Device-Free Activity Recognition Using Ultra-Wideband Radios

Sarthak Sharma, Hessam Mohammadmoradi, Milad Heydariaan, Omprakash Gnawali
University of Houston
smsharma2@uh.edu, {hmoradi, milad, gnawali}@cs.uh.edu

***Abstract*—Human Activity Recognition (HAR) is a fundamental building block for the current trend of smart devices in Internet of Things (IoT). Ultra-Wideband RF technology has been used in localization research while Wi-Fi Channel State Information (CSI) has been widely investigated for non-obtrusive activity recognition in the literature. This paper investigates the feasibility of using UWB technology for Human Activity Recognition (HAR). The key idea is to use machine learning classification algorithms most suited to train models to classify different activities using the Channel Impulse Response (CIR) data of the UWB signals. Our experiments show that by using CIR data as features we can classify simple activities such as standing, sitting, lying with an accuracy of 95%. To compare this performance, we have also trained statistical models using Wi-Fi CSI. We found that, for all models UWB CIR significantly outperformed Wi-Fi CSI. Thus, we believe UWB to be a very effective technology in the context of device-free activity recognition.**

***Index Terms*—UWB, activity recognition, machine learning, device free, Channel State Information (CSI), Channel Impulse Response (CIR)**

I. Introduction

Human Activity Recognition (HAR) is an active area of research. The primary goal of activity recognition is to infer a user's behavior based on analysis of sensor readings. The sensors may be worn by the user or installed in the users' environment. There are applications of HAR in areas such as healthcare, elderly care, and energy expenditure estimation.

Most current techniques for HAR require users to either carry sensors [1]–[3]. This main problem with this approach is it is inconvenient for the users to always carry the device or the users may forget to carry the device. Other common approach is to use cameras [4], [5] to find the activities performed by the users. The main disadvantage of this technique is the loss of privacy for users. In addition, the vision-based approach requires generally good lighting and does not work well when the user is occluded.

One approach for activity recognition is device-free activity recognition using radio signals [6], [7]. In this approach, radio devices are placed in the periphery of a monitored area. A transmitter sends a series of packets. The signals bounce off the environment (walls, objects, humans, etc.) and arrive at the receiver. When a human subject performs a different task, the signal reflections received at the receiver change. Thus, a change in activity changes the environment which can be inferred by the change in received signal at the receiver.

Measurements such as radio signal strength indicators (RSSI) have been successfully used for localization [8], [9] but are not informative in activity recognition. The different human activities generally cause negligible change in RSSI. Recent studies have therefore used Channel State Information (CSI) or Channel Frequency Response (CFR) for activity recognition in a device-free setting. However, such approaches are prone to multipath fading; thus, less reliable for activity recognition.

In this study, we use Ultra-Wideband (UWB) impulse signals for activity recognition. The use of ultra-wide frequency bandwidth leads to relatively narrower impulse signals in time domain compared to Wi-Fi and Bluetooth, which makes impulse-based UWB radios more accurate in detecting multipath propagation of signals. Our proposed solution uses high resolution (1 ns) Channel Impulse Response (CIR) which is equivalent to time domain CFR.

In this work, we focus on activities in which a subject is stationary. Examples of such activities include standing, sitting, and lying. The receiver extracts CIR of the received packets as the user performs different activities. We then carefully construct features, based on unique property of UWB propagation, e.g. first path components. These feature are used to classify the activity as one of the three activities. For Random Forest classification, which is commonly used in the device-free activity recognition literature to classify the activities, we obtained an accuracy of 95.6%.

Our accurate activity recognition solution demonstrates the feasibility of a passive, non-intrusive, and more accurate calorie counting application in comparison with most of fitness tracker watches and devices. Such devices either use activity dependent metrics like Metabolic Equivalent (MET) [10] to accurately estimate energy expenditure, or they use human body-type dependent metrics like Basal Metabolic Rate (BMR) to only estimate the calories burned for maintaining vital body functions. Activity recognition methods used by fitness tracker devices highly rely on the subject being in vigorous motion, hence they cannot distinguish between different activities when the subject is stationary. Our solution does not require subject to carry any device and it can distinguish between different activities when subject is stationary, hence we can make use of MET to provide a more accurate caloric expenditure in such scenarios.

We make these contributions in this paper:

- We present experiment design, hardware setup, and software implementation using UWB radios for human activity recognition. We collected extensive dataset using our setup.

- We present classification results and show that human activity recognition is possible with an accuracy of 95.6% using UWB radios with simple machine learning algorithms.

II. Related Work

We classify all existing Human activity recognition systems into four broad categories: RSSI based, Radar based, CSI based, and other wireless techniques.

