Wideband Radar Based Fall Motion Detection for a Generic Elderly

Baris Erol[†], Moeness G. Amin[†], Boualem Boashash[‡], Fauzia Ahmad[§], and Yimin D. Zhang[§]

[†]Center for Advanced Communications
Villanova University, Villanova, PA 19085, USA
[‡]Department of Electrical Engineering
College of Engineering, Qatar University, Doha, Qatar
[§]Department of Electrical and Computer Engineering
Temple University, Philadelphia, PA 19122, USA

***Abstract*—Radar-based automated fall detection systems are considered as an important and emerging technology for elderly assisted living. These radar systems provide non-intrusive sensing capabilities to detect fall events. Various studies have used micro-Doppler signatures to determine falls. However, Doppler radar fall detection systems suffer false alarms stemming from other sudden non-rhythmic motion articulations. In this work, we consider a textural-based feature extraction method which can determine the density variations between various motion articulations. For this purpose, textural features are extracted from the gray level co-occurrence matrix for each motion using time-integrated range-Doppler maps and micro-Doppler signatures. Textural features are then used to train the support vector machine classifier. The sequential forward selection method is implemented to identify essential features and minimize the feature space while maximizing the fall detection rate. The results show that well selected range-Doppler based textural features can provide improved classification results compared to textural features based only on micro-Doppler signatures.**

I. Introduction

People aged 65 and over represent 14.5% of the total U.S. population in 2014. This number is expected to become 21.7% by 2040 [1]. Most of the elderly population prefer to exercise independent self-care in their own homes. One out of every three people over age of 65 fall every year, resulting in injuries, reduced quality of life, and sometimes even death. In these incidents, timely medical attention plays a crucial role to reduce complications after a fall event. Hence, fall detection systems are key to fast medical attention and improving the quality of life [2]. Fall detection systems can immediately detect the fall and alert the first responders.

There are various types of fall detection systems available. These systems can be categorized into two major groups: wearable and non-wearable. Wearable devices are inexpensive and easy to use. However, they have some major drawbacks. One of the biggest disadvantage is that the elderly needs to be conscious to activate the system after a fall. On the other hand, non-wearable systems are placed in the home living environment of the elderly people. These systems attempt to identify fall events from other daily activities. The elderly does not need to be conscious to activate the system. Non-wearable devices, however, require more intricate techniques to detect fall. In this work, we focus on radar-based fall detection system. Various studies have been shown that radar systems can be employed for fall detection and a plethora of features have been proposed for this purpose [3]–[14]. In radar based assisted living applications, time-frequency (TF) representation have been used for feature extraction [5]. These features are then presented to the classifier. Feature sets that have been proposed can be categorized in four different groups: (a) Spectrogram features to capture the physical properties of the motion [7], [8]; (b) Speech processing originated mel-frequency cepstrum coefficients extracted from spectrograms [15]; (c) Wavelet transform based features [10], [11] and (d) Power burst curve [9].

The main challenge in Doppler radar fall-based detection is to reduce the number of false alarms. One source of false alarms is the similarity between the Doppler signatures of falls and other sudden non-rhythmic motion articulations. For example, Doppler signatures for the sitting and falling events may become similar in the TF domain, depending on the speed of the activity. Wideband radars offer additional range information that can be used to reduce possible confusions. For example, sitting motions have a limited range extent determined by the depth of the chair used, whereas falls can extend over a downrange that is approximately equal to the subject's height. To effectively reduce the miss-classification and false alarm rates, and utilize the range information, time-integrated range-Doppler maps were employed in [16]. The range-Doppler representation of the received signal combines the effects of both target velocity and range. These maps are constructed by the agglomeration of the consecutive range-Doppler frames and considered a key feature for fall detection.

