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Doppler Radar Sensor Positioning in a Fall Detection System

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Abstract— **Falling is a common health problem for more than a third of the United States population over 65. We are currently developing a Doppler radar based fall detection system that already has showed promising results. In this paper, we study the sensor positioning in the environment with respect to the subject. We investigate three sensor positions, floor, wall and ceiling of the room, in two experimental configurations. Within each system configuration, subjects performed falls towards or across the radar sensors. We collected 90 falls and 341 non falls for the first configuration and 126 falls and 817 non falls for the second one. Radar signature classification was performed using a SVM classifier. Fall detection performance was evaluated using the area under the ROC curves (AUCs) for each sensor deployment. We found that a fall is more likely to be detected if the subject is falling toward or away from the sensor and a ceiling Doppler radar is more reliable for fall detection than a wall mounted one.**

I. Introduction

In the USA, falling is an important cause of death for elders above the age of 65. Over the past decade, the rate of fall triggered falls in seniors is rapidly increasing [1-3]. A fast response and medical intervention after the occurrence of a fall is positively correlated to the outcomes. The prompt assistance after a fall of the informed nursing personnel improves the chances for survival after fall [4].

Aside of the traditional wearable sensors for fall detection, such as push buttons and accelerometers, non-wearable sensors such as floor vibration sensors, video cameras, infrared cameras, smart carpets and microphone arrays [5-13] are also developed. In a non-wearable sensors based environment, seniors do not have to push buttons, pull cords or wear any devices even when they lost consciousness after a fall. The fall will be detected automatically regardless of the elder state of mind and an alert will be sent to the nursing personnel for timely help. The fall detection peace of mind allow elderly to live longer independently and reduce the healthcare costs [14]. At the University of Missouri, Columbia, we are currently developing another non-wearable fall detection system based on Doppler radar. A Doppler radar can detect moving objects and, consequently, can detect falls by producing specific signatures for various part of a falling human body. Radar sensor has been widely employed for target tracking, target recognition and surveillance of human activity. In a room environment, it has been successfully used for measuring gait parameters such as velocity and stride length [15-16].

Our previous work shows the possibility of using Doppler radars to estimate fall risk in a daily living environment based on gait velocity and stride length [17]. We also proposed an automatic fall detection system based on Doppler radar signatures and some preliminary results were shown in [18]. Considering that different classifiers preferentially detect certain falls, in [19] we developed a fusion framework for fall detection. From our previous work [18, 19], two questions surfaced. First, is the fall direction influencing the detection performance? What is the best sensor position for fall detection? In this paper we are trying to answer the above questions by performing two experiments. In one experiment we compare the fall detection performance for two floor installed radar and various fall directions. In the second experiment, we compare a wall mounted radar with a ceiling installed one.

This paper is organized as follows. In section II, we describe the experimental setup. In section III, we present the study methodology and algorithm. In section IV, we present and analyze the experimental results. We provide conclusions in section V.

II. Experimental Setup

The radar fall detection system uses the GE of range control radar (RCR), which has a center frequency of 5.8GHz. The radar was set to have a coverage range up to 6.1 meters. The room size is 9m × 8m × 3.5m.

Two configurations will be examined in this study to provide some insights about the radar positions on all detection performance. Each configuration has two radars. Configuration I (Fig. 1.a) has two RCRs placed on the floor while configuration II (Fig. 1.b) has a sensor on the wall and the other one on the ceiling. The first configuration is similar to the one used in [18, 19]. In Fig.1 (a, right), the two floor sensors are oriented toward the center of the room. The distance from RCR1 to the room center is about 3.7 m, denoted by L1. The distance from RCR2 to room center is 1.85, denoted by L2. In the image Fig.1 (a, left), the subject is performing a forward fall towards RCR1 and crossways RCR2. We note that RCR2 is closer to the fall than RCR1. In the second experimental configuration, one RCR is placed in the center of the ceiling and the other one is attached to the north wall at a height of 1.27 meters as shown in Fig. 1

