Radar Signal Processing for Elderly Fall Detection

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***Abstract*—Radar is considered an important technology for health monitoring and fall detection in elderly assisted living due to a number of attributes not shared by other sensing modalities. In this paper, we describe the signal processing algorithms and techniques involved in elderly fall detection using radar. Radar signal returns from humans differ in their Doppler characteristics depending on the nature of the human gross-motor activities. These signals are nonstationary in nature, inviting time-frequency analysis in both its linear and bilinear aspects, to play a fundamental role in motion identification, including fall features determination and classification. The paper employs real fall data to demonstrate the success of existing detection algorithms as well as to report on some of the challenges facing technology developments for fall detection.**

I. Introduction

The elderly population aged over 65 years is growing and their ratio to the population aged 20–64 will reach 35% in 2030 [1]. The worldwide population over 65 is projected to increase to one billion in 2030. The overwhelming majority of elderlies exercise self-care at their own homes most of the time. One out of three elderlies will fall every year; the fall can result in injuries, reduced quality of life and, unfortunately, it represents one of the leading causes of death in the elderly population. Eventually, the high fall risk elderly will have to move to institutionalized care, which can cost in US about \$3,500 per month. Most seniors are unable to get up by themselves after a fall and it was reported that, even without direct injuries, half of those who experienced an extended period of lying on the floor (more than an hour) died within six months after the incident. Therefore, prompt fall detection saves lives, leads to timely interventions and most effective treatments, and reduces medical expenses. Further, it avoids major burdens on the elderly family. Driven by a pressing need to detect and attend to a fall, elderly fall detection has become an active area of research and development and is identified as a major innovation opportunity to allow seniors to live independently [2]. There are competing methods for fall detection of which wearable devices, like accelerators and “push buttons”, are most common. The shortcomings of these devices are that they are intrusive, easily broken, and must be worn or carried. In addition, “push-button” devices are less suited for cognitively impaired users.

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Although in-home radar monitoring of elderly for fall detection, which is the subject of this paper, is still in its early stage of development, it carries great potential to be one of the leading technologies in the near future. The attractive attributes of radar, related to its proven technology, non-obstructive illumination, non-intrusive sensing, insensitivity to lighting conditions, privacy preservation and safety, have brought electromagnetic waves to the forefront of indoor monitoring modalities in competition with cameras and wearable devices [3]. Radar backscatters from humans in motion generate changes in the radar frequencies, referred to as Doppler effects. The Doppler signatures determine the prominent features that underlie different human motions and gross-motor activities. Recently, enhanced detection and classification techniques of radar signals associated with micro- and macro-motions have been developed to identify falls from standing, sitting, kneeling and other motion articulations, with a high detection probability [4]–[10]. Reference [4] explored the dynamic nature of a fall signal and used the mel-frequency cepstral coefficients (MFCCs), in conjunction with machine learning approaches, to differentiate radar echo behaviors between falls and non-falls. References [4], [6], [7], [9] used features extracted from time-frequency signal representations to discriminate between fall and non-fall motions. Radar fall signals were analyzed using Wavelet transform (WT) in [8] and [10] and features extracted in the joint time-scale domain were used for fall classification. In [5], data from a multiplicity of Doppler sensors were fused via feature combination or selection to distinguish falls from other gross motor activities.

A Doppler radar obtains target Doppler information by observing the phase variation of the return signal from the targets corresponding to repetitively transmitted signals. An important property of Doppler radar is its ability to effectively suppress clutter, represented by strong scatterings of the electromagnetic waves from room furniture, floors, ceiling, or from interior walls. Radars have also the capability to separate motions of animate and inanimate targets, like fans and pendulums [11]. Radar units in homes can be low cost, low power, small size, and can be mounted on walls and ceilings in different rooms, depending on needs and signal strength.

The role of radars in assisted living predicate on its ability to perform detection, classification, and localization. Successful detection of a fall as well as locating its occurrence to, at

Fig. 1. Types of falls: Heart-attack (top) and tripping (bottom) [12] (Reproduced by permission).

least, room accuracy, and classifying its type (see Fig. 1) with low false alarm and high classification rates would provide key information to the first responders. On the other hand, distinguishing between a heart attack type of fall and a tripping type of fall can certainly aid in mobilizing the necessary care and treatment.

