Radar Fall Detection Using Principal Component Analysis

Branka Jokanovic[†], Moeness Amin[†], Fauzia Ahmad[†,*] and Boualem Boashash[‡]

[†]Center for Advanced Communications, Villanova University, Villanova, PA 19085, USA
[‡]Department of Electrical Engineering, College of Engineering, Qatar University, Doha, Qatar

ABSTRACT

Falls are a major cause of fatal and nonfatal injuries in people aged 65 years and older. Radar has the potential to become one of the leading technologies for fall detection, thereby enabling the elderly to live independently. Existing techniques for fall detection using radar are based on manual feature extraction and require significant parameter tuning in order to provide successful detections. In this paper, we employ principal component analysis for fall detection, wherein eigen images of observed motions are employed for classification. Using real data, we demonstrate that the PCA based technique provides performance improvement over the conventional feature extraction methods.

Keywords: Fall detection, micro-Doppler, principal component analysis, radar, time-frequency

1. INTRODUCTION

In many countries, a rapid growth of the elderly population, aged 65 and over, is expected over the next 40 years.[1-3] This will lead to a greater burden not only on those of working age, but the overall economy as well, in supporting the aging population. As such, there is a increasing interest in assisted living technologies that enable self-dependent living within homes for the elderly. Approximately 30% of people over the age of 65 fall each year, and for those over 75, the rates are even higher. Most seniors are unable to get up by themselves after a fall, and it was reported that, even without direct injures, half of those who experienced an extended period of lying on the floor (>1 hour) passed away within six months after the incident. Thus, prompt fall detection can save lives, lead to timely interventions and most effective treatments, and reduce incurred medical expenses.

Unlike camera based systems which have garnered considerable research interest in recent years, radar technology offers non-invasive monitoring capability regardless of lighting conditions and its use does not raise any privacy concerns.[4] A radar transmits an electromagnetic signals and records the backscatter from targets. It estimates the velocity of a moving target by measuring the frequency shift of the wave scattered by the object relative to the transmitted signal which is known as the Doppler effect. Doppler measurements play a fundamental role for target detection, tracking, and classification in radar systems and find broad applications, ranging from defense and security to weather forecasting.[5-7]

Radar can detect both biomechanical and biometric human signatures.[8-11] The former correspond to the gross-motor motions of different body components, such as torso, arms and legs. The latter monitor heart beat and respiration, which provide information about the health condition and enable detection of persons in stationary activity modes, including standing, sitting, sleeping and laying down. As such, radar technology has been successfully used for human motion classification in defense and security applications.[8] Recently, radar has found applications in health care industry.[12-14]

For assisted living applications, most of the proposed radar fall detectors are based on manual feature extraction which can be a tedious task involving tuning of parameters and thresholds. In this paper, we propose an approach based on principal component analysis (PCA) which alleviates the burden on the human operator. The proposed approach is similar to the one used for face recognition.[15] We process spectrograms of human motions as images and use them to perform eigen decomposition. The eigen images can be considered as features of human motions and employed in the classification process. The use of principal components for extracting features from micro-Doppler signatures has been successful in the radar community for defense related applications.[16]

* Corresponding author; fauzia.ahmad@villanova.edu

The remainder of the paper is organized as follows. In Section 2, we present the radar signal model and briefly review the conventional fall detection approach, which extracts features from the time-frequency (TF) signal representations for motion classification. TF signatures of common human activities are also depcited therein. The PCA based approach is described in Section 3. Results based on real data experiments are provided in Section 4. Section 5 contains the conclusion.

2. SIGNAL MODEL AND CONVENTIONAL FALL DETECTION APPROACH

Considering a CW radar operating at frequency f_0, the baseband return from a point target can be expressed as,

$$s(t) = \rho(t)\exp(-j\phi(t)), \tag{1}$$

where $\rho(t)$ and $\phi(t)$ are, respectively, the range-dependent amplitude and phase of the return. The phase contains the information about the target motion, while the derivative of the phase provides the corresponding Doppler frequency. In contrast to the point target model in (1), the baseband return from an extended target, such as a human, can be considered as a sum of returns from a multiplicity of point scatterers comprising the target extent. In this case, the corresponding Doppler signature is the superposition of the various component Doppler frequencies. Human motions typically produce time-varying Doppler frequencies, and the nature of the corresponding Doppler signature is tied to the specific motion articulation and target shape.

