Comparative Analysis of Artificial Intelligence on Contactless Human Activity localization

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***Abstract*—Ambient computing is getting popular as one of the most substantial technological advances in the future. In the present era, human activity tracking, indoor localization, and healthcare systems are all developing rapidly. Researchers are able to find practical solutions in healthcare facilities that often need to locate humans with the growing affordability and power of Radio Frequency (RF) technology. RF is appealing to monitor human activities in an unobtrusive and remote manner. Channel State Information (CSI) can be used as a contactless method to identify and locate human activity indoors. This paper presents the results of an experiment utilizing Universal Software-Defined Radio Peripherals (USRP) to locate the location of activity. A single subject is observed performing sitting, standing, no activity and leaning forward in six different locations inside a room to collect CSI samples. Additional CSI is collected when the subject walks in both directions within the designated area. Three Machine Learning (ML) classification algorithms were used in the comparison: Random Forest, Extra Trees (ET), and Multilayer Perceptron (MLP). When compared to other ML algorithms, the ET classifier has the best performance, with an average of 95% accuracy.**

***Index Terms*—Localization, Machine Learning, Occupancy Monitoring.**

I. Introduction

Recent research has focused on developing accurate RF-based localization systems that work like GPS outdoors. Maps with GPS coordinates have changed outdoor navigation completely (such as Google Maps). However, the study revealed that a human can be located without carrying a wireless device [1]. Some of the applications are battlefield monitoring, catastrophe prediction, intelligent traffic, and indoor navigation [2]. Systems using RF sensing include varying hardware and software specifications, radio frequency operations, classification algorithms, activity monitoring and the number of subjects. The Received Signal Strength Indicator (RSSI) or the CSI can be used to determine the strength of an RF signal. according to a study [3], CSI monitors each Orthogonal Frequency Division Multiplexing (OFDM) packet, whereas RSSI offers coarse data. This study's goal is to collect CSI data on human activities in a single room using two USRP (Tx and Rx) devices and ML. Using collected data, we compared ML algorithms for human activity classification in contactless indoor localization.

The following is a summary of the paper's structure: Related work is described in the section II. The Experimental Setup is described in Section III and Section IV concludes the paper.

II. Related Work

In the field of contactless healthcare and activity identification, using target localization has attracted a lot of interest and development. Systems that can identify activities and provide information on the target's location can help answer concerns of physical and mental health, as well as disease early diagnosis and prevention. Intrusive techniques [4] are widely available and quite accurate but they are considered burdensome and inconvenient for the elderly or childcare. In order to successfully extract activity in crowded environments, contactless long-term health monitoring approaches are highly desirable [5]. Radar-based solutions proved accurate localization and real-time health monitoring in situations involving multiple targets using wide bandwidths and large antenna systems [6]. However, such solutions are costly, energy-intensive, and not easily and widely available.

The authors in [7] used classification algorithms such as Random Forest, SVM, KNN, and Linear Discriminant Analysis (LDA) with different features to evaluate classifiers on the Human Activity Recognition (HAR) dataset. The classifier RF had the highest accuracy (98.16%). Wi-Fi, GSM, and radar technologies can localize and identify activity without cameras or wearable sensors. As a result, contactless RF sensing has attracted popularity in healthcare and security domain. Similarly, authors in [8] used a smartphone-based inertial sensor, a Longistic Model Tree (LMT) to recognize human activity and then compared the LMT HAR system outperforms RF and Logistic Regression Tree (LRT). Using the proposed LMT approach, they achieved 90% WISDM and 94% UCI HAR recognition accuracy. Using the Random Forest method, the study [9] differentiated sitting and standing activities using USRPs (X300 and X310) and the proposed dataset was compared to a benchmark dataset, the results revealed that the proposed dataset had nearly 90% accuracy. The authors in [10] used a deep-learning algorithm to distinguish user movement states such as move forward, move backward, and no movement. According to their study, at a distance of 1.5 metres, the model has an accuracy of 89%, but as the distance increases to 2 metres, the accuracy reduces to 74%. As a result, as the location of movements moved away from the passive sensing system, the model's accuracy dropped.