The emerging area of fall detection using radar builds on three foundations:

1) *Information Technology*, via the development of signal processing algorithms and the corresponding software for elderly fall detection, localization, and classification.
2) *Human Factors and Behavior Science*, via the understanding of human normal gross-motor activities and those affected by medications and physically impairing illnesses.
3) *System Engineering and Engineering Design*, via efficient integrations of hardware and software modules to produce a cost-effective, reliable, and smart system which realizes the full potential of fall detection algorithms.

In this paper, we discuss only the first foundation, though the other two foundations are essential for the development of an overall system for fall monitoring. The main challenges in fall detection using radar are as follows:

i) High false alarm rates stemming from confusion of falls with similar motions, like sitting and kneeling;
ii) Presence of scatterers caused by interior walls which create clutter and ghost targets;
iii) Occlusion of the fall due to large stationary items, like filing cabinets.
iv) Weak Doppler signatures stemming from orthogonality of motion direction to the radar line of sight;
v) Reliability of fall detection irrespective of the immediate preceding motion articulations;
vi) Similar Doppler signatures of pets jumping off tables and chairs to those of a human falling; and
vii) The presence of multiple persons in the radar field of view.

Although it is important to develop superior fall-detection algorithms, some of the above challenges can be addressed through logistics and increased system resources. In reference [5], multiple Doppler sensors are exploited to raise the precision of fall detection by covering the target movement from multiple directions and to combat occlusions. The fusion of data is performed by either feature combination or selection. Although more complex to implement, the combination method is shown to outperform the selection method for different fall and non-fall motion classifications. When using multiple radars, a change in the carrier frequency is recommended to avoid mutual interference. The radar operational frequencies should not, in general, intervene with other services, such as terrestrial TV, cellular phones, GPS, and Wi-Fi, and should adhere to the frequency allocations guidelines.

In [4]–[6], [8], [9], a fall is isolated from a preceding motion by identifying the beginning and the end of a fall event. The fall micro-Doppler features are then extracted within the identified time interval. An ultra-wideband (UWB) range-Doppler radar with 2.5 GHz bandwidth is used in [13] to provide range information, revealing the spatial extent of the fall which typically exceeds that of sitting or kneeling. A range-Doppler radars can also resolve targets and thereby permits the radar to handle more than one person in the field of view (e.g., [14]). In this case, both the intended elderly and other person(s) in the room will be monitored. While the radar system may be deployed as a unit involving a single antenna, one can incorporate an increasingly distributed transmitter and receiver system to cope with occlusions and other practical challenges. When used in a multi-unit system, the range information localizes the target, through trilateration, and as such, can eliminate ghosts [5].

The remainder of the paper is organized as follows. The signal model is presented in Section II. Domains appropriate for analyzing the Doppler signature associated with falls are delineated in Section III. Section IV describes the features suitable for fall detection and briefly discusses the classifiers. Supporting results based on real data experiments are provided in Section V. Section VI discusses open issues and Section VII contains the concluding remarks.

II. Signal Model

Consider a monostatic continuous-wave (CW) radar which transmits a sinusoidal signal with frequency f_c over the sensing period. The transmitted signal is expressed as $s(t) = \exp(j2\pi f_c t)$. Consider a point target which is located at a distance of R_0 from the radar at time $t = 0$, and moves with a velocity $v(t)$ in a direction forming an angle θ with the radar line-of-sight. As such, the distance between the radar and the target at time instant t is given by

$$R(t) = R_0 + \int_0^t v(u)\cos(\theta)du. \tag{1}$$

The radar return scattered from the target can be expressed as

$$x_a(t) = \rho \exp\left(j2\pi f_c\left(t - \frac{2R(t)}{c}\right)\right) \tag{2}$$

where ρ is the target reflection coefficient and c is the velocity of the electromagnetic wave propagation in free space. The Doppler frequency corresponding to $x_a(t)$ is given by $f_D(t) = 2v(t)\cos(\theta)/\lambda_c$,where $\lambda_c = c/f_c$ is the wavelength. A spatially extended target, such as a human, can be considered as a collection of point scatterers. Therefore, the corresponding radar return is the integration over the target region Ω and is expressed as

$$x(t) = \int_\Omega x_a(t)da. \tag{3}$$

In this case, the Doppler signature is the superposition of all component Doppler frequencies. Torso and limb motions generally generate time-varying Doppler frequencies, and the nature of this variation defines the Doppler signature associated with each human gross-motor activity, including a fall. The exact Doppler signatures depend on the target shape and motion patterns.

