DEVICE-FREE ACTIVITY RECOGNITION USING ULTRA-WIDEBAND RADIO COMMUNICATION

A Thesis Presented to
the Faculty of the Department of Computer Science
University of Houston

In Partial Fulfillment
of the Requirements for the Degree
Master of Science

By
Sarthak Sharma
April 2018

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Abstract

Human Activity Recognition (HAR) is a fundamental building block in many Internet of Things (IoT) applications. Although there has been a lot of interest in HAR, research in non-intrusive activity recognition is still in nascent stages. This research investigates the capability of Ultra-Wideband (UWB) communication technology to be used for HAR. In this work, UWB radio devices are placed in the periphery of a monitored area. This setup infers user activities without the need of any additional sensors or physical device. Packets are exchanged between these UWB devices, and received packets are used to obtain information of the environment. The key idea is that these received packets are affected by environmental modification due to the human activities. We collect Channel Impulse Response (CIR) data from the received packets of the UWB signals. We then use machine learning algorithms to classify the activity (standing, sitting, lying) being performed. The experiments show that by using CIR data as features we can classify simple activities such as standing, sitting, lying and when the room is empty with an accuracy of 95%. To compare this performance, we trained classification models using Wi-Fi Channel State Information (CSI). We found that for all the models UWB CIR significantly outperformed Wi-Fi CSI in activity classification. This study also includes an application for this system. We used the HAR system for caloric expenditure estimation during a time period. We use HAR to infer the pose and time spent at each pose and use models from the literature to estimate the caloric expenditure for each pose. Our approach reports 32% more calories than what is reported by commercial devices, which are known to severely under-report calories when the subjects are not very active.

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Chapter 1

Introduction

There has been an increase in the research activities in the field of Human Activity Recognition (HAR). The primary goal of activity recognition is to generate information about the users behavior to assist in their tasks. There are various applications to it [19], including healthcare, elderly care, and energy expenditure estimation.

Most current practices to recognize human activity require subjects to either carry sensors [18, 6, 21, 12, 29] or use sophisticated camera equipment [20, 13, 33, 7]. These come with the limitations of installing and maintaining sensors and cameras that breach subject privacy and require very strict lighting conditions. Further, existing vision-based systems have the known drawback of failing across all significant obstructions (such as walls).

One interesting approach for activity recognition is device free activity recognition using radio signals [25, 22]. In this approach, radio devices are placed in the periphery of a monitored area. Packets are sent and received by these radio devices continuously, the received packets are used to obtain information about the environment. The key idea here is that the environment is being affected by the activity taking place in the observed area.

Measurements such as radio signal strength indicators (RSSI) have been successfully used for localization [30, 27] but are not informative in activity recognition. Recent studies have therefore used Channel State Information (CSI) or Channel Frequency Response (CFR) for activity detection in a Device-free setting. However, CSI signals are noisy and thus have poor accuracy. This solution uses Channel Impulse Response (CIR) which is time domain CFR.

In this study, we use Ultra-Wide Band (UWB) signals for recognition. UWB waves are structurally different and can be measured more precisely as compared to Wi-Fi or Bluetooth waves. Moreover, UWB consumes significantly less power than Wi-Fi. To the best of our knowledge, there has been no research in activity recognition using UWB signals.

In our research we mainly focus on activities in which the subject is still, these are activities such as standing, sitting and lying. Since we can classify these activities accurately, this gives us an upper hand in applications such as device free calorie estimation. Most fitness devices cannot classify activities and hence can't estimate calories used. They either do not count calories when the user is not in motion (standing, sitting, lying) or use basal metabolic rate (BMR) to estimate overall calories when the user is stationary. The BMR is calculated using HarrisBenedict equation which is based on subjects weight, height, and age. This approach suffers inaccuracy because calorie expenditure varies as per the activity. Our method does not suffer from this drawback and will be very useful for patients who are restricted to an indoor environment due to illness/injury. The main contributions can be summarized as follows:

- We present the first method to use UWB signals as an efficient candidate to recognize human activity.
- We compare the performance of different machine learning algorithms for the purpose of HAR.
- We explore the application of UWB HAR for estimation of Caloric Expenditure.

Chapter 2

Related Work

In this chapter, we explore previous research works in the field of HAR. While there has been a lot of study in this domain, there is no previous work that uses UWB for HAR. Accurate caloric Expenditure Estimation is also an open problem and has attracted a lot of research. We explore Caloric Expenditure Estimation using HAR.

