Compressed Domain Contactless Fall Incident Detection using UWB Radar Signals

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***Abstract*—Falling down is one of the main reasons for hospitalization among the elderly. Constant monitoring of such vulnerable older adults and timely detection of fall incidents may significantly improve healthcare services. This paper presents a radar-based fall detection method using compressed features of the radar signals. The compressed features are obtained by using determinisitc row and column sensing. The time-frequency analysis is first performed on the radar time series and resulting spectrogram is projected onto a binary image representation. The binary images are then compressed using a 2D deterministic sensing technique by preserving the aspect ratio of the images in the compressed domain. The performance of the proposed method is evaluated using several classifiers such as support vector machine, nearest neighbors, linear discriminant analysis and decision tree. It is shown that the proposed compressive sensing based method can improve fall versus non-fall activities recognition, as evidenced by high classification metrics for low compression ratios.**

***Index Terms*—Smart home, biomedical signal processing, compressive sensing, classification, fall detection.**

I. Introduction

Human activity recognition techniques can be extended to identify critical situations such as automatic fall detection [1]. Falling down is one of the greatest risks for seniors living alone. Thus, developing new technologies for fall detection and reducing the risk of injuries is crucial. Existing methods mostly rely on the use of wearable accelerometers and/or gyroscopes, cameras-either wearable or static, smart floors and combination of several such methods. Non-contact indoor monitoring has become popular for home care purposes, especially for detection of vital signs or detection of falls in health care applications. The radar-based sensing technology is increasingly used in smart homes as it avoids the privacy issue of the camera-based techniques [2] and precludes the need for wearing a tag [3].

The use of radar in contactless medical sensing applications has extensively been explored [4]. In [5], features were extracted from the cadence-velocity diagram of continuous wave radar signals in order to detect and classify people based on the Doppler signatures. In [6], a human gait classification method was proposed by taking into account the motion signature from arm and leg movements. In [7], using micro-Doppler signature, different human activities over extended time duration, through wall, and at multiple angles to the radar, were classified. In [8], a human activity recognition method was developed based on radar micro-Doppler data by extracting features from time-velocity and cadence-velocity domains.

Among radar sensing technologies, ultra-wideband radars are promising candidates for short range localization, non-contact indoor monitoring and fall detection [9]–[12]. There exist several works that employ a radar system for fall detection. For instance, a wavelet-based approach was devised in [13] for fall detection. In [14], a fall detection method was presented by applying a time-frequency analysis of the radar returns and the events were classified by a sparse Bayesian classifier using the joint statistics of three different features. The basic drawbacks among such methods are the limited number of features extracted and manual engineering of such features. The results in these works have shown that any improvement in the accuracy of the fall detection method depends to a great extent on the type of features extracted. However, none of these works have addressed the radar-based fall detection problem using compressed features.

Compressive sensing (CS) may be used as a technique for dimensionality reduction through projection of high-dimensional sparse data into a lower dimensional measurement space [15]. Performing learning directly in the compressed domain, would significantly reduce the dimensionality of high-dimensional feature space. In [16], classification was attempted to the compressed domain signals in order to detect faces. A theoretical analysis on the applicability of compressed domain learning for support vector machine-based classification has been studied in [17]. Compressed domain learning has so far been used for applications ranging from video streaming to language processing [18]. However, to the best of our knowledge, detection of human fall using radar signals in the compressed domain has not been reported.

In view of this, in this paper, a fall detection method is proposed based on compressive sensing. The proposed method is realized by projecting the spectrogram of the radar signal onto a binary image representation followed by compressive sensing technique. The compressed binary images are directly used as input to a classifier to determine whether a radar data of a human activity contains a fall incident or not. Several classifiers such as decision tree, k-nearest neighbors, linear discriminant analysis and support vector machines are used for studying the detectability using the proposed method. Experiments were conducted to evaluate the performance of the proposed fall detection method using compressive sensing with different compression ratios.