The time-varying nature of Doppler and micro-Doppler frequencies can be revealed in the TF domain. The simplest TF representation is the spectrogram,[17] which is obtained by computing the Fourier transform of the windowed data as

$$SPEC(t,f) = \left| \int s(t+\tau)w(\tau)e^{-\jmath 2\pi f \tau} d\tau \right|^2, \tag{2}$$

where $w(\tau)$ is the employed window function.

Figure 1 depicts the micro-Doppler signatures of some common human activities, namely, falling, sitting, bending and straightening, and walking, obtained using the spectrogram. From Figure 1, we can make the following observations about the considered human motions. Fall is a short-term event characterized by the high speed of the human body, which translates to high Doppler frequency in the TF domain. Sitting can be also described using these characteristics, except that a lower speed is associated in general with sitting. For the bending followed by straightening motion, each of the two parts of the micro-Doppler signature bears resemblance to a fall signature, albeit with lower Doppler frequency. However, the occurrence of the bending and straightening motions in close time proximity sets it apart from the fall. Walking, on the other hand, is a periodic motion, which is characterized by high Doppler frequency resulting from the motion of the limbs. In short, there are intrinsic differences between the TF signatures corresponding to various human activities.

Conventional radar fall detection approach extracts features from micro-Doppler signatures that capture the differences in order to classify motions.[18] For fall detection based on spectrograms, relevant features include extreme frequency magnitude, extreme frequency ratio, and time-span of event.[10,11] The extreme frequency magnitude is defined as

$$F = \max(f_{+\max}, -f_{-\min}), \tag{3}$$

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. The extreme frequency ratio is defined as

$$R = \max(|f_{+\max}/f_{-\min}|, |f_{-\min}/f_{+\max}|). \tag{4}$$

The time-span of the event which describes the length of time, in milliseconds, between the start and the end of an event is defined as

$$L = t_{\text{extrm}} - t_{\text{begin}}, \tag{5}$$

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 as the time when the magnitude of the signal frequency content exceeds a pre-determined threshold.

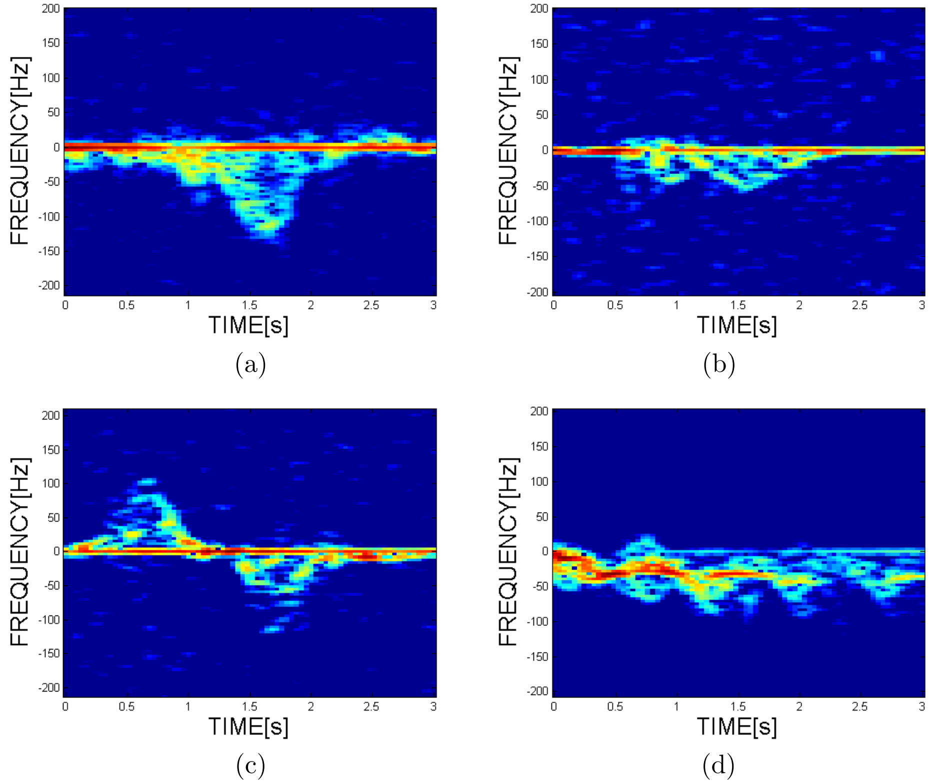

Figure 1. Spectrograms of human motions: (a) Falling, (b) Sitting, (c) Bending and straightening, (d) Walking.

