Acceleration-Based Low-Cost CW Radar System for Real-Time Elderly Fall Detection

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***Abstract*—Falls can be one of the most damaging events that elders may experience in their lives, especially when they live alone. The impact of a fall can vary from minor bruises, to life altering fractures and even become fatal. The purpose of this study is to establish a novel non-contact radar method of detecting an elderly fall when occurred in home staying. The novelty of the proposed detection technique is the exploitation of a 1D effective acceleration derived from Short Time Fourier Transform (STFT). This technique was tested utilizing a 2.45 GHz Continuous Wave (CW) Radar implemented with a Software Defined Radio (SDR) and low-cost, off-the-shelf components. Herein, we present test results that classify incidents as either falls or non-falls in line-of-sight cases. Firstly, the results are compared with the corresponding values measured with a commercial marker-based optoelectronic motion capture multi-camera system (VICON) showing high similarity. Furthermore, real-time scenarios were conducted to estimate the accuracy and the number of false alarms of the proposed method. The proposed algorithm is proved capable of exploiting the Power Burst Curve (PBC) as a preliminary factor to yield an efficient fall incident classifier based on the effective acceleration, while minimizing the required processing resources.**

***Index Terms*—Radar applications, acceleration, software radio, medical devices and systems, indoor environments, telemedicine.**

I. Introduction

In RECENT decades, the life expectancy has increased in the developed world, causing the median age to follow suit. In conjunction with the decrease in birthrates, societies are becoming dominated by older people. According to the World Health Organization [1] the total elderly population is expected to be doubled and reach 2 billion people by 2050. Greece has one of the oldest populations in the European Union, ranking 3rd with 22.5%, after Italy and Finland, according to the official statistics of Eurostat [2]. These statistics show a strong upward trend in aging, which is expected to intensify in the coming years. These data represent a serious challenge for the operation of healthcare systems. Around 30% of adults over 65 live alone, while the majority live in private homes with their partner based on recent studies [3]. However, the various societies around the world are not prepared to deal with the needs and demands arising from the global increase in the elderly population.

Falling can be extremely damaging to the elderly people, causing harm that can affect their families while straining healthcare systems. Especially, when they live alone in their private home it is crucial for the fall to be detected as quickly possible. In order to minimize the potential risks of fall, fall detection systems are needed to quickly alert the medical services to respond. Different sensors, such as accelerometers, optical or infrared cameras, vibration/acoustical sensors, as well as radars, have been proposed in the literature. The most popular sensors are accelerometers. These devices measure acceleration or the rate of velocity change with respect to its instantaneous rest frame, providing the greatest accuracy of all other methods [4], [5] with even commercially available products [6], [7]. However, the need for the person to wear such a device for the whole day is impractical and uncomfortable.

For the above reasons, contactless falling detection sensors began to emerge in the literature. Indicative examples are optical [8], infrared [9], vibration/acoustical [10] and radar [11], [12], [13] sensors. Camera-based methods take advantage of the rapid development of image processing technology in which computer vision-based algorithms or machine learning methods can be used to determine the occurrence of a fall [8]. Nevertheless, privacy should be protected (especially in private areas such as restrooms and bathrooms), which means that the application of an optical camera needs to be restricted. Furthermore, camera sensors accuracy of detection depends greatly on the viewing angle, brightness and position of the fall [8] greatly limiting the benefits of this non-contact method. Infrared cameras are a good solution for overcoming brightness issues, especially at night-time. However, in large houses, every room would need a camera to detect possible falls, which increases the system's complexity and cost. From the other side, the merits of acoustical systems are

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the relative low cost of sensors, immunity from electromagnetic interference and long-term reliability. The vibration/acoustical systems are based on ultrasonic sensors [14] or floor based pressure sensors [15]. Still, they typically require an array of sensors to achieve satisfactory accuracy, which increases the overall system cost and complicates the installation process.

On the contrary, radar-based systems for indoor applications have become quite popular for target localization, velocity measurements, and vital signs extraction [16]. Their main benefits when detecting human movements are not affected from external factors such as acoustical noise, lighting and smoke, their strength includes "seeing" through different objects or through walls, permitting detection and ensuring privacy in almost every situation [17]. Radar-based techniques have been proven to separate falls from other physical activities such as walking, standing, sitting, kneeling [18]. Most common radar types utilized in such cases are: Continuous Wave (CW) [19], Ultra-Wide Band (UWB) [20], [21] and Frequency Modulated Continuous Wave (FMCW) [22], [23] radars. CW radars provide only information about velocity, while pulsed-UWB radars offer distance measurements for multiple targets, and FMCW radars enable monitoring of both distance and velocity for more than one target [18]. Similar to optical sensors, radars accuracy greatly depends on the viewing angle of the antennas, since radars can estimate only radial velocity. This drawback is not always catastrophic, as it is proved below that non-perfectly transverse side falls can be detected but with a lower probability. Moreover, to overcome this expected weakness, some studies have applied sensor fusion techniques [20], [24] to improve fall detection accuracy, albeit at the expense of more complex structures and algorithms.

According to literature, supervised learning is preferred as a classification method distinguishing falls from other daily activities [11], [13], [20], [22], [25]. The complexity and the quantity of data of modern classification problems are enormous, meaning that the multi-dimension data (e.g. images) have to be compressed estimating the so-called features, to decrease the computational burden. For radars, these features are usually derived from Short Time Fourier Transform (STFT) spectrograms. The most common practice is importing the entire STFT spectrum as input data in a machine learning method such as Support Vector Machines [12], Convolutional Neural Networks [23], Recurrent Neural Networks [26] and Long Short-Term Memory networks [27]. The merit of using the entire spectrogram of STFT is the increased accuracy of classification. Machine learning methods can derive abstract features, sometimes unobservable by humans, which help accurately predict the type of action (e.g., falling, sitting, kneeling). However, these methods require significant computational power, time, and memory, making them impractical for real-time scenarios due to the vast amount of data produced by the STFT.