2.1 Human Activity Recognition

The goal of activity recognition is to recognize common human activities in real life settings. All existing Human activity recognition systems can be classified into four broad categories: RSSI based, Radar based, and CSI based, and other wireless techniques.

2.1.1 RSSI Based

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 [1]. 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). [22, 23] uses RSSI based signal features to classify activities such as standing, lying, walking, and crawling. These use software radios and report an accuracy of 86.4%. Thus, accuracy and coverage of RSSI based systems is lower than the proposed system.

2.1.2 Radar Based

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 [3]. Where as, WiTrack can detects 3D pointing gestures with an orientation error of 11.2° [2]. Radar based systems have a much higher bandwidth and can extract micro-Doppler information. There has been some work to estimate the human motion parameters from radar spectrograms. [24]. However, even these require very specific and expensive hardware.

2.1.3 CSI Based

More recently, CSI information extracted from Wi-Fi network interface cards (NICs) are being used for human activity recognition. Research has been done for several applications such as fall detection, presence detection, human crowd counting [28]. Some work for classifying human micro-movements includes classifying lip-movement [34], keystrokes [5], and heartbeat [32].

WiFall [26] can detect fall scenario of a single person with 90% precision and 15% false alarm rate by using one-class SVM classifier and 94% fall detection precision and 13% false alarm rate with Random Forest classifier. CSI has also been used for presence detection [35] with average false positive of 8% and false negative of 7% in four directions.

2.1.4 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 [31]. Allsee uses a custom low-power circuit to extract received signal to recognize hand gestures [17]. 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 [14, 15].

2.2 Caloric Expenditure Estimation

Although there has been a lot of interest in HAR, to the best of our knowledge no research has been done for Caloric expenditure estimation in a device-free setting. Calorie estimation using devices/sensors has been extensively studied. A lot of devices such as fitness trackers, smart watches, and body sensors are available for this purpose. There have been various studies to compare these devices [9], [16]. The inaccuracy for sitting tasks (resting calories) was found to be as high as 52.4%. We believe to have an accurate calorie estimation in a device free setting, we need precise HAR.

Chapter 3

Background

Ultra-Wideband radio technology uses a very low energy level for short range, high-bandwidth communication, over a large spectrum of the radio spectrum.UWB signals are sent in short bursts of pulses (1 ns). This enables in signal echo from different paths at different time intervals. This unique feature leads to accurate distance measurements with associated time stamps. The methodology to collect CIR data is depicted in figure 3.1.

3.1 Hardware Specifications

The DecaWave EVB1000 allows the development of applications in real-time location systems (RTLS) and wireless sensor networks (WSN).Figure 3.2 contains the layout of a standard EVB1000 node.

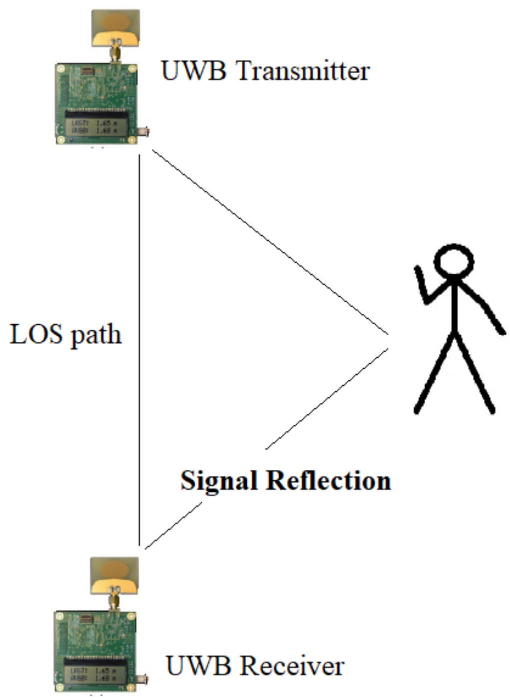

Figure 3.1: Key Idea

The evaluation board incorporates DecaWave's DW1000 IEEE 802.15.4-2011 UWB compliant wireless transceiver IC, STM32F105 ARM Cortex M3 processor, USB interface, LCD display and off-board antenna. The DW1000 IC supports 6 frequency bands with center frequencies from 3.5 GHz to 6.5 GHz with a bandwidth of 500 MHz or 900 MHz. It supports packets up to 1023 bytes. EVB1000 has DecaRanging pre-installed which was modified for collecting CIR data. This chip can estimate and report CIR.