In this paper, we investigate the importance of textural-based features for identifying fall and other types of non-fall motion articulations. More specifically, our proposed method includes a three-step process. First, time-integrated range-Doppler maps are constructed. Second, the gray level co-occurrence matrix (GLCM) is computed in order to capture the spatial dependence of gray-level values which contribute to the perception of motion articulations. Then, 13 textural-based

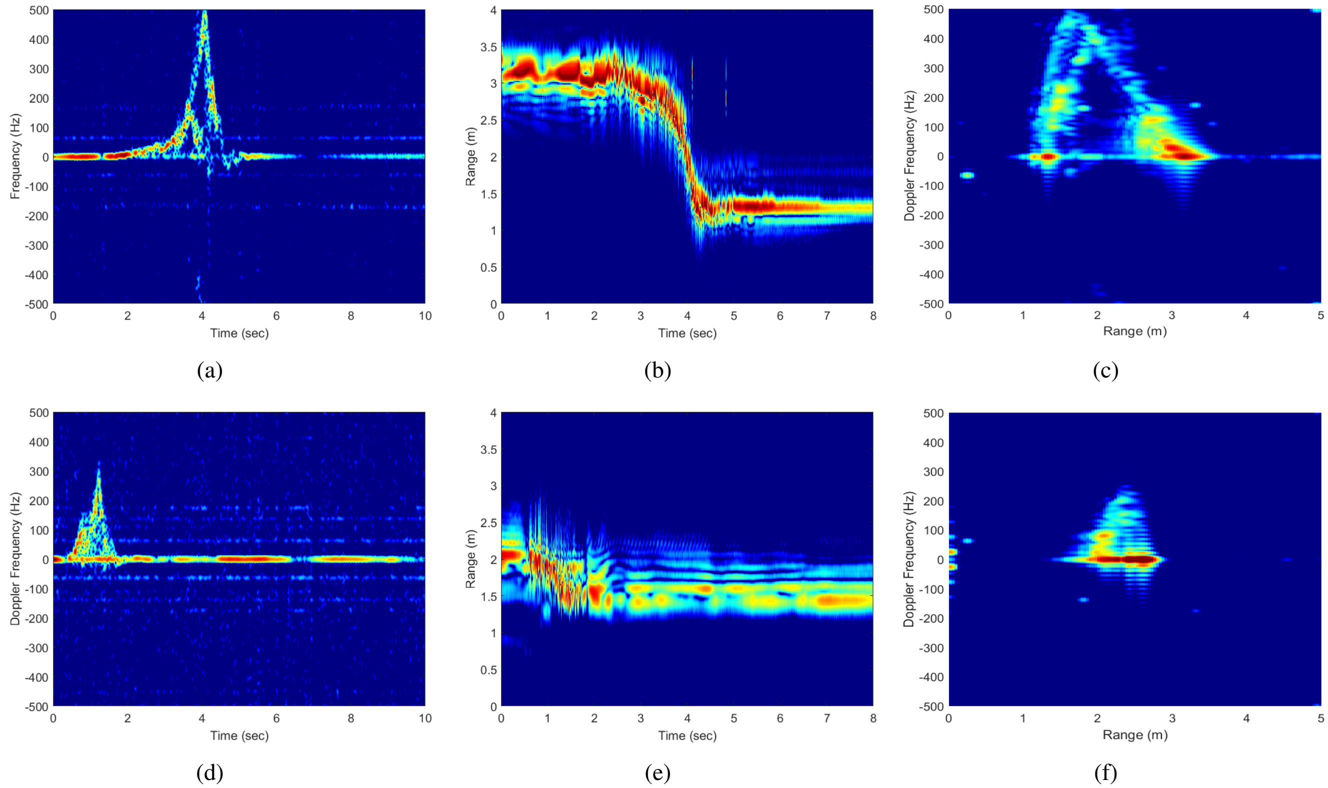

Fig. 1: Tri-domain representations of falling (a) Range-slow time (b) Micro-Doppler signature (c) Time-integrated range-Doppler map; and tri-domain representations of sitting (d) Range-slow time (e) Micro-Doppler signature (f) Time-integrated range-Doppler map.

features, such as contrast, correlation, and energy, are extracted from GLCM which contain information about image textural characteristic, such as the boundaries, linear dependencies, and the complexity of the image [17], [18]. However, inclusion of the features with irrelevant information can hinder the classification performance. Also, redundant features increase the feature space dimensionality which leads to a degraded classification performance. Therefore, in the final step of our proposed method, we implemented sequential forward selection (SFS) that heuristically searching the original feature space for a feature subset that yields the best classification performance for a provided classifier. An alternative approach is to use dimension reduction algorithms, such as principal component analysis (PCA), to reduce the size of the feature set [19]. However, these algorithms do not contain any constraint about class separability and hence classification performance [20].

The reminder of this paper is organized as follows. In Section II, the ultra-wideband (UWB) radar system and the data experimental setup are introduced. In Section III, the textural-based feature extraction algorithm is discussed in detail. Section IV evaluates the performances of the statistical features on micro-Doppler signatures and time-integrated range-Doppler maps. Finally, conclusions are drawn in Section V.

