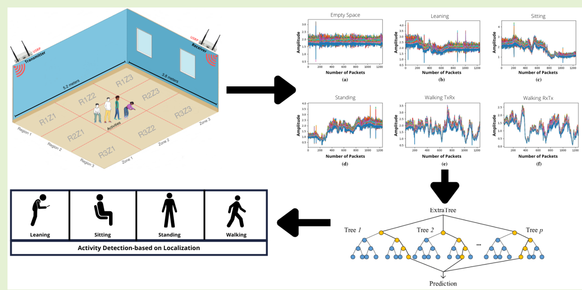
Software-Defined Radio Based Contactless Localization for Diverse Human Activity Recognition

Umer Saeed, Syed Aziz Shah, Muhammad Zakir Khan, Abdullah Alhumaidi Alotaibi, Turke Althobaiti, Naeem Ramzan, Muhammad Ali Imran, Qammer H. Abbasi



***Abstract*—This paper presents a study on contactless localization for activity recognition based on radio-frequency sensing. The focus of this study is on the quantitative analysis of the collected data, which is in the form of channel state information (CSI). The proposed method utilizes a software-defined radio (SDR) system in combination with an ensemble learning technique to localize and identify daily living activities such as leaning, sitting, standing and walking. Specifically, SDR device, Universal Software Radio Peripheral (USRP) models X300/X310 are utilized to collect data on the aforementioned activities. The data is collected from an empty space and a participant performing daily living activities in different territories. The acquired data is labelled based on the region, zone and performed activity. The CSI data is subsequently preprocessed and fed into an ensemble-based machine learning algorithm for classification. Furthermore, the stability analysis of the proposed method is performed to evaluate its reliability and robustness. The performance of the algorithm is evaluated using various metrics, including a confusion matrix, accuracy, cross-validation score and training time [1], [2]. The results demonstrate that the proposed ensemble-based approach achieves a high accuracy of up to 90% in activity recognition, highlighting the effectiveness of the proposed method in contactless localization for activity recognition.**

***Index Terms*—USRP, indoor localization, radio-frequency sensing, software-defined radio, human activity recognition, ensemble learning**

I. Introduction

The Tactile Internet (TI) is an innovative network architecture that provides real-time, reliable communication with high bandwidth and low latency [3], [4]. By providing remote control and real-time monitoring of objects and systems, the TI has the potential to revolutionise sectors as diverse as education, gaming, transportation and healthcare [5]. In the healthcare sector, radio sensing has experienced a trend towards achieving reliable detection even for small limb movements. High data rates, higher carrier frequencies, increased system capacity, scalable hardware systems and the ability to focus energy radiation in an area of interest such as beamforming, are all capabilities of radio-based communication systems [6]. This paper focuses on indoor localization-based on software-defined radio (SDR) systems. The objective of an indoor localization system is to estimate the position of an object in an indoor space [7]. To determine the position of an object and for several other applications, technologies such as Bluetooth, Wi-Fi, infrared, ultra-wide-band (UWB) RADAR, radio-frequency (RF) sensing, cameras and wearables can be used [8], [9].

Indoor localization has been a significant topic in recent years owing to its wide applicability in a variety of fields, including indoor navigation, catastrophe prediction, surveillance, intelligent traffic systems and smart healthcare [10]. In healthcare monitoring technology, accurate indoor localization and tracking systems are becoming essential. As a consequence of breakthroughs in illness detection and treatment, the life expectancy of the senior population is rising. Consequently, hospitalisation capacity is quickly diminishing. According to United Nations estimates, by 2050, the elderly population will grow by more than two billion [11]. This highlights the need to employ non-invasive technology like SDR in elderly care homes and centres.

Indoor localization can be affected by noise, signal distortion and obstructions like furniture that is something to take

Umer Saeed and Syed Aziz Shah are with the Research Centre for Intelligent Healthcare, Coventry University, Coventry CV1 5FB, UK. e-mail: saeedu3@uni.coventry.ac.uk; syed.shah@coventry.ac.uk.

Muhammad Zakir Khan, Muhammad Ali Imran and Qammer H. Abbasi are with the James Watt School of Engineering, University of Glasgow, Glasgow G12 8QQ, UK. e-mail: m.khan.6@research.gla.ac.uk; muhammad.imran@glasgow.ac.uk; qammer.abbasi@glasgow.ac.uk.

Abdullah Alhumaidi Alotaibi is with the Department of Science and Technology, College of Ranyah, Taif University, P.O. Box 11099, Taif 21944, Saudi Arabia. e-mail: a.alhumaidi@tu.edu.sa

Turke Althobaiti is with the Faculty of Science, Northern Border University, Arar 91431, Saudi Arabia. e-mail: turke.althobaiti@nbu.edu.sa

Naeem Ramzan is with the School of Engineering and Computing, University of the West of Scotland, Paisely PA1 2BE, UK. e-mail: naeem.ramzan@uws.ac.uk

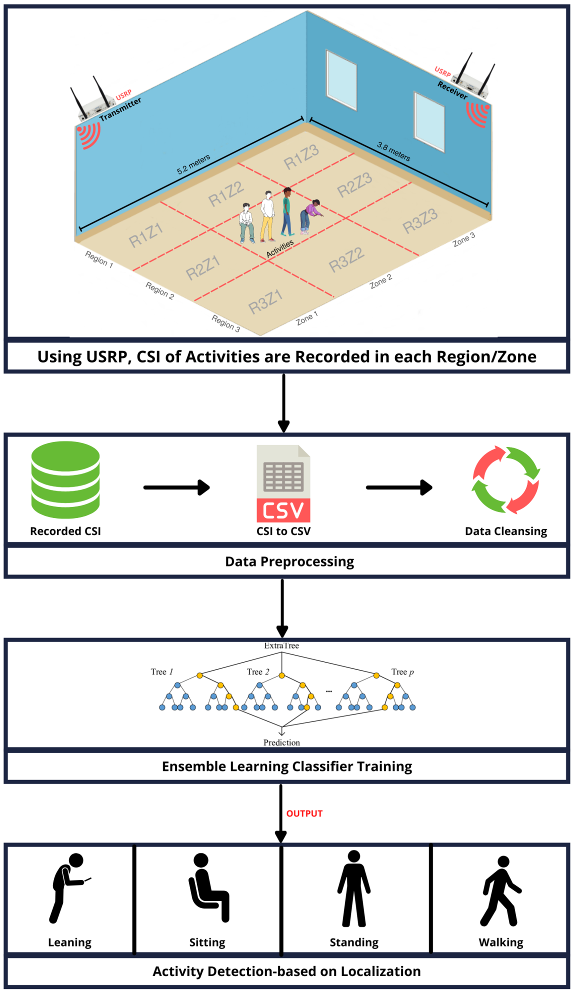


Fig. 1: Block diagram of SDR-enabled localization setup for diverse human activity recognition.