3. PRINCIPAL COMPONENT ANALYSIS BASED APPROACH

The PCA-based approach follows similar steps as those employed in conventional face recognition methods.[15] The first part of the approach entails use of training data to generate eigen images, as delineated below:

procedure TRAINING(input:radar data of human motions)
  Compute spectrogram and convert it to a gray-scale image
  Vectorize images and stack them in a training matrix
  Perform the normalization by subtracting the average from each column of the training matrix
  Perform the eigen decomposition of the normalized training matrix
  Project the training set onto the space spanned by the selected eigen images
end procedure

The selection of eigen images is based on the eigenvalues, i.e., only components corresponding to high eigenvalues are chosen. The outputs of the training process are projections of the training images. When the test data arrives in the form of a vectorized version of the gray-scale spectrogram, it is projected onto the eigen space and the resulting projection is compared with all projections obtained for the training images. Minimum Euclidean distance classifier is employed to determine the class with the closest match to the observed test motion.

An alternate version of the PCA based motion classification approach was presented in Ref. [16]. Namely, eigen space is generated for each class separately and then the test image is projected onto each individual eigen space. The distances for each class are compared and the minimum value determines to which class the observed data belongs.

Table 1. Confusion matrix for the PCA-based approach I. Numbers correspond to the case when 3 components are used.

Predicted/Actual Class	Fall	Non-fall
Fall	12	0
Non-fall	3	15

Table 2. Confusion matrix for the PCA-based approach II. Eigen space is generated for each class.

Predicted/Actual Class	Fall	Non-fall
Fall	14	4
Non-fall	1	11

4. EXPERIMENTAL SETUP AND RESULTS

A CW radar system was set up in the Radar Imaging Lab at Villanova University. The feed point of the antenna was positioned 1 m above the floor. Agilent's E5071B RF network analyzer was used for generating the transmit signal and recording the 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 four different motions (falling, sitting, bending and straightening, walking) using several male and female human subjects. A total of 60 experiments were recorded.

One-half of the recorded data, i.e., 30 signals, are used for training, whereas the remaining 30 are employed in the testing phase. For each experiment, the spectrogram corresponding to a time span of 3 s containing the motion is preprocessed and the resulting gray-scale image consists of $76 \times 76 = 5776$ pixels. These images are used for eigen decomposition. The normalized eigenvalues corresponding to the training set with 30 images are plotted in Fig. 2, which shows that there are three dominant components. The first three eigen images are depicted in Fig. 3. Since the underlying objective is fall detection, only two classes are considered, namely, fall motions and non-fall motions. Table 1 provides the confusion matrix when the first three eigen images are used in the PCA-based scheme I. We observe that a classification accuracy of 90% is achieved. Use of all 30 eigen components does not provide any change in performance over the three eigen images based results since most of the information is captured by few strongest components. It should be noted that the use of one and two components yields 76% and 86% classification accuracy, respectively.

The classification results for the PCA-based scheme II are provided in Table 2. Recall that scheme II employs separate eigen spaces for each class. Based on the eigenvalues shown in Fig. 4, we extract two strongest components for non-falls and six strongest components for falls, leading to a classification accuracy of 83%. As expected, inclusion of additional eigen components for each class does not any improvement in the classification performance. Comparing Tables 1 and 2, we observe that in addition to a lower classification accuracy, scheme II produces a higher number of false alarms as compared to scheme I. However, the number of missed detections is lower for scheme II than for scheme I. The lower classification accuracy of scheme II demonstrates that when observing distinctive motions as in the underlying case, it is better to find common features across the entire dataset containing different motions instead of focusing on specific classes.

For comparison, we also present, in Table 3, the confusion matrix corresponding to the conventional feature based approach. Three features, namely, the extreme frequency magnitude, extreme frequency ratio, and time interval of event, are extracted and fed into a support vector machine (SVM) classifier. Comparing Tables 1 and 3, we note that the PCA-based scheme I provides better fall detection capability with higher accuracy. It should be noted that in the conventional approach, special care was exercised for the tuning of various parameters and thresholds in order to find the best match for the considered data.