II. Data Experimental Setup

The UWB radar experiments were conducted in the Radar Imaging Lab at the Center for Advanced Communications, Villanova University. The UWB system used in the experiments, named SDRKIT 2500B, is developed by Ancortek, Inc. Operating parameters of the radar system are transmit frequency 24 GHz, pulse repetition frequency (PRF) 1,000 Hz, and bandwidth 2 GHz which provides 0.075 m range resolution.

Extensive measurements were made in order to utilize a database. The database contains a total of 106 motion articulations belonging to four different subjects engaged in four different motion articulations: falling, sitting, picking up an object, and walking. Each measurement was recorded for a duration of 10 seconds. Among these 106 measurements, 33 belong to falling, and the remaining signatures associated with non-fall motions. The test subjects posed heights ranging from 1.73 m to 1.90 m, weights ranging from 70 kg to 100 kg, and included 4 males. Micro-Doppler signatures, range-slow time and range-Doppler maps of the falling and sitting motions are depicted in Fig. 1.

III. Textural Feature Based Fall Detection

The one-dimensional histogram-based methods do not contain any information about the relative spatial position of the

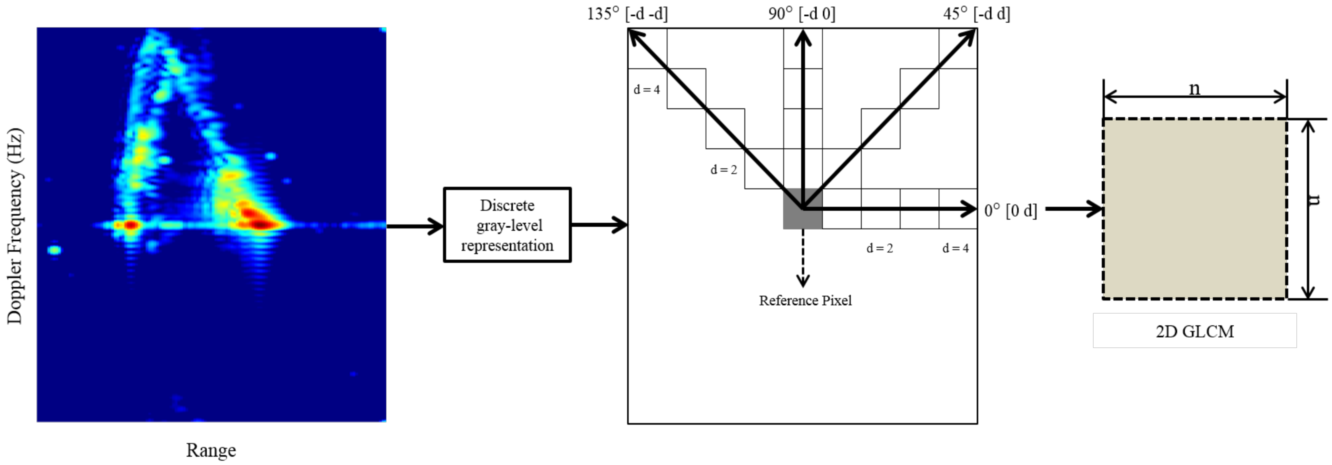

Fig. 2: 2D GLCM computation scheme.

image pixels. However, textural analysis provides useful information to characterize the structural heterogeneity of images. The texture is related to the spatial distribution of the intensity values that contains information about contrast, uniformity, and regularity. Therefore, texture provides important characteristics to perform surface inspection, scene classification, surface orientation, and shape determination [17], [21]. Utilizing time-integrated range-Doppler maps as gray level images reveals key differences between fall and other type of non-rhythmic motions, such as density and repetition of the pixel values. As it can be easily seen in Fig. 1(c), falling motion exhibits gaps in range-Doppler map, whereas sitting has a more filled structure which effects the repetition of the pixel values. For our purposes, repeating patterns of local variations in the time-integrated range-Doppler maps are defined as textural information. In the literature, different methods have been proposed to capture the textural properties of an image, such as GLCM, gray-level run length matrix, Gabor filters, and wavelet transform [18]. In this work, we implemented a GLCM based feature extraction method to successfully detect the fall and non-fall human motion articulations.