A. RSSI-Based Activity Recognition

Received Signal Strength Indicator (RSSI) based activity recognition relies on the fluctuations in the received signal strength to classify the activity.

WiGest leverages changes in Wi-Fi signal strength to sense in-air hand gestures around the user's mobile device [11]. They classified primitive hand gestures like move up-down, down-up, up-pause-down with an accuracy of 87% for a single Access Point (AP).

B. Radar-Based Activity Recognition

In some notable works, radar has been used for activity recognition. WiZ is a prototype that can localize up to five users with median accuracy of 8-18 cm [12]. Where as, WiTrack can detects 3D pointing gestures with an orientation error of 11.2° [13]. Radar based systems have a much higher bandwidth and can extract micro-Doppler information. However, even these require very specific and expensive hardware.

C. CSI-Based Activity Recognition

More recently, CSI information extracted from Wi-Fi network interface cards (NICs) are being used for human activity recognition. Some work for classifying human micro-movements ha also been done. This includes classifying lip-movement [14], keystrokes [15], and heartbeat [16]. Other work such as WiFall [17] can detect fall scenario of a single person with 94% fall detection precision and 13% false alarm rate with Random Forest classifier.

D. Other Wireless Techniques

Many activity recognition systems use hardware that has been specifically designed to serve the purpose. For example, WiSee uses USRP and measures Doppler shift in wireless signals [18]. Allsee uses a custom low-power circuit to extract received signal to recognize hand gestures [19]. It classifies gestures such as flick, zoom in, zoom out, push, pull etc. with an accuracy of 97%. All these usually report very fine-grained signal measurements.

III. System Design

This section describes the details of how our system works. The system architecture is shown in Figure 1.

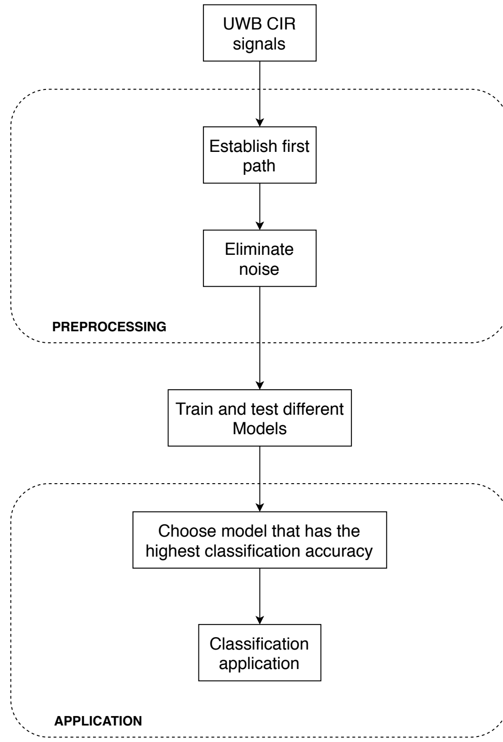

Fig. 1: System Architecture

A. CIR Extraction

We use the raw CIR values that were obtained during communication between the nodes. UWB signals are sent in short bursts of pulses by the sender (every 50 ms). The receiver, constantly monitoring the channel, records CIR information upon receiving a packet from a sender. The receiver node estimates the components of channel's CIR every 1 ns. It reports the component in polar coordinates. We treat this stream of polar coordinate values as our raw data. This raw data is fine grained and has a very high resolution compared to Wi-Fi. Figure 2 shows the experiment setup used to collect the data.

B. Pre-processing

We process the raw data in two steps. For the packets that are received we determine the first path and use only a part of the raw data sequence to eliminate noise.

1) First Path: The collected CIR data contains the information about the first path delay. This is the channel's delay to receive the signal on the first path of propagation. To train models for activity recognition it is important to remove this noise prior to data model creation. So we remove the samples in the data stream before the first path component (e.g., before the first peak in Fig 1) using the first path delay information.

2) Filtering Noise: Not all the data after the first path is informative for classification. We tested the amount of data that is useful after the first spike in amplitude. After careful analysis, we found that using 200 samples (100 ns) starting from first path gives the best classification results. Figure 3

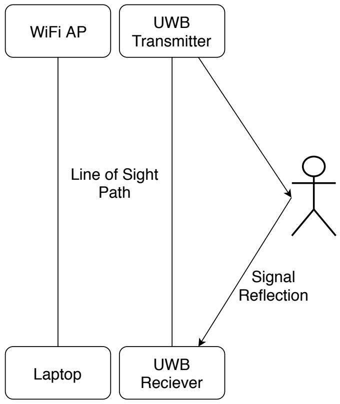

Fig. 2: Experiment Setup

shows the change in the accuracy with different number of samples that are used as features.