For this reason, several methods of feature extraction [12], [16], [18], [28] from STFT spectrogram were proposed in literature to simplify the classification process, aiming at the reduction of the required computational resources allowing the fall detection in real time. These metrics/features usually have some physical meaning behind them such as the "power variation" or a "moving average" in time. Another way of reducing the data size retaining as much information as possible are the dimensional reduction techniques as: Principal Component Analysis (PCA) and Independent Component Analysis (ICA) [29]. In these methods, however, the resulting features do not have a physical meaning, but are vaguer just like the case of deep neural networks data produced from the first hidden layers.

In this paper, we propose a novel technique for real-time detection of a single elder person falling in their house. The technique is a combination of two different features: the power burst curve (PBC) and an effective acceleration of target. A CW radar system operating at a frequency of 2.45 GHz, implemented on a software-defined radio (SDR), was employed for the measurements. However, it is important to note that various types of radar systems could be utilized for these measurements, including commercial FMCW on-chip radar. The novelty of the aforementioned method lies in exploiting a 1D effective acceleration as a metric for the classification procedure aiming at reduction of computational resources and time. Tests were conducted using two different data sets to ensure the proper operation of the proposed technique. In addition, real time experiments took place to test its capabilities when operating in real life scenarios.

II. Materials and Methods

In this section, the metrics to discriminate the fall and non-fall cases will be presented and analyzed. In addition, the experimental setup will be addressed along with the proposed algorithm for the fall detection.

A. Experimental Setup

The proposed method was tested using a low cost system with purpose to detect the fall of elders with the best possible accuracy. In the introduction, various radar types were presented for potential fall detection systems. In the proposed work, a CW radar system was incorporated based on SDR. This choice was made to assess the capabilities of the methodology using a simple and re-configurable system. Additionally, SDR provides a "real-time" and autonomous operation, when the detection algorithm is implemented in the digital processor of the SDR, ensuring a quick system response while maintaining a compact structure.

While a commercial FMCW radar is an excellent option capable of estimating both distance and velocity for multiple targets also implemented using SDR, its use in small-distance applications, demands a wide bandwidth (an order of 1 GHz) typically available in the millimeter regime. However, at mm-wave frequencies, only line-of-sight detection is possible, as furniture and walls become almost impenetrable. So, to explore the possibility of behind-the-wall or behind objects detection with the adopted methodology demands a lower operating frequency (e.g. 2.45 GHz). Moreover, our investigation targeted fall detection for elders living alone at home, and thus, isolating multiple targets was not a priority. For future work, we plan to utilize a millimeter wave radar following the FMCW approach, which also enables measurements various biological parameters (e.g., respiration and cardiac beat-rate).

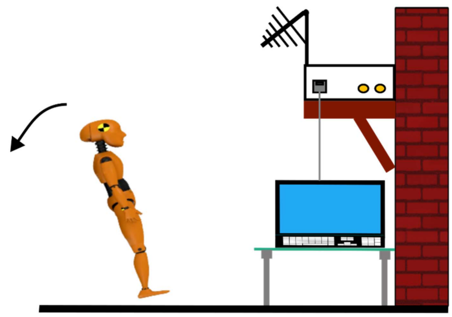

Fig. 1. Example of antenna's placement enabling the measurements of an elder person movements.

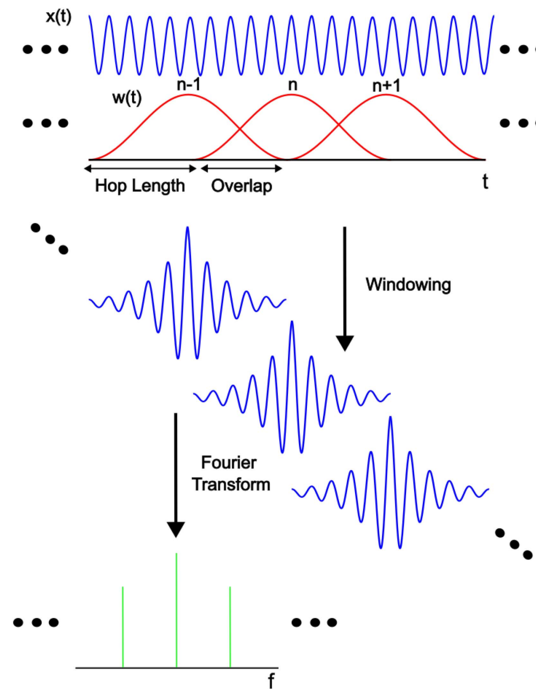

Fig. 2. Example of short time fourier transform procedure including overlapping windows.

The system consists of a Software Defined Radio, a low-cost processing unit (laptop), and two horn antennas. The SDR was chosen to be Ettus USRP N210 [30], a general low cost and footprint transceiver that has limited computational power and operational bandwidth. In the tests, as processing unit a mid-range laptop with central processing unit (Intel Core i5-10210 U) was used. For the experiment, we utilized either a low-cost printed log-periodic antenna for the compact system or a more directive horn antenna. The horn antenna used to minimize the interference of the other people in the room where the tests were conducted and because the compact system will be placed at a high point, such as mounted on a wall or in a furniture in front of a wall (Fig. 1). Generally, we would prefer a more omni-directional antenna type, such as printed dipoles, in order to cover the entire room or house space. However, wide beam antennas (dipole or log-periodic) are expected to better serve our purposes when only one elder lives inside the house. The central operating frequency was determined to be 2.45 GHz, because it belongs to free ISM band. It is important to note that the low power level Wi-fi signal was not interfered with the relative higher power radar signal.

