 https://doi.org/10.24191/jeesr.v24i1.001

A Review: Radar-Based Fall Detection Sensor

Hidayatusherlina Razali, Nur Emileen Abd. Rashid*, Muhammad Nazrin Farhan Nasarudin, Nor Najwa Ismail, Zuhani Ismail Khan, and Siti Amalina Enche Ab Rahim

***Abstract*— Age-related physical changes make 60-year-olds more susceptible to injury and mortality. Fall detection sensors come in many varieties. However, the radar system is the most reliable detection method since it avoids the downsides of other sensors, such as discomfort, heavy computational processing, and privacy problems. Radar-based sensors can accurately capture Doppler frequency variations from human motion by utilising time-frequency representations and classification algorithms. Fall recognition involves steps: sensor type, data pre-processing, and data classification. This study examines radar's use in fall detection and how fall detection systems can enhance people's lives.**

***Index Terms*—Detection, Elderly, Fall, Radar, Sensor, Signal processing**

I. INTRODUCTION

The World Health Organisation (WHO) defines the elderly as 60 or older [1].In Malaysia, 6% of the population is over 60 years old [2], and by 2035, that number is projected to increase to 15%. According to a study done in the US, one in three seniors (aged 65 and over) experience at least one annual fall. The causes of the old person's fall can be divided into intrinsic and extrinsic. Balance and eyesight issues are intrinsic concerns, whereas extrinsic variables can be brought on by inadequate lighting, an uneven floor, or a stairway without a handrail [3]. Falls among the elderly can be severe, particularly regarding health issues, including injuries, fractures, and fatalities [3],[4]. Fall detection and monitoring systems are therefore essential for assisting the living community, especially in lowering injuries among the elderly.

Due to technological advances, various types of detectors have been devised to meet the demands of the elderly. The use of sensors can assist in detecting human actions, such as walking, leaping, sitting, and bending. The information gathered by sensors will come in various forms depending on the type of sensor used. Sensors can collect more data; therefore, in-depth examinations of that data may be possible. Currently, there are two types of detection systems which are wearable and non-wearable. A wearable sensor or contact sensor is a detecting device that is permanently attached and worn by the patient, for example, push buttons, gyroscopes, accelerometers, and proximity sensors[5]–[7]. Meanwhile, a non-wearable sensor, also known as an external sensor, is a non-attachable device that allows the subject to move freely while still being detected. An ambient sensor such as a pressure or Pyroelectric IR sensor uses the surrounding factor to measure. On top of that, the latest trend shows attraction to the visual detection system. A camera-based sensor is frequently utilized as a non-wearable sensor to collect human movements or its surroundings' thermal readings [8], [9]. Nevertheless, the camera-based sensor is generally associated with privacy concerns in subject's life.

Radar is another type of non-wearable sensor that has generated considerable interest in human motion detection. Radar uses an electromagnetic system to sense, detect, and locate an item [10] by sending electromagnetic (EM) waves to a target and measuring the distance between them. The radar consists of two major physically separated components: a transmitter and a receiver. In the current development of radar technology, Wi-Fi and Long-Term Evolution (LTE) signals have been used as passive transmitter sources replacing active radar [11], [12]. Fall motion can be detected using passive radar due to the Doppler effect. Doppler effect is displayed as a distinct signature caused by frequency shift. Human fall motion can be differentiated from non-fall motion using appropriate signal processing.

This paper will review fall detection sensors for indoor applications. The next section will cover falls among the elderly followed by a look at sensor development. Section 4 will provide an overview of radar technology before delving into signal processing methods.

II. FALL AMONG ELDERLY

Falls may occur by accident; particularly for the elderly, a fall can have grave health consequences. A fall can result in severe or minor injuries of the most common causes of disability and death among the elderly.

A. *Factors of Fall Among Elderly*

A fall is described as a person's body coming to a sudden and unexpected rest on the ground, except for people resting or

This manuscript is submitted on 7 May 2023, revised on 26 January 2024, accepted on 19 February 2024 and published on 30 April 2024.
Hidayatusherlina Razali, Nur Emileen Abd. Rashid, Muhammad Nazrin Farhan Nasarudin, Zuhani Ismail Khan and Siti Amalina Enche Ab Rahim are from the School of Engineering, College of Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia and Nor Najwa Ismail is from NR Electrical & Electronic Enterprise, 43500 Semenyih, Selangor, Malaysia.

*Corresponding author

Email address: emileen98@uitm.edu.my

changing position on a wall or piece of furniture [1]. Anyone is at risk for a fall, but older people are more at risk than younger people due to age-related health issues. According to the Behavioural Risk Factor Surveillance System (BRFSS), 10.2% of older individuals reported suffering a fall-related injury in the previous year. In comparison, 27.5% of older persons reported falling at least once [13]. Falls account for over half of all elderly injuries and affect the victim's confidence [14]. Falls and repeated falls also result in catastrophic injury[15]. Therefore, falls significantly reduce the quality of life for the elderly.

Injuries due to falls can be classified into two types, which are intrinsic and extrinsic [14]. The human itself can cause intrinsic injuries. From the physical factor, the obese elderly were more likely to fall than other body mass index (BMI) due to poor stability and health problems [15]. The most common factors are poor gait and balance, muscle weakness (Parkinson's or stroke), knee joint disorder, and cognitive problems due to cataracts [16]. In clinical factors, the factor of falls is due to polypharmacy, which is the use of four or more types of medication, such as anti-diabetes, anti-hypertension, cardiogenic, or anti-depression medication that causes tiredness, sleepiness, or decreased alertness which led to falls [17]. In addition, the elderly who smoke or consume alcohol also tend to experience falls due to poorer health. The external or environmental factors contributing to falls are extrinsic factors, such as walking on a slippery floor or in unfamiliar places. Extrinsic falls are also linked to impaired vision, bed height, inadequate lighting, disorganized furnishings, and a lack of handrails on stairwells.

B. Consequences and Complications of Fall

Falls lead to health complications, affecting the elderly's quality of life. Research in Japan shows that 37.7% of older people experienced soft tissue bruises, and another 5% experienced hip fractures [3]. Following the findings of another study, 21.8% of people will have physiological repercussions that would either lead to death or mobility [4]. The same research found that seniors who fell experienced injuries such as lacerations, dislocations, sprains, hematomas, and pains because of their accidents. A finding in Singapore [14] stated that admission to the emergency department for the elderly due to falls is at 85%.

Consequently, elderly falls may lead to serious health problems such as bone fractures at the wrist, ankle, arm, or hip fractures. A study stated that the elderly who fall 3 times or more are more likely to talk to healthcare about falls compared to the elderly who have fallen fewer times [18]. From fall, or a series of falls, may cause a severe head injury, reduce mobility, long-term care admission and even death.

Even though a small fraction of older people fall and are uninjured, there will always be a suspicion of falling. A person's daily activities may be impacted by their dread, which may weaken over time. According to a study by [19], most of the senior people who participated in the study experienced chronic symptoms after experiencing a fall. The elderly are more likely to have limits in everyday activities (0.5%) and fear of falling (24.49%) as a direct effect of having fallen previously. The elderly with dementia are the most important to monitor because they are more likely to forget about a fall incident. In healthcare, it would be beneficial to inquire about previous falls suffered by the elderly [7], [20].

III. DEVELOPMENT OF SENSORS

According to [15], 75.8% elderly experienced falls in the indoor area, especially in the bathroom, house compound, and kitchen. Hence, it clearly shows that a detection sensor is needed to detect abnormalities in daily living and alert the caretaker. This section will describe the development of wearable and non-wearable sensors to detect and identify human movement.

A. Wearable Sensors

Wearable sensors are prevalent today due to their tiny size and compactness. Many sensors allow for further analysis for the detection of fall motion. Besides, it is also known as a low cost and has a moderate installation by wearing the sensor on the subject's body and ensuring it takes place well. Hence, it can be said it is an attractive sensor and suitable for a low-cost choice for a project [6], [20].

