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Indoor localization using software defined radio: A non-invasive approach

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Abstract

In the field of data-driven healthcare systems, wireless-based human activity monitoring in an indoor environment is getting popular. Localization of human activities can help patients to get remote healthcare. Wearable devices are employed in modern healthcare monitoring systems, despite the fact that they can be inconvenient and expensive. Several studies have shown that analyzing variations in Channel State Information (CSI) can be used to identify activities in an indoor environment and monitor health utilizing radio frequencies. The results of an experiment using Software Defined Radio (SDR) to identify and localize human activities while a human subject performed six different classes of activities (no-activity, leaning forward, sitting, standing, walking-Rx, walking-Tx). The CSI extracted from the communication channel between two Universal Software Radio Peripherals (USRP) devices communicating and operating as SDRs was used to collect a total of 2100 sample data. The Extra Tree (ET) classifier outperformed the prior benchmark approaches in localizing six activities across the 21 classes. The proposed ET classifier can identify if the room is occupied and a human subject's walking directions in two separate zones, as well as localize six distinct activities inside the room with an accuracy of 91% and 100% respectively.

1 Introduction

As wireless communication technology advances and becomes more popular, the need for location-based services (LBS) is increasing [1]. Advanced satellite positioning systems, such as the Beidou Satellite Navigation System and GPS, will provide users with more exact location services outside and will also meet the positioning requirements of most outside environments [2]. The satellite positioning system can work effectively in indoor environments due to low satellite signals, low penetration, and other issues. For instance, using a satellite positioning system, mobile devices can be traced to a certain building but not to a specific floor or room. On the other hand, wireless indoor signal-based positioning technologies such as Wi-Fi [3], Bluetooth [4], and Ultra-Wide Bandwidth (UWB) [5] have been extensively researched and implemented due to the limited and complicated indoor environment, as well as the high accuracy and stability of positioning requirements.

Wi-Fi is becoming increasingly popular in indoor positioning systems due to its low cost, wide signal transmission range, and extensive application. A transmitter (Tx) and receiver (Rx) are often used in a Wi-Fi-based indoor positioning system, which eliminates the need for expensive equipment and outperforms other indoor positioning systems [6]. Indoor positioning technology based on Received Signal Strength Indication (RSSI) and CSI signal can be separated into two categories based on different acquisition signals [7]. The RSSI signal, as a poorly graded signal, is very susceptible to interference from other signals and the indoor multipath effect in the indoor environment, and hence cannot guarantee enough accuracy and reliability [8]. For indoor positioning, CSI provides more fine-grained signal characteristic information than RSSI, which improves indoor positioning accuracy [9]. CSI represented multipath transmission to some extent by including the amplitude and phase information of each subcarrier. This can be done by utilizing Wi-Fi-CSI to look at the amplitude of the CSI when a human performed activity between the radio waves [10].

The goal of this research is to use two USRPs to collect CSI data on human activity and then apply Machine Learning (ML) to recognize human walking and locate six distinct human activities. The room is divided into two zones and four locations (L1Z1, L1Z2, L2Z1, L2Z2) as shown in Figure 1. Each activity took place in one of four marked locations within the experimental room. This paper highlights two significant contributions. The first contribution is to determine the position of an activity in four different locations inside the designated room. secondly, to localize the activity inside the room. The rest of the paper is organized as follows: Section 2 describes the related work. Section 3 describes the research methodology and introduces the experimental environment and analyzes the performance of this method through experiments. Section 4 describes the results and discussion. Finally, we conclude the work in Section 5.

2 Related Work

In recent years, fine-grained CSI-based methods have become more popular. CSI contains more detailed amplitude and phase information than RSSI. Alshamaa et al. [11] utilized two USRPs that form a transceiver pair to recognise hand movements, but they don't use the WiFi protocol. Zhang et al. [12] combined WiFi protocol with USRP, a transformation from their previous work and testing results showed that it performs well. There are two major benefits of using WiFi in combination with USRP. To begin, when we utilize USRP to receive WiFi signals, the OFDM receiver's algorithm can rectify frequency and phase offsets [10]. Secondly, the USRP can receive all signals from 64 subcarriers as a result, the CSI values obtained are more comprehensive and reliable [13]. CSI is more applicable to non-invasive since it depicts frequency diversity at the granularity of OFDM subcarriers, and it has been employed in non-invasive motion detection [14], entity localization [11], and walking activity identification [15].

