Indoor Activity Position and Direction Detection Using Software Defined Radios

Ahmad Taha[1(✉)], Yao Ge[1], William Taylor[1], Ahmed Zoha[1], Khaled Assaleh[2], Kamran Arshad[2], Qammer H. Abbasi[1], and Muhammad Ali Imran[1,3]

[1] James Watt School of Engineering, College of Science and Engineering, University of Glasgow, Glasgow G12 8QQ, UK
ahmad.taha@glasgow.ac.uk
[2] Faculty of Engineering and IT, Ajman University, 346, Ajman, UAE
[3] Artificial Intelligence Research Center (AIRC), Ajman University, Ajman, UAE

Abstract. The next generation of health activity monitoring is greatly dependent on wireless sensing. By analysing variations in channel state information, several studies were capable of detecting activities in an indoor setting. This paper presents promising results of an experiment conducted to identify the activity performed by a subject and where it took place within the activity region. The system utilises two Universal Software Radio Peripheral (USRP) devices, operating as software-defined radios, to collect a total of 360 data samples that represent five different activities and an empty room. The five activities were performed in three different zones, resulting in 15 classes and a 16^{th} class representing the room whilst it is empty. Using the Random Forest classifier, the system was capable of differentiating between the majority of activities, across the 16 classes, with an accuracy of almost 94%. Moreover, it was capable of detecting whether the room is occupied, with an accuracy of 100%, and identify the walking directions of a human subject in three different positions within the room, with an accuracy of 90%.

Keywords: Artificial intelligence · Indoor positioning · Human activity recognition · Occupancy monitoring

1 Introduction

Localisation and detection of human motion and activity have been of great interest to many researchers in recent years [3]. This reasons to the technological advancements in the fields of wireless communication, computing, and sensing techniques, through which studies have emerged that made significant contributions to the field. A system that is capable of identifying the activity and the position of the subject has numerous applications in several domains including healthcare, energy management, and security [20].

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Several studies have emerged over the past years that utilised Radio Frequency (RF) to detect small scale activities such as vitals [22,24], large scale body movements [6,19,21], and for localisation and tracking [5,15,18,25]. The studies reported the use of various types of radio devices including the Universal Software Radio Peripheral (URSP) device [12,23], Commercial off-the-shelf (COTS) Wi-Fi devices [8,11,27], Frequency-Modulated Continuous Wave radar (FMCW) [26], and Impulse Radio Ultra-Wideband (IR-UWB) [10].

The systems presented in the literature performed a distinct functionality, that is, either localisation or small/large scale activity detection. For instance, the activity detection systems presented by [13,23] reported accuracies of 91% and 94% respectively, with both using the USRP N210 model. Other studies that performed localisation and tracking such as [5,18] reported accuracies of 81% and an error of 5 cm in a $20 \times 70\,\text{cm}^2$ area.

This paper improves on the studies presented in the literature by presenting a single system that is capable of utilising RF signals to detect, similar and different, activities performed in different locations, within the same room. As well as identify occupancy and the direction of movement across the activity area. The proposed system makes use of the USRP, operating as a Software-Defined Radio (SDR), to differentiate between five different activities and when the room is empty. Each of the activities was performed in three different positions, marked within the experimental area. The contributions in this paper can be summarised to, the integration of Machine Learning (ML), namely the Random Forest classifier, and Channel State Information (CSI), from SDRs, to recognise, with high accuracy, five different activities and their position within a room. The contributions can be summarised to the following:

– Localisation of activities in three different zones within a room
– Identifying direction of movement in three different positions within a room
– Identifying an empty room from one that is occupied

2 Materials and Methods

Having introduced the aim and focus of this paper, this section goes on to present details of the methodology adopted to conduct the experiments. Section 2.1 details the hardware and software components that were designed and utilised to enable collecting CSI data, depicting human activity, from the sensing devices. Whilst, Sect. 2.2 outlines the details of the conducted experiments, including, experimental setup, data collection, and training of the ML algorithm.

2.1 Technical Specifications

SDR models, particularly the USRP devices [7], X300 and X310, were used as the activity sensing nodes. The hardware and software specifications associated with the system are detailed in the following subsections.