A. Gray Level Co-occurrence Matrix

The GLCM, $P_{d,\theta}$, can be defined as a two-dimensional (2D) histogram of gray levels and computed by first defining various values of distance d and angle θ between neighboring image pixel pairs. Each pixel in the image has eight angular neighboring pixels, as depicted in Fig. 2. Hence, eight possible θ values can be defined ranging from 0° to 315° in 45° increments. In this work, we only consider values of 0°, 45°, 90°, and 135°. The distance, d, takes a positive integer values. However, using relatively large values of d does not guarantee to capture detailed textural information [18]. It is noted that the highest classification performances are obtained for $d = 1$ and 2. Therefore, d is determined as 1. The GLCM in four different angles can be mathematically expressed as [18]:

$$P_{d,0}(i,j) = \sum_{n=1}^{N}\sum_{m=1}^{M}\begin{cases}1, \text{ if}(n=m)=i \\ \quad \& \ I(n,m+d)=j \\ 0, \text{ otherwise}\end{cases} \tag{1}$$

$$P_{d,45}(i,j) = \sum_{n=1}^{N}\sum_{m=1}^{M}\begin{cases}1, \text{ if}(n=m)=i \\ \quad \& \ I(n-d,m+d)=j \\ 0, \text{ otherwise}\end{cases} \tag{2}$$

$$P_{d,90}(i,j) = \sum_{n=1}^{N}\sum_{m=1}^{M}\begin{cases}1, \text{ if}(n=m)=i \\ \quad \& \ I(n-d,m)=j \\ 0, \text{ otherwise}\end{cases} \tag{3}$$

$$P_{d,135}(i,j) = \sum_{n=1}^{N}\sum_{m=1}^{M}\begin{cases}1, \text{ if}(n=m)=i \\ \quad \& \ I(n-d,m-d)=j \\ 0, \text{ otherwise}\end{cases} \tag{4}$$

where I is the time-integrated range-Doppler map, N and M size of the image, and $i, j = 0, 1, 2, ..., L$, with L denoting the number of gray scale levels. In this way, a structure that describes the co-occurring intensity values at a given offset is constructed.

B. Feature Extraction

In this work, thirteen different statistical features proposed by Haralick [17], namely, angular second moment, contrast, correlation, summation of squares variance, inverse difference moment, summation average, summation variance, summation entropy, entropy, difference variance, difference entropy, information measure of correlation 1 and 2, are extracted from each GLCM. Some of these features contain specific textural properties of the image such as homogeneity, contrast, and presence of the organized structure within the image. Other features help characterize the complexity and the nature of gray level transitions occurring in the image. In [17], it is suggested that the angularly dependent features not to be used

TABLE I: Scores (%) for each method by four different metrics

	Accuracy	Fall detection rate	False alarm rate	Missed rate
13 micro-Doppler based Haralick features	87.65	84.49	9.19	90.81
13 time-integrated range-Doppler based Haralick features	91.62	89.42	6.17	93.83
3 time-integrated range-Doppler SFS based Haralick features	96.22	94.73	2.28	97.72

directly. Instead, the mean value of the features for the four different directions can guarantee rotation invariance and yield better classification performances.

C. Feature Selection

Utilization of all possible textural features generally does not imply a potential increase in classification performance. In some cases, a well selected sub-feature set is sufficient to yield the desired performance. This can be explained by the curse of dimensionality. The theme of this phenomenon is that when the dimensionality increases, the volume of the space also increases so fast that the available data become sparse. Therefore, we implement SFS approach to construct a new reduced set of features by mapping the multi-dimensional feature space into a lower dimensionality. The performance is directly computed using a specific classifier, support vector machine (SVM), which makes the selected features classifier dependent. As the number of the features to be evaluated increases, SFS tends to be much more computationally intense than other types of filter methods. In other words, SFS selects features that yield the highest value of a pre-defined objective function, in this case, classification accuracy for a given classifier. This process involves:

1) Start with an empty set of feature;
2) Select the next feature, the one that yields the highest accuracy when used together with previously selected features;
3) Update the selected feature set, and move to the next feature; and
4) Repeat Step 2 until the total number of desired features is reached.

IV. Experimental Results

The performance of the SFS method in Fig. 3 shows the classification accuracy achieved for two classes, i.e., fall and non-fall, utilizing an SVM classifier when a different number of features is selected. The SFS algorithm yields the best performance when three carefully selected subsets [5] of features is utilized. For example, when all the features are used, SFS provides a classification accuracy around 92%, whereas a 95% accuracy is achieved when three features are used. This result clearly shows the advantage of the feature selection.