III. Appropriate Signal Analysis Domains

A human fall has a quick acceleration motion of short duration at the beginning until reaching the ground and a slow deceleration motion of long duration towards the end upon lying on the floor. Such a dynamic creates a Doppler radar return that is nonstationary, as in eq. (3). This type of nonstationary signals can be well described and analyzed by joint time-frequency representations that reveal the local behavior of the signal and depicts its time-varying Doppler frequency signatures, thereby supporting the radar primary tasks of detection and classification.

A number of methods are available to perform time-frequency analysis of the Doppler signatures [4], [6], [7], [9]. These methods can be generally divided into the linear time-frequency analysis and quadratic time-frequency analysis methods. Short-time Fourier transform (STFT) is a commonly used technique to perform linear time-frequency analysis [15]. Time-scale analysis using wavelet transform (WT) [16] is also considered an effective linear method to analyze and extract the characteristics of radar fall signals that exhibit nonstationary behaviors [8], [10].

Quadratic time-frequency distributions (QTFDs) involve the data bilinear products, and are defined within Cohen's class [17]. QTFDs have been shown to be most suitable in analyzing wideband signals which are instantaneously narrowband. The spectrogram $S(t, f)$ in a key member of Cohen's class, and is obtained at time index t and frequency f by computing the squared magnitude of STFT of the data $x(t)$ with a window $h(t)$. Other members of Cohen's class are obtained by the two-dimensional Fourier transform of its kernelled ambiguity function, expressed as

$$D(t, f) = \sum_{\theta=-\infty}^{\infty} \sum_{\tau=-\infty}^{\infty} \phi(\theta, \tau)A(\theta, \tau)\exp(j4\pi f\tau - j2\pi\theta t), \tag{4}$$

where

$$A(\theta, \tau) = \sum_{u=-\infty}^{\infty} x(u + \tau)x^*(u - \tau)\exp(-j2\pi\theta u) \tag{5}$$

is the ambiguity function, $\phi(\theta, \tau)$ is the time-frequency kernel, and $(\cdot)^*$ denotes the complex conjugate. Here, θ and τ, respectively, denote the frequency shift (also referred to as Doppler frequency) and time lag. The properties of a QTFD are heavily dependent on the applied kernel.

The Wigner-Ville distribution (WVD) is often regarded as the basic or prototype QTFD, since its filtered versions describe Cohen's class. WVD is known to provide the best time-frequency resolution for single-component linear frequency modulated signals, but it yields undesirable cross-terms when the signal frequency law is nonlinear or when a multi-component signal is analyzed. The kernel function of the WVD is unity across the entire ambiguity function. Various reduced-interference distributions (RIDs) have been developed to reduce the cross-term interference. Majority of signals have auto-terms located near the origin in the ambiguity domain, while the signal cross-terms are distant from the time-lag and frequency-shift axes. As such, RID kernels $\phi(\theta, \tau)$ exhibit low-pass filter characteristics to suppress cross-terms and preserve auto-terms. For example, the Choi-Williams distribution uses a Gaussian kernel in both frequency shift and time lag axes, which is expressed as $\phi(\theta, \tau) = \exp(-\mu(\theta\tau)^2)$, where μ is a

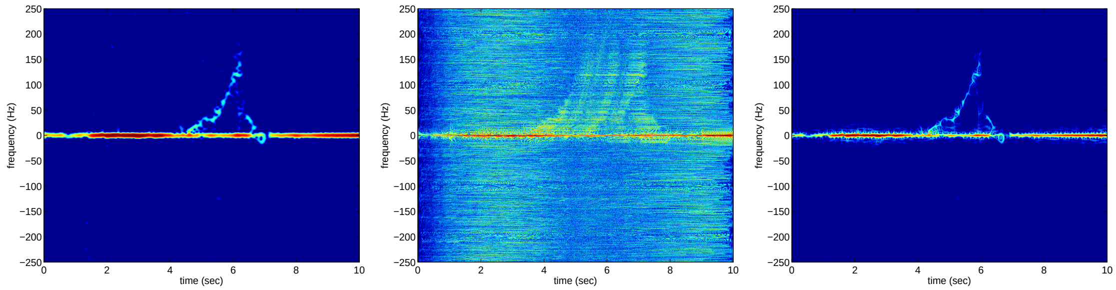


Fig. 2. Time-frequency distributions of fall motion: Spectrogram (left), WVD (center), and EMBD (right).