Hardware. The set-up for data collection involved using two USRP devices communicating with each other while the activity was taking place within the area covered by them (see Fig. 1). The USRP X300 was used as the transmitter and the X310 was used as the receiver, with each using the VERT2450 omnidirectional antenna. Both devices were connected to a separate Personal Computer (PC), through a 1G Small Form-Factor Pluggable (SFP) connector. The PCs were equipped with the Intel(R) Core (TM) i7-7700 3.60 GHz processors and each has a 16 GB RAM and had an Ubuntu 16.04 virtual machine running on it. The virtual machine hosted the python scripts used to configure the USRP devices as well as collect and process the data.

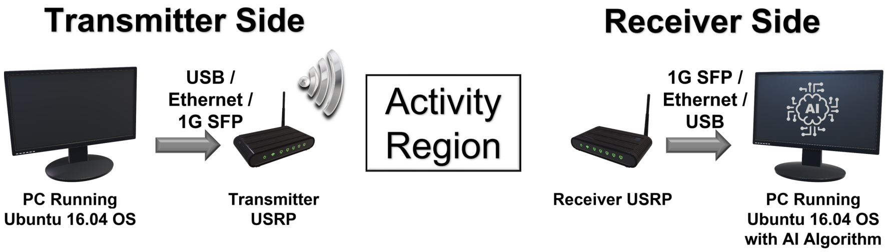

Fig. 1. System architecture.

Software. The software design stage involved two main activities, the first was the configuration of the USRP transmitter and receiver devices to communicate together. This was performed using the GNU radio python package to set parameters such as central frequency, which was 3.75 GHz, number of Orthogonal Frequency Division Multiplexing (OFDM) subcarriers, and power levels (see Table 1).

GNU Radio is a free and open-source software that is used in research for SDRs and signal processing [2]. GNU Radio comes with examples of OFDM signal processing where the CSI can be extracted. The GNU Radio software publishes the configuration in the format of a flow diagram which can be used to set up the blocks of the USRP and OFDM communication. The flow diagram can then be converted into a python script, which can be executed to begin OFDM communication.

Table 1. System parameters

Parameter	Value
Operating frequency	3.75 GHz
Number of OFDM subcarriers	52
Transmitter gain (dBm)	70
Receiver gain (dBm)	50

The second activity was to collect the CSI and create data sets from them in the form of "Comma-Separated Values" (CSV) files. The CSV files would hold the data sets that will be used for training and testing the ML algorithm. For this, another python script is used to process the raw data extracted by GNU radio from the receiver USRP, and filter out the CSI complex numbers. Python carries out mathematical functions to calculate the amplitude of the RF signal from the CSI complex numbers. The amplitude values are then saved to CSV format for ML and to visualise the signal propagation through line graphs. The "CSV file" creation process (see Fig. 2) was repeated for all the data collected in all the experiments.

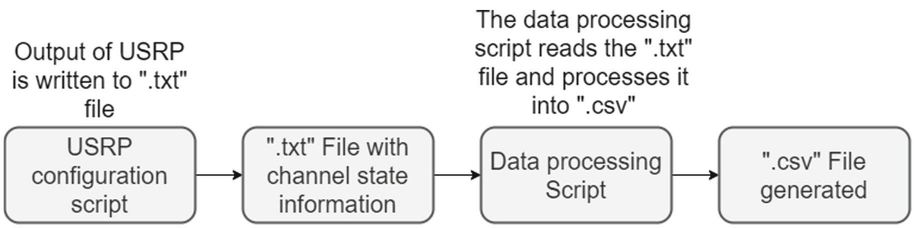

Fig. 2. Data flow diagram.

2.2 Experimental Design

The experiments presented in this paper were conducted at the University of Glasgow's James Watt South Building in a $3.8 \times 5.2\,\mathrm{m}^2$ room, where there is an active and approved ethical application. Three zones were marked in the room and all activities were repeated in them. The transmitter and receiver USRP devices were installed in the corners of the room, facing each other at an angle of 45°. The five activities performed were: Sitting, Standing, Walking along the 3.8 m side of the room from the transmitter to the receiver, Walking along the 3.8 m side of the room from the receiver to the transmitter, and Leaning forward.