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II. Experimental Setup and Measurement

The radar used in this experiment is the Xethru X4M03 development kit, which uses an ultra wide-band transceiver. This particular radar is chosen because of its low cost, small size and high spatial resolution. The experiments were conducted in a room environment at the University of Ottawa after obtaining approval from the University's ethics board. The room had the following dimension: $12.6 \times 4.1\ m^2$. The radar is mounted 1.5 m above the floor level. The sampling rate of the radar is 200 Hz.

The dataset used in our experiments includes different types of fall and non-fall activities performed by five different healthy subjects aging from 20 to 26, namely, walking toward radar and falling down at different distances to the radar i.e., 3 or 4 m, standing in front of radar and falling down at different distances to the radar, standing and falling down perpendicular to the radar line of sight, lying down with or without side rolling or other movements, and standing up in front of the radar, and lying down and standing up perpendicular to the radar line of sight. Each experiment lasted 15 seconds, within which only one of these activities occurred. The signals were then digitized at a rate of 200 samples/second. The range of the radar used in this study is set to 10 m.

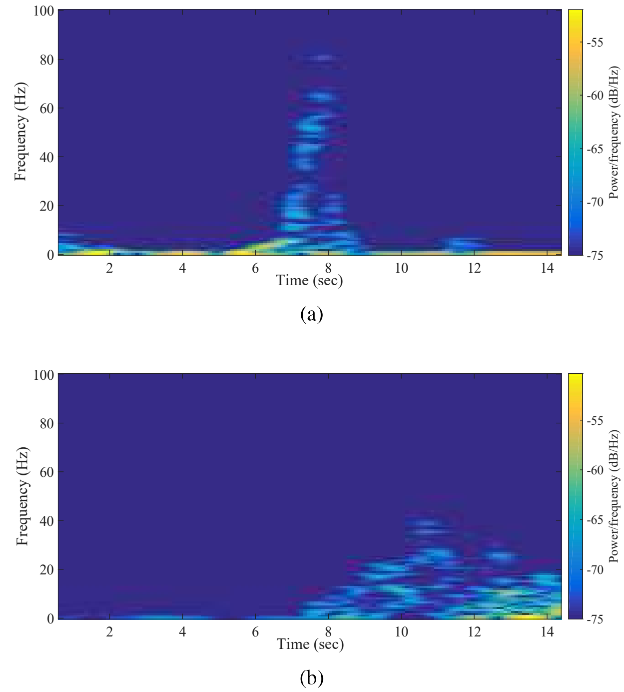

Fig. 1. Time-frequency analysis: Spectrogram resulted from (a) Falling down, (b) Standing up.

III. Proposed Fall Detection Method

In this section, the proposed fall detection method based on time-frequency representation of the radar return signals and compressive sensing is presented.

The radar return signals are recorded into a matrix, where each column represents the spatial samples from different ranges (fast-time), while the data in each row corresponds to observations recorded at different time intervals (slow-time). The first 20 range bins, corresponding to 1 m radius, are noisy and removed before further processing. It is noted that the observations from the range bin having the highest variance over slow-time is chosen to be the target range bin and used for further processing.

A. Time-Frequency Analysis

In order to analyze the radar return signals, a joint time-frequency representation is obtained by applying the short-time Fourier transform (STFT) [11]. For a radar return signal from the target range bin $x[.]$, STFT is defined as $X[n, k] = \sum_{r=-\infty}^{\infty} x[r] W[r-n] \exp(-j2\pi rk/N)$, where $W[.]$ is a finite length sliding window function, n is the time index, $k = 0, 1, ..., N-1$ is the frequency index and N is the number of frequency points. The squared magnitude of STFT yields the spectrogram, i.e., $S(n, k) = |X[n, k]|^2$, and is represented by the hue of the point's color in Fig. 1. The image intensities indicate the energy corresponding to the micro motion signature at each time instant [20].

In the experiments, the STFT is applied using a Hamming window of size 256 samples [11]. Fig. 1 shows time-frequency plots of the falling down and standing up activities, where the horizontal axis is time and vertical axis is frequency. It is seen from this figure that the energy content of these activities are distinguishable in their time-frequency signatures. More specifically, a fall incident results in an instantaneous high frequency content with a specific distribution of energy over time, whereas non-fall activity exhibits lower frequency peak and different energy distribution.