Human gait is measured using a wearable sensor. Traditional wearable sensors track body movement with accelerometers and gyroscopes. The study [20] employed an accelerometer and Arduino to interpret and display data on a computer. Similar research [21], [22] described an elderly fall detection and monitoring alarm system using a three-axis accelerometer. The accelerometer and gyroscope sensors read acceleration and angular velocity data to measure body impact acceleration and inertial changes. The detection of linear acceleration along three perpendicular axes and gravitational force units is notified as fall.

An accelerometer and gyroscope can be integrated into an inertial measurement unit (IMU) [23]. It is linked to the subject's waist. The IMU has an accelerometer, gyroscope, Bluetooth, lithium polymer battery, and microcontroller. Bluetooth modules and receivers connect the device to the main workstation. Peak acceleration and angular velocity data help distinguish between Actual falls and almost falls. A modified DAG-CNN model classified IMU data with 99% accuracy after pre-processing and feature extraction. Another integrated module is interpreted in [5] by combining MPU6050 with three accelerometers and three gyroscopes as a belt and attaching it to the subject's waist. Daily activities include walking, running, jogging, bending, and squatting, as well as front, side, and back fall data were taken. This study found that a gyroscope responds faster than a three-axis accelerometer. Unlike a gyroscope, an accelerometer has a delayed response time that aids long-term motion even though it is noise-free. Hence, a complimentary filter is used to compensate for each other's shortcomings.

Besides accelerometer and gyroscope, paper [24] implements ambient-type sensors that appear non-invasive towards daily fall detection activities using passive radio-frequency identification (RFID) sensor tags. It works by measuring the received signal strength and pressure values. A passive RFID tag comprises an embedded RF chip and battery-free device antenna. Data from RFID is then gathered through IoT Gateway Hub, which provides communications in a Microsoft Azure (cloud server). Stream Analytics performs the classification to train the model and data accumulation. The classification is carried out in this study by making use of real-time input data; as a result, a fall notification will be sent to the carer if any fall event occurs. It was determined that the classification accuracy reached at least 90%.

Current wearable technology includes a cloud-based caretaker alert system. The wearable sensor identifies fall events when amplitude varies quickly [25]–[28]. The cloud stores all subject movement data and will immediately notify the caretaker if a fall happens. The prompt can be done with any fall application or the internet cloud. Consequently, the caregiver can act immediately. Despite these benefits, studies have shown that placing an accelerometer on the subject's hip or lower back yields the best results [21]. However, sensor placement in the same position for a long time may cause discomfort. Although a multitude of sensors can gather vast amounts of data from different parts of the body but it may make it difficult to limit the subject's movement. Moreover, practical considerations include the increased likelihood of forgetting to wear and charge the sensor and the requirement for frequent charging.

B. Non-Wearable Sensors

In contrast with wearable, non-wearable sensing devices do not require the subject to attach any sensors to their body. Due to the advances in computer vision, fall detection based on vision is the most common detection sensor nowadays. Research by [29] implemented vision detection using a Microsoft Kinect sensor with a 94.64% accuracy. Most methods utilizing camera-based sensors have a similar detection process, beginning with depth image acquisition. Next, progresses through background subtraction and ground segmentation to extract features of human motion and body shape, and finally acts as input to feature extraction and classification [29], [30]. The vision-based sensor is easily installed and can give various inputs such as location, actions, and motion.

Another camera-based sensor combined with a microprocessor call “Fallert” was developed to detect falls [8]. The 2D camera module Raspberry Pi 2 collects all data and proceeds with image acquisition. The camera module is connected using the Raspberry Pi's camera serial interface, and it consumes far fewer central processing unit (CPU) systems than a standard universal serial bus (USB) camera. After image acquisition, the process proceeded with background subtractor, filter, and classification. If any fall is detected during classification, an alarm will be sent to notify the caretaker. In the same research, a classification Kalman Filter to reduce noise and absorb repetitive changes caused by humans in their daily lives. According to the research, the system works 96% efficiently in a controlled setting.

Additionally, wearable and camera-based sensors have been put together in [31]. Researchers in the United States have merged the usage of an accelerometer, heart rate sensor, and camera into a single gadget called "Good Eye." The gadget can detect and forecast falls caused by accidents. According to the study, a fall is identified when the accelerometer changes are at ±3 g in the Y-axis, a fast change in heart rate is observed, often at ±10 bpm, and camera changes in 45% of pixels. Six participants obtained 144 different sitting and falling samples and 95% accuracy.

The camera-based sensor can recognize multiple people at once. As subjects don't have to wear equipment, it reduces the wearable's downsides. Data on location, time, and motion can also be recorded. Despite its efficiency, it has significant downsides. The subject's privacy may be compromised because it may lead to personal data leakage. The camera range was also obscured, hence, several expensive cameras are needed to cover the subject's field of vision. In addition, a high-resolution picture camera improves fall detection accuracy. More downsides appear when the camera's distance from the subject increases because the depth of the image's clarity will drop. Hence, decreased resolution makes background removal and depth picture segmentation harder.

Another non-wearable sensor named radar also can be used as a fall detection sensor. The radar-based sensor was introduced to solve the shortcomings of the sensors mentioned before. The radar system offers benefits over other detection technologies since it eliminates problems from other sensors, such as discomfort, privacy concerns, simple theft, forgetting to wear and charge, and restricted coverage areas. It employs electromagnetic waves to determine an object's distance and precise location by transmitting the electromagnetic waves to the target and capturing the reflected waves formed by the target. When a signal is reflected or impeded, it generates a distinct set of characteristics known as a Doppler signature. The difference in the characteristics of the returning signal reveals the target's features of interest. The amount, direction, and velocity of human motion are all encoded in the human Doppler signature.

There have been a lot of successful investigations into identifying humans using the Doppler method as in [32]. The Doppler signature recorded for walking had dominant positive and negative Doppler shift signatures because it employs entire body movement, whereas bending caught a frequency centre at 0 Hz since it does not need a significant movement of the human body component. Another study [33] shows that a Doppler can help detect human's daily activities by detecting six different Doppler signatures with an operating frequency range of 2.4 – 4.5 GHz. Hence, it shows that the signature of Doppler between the activities differs and can be detected and classified according to their daily activities. It is also helpful since it is not only able to identify the subject's location but also able to measure its speed. Radar's ability to cover a wider area allows it to detect and transmit information on several objects simultaneously.

IV. Radar Technology

Among all indoor fall detection sensors, the radar-based method is considered one of the optimum solutions. As stated in the previous chapter, it can overcome drawbacks from other sensors. The design of radar is crucial in achieving objectives. This section will discuss a few parameters for radar design, including radar system configurations, types of radar, and more discussion on the radar as a fall detection sensor.

A. Radar Configuration

There are two modes of operation for radar: transmission and reception. Radar is categorized into three topologies which are monostatic, bistatic, and multistatic. The transmitter and the receiver are in the same antenna or monostatic radar, while separated antennas are called bistatic radars [34], [35]. Monostatic radar is 0° bistatic angle, as Fig. 1 depicts. Monostatic radar minimizes the cost because it implements the same antenna for transmission and reception; however, the duplexer in a radar system isolates the two signals. Paper [36] described the implementation of monostatic radar to recognize human movement using an IR-UWB sensor. The radar system calculates the distance to an object based on the time difference between when it was transmitted and received. The data is then pre-processed, and CNN classification is implanted with a final accuracy of 96.65%.

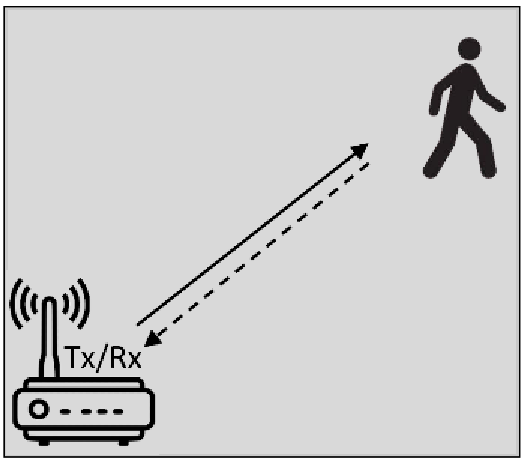

Fig. 1. Monostatic radar.