into consideration in the scenario of indoor localization [12]. With the development of advanced wireless communication systems, computational power and various sensing approaches, significant advancements in the area of indoor localization have been made. Context-aware systems [13], wearable technology [14] and contactless approaches are a few of the methods that are effectively utilized to identify human activities in an indoor setting [15]. It has been shown that it is possible to identify human activities without invading the privacy of the user by employing a device that the user is wearing to detect behaviours. A context-aware system employs sensors for monitoring such as microphones, cameras, sensors etc [16]. The drawback of these systems is that it is inconceivable to identify activity once the user leaves the surveillance zone. Video surveillance systems are the most common instance of context-aware technology. However, camera-based technology has the drawback of potentially negatively affecting patient privacy concerns [17].

With the use of cutting-edge satellite positioning technologies like GPS, localization in outdoor situations has been effectively deployed, giving consumers more accurate location services [18]. However, in indoor situations, the location services are not precise due to weak signals and low penetration [19]. To accomplish indoor localization, researchers have suggested some well-known technologies like radio-frequency identification (RFID) [20], UWB [21], Bluetooth [22], Wi-Fi [23], light [24] and audio [25]. Since many households already have Wi-Fi infrastructures in place, this article uses RF-based Wi-Fi sensing to avoid the need to incorporate extra sensing technologies. Systems based on RF sensing varies in terms of the hardware needed, operating frequencies, classification methods, amounts of monitored activities and subjects. The channel state information (CSI) and received signal strength indicator (RSSI) are two methods that are now used by tracking systems to determine RF-based activities [26].

According to studies, CSI evaluates every orthogonal frequency division multiplexing (OFDM) whereas RSSI provides coarse information. Wi-Fi-enabled CSI may be used to detect and identify human activity by tracking radio signal amplitude changes that occur when human activity occurs [27]. Due to their higher attention to detail, CSI is a preferable alternative for activity recognition and localization. To perform tracking, localization and detection of small and large-scale activities, researchers have utilized the CSI comparable to Wi-Fi [28]. The experiment described in this article utilizes universal software radio peripheral (USRP) devices that employ OFDM to create 64-frequency carriers [29].

Using two USRP devices, one serving as a transmitter and another as a receiver, the aim of this study is to collect CSI data from a single human subject doing actions including leaning, sitting, standing and walking at different locations within a single room. Figure 1 illustrates a block diagram of the proposed system in this paper. It also illustrates the experimental space split into 3x3 territories (regions/zones) in both the horizontal and vertical dimensions. Activities were performed in each of the nine territories in the experimental space. The amplitude shifts in the CSI distinguish between the activities carried out at each site. As a result, CSI can be used to locate an individual since various human motions at distinct locations have an impact on radio signals differently. Once the CSI data is acquired, it is fed into different machine learning algorithms for the classification of activities as well as regions and zones it occurred in. The application of machine learning classifiers to generate predictions on CSI from the USRP device allows for the precise identification and localization of various activities.

The problem addressed in this paper is basically the development of a contactless localization method for activity recognition using RF sensing. The authors aim to overcome the limitations of existing localization methods that require physical contact with the individuals being monitored, which can be invasive and impractical in certain scenarios. The authors also emphasize the importance of quantitative analysis in the form of CSI for the collected data, which is a critical aspect in the proposed method. The ultimate goal of this work is to provide a reliable and robust method for contactless activity recognition that can be applied in various fields such as healthcare, sports and security.

II. Literature Review

This section examines the most recent research on several contactless sensing techniques that have been successfully employed in the past for abnormality detection, including particular human activities. The three most common methods for contactless sensing are RADAR, RSSI and CSI.

RADAR [30]: The detection of human activity can be performed using RADAR-based monitoring that has a significantly larger bandwidth [31]. RADAR utilises a bandwidth of up to 1.79 GHz, while WiFi technology only uses up to 20 MHz [32]. The micro-Doppler information extraction methods based on RADAR provide a higher spatial resolution of around 20 cm [33]. However, RADAR-based systems need specialised hardware and cutting-edge computers [34].

RSSI [35]: Essentially dependent on variations in received signal strength brought on by various human activities, RSSI-based sensing can be used to monitor human activity [36]. Compared to SDR and CSI, the RSSI-based system has a lower detecting accuracy [37]. The SDR-based method improves detection performance while allowing for higher RSSI collecting resolution. Since CSI-based systems include frequency diversity, RSSI-based systems have lower accuracy and a smaller coverage area [38]. The CSI out of each transmission is evaluated using OFDM while the RSSI is captured as a single value per packet [39]. The CSI method is therefore more stable and provides more data when compared to RSSI. As result, this makes CSI more adaptable in difficult situations [40].

CSI [41]: Regarding extraction of features in the recognition of various human activities, CSI-based sensing that uses WiFi technology has recently grown in popularity. Various research has focused on creating CSI-based applications such as those for spotting individuals, counting individuals in a crowd, localizing individuals in indoor settings and recognising elderly activity if collapses [42]. Recent studies assert that WiFi transmissions can distinguish between even the tiniest movements of the human body, including those generated by the mouth, the fingertips on a keypad and the heart rate and respiratory rate [43]. Moreover, authors in [44] explored a novel approach towards localization-based activity recognition using CSI and made the dataset publicly available, which inspired our research to conduct analysis.