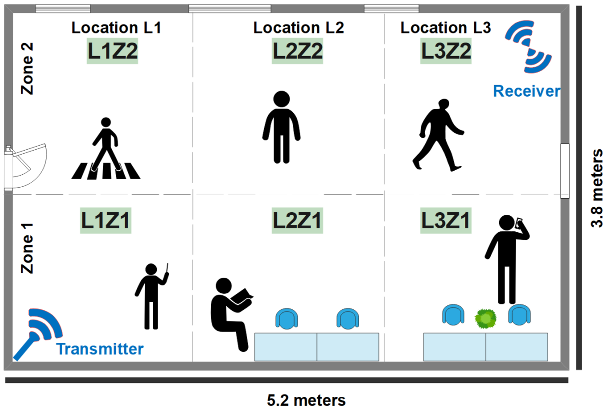

Fig. 1. Horizontal and vertical zones shown in experiment setup diagram.

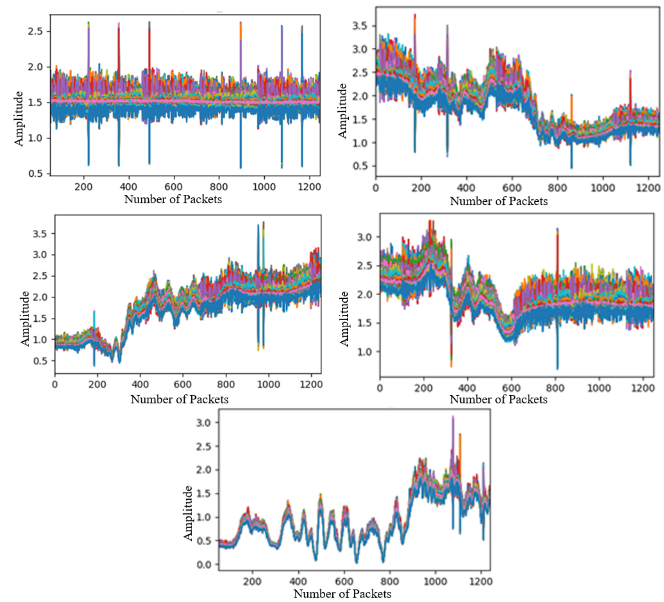

Fig. 2. Wireless CSI data samples from different activity zones.

III. Experimental Setup

The experiment was carried out in a $3.8 \times 5.2m^2$ room on level 5 at James Watt South Building, with ethical approved. The room is partitioned into three zones, one meter apart. The USRP transmitter (T_x) and receiver (R_x) devices were angled at 45°. Figure 1 illustrates zones for seven activities: sitting, standing, leaning, no activity, walking in both direction from T_x - R_x and from R_x - T_x, and empty. It shows the subject walking horizontally between T_x and R_x direction. Figure 2 depicts CSI amplitude variations in all six activities and empty classes. During an activity, each color represents a subcarrier, with the number of packets on the x-axis and the subcarrier's amplitude on the y-axis. Three seconds of OFDM transmission are represented by each data sample. As a result, 1200 packets size is created as a sample. 100 samples of each activity are collected totaling 2900 data samples. Each of the six locations in Figure 1 includes 100 sitting, standing, leaning, and no activity samples. Walking in each zone produced 200 samples (2 activities) and 100 empty samples for whole room. There are 100 samples in each class. Each data sample has a name that corresponds to the zones and locations from where it was collected, such as L1Z1 for a mean data sample from zone 1 and location 1. Table I lists the 29 classes as well as the total number of data samples collected at each location.

A. Data Preprocessing and Machine Learning

We use *Scikit*, a popular Python data analysis toolkit, to preprocess and analyze the data. Also, the Python library *Pandas* can parse CSV files. Data frames are created from CSV files and can be examined using *scikit-learn*. Dimensions are reduced using the PCA method fit-transform. The Butterworth digital and analogue filters produce a n^{th} order digital or analogue Butterworth filter signal. Using the *butter* (1, 0.05) function returns the filter coefficients in (B, A) form. Data frames in the first column now have labels. The dataset generated by merging the data frames of each sample includes NaN due to minor mismatches in received packets during the connection between the USRP devices. The mean of each row is replaced with NaN using the *SciKit* built-in function *SimpleImputer*.