The primary factor differentiating monostatic and bistatic radars is the distance or separation of the transmitter and receiver. The separation between the transmitter and the receiver should be considered to classify a system as a bistatic radar system. Generally, the separation of the two antennas, transmitter and receiver, is called a direct path. The distance range of the transmitter to the subject is denoted as R_Tx, while the distance range from the subject to the receiver is denoted as R_Rx. The angle between the transmitter and receiver is called the bistatic angle, β, as shown in Fig. 2.

Referring to Fig. 3, the multistatic radar topology combines monostatic and bistatic, depending on the type of radar employed. Due to its ability to take in data from various sources and analyze it in various ways, this type of radar excels in detection and resolution. A study by [37] used a transmitter with three receivers in the same environment. The transmitter emits a linear frequency modulation (LFM) wave at the ultra-high frequency (UHF) band. In order to detect targets and estimate measurements, a range Doppler picture is utilized while three subjects are in motion. By correlating distance and speed, multi-target localization can be detected. However, multi-static radar faces a problem of time delay estimation (TDE) between two received signals originating from the same transmitter [38]. This estimation problem is crucial in radar signal processing for locating targets and determining the identity of radar transmitters.

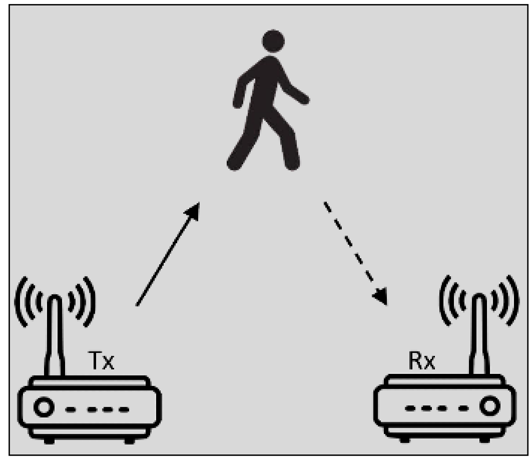

Fig. 2. Bistatic radar.

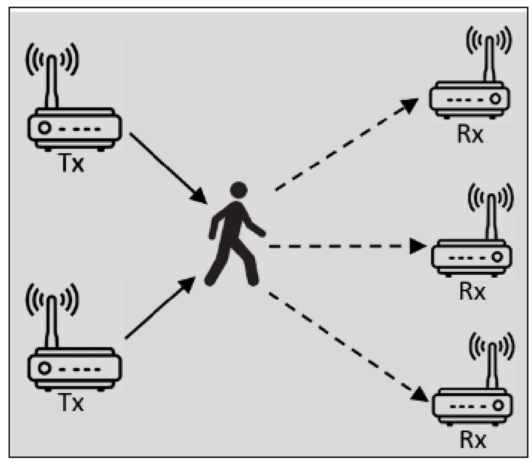

Fig. 3. Multistatic radar.

Meanwhile, an example of bistatic radar is implemented in [32], which uses an FMCW off-shelf as a transmitter and is coupled with a Yagi antenna that operates at 5.8GHz. Four movements were taken into account and each activity was recorded multiple times for each recording. The micro-Doppler signatures were extracted from the data by applying the Short Time Fourier Transform (STFT) to generate spectrograms. The micro-Doppler signature's centre of gravity can be roughly estimated using the Doppler centroid, and the energy extent of the signature can be determined using the Doppler bandwidth.

A particular type of bistatic radar is forward scattering radar (FSR). The main difference is the transmitter and receiver are facing each other and create a direct path called a baseline. Since an angle separates bistatic radar, a forward scattering radar is stretched along the baseline, which is close to 180°. The existence of a subject at the baseline in forward scattering will partially block the signal wavefront from the transmitter. The subject's shadow is formed as a result of the blocking. The shadow represents an electromagnetic field being scattered by the object [39].

An example of bistatic radar is implemented in [40], which uses a signal generator as a transmitter and is coupled with a horn antenna that operates at 2.5-7.5GHz. The receiver comprises a low noise amplifier, non-linear detector, low pass filter, and analogue-digital converter. The transmitter and receiver's distance or baseline is separated by 4m and a bistatic angle of 130.8º. In order to acquire Doppler signatures, the study combines simulated fall motions, such as free fall and falling while seated on a chair. The amplitude changes in the result are correlated with particular motions, such as when the subject's body crosses twice while sitting in a chair. The study employs a classification method with Support Vector Machine (SVM) and attains a preliminary result accuracy of 100%. This study highlights the appropriateness of using a bistatic Frequency-Shift Radar (FSR) topology for accurate fall detection. The next sections will explore other radar types to provide a thorough explanation.

B. Types of Radar

Radar can be categorized as active and passive radar. A radar system that transmits its signal is called an active radar system. In contrast, a passive radar system does not transmit its signal and instead focuses solely on detecting reflections of incoming waves. Active radar works by broadcasting the radio wave from the antenna, and then the wave reflects off an object. It works by calculating the distance to the target via a straightforward time-of-flight formula. An example of active radar is shown by [41] using Universal Software Defined Radio (SDR) X300/X310 as a transceiver. It operates at 5.32 GHz. The system detects motion signals associated with actions like sitting and walking and compares them to a reference signal. Preliminary findings emphasize the importance of the reference signal, which shows a constant output in the absence of measurement activity. However, differences in amplitudes might be observed while engaging in walking and sitting activities. Hence, it shows the ability of SDR to detect motion signals accurately but it comes with a higher cost of hardware.

Besides SDR, the study by [42] utilized frequency-modulated continuous wave (FMCW) to detect soft falls. The FMCW radar consists of one transmitter and four receiver antennas. The FMCW radar is installed on the inside ceiling and consists of a transmitter and four receiver antennas. It operates at a distance of around 2.5m above the ground. The output signal processing utilizes the Short-Time Fourier Transform (STFT) to generate Doppler Time maps, which offer a comprehensive frequency-time analysis of the Doppler fingerprints linked to various movements. The FMCW radar is capable of differentiating between sudden and gentle falls by detecting distinct Doppler signatures associated with each type of motion but it has its own signal processing complexity.

The research carried out in [43] demonstrates the use of a fall detection system that utilizes a continuous-wave Doppler radar operating at a frequency of 24 GHz in the K-band. As per the previous researcher, the radar was located at a distance of 250cm above the ground, which the researcher found to be more accurate than chest level. The research highlights the efficacy of the system in detecting simulated falls, utilizing pre-processing techniques to refine the data and comparing different categorization approaches. Support Vector Machine (SVM) classification algorithm obtains a notable accuracy rate of 85%. This method makes it possible to quickly find people who have fallen, but it can be hard to see movements that are hidden by things or that do not have a clear line of sight.

A study explaining radar signal are capable of capture motion through a wall that separated in two different two rooms [44]. A signal generator was used to generate a single-tone signal as a transmitter and coupled to a wideband horn antenna. To get the data variance, the participants had to perform normal human tasks over the baseline. The raw output signal from the receiver is digitized, and the signal spectrum is obtained using a Fast Fourier Transform. The amplitude is retrieved after identifying the signal peak in the signal spectrum, which is used to drive the micro-doppler sign. This hardware is capable of perceiving human motion even when not in direct line of sight but it needs more processing to identify the various forms of motion.

From here, it can be concluded that different types of active radar can detect different types of falls. However, compared to active radar, passive radar has the advantage of using any available communication transmission. It has no dedicated transmitter and waits for a signal transmitted from a pre-existing transmitter to track a subject. It measures location by comparing the arrival times of the original signal from the transmitter and the reflected signal from the subject.

A passive radar transmitter employing Digital Video Broadcasting – Satellite (DVB-S) detects small, nearby targets such as drones and human motion [45]. Using passive bistatic radar, two directional antennas are used for reference and surveillance. Both outputs then proceed for the noise cancelling procedure, and the undesired signals are removed by subtracting the reference signal from the surveillance signal. The output of the noise cancellation phase is then fed to more processing evaluation using the cross-ambiguity function. While DVB-S provides the advantage of extensive coverage, drawbacks include the need for multiple DVB-S devices to be upgraded and the challenge of establishing an unreliable provider as a transmitter

Besides DVB-S, FM radio also can be used as a passive illuminator of opportunity. A study by [46] implemented PSFR using FM radio signals with carrier frequency 106.2MHz as an illuminator of opportunity. This technology uses terrestrial FM radio transmissions to detect civil aircraft. The study maintains the exact configuration of two antennas for reference and surveillance. It shows that implementing PSFR can locate the target despite the considerable distance between the transmitter and receiver. However, FM transmitters face problems with multi-channel effects, low echo signal power, and direct path interference. It requires sophisticated signal processing techniques to overcome the difficulties.