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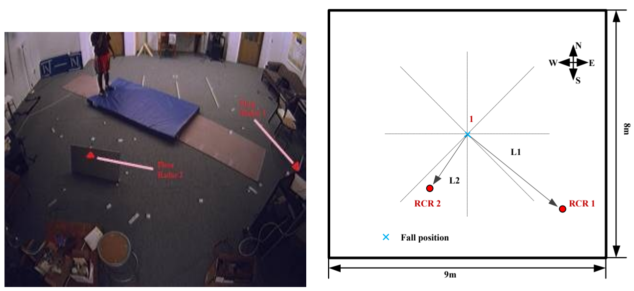
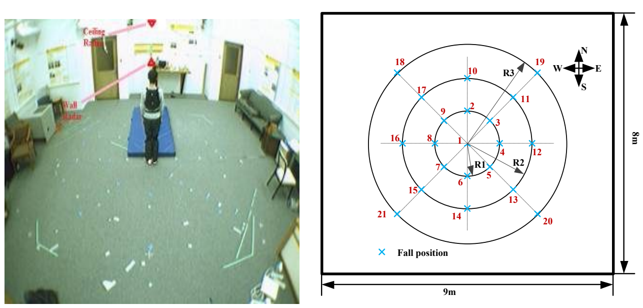
(b). The ceiling RCR is vertically pointing down to the center of the room. The wall RCR is pointing horizontally towards the center of the room. In Fig. 1 (b, right) falls were performed in a radial pattern, where radius R1 is 1 m, R2 is 2 m and R3 is 3 m. In the image of in Fig. 1 (b, left), the subject is standing in the room center and facing the north wall.

In configuration I, we collected 90 falls from 2 subjects who were falling in the center of the room to perform (see Fig. 2) 20 forward falls towards RCR1, 25 falls towards RCR2, 25 falls between RCR1 and RCR2, and 20 falls away from RCR1. In configuration II, we collected 126 falls from 2 subjects at 21 positions shown in Fig.1 (b, right). At each position, each of the subjects performs 3 types of falls (see Fig. 3): forward fall, left side fall, right side fall.

In configuration I, 341 non fall activities are selected from walking, body sway, cylinder sway, squat, pick up a book from the floor, *etc*. In configuration II, 817 non fall activities such as walking and bending down are selected from the recorded radar signal at locations that show high energy density in the related spectrogram. Details about both datasets can be seen in TABLE I.



(a) two floor radars system. (left) real view; (right) position diagram.



(b) wall and ceiling radars system. (left) real view; (right) position diagram.
Fig. 1. sensor deployment setups in motion lab.


Fig. 2. Four types of fall for configuration I. (a) forward fall toward RCR1; (b)forward fall toward RCR2; (c) forward fall between RCR1 & RCR2.


Fig. 3. Three types of fall for configuration II. (a) forward fall; (b)left side fall; (c)right side fall.

TABLE I. DATASET AND SUBJECT INFORMATION

System #	subject #	Height (cm)	Weight (kg)	Fall #	Fall direction
System I	1	188	88	20 20 5	Forward to RCR1 Forward to RCR2 Forward to RCR1&2
	2	162	53	20 20 5	Forward to RCR1&2 Away from RCR1 Forward to RCR2
System II	3	183	83	21 21 21	Forward Left side Right side
	4	171	61	21 21 21	Forward Left side Right side

III. METHODOLOGY AND ALGORITHM

The sampling frequency of the radar signal is 960Hz. We divided the whole fall detection procedure into three parts: data preprocessing; feature extraction; classification and result evaluation.

A. Data preprocessing

The fall signal segment, shown by the red block in Fig. 4, can be located using the timestamp provided by a synchronized web camera. If the fall timestamp is unavailable, we take the short time Fourier transform (STFT) to the given fall signal segment $r(n)$, as shown in Fig. 4, to obtain:

$$STFT(m,f) = \sum_{n=-\infty}^{\infty} r(n)w(n-m)e^{-jwn} \,. \tag{1}$$

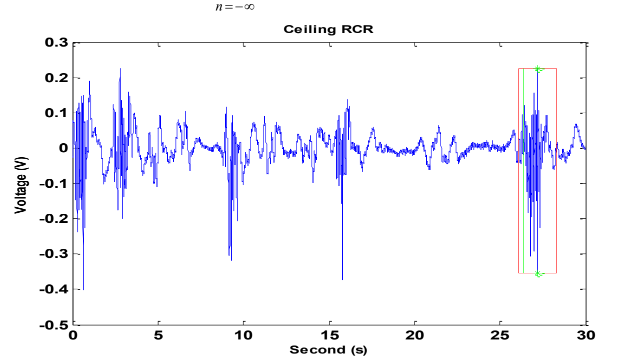


Fig. 4. A fall signal.