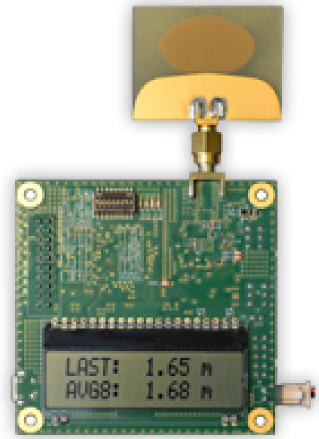

Figure 3.2: EVB 1000 Node [8]

3.2 Channel Impulse Response

CIR is the response of the wireless links to the impulses. It can be formulated as follows:

$$h(\tau) = \sum_{i=1}^{N} a_i e^{-j\theta_i} \delta(\tau - \tau_i) \tag{3.1}$$

where a_i,θ_i, and τ_i are the amplitude, phase, and time delay of the i^{th} path respectively

As per equation 3.1, CIR is a good indicator of reflected multipath components which are being used in this experiment for activity recognition. Figure 3.3 illustrates the CIR raw data collected for two different activities. The first path, marked with a peak is at around 45 ns. In this experiment we consider the data between the first peak and subsequent 100 ns to reduce the effect of noise in the results.

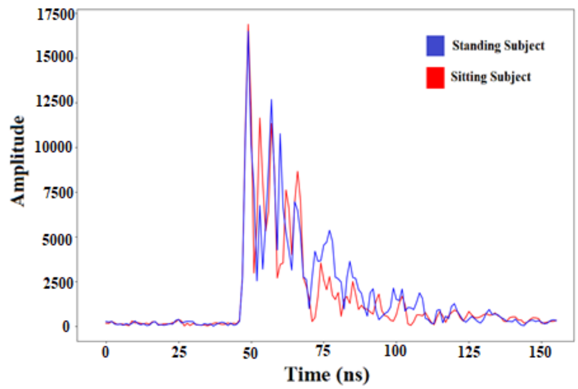

Figure 3.3: CIR collected for 2 different activities

3.3 Feature Selection

We used the raw CIR values that were obtained during communication between the EVB1000 nodes to build feature. The communication consists of a sender that is sending messages every 50 ms. The receiver, constantly monitoring the channel, records CIR information upon receiving a packet from a sender. EVB nodes estimate the components of channel's CIR every 1 ns. It reports the component in polar coordinates. We used the raw values of samples as features in our machine learning algorithm. After careful analysis of our data, we realized using 200 samples starting from the first path will generate accurate enough results.

Chapter 4

Methodology

The proposed approach consists of processing UWB signals to determine the pose of a subject and the time spent in each pose. Our methodology is specially designed to identify the poses of standing, sitting and lying. According to the Compendium of physical activities [18] these poses are classified as ”Light inactivity”. Figure 4.1 shows the proposed methodology for our approach.

CIR Extraction UWB signals are sent in short bursts of pulses by the sender (every 50 ms). This enables in a signal echo from different paths at different time intervals. This unique feature leads to accurate distance measurements with associated time stamps. We use the raw CIR values that were obtained during communication between the nodes. The receiver, constantly monitoring the channel, records CIR information upon receiving a packet from a sender. The receiver node estimates the components of channels CIR every 1 ns. It reports the component in polar coordinates. We treat this as our raw data.

4.1 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 it to eliminate noise.

4.1.1 First Path

The collected CIR data contains the information about the first path delay. This is the channel's delay to receive the first path. The CIR values that are reported are inherently noisy. But, to train models for activity recognition, it is important to remove this noise prior to data model creation. All signal measurements before the first path are considered as noise and eliminated. Noise elimination is an important step to reduce the impact of environmental factors in the monitored area. This includes any disturbances by other human beings in the vicinity of the monitored area, movement/ activity of other objects. To incorporate this we remove the samples before the first path component using the first path delay information.

4.1.2 Filtering Noise

We tested the data after the first path to determine, the amount of data that is useful after the first spike in amplitude. Once a signal is pre-processed the available data which is in the form of polar coordinates. We then find the most optimal number of features that give highest accuracy. For all models trained, 200 features are used. Figure 3.2 shows that this is observed at around 50 ns for the depicted experiment.

