Threshold-Based Fall Detection System Utilizing Passive Wi-Fi Radar Technology

Hidayatusherlina Razali
School of Engineering
Universiti Teknologi MARA
Shah Alam, Selangor
hida.sherlina@gmail.com

Nur Emileen Abd Rashid
Microwave Research Institute
Universiti Teknologi MARA
Shah Alam, Selangor
emileen98@uitm.edu.my

Afif Badiuzzaman Azman
School of Engineering
Universiti Teknologi MARA
Shah Alam, Selangor
afifazman7@gmail.com

Muhammad Nazrin Farhan Nasarudin
School of Engineering
Univerisiti Teknologi MARA
Shah Alam, Selangor
nazrin_farhan98@gmail.com

Zuhani Ismail Khan
Microwave Research Institute
Universiti Teknologi MARA
Shah Alam, Selangor
zuhani629@uitm.edu.my

Siti Amalina Che Ab Rahim
Microwave Research Institute
Universiti Teknologi MARA
Shah Alam, Selangor
amalinaabr@uitm.edu.my

Abstract—**This research introduces a Wi-Fi passive radar approach to address key challenges in current fall detection systems, including privacy concerns associated with camera-based systems, and the inconvenience of wearable sensors. By leveraging existing Wi-Fi signals, this research offers a non-intrusive and low-cost solution for continuous fall monitoring in home environments. The primary objective is to enhance safety for individuals at risk of falling by developing a sensor capable of accurately differentiating between fall and non-fall incidents. The methodology involves analyzing a dataset of 10 radar signals, equally distributed between falls and non-falls by using effective thresholding techniques. The system examines features such as voltage drop and signal envelope characteristics to identify fall incidents. The threshold-based classification method demonstrates remarkable accuracy, successfully distinguishing between falls and non-falls with 100% precision in our experimental dataset. This research contributes to the development of non-intrusive, reliable fall detection systems, potentially improving the safety and independence of elderly individuals living alone.**

Keywords—passive radar, fall detection, threshold, Wi-Fi

I. Introduction

The global population is ageing steadily, resulting in a significant increase in the number of older adults living independently. However, falls pose a serious threat to their life and health, often leading to significant injuries or unconsciousness, which can delay their ability to seek help promptly. Additionally, falling frequently results in a marked decline in their ability to perform everyday tasks independently, causing them to feel incapable of ageing naturally and leading to a condition of "unstable incapacity" [1]. Despite these risks, many older individuals prefer to remain at home alone, underscoring the importance of conducting research and implementing reliable fall detection systems in their residences. To promote the independence of the elderly, it is imperative to establish and implement effective fall detection systems within their homes [2].

Fall detection systems can utilize various types of sensors, including wearable sensors, cameras, and radar systems. Wearable sensors, such as accelerometers and gyroscopes, track movement and identify falls. However, they have limitations, including the need to be worn and limited battery life. These factors can make wearable sensors impractical for long-term use, as not wearing them can hinder the system's effectiveness, and battery life issues can impact their reliability for continuous monitoring. Cameras also serve as sensors for fall detection, capturing visual data to assess motion patterns and identify irregularities that suggest a fall. However, video sensors may face challenges such as insufficient lighting or obstacles that can reduce their effectiveness, and there are potential privacy risks in everyday in-home scenarios.

On the other hand, radar systems have become popular for indoor fall monitoring due to their insensitivity to lighting conditions and limited privacy concerns. The use of radar technology for fall detection offers exceptional accuracy, durability, and privacy protection, making it a valuable enhancement to current technologies. Despite these advantages, radar or radio frequency (RF) based sensors often raise concerns about radiation from transmitting specific power frequencies. To address this, the study implements a passive transmitter using a Wi-Fi signal, which is commonly available in most homes and does not have adverse health effects.

The suggested method utilizes Wi-Fi-based radar technology to identify and characterize human movements by evaluating Doppler signatures and fluctuations in radar cross-section (RCS). This system employs a continuous wave radar transmitter and receiver, where the transmitted signal bounces off a moving target, resulting in a Doppler frequency shift proportional to the target's radial velocity. Once the receiver captures these Doppler-shifted signals, they undergo signal conditioning procedures, such as filtering, to isolate the Doppler frequency component. This Doppler information is then analyzed to calculate the target's movement.

