Residual Network-based Supervised Learning of Remotely Sensed Fall Incidents using Ultra-wideband Radar

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***Abstract*—Detecting falls using radar has many applications in smart health care. In this paper, a novel method for fall detection in human daily activities using an ultra wideband radar technology is proposed. A time series derived from the radar scattering matrix is used as input to the the residual network for automatic feature extraction. In contrast to other existing methods, the proposed method relies on multi-level feature learning directly from the radar time series signals. In particular, the proposed method utilizes a deep residual neural network for automating feature learning and enhancing model discriminability. The performance of the proposed method is compared with that of the other methods such as support vector machine, K-nearest neighbors, multi-layer perceptron and dynamic time warping techniques. The results show that the proposed fall detection method outperforms the other methods in terms of accuracy and sensitivity values.**

***Index Terms*—Biomedical signal processing, smart home care, ultra-wideband radar, fall detection, residual network, classification.**

I. Introduction

DEVISING technologies for fall detection and prevention is crucial in elder care systems, since sudden falls are considered the leading cause of injury and accidental death for seniors [1]. Fall is considered to be an uncontrolled, unintentional and sudden change of posture. Several methods developed so far for detecting falls are mostly based on wearable devices, video cameras and smart-phone sensors [2]. Radar-based fall detection has recently gained much attention due to the fact that this technology is privacy-friendly and non-contact unlike the techniques based on video-cameras and wearable sensors [3], [4].

A wavelet-based approach was devised in [5] for fall detection purpose using Doppler radar. In [6], a fall detection scheme was presented by exploiting time-frequency characteristics of the radar Doppler signatures. In [7], frequency domain features such as cepstrum coefficients were extracted from the radar signal in a fall detection approach. In [8], [9], several frequency domain features as well as the range information were used to develop a fall detection technique. In [10], [11], time-frequency domain analysis was presented for human posture classification and fall detection. These extracted features are limited in type, requiring expert knowledge to manually perform feature engineering.

Few attempts have so far been made to design an automated feature extraction method from radar data. In [12], a radar signal recognition was proposed using a deep restricted Boltzmann machine. In [13], a deep neural network approach was presented to reduce dimensionality of the extracted features from the radar signals based on the two-layer auto-encoder. A gait-based human identification was presented in [14] by using an acoustic sensor and a deep neural network. In [15], a human activity recognition method was proposed based on convolutional neural network applied to micro-Doppler signatures. However, automatic feature extraction from the radar time series signals used for various classification problems including fall detection has not been proposed in the literature.

To automate feature extraction from radar data, in this paper, a new fall detection method is proposed by incorporating time series derived from an ultra-wideband radar signals and a deep neural network. In particular, the proposed method is realized by adopting residual networks for extracting multi-level features from radar time series data. The radar time series are obtained by summing up over all the range bins in the radar scattering matrix. Experiments were conducted at Biomedical Signal Processing Lab in University of Ottawa to assess the performance of the proposed method and compare it with that of other existing methods.

The paper is organized as follows. In Section II, the experimental setup and radar used for data acquisition is described. In Section III, the proposed fall detection method using the proposed deep residual network is presented. Experimental results are included in Section IV. Finally, Section V concludes the paper.

II. Experimental Setup and Measurement

Xethru X4M03 kit was used in our experiments for collecting data. The UWB radar operates in $5.9-10.3$ GHz, providing high spatial resolution. The radar is placed 1.5 m above the floor level. Each scan is repeated for 15 seconds and digitized at a rate of 200 samples/second (fast-time). The range of the radar used in this study is 10 m with a range resolution of 5.35 cm, resulting in 189 range bins. The radar time series signal is obtained via summing up the signals in these range bins.