The feature set so derived is used in combination with four classification algorithms to predict the pose of a subject. We perform the experiment for a set of 13 subjects. We used 10-fold cross validation technique for this purpose.

4.2 Algorithm Selection

We trained models based on some common machine learning classification algorithms.

Naive Bayes: Our first model was trained based on the Naive Bayes classifier. However, it has a strong independence assumption between the features. This is not true in our case. We still use it as it is a popular algorithm for classifying problems. We are using the Gaussian Naive Bayes classifier for our experiment.

Neural network Multi-Layer Perceptron (MLP): MLP is a feed forward artificial neural network model that maps sets 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 some promising results with classification of activities using cell phone accelerometer data [18].

Nearest Neighbors: The principle behind nearest neighbor methods is to find a predefined number of training samples closest in distance to the new point and predict the label from these. The number of samples can be a user-defined constant (k-nearest neighbor learning) or vary based on the local density of points (radiusbased neighbor learning). Previous efforts to classify human activities using the common k-nearest neighbors classifier had an accuracy of 75% [11].

Random Forest: Random Forest Classifier is ensemble algorithm. It creates a set of decision trees from randomly selected subset of training set. It then aggregates the votes from different decision trees to decide the final class of the test object. Previous studies that used multi sensor data have shown to have high accuracy for HAR [10].

The trained models can be used in application for activity recognition. The accuracy's of these models are recorded and the model with the highest accuracy is chosen to determine calorie expenditure of subjects based of the predicted pose.

The detailed description, methodology, and results of this application are covered in Chapter 6.