Additionally, the method leverages changes in the received signal's amplitude, which are influenced by the target's RCS due to the shifting angle and movement of the subject's body. By capturing and analyzing these RCS fluctuations alongside Doppler information, the system enhances the understanding of various types of movements, including gait analysis and activity monitoring. The integration of Doppler analysis and RCS characterization aims to improve motion detection and recognition capabilities for applications such as fall detection, gait analysis, and activity tracking.

One significant challenge in fall detection is effectively distinguishing between falls and regular movements that may have similar characteristics. To address this, the study conducts experiments and develops an algorithm specifically targeting the identification of unique patterns associated with falls using radar. Threshold-based techniques are beneficial for detecting movement with radar systems due to their simplicity, efficiency, and real-time responsiveness. These methods are easier to implement compared to complex AI or deep learning algorithms, making them ideal for quick and accurate identification of fall events, which is crucial for fall detection.

Moreover, threshold-based methods enable prompt responses to unusual movements, making them well-suited for applications that demand real-time responses. The motivation for this study stems from the need to enhance the safety and well-being of individuals, particularly the elderly, through advanced fall detection technologies. Radar-based systems offer a non-intrusive and practical solution, accurately detecting falls while preserving user privacy.

II. Methodology

This study aims to develop an effective fall detection system utilizing radar data. Falls can have significant consequences, especially for the elderly. This approach encompasses the necessary processes to analyze radar data and identify specific fall-related patterns. Figure 1 illustrates the research framework for signal processing.

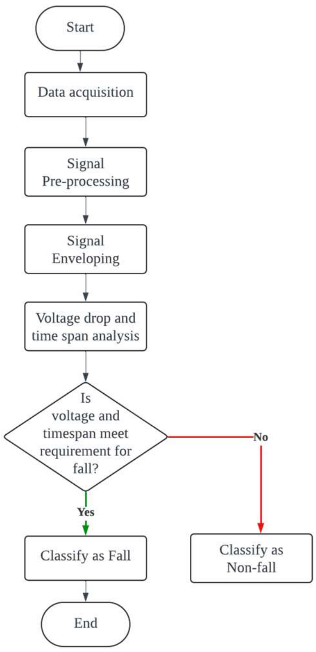


Figure 1: Fall detection process.

A. Data Acquisition

This research uses primary data that includes radar information from everyday human activities like walking normally (non-fall action) and falling while walking (fall action). An in-home Wi-Fi model ASUS RT-N12 Wireless N Router was utilised as the transmitter in the research activity. This router is equipped with two detachable 5 dBi high gain antennas and operates at a frequency of 2.4 GHz. Meanwhile, the receiver setup included an omnidirectional antenna, a low-noise amplifier (LNA), a diode detector, and a low-pass filter (LPF). The data collected from the receiver undergoes data acquisition, where it is connected to a laptop for saving the acquired information into a digital format. Subsequently, the data is extracted for further analysis in MATLAB.

A transmitter and receiver are positioned perpendicular to each other, creating a 4.5-meter baseline, with both devices placed 1.2 meters above the ground. The participant begins at point O, marked by a red dot. The intersection of the baseline is denoted as O'. During the experiment, the participant moves from point O, crosses the baseline at a 90-degree angle, and ends movement at point O", which is situated 4.5 meters away from the starting point O. For initial target signature detection, a 90-degree crossing of the baseline is chosen. This perpendicular trajectory produces a symmetrical and ideal target signature, offering advantages over alternative crossing angles. The dataset consists of ten signals in total, comprising five falls and five non-falls, allowing for a comprehensive analysis of different scenarios involving human movements.