C. Training and testing models

We train four models, one of each algorithm described in section III-D. We used 10-fold cross validation technique for this purpose. The trained models are used in application for activity recognition.

D. Machine Learning Classification Algorithms

We trained models based on some common machine learning classification algorithms widely used in activity classification literature.

1) Naïve Bayes: Our first model was trained based on the Gaussian Naïve Bayes classifier. It is a popular algorithm for classifying problems. However, it has a strong independence assumption between the features. This is not true in our case.

2) Neural Network Multi-Layer Perceptron (MLP): MLP is a feed forward artificial neural network model that maps set of input data onto a set of appropriate outputs. It consists of multiple layers and each layer is connected to the next one. MLP has shown accuracy over 91% with classification of activities using cell phone accelerometer data [1].

3) Nearest Neighbors: The principle behind nearest neighbor method is to find a predefined number of training samples closest in distance to the new point and predict the label from these. Previous efforts to classify human activities using the common k-nearest neighbors classifier had an accuracy of 75% [20].

4) Random Forest: Random Forest Classifier is ensemble algorithm. It creates a set of decision trees from randomly selected subset of training set. Previous studies that used multi-sensor data have shown to have accuracy of 92% for classification of activity category. [21].

IV. Experimental Setup

In this section we describe the hardware we used, setting and the parameters for performing the experiment.

The experiments have been performed in different indoor settings such as different apartments, and a conference room in our institution. For each of the locations multiple subjects

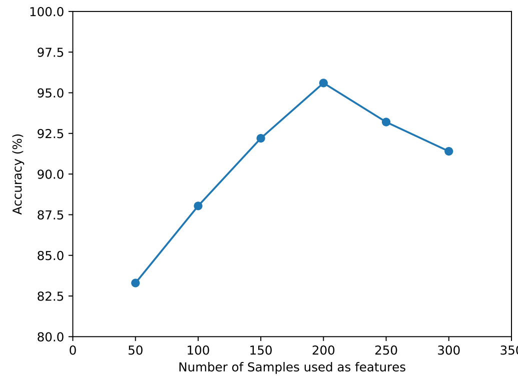

Fig. 3: Accuracy comparison for different number of features using Random Forest classifier: accuracy decreases for more than 200 features due to overfitting

have performed three activities i.e. standing, sitting, and lying. Additionally, the empty room has been considered as the baseline activity. Table I lists some basic information for all the subjects that performed the activities.

TABLE I: Subject Details

Subject	Height (cm)	Weight (kg)	Girth (cm)	Gender
1	178.0	69.8	83.0	Male
2	172.5	71.9	85.0	Male
3	175.1	72.1	89.0	Male
4	147.0	47.6	72.0	Female
5	190.5	122.5	120.0	Male
6	188.0	70.3	85.0	Male
7	172.0	80.0	95.0	Male
8	156.0	56.9	77.0	Female
9	185.4	93.9	100.0	Male
10	172.7	83.9	98.0	Male
11	184.0	78.9	96.0	Male
12	180.5	73.9	92.0	Male
13	165.0	62.2	79.0	Female

Note that we have taken multiple subjects into consideration so that our system gets trained to identify different subjects performing the same activity. This makes our system more robust for user related applications.

Some spatial restrictions have been employed and all the activities are performed between the two nodes. Moreover, to ensure a stable environment, 10 meters of area around the nodes was cleared. This was done to exclude any potential external interference like passing by subjects.

A. UWB Radio Configuration

We use DW1000 Evaluation Board (EVB1000) by DecaWave as our UWB transceivers, placed 2 m apart from each other and configured to operate in channel 2 (4.0 GHz center frequency and 500 MHz frequency bandwidth). UWB transmitter is configured to continuously send packets to the UWB receiver.

B. Wi-Fi Configuration

To compare the performance of UWB CIR, we use Linux 802.11n CSI Tool. We use one wireless Access Point (Buffalo

(a) Naïve Bayes

(b) Neural Network

(c) K Nearest Neighbors

(d) Random Forest

Fig. 4: Comparison of UWB CIR and Wi-Fi CSI with different algorithms in activity recognition. Most of the models that used UWB CIR have higher recognition accuracy than Wi-Fi CSI

WZR-HP-G300NH2) under 802.11 (2.4GHz) and one laptop with Intel Wi-Fi Wireless Link 5300 NIC running Ubuntu 12.10. We used the Linux 802.11n CSI Tool [22] to extract the CSI information. Experiments similar to UWB are performed using the CSI tool. The Wi-Fi hardware is placed right next to the UWB hardware for the experiment to ensure that models are trained on the same data.