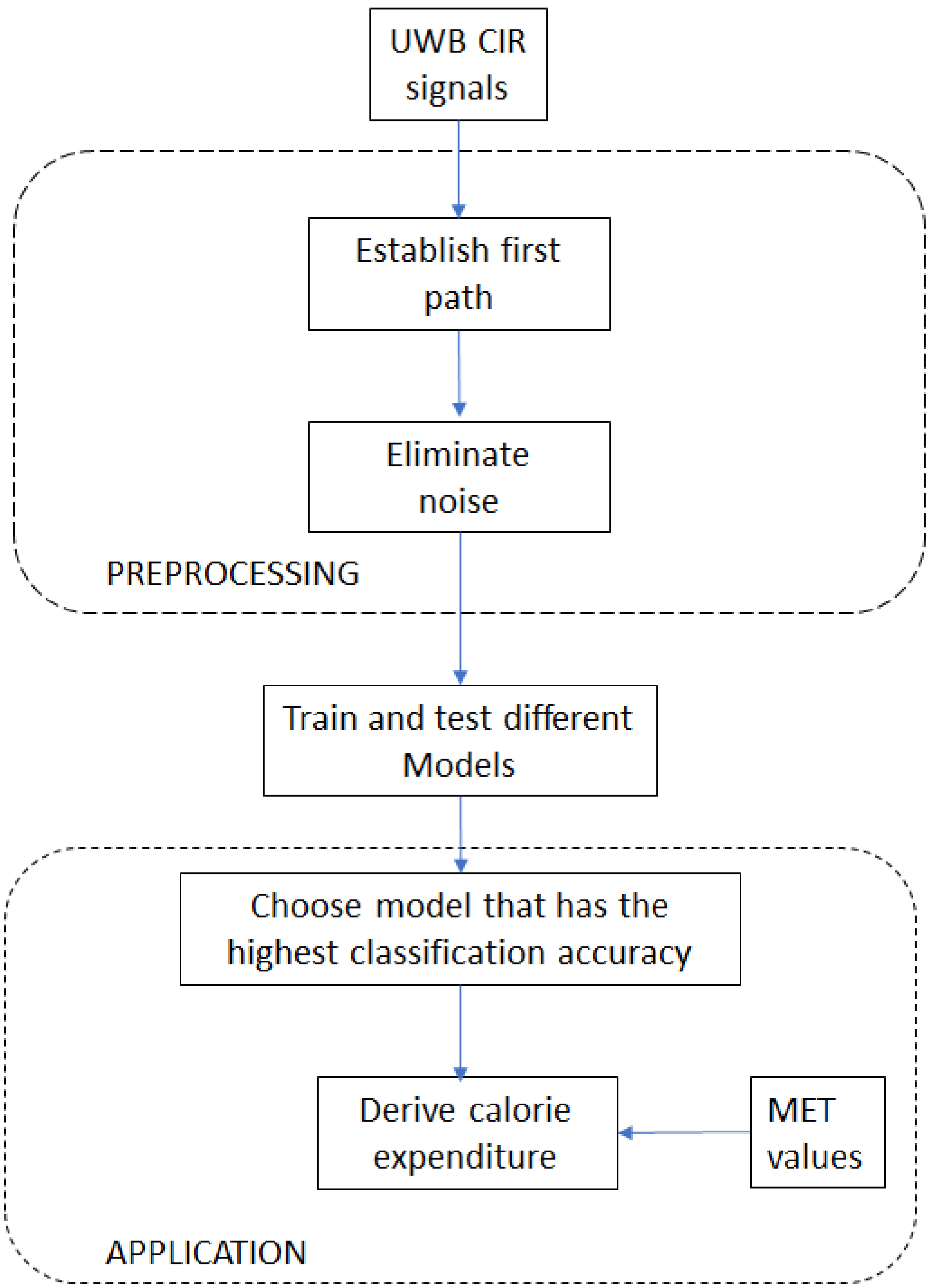

Figure 4.1: System Flowchart for Activity Recognition using UWB

Chapter 5

Evaluation

To evaluate the accuracy of activity detection, we try to classify CIR signals to predict the activity performed by a subject. We then leverage this information for calorie estimation. Similar, experiments were carried out using WiFi CSI for HAR. Additionally, we compared the results of both experiments in our evaluation process. Following sections describe the evaluation process in detail and the results for the same.

5.1 Experiment Design

The experiments have been performed in different indoor settings such as in a couple of different apartments, and a conference room in our institution. For each of the locations multiple subjects have performed three activities, i.e. standing, sitting,

Table 5.1: Subject Details

Subject	**Height (cm)**	**Weight (cm)**	**Girth (cm)**	**Gender**
1	178.0	154.0	83	male
2	172.5	158.5	85	male
3	175.1	159.0	89	male
4	147.0	105.0	72	female
5	190.5	270.0	120	male
6	188.0	155.0	85	male
7	172.0	176.4	95	male
8	156.0	125.6	77	female
9	185.4	207.0	100	male
10	172.7	185.0	98	male
11	184.0	174.0	96	male
12	180.5	163.0	92	male
13	165.0	137.8	79	female

and lying. Additionally, the empty room has been considered as the baseline activity. Table 5.1 lists some basic information for all the subjects that performed the activities.

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

To enhance the CIR altercation and improve the recognition accuracy, 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.

For the purpose of our experiment we have used 200 i/q values. Figure 5.1 shows the accuracy of a Random Forest classifier for different number of samples including

50,100,150 and 200. The accuracy consistently improves up to 200 samples as features and shows no improvement after it. Thus, 200 samples are selected as features for the models.

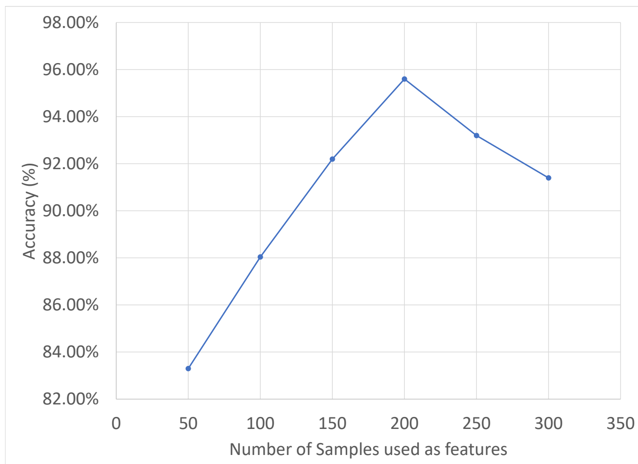

Figure 5.1: Accuracy comparison for different number of features

5.2 Experimental settings for UWB signals

Our system consists of a pair of EVB1000 boards which have been placed 2 m apart. One of the node (transmitter) is configured to continuously send packets to the receiver. When there is a human present near the setup, the human body reflects the packets. By monitoring the channel, the receiver can measure the change caused by the human movements and this is used to recognize the surrounding human activity.