Each of the five activities was repeated in three "Activity Zones", spaced by 1 m. Figure 3 shows the details of the experimental setup, including the activity areas, the location at which each activity was performed, and the positioning of the transmitter and receiver USRP devices.

Data Collection. The data collected for the proposed experiments were for a single subject performing the previously mentioned activities in three different zones within the room, as depicted in Fig. 3.

A total of 360 CSI samples were collected throughout the data collection stage, each consisted of approximately 1200 packets and this corresponds to about 3 s in time. The 360 CSI samples represent 16 different classifications, where each classification represents a data set, the "Empty Room" classification consists of 60 samples, that is, 20 samples collected to be used for every zone,

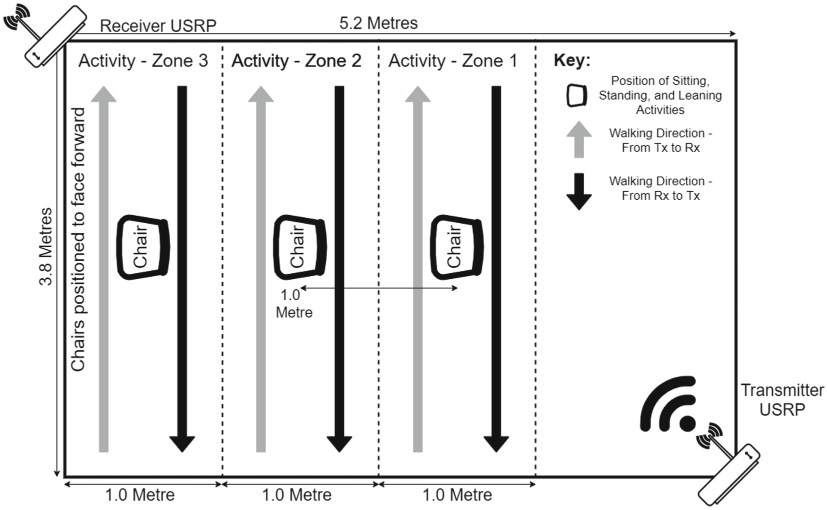

Fig. 3. Experimental setup.

and the remaining 15 classes each consists of 20 samples. A classification refers to a distinct class of data that represents an activity or the state of the room, for example, “Sitting” in “Zone One” is a classification, and “Sitting” in “Zone Two” is another. Given five activities are being captured in three different zones, this makes 15 out of the 16 classes. The 16^{th} classification represented the CSI data captured for the room without the human subject present inside it. The choice to incorporate this class with the rest of the data was to see if the system can identify if the room is occupied and is one of the main contributions of this paper. Table 2 shows all the 16 classes and the number of samples collected for each. Furthermore, Fig. 4 shows the distinct variation in the wireless CSI patterns amongst all five activities and the “Empty Room”.

Machine Learning. Having outlined the specifics of the data collection stage, using the USRP devices. This section provides an overview of the ML algorithm designed and used for classification in this paper. The choice of the algorithm was based on a study, previously conducted by the authorship team [21], where four ML algorithms were investigated, namely the Random Forest, K Nearest Neighbours (KNN) [14], Support Vector Machine (SVM) [16], and Neural Network [1,4,9]. In [21], the authors conducted two experiments to evaluate the accuracy of each algorithm, the first used 10-fold cross-validation and the second used train and test split. The 10-fold cross-validation takes the entire data set, and the data is split into 10 groups. One group is assigned as the test data and the other groups are assigned as the training data. The algorithm then uses the training data to create a model. The model is then applied to the test data to attempt to classify the data. This is then repeated until each group of data serves a turn as the test data. The predictions made each time are then compared to

