Unsupervised Learning of Fall Incidents using Radar-based Sensing

Hamidreza Sadreazami *, Marzieh Amini ⋆, Miodrag Bolic † and Sreeraman Rajan ‡
*Bio-engineering Department, McGill University, Montreal, QC, Canada
⋆School of Information Technology, Carleton University, Ottawa, ON, Canada
†School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON, Canada
‡Department of Systems and Computer Engineering, Carleton University, Ottawa, ON, Canada

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***Abstract*—Automatic fall detection using radar technology significantly advances assisted living and smarter healthcare solutions. In this paper, a novel unsupervised method for detecting fall incidents in human daily activities is proposed. By analyzing ultra-wideband radar returns, a radar time series is obtained and used to find the time-frequency signatures of different activities. These signatures are subsequently binarized and used as input to a deep stacked auto-encoder network for latent feature extraction. The latent features are then clustered through a clustering layer that leverages an auxiliary distribution function to fine-tune the samples clustered into fall and non-fall groups. The proposed fall clustering method is compared against several clustering approaches in terms of accuracy of clustered samples, normalized mutual information and adjusted rand index metrics. It is shown that the proposed method realizes automatic latent feature learning from the radar data and can distinguish fall from non-fall classes by uncovering patterns in a data set with no pre-existing labels. The results show that the proposed unsupervised fall detection method outperforms the other approaches in terms of providing higher accuracy of the clustered data samples. The advantage of the proposed method is that it does not need a large dataset to achieve distinctiveness between clusters.**

***Index Terms*—Smart homes, fall detection, deep learning, clustering, ultra-wideband radar.**

I. Introduction

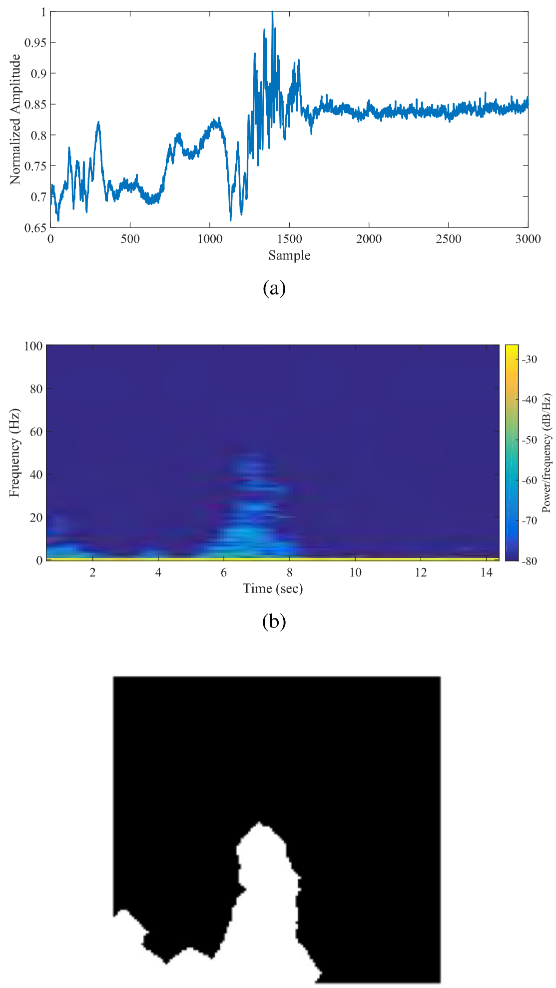
Falling down is regarded as the second cause of accidental death among seniors after road traffic accidents [1]. In addition, in the case of non-fatal fall injuries, the cost of medical expenses is substantial: from millions of dollars economic costs on individuals and care system to everlasting life implications such as decreased functioning and loss of independence [2]. This has necessitated an automatic and reliable fall detection system. The current fall detection methods are mostly based on wearable devices, video cameras and smart-phone sensors [3]. Remote indoor monitoring using radar is an alternative to the current approaches [4]–[9], since it avoids privacy issue of the video-based techniques and does not require people to wear a tag [10]. For instance, in [7], a radar-based time series signals classification approach using convolutional and recurrent neural networks was devised to distinguish falls from non-fall activities. In [8], a supervised learning approach was proposed for fall detection using a residual network to automate feature learning. A supervised wavelet-based approach was proposed in [11] to detect fall incidents using Doppler radar. In [12], micro-Doppler signatures of different simulated activities were classified using the convolutional neural network.