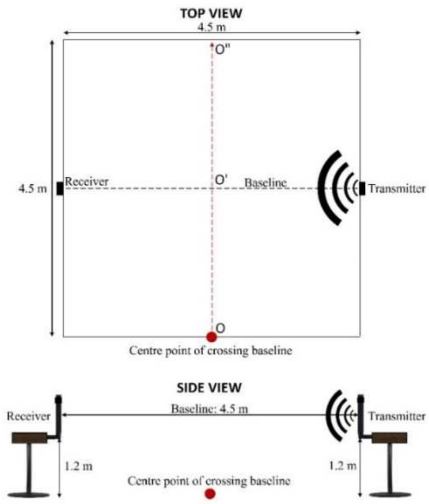
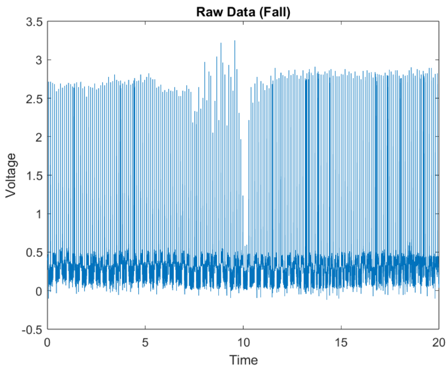


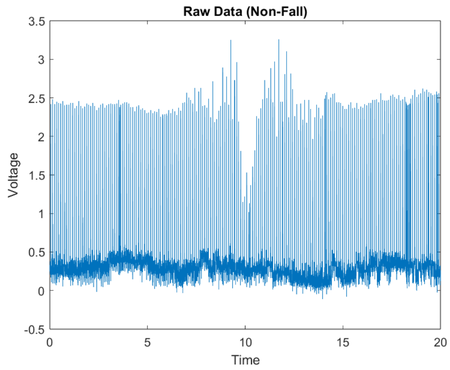
Figure 2: Experimental layout

B. Data Processing

In the initial stages of data processing, a crucial step is to define the sampling frequency and generate a time vector to create a well-organized framework for the analysis. The raw data as depicted in Figure 3 is normalized and smoothed using a Savitzky-Golay filter to enhance its quality. Additionally, the sample demonstrates a reduction in the noise signal after implementing adaptive thresholding, which relies on a moving average as shown in Figure 4. The conversion of signal pulses into sinusoidal waves is achieved through the use of the find peaks function. This function detects peaks in the data by finding local maxima, which are important for further analysis. The find peaks function works by scanning the data and identifying points where the signal amplitude surpasses a set threshold, indicating the presence of a peak. This method allows for accurate conversion of signal pulses into sinusoidal waves.

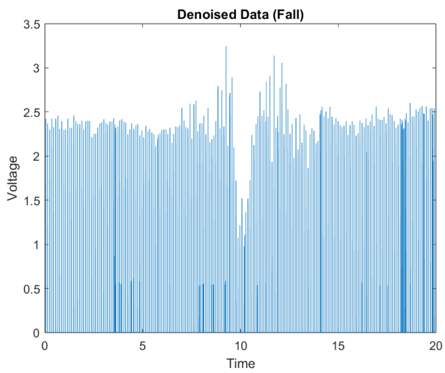


(a)

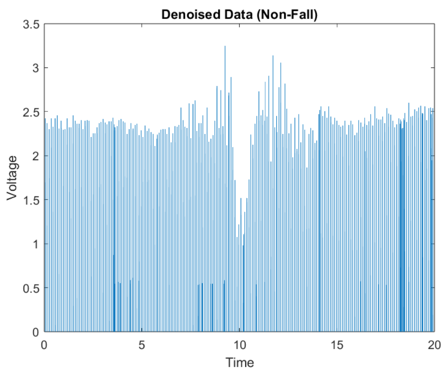


(b)

Figure 3: Sample of raw signal a) fall and b) non-fall movement.