III. Software-Defined Radio

Modern SDR employs software-based programming for the data as well as any necessary encrypting, decryption and data transmission coding. The Air Force Rome Labs financed the creation of a configurable modem as an upgrade to the ICNIA in 1987, which is when SDR design first emerged. A collection of several single-purpose radios that were combined into one piece of equipment under the name ICNIA. SDR was the first component of a communication system for which hardware was improved by software. The two major concepts that were taken into account at the outset of SDR were the reuse of hardware components and granting components additional flexibility. The first notion is shown by employing Viterbi codecs for channel coding. The second concept is shown by baseband processing where the characteristics of the receiver and transmitter can be changed immediately. Although this concept was originally used to describe software, it now allows for a great deal of flexibility in hardware components. When numerous frequency bands were allocated worldwide for 3G, a significant need for SDR developed [45].

SDR was used to limit the variety of baseband configurations that can be used. In SDR, radio waves are modulated and demodulated by software. The SDR does a substantial amount of signal processing and is a digital electronic device that can perform reconfiguration. The goal of this notion is to develop radios that can accept and broadcast new radio protocols by simply installing new software on them. Due to the need to offer a range of wireless protocols that are constantly changing in real time, SDR may be quite helpful for mobile phone services. Utilising a superheterodyne RF front end, RF signals are converted from and then into analogue RF signals. Using analog-to-digital converters and digital-to-analog converters, the digitized intermediate frequency signals are transformed from and back into analogue signals. With SDR, fundamental radio modem technologies can now be implemented [46].

Due to its clear advantages, the SDR is predicted to ultimately surpass all existing radio communication technologies. The following are some remarkable SDR features that were previously inconceivable. The universal communication system can adapt to its environment owing to SDR instant configuration changes. SDR might go from being a cordless phone to a mobile phone to a GPS receiver in the space of one minute. SDR can easily and quickly add new functionality. The update can be sent wirelessly. On an SDR, an individual can talk and listen to various channels. It is possible to make radios that have not been built before. Cognitive radios often referred to as intelligent radios, have the ability to analyse how well the RF spectrum has been utilised in their immediate vicinity and configure themselves for the best performance [47].

IV. Approach

A. Experiment Design

The experiment described in this study was conducted in a space measured as 5.2 by 3.8 metres at the University of Glasgow, UK. As illustrated in Figure 2, the experiments were carried out in a controlled space divided into 3 by 3 territories (regions and zones) both horizontally and vertically. All of the activities were carried out in distinct regions and zones as per localization. The transmitter and receiver USRP devices were positioned at a 45-degree angle in the opposite corners of the experimental space. Different activities were performed by a participant in the experimental space to acquire data. The prime factors in the data acquisition phase are the performed activities and the territories in which activities are carried out.

Hardware for data collection consists of two USRP devices that communicate with one another when activity takes place within the covered region. One of the PC is linked to the USRP X300 device and another PC to the USRP X310 device through an ethernet wire. The USRPs include 120 MHz baseband bandwidth and extended bandwidth daughterboards slot spanning DC6 GHz. To enable wireless communication, USRPs have VERT2450 omni-directional antennas installed.

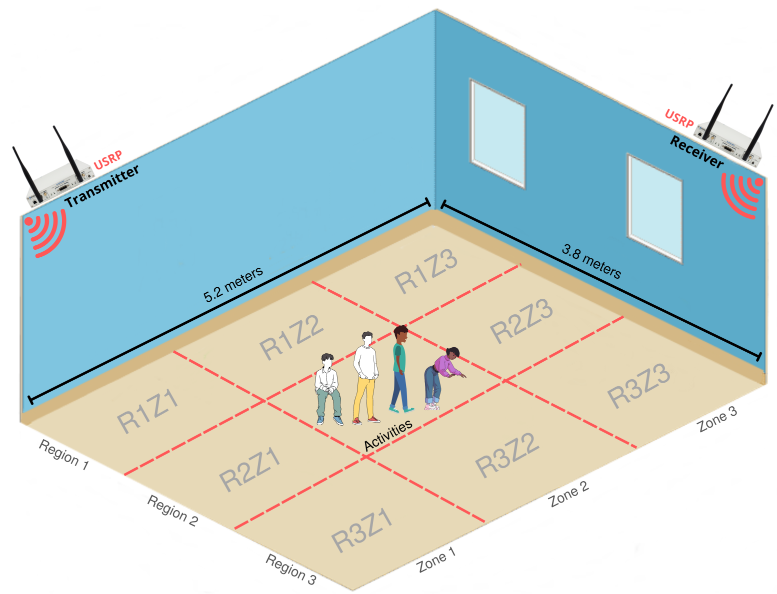


Fig. 2: Illustration of experimental setup divided into multiple territories. USRP devices are positioned in corners to obtain daily living activities information.