Most of the existing works rely on manual labeling of a set of data samples and develop a supervised approach to classify different features extracted from the radar returns either in time or frequency domain. In addition, the lack of enough fall data samples in real life scenarios has made the training process very difficult. Unsupervised approaches aim to overcome the lack of fall data samples. Only few attempts have so far been made to develop an unsupervised approach for activity recognition from radar data. In [13], a feature extractor was built using 3-D convolutions to construct the range-velocity-time features of radar signals along with a predictor to learn the pattern of non-fall actions. In [14], a radar signal recognition was proposed using a restricted Boltzmann machine to extract the feature parameters. In [15], radar-based fall data samples were detected in an unsupervised manner, as anomalous events. However, none of these works have addressed the radar-based fall detection problem using an unsupervised approach, where the feature learning and cluster identification are accomplished.

In this paper, a new unsupervised approach for fall detection is proposed which is based on time-frequency signatures of the ultra-wideband radar returns and deep neural networks for latent feature extraction and clustering. More specifically, the proposed fall detection method is realized by projecting the energy content of the fall and non-fall activities, contained in their corresponding spectrograms, into binary image representation followed by an automatic latent feature extraction using deep auto-encoder network. The latent features are fed into a clustering layer to assign data samples into different groups. To fine-tune the samples clustered into fall and non-fall groups, a centroid-based auxiliary distribution function is defined and used to train the clustering layer.

II. Experimental Setup and Measurement

A low-power ultra-wideband (UWB) radar system, the Xethru X4M03, was used to collect data from 10 subjects engaged in various activities, including: walking towards the



(c)

Fig. 1. Radar signal associated with fall after walking toward radar, (a) time series (b) time-frequency representation, (c) binary image.

radar and falling, standing in front of the radar and falling, standing and falling perpendicular to the radar's line of sight, lying down and standing up in front of the radar, and lying down and standing up perpendicular to the radar's line of sight. UWB radar offers high spatial resolution and safe monitoring through short, high-frequency pulses. The radar was positioned 1.5 meters above the ground. Each scan was conducted over 15 seconds and sampled at a rate of 200 samples per second. The radar range was set to 10 meters, providing a range resolution of 5.35 cm, with each scan divided into 189 bins.

III. Radar Image Generation

In the experiments, the radar scattering matrix $\mathbf{X} = [x_{i,j}] \in \mathbb{R}^{t_1 \times t_2}$, i.e., the received radar signal, is recorded, where t_2 columns represent the spatial samples from different ranges (fast-time) and t_1 rows correspond to observations recorded at different time intervals (slow-time). From the scattering matrix, columns are summed up resulting in a radar time series. To analyze the radar time series signals, a joint time-frequency representation is obtained by applying the short-time Fourier transform (STFT). The squared magnitude of the Short-Time Fourier Transform (STFT) produces the spectrogram, representing the energy associated with micro-motion signatures over time [16], [17]. Following the approach in [9], the radar spectrograms of fall and non-fall activities are projected into binary image representation. Fig. 1 illustrates an example of radar time series along with its corresponding spectrogram and binary image for a fall activity.

IV. Proposed Fall Detection Method

In this section, we describe the proposed fall detection method, which leverages a stacked auto-encoder to map input images to latent features. The stacked auto-encoder consists of multiple hidden layers, where adding layers allows the model to capture more complex features. However, excessive layers may lead to overfitting, reducing the model's generalizability. The structure of the stacked auto-encoder used in this approach is illustrated in Fig. 2. To determine the optimal number and size of hidden layers, we applied random search optimization, resulting in a model with four hidden layers containing 750, 350, 350, and 250 neurons in the encoder block. Binary images from Section III serve as input for the stacked auto-encoder, which is trained using a reconstruction loss L_{ae} given by [18]

$$L_{ae} = \frac{1}{n} \sum_{i=1}^{n} \|x_i - \widehat{x}_i\|_2^2, \tag{1}$$

where x is the input binary image, $\widehat{x}$ is the stacked auto-encoder reconstructed image and n is the number of data samples. The mean squared error loss function realizes the preservation of significant features in the reconstructed image. The common approach for latent feature learning is to only use the pre-trained encoder to map the radar binary image data into latent features, i.e., once the training is finished, the decoding block will not be used in clustering. In the proposed clustering model, a clustering layer is stacked to the trained encoder and is further trained. Inspired by the t-distributed stochastic neighbor embedding (t-SNE) algorithm [19], to convert the latent features onto cluster label probability, the clustering layer is built by using the student's t-distribution as given by [19]

$$f_{ij} = \frac{\left(1 + \|h_i - c_j\|^2\right)^{-1}}{\sum_{\acute{j}} \left(1 + \left\|h_i - c_{\acute{j}}\right\|^2\right)^{-1}}, \tag{2}$$

where $\{h_i\}_{i=1}^{n}$ is the encoded input in the latent space, $\{c_j\}_{j=1}^{m}$ is the cluster centroid for cluster j and m is the number of clusters. It is noted that (3) measures the similarity between the encoded data sample and a centroid. The weights in the clustering layer are specified by the cluster centroids and are initialized by performing a K-means clustering on the latent features. Since the false positives should strongly