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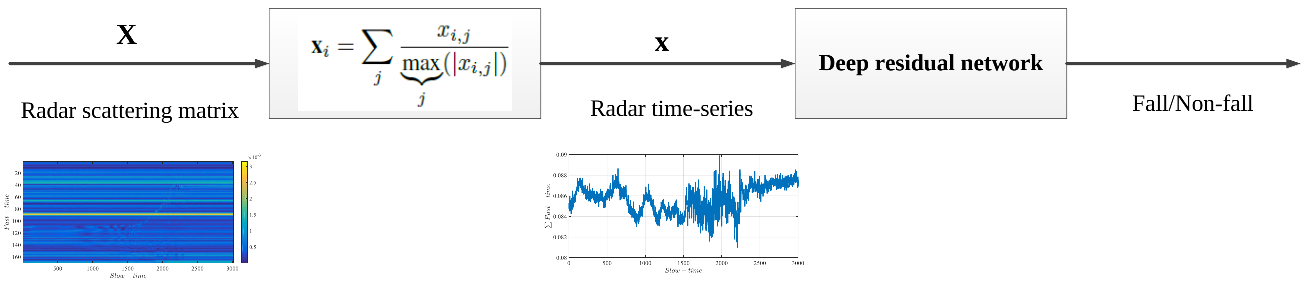


Fig. 1. Block diagram of the proposed radar-based fall detection method.

The collected data includes different types of fall and non-fall activities, performed by ten healthy male subjects aging from 20 to 35. The dataset includes the following activities: walking toward radar and falling down, standing in front of radar and falling down, standing and falling down perpendicular to the radar line of sight, lying down and standing up in front of the radar, and lying down and standing up perpendicular to the radar line of sight. The number of different experiments performed are 187 fall and 149 non-fall samples. It should be noted that the ethics approval for conducting the experiments was obtained from the Research Ethics Board at the University of Ottawa.

III. Proposed Fall Detection Method

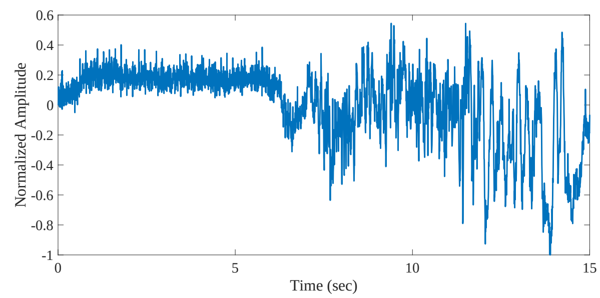
In this section, the proposed fall detection method based on automatic feature extraction and classification using residual network is presented. Fig. 1 shows schematic of the proposed fall detection method.

A. Preprocessing

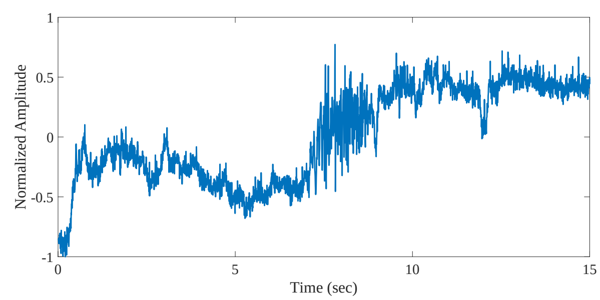
In the experiments, the radar scattering matrix $\mathbf{X} = x_{i,j} \in \mathbb{R}^{m \times n}$, i.e., the received radar signal, is recorded, where n columns represent the spatial samples from different ranges (fast-time) and m rows correspond to observations recorded at different time intervals (slow-time). A radar time series is derived by integrating the fast-time data in all the columns and normalizing it as $\mathbf{x}_i = \sum_j \frac{x_{i,j}}{\underbrace{\max}_{j}(|x_{i,j}|)}$. The resulting time series includes sampled in slow time and is used as input to the residual network for automatic feature extraction and classification. Fig. 2 shows the normalized radar time series corresponding to standing up and falling down activities.

B. Deep Residual Network

Common approaches to detect falls include extraction of a set of features from various domains such as time, frequency, and time-frequency [5], [6], [8]–[10]. It is known that any improvement in the detection performance of such approaches is highly reliant on the type of features extracted. Automatic feature learning using deep neural networks has obviated the



(a)



(b)

Fig. 2. Radar time series associated with (a) Stand up from a lying position, (b) Fall after walking toward radar.

need for manual feature engineering and domain knowledge of the data. In other words, creating relevant features, testing them, examining the importance of various features and feature selection can all be handled using automatic feature extraction.