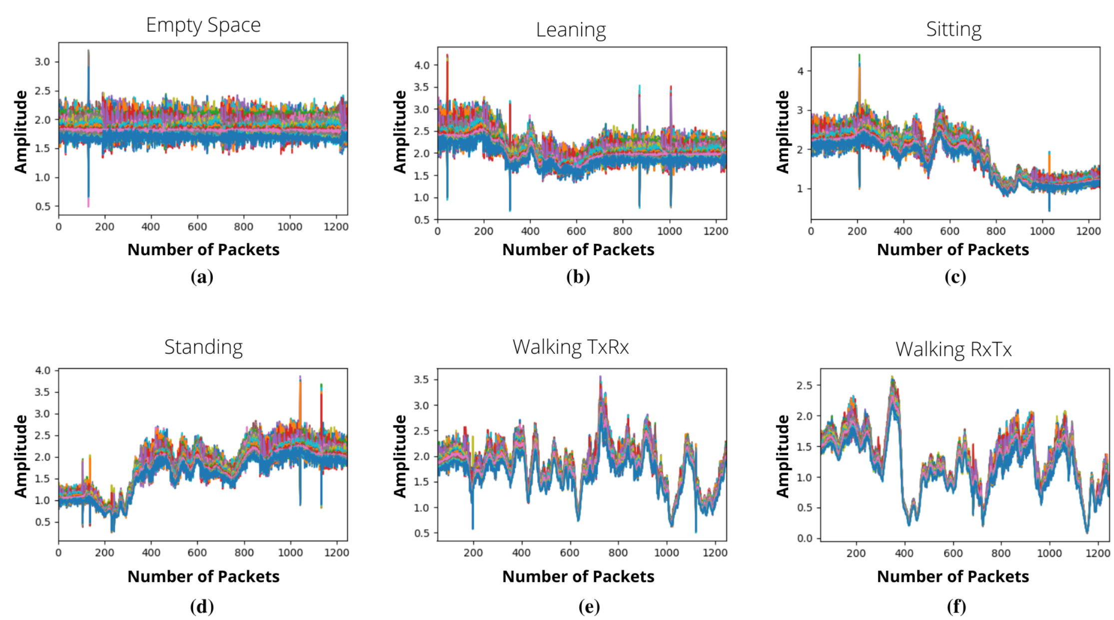


Fig. 3: Based on different localization, CSI samples of performed activities. (a) empty space with no activity (b) leaning activity in Region 2 Zone 2 (R2Z2) (c) sitting activity in R2Z2 (d) standing activity in R2Z2 (e) walking activity from transmitter to receiver in Z2 (f) walking activity from receiver to transmitter in Z2 [44].

For the two PCs connected to USRP, Linux distribution based on Debian - Ubuntu 16.04 operating system was used.

Software package based on GNU radio is utilised to configure USRPs communication. GNU radio is an open-source software package used for digital signal processing and it offers instances of OFDM signal processing that can be modified to function with USRP hardware and enable CSI extraction. GNU radio enables the setting of USRP characteristics such as 64 OFDM subcarriers, 3.75 GHz frequency and gain values of 70 dB for the transmitter and 50 dB for the receiver. A python script based on the GNU radio flow diagram is created and used to launch OFDM communication on the USRPs. The output of the python coding is the acquired CSI. First, complex numbers are used to represent the CSI. Afterwards, by calculating the complex number's absolute value, the amplitude of the signals can be determined. The amplitude of CSI is subsequently transformed into CSV files that are employed to train the machine learning classifier.

B. Data Acquisition and Preprocessing

During the experiment, five different classes of data are collected using USRP devices. Four classes are based on daily living activities that are leaning, sitting, standing and walking. One class belongs to an empty space with no activity happening. The data on empty space is recorded to compare it with the CSI gained from distinct daily living activities. The inactive activities such as leaning, sitting and standing are performed by the participant in separate regions and zones in the experimental space and CSI is recorded. The walking activity CSI is recorded while the participant moves towards the receiver from the transmitter side and vice versa. As shown in Figure 2, the experimental space is divided into 3 by 3 blocks called regions and zones. This is executed to localize the performed activities and subsequently verify how the localization based on distinct regions and zones affects the gathered data. The CSI samples obtained from the empty space and different activities are shown in Figure 3. On the x-axis, the number of packets is plotted. On the y-axis, the subcarrier's amplitude is shown where each colour constitutes a subcarrier in the course of an activity. Each data sample that was gathered corresponds to three seconds of an OFDM transmission. As a consequence, the sample size is around 1250 packets. The empty space collected data samples are 300x1250. 1200x1250 data samples are collected for three activities: leaning, sitting and standing. For walking, 900x1250 data samples are collected. The final dataset consists of 4800x1250 data samples including all activities and an empty space class. The data on different activities are classified based on localization such as sitting activity in region 2 zone 1 is labelled as Sitting-R2Z1. The data on leaning, sitting and standing activity are recorded in each region/zone and are labelled accordingly while the data on walking activity are recorded diagonally from the transmitter (R1Z1) to the receiver (R3Z3) and conversely. Figure 2 illustrates the experimental space along with distinct regions and zones the space is divided into to analyze activities based on localization.

For data preprocessing, python libraries including NumPy and Pandas are used. The CSV files can be parsed using the Pandas library. The scikit-learn library can then be used to evaluate the python data frames created from the converted CSV files. In the first column, labels are applied to data frames. Due to minimal packet mismatches during communication between the USRP devices, NaN values are generated in the dataset created by merging the data frames of each sample. These NaN values are changed to the average of each row using python's function. It should be emphasised that this method of data cleansing does not affect the overall structure of the data. After preprocessing the data, machine learning classifiers based on ensemble structure are employed to classify the data.

C. Machine Learning

An ensemble machine learning classifiers, Extremely Randomized Trees (ERT) [48] and Decision Tree (DT) are used to evaluate CSI data gathered through indoor localization setup. In the past, we have used ERT for distinct applications including fault detection and diagnosis [49]. Several deep learning algorithms have also been utilised for multiple purposes such as fall detection [50], post stroke rehabilitation [51], human gait trajectory generator [52] and human activity recognition [53]–[55]. In this paper, the overall accuracy, cross validation score and training time are used to assess the performance of the algorithms. For the experimental scenarios based on activity and locality, the accuracy of machine learning algorithms is evaluated individually. To provide robust analysis, the accuracy is assessed using the train test split method as well as the k-fold cross validation method with k=5. K-fold cross validation, where k is the recommended number of groups to be created from a given dataset, is a popular technique for assessing how well a machine learning algorithm performs. Since the k parameter is fixed to 5 in this experiment, the dataset is divided into five groups. Four of the five are used as training data, while one is used as testing data. The dataset is split into a training set of (70% and a testing set of 30% for further analysis using the train test split technique. The following provides a detailed description of the results of the localization-based machine learning techniques.

V. Results and Discussion

Two different ensemble learning-based algorithms ERT and DT are put to the test to verify the efficacy of the proposed scheme. Both of the algorithms are tree-like structures where the final output is made based on majority voting by the tree. DT is a single enormous tree-like structure that is used to make a decision based on the input data. On the other hand, ERT is an ensemble of decision trees that audits the output of the trees and makes a decision based on majority voting. For instance, if an ERT classifies a data sample as a standing activity that means the majority of the trees made a decision that specifies the data sample belongs to the standing activity. Reason to choose ERT and DT as classifiers is to evaluate their performances and see whether a combination of multiple trees is better than a single large tree. Using the python scikit-learn library, we have designed the ERT and DT algorithm. The hyperparameters of these algorithms are fine-tuned for optimal performance such as in the case of ERT, $n\_estimators = 15$. The final dataset in the form of CSV files is fed into the algorithms and performance is accessed in terms of confusion matrix, overall accuracy, cross validation score with k=5 and training time of the algorithm.