5. CONCLUSION

In this paper, we applied PCA for radar-based fall motion detection. Performance of the PCA based scheme was evaluated using real data measurements corresponding to four human motions, namely, walking, falling, bending/straightening, and sitting. For the considred data, the PCA based approach provided superior performance

Table 3. Confusion matrix for the conventional feature extraction based approach.

Predicted/Actual Class	Fall	Non-fall
Fall	9	0
Non-fall	6	15

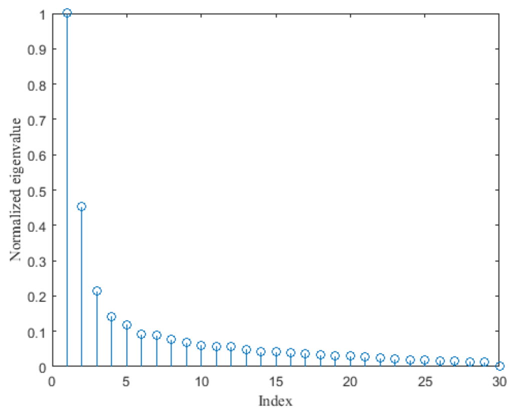

Figure 2. PCA Scheme I: Normalized eigenvalues corresponding to the 30 training images.

over the conventional method in discriminating between fall and other human motions. We note that these are preliminary conclusions that would have to be verified by application of the considered classification techniques to a broader data set, including a variety of motions observed in real life with different aspect angles relative to radar.

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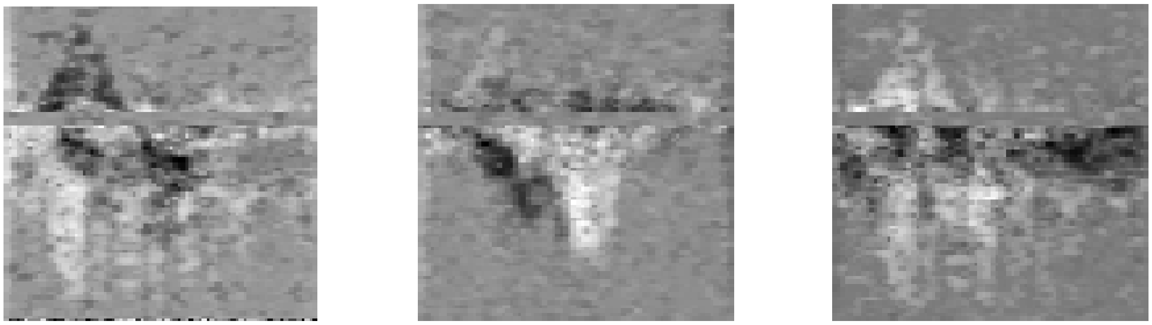
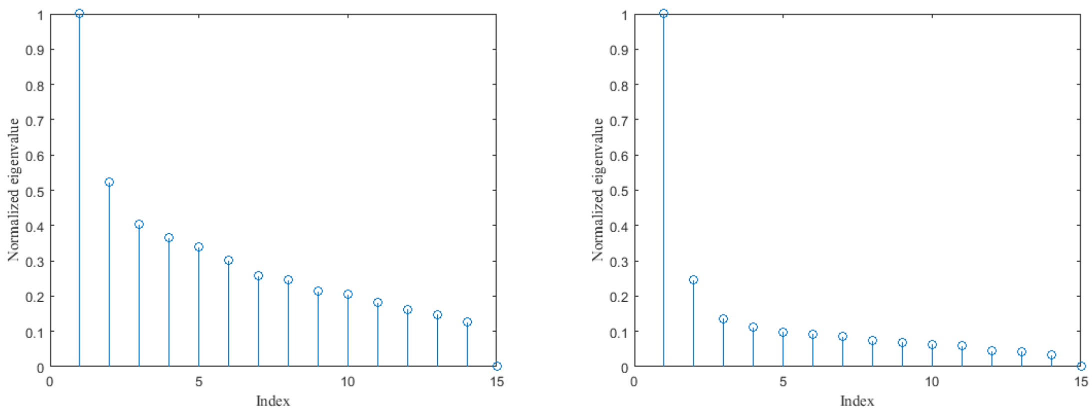


Figure 3. Eigen images corresponding to the first three principal components.



(a) (b)

Figure 4. PCS Scheme II: Normalized eigenvalues corresponding to the 15 training images for(a) falls, and (b)non-falls.

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