The most recent wireless technology that uses LTE (2.635 GHz) signals can also be used as a passive transmitter. The LTE signal's wide bandwidth is between 1.4 and 20 MHz, allowing for superior range resolution. Research [47] implementing LTE as a transmitter to detect the vehicle. This study dedicated two antennas for reference and surveillance. The receiver has a surveillance antenna and a low-noise amplifier to amplify the received RF signal. Three vehicles with different sizes and speeds are used as the subject. Both reference and surveillance data are then going through cross-ambiguity function coherent processing. LTE offers last-mile broadband wireless coverage, but this wireless communication service is currently not fully developed in all cities yet, and more towers are needed to receive good coverage.

Another wireless communication that is available widely and can become an excellent passive transmitter is Wi-Fi. The essential idea behind Wi-Fi sense for fall detection is that the body's movement will impact the communication channel in terms of frequency shift, signal attenuation, and propagation pathways. A study in [48] explains on capability of detecting number of people using Wi-Fi. The system is specifically designed to utilize Wi-Fi signals, such as continuous high data-rate OFDM transmissions and periodic Wi-Fi beacon signals, to detect and monitor human presence. These applications are particularly useful in situations where targets cannot be assumed to be cooperative, like security and through-the-wall applications.

Table 1 presents a thorough summary of different radar sensors used for motion detection, including human activity detection and monitoring. Radar sensors are essential in several applications, such as detecting falls in healthcare environments and monitoring and tracking targets for surveillance purposes. Recent research has summarized important data which details the radar hardware, detected activities, and benefits of each type of sensor.

TABLE I. OVERVIEW OF TYPES OF RADAR SENSORS

No	Radar Hardware	Advantages	Disadvantages
1	Active radar-Universal Software Defined Radio (USRP) [41]	Software-based architecture that possible to adapt to different tasks and settings	Huge amounts of training data are required and higher costs in terms of hardware
2	Active radar-Frequency-modulated continuous wave (FMCW) [42]	Precisely identifying small motions caused by soft falls	Signal processing complexity
3	Active radar-Continuous wave Doppler [43]	Motions can be tracked in real-time which enables the rapid detection of falls	Constraints in identifying motions behind obstructions or no direct line of sight
4	Active radar-Signal generator [44]	Capable of perceiving human motion even when not in direct line of sight	Difficulties in differentiating precisely between various forms of motion
5	Passive radar-Digital Video Broadcasting – Satellite (DVB-S) [45]	Cost-effective surveillance using existing signals	Detection range and accuracy limits
6	Passive radar-Frequency modulated (FM) signals [46]	Ability to detect moving targets in dynamic environments	Difficulties in separating environmental noise and clutter.
7	Passive radar-Long-Term Evolution (LTE) [47]	Potential for long-range monitoring and detection	Challenges caused by signal properties and distinguishing between different targets.
8	Passive radar-Wireless Fidelity (Wi-Fi) [48]	Wi-Fi connections are prevalent in many places	Present obstacles caused by signal reflections and external variables

Wi-Fi provides an acceptable bandwidth or range resolution, broad accessibility, and coverage. It is an ideal illuminator of opportunity for a short-range target or an indoor space [32], [49], [50]. The Wi-Fi transmission is at a frequency of 2.4 GHz spectrum and lies between 2.412 GHz and 2.472 GHz. Wi-Fi is already installed in many private homes and care facilities. The widespread use of these transmitters can greatly benefit healthcare facilities. Therefore, Wi-Fi is the type of passive radar best suited for detecting humans. Since Wi-Fi transmission is in pulsed type [50]–[53], there are few methods of motion detection using Wi-Fi such as using various of signal strengths, changes value in channel state information or cross ambiguity function.

Research [54] uses Wi-Fi as a transmitter and a received signal strength indicator (RSSI) to recognize the activity. The study first learns the values of RSSI for absence, presence, and also fall actions made by humans. Then, it determined the activity by measuring the fluctuated RSSI using Shell commands. After RSSI along time is collected, it proceeds to the following data normalization process but hardware malfunctions or subject movement might cause false alarms. Hence, to improve the accuracy, a filter method named Hampel identifier is used to differentiate between points inside and outside of a range. The normalized data is then fed to ANN for classification. The RSSI method is one of the most known to classify falls. Still, the multipath propagation effect, such as reflection, refraction and scattering, affects measurement performance, which can lead to significant false positives.

A different method of human detection system called WiFall is conducted by [55] by analyzing motion based on changes in channel state information (CSI) amplitude and radio propagation. By applying MIMO topology, two TP-Link routers or Access Points (AP) act as the transmitter while two receivers, laptops including Intel Wi-Fi Link 5300(i-wl5300) 802.11n NICs, are on the receiver side. Three human motions are collected, and data are extracted and kept. The method includes data processing, anomaly detection, and classification. CSI data is collected, and the noise is reduced using a weighted moving average. For anomaly detection, it shows that static movement does not impact CSI data, while the other activities result in a variance in CSI data reading. The signature of each human motion detection is then fed to SVM for activity classification.

A NotiFi system in [56] uses Wi-Fi as a transmitter and a laptop with Intel 5300 NIC as a receiver. As compared to the previous researcher, this study analyses motion using CSI amplitude and phase. Three test scenarios show different detection results for line-of-sight (LOS), non-line-of-sight (NLoS), and lastly, through-one-wall. Distance between AP and laptop for all situations is kept the same. The outcome shows an average accuracy of 89.2% in LoS, 85.6% in NLoS, and 75.3% in a through-one-wall scenario. This study also shows that the location of an experiment is crucial as it shows accuracy for a laboratory and office is higher than for an apartment. One of the significant reasons is less furniture in offices and laboratories. Hence, less propagation is made by the signals. Besides, this study also shows an accuracy of over 86% when the distance between the transmitter and receiver is shortened. This is due to increased Wi-Fi signal strength and a more reliable distance for CSI extraction to capture human movement. However, CSI has the drawbacks of differentiating stationary users apart from furniture. Another author also finds that the CSI method has difficulty separating functional signal dynamics from random noise. A CSI-based system requires a modified laptop with WIFI NIC to act as a receiver in hardware performance.

Another study implementing Wi-Fi as an illuminator of opportunity proposes a Wi-Fi signal-based passive wireless radar (PWR) sensing system that can detect a wide range of human motions indoors, including those of the whole body, Individual limbs, and the chest. Real-time signal processing is utilized by a software-defined radio (SDR) demonstration system to identify people’s movement [42]. The method of PWR is to collect the signal from the source while the second captures the echoes bouncing off the target. Two antennas’ transmissions are called the reference signal and the surveillance signal. Correlation and processing of the two signals are accomplished with the help of cross ambiguity function (CAF) in an equation that helps to measure the velocity or relative range of a target based on the transmitter. The PWR method has the advantage of low power consumption, a less complex system and the ability to detect and track non-cooperative targets.

The identification of motion through Wi-Fi requires a unique signal processing strategy and a more in-depth investigation of this method will be elaborated upon in the following part.

V. Radar-Based Signal Processing

The previous chapter explains the type of radar and how it captures human motion. This chapter, it will explain more about the processed after the signal has been captured and various types of classification made to get more precise results.

A. Doppler Extraction for Signal Processing

Whenever a signal is reflected or obstructed, it takes on a unique set known as a Doppler signature. The difference in the returned signal's characteristic reflects the target's properties of interest. The human Doppler signature carries data about human motion's magnitude, direction, and velocity. It is necessary to perform a transformation to the time-frequency domain to extract features after obtaining its Doppler signature. In the case of time-frequency analysis, many linear and non-linear methods are available. Commonly, the Fourier Transform is used to translate the time domain signal that contains a Doppler signature alongside the signal. The signal pattern is turned into a domain that supplies more stable information about how the signal's energy is dispersed across some frequencies.