In the proposed fall detection method, deep residual network is applied to the radar time series data for automatic feature learning and classification tasks. Residual networks are known for their advantage in providing direct gradient flow through the bottom layers, which is realized by adding the shortcut connection in each residual block [16].

In the proposed scheme, each residual block is constructed by three convolutional layers. Each convolutional layer is followed by batch normalization and rectified linear unit activation function (ReLU), i.e., $f(x) = \max(0, x)$. The output feature map $\mathbf{S}$ of each convolutional layer i is obtained as

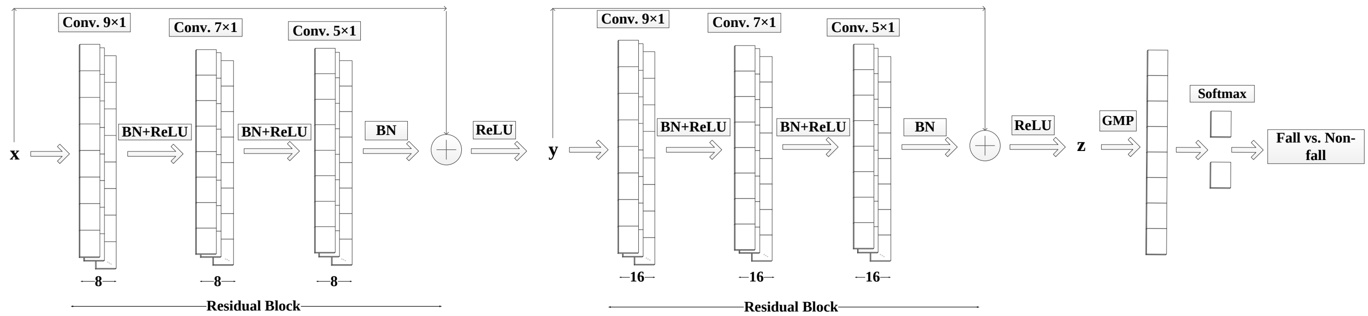


Fig. 3. Architecture of the proposed deep residual network used in the fall detection problem.

$\mathbf{S}^{c_i} = \mathbf{S}^{c_{i-1}} * \mathbf{K}^{c_i} + \mathbf{b}^{c_i}$, where $*$ is the convolutional operator, c denotes the convolutional layer index, $\mathbf{K}$ and $\mathbf{b}$ denote the trainable kernels and biases, respectively. The network structure including the number of convolutional layers, number of kernels and kernel sizes are tuned via random search optimization to provide the best classification results in the proposed fall detection method. In particular, in the first block, there exist three convolutional layer $\{c_i\}_{i=1}^{3}$, each having 8 kernels $\left\{k_j^{c_i}\right\}_{j=1}^{8}$ of size 9×1, 7×1 and 5×1, respectively. It is noted that the kernel size controls the number of time steps in each read of the input time series. It is noted that the relatively small kernel sizes makes the reading of the time series more rigorous and captures the local temporal information more accurately. The resulting feature map from the final convolutional layer in the first block is added to the input vector $\mathbf{x}$, and the result is passed through ReLU function function. The output feature map $\mathbf{y}$ has a depth of 8.

In the second block, similar procedure is followed with convolution layers having 16 kernels. The batch normalization (BN) is performed after each convolutional layer to speed up the feature learning process and improve the stability of the network. The second and final residual block is followed by a global maximum pooling (GMP) layer and an output layer. In order to lower the spatial dimensionality of the extracted features, instead of the common choice of fully-connected layers, the GMP layer is employed, since it is less prone to overfitting [17]. The pooling mechanism is performed by selecting the maximum value of the features in the last residual block. For the output layer, the softmax activation function is used to give the probabilities of the predicted classes. The proposed residual network is trained using the back-propagation algorithm. The learning model minimizes the categorical cross-entropy cost function [20] via an optimization process, i.e., Adam optimizer [18], with a learning rate equal to 0.001. The loss value decreases after each training iteration, i.e. epochs. The number of epochs is set to 200.