constant [18]. Another alternative is the extended modified B-distribution (EMBD) which is a product of a Doppler-domain filter and a lag-domain filter, expressed as [19]

$$\phi(\theta,\tau)=\frac{|\Gamma(\beta+j\pi\theta)|^2}{\Gamma^2(\beta)}\frac{|\Gamma(\alpha+j\pi\tau)|^2}{\Gamma^2(\alpha)}, \qquad (6)$$

where $-0.5\le\theta\le0.5$, $-0.5\le\tau\le0.5$, $0\le\alpha\le1$, and $0\le\beta\le1$. The lengths of the Doppler and lag windows are controlled by separate parameters α and β, respectively. The extra degree of freedom in the formulation of the EMBD allows to independently adjust the lengths of the windows along both lag and Doppler axes.

Fig. 2 compares different time-frequency representations of the Doppler signature of a human fall from standing in the form of the spectrogram, WVD, and EMBD. A 255-point Hamming window is used for the computation of the spectrogram. All results are depicted on a logarithm scale with a 25 dB dynamic range. It is clear that the spectrogram provides a clean distribution without cross-terms, but with a coarse resolution. Due to signal containing multiple irregular components as well as a strong residual clutter, the WVD exhibits a high level of cross-term and sidelobe contamination, thereby rendering TFD-based motion classification challenging. The EMBD, on the other hand, provides better contrast and connectivity and reveals a higher level of detail as compared to the spectrogram.

Similar to the STFT, the WT uses the inner products to measure the similarity between a signal and an analyzing function. In STFT, the analyzing functions are windowed complex exponentials, and the STFT coefficients represent the projection of the signal over a sinusoid in an interval of a specified length. In the WT, the analyzing function is a wavelet. According to the uncertainty principle [20], the product of the time resolution and the frequency resolution is lower bounded, that is, we cannot achieve a high resolution in both the time domain and the frequency domain at the same time. Therefore, although STFT can observe the time-varying frequency signatures, the question always arises as the optimum window length for the given data for the best tradeoff between spectral and temporal resolutions. In the WT, the analyzing function is a wavelet. The WT implements the multi-resolution concept by changing the position and scaling of the mother wavelet function and thereby captures both short duration, high frequency components and long duration, low frequency components [21]. There are many choices of the wavelet functions, depending on the properties imposed on the wavelets. When the data is in discrete form, the WT can be computed very efficiently by restricting the scales to be dyadic and the positions to be integer. Such a fast computation uses a high-pass and a low-pass filter to represent the wavelet function, and successive filtering generates the Discrete Stationary Wavelet Transform (SWT) [22]. SWT is redundant and it produces the same number of samples as the data at each scale. However, it avoids the shift variant behavior that appears in the non-redundant discrete WT.

It is noted that Mel-frequency cepstrum is another representation of the short-term power spectrum for nonstationary signals and has been used in [4] to represent the Doppler signatures. Empirical mode decomposition (EMD) has also been used to examine human Doppler signatures [23], [24]. EMD is an adaptive technique that decomposes a signal into time-frequency components called intrinsic mode functions (IMFs). Each IMF comprises signal components that belong to a specific oscillatory time scale. The energy as a function of the IMF index provides a unique feature vector with which human motion classification can be achieved. Further, time-frequency representations based on compressed sensing and sparse reconstructions have been successfully employed in [25], [26] for high-resolution Doppler signature analysis and radar operation with non-periodic sub-Nyquist sampling.

IV. Feature Extraction and Classification

Fig. 3 shows the data processing blocks for fall detection. The radar data is first transformed to an appropriate domain, followed by a prescreening step which determines whether an important event may have occurred and, if so, its time location. Once an event is detected by the prescreener, a classification process is initiated to detect whether such an event is a fall. More specifically, windowed transformed data around the identified event time location is used to extract pertinent features, which are used by a classifier to perform fall versus non-fall classification. A power burst curve (also referred to as the energy burst curve), which represents the signal power within a specific frequency band as a function of time, can be utilized for prescreening [4], [9]. The frequency band chosen for prescreening should be a low-frequency band

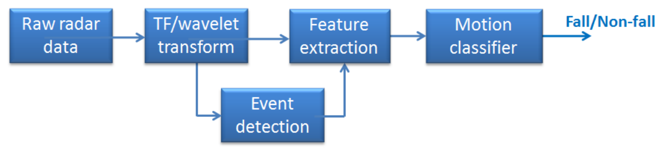


Fig. 3. Data processing blocks for fall detection.

that excludes the clutter-dominated zero-frequency region but effectively captures human activities. An event is triggered for classification when the signal power in the specified frequency band exceeds a certain level. The coefficients of wavelet decomposition at a given scale have also been used in the prescreening stage to identify the time locations where fall activities may have occurred [10]. The details of the classification stage are elaborated using an STFT-based approach in Subsections A–C, and a wavelet-based approach is described in Subsection D.