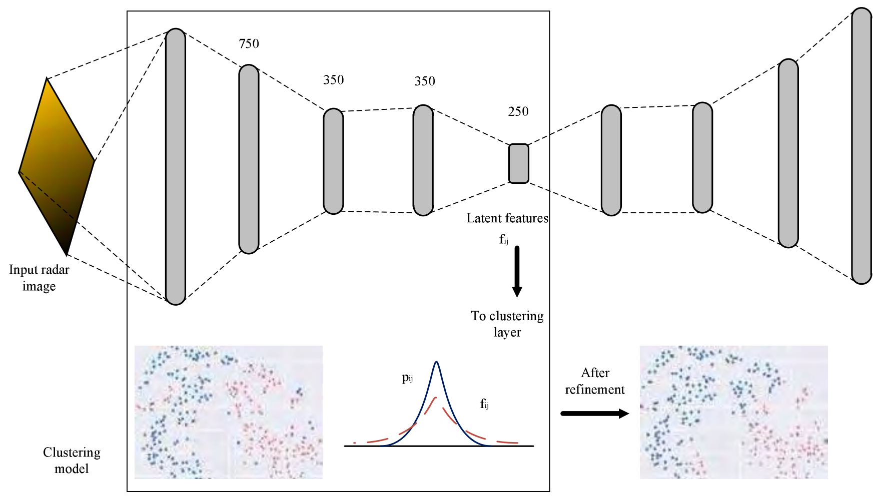


Fig. 2. Block diagram of the proposed unsupervised radar-based fall detection method.

be avoided in a fall detection system, i.e., assigning a low confident non-fall data sample to a fall cluster is not desired, the clustering assignment should be tuned. To this end, an auxiliary probability distribution is defined as in [20]

$$p_{ij} = \frac{f_{ij}^2 / \sum_i f_{ij}}{\sum_{\acute{j}} \left(f_{i\acute{j}}^2 / \sum_i f_{i\acute{j}} \right)}, \tag{3}$$

which highlights the data samples having high likelihood of assignment by squaring the original distribution and iteratively updating the cluster assignments. Tuning is realized by minimizing the Kullback-Leibler divergence (KLD) [21], given by

$$L_{clustering} = \mathrm{KLD} = \sum_i \sum_j p_{ij} \log \frac{p_{ij}}{f_{ij}}, \tag{4}$$

which is calculated between the clustering model output and auxiliary probability distribution. The tuning results in iteratively improving the clustering assignment of the latent feature representation.

It is noted that for comparison purpose the latent features obtained by training the stacked auto-encoder are used as input to the other clustering methods such as K-means [22], agglomerative or density-based approaches [22]. K-means creates cluster centers and employs metric relations to assign each data sample into a cluster with the closest center. Agglomerative-based method builds hierarchy of clusters and data samples. Density-based clustering identifies dense clusters of data samples.

Fig. 2 presents a block diagram of the proposed fall detection method, which consists of three main stages:

- An abstracted and non-linear data representation for the unlabeled dataset is learned by a stacked auto-encoder neural network.
- The encoder output is stacked to a clustering layer, where clustering layer weights are initialized with K-Means cluster centers.
- The clustering model is trained to refine the clustering layer by minimizing $L_{clustering}$.

V. Experimental Results

Experiments were made as realistic as possible with subjects performing fall and non-fall activities to evaluate the performance of the proposed unsupervised fall detection method. The number of different fall and non-fall experiments performed are 187 and 149, respectively. All deep learning tasks were implemented using Keras that is back-ended by TensorFlow package.[1] In order to evaluate the performance of the proposed method, clustering accuracy (CA) is obtained, which is defined as

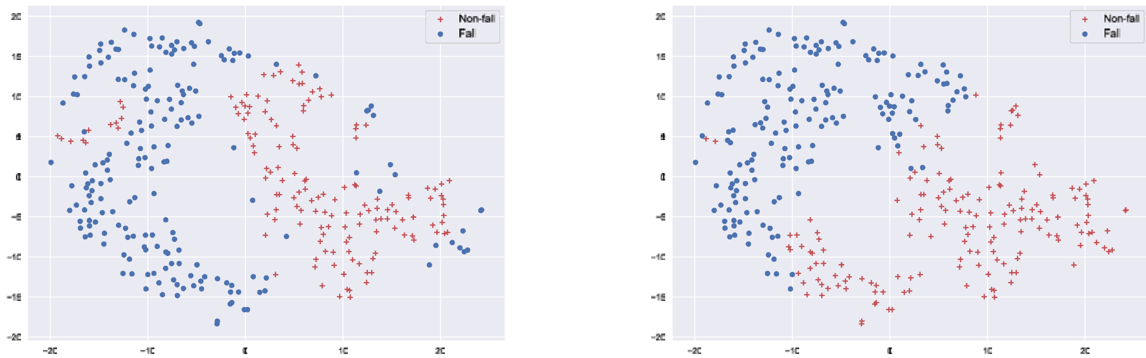
$$CA\left(l_i, c_i\right) = \underbrace{max}_{T} \left\{ \frac{\sum_{i=1}^{n} \mathbf{1}\left\{ l_i = T\left(c_i\right) \right\}}{n} \right\}, \tag{5}$$