Activities of leaning, sitting, standing and walking are classified based on different regions and zones such as leaning R1Z1, leaning R1Z2, leaning R1Z3 etc. Different test cases as per regions and zones are created to verify the hypothesis. An empty space class is added to each activity dataset. The leaning, sitting and standing activity consists of 8 classes in total plus an empty space class. The walking activity consists of 6 classes in total plus an empty space class. Figure 4 and Figure 5 reveal classification reports in terms of a confusion matrix for the ERT and DT, respectively. As can be noted, an empty space class is detected with high accuracy by both algorithms since no activity occurs which makes the CSI easy to classify. The classifier's performance based on different regions and zones can be noted in these confusion matrices. The

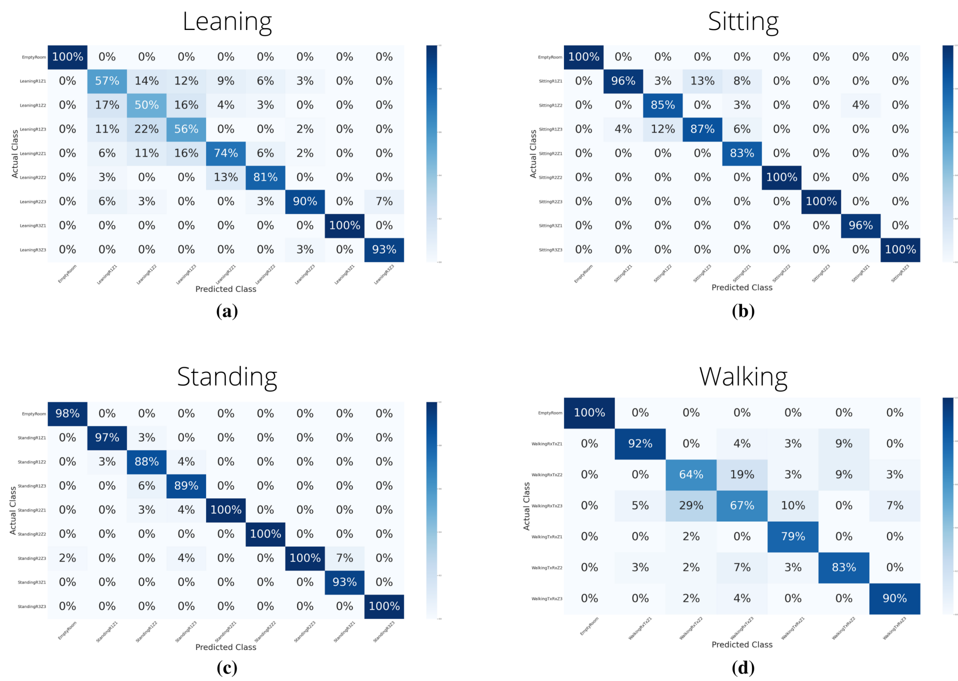


Fig. 4: Extremely randomized trees classification report of empty space and various activities based on diverse localization such as R1Z3 = Region 1 Zone 3. (a) leaning activity (b) sitting activity (c) standing activity (d) walking activity.

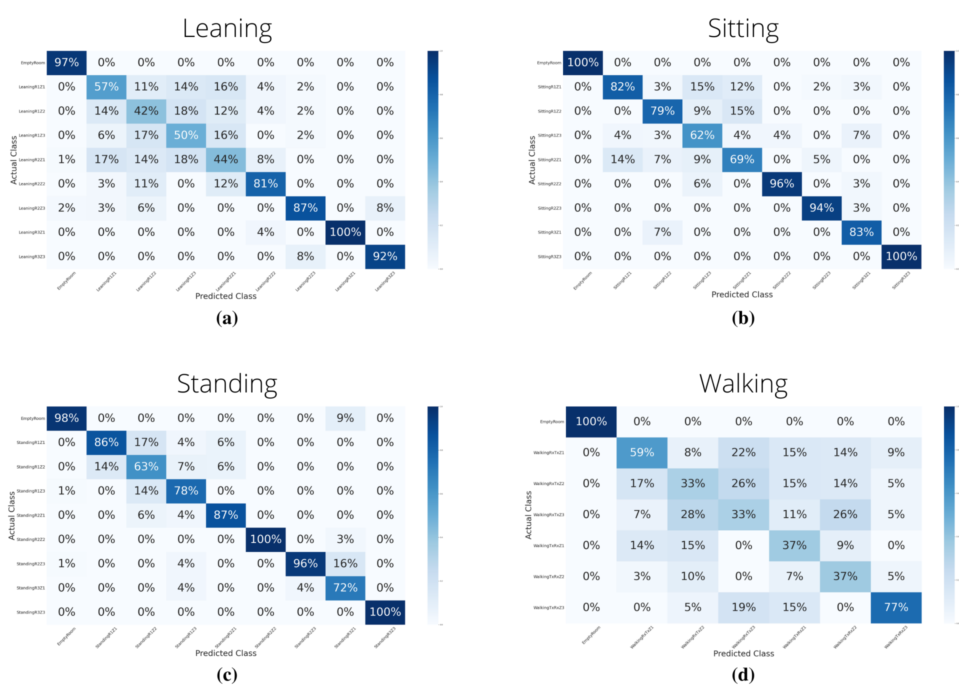


Fig. 5: Decision tree classification report of empty space and various activities based on diverse localization such as R1Z3 = Region 1 Zone 3. (a) leaning activity (b) sitting activity (c) standing activity (d) walking activity.

leaning, sitting and standing activity holds the same number of classes and combinations of it using distinct regions and zones such as R1Z1, R1Z2, R1Z3, R2Z1, R2Z2, R2Z3, R3Z1, R3Z3. The walking activity occurs diagonally in multiple regions and zones from transmitter to receiver and receiver to transmitter, as illustrated in Figure 2. The walking activity holds 6 prime classes such as TxRx-R1Z1, TxRx-R2Z2, TxRx-R3Z3 and RxTx-R3Z3, RxTx-R2Z2, RxTx-R1Z1. As can be noted in the confusion matrix graphs, the detection accuracy is high when activity occurs near the transmitter and receiver. This shows that acquired CSI are more precise when activity occurs close to the devices.

