ON THE USE OF ULTRA WIDEBAND RADAR AND STACKED LSTM-RNN FOR AT HOME FALL DETECTION

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ABSTRACT

Fall detection problem for smart home-care systems using an ultra wideband radar is considered in this paper. The goal is to identify the occurrence of fall from the radar return signals through a supervised learning approach. To this end, a new framework is proposed based on stacked long-short-term memory (LSTM) recurrent neural network to develop a robust method for feature extraction and classification of radar data of human daily activity. It is noted that the proposed method do not require heavy preprocessing on the data or feature engineering. It is known that LSTM networks are capable of capturing dependencies in time series data. In view of this, the radar time series data are directly fed into a stacked LSTM network for automatic feature extraction. Experiments are conducted on radar data collected from different subjects, when performing fall and non-fall activities. It is shown that the proposed method can provide a classification accuracy higher than that yielded by the other existing methods.

Index Terms— Ultra wideband radar, stacked LSTM-RNN, smart home care, time series, fall detection.

1. INTRODUCTION

Fall detection has been a trending research area in public healthcare resulting in technological developments in smart homes which help the elderly living alone. In order for the caregivers to provide a timely and efficient help, it is of great importance to establish highly accurate technologies for fall detection in human daily activities. Several methods have so far been developed to provide reliable means of detecting fall incidents and alerting caregivers including wearable sensors, smart-phone sensors and video cameras [1]. On the other hand, non-contact radar-based monitoring has received a great deal of attention in recent years [2,3]. This is due to the fact that the radar-based indoor monitoring provides a simple, inexpensive, and privacy-friendly system as compared to wearable devices and video-based techniques [2]. For instance, posture classification has been studied in [4] using a radar sensor. A human activity recognition method has been developed using radar micro-Doppler [5]. Gait abnormalities have been detected in [6] using radar Doppler features. A wavelet-based approach has been devised in [7] for fall detection purpose using Doppler radar. In [8], a fall detection scheme has been presented by exploiting time-frequency characteristics of the radar Doppler signatures. In [9], a stack auto-encoder has been used for dimensionality reduction of the radar-based features. In [10], a human identification technique has been presented using an acoustic sensor and a deep neural network. In [11], a radar signal recognition has been proposed based on deep restricted Boltzmann machine. However, none of these works have addressed a fall detection method with an automatic feature extraction from the radar time series signals.

In view of this, we propose a novel fall detection method using ultra wideband radar return signals. The proposed framework is realized by using a novel feature extraction and classification using the stacked LSTM recurrent neural network which takes into account the dependencies among the instances in radar slow-time time series. In particular, signals reflected from the target are summed up over all the range bins in fast-time and the resulting time series in slow-time is fed into the proposed LSTM network. The LSTM network provides a mean to extract relevant features from time series and recognize the fall or non-fall classes. Experiments are conducted to evaluate the performance of the proposed method and compare it with that of the other fall detection methods.

The paper is structured as follows. Section II presents the proposed fall detection framework. Simulation results are given in Section III. Finally, Section IV concludes the paper.

2. THE PROPOSED FALL DETECTION FRAMEWORK

The proposed fall detection method consists of the following main steps: (i) preprocessing; (ii) feature extraction and classification. In the following, these steps are described in details.

(a)

