A Portable Continuous Wave Radar System to Detect Elderly Fall

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Abstract. Fall is the leading cause of death among elderly people worldwide. In this work a low power portable continuous wave radar (CWR) system is proposed to detect elderly fall. This paper presents experimental evaluation of the system to detect human fall motion among various sitting, standing and walking activities. Signals from three subjects with different heights and weights engaged with the different movement activities including walking, sitting, standing and fall in front of the proposed radar system are analyzed. Overall, 60 fall and 180 non-fall activities were recorded. The Short-time Fourier Transform (STFT) is employed to obtain time-frequency Doppler signatures of different human activities. Radar data is analysed by using MATLAB and an algorithm is employed to classify the fall on the basis of analysed data. The results show that the proposed portable CWR can be used to detect fall from non-fall activities with almost 100% accuracy.

Keywords: Fall detection · CWR · STFT

1 Introduction

In recent years average life expectance of human beings has increased unprecedently. By 2050 more than 50% of the total population of the world will be over 60+ age [1]. Each year approximately 37.3 million falls occur which require intense medical attention. Approximately 646,000 deaths occur every year due to fall and majority of these are above age of 60 years [1]. In United States, unintentional fall of elderly people above 65 age is the leading cause of death. This situation is same among the less developed countries [2]. Besides fatal injuries, fall also causes serious implications which affect the quality of life of elderly people. Fractures resulted from a fall can reduce the mobility of elderly people to bed only and most of them die within 1 year of fall [3]. Early and accurate fall detection can significantly contribute towards immediate response and proper care of the elderly people which will alleviate the risk of mortality [4].

Wearable and non-contact devices are the two most competing technologies for fall detection. Wearable devices like accelerometer sensors can detect a fall by calculating the vertical acceleration of the body [5]. Although wearable technologies; accelerometer sensors or emergency push buttons are widely used, the major drawbacks of such devices are that they have to be worn by a person all the time which may

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impede one's daily routine. Moreover, elderly people are required to remember wearing them all the time and they must be mentally conscious after the fall to press the push button. Furthermore, these devices suffer from intrusiveness, fragility and degradability. Cameras can be used to monitor movements of the elderly but in this way, their privacy is compromised. The striking attributes of a radar system include nonintrusive sensing, immune to lighting and weather conditions and preservation of privacy [6].

Radar back scatter by a moving object changes the frequencies of the radar signal and this phenomenon is called Doppler Effect. A fall motion can be detected by a radar by analyzing the back scattering caused by a fall. In literature target back scatterings have been recorded for different types of motion [7–9]. To analyze these back-scatter signals different processing techniques such as STFT [10], Wavelet Transforms [11] and Fractional Domain Fourier Transform (FrFT) [12] have been employed. Depending on the operating frequency and power of the equipment, unique Doppler signatures have been achieved for different type of motions. Once the radar signals are analyzed, their unique features are extracted and a fall is determined by using different classifiers. Most common classifiers used are Support Vector Machine used in [13], k-nearest neighbours used in [7] and machine learning based on Hidden Markov model has been used in [14].

In this work a low power, low frequency, portable yet efficient Doppler radar system to detect a human fall is proposed. In [6–14] the radar systems used were quite large and expensive. A comparatively portable Doppler radar system was proposed in [15] but for physiological parameter measurements. This paper presents experimental evaluation of the system to detect fall motion in various sitting, standing and walking activities. The proposed portable Doppler radar system can detect a fall very efficiently from other human motions even with the events which involve immediate falls during walk activity. Radar data is analysed by using MATLAB and an algorithm is employed to classify the fall on the basis of analysed data.

The rest of the paper is divided in the following sections. Section 2 describes signal model. Section 3 explains hardware model. Section 4 deals with signal processing. Section 5 includes results and discussions. Section 6 concludes the paper followed by references.

2 Signal Model

The signal transmitted by the radar is given by

$$\mathrm{T_x(t) = A\ cos(\omega_c t)} \tag{1}$$

where $\boldsymbol{\omega c = 2\pi fc}$ is the central operating frequency of the CWR. The signal received by the radar at any time interval $\boldsymbol{t}$ is given by

$$R_x(t) = T_x(t - \phi(t)) \tag{2}$$

where

$$\phi(\mathrm{t}) = \frac{2}{\mathrm{c}}(\mathrm{d_o} - \mathrm{vt}) \tag{3}$$

Where $\boldsymbol{d_0}$ be the distance of the body from the radar at time t_0 and v is the target velocity component. Substituting (1) and (3) in (2)