Furthermore, Table I and Table II exhibit performance in terms of classification accuracy, cross validation score and training time for the ERT and DT, respectively. For activity leaning plus empty class, ERT attained an accuracy of up to

TABLE I: Extremely randomized trees performance report.

Activity Class	Accuracy	CV5 Score	Training Time (s)
Empty + Leaning	82%	82%	0.07
Empty + Sitting	96%	96%	0.06
Empty + Standing	97%	96%	0.07
Empty + Walking	85%	85%	0.06
Overall Accuracy: 90%			

TABLE II: Decision tree performance report.

Activity Class	Accuracy	CV5 Score	Training Time (s)
Empty + Leaning	77%	75%	0.64
Empty + Sitting	88%	87%	0.66
Empty + Standing	89%	88%	0.63
Empty + Walking	61%	69%	0.45
Overall Accuracy: 78%			

82% whereas DT attained an accuracy of up to 77%. For activity sitting plus empty class, ERT attained an accuracy of up to 96% whereas DT attained an accuracy of up to 88%. For activity standing plus empty class, ERT attained an accuracy of up to 97% whereas DT attained an accuracy of up to 89%. For activity walking plus empty class, ERT attained an accuracy of up to 85% whereas DT attained an accuracy of up to 61%. Moreover, we also compared cross validation scores with $k = 5$ for both algorithms. For activity leaning, ERT reached up to an accuracy of 82% while DT reached up to an accuracy of 75%. For activity sitting, ERT reached up to an accuracy of 96% while DT reached up to an accuracy of 87%. For activity standing, ERT reached up to an accuracy of 96% while DT reached up to an accuracy of 88%. For activity walking, ERT reached up to an accuracy of 85% while DT reached up to an accuracy of 69%. The overall accuracy achieved by ERT and DT is up to 90% and 78%, respectively.

Table I and II also present the average training time taken by the algorithm in seconds. Three main aspects that determine how long it takes for an algorithm to train are the type of data, the algorithm's structure and the available computing resources. A machine learning model's training time can be estimated using these criteria. The research in this paper relied on simulations run on a MacBook Air equipped with an M2 chip, an 8-core CPU/GPU and a 16-core neural engine. The training times of the investigated machine learning algorithms were measured using data of the same numerical kind saved in CSV files. Algorithm training time might be longer or shorter depending on the aforementioned three variables. There is no appreciable difference in the number of seconds required to train an algorithm given the similarity in the number of data points between the two cases. However, ERT required less training time compared to DT. From the overall performance evaluation, it is clear that an ensemble of decision trees in the form of ERT carries out better execution than a single large tree. This paper proposes a technique based on SDR for localization-based detection of activities and a cutting-edge lightweight ensemble learning approach for accurate classification.

VI. Conclusion

In this study, a novel localization system utilizing RF sensing has been proposed to detect daily living activities such as leaning, sitting, standing and walking with high precision in different areas of the same space. The system not only tracks when and where an activity occurs but also identifies which activity took place and how many individuals were present at a specific time. The research demonstrates the feasibility of detecting individual activities in an indoor setting using RF sensing, which enables contactless communication without the need for wearables or cameras. The acquired data is classified using an ensemble-based ERT algorithm, which achieved an overall accuracy of up to 90%. The study has yielded interesting findings. Future research will explore the robustness of the approach in various indoor settings such as living rooms and kitchens. In addition, we aim to investigate other daily living activities including bathing, cooking, eating etc.

Acknowledgement

This work is supported in part by the Engineering and Physical Sciences Research Council (EPSRC) under Grant EP/W037076/1.

References

[1] S. A. Shah, Z. Zhang, A. Ren, N. Zhao, X. Yang, W. Zhao, J. Yang, J. Zhao, W. Sun, and Y. Hao, "Buried object sensing considering curved pipeline," *IEEE antennas and wireless propagation letters*, vol. 16, pp. 2771–2775, 2017.

[2] W. Taylor, Q. H. Abbasi, K. Dashtipour, S. Ansari, S. A. Shah, A. Khalid, and M. A. Imran, "A review of the state of the art in non-contact sensing for covid-19," *Sensors*, vol. 20, no. 19, p. 5665, 2020.

[3] X. Yang, D. Fan, A. Ren, N. Zhao, and M. Alam, "5g-based user-centric sensing at c-band," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 5, pp. 3040–3047, 2019.

[4] S. A. Shah and F. Fioranelli, "Human activity recognition: Preliminary results for dataset portability using fmcw radar," in *2019 international radar conference (RADAR)*. IEEE, 2019, pp. 1–4.

[5] N. Zhao, X. Yang, Z. Zhang, and M. B. Khan, "Circulating nurse assistant: Non-contact body centric gesture recognition towards reducing latrogenic contamination," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 6, pp. 2305–2316, 2020.

[6] M. Chen, S. Gonzalez, A. Vasilakos, H. Cao, and V. Leung, "Body area networks: A survey," *Mobile networks and applications*, vol. 16, no. 2, pp. 171–193, 2011.

[7] S. I. Shah, S. Y. Shah, and S. A. Shah, "Intrusion detection through leaky wave cable in conjunction with channel state information," pp. 1–4, 2019.

[8] S. A. Shah and F. Fioranelli, "Rf sensing technologies for assisted daily living in healthcare: A comprehensive review," *IEEE Aerospace and Electronic Systems Magazine*, vol. 34, no. 11, pp. 26–44, 2019.

[9] U. Saeed, S. Y. Shah, J. Ahmad, M. A. Imran, Q. H. Abbasi, and S. A. Shah, "Machine learning empowered covid-19 patient monitoring using non-contact sensing: An extensive review," *Journal of pharmaceutical analysis*, 2022.