(b)
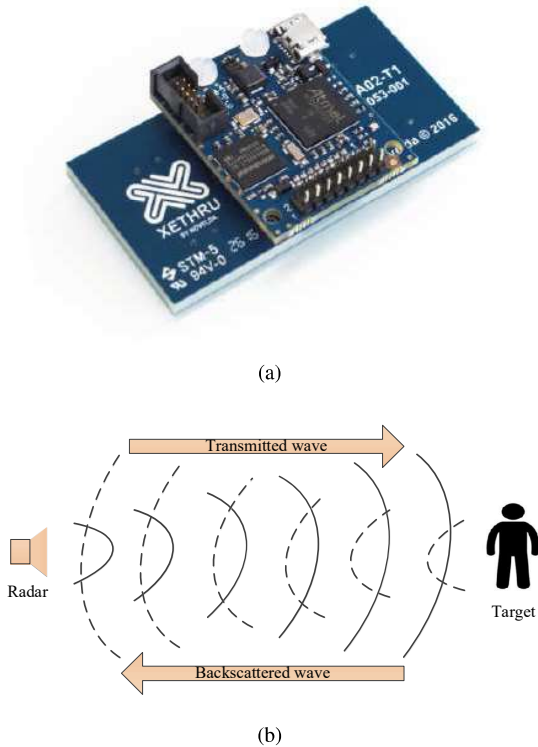
Fig. 1. (a) Novelda Xethru X4M03 radar used in the proposed fall detection system, (b) Radar signal transmission.

2.1. Preprocessing

We consider supervised learning from ultra wideband radar return signals. The Xethru X4M03 development kit, shown in Fig. 1, which uses a UWB transceiver operating in the range of $5.9 - 10.3$ GHz is used in the experiments. Various experiments including fall and non-fall activities were conducted at the University of Ottawa in a room measuring 12.6×4.1 m^2. Each experiment lasted 15 seconds which is digitized at a rate of 200 samples/second, resulting in a back-scattered radar matrix, where each column represents the spatial samples from different ranges (fast-time) and each row represents observations recorded at different time intervals (slow-time). The ethics approval for conducting the experiments was confirmed by the Research Ethics Board at the University of Ottawa.

After removing clutter from the radar returns, time series signal is derived from the radar back-scattered matrix. In particular, a time series in radar slow time of length L with elements $x[k], 1 \leq k \leq L$ is obtained, where each $x[k]$ is obtained by summing up the radar fast-time data at that particular slow time k. Figs. 2 shows the radar time series signals corresponding to non-fall and fall activities. The time series dataset is denoted by $\{(\mathbf{x}_i, L_i)\}$, for $(1 \leq i \leq N_{tr})$, where L_i
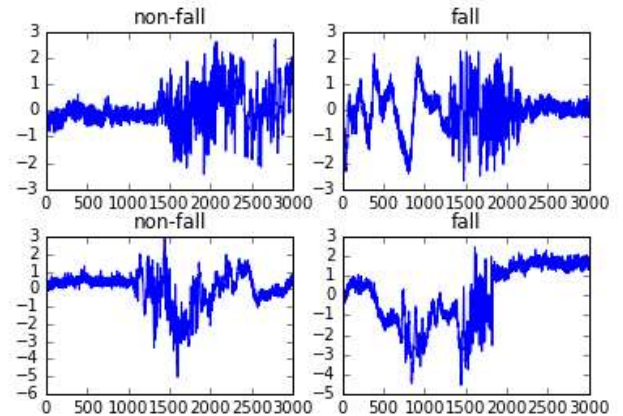

Fig. 2. Radar time series signals corresponding to non-fall (left-column) and fall (right-column) activities.

represents the label corresponding to the ith experiment, e.g., L_i can be "fall" or "non-fall", and N_{tr} is the total number of data samples.