B. Short Time Fourier Transform

The conventional Discrete Fourier Transform (DFT) is obtained by summing the time function of the signal $x[n]$ from $-\infty$ to ∞. This means that the frequency response will be an average response of the whole signal waveform. This might be useful sometimes, but in cases where the frequency components change over time the above transformation is not suitable. This is the case herein, where the frequency components represent the velocity of the target which is varying over time, namely the target changes velocity. Instead the proposed STFT considers only a short-duration segment (window) of a longer time signal and computes its Fourier transform. For this purpose, the long time series is divided into sufficiently short time intervals (as illustrated in Fig. 2), during which the velocity can be considered approximately constant. This idea is similar to approximating a non-linear curve with a stair-case. The window selection could be called "time gating" or passing the long time-series through a rectangular window. The whole procedure is illustrated in Fig. 2, where the received signal is divided into segments-windows, which will be overlapping. Each window undergoes a Fourier Transform (FFT) and the resulting spectrum is depicted versus time (Fig. 2). Although this window may offer the best temporal resolution (and, by extension, the best spatial resolution in radars), it suffers from energy leakage in the spectral domain. Thus preferably, this is performed by multiplying the long time signal $x[n]$ by a special waveform called window function $w[n]$ that has short duration [31]. Two commonly-used finite duration windows exhibiting a compromise between spatial resolution and spectral leakage are:

- the rectangular window, which essentially extracts only the desired short sequence without further modification and,
- the Hamming window, which applies a taper to the ends to improve the representation in the frequency domain.

The rectangular window has the narrower main lobe and highest side lobes, which yields the best resolution and the worst leakage. The Hamming window utilized herein, offers a good compromise between resolution and leakage. The result of STFT can be represented as a $N \times M$ matrix where N is the number of total time samples and M is the number of samples per window function. This means that the STFT is evaluated at a finite set of equally-spaced frequencies, just like DFT, where M is the total number of sample-frequencies, and reads [31].

$$S[n,m] = \sum_{k=n-(M-1)}^{n} w[n-k]x[k]e^{-j\omega_m k} \tag{1}$$

Note that $S[n,m]$ is a function of both time and frequency where all variables are discrete. The variable n denotes the location of the analysis window on the time axis. The segment of time delimited by the window is frequently referred to as the analysis frame. The variable m is a frequency index, and is sometimes referred to as a frequency bin. We can think of the STFT as representing the short-DFT of a finite-duration time function [31].

A challenging question refers to the selection of the overlap's extend. It is expected that the STFT of each window is accurately corresponding to its temporal mean ("Center of mass"). Thus a high overlapping factor could be allowed but this may delay the processing. Intuitively, successive windows could be "orthogonal" by means that the beginning of the next window will coincide with the maximum response of the current window. In any case, this option will be examined in the numerical results.

C. Power Burst Curve (PBC)

In real-time processing, the received signal is typically a long time sequence signal that may contain multiple and consecutive motions of human body. Intense moving, such as running or jumping, is quite uncommon during everyday life of an elder. So it does not make sense for the classifier to work non-stop, because the only result from that will be waste of energy and ageing of the electronic system. In contrast, the classifier needs to work only when a movement with noticeable power density is detected. Also unlike most movements, after the fall the person's movements stop so the radar only sees static targets. Thus the situation of, high density move and then zero movement for a long duration (minutes), may also be an indication of a fall [18]. Finding the onset and offset instants of motion becomes necessary to determine the individual motion boundaries and time span. These time instants can be determined from employing a threshold in the received power burst curve (PBC) [32]. This is a measure of the signal energy, in the spectrum within a specific frequency band and is defined as [32]:

$$S[n] = \sum_{m=-M/2+1}^{M/2} |S[n,m]|^2 - \sum_{m=M_1}^{M_2} |S[n,m]|^2 \quad (2)$$

where M_1 and M_2 are the indices of the frequency band which is going to be excluded from calculation of PBC. Usually the band to be excluded is chosen at low frequencies depending on the central operating frequency of radar. Specifically, in higher operating frequencies (f_o) the Doppler frequency shift for a given radial velocity v_r will be higher, permitting to exclude a wider band.[1] The reason is that slower movements have a result of low velocity and Doppler frequency shift (f_d). Falls, especially dangerous ones, will occur at high frequencies. For example utilizing a CW Radar with central frequency 2.45 GHz a range of DC to 5 Hz can be neglected, corresponding to a velocity between 0 to 0.35 m/s. A high value of PBC above a certain threshold will enable (turn-on) the classifier in order to assess if the intense movement was a fall or not [18].

This threshold can be a fixed empirical value that can be determined for each case based on the lifestyle of the monitored person and the indoor environment. A qualitative example is displayed in Fig. 3 where a fall occurred at 8.4-second mark. The threshold is estimated using an empirical value of $a = 0.1$,

[1]Based on the Doppler principle as $f_d = 2f_o v_r / c_0$

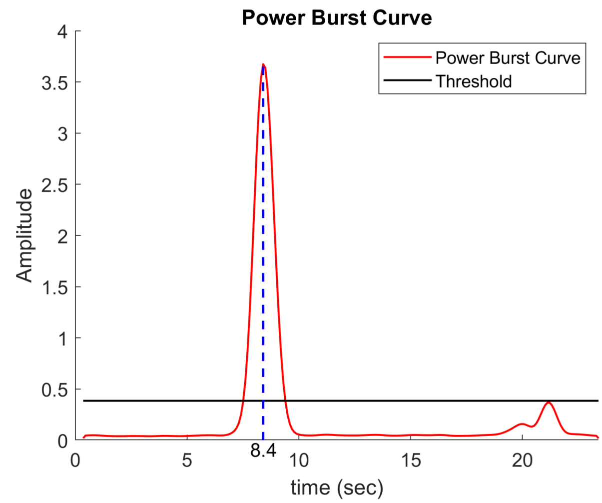

Fig. 3. Example of power burst curve for a fall occurring at the 8.4th second of measurement. This processed using an empirical value of $a = 0.1$ for a noisy environment with an estimated signal to noise ratio 20 dB.

based on the collected data, representing a noisy environment. The environment was a laboratory where too many people were moving around, e.g. the movement at time instance of 22-second mark is the response of a walking person. Otherwise it is possible to use an algorithm where the threshold value (T) will be adjusted-adapted to the operating conditions. Such an algorithm is the moving average that can be defined as [18]:

$$T = \frac{1}{K}\sum_{i=0}^{K} S[n-i] + a \quad (3)$$

where K is the window length of the moving average and a is an empirical value depending on the environment and the electronic noise of the system. The K needs to have an appropriate value which ignores the ordinary activities and is activated at singularities, in other words at high density movements. The parameter a would be estimated based on the lifestyle of each elder. The target is to install the device in the under-surveillance space, record the response of PBC due to elder's daily routine, and then to estimate a (calibration). For example, if the elder is away from home for a long time or is sleeping, the motion sensor will record a median PBC value of zero. This calibration ensures that the alarm will not be triggered unnecessarily when the elder starts moving. In our case, experiments, the empirical value of a was set to 0.2 to balance fall detection accuracy with minimizing false alarms. On the contrary the proposed algorithm will be operating adaptively.