B. Radar Binary Image Generation

Radar signals including fall and non-fall activities are processed and projected onto image representation having frequencies as rows and time instants as columns at which the spectrogram is computed. It is known that the raw spectrogram images exhibit a high level of noise, which may affect on the true signature of the activity under study [21]. This may result in a lower classification performance. To address this issue, a binary time-frequency signature of each activity is obtained by separating the target event from the background regions using a threshold-based method. Fig. 2 shows binary time-frequency signatures, corresponding to the fall and non-fall spectrograms, respectively.

C. Compressive Sensing on Radar Binary Image

In this section, compressive sensing concept used to perform compression on sparse radar binary images is presented. Let us assume a signal $\mathbf{x} \in \mathbb{R}^N$. The goal in CS is to design a measurement matrix $\mathbf{\Phi}_{M\times N}$, which transforms the N-dimensional signal $\mathbf{x} \in \mathbb{R}^N$ into a M-dimensional vector $\mathbf{y} \in \mathbb{R}^M$, where $M << N$, as given by

$$\mathbf{y}_{M\times 1} = \mathbf{\Phi}_{M\times N}\mathbf{x}_{N\times 1} \tag{1}$$

The design criterion for measurement matrix, such as maintaining restricted isometry property (RIP), $\mathbf{\Phi}_{M\times N}$ has been

(a) (b)

Fig. 2. Binary images obtained from spectrogram. (a) Falling down, (b) Standing up.

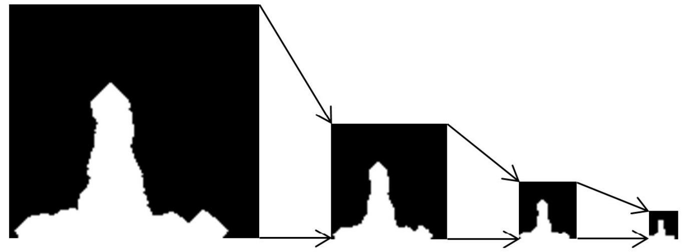

Fig. 3. Compressed radar binary images when from left to right ρ is 1, 0.5, 0.25 and 0.125, respectively.

discussed in [22]. In compressed domain applications, the original signal is recovered from the compressive measurements, $\mathbf{y}_{M\times 1}$ through solving an optimization problem [23]. It is known that random matrices satisfy RIP with high probability [23]. However, it is challenging to realize random matrices due to storage issue. In [24], a linear filtering-based deterministic measurement matrix has been constructed, known as deterministic binary block diagonal (DBBD) matrix. Construction of a such matrix of size $M\times N$ may be regarded as a shift-invariant linear filter followed by a decimation. In the proposed method, DBBD matrix is used as preferred measurement matrix for the following reasons:

1) As the matrix construction of DBBD is based on linear filtering, the morphology of the binary images remain unchanged in the compressed domain. No sophisticated signal processing algorithms are required to be developed before feature learning and classification in the compressed domain.
2) Generation of the DBBD deterministic matrix requires no multiplication and storage space. On the contrary, most of the random matrices of size $M\times N$ require $M\times N$ multiplications and storage space.
3) DBBD matrix is straightforward to implement. When recovery is needed, the deterministic measurement matrix provides guarantee in recovery without any probabilistic notion.

In traditional column-wise CS for 2D signal, individual columns of a 2D signal $\mathbf{X}_{N\times N}$ is sensed and a compressed domain representation $\mathbf{Y}_{M\times N}$ is specified [15]. In other words, by repeating (1), N times, for N columns, the compressed domain representation $\mathbf{Y}_{M\times N}$ is devised. However, the aspect ratio of the image is not maintained in the column-wise approach. As a result, the number of measurements in the compressed domain remains to be $M\times N$. For large N, the number of measurements are large and significant reduction in the dimensionality in the training set may not be obtained. In order to preserve the aspect ratio of the images in the compressed domain, a row and column-wise sensing-based 2D CS technique is used in this work [25], where the compressed measurement domain representation of the 2D compressible signal $\mathbf{X}\in\mathbb{R}^{N\times N}$ is represented as $\mathbf{Y}_{M\times M}$, and can be obtained as

$$\mathbf{Y}_{M\times M}=\mathbf{\Phi}_{M\times N}\mathbf{X}_{N\times N}\mathbf{\Phi}^T_{M\times N} \tag{2}$$