The proposed indoor human activity location is evaluated using Random Forest, ET and MLP algorithms. Our experiment evaluates the accuracy of successfully localizing the activities. Each algorithm's accuracy is evaluated and the results for each dataset using k-fold cross-validation. In this experiment, k = 10, dividing the dataset into 10 groups. Each group is tested, while the other nine are used for training. The results of each classification group include all samples in the dataset. The ET algorithm is the most accurate in two zones and six locations. The test was designed to show that the activities were correctly classified. The ET algorithm has a 95.40% combined accuracy rate. This is likely due to CSI variations becoming more apparent as the horizontal distance from the transmitter increases. The normalized confusion matrix of the ET classifier on L3Z1 dataset is shown in Figure 3. As demonstrated in Table II, all activity in Zone-1 and Zone-2 with location 3 is dominantly categorized by all algorithms. The ET algorithm provides a 95% classification rate followed by RF 91.41% and MLP 82.64% when identifying the location of six different activities. The system can also accurately identify empty CSI with 100%. Table III lists the parameters used to configure the algorithms.

IV. Conclusion

This paper proposes an indoor activity localization system that uses RF sensing to locate seven distinct activities taking place in six different locations inside the same room. The use of RF sensing enables contactless activity detection without the need of wearable device. In all dataset, the results indicate the identification of a particular activity in an indoor environment due to their proximity to the Rx. The localization of various activities in locations 3 in zone 1 and 2 is found to

TABLE I
DATA CLASSES AND THEIR DESCRIPTION

S.No	Class	Class Descriptions	No. of Classes	Count
1	Empty Room	Absence of a human subject	1	100
2	No Activity	No human activity performed	1×6	600
3	Sitting	"Sitting" activity at a designated location inside Zone.	1×6	600
4	Standing	The action of "Standing" activity at the designated location inside Zone	1×6	600
5	Leaning	Leaning forward with the upper body in Zone	1×6	600
6	Walking Rx-Tx and Tx-Rx	From USRP X310 Rx to USRP X300 Tx	2×2	400

TABLE II
ALGORITHM COMPARISON ON ZONE-1 USING CROSS-VALIDATION

Algorithm	L1Z1 Accuracy	L2Z1 Accuracy	L3Z1 Accuracy	L1Z2 Accuracy	L2Z2 Accuracy	L3Z2 Accuracy
Multilayer Perceptron	70.76%	76.01%	82.64%	57.88%	64.84%	79.64%
Random Forest	81.58%	83.59%	91.41%	73.11%	75.78%	89.90%
Extra Tree	**88.22%**	**89.71%**	**95.40%**	**80.82%**	**85.01%**	**93.74%**

TABLE III
MACHINE LEARNING ALGORITHM PARAMETERS

S.No	Algorithm	Hyperparameters	n-estimator
1	Multilayer Perceptron	hidden-layer-sizes = (128, 64)	activation='relu'
2	Random Forest	Kernel = rbf and sigmoid	n-repeat = 10, gamma='scale'
3	Extra Tree	Euclidean distance and K = 3,7	n-repeat = 10

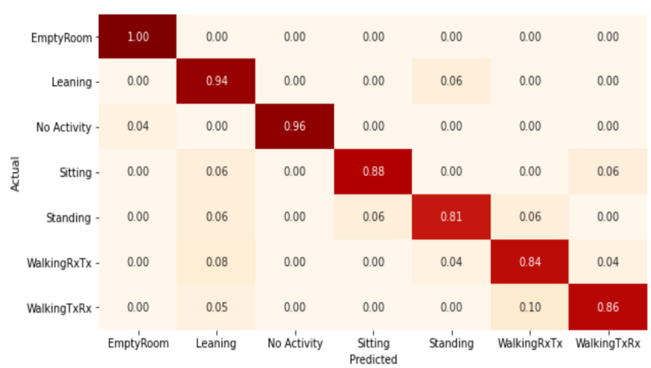

Fig. 3. The ET algorithm's normalized confusion matrix on dataset L3Z1.

be better than in other locations, with a precise increase of an average 7-12% in Zone-1 and average 13-22% in Zone-2 for every 1 metre away from the Tx.

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