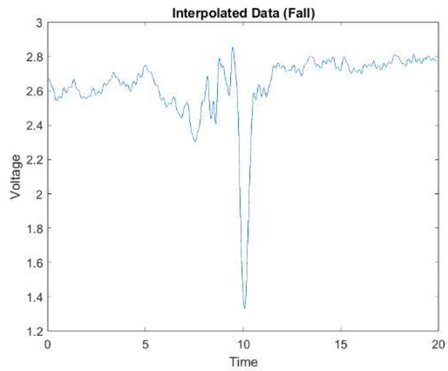
(a)



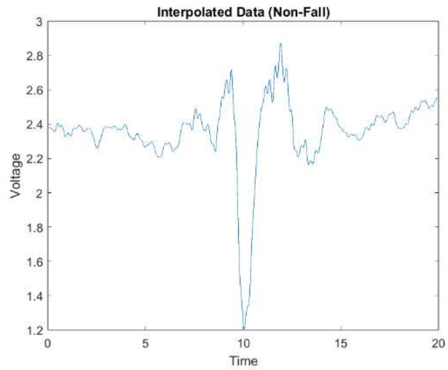
(b)

Figure 4: Denoise signal (a) fall and (b) non-fall movement.

In Figure 5, the signal is transformed smoothly using cubic spline interpolation. This method uses cubic polynomials to create a smooth curve that connects the data points. The intention is to ensure that the curve passes through the original data points while presenting a more continuous signal representation. This refined curve is then utilized for additional analysis, such as identifying peaks and generating envelopes. The cubic spline interpolation technique is very efficient in maintaining the original shape of the signal, minimizing noise, and improving the precision of peak identification.



(a)



(b)

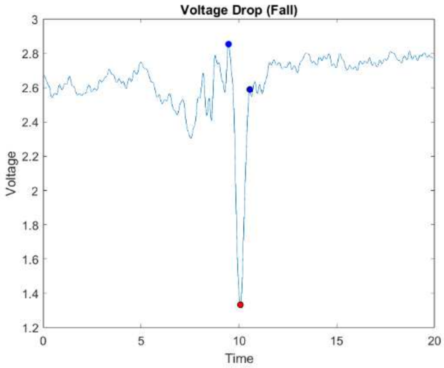
Figure 5: Interpolated signal a) fall and b) non-fall movement.

C. *Voltage Drop Analysis*

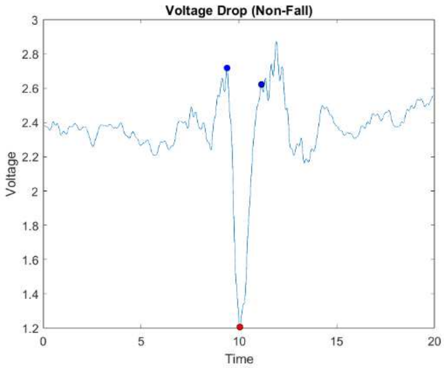
After observing the differences between the peaks along the time series, the envelope signal is analysed to identify key points such as the minimum peak, peaks before and after it, and subsequently, the voltage drop (V) as depicted in Figure 6. The voltage drop can be calculated using:

$$\Delta V = V_{peak} - V_{min}$$

where V_{peak} is the peak voltage before the voltage drop and V_{min} is the minimum voltage after the drop. The use of voltage drop in this experiment serves as a crucial metric for assessing the magnitude of change in signal intensity, providing insights into variations within the data. By quantifying the voltage drop, this study can gain a deeper understanding of the transitions occurring within the signal. Additionally, analysing the time duration of these events is essential for determining the temporal aspects of signal fluctuations. Analyzing voltage drops and patterns over time provides a thorough understanding of signal behaviour, making it easier to accurately categorize and detect falls within the system.



(a)



(b)

Figure 6: Positive and negative peaks a) fall and b) non-fall movement.

D. *Thresholds for detection*

The fall detection system works by establishing certain thresholds for voltage drop and time values to distinguish between falls and non-fall scenarios. These thresholds are set through an analysis of radar signals to ensure accurate detection. The distance (d) can be calculated using:

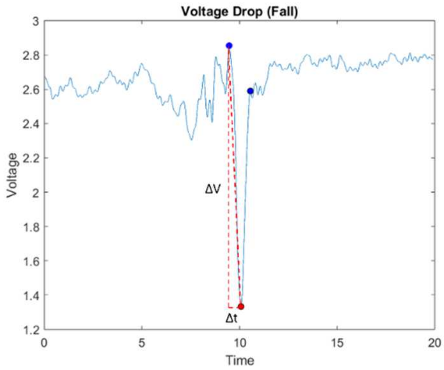
$$d = \sqrt{(d_x)^2 + (d_y)^2}$$

Where d_x and d_y are distance along the x and y axes, respectively. With the use of thresholds, the system can accurately classify each incident as a fall or non-fall by comparing the measured values of voltage drop and time with the predefined criteria. The benefits of utilizing thresholds include providing clear guidelines for classification and allowing the algorithm to make precise differentiations between fall and non-fall occurrences.

