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Localization using wireless sensing for future healthcare

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***Abstract*—Human activity detection in indoor environments is an attractive research field that can assist the elderly and disabled live independently. To detect human activity, various technologies have been proposed, including the use of sensors, cameras, wearables, and contactless radio frequency (RF). With applications in localization, smart homes, retail, gesture recognition, intrusion detection, etc., RF sensing has the potential to become a universal sensing mechanism due to the omnipresent of electromagnetic signals. Recently, there has been a lot of interest in RF sensing's ability to solve the discomfort of wearables and the privacy concerns with cameras using Channel State Information (CSI). This study reports the findings of an experiment to locate activity in an indoor environment utilising Universal Software-Defined Radio Peripherals (USRP). A single subject is observed while sitting, standing, and walking in two directions to collect samples of CSI. Classifications are made using artificial intelligence using CSI data. The proposed method outperforms current benchmark techniques while combining machine learning and deep learning techniques for improved accuracy and makes use of a K- Nearest Neighbor (KNN) that can identify the location of various activities with a 98.43% accuracy .**

***Index Terms*—Indoor localization, wireless healthcare, activity detection**

I. Introduction

The research community has gained significant interest in human activity detection in indoor environments due to its potential uses in independent living, remote healthcare monitoring, and intrusion detection. In fact, the UK's national strategy for 2030 includes independent living as part of its policy of healthy communities [1]. The United Nations estimates that there were 901 million people over 59 years old globally in 2015, and that number will increase to 2.1 billion by 2050 [2]. The growing number of elderly people with chronic diseases, medical emergencies, and disabilities have an effect on the social and economic situations of all nations and ultimately raise the cost of healthcare systems substantially [3]. To address these challenges, some countries and nonprofit organizations began to advocate for ambient computing (ambient assisted living). Its primary objective is to extend the period of time that older people can live freely in their homes. During the last decade, human activity detection (HAD), vital sign monitoring, and location tracking have attracted the most interest in ambient computing [4]. Since it can provide doctors access to clinical information and people to health management, HAD is an important indicator for evaluating the health of the elderly. Due to the GPS's (Global Positioning System) low accuracy and signal attenuation imposed by various physical infrastructures, localization in this type of environment is not practical [5]. However, as of right now, there isn't a de facto system like GPS for outside localization. Instead, there are many different kinds of indoor localization systems.

In the literature, a number of HAD systems that make use of wearable, cameras, and ambient sensors have been presented. However, these methods either cause discomfort or cumbersome from wearing wearable all the time or privacy concerns. Using a system for wireless HAD can help with these issues. Numerous wireless sensing alternatives are suggested in the literature in this area, using Doppler fingerprints from radar systems [6] or CSI from WiFi [7] and 5G wireless networks [8]. This paper uses RF-based Wi-Fi sensing due to the usage of Wi-Fi infrastructures already installed in many homes, eliminating the need to introduce extra sensing equipment. Different RF-sensing-based systems have different hardware requirements, operating radio frequencies, classification algorithms, quantities of monitored activities, and quantities of subjects. Available tracking methods for RF signal activity detection can use either the Received Signal Strength Indicator (RSSI) [9] or CSI [7]. According to studies such as [10], although RSSI gives coarse information, CSI is fine-grained and measured each Orthogonal Frequency Division Multiplexing (OFDM) packet. CSI is thus a better option for activity detection and localisation due to its increased attention to detail. The goal of this study is to collect CSI data on a single human subject performing four different activities (sitting, standing, walkingTx-Rx and walkingRx-Tx) in two separate locations in a single room using two USRP devices, one acting as a Tx and the other as the Rx, as shown in Figure 1. The amplitude shifts in the CSI distinguish between the activities carried out at each location. As human movement affects radio signals differently depending on where it occurs, this enables CSI to be used to locate a target.

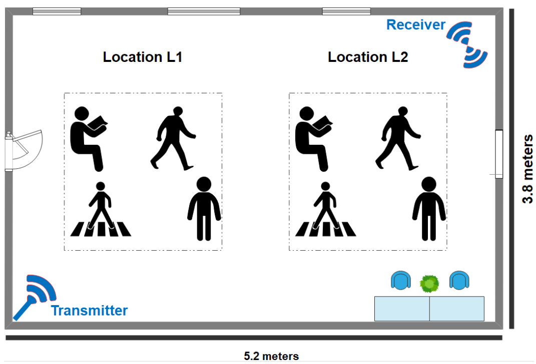

Fig. 1. Experimental Setup illustrating activities in two locations

Machine learning (ML) is used to categorize four separate human activities that are carried out in two different locations. The main contribution of this work is the use of ML and Deep Learning (DL) algorithms, namely Random Forest (RF), Support Vector Machine (SVM), Naive Bayesian (NB), K-Nearest Neighbor (KNN), Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), to provide predictions on CSI, collected from USRP devices, to accurately identify and localise four different activities inside a room. Additionally, the system is capable to identify the direction of the walking in the designated area. The structure of this paper is as follows: The literature's related work is described in Section II. The experimental setup are described in Section III, and the results and discussion are presented in Section IV. The paper is concluded in Section V.