A. Feature Definitions

For fall detection based on STFT, pertinent features include extreme frequency magnitude, extreme frequency ratio, and time-span of event [9].

1) Extreme Frequency Magnitude: The extreme frequency magnitude is defined as $F = \max(f_{+\max}, -f_{-\min})$, where $f_{+\max}$ and $f_{-\min}$, respectively, denote the maximum frequency in the positive frequency range and the minimum frequency in the negative frequency range. Critical falls often exhibit a high extreme frequency magnitude when compared to other types of observed motions.

2) Extreme Frequency Ratio: The extreme frequency ratio is defined as $R = \max(|f_{+\max}/f_{-\min}|, \quad |f_{-\min}/f_{+\max}|)$. For falls, due to the translational motion of the entire body, high energy spectrogram is concentrated in either the positive or negative frequencies, resulting in a high extreme frequency ratio. On the other hand, other types of motions, such as sitting and standing, often demonstrate high energy content in both the positive and negative frequency bands because different body parts undergo different motion patterns, thereby corresponding to a low extreme frequency ratio.

3) Time-Span of Event: This feature describes the length of time, in milliseconds, between the start and the end of an event, i.e., $L = t_{\text{extrm}} - t_{\text{begin}}$, where t_{extrm} denotes the time where the extreme frequency occurs and t_{begin} denotes the initiation time of the event. The latter is determined by the time when the magnitude of the frequency content of a signal passes a specific threshold. The different motion patterns being compared in this work generally show distinct time spans.

The aforementioned three features extracted from the spectrogram have been used for fall detection in [9]. Additional features have also been extracted from time-frequency distributions for classification of human activities (see, e.g., [27], [28] and references therein). These include torso Doppler frequency, total bandwidth of the Doppler signal, offset of the total Doppler, normalized standard deviation of the Doppler signal strength, period of the limb motion, shape of the spectrogram envelope, ratio of torso echoes to other echoes in the spectrogram, and Fourier series coefficients of spectrogram envelope. Nonparametric features derived from subspace representations of the time-frequency distributions have also been proposed. Effective and reliable fall detection often requires the combined use of multiple features. Once a set of features is extracted, a classification algorithm can be applied to determine whether an event is a fall or non-fall activity.

B. Classifiers

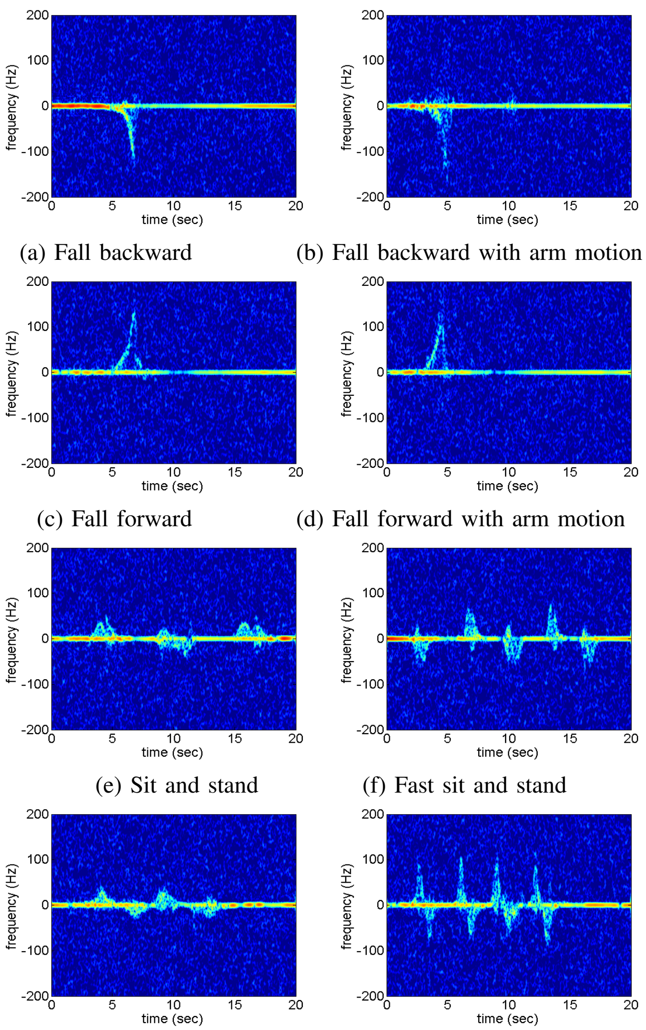
A variety of classifiers have been employed for fall detection [4], [27], with the SVM being the most commonly used classifier. Different classifiers, including k-nearest neighbor, are used to automatically distinguish falling from activities, such as walking and bending down [4]. Sparse Bayesian learning method based on the relevance vector machine improves fall detection performance over the SVM with fewer relevance vectors and its effectiveness is demonstrated in [9]. Hidden Markov model based machine learning is used in [6] to characterize the signal spectrogram for fall detection. However, the choice of employed features has been determined to have a greater impact on the classification performance than the specific classifier applied (see [28] and references therein).