D. Acceleration Curve

This classifier aims at processing only the power burst curve and the acceleration of the main scatterer. Due to the short wavelength of the radar (about centimeters in the L, S and C band of sub 6 GHz region) in conjunction with the small distances, inside a room-building (of the order of a few meters) for targets such as a person the multi-body approach apply. Based on this approach, the human body is considered as an assembly of

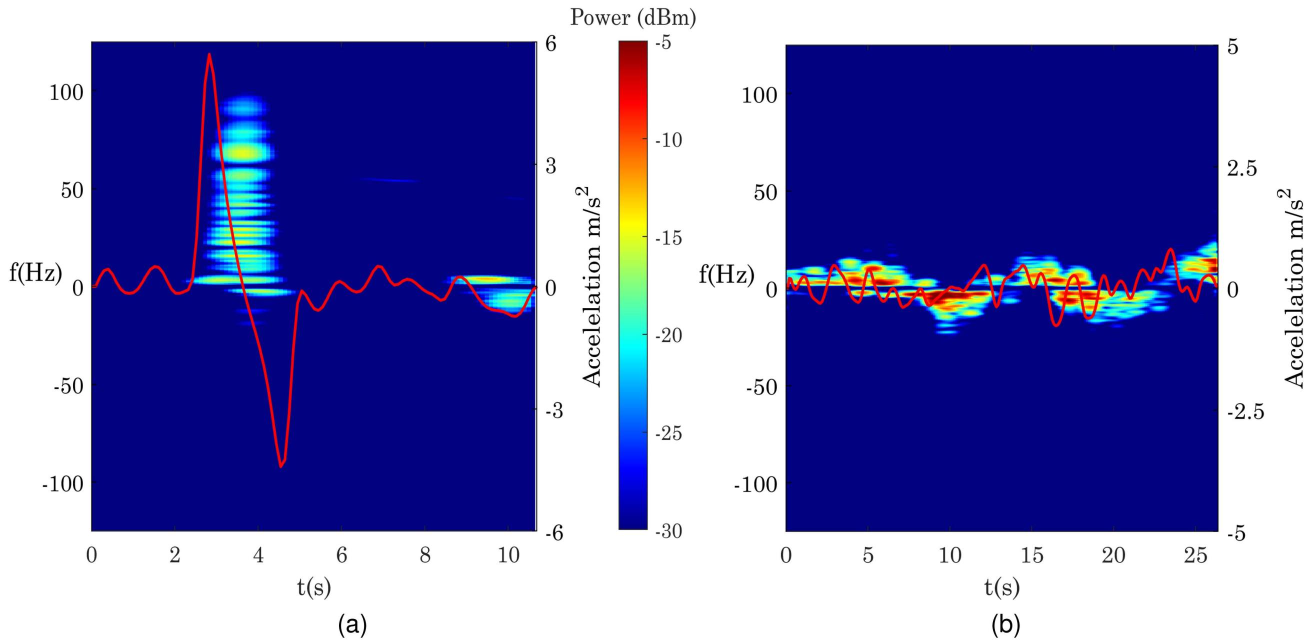

Fig. 4. Spectrogram of short time fourier transform and with the red curve the estimated acceleration when (a) a doll falls forward and (b) a person walking around a room.

separate segments-scatterers. When a body moves each segment performs a different movement, sometimes even independent. The main scatterers of a human body are the trunk, the limbs and the head. During a fall, however, the whole body is expected to have the same velocity towards the ground due to the gravity. So the main interest lies in the movement of the body trunk as its largest-main scatterer.

Besides the direction one takes whilst falling, another important aspect is the duration of the fall. The duration can be influenced by age, health and physical condition of the elder along with any consequences of activities that the individual was undertaking [33]. There are two main categories of elders' falls, according to the duration: long-slow and abrupt falls [33]. The low speed falls are caused by health or physical issues of the elder. For instance, in fainting or chest pain related episodes an elderly person might try leaning on a wall before lying on the floor. In other situations, such as injuries due to obstacles or dangerous settings (e.g., slanting or uneven pavement or surfaces), an elderly person might fall abruptly. Some studies [34] have showed, more than 60% of elderly falls are due to environmental causes (e.g. poor lighting, slippery floors, and uneven surfaces) or significant external factors (i.e., those that would lead to a fall even a healthy elder person). For the above reason the proposed method targets the detection of abrupt falls which display higher velocities.

In this work, we are going to study the abrupt and slow falls in which the acceleration is determined mainly due to gravitation acceleration $g = 9.81$ m/s^2. The proposed classifier takes into accounts the acceleration of the target, trying to grasp the benefits of the accelerometers as in [4]. Acceleration is more indicative of a fall than velocity, as demonstrated by the widespread use of wearable accelerometers. Acceleration is estimated by taking the derivative of the velocity versus time. A CW radar according to the Doppler effect gives an output a spectrum of frequencies, due to the displacement of the multibody target. In the special case of a point (comprised of a nearby target size much smaller than wavelength or any target at a large distance) only a single frequency will appear. The results of an experimental test applying an STFT and having suppressed the static targets, is shown in Fig. 4. As seen in Fig. 4(a), it is almost impossible to estimate the speed of each separate target. This challenge arises from the difficulty in distinguishing the speed of each scatterer over time.