where l_i is ground truth assignments and T is the best mapping that matches the cluster indexes and ground truth assignments. This mapping is computed using the Hungarian algorithm [23]. The normalized mutual information (NMI) metric is also obtained, defined as

$$NMI\left(l_i, c_i\right) = \frac{2I\left(l_i, c_i\right)}{\left[H\left(l_i\right) + H\left(c_i\right)\right]}, \tag{6}$$

where $I\left(l_i, c_i\right) = H(l_i) - H(l_i|c_i)$ denotes the mutual information of l_i and c_i, $H(l_i)$ is the entropy of the ground truth assignments, $H(c_i)$ is the entropy of the cluster assignments and $H(l_i|c_i)$ is the entropy of the ground truth assignments within each cluster. NMI measures the amount of information

[1]The dataset and code used in this research work will be made publicly available.



(a) (b)

Fig. 3. Cluster assignment of fall and non-fall activities using (a) K-means and (b) the proposed clustering approaches.

shared by the random variables representing the predicted cluster distribution and the ground truth assignment distribution of the data samples [24]. The NMI value close to 1 indicates a perfect assignment, while random prediction results in an NMI close to 0. In addition, adjusted rand index (ARI) is computed to see how similar the clusters are to the benchmark classifications [25], which is defined as

$$ARI = \frac{RI - E\{RI\}}{\max(RI) - E\{RI\}}, \tag{7}$$

where $RI = \frac{TP+TN}{TP+FP+FN+TN}$, $E\{.\}$ denotes expected value, TP denotes a true positive decision which assigns two similar data samples to the same cluster, TN denotes a true negative decision which assigns two dissimilar data samples to different clusters, and FP (false positive) and FN (false negative) are the two types of errors. More specifically, a FP decision assigns two dissimilar samples to the same cluster and a FN decision assigns two similar samples to different clusters. It is noted that ARI ranges from -1 to 1, where negative and zero values indicate chance-level assignments and positive values indicate similar assignments. For comparison purposes, several approaches are considered, namely, K-means clustering, spectral clustering, agglomerative clustering, density-based spatial clustering and its variant which is ordering points to identify the clustering structure (OPTICS) [26], and Gaussian mixture models (GMM) [26]. Table I gives clustering accuracy, normalized mutual information and adjusted rand index obtained using the proposed method and those of the other methods. It is seen from this table that the proposed method outperforms the other methods by providing AC, NMI and ARI higher than those yielded by the other clustering methods. In particular, the proposed method achieves 78.27% accuracy, 24.56% NMI and 31.72% ARI, which are higher than those of the other methods. Remarkably, the proposed method performs better than the baseline K-means clustering about 13% in terms of clustering accuracy. The superior performance of the proposed method based on deep clustering network is due to the fact that the proposed method fine-tunes the latent features by the clustering layer to refine the allocated data samples.

TABLE I
CLUSTERING ACCURACY, NORMALIZED MUTUAL INFORMATION AND ADJUSTED RAND INDEX (ALL IN %) OF THE PROPOSED FALL DETECTION METHOD AS WELL AS THOSE OBTAINED USING THE OTHER METHODS.

Method	CA	NMI	ARI
K-means	68.75	10.59	13.80
Spectral Clustering	69.34	11.21	10.97
Agglomerative	58.63	5.26	4.65
OPTICS	56.84	11.26	7.81
GMM	68.45	10.30	13.36
Proposed	**78.27**	**24.56**	**31.72**

Fig. 3 shows the cluster assignment of fall and non-fall data samples obtained using the baseline K-means clustering method and the proposed clustering approach with deep clustering layer. It is seen from this figure that the proposed approach can assign data samples to clusters more accurately than K-means clustering method.

VI. CONCLUSION

A novel fall detection method using ultra-wideband radar and an unsupervised deep clustering network was proposed. Radar data was collected in a room environment by considering the home healthcare setting. The proposed method converted time-frequency radar signatures into binary images, which were then processed by a deep clustering model to automatically learn and categorize latent features. Experimental results demonstrated that the proposed fall detection method outperforms several state-of-the-art unsupervised methods, including K-means, spectral clustering, and GMM, in clustering accuracy and normalized mutual information. The significant advantage of the proposed method is its ability to distinguish fall from non-fall events without requiring a large dataset or human supervision.

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