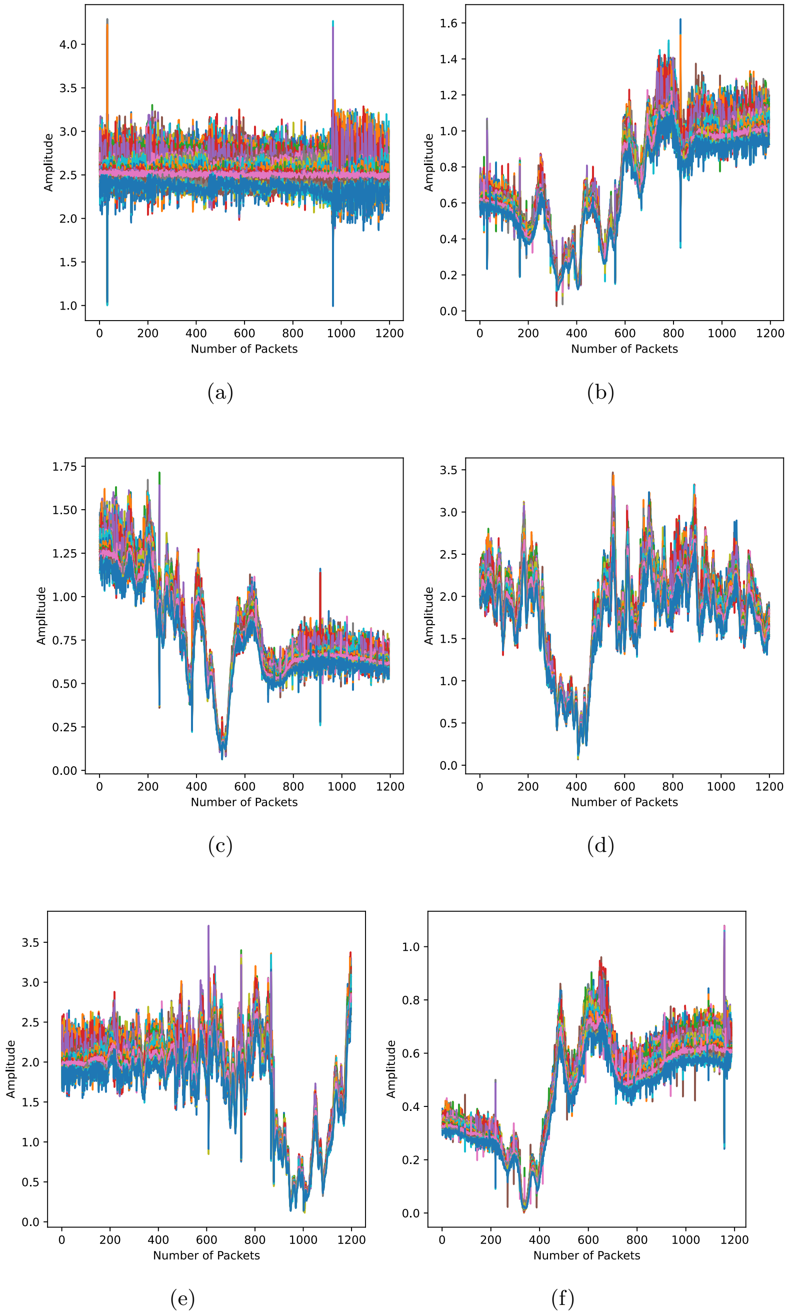

Fig. 4. Wireless CSI data samples representing various activity classes in activity Zone 1: a) Empty, b) Sitting, c) Standing, d) Walking from Tx to Rx, e) Walking from Rx to Tx and f) Leaning Forward.