The scope is to estimate the acceleration of the main scatterer (i.e. human torso) in time. The novelty of the proposed work is to derive an effective velocity versus time, taking into account the whole spectrum of the STFT. The effective acceleration is derived under the assumption that the elder lives alone, a scenario where falls are challenging to identify. Herein, a weighted average of the Doppler's frequency at every time step can be exploited to estimate the effective acceleration. For this purpose we utilize the normalized received reflected power of the frequency components as a weighted factor to estimate the average and a filter based on Gauss distribution. The reflected power is exploited to discriminate the main reflector from the smaller scatterers and the environmental noise. The filter is used to define the appropriate velocity range of a falling person removing slow moving behavior. Indeed, the latter acts decrease the influence of low frequency components that can be produced from non-fall cases such as sitting in a chair or standing up. A band-pass behavior was chosen instead of a high pass to minimize the interference of environmental electronic noise and external signals. This is feasible due to the limited range of velocity/acceleration during elderly fall or everyday movements which do not exceed 5 m/s [35]. The STFT spectrum includes

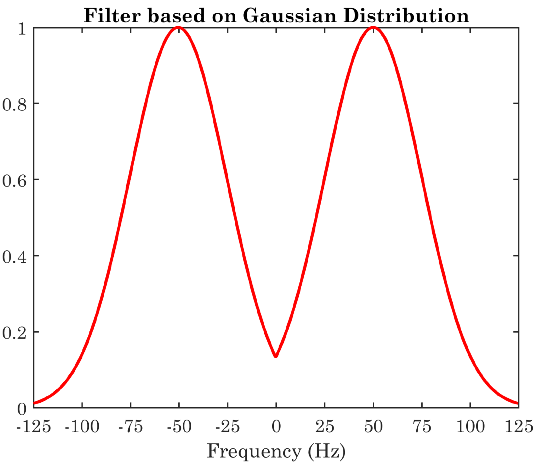

Fig. 5. Band pass filter response based on Gaussian distribution.

a positive and a negative frequency bands, where positive frequency components represent the movements toward the radar and negative distancing from it. For this reason, both positive and negative velocities (Doppler's Frequencies) need to be detected so two Gauss distribution are demanded to cover the two bands. The Gauss distribution will selected to have the same variance and opposite mean values and the final response of the band pass filter is depicted in Fig. 5.

$$u_n = \frac{\sum_{m=-M/2+1}^{M/2} S[n,m]G[m]f[m]}{\sum_{m=-M/2+1}^{M/2} S[n,m]} \tag{4}$$

$$G[m] = e^{\frac{(f[m]-f[M])^2}{2\sigma^2}} \tag{5}$$

where the u_n is the velocity at time instance n, the $f[m]$ is the frequency component derived from STFT and $G[m]$ is the filter based on Gauss Distribution with a mean value of M, $-M$ and a variance of σ^2. In the implemented 2.45 GHz CW radar, the center frequency of the filter was set at 50 Hz corresponding to a fall velocity of 3 m/s while the $\sigma = 25$. These parameters were defined based on the measurements of a falling doll recorded with the VICON system. After the effective velocity of the main scatterer was estimated using the above method, the acceleration can be derived versus time using a numerical derivative scheme. The central finite differences scheme was used to improve the accuracy of this variable. Thus for the obtained velocity vector $[u_n]$ and a time step Δt, the acceleration $[a_n]$, is approximated as:

$$a_n = \frac{u_{n+1} - u_{n-1}}{2\Delta t} \tag{6}$$

E. Fall Detection Using Acceleration Via Doppler Shift

Considering a simple case of a CW radar (separate antennas for transmit and receive) the procedure is illustrated in Fig. 6 and is as follows:

1) The radar transmits a signal (sine waveform) utilizing the transmitting antenna which was generated from the SDR and converted into analog.
2) The signal propagates in free space until it reaches a multibody target (elder) which scatters the signal.
3) Some of the scattered field is reflected towards the radar where it is collected by the receiving antenna, amplified converted again into digital in order to be processed.
4) An algorithm perform removal of stationary targets, suppressing the DC component in time domain, utilizing a moving average in each window size is estimated with (3) where $a = 0$, and then it is subtracted from the original data for real time processing.
5) Short time Fourier transform is performed on the received signal to extract the Doppler shifted frequency response caused by moving targets over time.
6) The power burst curve (2) and its moving average (3) T is calculated. If the PBC is above threshold T then the acceleration is derived based on the proposed methodology.
7) The effective velocity of the main scatterer is estimated utilizing the STFT's amplitude and a band-pass filter in every time window. The acceleration curve is estimated utilizing numerical derivative and the whole curve or some metrics of it (mean value, standard deviation, maximum value) will be fed to a classifier to determine if it is a fall or not.
8) If a fall is detected the emergency services will be contacted.

F. Data Collection

The proposed algorithm is implemented utilizing the commercial software Mathworks Matlab [36]. For the validation of the algorithm two data sets were recorder. The first data set included a total of 15 different cases of daily activities such as walking around, sitting on a chair, kneeling and falling at different angles. The tests conducted in the facilities at Department of Physical Education and Sport Sciences of Democritus University of Thrace in Komotini. The falling cases where performed utilizing a wrestling dummy (approximately 15 kg) while the non-falling cases with a human volunteer. The radar's antennas were placed parallel to the ground on a table because in the bio-mechanics laboratory it was impossible to mount it on a wall. In order to verify the results, a commercial optical system was simultaneously employed. Thus, in all scenarios the VICON was utilized to measure the position of the object at each time frame from which the velocity and acceleration can be approximated. We used the acceleration data from both the dummy and the human volunteer to verify the proposed algorithm. The aim is to validate the classified results from both the detection contact-less sensors exploiting three different metrics (the maximum value, the mean value and the variance of the acceleration) as detection parameters. With this way the classifier can be further simplified. These metrics were estimated from ten (10) consecutive time windows after the PBC curve surpass the threshold value as discussed in Section II-C.