Fig. 4 shows the ground truth of the selected three features defined in Section III, i.e., difference entropy, inverse difference moment, and information measure of correlation 2. More specifically, Fig. 4 shows the three-dimensional scatter view of the three features. It is observed that these features generally provide a clear distinction between the fall and non-fall events, proving the efficiency of the SFS method.

Finally, the 13 statistical features are extracted from both time-integrated range-Doppler maps and micro-Doppler signatures. The performance comparison between micro-Doppler and range-Doppler statistical features is done by computing four different performance metrics: accuracy, fall detection

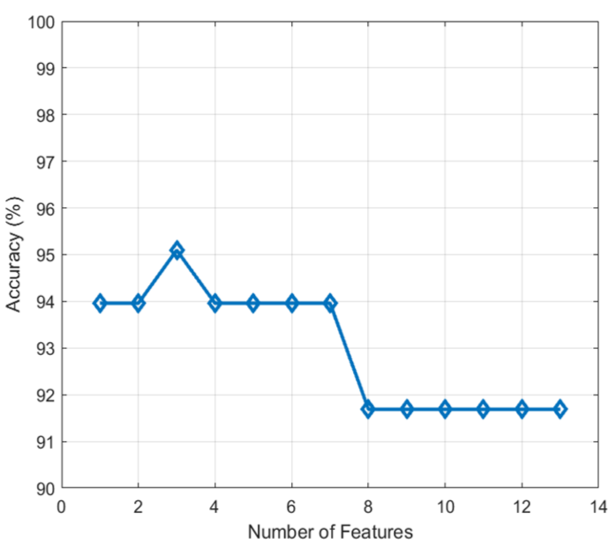

Fig. 3: Influence of feature subset size on SFS wrapper.

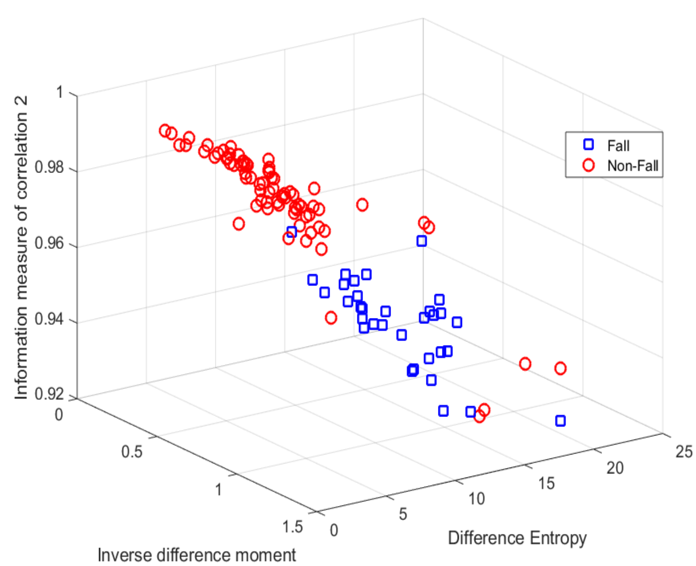

Fig. 4: Ground truth scatter plots of the selected features.

rate, false alarm rate, and missed rate, as tabulated in Table I. From these metrics, a number of important observations can be made. It is observed that 13 micro-Doppler based statistical features fail to provide a desirable detection performance and exhibit a degraded classification performance in every metric. 13 range-Doppler based statistical features provide an acceptable level of classification performance, but require high computational time due to the high feature space dimensionality. On the other hand, three well selected range-Doppler-based statistical features provide the best performance. This is anticipated due to the properties of the SFS method.

V. Conclusion

In this paper, we presented a textural feature based fall detection scheme for detecting fall and non-fall motions in assisted living applications. Time-integrated range-Doppler maps were first constructed to examine the motion signatures. Several textural features were then extracted from the four-angle nearest-neighbor GLCM of the target range-Doppler map. SFS based feature selection was then implemented to determine the relevant features that provide the best classification performance. The results showed that textural features were more suited for range-Doppler domain than micro-Doppler signatures. It was also observed that feature selection increased the classification accuracy by 3%, which is a significant improvement towards advancing radar in-home monitoring for assisted living.

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