A study by [57] mentions that the short-time Fourier transform (STFT) domain is the most effective at revealing the Doppler signal. By focusing on the energy content of a signal, time-frequency analysis can expose its unique properties and show how the signal's Doppler signature changes over time. The same study discussed the process after the data relating to the micro-doppler signature had been extracted using STFT. The generation of spectrogram results in the statement that the micro-doppler signature obtained for walking has dominant positive and negative micro-doppler shift signatures because it uses whole-body movement. On the other hand, the frequency centre of the micro-doppler signature obtained for other movements, such as bending or waving, is 0 Hz because these movements do not require a significant movement of a human's body part. Therefore, this demonstrates that the signature of micro-doppler varies between the activities.

There are several successful studies on detecting humans by utilizing the Doppler approach. Studies in [33], [58] show that doppler can help to detect daily human activities. It can detect six different Doppler signatures with an operating frequency range of 2.5 GHz-4.5 GHz. Doppler signatures help recognize daily human activities, including sitting, walking, and standing, using crucial body parts such as arms, legs, and torso. Doppler is often used to track every human gait with unique Doppler pattern signals.

B. Features Extraction and Classification

Features are a set of data that can represent a group or class's behaviour. Taking care of the Radar system, the features representing a class of signal must be a range spectrum representing the Doppler signature along with the received signal. The most frequent feature used in aiming to classify human movement using radar systems is a set of numerical data that comes from the Fourier Transform and the images generated by the application of the Mel-Frequency Cepstral Coefficient and also Continuous Wavelet Transform such as in [59], [60].

The research presented in reference [61] offered three features for fall detection that were retrieved from the spectrograms of the radar data. According to [62], and [63] the first step for detecting falls is the data's short-Time Fourier Transform (STFT) and extracting power burst curves. This step aimed to identify a potential fall event based on a threshold. This involved looking for time bins in the spectrograms that exhibited a sudden increase in velocity, which could be related to falling events. To create binary black-and-white images, this was followed by the application of segmentation and morphological processing, which are both methods of image processing, to the area of the spectrogram that had been detected. After this, appropriate features were extracted from the images. These features included the extreme frequency magnitude, the extreme frequency ratio, and the length of the event. The data included falling forward and backwards with and without waving arms throughout the movement. Additionally, the data included non-fall activities such as sitting and standing or bending and standing done at average and high speeds. This strategy for feature extraction was used in conjunction with Naive Bayesian learning, Random Forest and Support Vector Machine (SVM), and the SVM showed some encouraging results.

Conversely, the researcher [64] used the Fractional Fourier Transform (FrFT) to extract the features from the time-domain data of fall and non-fall movement. The FRFT is a linear operator that corresponds to the rotation of the signal through an angle that is not a multiple of $\pi/2$. It represents the signal along the axis, making an angle with the time axis. This technique achieves a more significant signal energy concentration and improves classification outcomes for situations with a low signal-to-noise ratio (SNR). The processing method works by applying the FrFT to the data, and the results would then be compared with a threshold. If the threshold were found to be crossed, the strategy would then commence the classification routine based on the FFT. As a result, the researcher achieves high accuracy when feeding the FrFt features to a simple Bayesian classification.

Besides, The Scalogram is an image that can be gained by applying Continuous Wavelet Transform (CWT). The CWT compares the signal to variants of a wavelet that have been shifted, compressed, or stretched. Expanding or contracting a function is collectively called dilation or scaling, corresponding to the idea of scale in physical theory [62]. The use of CWT in image creation is by plotting the absolute value of the CWT. It will result in a scalogram indicating the relationship between scale and frequency to generate a time-frequency spectrum. The continuous wavelet function was used to process the data [57], followed by the extraction of three features from the resulting Doppler vs. time pattern, referred to as a scalogram. These characteristics include the component with the lowest scale or the correspondingly most excellent frequency, the energy ratio, and the scale change rate. This strategy produced favourable outcomes. However, it was only subjected to early testing in a laboratory setting on a modest dataset. The dataset comprised falling backward movements instead of standing and sitting movements carried out by two people. At a frequency of 8 GHz, the radar was a Vector Network Analyzer (VNA) functioning as a Doppler radar.

The researcher working with the same equipment presented in [65] used the Wavelet Transform in [66] to extract relevant characteristics for fall detection. This researcher also tested different types of wavelet functions at a relational scale to acquire the best classification accuracy. Three large datasets were analyzed, which included data collected in laboratory conditions as well as data collected in actual apartments that had elderly people living in them. The datasets contain exhaustive information on a wide variety of falls and movements that do not constitute falls, such as tripping and falling, slipping and falling, losing balance and falling, losing consciousness and falling, reaching for a chair or sofa and falling, and so on. The feature samples were put through a straightforward NN classifier that just used a single threshold, and the results were satisfactory. The researchers also tested the SVM classifier using both a linear and a Gaussian kernel.

Next, the Mel-Frequency Cepstral Coefficient (MFCC) is an additional method that be applied to the STFT to create a Mel spectrogram. The MFCC creates a band-pass filter called a Mel-filter bank in a triangle shape [67]. The Mel spectrogram s(m) is created by multiplying the magnitude spectrum by each triangle Mel weighting filter. The use of STFT together with MFCC was applied by the researcher [68]. The researcher used an overlapping hamming window together with a Mel filter bank. The work cited in the reference reported an interesting investigation into applying various features to the same dataset [62]. The data presented was gathered using a commercial Doppler radar operating at 24 GHz and then processed with an SVM classifier employing radial basis functions. The experiment was conducted with four participants, and the movements of falling, sitting, walking, and picking something up were considered. The different types of features included the three empirical features extracted by the spectrograms as described in [69], the power burst curves used as a whole vector for classification, the energy between the start and the end of the fall event calculated on the result of the Wavelet Transform as described in and the MFCC coefficients. It appeared that the first set of features retrieved from the spectrograms performed significantly better than the other characteristics.

The use of machine learning was highly explored in the classification task of fall detection systems as per Table 2. The most frequently used is the Support Vector Machine (SVM), as in [57]. According to the author, SVM behaviour creates a linear hyperplane that acts as a divider that divides the features of fall and non-fall events. The researcher feeds the SVM with a feature selected from the power spectrum density of the signal that gains after applying FFT on the time-domain signal. Then the SVM will update the gradient to minimize the loss function and get higher accuracy. As a result, the researcher gained great accuracy in the fall and non-fall data classification tasks.

Another type of classification using the K-nearest Neighbour (KNN) method widely explored for human fall and non-fall classification. In [70], the author used the KNN with various values of K. The K value denotes the neighborhood size considering the same class as the main point. The KNN the algorithm created the main data point by finding the centre of the features fed as the input to the classifier. Then, the surrounding data point within the K size will be assigned as the same class. The author used a 12 K value to classify the fall and non-fall movement based on the features that have been extracted via applying FFT, and the highest accuracy with a K value is 6. The study by [71] proved that the KNN highly depends on the value of K, where the different types of input will desire a different value of K. Consequently, the dependence of the algorithm will make the classifier unrobust system where it needs an outsource optimizer to update the K value.