$$\mathrm{R_x(t)} = \mathrm{Mcos}\left[2\pi\left(\mathrm{f_c t} - \mathrm{f_c}\frac{2\mathrm{d_o}}{\mathrm{c}} + \frac{2\mathrm{f_c vt}}{\mathrm{c}}\right)\right] \tag{4}$$

where $\boldsymbol{M}$ is a constant and the phase given by

$$\Theta = 2\pi\mathrm{f_c}\frac{2\mathrm{d_o}}{\mathrm{c}}\cdots \tag{5}$$

The doppler frequency is given by

$$\mathrm{f_D} = \frac{2\mathrm{f_c v}}{\mathrm{c}} \tag{6}$$

The in-phase and quadrature components are given by

$$I(t) \approx \cos(\omega_o + \Theta + f_D t) \tag{7}$$

and

$$Q(t) \approx \sin(\omega_o + \Theta + f_D t) \tag{8}$$

STFT is computed by

$$R(a,b) = \sum\nolimits_{n=1}^{m} x[n]\omega^*(nT - aT)e^{-i\omega t}bFn\ldots \tag{9}$$

where $\boldsymbol{a}$ is the time index, $\boldsymbol{b}$ is the frequency index, $\boldsymbol{T}$ is sampling period, $\boldsymbol{F}$ is frequency step size, $\boldsymbol{\omega}$ (.) is Hamming window function, and * denotes complex conjugate [14].

3 Hardware Model

Radar hardware is shown in Fig. 1.

Fig. 1. Radar hardware

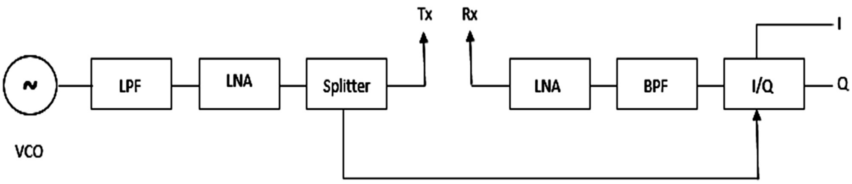

Fig. 2. Radar hardware block diagram

As described in Fig. 2, an 887 MHz signal was generated using a voltage control oscillator (VCO) with 10dBm power. The signal is then passed through a low pass filter (LPF) to remove high frequency noise components of the VCO, which may cause non-linearity at the receiver side. The signal is then amplified by a low noise amplifier (LNA) and split by using a two-way power splitter. One part of the signal goes to transmitter antenna while the other goes to a local oscillator (LO) input of an in-phase-quadrature (I/Q) demodulator. Radar back scatter received by the receiver antenna are very low in power, so an amplifier of 16 dB gain is applied. Finally, to eliminate unwanted frequency components the signal is passed through a bandpass filter (BPF) before down-converted to baseband signal.

Ultrawideband (UWB) patch antennas are used for transmitter and receiver purposes with return loss lower than −10 dB at operating frequency.

3.1 Data Experimental Setup

Figure 3 shows the experiment setup. Radar uses 887 MHz center frequency, as the system is portable it can be placed anywhere in a room. For this setup, the antennas were setup at a height of 2 m above the ground. Three subjects with different heights and weights volunteered for different movement activities including walking, sitting, standing and fall in front of the radar. All of these activities are monitored within a distance of four meters in front of the Radar. Four different experiments were conducted involving the above-mentioned activities. In the first experiment the subjects were asked to stand in front of the radar system and fall on a mattress, then stand up and again perform fall. Ten number of falls for each subject were recorded. In the second experiment the subjects were asked to walk in front of the radar and then fall on the mattress, again ten number of falls for each subject were recorded. To distinguish between walk and sit with a fall, in the third experiment the volunteers were asked to sit on a chair in a fast manner while walking. Each subject was asked to sit ten times while walking. Finally, in the fourth experiment the subjects were asked to sit and stand quickly on the chair, again each subject was asked to sit and stand ten times. Overall, 60 fall and 180 non-fall activities were recorded.