Table 2. Data collection - The data classes and their description

Class	Class description	Number of samples
Empty Room	No human subject in the activity area	60
Sitting Zone 1	The action of "Sitting" at the designated location within Zone 1	20
Standing Zone 1	The action of "Standing" at the designated location within Zone 1	20
Walking Tx - Rx Zone 1	Walking from the USRP Tx side to the USRP Rx side within Zone 1	20
Walking Rx - Tx Zone 1	Walking from the USRP Rx side to the USRP Tx side within Zone 1	20
Leaning Forward Zone 1	Leaning forward with the upper body at the designated location within Zone 1	20
Sitting Zone 2	The action of "Sitting" at the designated location within Zone 2	20
Standing Zone 2	The action of "Standing" at the designated location within Zone 2	20
Walking Tx - Rx Zone 2	Walking from the USRP Tx side to the USRP Rx side within Zone 2	20
Walking Rx - Tx Zone 2	Walking from the USRP Rx side to the USRP Tx side within Zone 2	20
Leaning Forward Zone 2	Leaning forward with the upper body at the designated location within Zone 2	20
Sitting Zone 3	The action of "Sitting" at the designated location within Zone 3	20
Standing Zone 3	The action of "Standing" at the designated location within Zone 3	20
Walking Tx - Rx Zone 3	Walking from the USRP Tx side to the USRP Rx side within Zone 3	20
Walking Rx - Tx Zone 3	Walking from the USRP Rx side to the USRP Tx side within Zone 3	20
Leaning Forward Zone 3	Leaning forward with the upper body at the designated location within Zone 3	20

the correct labels from the data set and the performance can be measured. The train test split method only splits the data set between training and testing one predefined time. In the experiment in [21], the data set was split into 70% training data and the other 30% is set as the testing data. The algorithm performance was measured by comparing the Accuracy, Precision, Recall and F1-score. These performance metrics are calculated by looking at four classification values. The classification values are True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). The results of the evaluation, presented in [21], showed that the Random Forest algorithm had the highest accuracy of 92.47% with cross-validation and 96.70% using 70% training and 30% testing.

The Random Forest algorithm deploys a collection of decision trees where each tree predicts the output by looking for features found in the training phase. Each prediction is considered a vote and the majority of the votes decide on the overall Random Forest prediction [17].

System Testing. As mentioned earlier in Sect. 1, the paper aims to present a system that is capable of recognising with high accuracy the activity, its position within a room, and, where applicable, the direction of movement. The contributions of the paper are reiterated below:

1. Positioning of a human subject
2. Identifying the direction of movement in three different positions within a room
3. Identifying an empty room from one that is occupied
4. Establishing a relationship between the detection accuracy and the position of the activity

To do so, two different experiments were performed using the Random Forest classifier. The first involved applying ML to all classes representing each zone, individually. This means that ML was applied to data sets with the following labels: Empty, Sitting, Standing, Walking Tx-Rx, Walking Rx-Tx, and Leaning Forward, from each zone, to get three different outputs. The purpose of this experiment was to mainly meet the fourth contribution point mentioned above. The second experiment involved building a single data set with all 16 classes together. This experiment was to test the "Positioning", "Direction Detection", and "Occupancy" features of the system.

3 Results and Discussion

Two sets of results are presented in this section to showcase the contributions of this paper. The first set of results, which are from experiments performed for each "Activity Zone" separately and are presented in Sect. 3.1, focused on establishing a relationship between the activity position and the system's detection accuracy. However, they are also used to further validate the ability of the system to identify the direction of movement and occupancy.

The second set of results, which are from experiments performed for all "Activity Zones" combined and are presented in Sect. 3.2, are used to highlight the main contributions of the paper by measuring the system's ability to identify "Position of Activity", "Direction of Movement, and "Occupancy". The 10-fold cross-validation method was used to evaluate the system in all scenarios.

3.1 Detection Accuracy vs. Activity Position

This experiment was designed to evaluate the system's response to moving the activity area further away from the transmitter. Data for the following classes: 1) Empty, 2) Sitting, 3) Standing, 4) Walking Tx-Rx, 5) Walking Rx-Tx, 6) Leaning

Forward, were collected in all three "Activity Areas", and three separate data sets were built. The Random Forest 10-fold cross-validation was applied to each data set, and the results alongside the confusion matrices are shown in Table 3. As can be seen in Table 3, the accuracy for the data set from "Activity Zone One" was 100%, that is, the system was capable of fully differentiating between all 6 classes, without confusion. Whilst the accuracy was 97.5% and 95%, with the data sets from "Activity Zone Two" and "Activity Zone Three", respectively. The results presented by the confusion matrix clearly show a decrease in accuracy as the activity area moves further away from the transmitter, particularly with the "Leaning Forward", which was the most affected in "Zone Three". The reduction in the accuracy is believed to be linked to the CSI pattern which becomes less evident as the subject moves away from the transmitter. It can be seen in Fig. 5, that the wireless CSI pattern of a "Sitting" activity performed in "Zone One" (see Fig. 5a) is more evident than that of the same activity but performed in "Zone Three" (see Fig. 5b).