Besides, [72] shows the utilization of artificial neural networks (ANN) in classifying fall and non-fall events. The researcher used the simplest neural network architecture, the Feed-Forward Neural Network (FNN). This classification method is highly dependent on the number of neurons and layers in hidden layers. The study by [70] shows a set number of neurons and utilized only a single layer or neurons in the hidden layer was capable of differentiating the time-frequency features of fall and non-fall events. The size of the hidden layer chosen by the author is by considering the thumb rules of the hidden layer where the number of neurons must be 2/3 of the input neurons and not less than the output neurons. The study by [72] fed the FNN with 40 features that fully connected to the 240, 60 and 8 neurons in three hidden layers resulting in two classes which are fall and non-fall movement. Another study [73] shows 16 selected features from the frequency domain using PCA were assigned as input to the FNN to classify upper limb motions with binary output. The researcher used 7 sizes of the hidden layer in the architecture of the FNN. As a result, all the studies [72], [73] achieved excellent accuracy with 95% and above. The Convolutional neural network (CNN) performs well when adapting the algorithm as a radar-based human movement detection classifier. After a pre-processing step, during which the images' noise is reduced and grayscale is applied, the spectrograms and related class labels are directly provided as inputs to the CNN. This comes after a pre-processing step, during which the images' grayscale is applied. The advantage of this method is that the feature extraction step is skipped. It is up to CNN to recognize recurring patterns within a class and characteristics that differentiate one class from another. This eliminates the risk of throwing away information that could be useful during the feature extraction process, which is carried out using methods devised by human operators. In a study applying CNN architecture to classify human movement using AlexNet, ResNet and VGG16. In [74], the author used the signal of simple head movements such as coughing, shaking head and scratching head to translate into an image by using pseudocolour MATLAB with the size of 227x227. The data set was then fed into the AlexNet algorithm to be classified. The result of this experiment shows excellent accuracy with 0.23 loss and 10 epochs of convergence. Next, the author [75] utilizes the ResNet algorithm in classifying the repertory pattern by recording the signal of the chest movement of the subject. The signal was then converted into a spectrogram by applying STFT fed into the ResNet classifier. The results gained by the researcher also show an actable accuracy. Finally, [76], VGG16 also had been used to classify human walking tempo. The signal collected was transformed into a 224x224 time-frequency spectrogram by applying the STFT. Then, the image is fed into the VGG16 architecture for the classification task. The result shows a great value of accuracy achieved by the researcher. The training of CNNs will require more processing resources. Still, given the current trend in technology toward greater computational power at lower cost, this method is expected to become more widespread soon.

TABLE I. OVERVIEW OF CLASSIFICATION METHODS

No	Classification Method	Advantage	Disadvantage
1	Support Vector Machine (SVM) ([57])	Great accuracy in fall and non-fall classification tasks	Linear hyperplanes may be incapable of capturing complicated interactions
2	K-nearest Neighbour (KNN) ([70])	Achieves the highest accuracy with optimal K value.	Sensitive and requires tuning for K value
3	Artificial Neural Network (ANN) ([72], [73])	High accuracy (95% and above) in fall and non-fall classification	Architecture tuning is crucial and is dependent on neuron and layer counts.
4	Convolutional Neural Network (CNN) ([74], [75], [76])	Excellent accuracy with low loss	Increased processing resource requirements; training and architecture selection complexity

VI. CONCLUSION

In conclusion, everyone is at risk of falling, but the elderly are especially vulnerable. The elderly are particularly vulnerable to harm because of their age-related physical and health declines, which can result in many injuries and even death. The purpose of fall detection is to improve the quality of life for those who are vulnerable to a fall event and for those who are not able to withstand the effects of a fall. Numerous fall detection systems employing various sensors have been developed but radar stands out as the most advantageous option among the many different sorts of sensors. Since passive radar uses Wi-Fi which relies on existing signal infrastructure, it is more practicable for broad implementation. Furthermore, research reveals that the combination of passive radar and Wi-Fi is able to capture unique Doppler signatures due to human movement which is used to differentiate between falls and nonfall occurrences in a certain situation. Hence, to enhance the precision of detection, it is crucial to choose appropriate techniques for both data pre-processing and data classification. The fall recognition system's robustness and reliability can be assured by using appropriate pre-processing procedures and employing advanced classification methods. By improving these features, the system will be able to identify fall accidents more quickly and accurately, improving safety and well-being in a variety of settings.

REFERENCES

[1] A. Kalache, D. Fu, and S. Yoshida, “WHO Global Report on Falls Prevention in Older Age,” 2007.

[2] S. H. M. Bakeri, “Malaysia 2030: Cabaran Negara Tua,” 2020.

[3] P. L. Yu et al., “Prevalence and related factors of falls among the elderly in an urban community of Beijing,” Biomed. Environ. Sci., vol. 22, no. 3, pp. 179–187, 2009, doi: 10.1016/S0895-3988(09)60043-X.

[4] M. Terroso, N. Rosa, A. Torres Marques, and R. Simoes, “Physical consequences of falls in the elderly: A literature review from 1995 to 2010,” European Review of Aging and Physical Activity, vol. 11, no. 1. Springer Verlag, pp. 51–59, 2014. doi: 10.1007/s11556-013-0134-8.

[5] K. Desai, P. Mane, M. Dsilva, A. Zare, P. Shingala, and D. Ambawade, “A novel machine learning based wearable belt for fall detection,” in 2020 IEEE International Conference on Computing, Power and Communication Technologies, GUCON 2020, Oct. 2020, pp. 502–505. doi: 10.1109/GUCON48875.2020.9231114.

[6] F. Attal, S. Mohammed, M. Dedabrishvili, F. Chamroukhi, L. Oukhellou, and Y. Amirat, “Physical human activity recognition using wearable sensors,” Sensors (Switzerland), vol. 15, no. 12, pp. 31314–31338, Dec. 2015, doi: 10.3390/s151229858.

[7] Y. S. Delahoz and M. A. Labrador, “Survey on fall detection and fall prevention using wearable and external sensors,” Sensors (Switzerland), vol. 14, no. 10. MDPI AG, pp. 19806–19842, Oct. 22, 2014. doi: 10.3390/s141019806.

[8] K. De Miguel, A. Brunete, M. Hernando, and E. Gambao, “Home camera-based fall detection system for the elderly,” Sensors (Switzerland), vol. 17, no. 12, Dec. 2017, doi: 10.3390/s17122864.

[9] V. D. Nguyen, M. T. Le, A. D. Do, H. H. Duong, T. D. Thai, and D. H. Tran, “An efficient camera-based surveillance for fall detection of elderly people,” in Proceedings of the 2014 9th IEEE Conference on Industrial Electronics and Applications, ICIEA 2014, Oct. 2014, pp. 994–997. doi: 10.1109/ICIEA.2014.6931308.

[10] N. P. Bhatta and M. Geethapriya, “RADAR and its Application,” 2016. [Online]. Available: https://www.researchgate.net/publication/317427496

[11] P. Falcone, F. Colone, and P. Lombardo, “Potentialities and Challenges of WiFi-Based Passive Radar,” IEEE A&E SYSTEMS MAGAZINE, 2012.

[12] B. Tan et al., “Wi-Fi based passive human motion sensing for in-home healthcare applications,” IEEE World Forum Internet Things, WF-IoT 2015 - Proc., pp. 609–614, 2015, doi: 10.1109/WF-IoT.2015.7389123.

[13] B. Moreland, R. Kakara, and A. Henry, “Trends in Nonfatal Falls and Fall-Related Injuries Among Adults Aged ≥65 Years — United States, 2012–2018,” MMWR. Morb. Mortal. Wkly. Rep., vol. 69, no. 27, pp. 875–881, 2020, doi: 10.15585/mmwr.mm6927a5.

[14] G. C. Ang, S. L. Low, and C. H. How, "Approach to falls among the elderly in the community," Singapore Med. J., vol. 61, no. 3, pp. 116–121, Mar. 2020, doi: 10.11622/smedj.2020029.

[15] Y. Uy, Y. Jf, and C. Wy, "Prevalence of falls among community-dwelling elderly and its associated factors: A cross-sectional study in Perak, Malaysia," 2016.

[16] N. Sahril et al., "Prevalence and factors associated with falls among older persons in Malaysia," Geriatr. Gerontol. Int., vol. 20, no. S2, pp. 33–37, Dec. 2020, doi: 10.1111/ggi.13980.

[17] Wafaak E, Noran H, and Hamid NA, "Falls and Its Associated Factor Among The Elderly Results From an Elderly Screening Programme in Kelantan," Malaysian J. Public Heal. Med., vol. 21, no. 2, pp. 141–148, 2021.

[18] J. A. Stevens, M. F. Ballesteros, K. A. Mack, R. A. Rudd, E. DeCaro, and G. Adler, "Gender differences in seeking care for falls in the aged medicare population," Am. J. Prev. Med., vol. 43, no. 1, pp. 59–62, Jul. 2012, doi: 10.1016/j.amepre.2012.03.008.