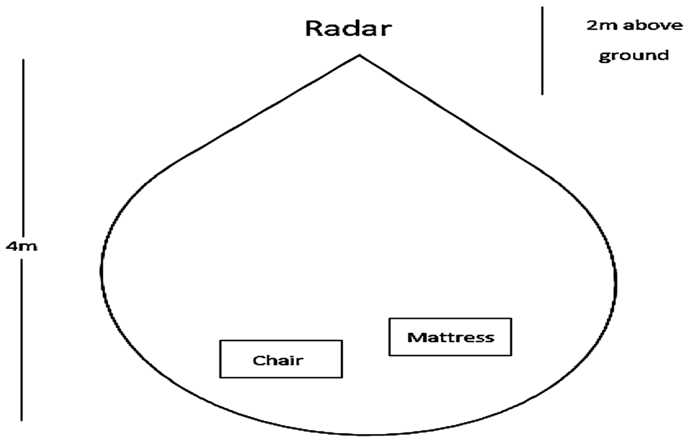

Fig. 3. Experimental setup

In all these experiments the data was recorded for a duration of three minutes for each experiment and activities were performed at different locations in front of the radar system.

4 Signal Processing

Figure 4 surmises the signal processing unit. A MATLAB program was developed to fetch data from the radar system. The in-phase (I) and quadrature (Q) data were sampled at 1000 samples per second and stored in a m.file for signal processing.

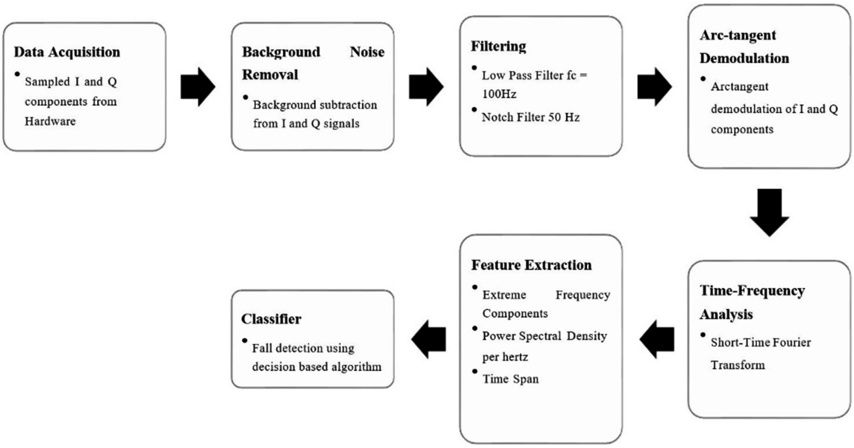

Fig. 4. Signal processing flow chart for fall detection

First of all, in order to remove background noise or dc level, the I and Q signals were subtracted with the data recorded without any activity and sampled at same rate i.e. 1000 samples per second. As STFT proved to be very effective in obtaining time-frequency signatures of Doppler radars [16], the main goal was to get the time- frequency signature of the radar by applying STFT. To do so, different filtering techniques were applied to remove additional frequency components from the signals. At the end an algorithm was developed to detect fall on the basis of features generated by STFT. Power spectral density in dB/Hz was extracted from STFT and an algorithm was applied making decision based on the value of dB/Hz on extreme frequency components. For instance, a low pass infinite-impulse response IIR filter was first applied with cut-off frequency of 100 Hz. After that a constant noise was noticed at 50 Hz, so a notch filter with 50 Hz center frequency was applied on I and Q channels.

Once the noise components were filtered then the arctangent demodulation was performed to get the best of I and Q signals. Finally, for linear time-frequency analysis STFT was employed. The results from the spectrogram obtained clearly distinguished a fall from other non-fall activities.

For STFT following settings were employed: window size of 1024, 1000 non-overlap, sampling frequency of 1000 samples per second and minimum threshold of 0db were set. The values of window size and non-overlap sample were set to get best temporal resolution. The threshold level was set to eliminate weak reflections as we were concerned with only gross motor activities to detect fall.

For fall classification features such as, extreme frequency components, power spectral density per frequency and time span of event were extracted and sent to a decision-making algorithm.

5 Results and Discussions

Figure 5 shows different time-frequency Doppler signatures of human activities in the form of the spectrogram. The spectrogram is computed using Hamming window of 1024 point, logarithm scale and 0 dB power/frequency threshold. This threshold is set to record only those reflections which contain sufficient amount of energy. The highest frequency component with at least 0 dB power is below 25 Hz because at low center frequency, 887 Hz in our case, most of the energy is reflected back by the target on lower frequency components [14]. The results of all the spectrograms in Fig. 5 are consistent with previous works [10–14] yet with low power, low frequency and portable equipment.

