Would a Generalized Wi-Fi-based Fall Detection System Be Possible?

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Abstract— **Falls are among the most fatal problems faced by elders. Several methods has been proposed to address the issue, however, they are either impractical, inconvenient, or lack robustness. In this research, we aim to improve the current state of ubiquitous fall detection systems with robust deep neural networks for Wi-Fi based devices. We evaluate different network structures with a state-of-the-art generalizing method. A yielded robust model would be the first deep learning-based model to perform consistently across Wi-Fi domains and could open the opportunity for a commercial-ready system to be deployed in the real world.**

I. INTRODUCTION

Falls are known to be one the most fatal clinical problems faced by elderly people [1]. Half of those who experienced an extended period of lying on the floor died within six months after the incident [2]. In addition to physical injuries, falls also cause psychological damage to elders, creating the fear of falling cycle, and consequently lead to the functional decline in physical activities [3]. This means that after a fall, even without injury, elders will reduce their physical activities in respond to the fear of falling again. Such functional decline, in turn, decrease the fitness, mobility, and balance of elders, and thus, negatively affect their quality of life. To that end, timely and automatic detection of falls assisting the elders, especially who live alone and independently, and their family is a critical need of the community [3].

Various techniques have been proposed and studied to address the need of an automatic fall detection system [4], [5]. *Wearable sensor-based approaches* are among the first since Lord and Colvin's proposal of an accelerometer based approach in 1991 [6]. Following the work are proposals of numerous kinds of sensors, ranging from gyroscopes, barometric pressure sensors, RFID, to smartphones with combinations of sensory information[7], [8]. However, these systems only work when carried by users while the always-on-body requirement [9] for the elders is not always applicable[10]. *Ambient device-based approaches* try to make use of ambient information caused by falls to detect the accident. The ambient information being used includes audio noise, floor vibration, and infrared sensing data.[11] *Computer vision-based approaches* use cameras to monitor the environment, either by capture images or video sequences[12]. However, these approaches either come with an on-body requirement, which is ineffective in many situations, high rate of false alarm due to ambient noise, or privacy intrusion issues.

A recent set of methods that are able to remove many limitations out of the scene is the *WiFi-based method*[13], [14], [15], [16], [17], [18], [19], [20]. These research efforts achieve automatic fall detection with cheap commercial WiFi devices, without requiring users to wear or carry anything. The rationale behind these efforts is that different human activities correspond to different patterns in the change of the Channel State Information (CSI). These attempts then employ machine learning techniques to create models that can identify falls from CSI patterns. However, they suffer a considerable decrease in reliability when working with different environments. Most often, these systems are trained and tested on the same environments with the same actors and cannot generalize to new people in new contexts. Hence, high performance deep learning models tend to degrade significantly in unseen testing domains, while it is not feasible in practice to have all user domains trained beforehand. In this research, we aim to explore if a Wi-Fi-based fall detection system implemented with a deep neural network can achieve robustness across different testing domains.

In order to improve the current state, we adapt a domain generalization method for the Wi-Fi data. Specifically, we evaluate the Domain Generalization via Adversarial Data Augmentation (ADA) method [21] on the FallDeFi dataset, created by the Cork Institute of Technology[17] and has also been used in a recent work of MIT researchers[22]. The initial evaluation of the ADA method employs a 6-layer ConvNet as the classifier. Our preliminary results point out that the latent space of the ConvNet is not good enough for generalizing domains of raw Wi-Fi signal data. We plan to evaluate the ADA method with classifiers more suitable for time series data such as Hierarchical Attention Networks and Recurrent Neural Networks, as well as incorporate some manual signal processing techniques on the data.

A robust model presented in this work would be the first of its kind to achieve the respective robustness. Such model would be the fundamental for the future of efficient ubiquitous fall detection systems. Furthermore, it would be a concrete demonstration for the possibility of domain generalization methods beyond image processing tasks.

The remaining of the this paper is organized as follows. Section 2 presents recent related works in the field. The procedure and employed models are depicted in Section 3. Section 4 is dedicated for the dataset description before moving on to the experimental results in Section 5. Finally, (2).pdf (2).pdf

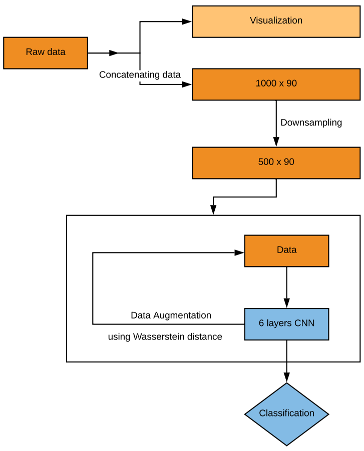

Fig. 1: An overview of the procedure

conclusions are drawn in Section 6, along with further discussions.

II. Related Works

III. Generalize Wi-Fi-based Fall Detection Models

In this work, our main goal is to find the most suitable network structure for a domain independent Wi-Fi-based fall detection system. Figure 1 depicts an overview of our procedure.

First, we convert the binary data into numerical data and investigate it with visualization. Then, the numerical data is further preprocessed before being suitable and passed in to the model.

Our methods focus on generalizing across different domains while using only one domain in the training phase. In order to do so, we employ the method of Adversarial Data Augmentation introduced by Volpi et al. [21]. The underlying network structure of ADA is tested with various network structures to find the most suitable. Initially, a simple CNN with 6 layers is used.

A. Data Preprocessing

First, we need to convert the original binary data into numerical matrices using MATLAB. The numerical data is investigated through visualization for better insights. For the sake of information loss tolerance in downsampling, we then concatenate signals from all three antennas to create a set of 1000×90 matrices, each represent the CSI in a second, matching the source sampling rate of the device at $1000Hz$. Originally, the data should be 1000×180 because there are 90 columns (30 subcarriers $\times$ 3 antennas) recording the amplitude and 90 columns (30 subcarriers $\times$ 3 antennas) recording the current phase. However, according to the experiments conducted by [23], there is no correlation between the phase of CSI and human interactions. As we observe in the visualization step, there are information redundancy in overlapped sampling periods. Hence, we can downsample the data to 500×90 matrices to prevent memory error without worrying about data loss.

B. Adversarial Data Augmentation

The problem adversarial data augmentation try to achieve [21] is to get the data from a single source and try to discern other unexplored domains. This problem can be solved by considering the worst case scenario: The distribution of the target domain is a distance ρ away from the source domain's distribution on the semantic space (this distance is the Wasserstein distance [24]). The space that is actually used is the learned representation since there are correlation between the distance in the semantic space and the distance in learned representation in high capacity model[21].

Adversarial data augmentation is simply running the following procedure for k times[1]: Firstly, we perform stochastic gradient descent on the current model. Secondly, we add generated samples into the dataset.

However, it is undetermined what might be the best value for the latent difference ρ. Therefore, we consider different values for the distance ρ and advesarially generate perturbed samples for each value. After that, we train a model for each value of ρ. Consequently, we have an ensemble of models. Because we are not sure which model performs best, during test time we would choose the most fitting model.

C. Convolutional Neural Network

The first network structure employed along ADA is a simple 6-layer CNN. First, we have two convolution layers interchanged with two max pooling layers. After that, there are two fully connected layers follow by a softmax layer for classification. Since this model is a very primitive CNN, we are planning to test with more complex models and trying different kinds of neural network such as Long Short Term Memory Networks, Hierarchical Attention Networks, and Bayesian Neural Networks.

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[1] k can be an arbitrary number. In our implementation, we use k = 1000.

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