C. Classification Results

A CW radar was set up in the Radar Imaging Lab at Villanova University. A vertically polarized horn antenna (BAE Systems, Model H-1479) with an operational frequency range of 1–12.4 GHz and 3-dB beamwidth of 45 degrees was used as a transceiver for the CW radar. The feed point of the antenna was positioned 1 m above the floor. Agilent's E5071B RF network analyzer was used for signal generation and measurement of radar returns. A carrier frequency of 8 GHz was employed and the network analyzer was externally triggered at a 1 kHz sampling rate. Data were collected for eight different motion patterns using two test subjects, with each experiment motion pattern repeated 10 times (five times each for two test subjects). Considered motion patterns include i) forward falling, ii) backward falling, iii) sitting and standing, and iv) bending over and standing up. Two different variations of each motion pattern were measured, one being a standard type of motion whereas the other demonstrating a high-energy form of the same motion in order to study the impact of such variations on the classification performance. The recording time for each experiment is 20 seconds [9].

The typical spectrograms of the eight considered motion patterns are shown in Fig. 4. The first four patterns are collectively considered as falls, whereas the last four patterns are collectively considered as non-fall motions. Our objective is to correctly detect fall events from non-fall events. Fig.

5 depicts the ground truth of three aforementioned STFT-based features, i.e., the extreme frequency magnitude, the extreme frequency ratio, and the time-span of event [9]. Specifically, Fig. 5(a) shows the three-dimensional view of the three features, whereas their pairwise two-dimensional plots are respectively provided in Figs. 5(b)–5(d). It is observed that these features generally provide a clear distinction between the fall and non-fall events, except one outlier fall event (marked with a circle). Examination of the spectrogram of this outlier fall event shows that the corresponding signal is very weak, yielding low extreme Doppler frequency as well as a short time-span of the event. The fall events exhibit larger extreme frequency magnitudes, higher extreme frequency ratios, and longer lengths of event time than the non-fall counterparts. These features, however, do not robustly classify the fall and non-fall activities based on a single feature alone.



(a) Fall backward (b) Fall backward with arm motion

(c) Fall forward (d) Fall forward with arm motion

(e) Sit and stand (f) Fast sit and stand

(g) Bend and stand up (h) Fast bend and stand up

Fig. 4. Spectrograms of typical motion profiles [9] (Reproduced by permission of the Institution of Engineering & Technology).

The SVM classifier is applied by using a Gaussian kernel. Five-fold cross-validation is used on the motion data. The entire sample set is randomly partitioned into five equal-size subsets. Out of the five subsets, a single subset is retained as the validation data for testing the classifier, and the remaining four subsets are used as the training data. The cross-validation process is repeated five times, with each of the five subsets used exactly once as the validation data. The classifier is successfully able to detect fall from non-fall events except for the misclassification of the outlier fall event as described earlier and marked in circle in Fig. 5(a).

