Software Defined Radio Based Activity Recognition for Remote Healthcare Driven by Machine Learning

William Taylor
School of Engineering
University of Glasgow
Glasgow, United Kingdom
2536400t@student.gla.ac.uk

Aboajeila Milad Abdulhadi Ashleibta
School of Engineering
University of Glasgow
Glasgow, United Kingdom
abomilad7@gmail.com

Syed Aziz Shah
Department of Computing and Mathematics
Manchester Metropolitan University
Manchester United Kingdom
azizshahics@yahoo.com

Muhammad Imran
School of Engineering
University of Glasgow
Glasgow, United Kingdom
muhammad.imran@glasgow.ac.uk

Qammer Abbasi
School of Engineering
University of Glasgow
Glasgow, United Kingdom
qammer.abbasi@glasgow.ac.uk

***Abstract*—The increase of life expectancy inevitably leads to an increase of elderly people within the population. To assist with allowing elderly people to remain independent at home as opposed to care homes, systems are being implemented to monitor the health of individuals. Current systems make use of wearable devices for monitoring but these can be intrusive and expensive. Use of radio frequencies already present in most home to monitor health is possible and can detect movement such as falling over. This paper looks at the use case software defined radio exploiting the channel state information (CSI) of radio frequencies as they are presented everywhere these days, to identify human activities in indoor settings.. The experiments conducted take the CSI of two Universal Software Radio Peripherals (USRP's) communicating while a human subject performs an activity. Various machine learning algorithms are used on the recorded data to classify these activities. Results show that using Random Forest an accuracy of 81% was achieved when full data was used for training and testing.**

Keywords—Chanel State Information, CSI, Universal Software Radio Peripherals, USRP, Machine Learning, Random Forest

I. INTRODUCTION

Due to advances in medical science, the number of elderly people is increasing throughout the western world [1]. Mindful of the high costs of care homes and people desire for independence, more and more elderly people are choosing to remain living at home. However, leading an independent life at home raises several concerns and presents new challenges as well.

Elderly people can wear devices that can monitor activity around the home and measure vital signs. This can ensure that health care can be provided if required. The disadvantage of wearable devices is that it is considered intrusive and users may forget to wear the devices. By making use of wireless communications around the home, channel state information can be used to detect the movements. The CSI is a monitoring process where the changes in signal amplitude and phases during transmission of wireless signals can be reviewed [2]. This information can be recorded when known activity is taking place in order to build labelled datasets for machine learning. Once learning models have been developed then the models can make use of radio frequencies already present in the home such as Wi-Fi to identify human movement. This provides a low cost and non-invasive solution [3]. The work of this paper explores this practice by using machine learning to try to accurately classify five different activities carried out by humans.

II. RELATED WORK

The work of [4] made use of accelerometers to detected human activity. They used the HMP (Human Motion Primitives) dataset which includes 14 activities collected from acceleration measuring devices attached to the wrists of humans. They used Random forest for accuracy and achieved an accuracy score of 79.58%. [5] used Universal Software Radio Peripherals (USRP) to detect human movement and vital signs. This is achieved by monitoring the signal propagation as the subject moves between the USRP devices. [6] Was able to identify a difference in the positions patients lay in a bed. The research was aimed at help patients who are in bed for long periods of time from developing bedsores from saying too long in the one position. The results showed clear differences in the Channel State Information when patients lay in different positions. Wi-Fi signals were used in the work of [7] to detect if people and how many are behind a wall. They then used machine learning to classify the CSI to establish if there is a person behind a wall and if so how many. The experiments included collecting data for no person behind the wall then one, two, three then four persons are present behind the wall. Experiments showed decision tree to be the most accurate algorithm for machine learning.

III. METHODOLOGY

The first steps for human activity recognition involves the collection of data that can be used to create a dataset for the machine learning process. The data is collected by using two Universal Software Radio Peripherals, manufactured by National Instruments. In between the two USRPs, USRP N210 where a human volunteer was performed various activities between transceiver model. As the USRPs communicate with each other by sending wireless radio signals through the atmosphere, the volunteer was asked to start doing motions for instance, walking back and forth, sitting down on a chair, standing up from a chair and so on. The core idea is to exploit the change in wireless medium due to body motion. Each activity was repeated ten times to provide a range of signal propagation as the movement will never truly be exact due to the various factors such as timings and slight differences in the movement.