II. Related Work

Radar, Wi-Fi, and GSM technologies can be used to detect and identify activities without the need of cameras or wearable sensors. Radar-based approaches exhibited accurate localization and continual medical monitoring [11] when there are several targets present by using large antenna arrays and bandwidths. However, such solutions are not yet available or widely accessible, are costly, and need a lot of energy. Since RF sensing is becoming more and more popular in the security and healthcare industries due to the extensive use of low-power sensors. A deep-learning-based approach was used by Iqbal et al. [12] to categorise various user movement states, such as forward, backward, and no movement. Their system was trained using data from Wi-Fi sensors. According to their research, the model has an accuracy of 89% at a distance of 1.5 meters, but as the distance increases to 2 meters, the accuracy decreases to 74%. As a result, the model's accuracy decreased as the position of motions shifted away from the passive sensing system. Nipu et al. [13] attempted to distinguish between various participants using CSI data. Different participants crossed two devices throughout the experiment while data was being transferred, saving the CSI data they picked up in the process. After that, ML algorithms such as RF and Decision tree were applied to the data. Their study demonstrates how a human's movements vary from the CSI patterns. In the research [14], USRP N210 devices were utilized to accurately identify activity with 95%, respectively. The authors in [15] evaluated classifiers using a range of features and classification techniques such RF, SVM, KNN, and Linear Discriminant Analysis on the HAR dataset,. Highest accuracy was achieved by the classifier RF 98.16 %. Similar to this, Usman et al. [16] achieved high accuracy of 93.75% on a single subject in line of sight scenario of a corridor having a distance of 20 metres by using USRPs X300 and X310 to distinguish between sitting, standing, and walking activities using the RF, Extra Tree, and Multilayer Perceptrons algorithms.

TABLE I
Data Classes and their Description

S.No	Class	Class Descriptions	No. of Classes	Count
1	Sitting	"Sitting" activity at a designated location.	1×2	200
2	Standing	The action of "Standing" activity at the designated location	1×2	200
3	Walking Rx-Tx and Tx-Rx	From USRP X310 Rx to USRP X300 Tx	1×2	200

III. Experimental Setup

The experiment was conducted with ethical approval in a $3.8 \times 5.2 \quad m^2$ room on 5^{th} floor of the James Watt South Building, University of Glasgow. The room is divided into three parts that are spaced one metre apart. The USRP devices were kept at a 45° angle for the transmitter (Tx) and receiver (Rx). Figure 1 depicts four different activities, including sitting, standing, walking in both the direction of T_x - R_x and R_x - T_x in two different locations. All four activities are shown in Figure 2 along with CSI amplitude fluctuations. Each colour represents a subcarrier during an activity, with the number of packets on the x-axis and the amplitude of the subcarrier on the y-axis. Each data sample represents an OFDM transmission of three seconds. As a consequence, a sample of 1200 packets is created. Each activity receives 100 samples, for a total of 600 data samples. There are 100 examples of sitting, standing, and walking in both directions. Table I lists the 6 classes as well as the total number of data samples collected at each location (Location L1 and Location L2).

A. Preprocessing

It is common for the data to have some missing data after it has been collected and saved in CSV files owing to loss

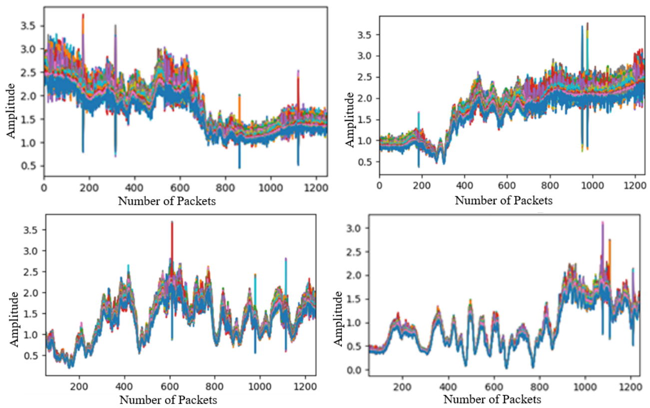

Fig. 2. CSI wireless data samples of four activities. From Left to Right (a) Sitting (b) Standing (c) Walking-RxTx (d) Walking-TxRx

of received packets, requiring data cleansing. For data preprocessing and the implementation of ML and DL techniques, we utilize *Scikit*, a widely used data analysis toolbox in Python [17]. Additionally, CSV files are interpreted using Pandas, a Python library. SciKit [18] is used to analyse Python data frames created by the conversion of CSV files. Labels are added into the first column of the dataframes. Not a number (NaN) values are included in the dataset obtained by merging the dataframes from each sample due to an inconsistency in data length. These NaN values are changed to the average of each row using SciKit's *SimpleImputer* built-in function. Remember that the overall pattern of the data is unaffected by this kind of data cleansing. The four ML algorithms (RF, SVM, NB and KNN) and DL algorithms (ANN, CNN and RNN) were used to process this data once it had been normalized.