The second data set included measurements from a more realistic scenario, an office was selected as the experimental site where the radar was positioned in a bookshelf as depicted in Fig. 7. The radar antennas are tilted towards the ground, in order

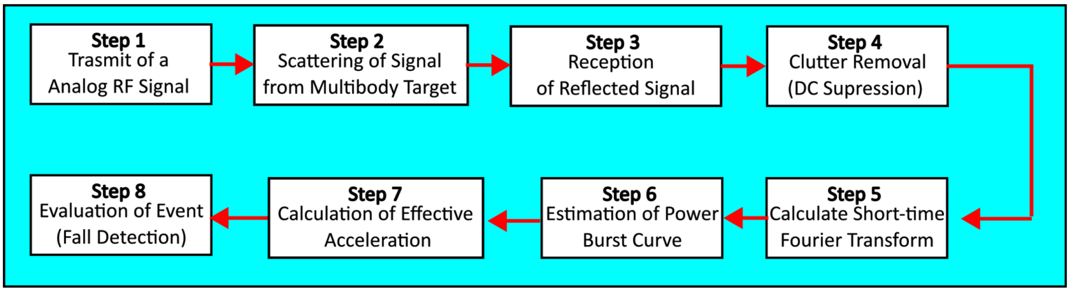

Fig. 6. Flow chart of proposed algorithm for fall detection based on acceleration.

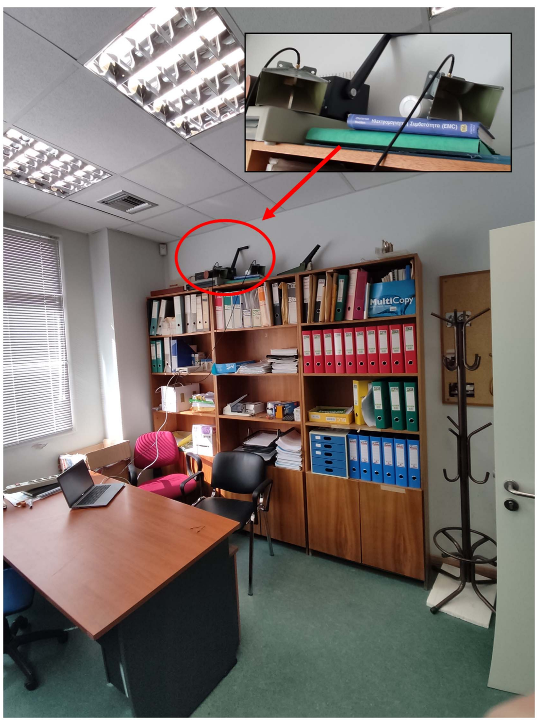

Fig. 7. Experimental site (office) where the second data sets measurements were recorded by the CW radar.

to enable the measurements of side-walls apart from the forward and backward. This time, different direction abrupt and slow falls and daily activities were conducted by a volunteer undergraduate student. The daily activities include walking around, sitting on a chair, standing up, and kneeling down. Falls may involve abrupt forward and backward falls, slow falls from a chair, falls while attempting to hang onto an object to maintain his balance, and tripping on an object. A total of 217 actions (duration 10 sec) were recorded by our CW radar. The collected data were separated in training and testing data set in order to train a simple classifier. In this test, due to small duration of actions the acceleration was estimated in the entire recordings without taking into account the PBC curve. We did this to test the validity of the proposed algorithm in the worst case scenario. Meaning that the fall and the ordinary movements produced high spectrum components yielding a PBC curve above the threshold in whole duration. For classification method of the three metrics (mean value, maximum value and variance of acceleration), a Support Vector Machine (SVM) [37] and a swallow neural network were exploited. We selected the corresponding methods trying to establish a trade-off between the best possible fall detection accuracy while demanding the lowest computational resources from the processing unit. It is determined that a simple threshold based algorithm was not enough and a deep neural network was an overkill. For this reason, the build-in functions of MatLab [36] implementing a SVM and neural were utilized and trained with the derived acceleration metrics and, then, tested. Support vector machine [37] exploits a simple mathematical model, and manipulates it to allow linear domain division of multi-dimension data (in this case 3D space). The linear support vector machine was considered because the data domain could be divided linearly (e.g., straight line or hyperplane) to separate the classes in the original domain. So it was not needed to be transformed to a space called the feature space where the data domain can be divided linearly to separate the classes (nonlinear support vector machine) which would increase the computational burden, [37]. The trained neural network is composed of two hidden layers with 8 and 4 neurons, respectively. It was trained using the one-step secant method with the cross-entropy loss function, as described in [36]. The processing time was estimate as 0.23 s for SVM while 0.4 s for neural network. Therefore, both of them can be utilized for real-time applications.

Herein, the system is comprised from off-the-shelf components (Horn antennas, laptop, SDR), thus the size, cost and power dissipation are not optimal. An alternative and more compact solution is to utilize a fully-analog implemented classifier in a chip form minimizing the entire system's footprint and power consumption. For that reason, a data-set produced from the proposed technique provided for the training of novel power-efficient and fully-analog integrated classifier architectures based on different approximations of the Decision tree classification model [38].

Finally, to validate the performance of the proposed method in real life scenarios, we performed eight (8) different test cases where the system was operating in real-time with the trained SVM model. A volunteer was instructed to perform different daily activities including kneeling, walking, sitting in chair, opening/closing door and at some point to fall toward the floor. The average duration of each test case was 2 minutes. An example of an experiment included: walking around the room for 20 s, followed by sitting on a chair for 30 s while reading a magazine. In the next step, the participant stood up, left the room, and closed the door. After spending 25 s outside the room, when he walked back in the participant slipped and fell to the ground. The radar detected the fall 8 s after it occurred. The parameters of threshold and filter based on Gauss distribution were chosen to detect the fall with high accuracy while minimizing the number of false alarms. A graphical user interface (GUI) was implemented where the PBC curve was presented for each time frame along with the threshold line. When the PBC exceeded the threshold, the system displayed a warning message. Also, the acceleration curve was estimated for a duration approximately of 8 seconds to match with the trained SVM model (10 seconds duration of actions). The acceleration was derived based on the current and the nine (9) next time frames, on total of ten (10) time frames. For this purpose, the system is waiting to collect a specific number of time frames and then the algorithm is executed to calculate the effective acceleration. As the time duration (time frames) of observation increased, the number of false alarms were decreased due to the more information delivered to classifier. However, the processed time frames were retained minimum to decrease the system's response time. It is always kept in mind that the abrupt falls are short time events which present the most harmful consequences for the elderly. The next step is to execute the classifier based on the estimated acceleration metrics to justify if a fall is occurred.