C. Machine Learning Classification Algorithm Parameters

In our experiment, we used the Gaussian Naïve Bayes classifier. For neural network MLP we used 1 hidden layer with 100 hidden units, and alpha of 0.1. Nearest Neighbor model was trained with number of neighbors set to 3 and leaf size of 30. In case of Random Forest, we use 50 estimators.

V. Results

In this section, we evaluate the accuracy of activity recognition for both UWB CIR and Wi-Fi CSI.

TABLE II: Naïve Bayes Confusion Matrix

	Empty	**Standing**	**Sitting**	**Lying**
Empty	0.856	0.004	0.086	0.054
Standing	0.018	0.308	0.343	0.330
Sitting	0.013	0.088	0.570	0.329
Lying	0.002	0.006	0.127	0.865

A. Activity Recognition Using UWB CIR

The data collected using EVB1000 was analyzed and used to train models using different classification algorithms mentioned in Section III-D.

TABLE III: Neural Networks MLP Confusion Matrix

	Empty	**Standing**	**Sitting**	**Lying**
Empty	0.995	0.002	0.002	0.001
Standing	0.001	0.913	0.037	0.049
Sitting	0.001	0.021	0.921	0.057
Lying	0.001	0.009	0.009	0.981

The overall classification accuracy of Naïve Bayes is reported at 65.6%. The confusion matrix for classification accuracy is mentioned in Table II. This accuracy is significantly low due to the independence assumption between features.

The overall classification accuracy for Neural Network MLP is 93.9%. The confusion matrix for NN MLP is shown in Table III.

TABLE IV: K Nearest Neighbors Confusion Matrix

	Empty	**Standing**	**Sitting**	**Lying**
Empty	0.996	0.002	0.002	0.000
Standing	0.001	0.881	0.052	0.066
Sitting	0.002	0.020	0.938	0.040
Lying	0.003	0.014	0.008	0.975

The overall classification accuracy for Nearest Neighbors algorithm is 94.5%. The confusion matrix for nearest neighbors is reported in Table IV.

TABLE V: Random Forest Confusion Matrix

	Empty	Standing	Sitting	Lying
Empty	0.993	0.003	0.001	0.003
Standing	0.000	0.929	0.027	0.043
Sitting	0.000	0.018	0.929	0.053
Lying	0.000	0.005	0.007	0.987

The overall classification accuracy for Random Forest is 95.6%. The confusion matrix of random forest is shown in Table V. Random Forest reports the highest accuracy among all algorithms.

For comprehensive analysis of the performance of UWB CIR, we selected four random human activities that are not related to each other. Further, poor accuracies were reported with Naïve Bayes largely due to the assumption of feature independence within a class. The feature set used in the experiment is a component of channel's CIR monitored continuously in time. This directly implies a correlation between the large number of features used to train the machine learning models. All ensemble learning algorithms perform much better than simple Naïve Bayes for the collected data. The high accuracy of Random Forest is attributed to its ensemble techniques. Further, Random Forest is an ideal classifier due to its lower susceptibility to over fitting the data.

B. Activity Recognition using WiFi CSI

To compare the performance of UWB CIR, we perform the same experiments using Linux 802.11n CSI Tool. The output of the experiment is then modeled using the same four algorithms.

The overall classification accuracy for Naïve Bayes is 46.8%. The comparison for CSI based Naïve Bayes is depicted in Figure 4a. The low accuracy of Naïve Bayes is attributed to its independence assumption.

The overall classification accuracy for Neural Network MLP is 69.6%. The comparison for NN MLP is shown in Figure 4b. As compared to Naïve Bayes, NN MLP performs better in the prediction of all classes. This improvement can be attributed to the fact that NN MLP does not assume feature independence.

The overall classification accuracy for Nearest Neighbors is 61.1%. The comparison for NN is depicted in Figure 4c.

The overall classification accuracy for Random Forest 74.1%. The comparison for a Random Forest is shown in Figure 4d.

VI. Conclusion

In this work, we studied the feasibility of using UWB radios for device-free human activity recognition. Our results suggest that using UWB radios is an effective way to recognize human activities even with one pair of UWB transceivers. UWB CIR-based models achieved better accuracy compared to Wi-Fi CSI-based models, since UWB CIR has higher resolution and it has relatively more information about how signals propagated in the environment. Only by using simple machine learning classification algorithms we achieved overall accuracy of 95.6% for line-of-sight scenarios. The next steps would be to test this scheme for non line-of-sight path between the UWB transceivers. Additionally, we identified that our system with improved accuracy in activity recognition, has the potential to be used for high-accuracy caloric expenditure estimation.

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