[10] J. Xiao, Z. Zhou, Y. Yi, and L. M. Ni, "A survey on wireless indoor localization from the device perspective," *ACM Computing Surveys (CSUR)*, vol. 49, no. 2, pp. 1–31, 2016.

[11] S. A. Shah, H. Abbas, M. A. Imran, and Q. H. Abbasi, "Rf sensing for healthcare applications," *Backscattering and RF Sensing for Future Wireless Communication*, pp. 157–177, 2021.

[12] S. A. Shah and F. Fioranelli, "Rf sensing technologies for assisted daily living in healthcare: A comprehensive review," *IEEE Aerospace and Electronic Systems Magazine*, vol. 34, no. 11, pp. 26–44, 2019.

[13] U. Saeed, Y.-D. Lee, S. U. Jan, and I. Koo, "Cafd: context-aware fault diagnostic scheme towards sensor faults utilizing machine learning," *Sensors*, vol. 21, no. 2, p. 617, 2021.

[14] M. Wu and J. Luo, "Wearable technology applications in healthcare: a literature review," *Online J. Nurs. Inform*, vol. 23, no. 3, 2019.

[15] M. Usman, J. Rains, T. J. Cui, M. Z. Khan, M. A. Imran, Q. H. Abbasi *et al.*, "Intelligent wireless walls for contactless in-home monitoring," *Light: Science & Applications*, vol. 11, no. 1, pp. 1–13, 2022.

[16] V. B. Semwal, N. Gaud, P. Lalwani, V. Bijalwan, and A. K. Alok, "Pattern identification of different human joints for different human walking styles using inertial measurement unit (imu) sensor," *Artificial Intelligence Review*, vol. 55, no. 2, pp. 1149–1169, 2022.

[17] T. Akter, B. Dosono, T. Ahmed, A. Kapadia, and B. Semaan, "" i am uncomfortable sharing what i can't see": Privacy concerns of the visually impaired with camera based assistive applications," in *29th USENIX Security Symposium (USENIX Security 20)*, 2020, pp. 1929–1948.

[18] S. A. Shah, J. Ahmad, F. Masood, S. Y. Shah, H. Pervaiz, W. Taylor, M. A. Imran, and Q. H. Abbasi, "Privacy-preserving wandering behavior sensing in dementia patients using modified logistic and dynamic newton leipnik maps," *IEEE Sensors Journal*, vol. 21, no. 3, pp. 3669–3679, 2020.

[19] A. Basiri, E. S. Lohan, T. Moore, A. Winstanley, P. Peltola, C. Hill, P. Amirian, and P. F. e Silva, "Indoor location based services challenges, requirements and usability of current solutions," *Computer Science Review*, vol. 24, pp. 1–12, 2017.

[20] H. Xu, D. Wang, R. Zhao, and Q. Zhang, "Adarf: Adaptive rfid-based indoor localization using deep learning enhanced holography," *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, vol. 3, no. 3, pp. 1–22, 2019.

[21] B. Großwindhager, M. Stocker, M. Rath, C. A. Boano, and K. Römer, "Snaploc: An ultra-fast uwb-based indoor localization system for an unlimited number of tags," in *Proceedings of the 18th International Conference on Information Processing in Sensor Networks*, 2019, pp. 61–72.

[22] S. Aziz Shah, J. Ahmad, A. Tahir, F. Ahmed, G. Russell, S. Y. Shah, W. J. Buchanan, and Q. H. Abbasi, "Privacy-preserving non-wearable occupancy monitoring system exploiting wi-fi imaging for next-generation body centric communication," *Micromachines*, vol. 11, no. 4, p. 379, 2020.

[23] A. M. Ashleibta, A. Zahid, S. A. Shah, M. A. Imran, and Q. H. Abbasi, "Software defined radio based testbed for large scale body movements," in *2020 IEEE International Symposium on Antennas and Propagation and North American Radio Science Meeting*, 2020, pp. 2079–2080.

[24] X. Wang, Z. Yu, and S. Mao, "Indoor localization using smartphone magnetic and light sensors: A deep lstm approach," *Mobile Networks and Applications*, vol. 25, no. 2, pp. 819–832, 2020.

[25] S. Xu, R. Chen, G. Guo, Z. Li, L. Qian, F. Ye, Z. Liu, and L. Huang, "Bluetooth, floor-plan, and microelectromechanical systems-assisted wide-area audio indoor localization system: Apply to smartphones," *IEEE Transactions on Industrial Electronics*, vol. 69, no. 11, pp. 11 744–11 754, 2021.

[26] T. Zheng, Z. Chen, S. Ding, and J. Luo, "Enhancing rf sensing with deep learning: A layered approach," *IEEE Communications Magazine*, vol. 59, no. 2, pp. 70–76, 2021.

[27] Y. He, Y. Chen, Y. Hu, and B. Zeng, "Wifi vision: Sensing, recognition, and detection with commodity mimo-ofdm wifi," *IEEE Internet of Things Journal*, vol. 7, no. 9, pp. 8296–8317, 2020.

[28] J. Liu, H. Liu, Y. Chen, Y. Wang, and C. Wang, "Wireless sensing for human activity: A survey," *IEEE Communications Surveys & Tutorials*, vol. 22, no. 3, pp. 1629–1645, 2019.

[29] S. A. K. Tanoli, M. Rehman, M. B. Khan, I. Jadoon, F. Ali Khan, F. Nawaz, S. A. Shah, X. Yang, and A. A. Nasir, "An experimental channel capacity analysis of cooperative networks using universal software radio peripheral (usrp)," *Sustainability*, vol. 10, no. 6, p. 1983, 2018.

[30] C. Waldschmidt, J. Hasch, and W. Menzel, "Automotive radar—from first efforts to future systems," *IEEE Journal of Microwaves*, vol. 1, no. 1, pp. 135–148, 2021.

[31] X. Li, Y. He, and X. Jing, "A survey of deep learning-based human activity recognition in radar," *Remote Sensing*, vol. 11, no. 9, p. 1068, 2019.