B. Machine Learning and Deep Learning

The proposed wireless sensing-enabled indoor human activity monitoring system is evaluated using four ML and three DL algorithm.The assessment criterion used in this experiment is the precision of accurately recognising different human activities. The accuracy was evaluated using test-train split validation. This method takes the dataset into two parts. The training dataset serves as the first set of data for the ML model. The test dataset is the second component of the dataset used to make the evaluation. In this research, training makes use of 80% while testing makes use of 20% of the data. The parameters that were utilized to train the classifiers are shown in Table II.

TABLE II
PARAMETERS OF MACHINE LEARNING AND DEEP LEARNING ALGORITHMS

S.No	Algorihthms	Hyper Parameters
1	Random Forest	n-estimators : 20, max-features: 'auto', max-depth: range(2,20), criterion: gini
2	Support Vector Machine	degree:3, c=1, kernel='poly', gamma=0.01
3	Naive Bayesian	split(8::2)
4	K-Nearest Neighbor	test-size=0.2, random-state=101, p:2, n-neighbors=4
5	Artificial Neural Networks	units=4, hidden-layer-activation='relu', kernel-inetiaizer:'uniform', optimizer='adam', batch-size=32, epochs = 200, connected-layer-activation:'softmax'
6	Convolutional Neural Networks	units=4, hidden-layer-activation='relu', kernel-inetiaizer:'uniform', optimizer='adam',layer:4, kernel-size:6, batch-size=28, epochs = 250, connected-layer-activation:'softmax', filter:(128,64,32,4)
7	Recurrent Neural Networks	Layer:5, Dense: horizon, dropout:0.2, activation-function: 'tanh', optimizer:(lr:0.01, momentum:0.9)

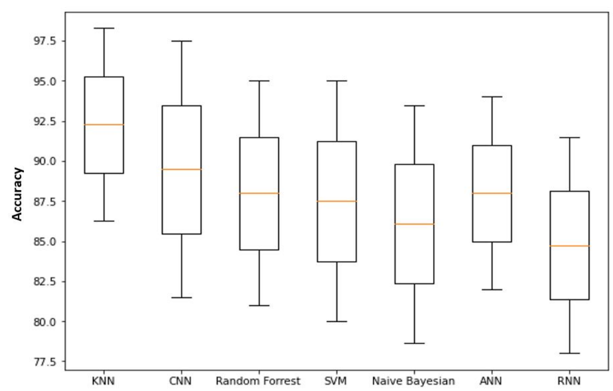

Fig. 3. Comparison of ML and DL Algorithms on Location-2 dataset

TABLE III
MACHINE LEARNING AND DEEP LEARNING ALGORITHMS COMPARISON

Algorithms	Location-1 Accuracy	Location-2 Accuracy
Random Forest	81.00%	95.00%.
Support Vector Machine	80.00%	95.00%
Naive Bayesian	78.65%	93.50%
K-Nearest Neighbor	**90.59%**	**98.43%**
Artificial Neural Networks	82.00%	94.00%
Convolutional Neural Networks	81.50%	97.50%
Recurrent Neural Networks	78.00%	91.50%

IV. RESULT AND DISCUSSION

The results of the ML and DL are shown in Table III. These results show the relationship between locating and identifying activity at two separate locations in the monitoring area. The KNN algorithm had the highest accuracy score of all the algorithms when compared to the results in the two experiments i.e. Location 1 and Location 2. The KNN algorithm is able to attain accuracy scores of 90.59% and 98.43%, respectively. ANN algorithm has 82.00% and 94.00% on Location-1 and Location-2. Similarly RF, SVM and CNN have accuracy scores 81% on dataset Location-1 and 95.00% on Location-2 respectively. On the other side, NB and RNN achieved lowest accuracy which is 78.00%. The comparison graph on Location-2 is shown in Figure 3 . The confusion matrix for the KNN algorithm's findings obtained using the train-test split strategy is shown in Figure 4. These results indicated that algorithms are better at discriminating between locations when they are separated from one another by a

Fig. 4. Normalised confusion matrix of Location-1 and Location-2 data samples of KNN using train test evaluation method

greater distance. The fact that CSI fluctuations increase with distance from the transmitter most probably explains this. As locations are closely connected to one another, the difference between CSI fluctuations becomes less. Despite this, the algorithms, particularly the KNN algorithm followed by CNN have proved to be very accurate.

V. Conclusion

The localization method for an indoor activity with the use of RF sensing, reported in this study was able to locate four distinct activities that can take place in a single room. The system's aim was to be able to determine the location of an activity in an indoor environment. The results suggest that certain indoor activities could be recognized using RF sensing which provides a wireless method for locating and detecting human activity without the need for a wearable device. In comparative studies, the KNN performed better than any other machine learning and deep learning algorithms. Several interesting results of the research will need to be investigated further by collecting more information. Due to its proximity to the receiver, location 2 is predicted to have a better localisation rate than other locations for four separate activities. The activity detection accuracy of the system improves in a horizontal direction when the activity is done more away from the Tx, but what's more notable is the precise rise of 14% for every 1m away from the Tx. In order to evaluate the model's scalability, future work will try to apply the classifications in other environments. Future research will also try to localize different topics and provide the locations of different subjects.

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