It is to be noted that in addition to preserving aspect ratio of the 2D signal in the compressed domain, the row and column-wise CS further reduces the number of measurements, when compared to the column-wise CS. In the compressed domain, a total of $M\times M$ measurements are obtained in the row and column-wise CS as opposed to $M\times N$ measurements obtained by the column-wise 2D CS approach. Hence, the dimensionality of the training set reduces, when learning is performed on the compressed domain. It is also noted that the radar binary images are compressed with different compression ratios, i.e., $\rho=\frac{M^2}{N^2}$ is varying in $[0.125-1]$. Fig. 3 shows compressed images with different ρ values.

IV. Results, Challenges and Future Directions

To evaluate the performance of the proposed fall detection method, experiments were conducted on a set of radar data collected in a realistic environment. The radar return signal is processed to obtain the spectrogram. The spectrogram is treated as an image containing the energy content of a particular activity. The experimental results are obtained using the proposed method with various classifiers such as support vector machine (SVM) [26], decision tree (DT), k-nearest neighbors (KNN) [27] and linear discriminant analysis (LDA). To evaluate the classification performance of the proposed algorithm, a 5-fold cross-validation is applied. Table I gives classification metrics obtained using the proposed method based on compressive sensing with various compression ratios. The compressed images are vectorized and used as input to various classifiers such as SVM, KNN, DT and LDA. In the case of KNN, different values for k are examined and the best results, i.e., $k=1$ is reported. In the case of SVM, linear SVM is employed. In the case of the decision tree approach, gini index (DTG) is considered. It is noted that the parameters of each classifier are tuned using random search optimization. It is seen from Table I that the proposed method is capable of detecting falls with higher precision, recall and specificity values. It is also seen from this table that increasing the compression ratio from no compression $\rho=1$ to $\rho=0.125$ results in an improvement in classification metrics using SVM and DTG classifiers as well as LDA up to $\rho=0.25$. This improvement may be attributed to eliminating redundant pixels from the radar binary images and feeding classifiers with more relevant features.

TABLE I

PRECISION (PR), RECALL (RE), SPECIFICITY (SP) (%) OBTAINED USING THE PROPOSED FALL DETECTION METHOD USING COMPRESSIVE SENSING WITH VARIOUS COMPRESSION RATIOS IN A 5-FOLD CROSS VALIDATION.

	$\rho = 1$			$\rho = 0.5$			$\rho = 0.25$			$\rho = 0.125$		
Method	PR	RE	SP	PR	RE	SP	PR	RE	SP	PR	RE	SP
SVM	91.58	95.53	89.08	93.54	89.74	94.28	93.54	96.67	91.10	93.54	94.99	90.92
KNN	94.34	100	92.44	93.47	91.66	100	94.18	99.05	93.70	94.18	99.05	93.70
DTG	80.69	91.61	77.97	82.99	92.98	81.21	89.70	93.16	86.30	93.69	96.04	90.71
LDA	92.47	92.52	89.29	93.38	94.11	90.53	95.28	93.43	92.91	86.56	90.35	84.50

V. CONCLUSION

In this work, a novel radar-based fall detection system has been proposed based on time-frequency analysis and compressive sensing. Fall and non-fall activity data have been collected using a radar sensor in a room environment. The time-frequency analysis has been performed by using the short-time Fourier transform and obtaining the spectrogram for different activities. The spectrograms have been further processed to obtain binary images. The binary images are then compressed using a 2D deterministic compressive sensing technique by preserving the aspect ratio of the images in the compressed domain. The compressed images are then used as input to many classifiers including support vector machine, nearest neighbors, linear discriminant analysis and decision tree. The experimental results have shown that the proposed fall detection method using compressive sensing considerably improves precision, sensitivity and specificity metrics.

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