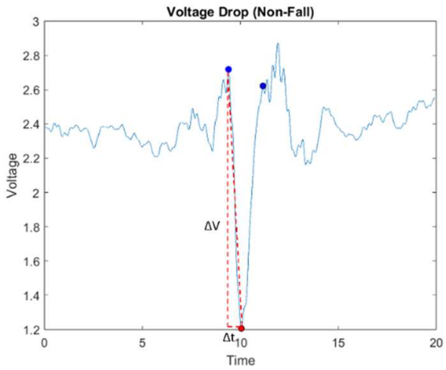
This technique improves the effectiveness of the fall detection system by producing reliable and consistent outcomes, particularly when utilized in the real world. The flexibility of threshold-based techniques allows customization according to the characteristics of radar data. Besides, it also efficiently reduces false positives and negatives. This flexibility guarantees that the system can be fine-tuned to achieve the necessary sensitivity for effective fall detection.

III. Result and Discussion

This section will explain on signal's behaviour by analyzing the voltage drop and time information and help to identify important points such as the lowest peak, and peaks preceding and following it to differentiate the fall and non-fall event.



(a)



(b)

Figure 7: Threshold selection for a) fall and b) non-fall movement.

The graphs illustrate how a radar system captures voltage drop patterns to distinguish between fall and non-fall human movements. Figure 7a highlights a significant voltage spike shown as a tall red line. This sharp increase in voltage is likely attributed to the sudden motion and drastic movement change in radar cross-section during a fall event. The spike reaches a maximum voltage labelled as "ΔV," indicating the maximum voltage difference from the surrounding signal levels. The voltage signal exhibits small, irregular changes both before and after the fall, which reveal the subject's initial motions and their last resting posture. In contrast, the non-fall movement depicted in Figure 7b does not display a clear and significant voltage spike. A broader voltage spike labelled "ΔV" is present due to the subject engaging in more relaxed activities like walking. The signal is generally lower in amplitude and wider in time taken compared to the abrupt spike observed in fall action. By using the variation in voltage spike characteristics, and the length of time during the cross-section event, the system may be able to distinguish between instances of fall and non-fall event.

The confusion matrix depicted in Figure 8 presents compelling evidence of the effectiveness of passive Wi-Fi radar systems in distinguishing between fall and non-fall events. The matrix shows accurate classification accuracy across all 10 test cases, comprising 5 fall events and 5 non-fall (walking) events. Specifically, the system correctly identified all 5 fall incidents (100% true positive rate) and accurately classified all 5 walking scenarios as non-falls (100% true negative rate). This result indicates a sensitivity and specificity of 100%, with no false positives or false negatives observed. Such performance underscores the robustness of our threshold-based approach in analyzing voltage drops and temporal characteristics of the radar signals.

While these results are highly promising, it is important to note that the study conducted is based on a controlled experiment with a limited dataset. Further testing with a larger and more diverse set of scenarios would be beneficial to confirm the system's reliability in real-world applications. Nonetheless, these initial findings strongly support the potential of a passive Wi-Fi radar system as an accurate and non-intrusive solution for fall detection, particularly for enhancing the safety of at-risk individuals in home environments.