Figure 5(a) represents the spectrogram of the first experiment. The peaks in the spectrogram at different time intervals are the falls in the experiments. The reflected energies are concentrated to lower frequencies but at the time of fall maximum displacement can be observed in the frequency axis with at least 0 dB power. As described in [17], after a fall no higher energy was received due to negligible movement. Figure 5(b) represents the spectrogram of the second experiment in which falls during walk were detected. The peaks in the spectrogram at different time intervals are the falls in the experiments. The reflected energies are concentrated to lower frequencies but again at the time of every fall maximum displacement can be observed on the frequency axis.

As explained in [16], detecting a fall from walk is very challenging due to movement of the whole body. It can be seen in the Fig. 5(b) that due to acceleration of a fall high Doppler frequency components can still be easily distinguished from high energy walk t-f signatures.

Figure 5(c) shows the spectrogram of third experiment. It can be easily observed that sitting after walk generates high Doppler frequency but these are low as compared to fall during walk motion, hence can easily be distinguished from each other. Figure 5(d) is the spectrogram based on the fourth experiment. First spike represents sitting followed by standing and the subsequent spikes follow the same pattern. The Doppler frequencies of these motions are less than the ones of fall.

Based on the frequency components having high power spectral density and time information obtained from spectrogram an algorithm is developed to classify a fall from non-fall activities. Table 1 shows the fall detection based on the extracted features. Accuracy is determined by dividing the correctly detected activities with total activities.

Table 1. Fall detection based on extracted features

Experiment	Total activities	Actual falls	Detected fall	% Accuracy
1. Stand and Fall	60	30	30	100
2. Walk and Fall	60	30	33	95
3. Walk and Sit	60	0	2	96.6
4. Stand and Sit	60	0	0	100

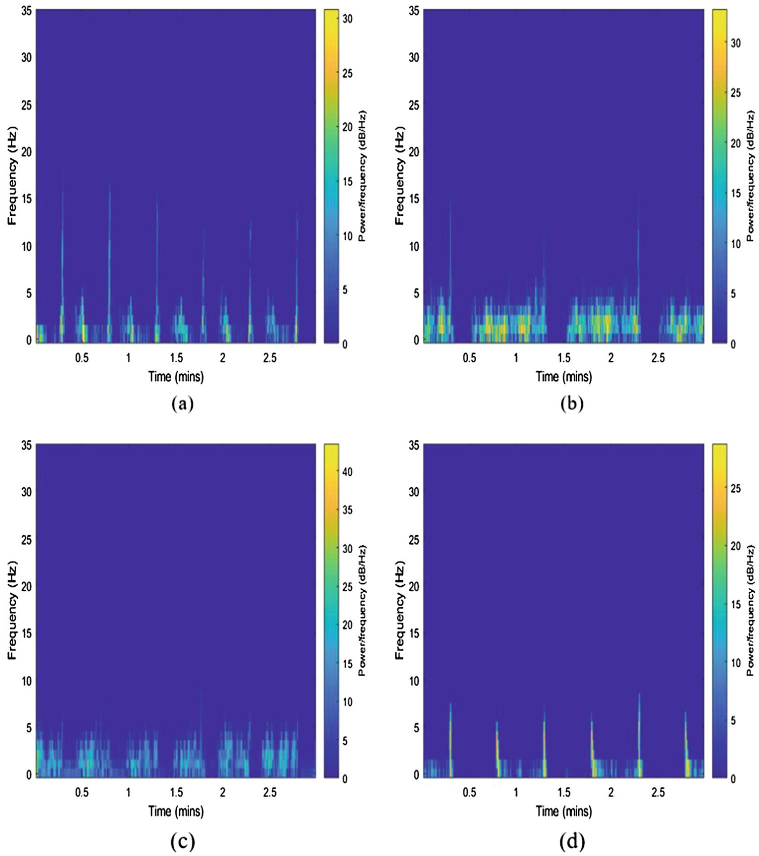

Fig. 5. Spectrogram of experiments: (a) Stand and Fall (b) Walk and Fall (c) Walk and Sit (d) Stand and Sit

6 Conclusion

This work demonstrates that a low power and portable CWR can be effectively used to detect fall among other human activities. Unique time-frequency signal for a fall are obtained by applying STFT on radar's sampled data. Based on the power spectral density and time information of the spectrogram, an algorithm analyzing radar signals has been developed to classify a fall. The results verified that a fall can be classified with high accuracy from the proposed system and processing techniques.

All of the experiments are conducted within a distance of four meters from the radar system and the classification algorithm makes decision on the basis of power spectral density and time information only. High gain amplifiers and appropriate filters can be used to maximize the fall detection range. A more powerful and efficient classification algorithm utilizing more features can be trained to minimize false detection of the system.

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