Although the focus of the experiment was to measure detection accuracy vs distance from the transmitter, the results also indicate the ability of the system to differentiate between when the room is "Empty" and "Occupied", that is, activity is being performed, and identifying the walking direction of the subject within each zone, as evident by the confusion matrices in Table 3.

Table 3. Three confusion matrices for each of the three zones with the Random Forest algorithm

Zone one - all activities (accuracy 100%)							
Class		Predicted class					
		Empty room	Leaning forward	Sitting	Standing	Walking Tx to Rx	Walking Rx to Tx
True class	Empty room	**20**	0	0	0	0	0
	Leaning forward	0	**20**	0	0	0	0
	Sitting	0	0	**20**	0	0	0
	Standing	0	0	0	**20**	0	0
	Walking Tx to Rx	0	0	0	0	**20**	0
	Walking Rx to Tx	0	0	0	0	0	**20**
Zone two - all activities (accuracy 97.5%)							
Class		Predicted class					
		Empty room	Leaning forward	Sitting	Standing	Walking Tx to Rx	Walking Rx to Tx
True class	Empty room	**20**	0	0	0	0	0
	Leaning forward	0	**19**	1	0	0	0
	Sitting	0	0	**20**	0	0	0
	Standing	0	0	0	**19**	1	0
	Walking Tx to Rx	0	1	0	0	**19**	0
	Walking Rx to Tx	0	0	0	0	0	**20**
Zone three - all activities (accuracy 95%)							
Class		Predicted class					
		Empty room	Leaning forward	Sitting	Standing	Walking Tx to Rx	Walking Rx to Tx
True class	Empty room	**20**	0	0	0	0	0
	Leaning forward	2	**14**	1	3	0	0
	Sitting	0	0	**20**	0	0	0
	Standing	0	0	0	**20**	0	0
	Walking Tx to Rx	0	0	0	0	**20**	0
	Walking Rx to Tx	0	0	0	0	0	**20**

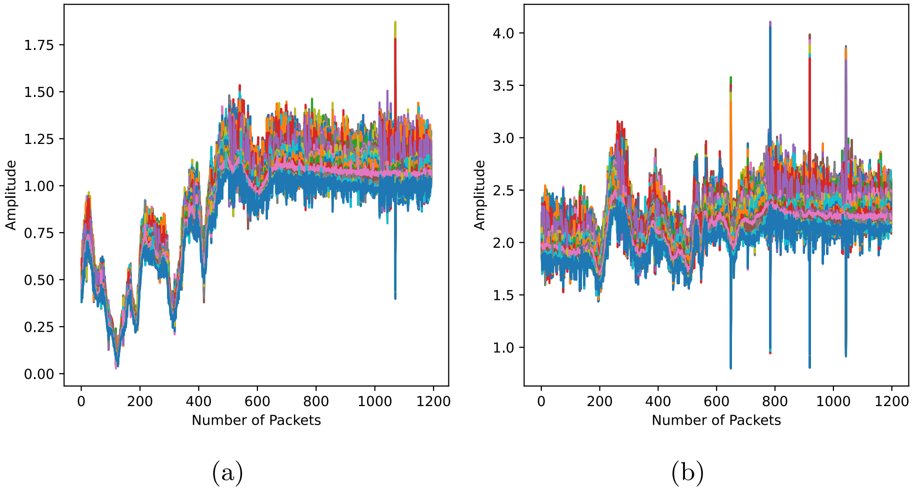

Fig. 5. Wireless CSI data samples for the Siting activity in: a) Zone 1, b) Zone 3.