2.2. Feature Extraction and Classification

The emerging field of deep learning offers a framework for automatic and hierarchical feature extraction and classification in many applications. In this work, leveraging the recent advances in deep neural networks, we propose the use of stacked LSTM recurrent neural networks for fall detection purpose. The recurrent neural networks (RNN) are a type of neural networks which contain loops in their architecture and are capable of characterizing the temporal behavior of a signal. However, it is known that these networks suffer from the vanishing gradients [12]. In view of this, the LSTM-RNNs have been proposed to overcome the vanishing gradient problem by incorporating a memory cell and gating functions into their state dynamics [12]. In particular, LSTM-RNNs process inputs with three multiplicative gates. These gates control the proportion of input that is either passed into the memory cell or is forgotten. They also improve gradient flow over long time sequences by performing additive interactions in the memory cell. In view of this, LSTM-RNNs are best suited for learning long-term dependencies from time series. It is known that there is a strong correlation among the radar time series data at different time steps. Thus, in order to account for this intrinsic dependencies, the stacked LSTM network is employed as our learning model to allow for persisting information about different activities over time. Fig. 3 illustrates the block diagram of the proposed fall detection method with a many-to-one stacked LSTM-RNN architecture. The stacked LSTM is realized by concatenating multiple layers of LSTM on top of each other. Compared to standard (single-layer)
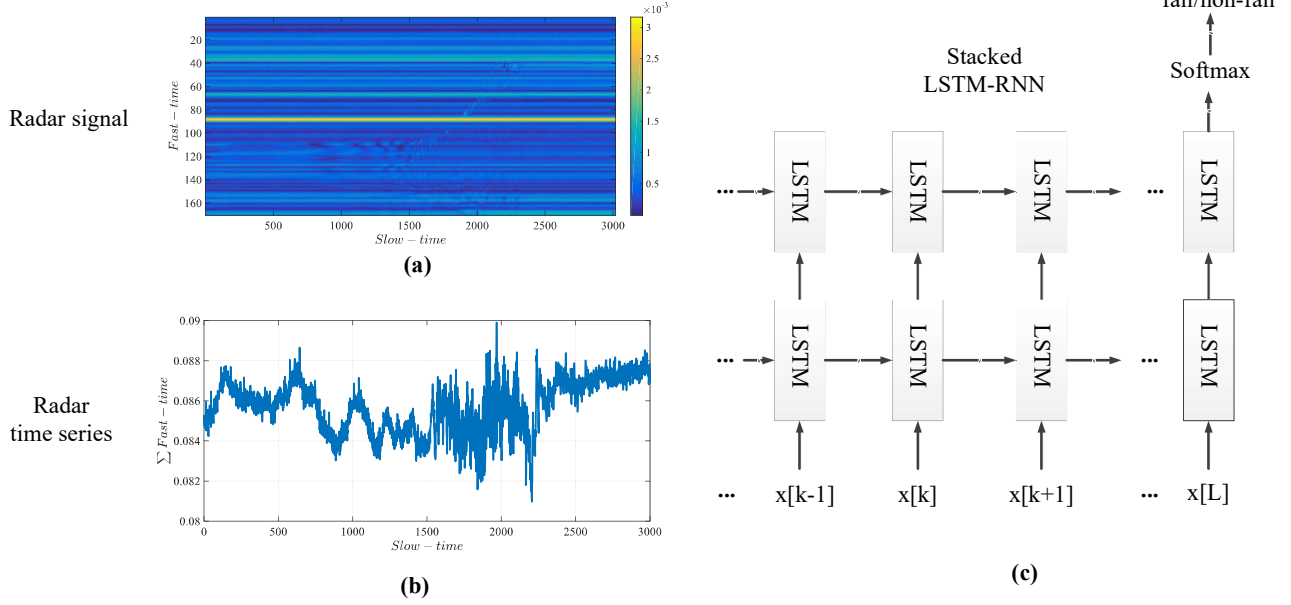
Fig. 3. Block diagram of the proposed radar-based fall detection method. (a) Radar signal. (b) Radar time series. (c) Stacked LSTM-RNN.

LSTM, the stacked LSTM is a more efficient approach to extract richer features and increase model capacity. The LSTM cell takes the input time sample $x[k]$ and the output from the previous time step. The weighted inputs are summed and passed through $tanh$ activation [12]. The final LSTM cell is connected to an output layer with softmax activation function for classification.

3. RESULTS

The proposed method is evaluated on a radar dataset collected in Signal Processing Lab at University of Ottawa. A total number of 206 samples are collected, where five different subjects perform activities including 121 falling down and 85 standing up, from both the radar line-of-sight and perpendicular to the radar positions. In the preprocessing step, clutter is first mitigated by a mean-removal strategy. The radar returns are then aggregated over all the range bins, resulting in a single time series in slow-time. Each time series has a length of 15 seconds and is fed into the stacked LSTM-RNN for feature extraction and classification.