This study shows how wireless frequency changes can be utilized to localize human activity. The USRP N210 model was used in a study published in the literature [16, 12], which showed activity detection systems with accuracy 91% and 92% respectively. Other localization and tracking studies, such as [17], reported an accuracy of 80% and a 0.5m error in a 1.5m^2. The study [18] used the USRP X300 and X310 to separate sitting and standing behaviours, with a 96% accuracy using the Random Forest algorithm. The proposed approach provides a framework for identifying both moving (walking) and stationary (no activity) movement, as well as locating the activity's position inside the designated area. This paper's utilizing ML approach such ET classifiers, and CSI, received from SDRs, to accurately identify and localize six different activities within a room.

3 Research Methodology

The experiment described in this paper took place in a 3.8 $* 5.2m^2$ room at the James Watt South Building at the University of Glasgow, where an active and approved ethics application was in place. The room is divided into two zones (four locations) with one meter apart from each other (see Figure 1). Two USRPs (X300/X310) models are used as a Tx and Rx with a gain of 70 and 50, are positioned at a 45° angle in the room's corners and covering DC–6 GHz and up to 120MHz bandwidth. Two Intel(R) Core (TM)i7, (TM)7700.360GHz processors, 16GB RAM, and an Ubuntu16.04 virtual system with two VERT2450 omni-directional antennas. Setting the centre frequency of 3.75 GHz, the number of OFDM subcarriers, and power levels can all be done with the GNU radio python package. During the data collection process, two USRPs were used for data collection where six different classes of activities (no activity, leaning forward, sitting, standing, walking towards Rx, and walking towards Tx) performed by a single subject in each location 600 data samples are collected, with approximately 1200 packets and a period of around 3 seconds. The total number of data samples collected are 2100, which are grouped into 21 classes, each of which represents a dataset. The "empty room" class has 100 samples, and each of the next 20 classes has 100 samples each. For example, "sitting" in "zone one" is one class, whereas "sitting" in "zone two" is another. The data is labeled with a name that correlates to the zones and locations, such as L1Z1, which shows that 600 data samples from the six classes of activity were collected in Zone 1 and Location 1.

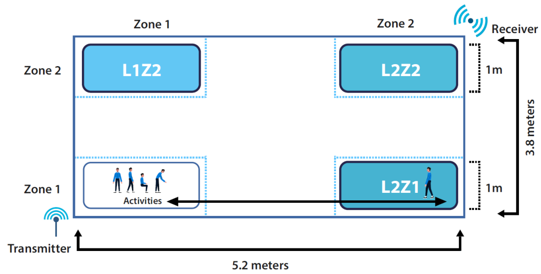

Figure 1. Experimental Setup Diagram

3.1 Data Pre-processing and Machine Learning

This section provides an overview of the data pre-processing and ML techniques that have been designed and used to classify the data.

3.1.1 Data Pre-processing

It is not unusual for some data to be missing when data is collected and saved in CSV files due to packet loss. We use *Scikit Pandas*, a widely used data analysis toolkit in Python [21], for data pre-processing and ML algorithms. Due to a data length mismatch, the dataset obtained by combining the dataframes of each sample includes not a number (NaN) values. These NaN values are replaced with the mean of each row using a *SciKit* built-in function called *SimpleImputer* that can be used to solve this problem. After data cleansing, the data set is then split into two variables: one for labels and the other for the actual data are then passed to ML algorithm namely ET classifier. The data flow diagram is described in Figure 2.

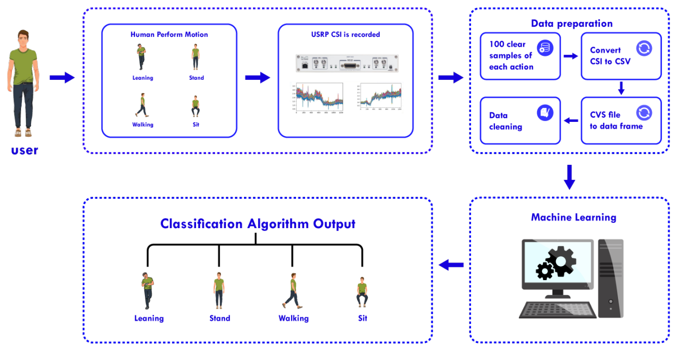

Figure 2. Data flow diagram of human activities

3.1.2 Machine Learning Process

To evaluate the accuracy of the ML algorithm on localization using SDR, the authors [18, 19] used 10 fold cross-validation and a train-and-test. We utilized the *scikit-learn* python ML toolkit's *RepeatedStratifiedKFoldclass* to perform a variant of k-fold cross-validation known as repeated stratified (RS) k-fold cross-validation. We consider (3) 10 fold cross-validation in particular, which means that the repetition cycle is set to 3 and the cross-validation is set to 10.