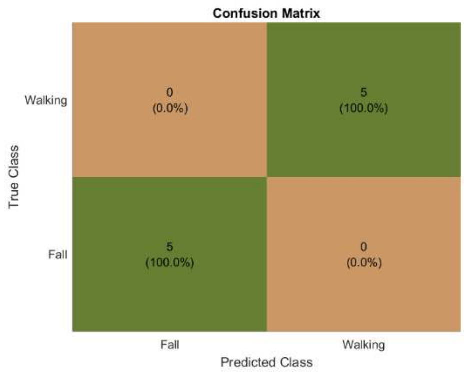


Figure 8: Confusion matrix illustrating the accuracy of fall and non-fall expressed as the number of elements and percentage

IV. CONCLUSION

This study proposes a passive radar system to address the problems with existing fall detection systems. The primary objective is to better protect individuals at risk of falls in healthcare and assisted living facilities by utilising effective thresholding techniques. The findings show accurate calculations of voltage drop and time for both fall and non-fall situations, which are then used in a threshold-driven decision-making process. The system demonstrates its effectiveness in human daily activities such as walking and falling, indicating its potential benefits in healthcare and supported living environments. Future studies could explore incorporating machine learning techniques to enable the system to adapt to individual behaviours and environmental factors dynamically.

V. ACKNOWLEDGMENT

The authors gratefully acknowledge the support of the Microwave Research Institute (MRI) and Universiti Teknologi MARA (UiTM).

REFERENCES

[1] S. A. Shah, A. Tahir, J. Le Kernec, A. Zoha, and F. Fioranelli, “Data portability for activities of daily living and fall detection in different environments using radar micro-doppler,” *Neural Comput. Appl.*, vol. 34, no. 10, pp. 7933–7953, 2022, doi: 10.1007/s00521-022-06886-2.

[2] B. Wang and Y. Guo, “Soft Fall Detection Using Frequency Modulated Continuous Wave Radar And Regional Power Burst Curve,” *Asia-Pacific Microw. Conf. Proceedings, APMC*, vol. 2022-Novem, pp. 240–242, 2022, doi: 10.23919/apmc55665.2022.9999763.

[3] X. Wang, J. Ellul, and G. Azzopardi, “Elderly Fall Detection Systems: A Literature Survey,” *Front. Robot. AI*, vol. 7, no. June, 2020, doi: 10.3389/frobt.2020.00071.

[4] M. Rantz *et al.*, “Automated in-home fall risk assessment and detection sensor system for elders,” *Gerontologist*, vol. 55, pp. S78–S87, 2015, doi: 10.1093/geront/gnv044.

[5] B. Jokanovic, M. Amin, and F. Ahmad, “Radar fall motion detection using deep learning,” *2016 IEEE Radar Conf. RadarConf 2016*, pp. 1–6, 2016, doi: 10.1109/RADAR.2016.7485147.

[6] K. Singh, A. Rajput, and S. Sharma, “Human fall detection using machine learning methods: A survey,” *Int. J. Math. Eng. Manag. Sci.*, vol. 5, no. 1, pp. 161–180, 2020, doi: 10.33889/IJMEMS.2020.5.1.014.

[7] G. Mei, Z. Cao, G. Wang, and X. Guo, *Radar-based 3d skeleton estimation enhanced with joint temporal-spatial constraints*, vol. 1090 LNEE, no. January 2024. Springer Nature Singapore, 2023. doi: 10.1007/978-981-99-6882-4_32.

[8] S. Hu, S. Cao, N. Toosizadeh, J. Barton, M. G. Hector, and M. J. Fain, “A Survey on Radar-Based Fall Detection,” pp. 1–14, 2023, doi: 10.1109/MRA.2024.3352851.

[9] Onur Tekir, B. Yılmaz, and C. Özdemir, “Signal preprocessing routines for the detection and classification of human micro-Doppler radar signatures,” *Microw. Opt. Technol. Lett.*, vol. 65, no. 8, pp. 2132–2149, doi: https://doi.org/10.1002/mop.33684.

[10] D. Bok, D. O’hagan, and P. Knott, “Effects of movement for high time-bandwidths in batched pulse compression range- doppler radar,” *Sensors*, vol. 21, no. 7, pp. 1–27, 2021, doi: 10.3390/s21072492.

[11] X. Yu, X. Chen, Y. Huang, L. Zhang, J. Guan, and Y. He, “Radar Moving Target Detection in Clutter Background via Adaptive Dual-Threshold Sparse Fourier Transform,” *IEEE Access*, vol. 7, pp. 58200–58211, 2019, doi: 10.1109/ACCESS.2019.2914232.