3.2 Detecting Position, Direction of Movement, and Occupancy

To evaluate the system's ability to identify the position of the subject, whilst performing an activity, all 360 CSI data samples, that is, the data representing all 16 classes, were combined into one data set with 16 labels, presented earlier in Table 2. The results of applying the Random Forest 10-fold cross-validation and the confusion matrix, are shown in Table 4. The results show the capability of the system to differentiate between all 5 activities when performed in different positions of the room, with a high accuracy of 93.6%. The results can be further interpreted to tell the following:

- The system is capable of identifying walking directions in three different activity areas in the same room. This is evident by classes number 4 and 5, representing two walking directions in "Zone One", classes number 9 and 10, representing those in "Zone Two", and finally classes number 14 and 15 for "Zone Three". Approximately two data samples were miss-classified in each zone, giving an accuracy of almost 90%.
- The system was capable of successfully classifying 60 data samples representing an "Empty Room" correctly, with an accuracy of 100%, which gives this system an edge over other activity monitoring systems in the literature, as it can identify occupancy.

Table 4. Confusion matrix for all sixteen classes with the Random Forest algorithm

All sixteen classes - accuracy (93.6%)																		
Class			Predicted class															
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
True class	1	Empty	**60**	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	2	SitZ1	0	**20**	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	3	StandZ1	0	0	**20**	0	0	0	0	0	0	0	0	0	0	0	0	0
	4	WalkTxRxZ1	0	0	0	**18**	0	0	1	0	0	0	0	0	0	0	1	0
	5	WalkRxTxZ1	0	0	0	0	**19**	0	0	0	1	0	0	0	0	0	0	0
	6	LeaningFZ1	0	0	0	0	0	**20**	0	0	0	0	0	0	0	0	0	0
	7	SitZ2	0	0	0	0	0	0	**18**	0	0	0	0	1	0	0	1	0
	8	StandZ2	0	0	0	0	1	0	0	**19**	0	0	0	0	0	0	0	0
	9	WalkTxRxZ2	1	0	0	0	1	0	0	0	**18**	0	0	0	0	0	0	0
	10	WalkRxTxZ2	0	0	0	0	0	0	0	0	0	**20**	0	0	0	0	0	0
	11	LeaningFZ2	0	0	0	0	0	0	1	0	0	0	**17**	0	1	1	0	0
	12	SitZ3	0	0	0	0	0	0	0	0	0	0	0	**20**	0	0	0	0
	13	StandZ3	0	0	0	0	0	0	0	0	0	0	2	0	**18**	0	0	0
	14	WalkTxRxZ3	0	0	0	0	0	0	0	0	0	0	0	0	0	**20**	0	0
	15	WalkRxTxZ3	0	0	0	0	1	0	0	0	0	1	0	0	0	0	**18**	0
	16	LeaningFZ3	0	0	0	0	0	0	2	0	0	0	3	0	3	0	0	**12**

4 Conclusion

This paper presented a novel system that utilises the USRP devices, working as SDRs, to detect multiple activities performed in different locations of the same room. The system aimed to offer a solution that is based on RF-sensing to identify, in an indoor setting, the position of a performed activity, the occupancy of a room, and, where applicable, the direction of particular activities. The conducted experiments resulted in interesting conclusion points, that still require further investigation through the collection of more data. Firstly, was the ability of the system to identify the position of the activity, with an accuracy of almost 94% (one of which was leaning which can be used to infer falling), the occupancy of the room with an accuracy of 100%, and the walking direction in three different positions within the room with an accuracy of 90%. Such capabilities can be used to develop systems for:

- Performing fall prediction and detection by inferring it based on the "Leaning" activity.
- Monitoring elderly people who live alone, without invading their privacy, to ensure they are active and conscious.
- The utilisation of the occupancy feature in energy saving systems, emergency evacuation, and security systems by monitoring the direction of movement of unauthorised subjects.

Secondly was the reduction in the system's activity detection accuracy when the activity is performed further away from the transmitter, as presented earlier in Table 3. However, further investigation is required due to the controlled nature of the experiment and the lack of a large data set that can be used to define a relationship between the accuracy of detection and the position of the activity.

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