4 Results and Discussion

In this section, the results of the RS-K-Fold cross-validations accuracy score used to compare the algorithm performance. A confusion matrix is also included, which demonstrates how each sample is well categorised.
Below are the test cases for the collected dataset description is given below.

- **L1Z1, L2Z1** : The dataset contains data from locations 1 and 2 for Zone 1, with a total of 11 classes of activities from both locations.
- **L1Z2, L2Z2** : The dataset contains data from locations 1 and 2 for Zone 2, with a total of 11 classes of activities from both locations.
- **Location 1-Z1Z2** : The dataset contains data from Zone 1 and 2 for Location 1, with a total of 11 classes of activities from both zones.
- **Location 2-Z1Z2** : The dataset contains data from Zone 1 and 2 for Location 2, with a total of 11 classes of activities from both zones.

Table 1 presents the accuracy of the ET classifier. The position of the activity is individually shown and localized in each location correctly. By combining the two locations datasets in the vertical direction such as Location-1 (L1Z1, L1Z2) and Location-2 (L2Z1, L2Z2) shows 86.01% and 94.28% accuracy, respectively. It is indicated in the table that Location-2 has higher accuracy as compared to Location-1, due to its close proximity with the Rx.
Figure 3 displays the normalized confusion matrix of the dataset's better accuracy, and the combined dataset Location-2 (L2Z1 and L2Z2) accuracy of the two locations, where walking is correctly classified with an accuracy of more than 90% and remaining activities have a classification accuracy of more than 97%. The activity of location-2 in Zone 2 such as *Empty, LeaningL2Z2, No-activityL2Z2, SittingL2Z2, StandingL2Z2* are perfectly classified (100% accurate), except *Walking* which has an accuracy of 91% in both directions. Similarly, the activities at location-2 in Zone 1 achieved an average accuracy of 96.42%. Whereas, activities performed at location-1 in Zone 1 are correctly classified with an accuracy of 94.28%, and the average accuracy of activities performed at location-1 in Zone 2 is 87.14%.
On the other side, combining the dataset of each location slightly reduces the overall classification accuracy. For instance, the combined accuracy of the two locations (L1Z1 and L1Z2) is 86.01%, whereas (L2Z1 and L2Z2) is 94.28%. As can be seen from the above results, the activities performed near Rx are better classified as compared to those performed near Tx.

Table 1. Extra trees classifier Results

Location wise	Dataset	Accuracy	Combined Accuracy
Location1-Z1Z2	L1Z1 L1Z2	94.28% 87.14%	(L1Z1 + L1Z2) **86.01%**
Location2-Z1Z2	L2Z1 L2Z2	96.42% 99.28%	(L2Z1 + L2Z2) **94.28%**

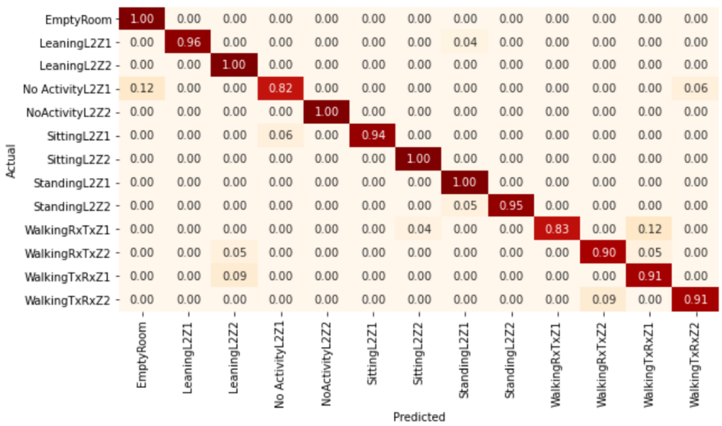

Figure 3. Normalized confusion matrix of location2-Z1Z2.

5 Conclusion

This paper proposed an indoor activity localization system that utilizes USRP devices as SDRs to identify six activities that take place in different locations of the same room. Using RF sensing, the system was designed to identify the location of a performed activity, the occupancy of a room, and, if necessary, the direction of specific activities in an indoor environment. The localization accuracy of different activities in location-2 and Zone 2 is noticed to be better than other locations due to its proximity to the Rx. When an activity is performed further away from the Tx, the system's activity detection accuracy increases in both horizontal and vertical directions, with a precise increase of 4% horizontal and 7% vertical direction for every 1m away from the Tx.

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