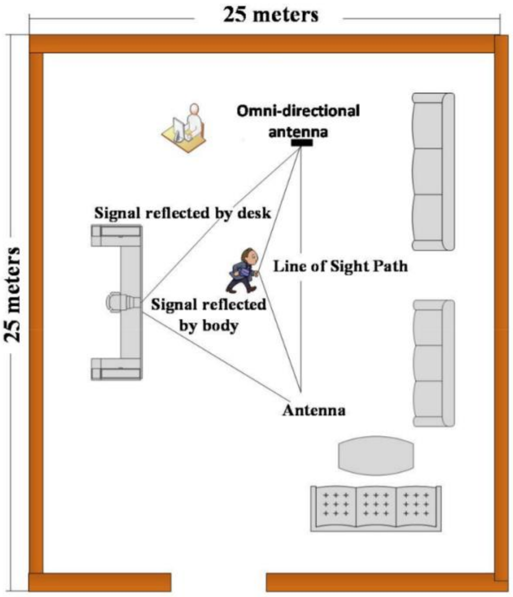

Figure 1: USRP sending data to USRP receiver while person is present

The data is then stored in Comma-separated values (CSV) files. The data for each activity instance is presented as 64 carrier frequencies in each column and the packets sent across between the USRPs represented as the rows on the CSV files. Due to the nature of the activities, there are various numbers of packets being sent over. The CSV files are then edited to ensure all CSV files represent the same amount of packets being sent across. 950 is the number of packets which are used across all of the CSV files. Each row in the CSV files is given the appropriate label for that activity. Two methods are used for processing the data for machine learning. The first method combines all of the data from each of the ten datasets from the five activities and randomises the rows. The second method used attempts to decrease the size of the dataset by using an average of each occurrence of human activity. Then the rows are randomised. The Python Library SciKit is used to apply machine learning to the datasets. The Dataset is divided between 80% for training data and 20% testing data. The next section will discuss the results produced from using machine learning on the two methods of processing the data.

IV. Results

Three machine learning algorithms were used on the collected data. The three algorithms are Random Forest, Support Vector Machine and Neural Networks. The below Figure shows the accuracy achieved using these algorithms on the full dataset and the average datasets.

It can be seen from the full dataset is vastly superior to taking the average of each activity and then combining. Random forest is the best performer with 81% accuracy using the full dataset. Support vector performed poorly compared to the accuracy of Random forest, with a low accuracy of 30%. Neural networks achieved an accuracy of 68%. All three algorithms performed better using the full datasets rather than using the averages.

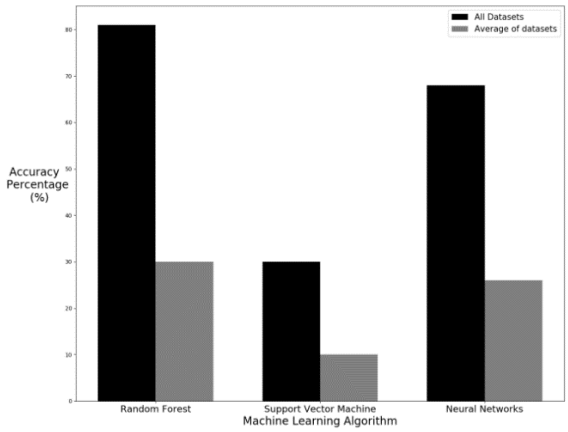

Figure2: accuracy results of Machine Learning algorithms

V. Conclusion

In this work, we have presented the application of software defined radios in conjunction with machine learning algorithm for human activity recognition. Change in wireless medium was used to detect different activities where data was recorded using two USRPs model exploiting 64 data sub frequency channels. The random forest presented classification best accuracy and perhaps with more examples of data taken, Random Forest will be able to create much more accurate models.

The core idea is to detecting these human activities for remote healthcare applications such as fall detection in elderly people, freezing of gait in Parkinson's patients, wandering behaviour in dementia and so on. Moreover, after validating the system using machine learning algorithms, next step is to integrate it into 5G system so that frail elderly people can be monitored and timely intervention can reduce risk of fatal injuries.

References

[1] A. L. I. Chelli, M. Pätzold, and S. Member, "A Machine Learning Approach for Fall Detection and Daily Living Activity Recognition," vol. 7, 2019.

[2] I. Interfaces, B. Soares, G. Teodoro, and L. Abdallah, "WiDMove : Sensing Movement Direction using," 2018.

[3] J. Liu, H. Liu, Y. Chen, Y. Wang, and C. Wang, "Wireless Sensing for Human Activity : A Survey," no. c, 2019.

[4] A. Jalal, "A Triaxial Acceleration-based Human Motion Detection for Ambient Smart Home System," no. December 2018, 2019.

[5] "EE Publishers (http://www.ee.co.za) Monitoring health using WiFi sensing and machine learning," pp. 1–5, 2018.

[6] S. A. Shah *et al.*, "Posture Recognition to Prevent Bedsores for Multiple Patients Using Leaking Coaxial Cable," *IEEE Access*, vol. 4, pp. 8065–8072, 2016.

[7] A. Hanif, M. Iqbal, and F. Munir, "WiSpy : Through-Wall Movement Sensing and Person Counting Using Commodity WiFi Signals," *2018 IEEE SENSORS*, pp. 1–4, 2018.