[19] A. M. Herghelegiu, G. I. Prada, A. M. Marin, and R. M. Nacu, "Risk factors and prevention strategies for falls in elderly," in 2015 E-Health and Bioengineering Conference, EHB 2015, Jan. 2016. doi: 10.1109/EHB.2015.7391398.

[20] T. T. Nguyen, M. C. Cho, and T. S. Lee, "Automatic fall detection using wearable biomedical signal measurement terminal," in Proceedings of the 31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society: Engineering the Future of Biomedicine, EMBC 2009, 2009, pp. 5203–5206. doi: 10.1109/IEMBS.2009.5334079.

[21] I. Cleland et al., "Optimal placement of accelerometers for the detection of everyday activities.," Sensors (Basel)., vol. 13, no. 7, pp. 9183–9200, 2013, doi: 10.3390/s130709183.

[22] O. C. Kurban and T. Yildirim, "Daily motion recognition system by a triaxial accelerometer usable in different positions," IEEE Sens. J., vol. 19, no. 17, pp. 7543–7552, Sep. 2019, doi: 10.1109/JSEN.2019.2915524.

[23] A. Choi et al., "Deep Learning-Based Near-Fall Detection Algorithm for Fall Risk Monitoring System Using a Single Inertial Measurement Unit," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 30, pp. 2385–2394, Aug. 2022, doi: 10.1109/tnsre.2022.3199068.

[24] K. Takatou and N. Shinomiya, "Cloud-based fall Detection System with Passive RFID Sensor Tags and Supervised Learning," in 2021 IEEE 10th Global Conference on Consumer Electronics, GCCE 2021, 2021, pp. 153–156. doi: 10.1109/GCCE53005.2021.9621999.

[25] B. Tan, K. Woodbridge, and K. Chetty, "A real-time high resolution passive WiFi Doppler-radar and its applications," in 2014 International Radar Conference, Radar 2014, Mar. 2014. doi: 10.1109/RADAR.2014.7060359.

[26] N. Harum, Z. Z. Abidin, W. M. Shah, and A. Hassan, "Implementation of Smart Monitoring System with Fall Detector for Elderly Using IoT Technology," Int. J. Comput., vol. 17, no. 4, pp. 243–249, 2018, [Online]. Available: www.utem.edu.my

[27] A. Gupta, R. Srivastava, H. Gupta, and B. Kumar, "IoT Based Fall Detection Monitoring and Alarm System for Elderly," in 7th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering, UPCON 2020, Nov. 2020. doi: 10.1109/UPCON50219.2020.9376569.

[28] A. Paramasivam, S. Bargavi, R. Priyadharshini, M. Subhiksha, S. Vijayalakshmi, and N. M. M. Banu, "Internet of Things based Fall Prediction and Alerting Device," in 2022 International Conference on Communication, Computing and Internet of Things, IC3IoT 2022 - Proceedings, 2022. doi: 10.1109/IC3IOT53935.2022.9767905.

[29] M. Bundele, H. Sharma, M. Gupta, and P. S. Sisodia, "An Elderly Fall Detection System using Depth Images," in 2020 5th IEEE International Conference on Recent Advances and Innovations in Engineering, ICRAIE 2020 - Proceeding, Dec. 2020. doi: 10.1109/ICRAIE51050.2020.9358330.

[30] H. Abdo, K. M. Amin, and A. M. Hamad, "Fall Detection Based on RetinaNet and MobileNet Convolutional Neural Networks," in Proceedings of ICCES 2020 - 2020 15th International Conference on Computer Engineering and Systems, Dec. 2020. doi: 10.1109/ICCES51560.2020.9334570.

[31] L. Rachakonda, S. P. Mohanty, and E. Kougianos, "Good-Eye: A Device for Automatic Prediction and Detection of Elderly Falls in Smart Homes," in Proceedings - 2020 6th IEEE International Symposium on Smart Electronic Systems, iSES 2020, Dec. 2020, pp. 202–203. doi: 10.1109/iSES50453.2020.00051.

[32] F. Fioranelli, M. Ritchie, and H. Griffiths, "Bistatic human micro-Doppler signatures for classification of indoor activities," in 2017 IEEE Radar Conference, RadarConf 2017, Jun. 2017, pp. 0610–0615. doi: 10.1109/RADAR.2017.7944276.

[33] Q. Chen, B. Tan, K. Chetty, and K. Woodbridge, "Activity Recognition Based on Micro-Doppler Signature with In-Home Wi-Fi," in IEEE 18th International Conference on e-Health Networking, Applications and Services (Healthcom), 2016.

[34] H. D. Griffiths, "Bistatic radar-Principles and practice," in 1993 SBMO International Microwave Conference/Brazil, SBMO 1993, 1993, vol. 2, pp. 519–526. doi: 10.1109/SBMO.1993.587208.

[35] M. I. (Merrill I. Skolnik, Radar handbook. McGraw-Hill, 1990.

[36] R. Nakamura and A. Kajiwara, "In-home monitoring sensor using stepped-FM UWB-IR," in 2013 IEEE MTT-S International Microwave Workshop Series on RF and Wireless Technologies for Biomedical and Healthcare Applications, IMWS-BIO 2013 - Proceedings, 2013. doi: 10.1109/IMWS-BIO.2013.6756179.

[37] M. Boutkhil, A. Driouach, and A. Khamlichi, "Detecting and localizing moving targets using multistatic radar system," in Procedia Manufacturing, 2018, vol. 22, pp. 455–462. doi: 10.1016/j.promfg.2018.03.070.

[38] D. Dash and V. Jayaraman, "Time delay estimation issues for target detection and transmitter identification in multistatic radars," Engineering Reports, vol. 2, no. 9. 2020. doi: 10.1002/eng2.12236.

[39] P. Bezousek, V. Schejbal, P. Bezoušek, and V. Schejbal, "Bistatic and Multistatic Radar Systems," RADIOENGINEERING, vol. 17, no. 3, 2008, [Online]. Available: https://www.researchgate.net/publication/26539588

[40] A. Alnaeb et al., "Human Activities Detection and Classification Based on Micro-Doppler Signatures Near the Baseline of Forward Scattering Radar," 2018.

[41] M. B. Khan et al., "Software Defined Radios Based Platform for Activity Recognition," IEEE Access, vol. 7, pp. 31083–31088, 2019, doi: 10.1109/ACCESS.2019.2902267.

[42] B. Wang, Z. Zheng, and Y. X. Guo, "Millimeter-Wave Frequency Modulated Continuous Wave Radar-Based Soft Fall Detection Using Pattern Contour-Confined Doppler-Time Maps," IEEE Sens. J., vol. 22, no. 10, pp. 9824–9831, 2022, doi: 10.1109/JSEN.2022.3165188.

[43] K. Hanifi and M. E. Karsligil, "Elderly Fall Detection with Vital Signs Monitoring Using CW Doppler Radar," IEEE Sens. J., vol. 21, no. 15, pp. 16969–16978, Aug. 2021, doi: 10.1109/JSEN.2021.3079835.

[44] H. Sun, "Through-the-wall human motion sensing based on forward scattering," in 2019 IEEE Radar Conference, RadarConf 2019, Apr. 2019. doi: 10.1109/RADAR.2019.8835770.

[45] Octavio Cabrera et al., "Detecting drones and human beings with DVB-S based COTS passive radar for short-range surveillance," IEEE Int. Radar Conf., 2020.

[46] S. Bayat, M. M. Nayebi, and Y. Norouzi, "Target detection by passive coherent FM based bistatic radar," in Proceedings of the 2008 International Conference on Radar, Radar 2008, 2008, pp. 412–415. doi: 10.1109/RADAR.2008.4653957.

[47] R. S. A. R. Abdullah, A. A. Salah, A. Ismail, F. Hashim, N. H. A. Aziz, and N. E. A. Rashid, "Ground moving target detection using LTE-based passive radar," in Proceeding - 2015 International Conference on Radar, Antenna, Microwave, Electronics, and Telecommunications, ICRAMET 2015, Jan. 2016, pp. 70–75. doi: 10.1109/ICRAMET.2015.7380777.