5.3 Activity prediction using UWB signals

The packet capture by EVB 1000 was analyzed and used to train models using different machine learning algorithms mentioned in Algorithm selection in Background (Chapter 3). The CIR values that are reported by the EVB1000 nodes are inherently noisy. However, to train models for activity recognition it is important to remove this noise prior to data model creation. To incorporate this we remove the samples before the first path component as a pre-processing step to model training.

The first algorithm used to model the data was Naive Bayes. The accuracy of Naive Bayes is reported at 65.6%. The confusion matrix for prediction accuracy is mentioned in table 5.2 . This accuracy is significantly low due to the independence assumption between features.

Table 5.2: Naive Bayes Confusion Matrix

	Empty	**Standing**	**Sitting**	**Lying**
Empty	0.856	0.004	0.086	0.054
Standing	0.018	0.308	0.343	0.33
Sitting	0.013	0.088	0.57	0.329
Lying	0.002	0.006	0.127	0.865

The second algorithm used to model the data was Neural Network MLP. The accuracy reported for classification of HAR is 93.9%. The confusion matrix for NN MLP is shown in Table 5.3.

The third classification algorithm used for data modelling is Nearest Neighbors. The overall accuracy reported is 94.5%. The confusion matrix for nearest neighbors is reported in table 5.4.

Table 5.3: 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

Table 5.4: K Nearest Neighbors Confusion Matrix

	Empty	**Standing**	**Sitting**	**Lying**
Empty	0.996	0.002	0.002	0
Standing	0.001	0.881	0.052	0.066
Sitting	0.002	0.02	0.938	0.04
Lying	0.003	0.014	0.008	0.975

The final algorithm used to model data is Random Forest with an accuracy report of 95.6%. The confusion matrix of random forest is shown in Table 5.5. Random Forest reports the highest accuracy amongst all algorithms.

Table 5.5: Random Forest Confusion Matrix

	Empty	**Standing**	**Sitting**	**Lying**
Empty	0.993	0.003	0.001	0.003
Standing	0	0.929	0.027	0.043
Sitting	0	0.018	0.929	0.053
Lying	0	0.005	0.007	0.987

5.4 Experimental settings for WiFi CSI signals

To compare the performance of UWB CIR, we use Linux 802.11n CSI Tool. The CSI Tool is built on the Intel Wi-Fi Wireless Link 5300 802.11n MIMO radios, using a custom modified firmware and open source Linux wireless drivers. WIFI NICs continuously monitor variations in the wireless channel using CSI, which characterizes the frequency response of the wireless channel. In this experiment we use one wireless Access Point (Buffalo WZR-HP-G300NH2) under 802.11n(2.4GHz) and one laptop (Dell, Ubuntu 12.10). Experiments described in Experiment design are performed using the CSI tool.

5.5 Activity prediction using WiFi CSI signals

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 modelled using the same four algorithms.

Naive Bayes is the first algorithm used for data modelling. Its average accuracy is 46.8%. The comparison for CSI based Naive Bayes is depicted in figure 5.2. The low accuracy of Naive Bayes is attributed to its Independence assumption.

The second algorithm used to train a model is Neural Network MLP. The average accuracy for it is 69.6%. The comparison for NN MLP is shown in figure 5.3. As compared to Naive Bayes, NN MLP performs better in prediction of all classes. This improvement can be attributed to the fact that NN MLP does not assume feature independence.

The third algorithm for modelling data is Nearest Neighbors that gives an accuracy of 61.1%. The comparison for NN is depicted in figure 5.4.

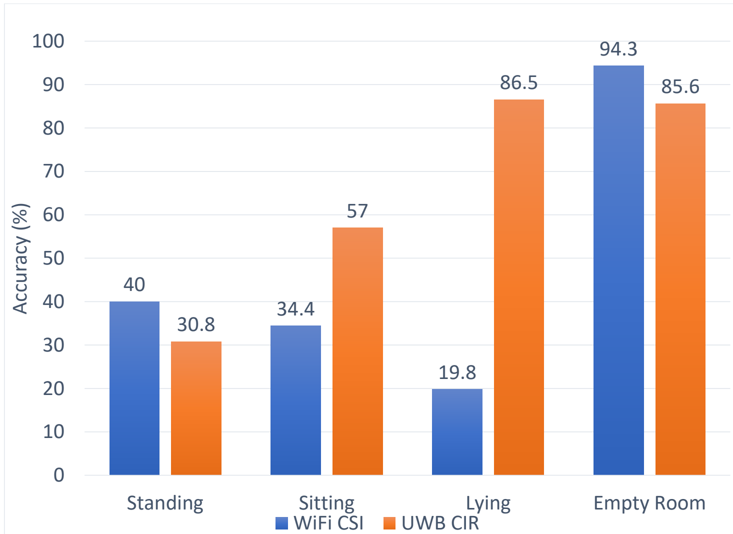

Figure 5.2: Naive Bayes Comparison

The final algorithm for to train the CSI data is Random Forest with an accuracy of 74.1%. The comparison for a Random Forest is shown in figure 5.5.