D. Wavelet-Based Approach

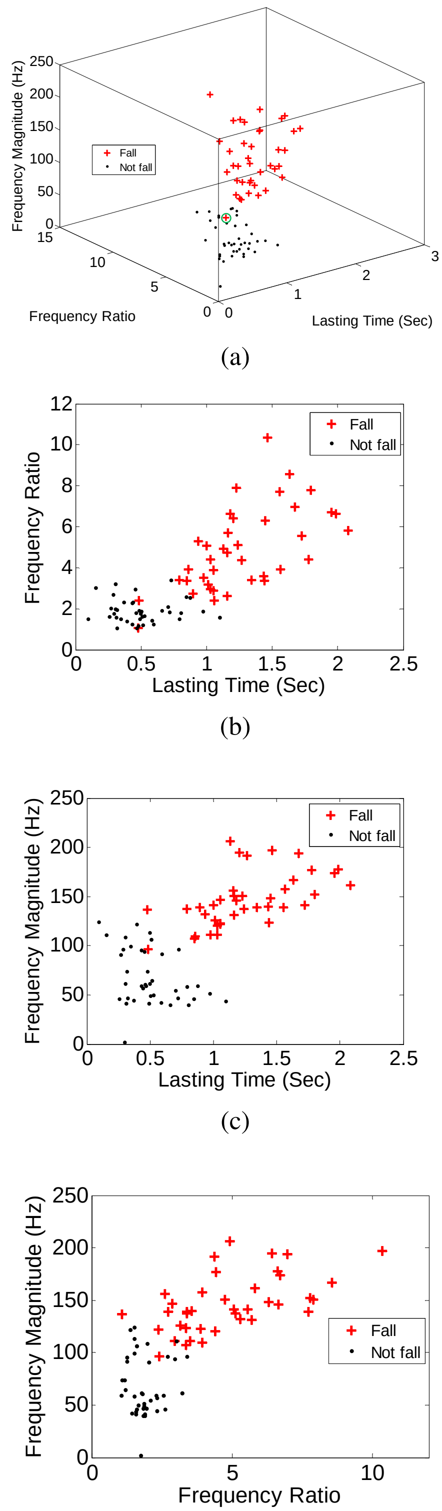
1) Feature Definition: WT-based features include the smoothed magnitude square of the discrete SWT coefficients of the radar signal at several dyadic scales, over a moving window (frame) typically of 0.5 second with 50% overlap [10]. The collection of features in 2.5 seconds centered at the event location identified by a prescreener forms the feature vector for classification. The smoothed magnitude square of the SWT coefficients is defined below.

Smoothed Magnitude Square of the SWT Coefficients. Let $\tilde{\xi}_i(k)$ be the sum of the square of the SWT coefficients at dyadic scale 2^i in frame k. There will be nine frames in a total of 2.5 seconds that contains a possible fall event. Normalization of $\tilde{\xi}_i(k)$ by the sum of the nine values is often needed, giving $\xi_i(k)$. The collection of the nine $\xi_i(k)s$ forms the row vector $\boldsymbol{\xi}_i$. Over the dyadic scales 2^{i_b} to 2^{i_e}, the feature vector for classification is $\mathbf{y} = [\,\boldsymbol{\xi}_{i_b} \cdots \boldsymbol{\xi}_{i_e}\,]$.

It is noted that the study in [4] applied cepstral analysis of the radar signal for fall detection. The MFCCs were extracted over a 4-second data segment that might contain a fall activity and encouraging classification results between falls and non-falls were observed.

2) Classification Results: Wavelet based fall detection results are presented using real data collected in three different bathrooms of senior residence apartments [29]. A bathroom is where falls of elderly people could occur often and yet other sensors, such as video cameras or acoustic sensors, are not suitable due to privacy reasons or strong interferences. The data collection was performed from January to May, 2013, where the Doppler radars were mounted above in the attic at the middle of the bathrooms. The dataset contains 19 different kinds of falls and 14 various typical non-falls that were performed by a professionally trained female stunt actor [10]. The fall types and their counts are tabulated in Table I.

The radar used in the experiment is a commercially available pulse-Doppler range control radar with a price close to that of a webcam. The pulse repetition rate is 10 MHz, the duty cycle is 40% and the center frequency is 5.8 GHz. The sampling frequency of the radar signal is 960 Hz. Based on the velocity range during a human fall, dyadic scales from 2 to 64 are used to generate the features, giving the feature vector length of $6(\text{scales}) \times 9(\text{frames}) = 54$. The



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

Fig. 5. Ground truth of motions with 3-D vision and three 2-D visions [9] (Reproduced by permission of the Institution of Engineering & Technology).

TABLE I
DESCRIPTION OF FALLS.