The spectrogram is formed by taking the magnitude square of the STFT,

$$spectrogram\{r(n)\} \equiv |STFT(m,w)|^2 \,. \tag{2}$$

which is shown in Fig. 5. We, next, generate the energy burst curve, Fig. 6.up, as

$$EB(m) = \sum_{w=25/(2\pi)}^{50/(2\pi)} STFT(m,w) \,, \tag{3}$$

and apply smoothing over K bursts to reduce noise:

$$\hat{EB}(m) = \sum_{i=0}^{K-1} EB(m-i) \,. \tag{4}$$

The peaks in this curve are marked in Fig. 6(up) by a red marker.

An example of using the energy burst curve to find energy peaks as non fall activities is shown on the top of Fig. 6. The located non fall activities, four 2 s windows marked by rectangles in the raw signal, are shown in Fig. 6. The corresponding non-falls spectrograms can be seen in Fig. 5.

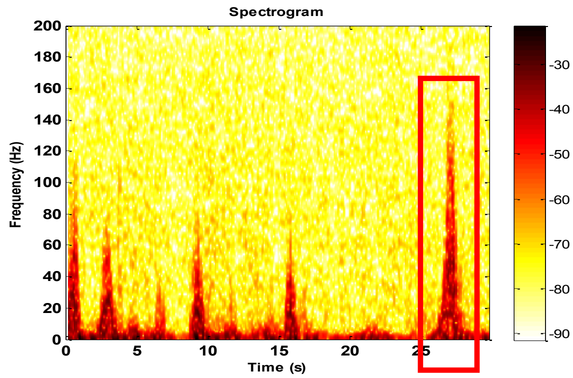


Fig. 5. The spectrogram of a fall signal (marked by rectangle).

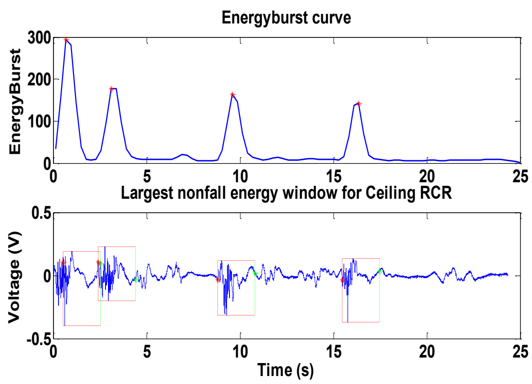


Fig. 6. Raw signal (down) and energy peaks (up) of non-fall activities.

If the timestamp from a synchronized web camera is available, the fall signal segment can be located directly and is indicated by the red rectangle in Fig. 4.

B. Feature extraction

For a selected 2-second window containing possible fall activities, we first segment the 2-second window into 166 sub-frames with an overlap rate of 0.5. Seven coefficients are extracted for each sub-frame. By discarding the dominant coefficient, we have 6×166=966 MFCC features to represent this motion instance.

C. Classification and result evaluation

In this paper we use support vector machine (SVM) to classify the radar signature in two classes: fall and non falls. We employed MATLAB to perform computational experiments and LibSVM [20] to implement SVM. For computational efficiency, we used only a linear kernel for SVM in all our experiment together with a leave-one-out cross validation framework (i.e. for N samples, each experiment uses N-1 samples for training and the remaining sample for testing). In order to evaluate the performance of our fall detection algorithms we produce a receiver operating characteristic (ROC) curve by thresholding the SVM scores at various values. Since the classifier and the extracted features are fixed in this paper, we can compare the performance the ROC curve to find the best sensor position.