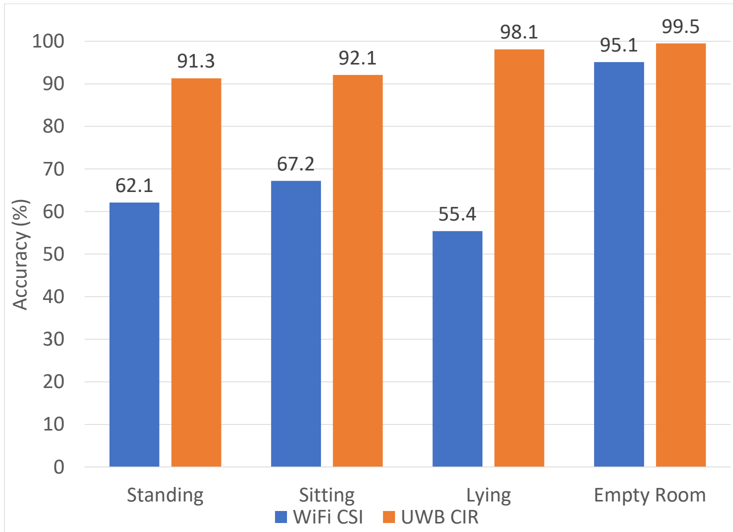

Figure 5.3: Neural Network Comparison

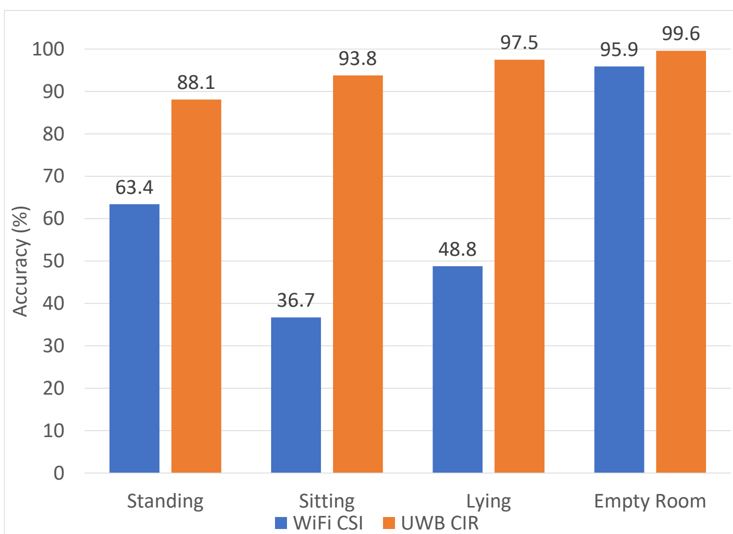

Figure 5.4: K Nearest Neighbors Comparison

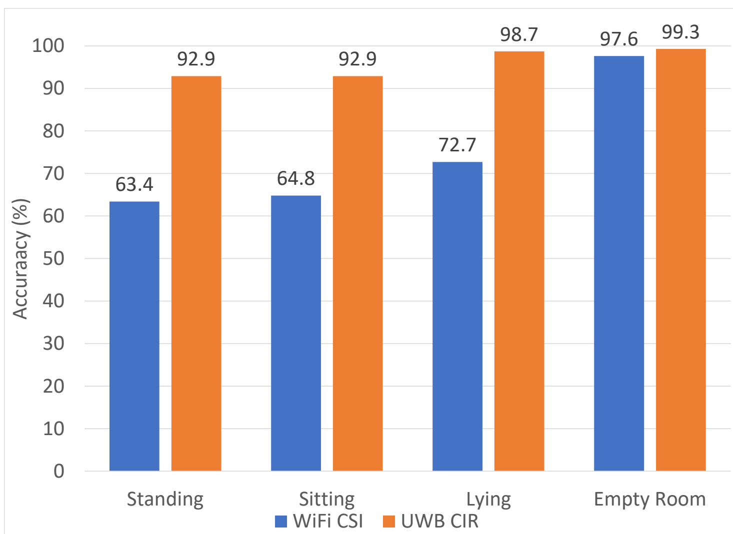

Figure 5.5: Random Forest Comparison

Chapter 6

Application

An application of UWB for Human Activity Recognition (HAR) is in calculating caloric expenditure. Once an activity is classified, these results are used to find the energy expenditure based on MET values. Metabolic Equivalent (MET value) is the amount of Oxygen a person consumes per unit of body weight while performing a certain activity. We use metabolic equivalent (MET) for each activity reported in the Compendium of Physical Activities [4].

$$Calories = METS(kcal/kg * hr) * weight(kg) * time(hours) \tag{6.1}$$

In our experiment, we asked 13 subjects to perform the three activities (standing, sitting and lying) for three minutes each, this is the ground truth. We then classify these activities using the proposed HAR system. We use equation 6.1 with corresponding MET values of the activities to estimate caloric expenditure for both the base condition and for our HAR system. We compare both these values to the caloric estimate found using the Basal Metabolic Rate (BMR). BMR is defined as the rate at which your body uses energy when you are resting in order to keep vital functions going. Most commercial devices that are available in the market use BMR in order to count calories. Equation 6.2 and 6.3 is used by most of these devices.

$$Women : BMR = 655 + (4.35 * weightInPounds) + (4.7 * heightInInches) - (4.7 * ageInYears) \tag{6.2}$$

$$Men : BMR = 66 + (6.23 * weightInPounds) + (12.7 * heightInInches) - (6.8 * ageInYears) \tag{6.3}$$

The results of Calorie Expenditure for the 13 subjects involved in this experiment are shown in table 6.1 The table also shows the corresponding Basal Metabolic Rate(BMR) values for the same subjects.

By using UWB HAR we are able to count calories with an error of less than 1% for stationary subjects. This is significant improvement over fitness devices which either do not count calories for inactive subjects or use BMR which is suffers from high inaccuracy. Our approach reports 32% more calories than the BMR approach which iis known to under reports calories.

Table 6.1: Calorie Estimation Results