[32] S. Narayan, J. Sreeja, V. Surya, B. Sangeetha, and R. U. Nair, "Radar absorbing structures using frequency selective surfaces: Trends and perspectives," *Journal of Electronic Materials*, vol. 49, no. 3, pp. 1728–1741, 2020.

[33] Z. Ni and B. Huang, "Human identification based on natural gait micro-doppler signatures using deep transfer learning," *IET Radar, Sonar & Navigation*, vol. 14, no. 10, pp. 1640–1646, 2020.

[34] U. Saeed, S. Y. Shah, A. A. Alotaibi, T. Althobaiti, N. Ramzan, Q. H. Abbasi, and S. A. Shah, "Portable uwb radar sensing system for transforming subtle chest movement into actionable micro-doppler signatures to extract respiratory rate exploiting resnet algorithm," *IEEE Sensors Journal*, vol. 21, no. 20, pp. 23 518–23 526, 2021.

[35] G. Li, E. Geng, Z. Ye, Y. Xu, J. Lin, and Y. Pang, "Indoor positioning algorithm based on the improved rssi distance model," *Sensors*, vol. 18, no. 9, p. 2820, 2018.

[36] U. Saeed, S. Yaseen Shah, S. Aziz Shah, H. Liu, A. Alhumaidi Alotaibi, T. Althobaiti, N. Ramzan, S. Ullah Jan, J. Ahmad, and Q. H. Abbasi, "Multiple participants' discrete activity recognition in a well-controlled environment using universal software radio peripheral wireless sensing," *Sensors*, vol. 22, no. 3, p. 809, 2022.

[37] M. A. Al-Qaness, M. Abd Elaziz, S. Kim, A. A. Ewees, A. A. Abbasi, Y. A. Alhaj, and A. Hawbani, "Channel state information from pure communication to sense and track human motion: A survey," *Sensors*, vol. 19, no. 15, p. 3329, 2019.

[38] F. Liu, J. Liu, Y. Yin, W. Wang, D. Hu, P. Chen, and Q. Niu, "Survey on wifi-based indoor positioning techniques," *IET communications*, vol. 14, no. 9, pp. 1372–1383, 2020.

[39] F. Gringoli, M. Schulz, J. Link, and M. Hollick, "Free your csi: A channel state information extraction platform for modern wi-fi chipsets," in *Proceedings of the 13th International Workshop on Wireless Network Testbeds, Experimental Evaluation & Characterization*, 2019, pp. 21–28.

[40] J. Wang and J. Park, "An enhanced indoor positioning algorithm based on fingerprint using fine-grained csi and rssi measurements of ieee 802.11 n wlan," *Sensors*, vol. 21, no. 8, p. 2769, 2021.

[41] J. Tack, S. Mo, J. Jeong, and J. Shin, "Csi: Novelty detection via contrastive learning on distributionally shifted instances," *Advances in neural information processing systems*, vol. 33, pp. 11 839–11 852, 2020.

[42] L. Ren and Y. Peng, "Research of fall detection and fall prevention technologies: A systematic review," *IEEE Access*, vol. 7, pp. 77 702–77 722, 2019.

[43] U. Saeed, S. Y. Shah, A. Zahid, J. Ahmad, M. A. Imran, Q. H. Abbasi, and S. A. Shah, "Wireless channel modelling for identifying six types of respiratory patterns with sdr sensing and deep multilayer perceptron," *IEEE Sensors Journal*, vol. 21, no. 18, pp. 20 833–20 840, 2021.

[44] M. Z. Khan, A. Taha, W. Taylor, M. A. Imran, and Q. H. Abbasi, "Non-invasive localization using software-defined radios," *IEEE Sensors Journal*, vol. 22, no. 9, pp. 9018–9026, 2022.

[45] B. A. Fette, *Cognitive radio technology*. Elsevier, 2006.

[46] J. Mitola, "Cognitive radio. an integrated agent architecture for software defined radio." 2002.

[47] T. Ulversoy, "Software defined radio: Challenges and opportunities," *IEEE Communications Surveys & Tutorials*, vol. 12, no. 4, pp. 531–550, 2010.

[48] P. Geurts, D. Ernst, and L. Wehenkel, "Extremely randomized trees," *Machine learning*, vol. 63, no. 1, pp. 3–42, 2006.

[49] U. Saeed, S. U. Jan, Y.-D. Lee, and I. Koo, "Fault diagnosis based on extremely randomized trees in wireless sensor networks," *Reliability engineering & system safety*, vol. 205, p. 107284, 2021.

[50] R. Jain and V. B. Semwal, "A novel feature extraction method for preimpact fall detection system using deep learning and wearable sensors," *IEEE Sensors Journal*, vol. 22, no. 23, pp. 22 943–22 951, 2022.

[51] V. Bijalwan, V. B. Semwal, G. Singh, and T. K. Mandal, "Hdl-psr: Modelling spatio-temporal features using hybrid deep learning approach for post-stroke rehabilitation," *Neural Processing Letters*, pp. 1–20, 2022.

[52] S. K. Challa, A. Kumar, V. B. Semwal, and N. Dua, "An optimized-lstm and rgb-d sensor-based human gait trajectory generator for bipedal robot walking," *IEEE Sensors Journal*, vol. 22, no. 24, pp. 24 352–24 363, 2022.

[53] V. B. Semwal, P. Lalwani, M. K. Mishra, V. Bijalwan, and J. S. Chadha, "An optimized feature selection using bio-geography optimization technique for human walking activities recognition," *Computing*, vol. 103, no. 12, pp. 2893–2914, 2021.

[54] N. Dua, S. N. Singh, V. B. Semwal, and S. K. Challa, "Inception inspired cnn-gru hybrid network for human activity recognition," *Multimedia Tools and Applications*, pp. 1–35, 2022.

[55] N. Dua, S. N. Singh, S. K. Challa, V. B. Semwal, and M. Sai Kumar, "A survey on human activity recognition using deep learning techniques and wearable sensor data," in *Machine Learning, Image Processing, Network Security and Data Sciences: 4th International Conference, MIND 2022, Virtual Event, January 19–20, 2023, Proceedings, Part I*. Springer, 2023, pp. 52–71.