The performance of the proposed method based on stacked LSTM-RNN is compared to those of the some of the existing methods such as K-nearest neighbors (KNN), support vector machine (SVM) [14] and dynamic time warping (DTW) [15], in terms of the classification metrics including
1) Accuracy (AC), $AC = \frac{TP+TN}{TP+FP+TN+FN}$
2) Precision (PR), $PR = \frac{TP}{TP+FP}$

3) Sensitivity (SE), $SE = \frac{TP}{TP+FN}$
where TP and TN denote true positives and true negatives, respectively, FP is the number of false positives and FN denotes the false negatives. To compare against KNN and SVM, statistical and geometrical features are extracted from the radar time series and used as input for the these models. The features include: max, min, mean, standard deviation, skewness, kurtosis, inter-quartile range, area under the time-observation curve, area under the squared time-observation curve of the radar time series and its first derivative.

In the case of KNN, different values for K are examined and the best results, i.e., $K = 5$, is reported. In the case of SVM, Linear SVM (LSVM) and Gaussian SVM (GSVM) are employed. The LSVM uses an l_2 regularization and a squared hinge loss function [16]. In the case of DTW technique, the warping window is experimentally tuned to be $W = 10$ for the best result. Table 1 gives the comparison results of various methods in a 3-fold cross validation, where the original dataset is partitioned into 3 equal sized data folds in random, i.e., $\frac{N_{tr}}{3}$. A fold is retained as the test set, while the other two folds are used as training set. The results from the folds are then averaged. From this table, it is seen that the proposed fall detection method provides classification accuracy, precision and sensitivity higher than those yielded by the other methods. It is observed from the experiments that the number of false positives are mostly related to the activities performed perpendicular to the radar. In general, the higher the angle of the subject to the radar is, the more the classification performance degrades. The superiority of the proposed method

Table 1. Classification metrics (AC, PR, SE) obtained using the proposed fall detection method as well as those obtained using LSVM, GSVM, KNN and DTW in a 3-fold cross-validation.

Method	Metrics		
	AC	PR	SE
LSVM	80.01	82.64	83.34
GSVM	79.13	85.12	80.46
KNN	78.64	82.64	81.30
DTW	83.49	87.60	84.80
Proposed	**89.80**	**95.04**	**88.46**

can be associated with pattern recognition capability of the stacked LSTM-RNN in time series of the radar return signals.

It should be noted that the LSTM network structure and hyper-parameters used in the proposed method are selected through random search optimization. More specifically, the optimal number of LSTM layers and their units, i.e., the number of LSTM units in a LSTM layer at every time step of the network, are selected over a range of 1 to 4 layers and 8 to 64 units. In addition, the learning rate is set to 0.005. The weights and biases are randomly initialized following a standard normal distribution. In order to make the network generalizable and prevent over-fitting, a drop-out regularization of 50% is employed. Drop-out makes the network learn more robust features from the radar data. The number of training epochs is set to 10000 epochs and using early-stopping, training is halted as soon as the validation accuracy decreases. The softmax activation is used in the output layer, where the cross-entropy loss function is used to measure the error. The error is then minimized through backpropagation using the Adam optimizer [13]. It is noted that the fitting process optimizes the parameters of the model to make it fit the training data as much as possible.

4. CONCLUSION

In this paper, a novel fall detection method has been proposed incorporating the signals obtained from an ultra wideband radar. The proposed method has been developed by leveraging advances in deep neural network. In particular, in the proposed method, time series derived from radar return signals has been fed into stacked LSTM recurrent neural network for classification with features that are extracted automatically. Experiments have been carried out on a set of radar signals collected in a room environment at Biomedical Signal Processing Lab in University of Ottawa. The results have shown that the proposed method produces promising results providing high recognition accuracy in binary classification of fall/non-fall activities, and that the stacked LSTM can accurately classify univariate time series of radar returns. For future, gated recurrent unit may be employed. The proposed method may also be extended to predict falls in human daily activities.

5. REFERENCES

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