IV. Experimental Results

A. Experiment1: influence of fall direction on RCR performance

We employed configuration I to explore the influence of fall direction on detector performance. In Fig. 7 and 8 we show the fall detection performance for different fall directions: towards, away, oblique and perpendicular the two sensors RCR1 and RCR2, respectively. From Fig. 7, we see that RCR1 has the best performance (AUC=0.996) when the fall is away from the sensor and the worst one (AUC=0.889) when the fall is perpendicular to it. In Fig. 8, the best detection of RCR2 was when the fall was towards the sensor (AUC=0.998) and the worst when the fall was perpendicular to the sensor (AUC=0.966). We note that RCR2 detection was, in general, better than RCR1's since the fall mat was closer to RCR2. From this experiment we can conclude that the fall direction has an important impact on detection performance, introducing about 10% variability in detection results. Best detection is obtained when the fall is along the sensor axis. Consequently, placing the radar on the floor might not be the best solution for fall detection. Instead, positioning the sensor higher up on the wall or on the ceiling of the room might improve the detection performance.

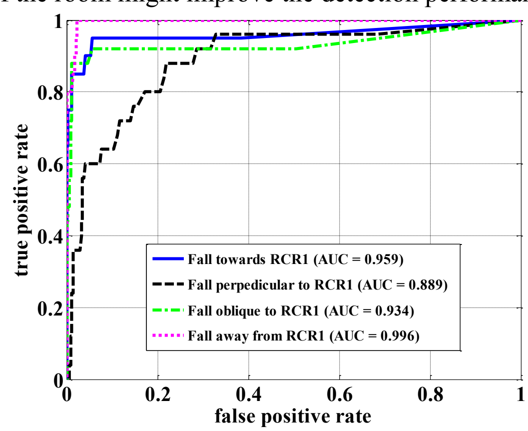


Fig. 7. Detection results for RCR1

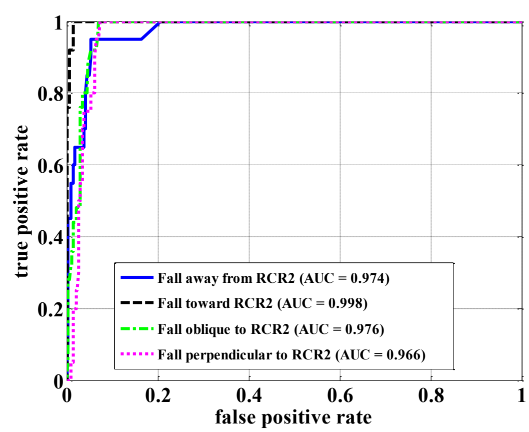


Fig. 8. Detection results for RCR2.

A. Experiment2: comparison between ceiling and wall mounted RCRs

We used configuration II to compare two sensor locations: wall and ceiling. In this configuration, two subjects performed three types of falls at each of the 21 positions shown in Fig. 1.b.right. The fall recognition results obtained for configuration II are given in Fig. 9. From Fig. 9, we can conclude that the ceiling mounted RCR has better performance than the wall mounted one.

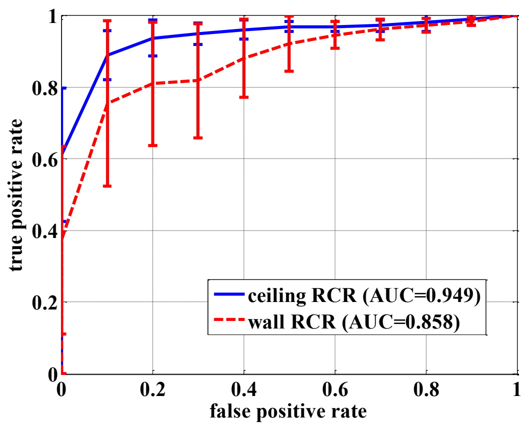


Fig. 9. Detection results for forward fall.

Moreover, although the ceiling RCR has some variability in detection due to fall direction, this is only about 30% from that of the wall and floor mounted sensors. However, comparing Fig. 7, 8 and 9 we see that the ceiling RCR has a slightly lower performance (3-4%) than the floor RCRs when falls are close to the sensor.

V. Conclusions

Based on the results, we have the following observations. For configuration I, better result is achieved when the fall is straightly towards or away from the RCR. The detection performance also improves as the falling subject and the RCR sensor is closer to each other. For configuration II, ceiling mounted RCR can always generate more stable fall detection results than wall mounted RCR and is less sensitive to the fall direction. The wall mounted RCR has stronger dependency on fall direction.

In conclusion, in further experiments, we consider to install a ceiling mounted RCR for the entire apartment and deploy a floor RCR in the most probable falling location (living room or bedroom).

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