Subject	**Perfect Recognition (Kcal)**	**UWB HAR (Kcal)**	**BMR (Kcal)**
1	16.07	15.95	10.99
2	16.54	16.42	11
3	16.59	16.47	11.1
4	10.95	10.88	8.12
5	28.17	27.98	15.9
6	16.17	16.07	11.35
7	18.4	18.26	11.68
8	13.1	13	9.2
9	21.6	21.43	13.29
10	19.3	19.16	12.04
11	18.15	18.01	11.96
12	17.01	16.87	11.42
13	14.38	14.28	9.96

Chapter 7

Conclusion

The proposed approach for Human Activity Recognition provides a high accuracy for indoor settings at 95%. The focus of this approach is to classify activities where the subject is stationary.We only use one UWB transmitting node and a UWB receiver node. We use four common machine learning algorithms namely, Naive Bayes, Neural Networks MLP, Random Forests, and K Nearest Neighbors.To evaluate our system, we perform the same experiments using WiFi CSI and show that our results have an accuracy 20% higher than WiFi CSI.

It is important to note that this performance is recorded for experiments with single subjects. Effects of multi-subject settings including public spaces have not been studied. Also, the proposed system is not resilient to changes in the environment, which means if big pieces of furniture are moved in the room, user will be required to train the system again. A fingerprinting approach can be used to notify the user whenever there is a need to train the system. Another important aspect of such studies will be cross channel communication handling. However, a lot of single subject settings such as patient monitoring in intensive care, athletic training, etc can most effectively make use of the proposed system to estimate Caloric Expenditure.

Current devices which are commercially available to measure Caloric Expenditure for a subject at rest focus only on the BMR (Basal Metabolic Rate). This leads to a generic calorie estimation for all activities. We investigated prediction of Caloric Expenditure using the results of activity classification. It makes use of the Metabolic Equivalent (MET) of each activity, physical attributes of a subject and the duration of each activity. We were able to estimate the resting caloric expenditure with an error of 1% which is 32% improvement over fitness trackers. This approach is being developed as an important application of HAR using UWB.

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