In all experiments, we estimated the values using 512-point STFT windows with an 80% overlap, while sampling the radar signal (raw data) at a rate of 250 Hz. This sampling rate was chosen to exceed the Nyquist rate, ensuring accurate signal representation. The selection of these parameters was empirically based on our measurements. For the radar operating frequency of 2450 MHz, the maximum expected Doppler shift is 125 Hz for a falling person. The selected parameters ensure a frequency resolution of 0.5 Hz. At the same time these settings minimize the recording time to 2 sec.

III. Numerical and Experimental Results

Starting, the STFT spectrum and the acceleration from the first experimental study (dummy falling towards the radar and person walking around) are depicted in Fig. 4. It is clear that the fall can be identified easily utilizing the acceleration curve where two peaks in Fig. 4(a) are displayed (acceleration due to fall and deceleration due to halt on the ground). This indicates a fall yields a huge amplitude and small event duration. On the contrary, for a person walking around (Fig. 4(b)) the amplitude is lower. The resulted effective acceleration from the 15 studied cases with both the VICON and radar systems was estimated and the metrics are displayed in Fig. 8. For the VICON system (Fig. 8(a)), the fall and non-fall cases can be distinguished utilizing a 2D plane making it easy to train a linear SVM classifier. On the contrary, the radar system, a problematic issue is displayed in Fig. 8(b). This refers to the side falls (left or right) with respect to the antennas' radiation direction gave similar response with the absent of fall activities. This behavior is attributed to radar's inability in detecting non radial movements with respect to the wave propagation of the EM wave leading to small accelerations which are marked with green circles in Fig. 8(a). This is a major drawback of exploiting radar to detect indoor falls limiting its accuracy. Recall that these measurements were performed with antennas placed only 50 cm above the ground. The proposed solution to this problem is to position the antennas, as seen in Fig. 1. This will ensure the detection of the velocity due to the fall.

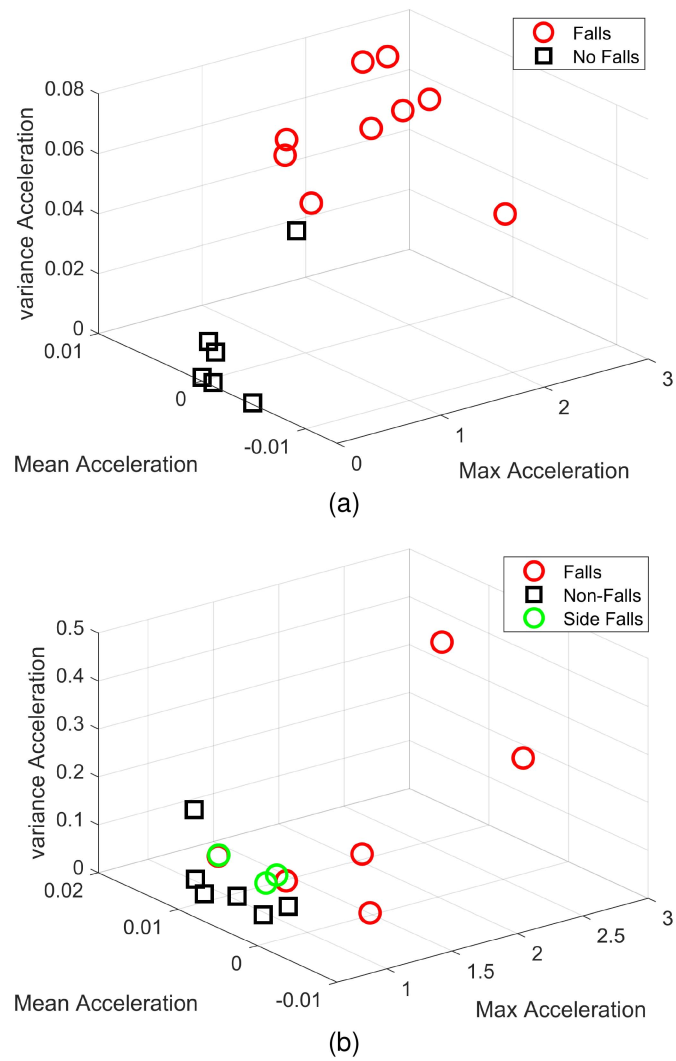

Fig. 8. 3D representation space of the estimated metrics of acceleration for the different cases of fall and non-fall measured utilizing (a) optical sensors and (b) SDR radar system.

In the second data set, the antenna's position (Fig. 7) has changed to be able to detect side falls' response with better accuracy. From the 217 total cases recorded (150 non-falls and 67 falls), the 67 were utilized as training data set and the 150 as the test case for the SVM. We choose this low number of training cases to highlight the capabilities of the proposed method. It can determine the abrupt and some slow falls without the need of a high complexity classifier model utilizing state-of-the-art neural networks. Herein, a simple 2D support vector is enough to discriminate the fall from non-fall cases showing an incredible 93.7% accuracy. A two-layered neural network can provide accuracy of 94.5% while maintaining low processing time.

One drawback of the current method is that some falls falsely indicated as non-fall cases, meaning that some cases even with the modification of the radar position are not recognized as falls. Some side falls occurred outside of the antennas' viewing angle range and some slow falls are not recognized as falls. For the latter case, the volunteer tried to hold up on a desk before the fall, decreasing the velocity of fall.

Finally, to test the real-time capabilities of the systems, real life scenarios were conducted while the systems was operating non-stop. In each scenario, a fall occurred in a random moment. The aim was to test if the radar system is able to detect the fall with the minimum time delay and display a warning message. From the eight (8) real time scenarios, when the fall took place the system identified it in 6 cases while the number of false alarm was zero. The mean response time of the detection alert was 15 seconds.