Fall Type	Count
Loose balance-Forward	11
Loose balance-Backward	9
Loose balance-Left	8
Loose balance-Right	10
Loss of consciousness-Forward	3
Loss of consciousness-Backward	3
Loss of consciousness-Left	2
Loss of consciousness-Right	3
Loss of consciousness-Straight down	3
Trip & fall-Forward	1
Trip & fall-Sideways	2
Slip & fall-Forward	4
Slip & fall-Sideways	5
Slip & fall-Backward	4
Reach-fall (chair)-Forward	2
Reach-fall (chair)-Left	1
Reach-fall (chair)-Right	2
Reach-fall (chair)-Sliding forward	4
Reach-fall (chair)-Sliding backward	5

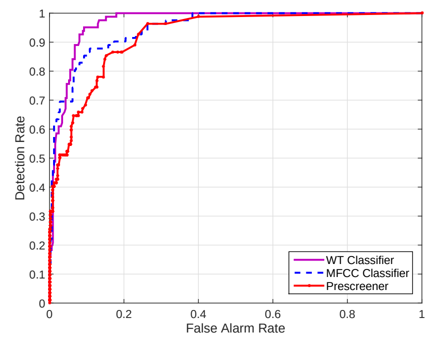


Fig. 6. Classification performance of WT features.

wavelet function for SWT is the reverse bi-orthogonal 3.3 wavelet. The window function is Hamming. The classifier is the k-nearest neighbor with $k = 1$ for fall versus non-fall classification. The data was acquired in a continuous manner as in practice. A prescreener based on the SWT coefficient values at scale equal to 4 gives the potential falls locations for feature extraction and classification. Fig. 6 examines the classification performance using the SWT and the MFCC features, using leave one out cross-validation between training and testing. The false alarm rate is the number of false alarms normalized by the total number of events from the prescreener. The WT classifier has comparable performance with the MFCC classifier for detection rate below 80% and has much better results otherwise. At a 100% detection rate, the WT classifier reduces the amount of false alarms by more than a factor of 4 from the prescreener.

V. Open Issues and Problems

There are many challenges still facing the radar-based fall detection technology. Classifying a fall, once the corresponding event time interval is identified, has been the subject of most work in this area. However, identifying such an interval is still an open question, specifically when fall is preceded by a high Doppler gross-motor activity. For example, experiments have shown that progressive fall from a rapid walk is not easy to reveal. Optimal sensor placement is also an open problem. It is well understood the Doppler frequency of a radar return is proportional to the relative motion between the object and the radar along the line joining them. Placing the radar several feet above the ground can provide the signal for gait analysis in addition to fall detection. On the other hand, the fall detection performance may not be as good as when it is mounted in the ceiling due to weaker relative motion that affects the features characterizing the falls [30]. The development of radar fall detection would finally be elderly specific. In this respect, it would require (a) tuning the fall detection algorithms to the elderly physical impairments and any awareness of the use of walking aid devices, and (b) making the system dynamic by unsupervised or supervised learning, which can occur by observing the elderly over an extended period of time.

There are limitations of using Doppler radar for fall detection. In fact, it is not straightforward for a Doppler radar to distinguish between a human fall and a pet jumping. Other normal activities, such as sitting on a chair, could also present challenges to a Doppler radar fall detection system. On the other hand, a pet has smaller size than a human and sitting down does not exhibit the full dynamics of a fall. It is anticipated that by extracting the reliable features and designing a proper classifier, some of these false alarms could be eliminated. The use of Doppler radar for fall detection is still in its infancy and there are many open issues that need to be addressed and further investigated.

VI. Conclusion

Real-time detection of falls and prompt communications to the first responders may enable rapid medical assistance, and thus, saves lives, minimizes injury, and reduce anxiety of elderly living alone. Successful use of radar technology for elderly fall detection relies on the signal processing techniques for Doppler signature analysis and motion classifications. In this paper, we provided an overview of the the main approaches for revealing pertinent features in joint-variable time-frequency domain. More specifically, time-frequency analysis in both its linear and bilinear aspects, including wavelet transform, was shown to play a fundamental role in fall features determination and classification. The success of feature-based fall detection schemes was demonstrated using real data experiments and some of the challenges facing technology development for fall detection were also discussed. Further developments in this area call for having a large repository of fall data which will provide means to compare the different algorithms and will help in the understanding of the nominal features of fall motions.

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