[48] C. Tang, W. Li, S. Vishwakarma, K. Chetty, S. Julier, and K. Woodbridge, "Occupancy Detection and People Counting Using WiFi Passive Radar," IEEE Natl. Radar Conf. - Proc., vol. 2020-Septe, 2020, doi: 10.1109/RadarConf2043947.2020.9266493.

[49] F. Viani, A. Polo, and E. Giarola, "Exploiting em simulation modelling for wireless indoor localization," in 2016 10th European Conference on Antennas and Propagation, EuCAP 2016, May 2016. doi: 10.1109/EuCAP.2016.7481965.

[50] D. Pastina, F. Colone, T. Martelli, and P. Falcone, "Parasitic exploitation of Wi-Fi signals for indoor radar surveillance," IEEE Trans. Veh. Technol., vol. 64, no. 4, pp. 1401–1415, Apr. 2015, doi: 10.1109/TVT.2015.2392936.

[51] P. Falcone, F. Colone, and P. Lombardo, "Potentialities and challenges of WiFi-based passive radar," IEEE Aerosp. Electron. Syst. Mag., vol. 27, no. 11, pp. 15–26, 2012, doi:

10.1109/MAES.2012.6380822.
[52] A. Losito, M. Stentella, T. Martelli, and F. Colone, "Automatic vehicles classification approaches for WiFi-based Passive Forward Scatter Radar," 2017.
[53] T. Martelli, F. Colone, and P. Lombardo, "First experimental results for a WiFi-based passive forward scatter radar," in 2016 IEEE Radar Conference, RadarConf 2016, Jun. 2016. doi: 10.1109/RADAR.2016.7485108.
[54] IEEE Region 10, IEEE Seoul Section, Institute of Electrical and Electronics Engineers. Korea Council, and Institute of Electrical and Electronics Engineers, "A Received Signal Strength Based Fall DetectionSystem Using Cognitive Sensing," in Proceedings of TENCON 2018 - 2018 IEEE Region 10 Conference (Jeju, Korea, 28-31 October 2018), 2018.
[55] Chunmei Han, Kaishun Wu, Yuxi Wang, and Lionel M. Ni, "WiFall: Device-free Fall Detection by Wireless Network," in IEEE INFOCOM 2014 : IEEE Conference on Computer Communications, 2014.
[56] D. Zhu, N. Pang, G. Li, and S. Liu, "NotiFi: A ubiquitous WiFi-based abnormal activity detection system," in Proceedings of the International Joint Conference on Neural Networks, Jun. 2017, vol. 2017-May, pp. 1766–1773. doi: 10.1109/IJCNN.2017.7966064.
[57] A. Gadde, M. G. Amin, Y. D. Zhang, and F. Ahmad, "Fall detection and classifications based on time-scale radar signal characteristics," Radar Sens. Technol. XVIII, vol. 9077, no. May, p. 907712, 2014, doi: 10.1117/12.2050998.
[58] Y. Kim and H. Ling, "Human activity classification based on micro-doppler signatures using a support vector machine," IEEE Trans. Geosci. Remote Sens., vol. 47, no. 5, pp. 1328–1337, May 2009, doi: 10.1109/TGRS.2009.2012849.
[59] A. Adya Pramudita, "Time and Frequency Domain Feature Extraction Method of Doppler Radar for Hand Gesture Based Human to Machine Interface," 2020.
[60] B. Tekeli, S. Z. Gurbuz, and M. Yuksel, "Information-Theoretic Feature Selection for Human Micro-Doppler Signature Classification," IEEE Trans. Geosci. Remote Sens., vol. 54, no. 5, pp. 2749–2762, 2016, doi: 10.1109/TGRS.2015.2505409.
[61] S. Palipana, D. Rojas, P. Agrawal, and D. Pesch, "FallDeFi," Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol., vol. 1, no. 4, pp. 1–25, Jan. 2018, doi: 10.1145/3161183.
[62] S. L. B. and J. N. Kutz, Fourier and Wavelet Transforms. 2019.
[63] L. Liu, M. Popescu, M. Skubic, M. Rantz, and P. Cuddihy, "An automatic in-home fall detection system using Doppler radar signatures," J. Ambient Intell. Smart Environ., vol. 8, no. 4, pp. 453–466, 2016, doi: 10.3233/AIS-160388.
[64] S. Gui, J. Li, Y. Yang, F. Zuo, and Y. Pi, "A SAR Imaging Method for Walking Human Based on mωka-FrFT-mmGLRT," IEEE Trans. Geosci. Remote Sens., vol. 60, 2022, doi: 10.1109/TGRS.2021.3087961.
[65] H. Sadreazami, M. Bolic, and S. Rajan, "Capsfall: Fall detection using ultra-wideband radar and capsule network," IEEE Access, vol. 7, pp. 55336–55343, 2019, doi: 10.1109/ACCESS.2019.2907925.
[66] Hoang Thanh Le, Son Lam Phung, and Abdesselam Bouzerdoum, "Human Gait Recognition with Micro-Doppler Radar and Deep Autoencoder," in 24th International Conference on Pattern Recognition (ICPR)., 2018.
[67] B. Erol, M. G. Amin, and S. Z. Gurbuz, "Automatic Data-Driven Frequency-Warped Cepstral Feature Design for Micro-Doppler Classification," IEEE Trans. Aerosp. Electron. Syst., vol. 54, no. 4, pp. 1724–1738, Aug. 2018, doi: 10.1109/TAES.2018.2801378.
[68] L. Liu, M. Popescu, M. Skubic, M. Rantz, T. Yardibi, and P. Cuddihy, "Automatic fall detection based on Doppler radar motion signature," in 2011 5th International Conference on Pervasive Computing Technologies for Healthcare and Workshops, PervasiveHealth 2011, 2011, pp. 222–225. doi: 10.4108/icst.pervasivehealth.2011.245993.
[69] B. Erol, "Radar-based Human Activity Recognition Algorithms using Machine Learning and Deep Neural Networks," 2018.
[70] R. Qi, X. Li, Y. Zhang, and Y. Li, "Multi-classification algorithm for human motion recognition based on IR-UWB radar," IEEE Sens. J., vol. 20, no. 21, pp. 12848–12858, 2020, doi: 10.1109/JSEN.2020.3000498.
[71] F. Luo, S. Poslad, and E. Bodanese, "Human Activity Detection and Coarse Localization Outdoors Using Micro-Doppler Signatures," IEEE Sens. J., vol. 19, no. 18, pp. 8079–8094, 2019, doi: 10.1109/JSEN.2019.2917375.
[72] B. H. Wang, J. Yu, K. Wang, X. Y. Bao, and K. M. Mao, "Fall Detection Based on Dual-Channel Feature Integration," IEEE Access, vol. 8, pp. 103443–103453, 2020, doi: 10.1109/ACCESS.2020.2999503.
[73] L. A. C. Rodriguez, E. Cardiel, A. L. Soto, J. A. B. Madrigal, and P. R. H. Rodriguez, "Human Upper Limb Motion Recognition Using IMU sensors and Artificial Neural Networks," CCE 2022 - 2022 19th Int. Conf. Electr. Eng. Comput. Sci. Autom. Control, pp. 1–4, 2022, doi: 10.1109/CCE56709.2022.9975957.
[74] U. Saeed et al., "Portable UWB RADAR Sensing System for Transforming Subtle Chest Movement into Actionable Micro-Doppler Signatures to Extract Respiratory Rate Exploiting ResNet Algorithm," IEEE Sens. J., vol. 21, no. 20, pp. 23518–23526, 2021, doi: 10.1109/JSEN.2021.3110367.
[75] E. L. Chuma and Y. Iano, "A Movement Detection System Using Continuous-Wave Doppler Radar Sensor and Convolutional Neural Network to Detect Cough and Other Gestures," vol. 21, no. 3, pp. 2921–2928, 2021.
[76] S. Zhang, S. K. Poon, K. Vuong, A. Sneddon, and C. T. Loy, "A deep learning-based approach for gait analysis in Huntington disease," Stud. Health Technol. Inform., vol. 264, pp. 477–481, 2019, doi: 10.3233/SHTI190267.