IV. Discussions

Comparing the results from the two systems, a similar behavior is observed in non-fall cases in which the metrics are close to zero. Acceleration measured by VICON indicates higher discrepancy between the two classes as seen in Fig. 8(a). This is due to the use of wearable sensors in different position of the dummy and human (torso, head and limbs) which can determine their position in 3D space. On contrary, the measured fall response utilizing the radar system is degraded due to the aforementioned inability of recording the radial velocity of each human body's scatterer separately. However, the fall cases have greater maximum and variance value of acceleration for both cases. Another reason for these differences in the responses in the two methods may lie in the capability of radar to measure only the radial velocity. Beside these, the electronic noise interference from electromagnetic sources (e.g. mobile phones) or interference resulting from field scatterer by the walls and objects in the room. However, this comparison verified the low cost radar capability to estimate the falling person acceleration and thus to identify a fall situation.

For a more practical validation, the method was tested in a data set including 187 total cases of human activities such as walking, sitting on a chair, standing up and falls. These are separated into test and train data set. The duration of each action was set to 10 seconds. Their effective acceleration is estimated at every time frame, and then the maximum, average and variance values were calculated. A SVM implemented in MatLab [36] was trained based on the aforementioned metrics and its fall detection capabilities tested. A 95.2% accuracy was achieved highlighting the operation of the methodology. In Table I, the accuracy of different proposed methods from the literature are depicted and compared against this low cost system. The proposed system's performance is comparable with state-of-the-art machine learning methods (e.g. LSTM and neural networks) maintaining the complexity and the cost at low levels.

Lastly, the developed algorithm (Fig. 6) was tested in real-time scenarios where a person performed different daily activities and falling at some point. The aim was to ensure a quick fall identification, while retaining the false alarms at minimum. It was displayed that the system is capable for non-stop operation in real life applications. A short time detection accuracy of 75% was achieved for a delay perceiving the fall.

TABLE I
Comparison Table of Fall Detection Accuracy for Different Methods in the Literature With Their Corresponding Data Set (Number of Cases/Number of Subjects)

Method	Accuracy	Data Set
Triaxial Accelerometer [4]	78.04 %	1296/66
Infrared Sensors [9]	93 %	160/5
Mel-Frequency Cepstral Coefficients [12]	91/97 %	450/3
LK Convolutional Neural Network [39]	95.24 %	231/11
LSTM Network [27]	95.2 %	100/2
Radar Sensor Fusion [24]	95.5 %	224/4
LSTM-CNN Combination [40]	89.8 %	206/5
This Work (SVM)	93.7 %	217/1
This Work (Neural Network)	94.5 %	217/1

All of the front and back fall with the respect of the radar were successfully detected from the system. The degraded accuracy is due to one side fall with respect to the radial axis defined by the antenna maximum radiation and the object/human. The other missed fall included a fall where the participant was tried to hang from a desk limiting the falling velocity. Among this cases, the peaks were displaced but their values were relatively lower ($0.8 - 1$ m/s^2) than the other falls (>1.5 m/s^2) and they are not recognized as falls from the SVM.

A way to mitigate the missed falls and false alarms cases was then brainstormed. Since, the missed falls were always toward side directions, the most reliable way is to employ an antenna array with multiple offset directional beams covering the room. A convenient way is to utilize a Butler matrix beamforming with four consecutive beams. These can be successively enabled-switched with the aid of a digitally controlled RF-switch. In turn the methodology described herein will be applied for a data measured-received from each beam. The results could then be fed to the SVM or any other machine learning algorithm aiming at an unambiguous fall estimation. A more general solution includes the combination of the proposed methodology with a sound or visual system to identify slow and side falls effectively. This is extremely crucial for slow falls, which may be challenging to recognize them due to their low acceleration. In such cases, it is necessary to incorporate a more biased fall-detecting algorithm, even if the false alarms increase. In this system, a separate system (utilizing visual cameras or sound sensor) is activated only when the radar system detects a fall. This complementary sensor system then determines whether the detected case is a fall or not. Collaboration with one of our partners can be established to implement this combined approach effectively [41]. Another potential aspect is the integration of a commercial device in our system [42]. However, the utmost importance lies in ensuring the privacy of the elderly. To achieve this, the processing of raw data must be executed locally, and only the classification results will be sent via the internet.

Overall in this study a novel method was established discriminate the fall cases from non-falls based on the acceleration which derived from a CW radar for one target presented. Although, the setup and the method need to modified accordingly to be applied in real life. The next task planned refers downloading the resulting software-code to an ARM processor embedded in the SDR. Our ultimate task is to combine this effort with the one submitted in [38] so as to implement a low cost and low power consumption system. The usage of multiple radar systems seems also a good solution but it highly increases the complexity of the total system as well as the cost. Furthermore, an FM-CW wide-band radar can be implemented to estimate both the velocity and radial distance of the target for better localization. In addition, a technique must be implemented to discriminate two different targets inside the house and to be able to detect if a fall in the presence of two persons. Lastly, a more representative data set needs to be established where the test subjects will be elders to test the reliability of the proposed method in a more realistic way. This is important because the falls of a young volunteer only partially approach the fall of an elder. The difficult task here is to ensure that the falling cases of the elder will not be harmful.

V. Conclusion

A novel elderly fall detection method was proposed exploiting the metrics of power burst curve and an effective acceleration estimated from the radar's STFT. The scope of the corresponding method is minimize the processing time and resources activating the classifier only when the PBC value exceeds a threshold value that can be either constant or adaptive estimated. The effective acceleration will take into account all the STFT's spectrum in order to derive a weighted average acceleration of each detected human part from the radar to synthesize a whole body response. To validate the above statements, a CW radar was implemented utilizing a SDR and a mid-range laptop as a processing unit and measurements conducted of different activities including fall and non-fall actions. For validation purposes, during the measurements with the radar the activities were recorded using a commercial system of optical sensors to measure the acceleration more accurately and to compare their response with the radaras. The recorded data were discriminate based on the effective acceleration with a simple algorithm and the accuracy was estimated 80% during a real-time scenario.

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