IV. Experimental Results

Experiments were conducted on a set of radar data collected in a realistic environment at University of Ottawa, to evaluate the performance of the proposed fall detection method. In the proposed method, the radar scattering matrix is first processed to obtain the sum of the fast-time data. The resulting time series is directly fed into the proposed deep residual network to test whether or not an specific time series represents a fall incident. For comparison purposes, Gaussian support vector machine (GSVM), K-nearest neighbors (KNN), multi-layer perceptron (MLP) and dynamic time warping (DTW) [21], [22] approaches are considered. In the case of KNN, different values for K are examined and the best results, i.e., $K = 5$, is reported.

DTW is a distance measure and calculates the optimal match between two given time series by combining Euclidean distance and window constraint. MLP is a classical neural network consisting of a number of layers each having an specific number of neurons.

Table I gives classification metrics obtained using the proposed method and those of the other methods, namely, three MLP networks having three hidden layers and 50, 100 and 200 neurons in each layer, and DTW with different warping window of sizes $W = 5$ and 10, i.e., DTW(5) and DTW(10). In the case of MLP, the hyper-parameters are drop out, which is set to 0.2 for each layer, and learning rate, which is set to 0.001. Similar to the proposed residual network, the categorical cross-entropy cost function and Adam optimizer are used in training process. In the case of DTW, the LB Keogh lower bound and locality constraint are considered to lower the computational complexity of DTW [19].

The classifiers are trained using the radar time series for 70% of the data and tested using the remaining data. In particular, in each run, 235 data samples are randomly chosen for training and 101 data samples for testing purpose. The results are averaged over 20 runs. It is seen from this table that the proposed method outperforms the other methods by providing higher detection rates on test set. In particular, the proposed method achieves 93.07% accuracy, 92.98% precision, and 90.91% sensitivity, which are higher than those yielded by the other methods. Noticeably, the proposed method based on residual network performs better than DTW, in detecting fall incidents with higher accuracy and sensitivity values. The superior performance of the proposed method using deep

TABLE I

ACCURACY, PRECISION AND RECALL (%) OBTAINED USING THE PROPOSED FALL DETECTION METHOD AS WELL AS THOSE OBTAINED USING KNN, SVM, MLP AND DTW.

Method	Accuracy	Precision	Sensitivity
5NN	75.25	78.84	71.93
GSVM	62.37	76.92	60.61
MLP50	74.26	82.69	71.67
MLP100	79.21	92.31	73.84
MLP200	77.23	86.54	73.77
5NN-DTW(5)	88.12	100	81.25
5NN-DTW(10)	90.10	100	85.25
Proposed	**93.07**	**96.15**	**90.91**

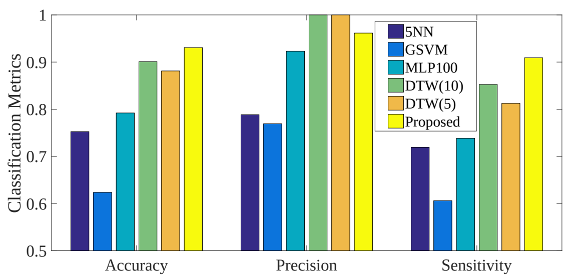


Fig. 4. Classification metrics comparison of the proposed fall detection method and those of the other methods.

residual network is due to the fact that the structure of the residual network can learn an internal representation of the time series data and their local relationships more accurately than the other methods for the fall detection problem.

Fig. 4 shows the classification metrics obtained using the proposed method as well as those obtained using the other methods. It is seen from this figure that the proposed method provides higher values for accuracy and sensitivity than the other methods.

V. CONCLUSION

A new fall detection method has been proposed using an ultra-wideband radar and supervised learning approach based on deep residual network. The radar time series have been derived from the radar scattering matrix and fed into a deep residual network for automatic feature learning. Experiments have been conducted to assess the performance of the proposed method and to compare it with that of the state-of-the-art. The results have demonstrated that the proposed fall detection method outperforms MLP and DTW algorithms in terms of providing higher classification metrics. The proposed deep residual network-based method can learn from the time series radar data directly and do not require domain expertise to manually engineer features extracted from traditional time-frequency analysis of the radar return signals.

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