	FP	Cost	Privacy issue	Rely on Training	Bathroom test
Multi-Sense	0%	0 per hour	\$150	No	No	Yes
(Wang) et al., 2017	2%	12%	\$80	No	Yes	No
(Skubic) et al., 2016	2%	1 per month	\$140	Yes	Yes	No
(Zigel et al., 2009)	3%	1.4%	\$60	No	Yes	No
(Li) et al., 2014	2%	0.4 per hour	\$140	No	No	No
(Debard et al., 2015)	24%	59%	\$200	Yes	Yes	No

8 CONCLUSIONS

We propose MultiSense, a novel fall detection system, which is wearable-free and reasonably inexpensive. MultiSense combines a motion sensor, a heat sensor and a vibration sensor to detect human falls. Multisense does not require extensive training data and is not invasive to privacy. Our evaluation showed that MultiSense was able to detect human falls accurately each time in the False Negative stress tests, and did not make any error in a daily use test. Errors were only found in two types of unusual activities in the False Positive stress tests, i.e., keeping still after jumping or hard stomping while staying out of the view of the heat sensor, which are unlikely to occur often in the daily life of seniors. Therefore, we believe MultiSense can be used to accurately detect human falls and can be extremely helpful to seniors living alone. Our future work includes more extensive tests of the system, as well as enhancing MultiSense with even more sensors.

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