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Taylor, W., Taha, A., Tahir, A., Shah, S. A., Abbasi, Q. H. and Imran, M. A. (2022) Novel Contactless Sensing Technique for Real-time Human Activity Detection. In: 2022 IEEE International Symposium on Antennas and Propagation and USNC-URSI Radio Science Meeting, Denver, CO, USA, 10-15 Jul 2022, pp. 1562-1563. ISBN 9781665496582 (doi: [10.1109/AP-S/USNC-URSI47032.2022.9886894](https://doi.org/10.1109/AP-S/USNC-URSI47032.2022.9886894)).

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Deposited on: 28 March 2022

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# Novel Contactless Sensing Technique for Real-time Human Activity Detection

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**Abstract**—Recent research has looked to implement real-time contactless sensing within a healthcare application which can provide monitoring of vulnerable people living at home. Currently systems make use of wearable devices to achieve this but this requires users to always be wearing devices. This paper presents a real-time contactless system which makes use of radio frequency signal propagation to determine if a person is sitting or standing. This is achieved by observing incoming channel state information to detect movements and passing detected movements to an AI model that can predict sitting or standing motions from changes the signal amplitude described in the channel state information. The system is able to make accurate real-time classifications in multiple environments.

**Index Terms**—Human motion detection, Channel State Information, RF signals, Machine Learning, Real-time

## I. INTRODUCTION

In-home healthcare monitoring technologies are vital to allow vulnerable people to live independently within their own homes [1]. Healthcare monitoring systems allow for incidents such as falls to be raised instantaneously to care givers and/or family members who can aid. The monitoring systems can be set up in the home and provide real-time alerts of detected incidents [2]. Falling is an example of an incident which can cause serious injuries requiring immediate attention and treatment. Accordingly, a monitoring system that can detect movements can alert caregivers of detected falls.

The work of this paper looks at the use of Radio Frequency (RF) signals to provide real-time contactless monitoring. Artificial Intelligence (AI) algorithms have been implemented in recent published work to learn and detect RF signal amplitude changes caused by movements [3]–[5]. RF signal motion detection works by observing the changes in signal propagation while human movement takes place. Channel State Information (CSI) is a feature of RF signals that allows for observation of amplitude or phase of the signal transmission between the transmitter antenna and the receiver antenna. WiFi is an example of a technology which uses RF signals and WiFi is available in most homes allowing [6]. When the human moves the signal is reflected off the body and this causes changes in the signal propagation which can be observed in the CSI. ML can then be used to differentiate which activities took place while movement is detected.

This paper makes use of a Universal Software Radio Peripheral (USRP) X300 device to create a communication link between a transmitter and receiver from which CSI amplitude data can be mined. Previous work has been able to classify different activities from recognition of CSI amplitude patterns in non

real-time applications [7]. Real-time applications have been able to detect if there has been movement events in a monitored area [8]. This work uses a novel techniques to detect movements in overlapping windows of incoming CSI and then uses AI to classify if a person is performing sitting or standing motions in real-time.

## II. METHODOLOGY

The system works by using a single USRP device placed on a desk with two antennas attached. The USRP has software configured to allow transmission of OFDM signals between the antennas. The software outputs CSI which describes the signal propagation during transmission. The USRP is configured to simulate Wi-Fi communication at a frequency of 2.4GHz. The goal of the system is to detect if a person sits or stands from the desk. Training data is collected from a real-time stream of CSI during which time a person sits and stands from the desk. The amplitude of this CSI stream is extracted and then sliced into smaller overlapping windows of 80%. The windows are overlapped to ensure that the complete movement action is included in the entire sample. Large variations of amplitude values are indicative of movements occurring. Windows that include no movement or partial movement are dismissed. Partial movement is defined as movements occurring at the start or end of the windows. This suggests that the entire movement is in the next overlapping window. Windows that include the entire movement cycle are labelled appropriately as "Sitting" or "Standing" and stored for training data. Figure 1 shows the effect of the CSI amplitude stream when a person stands and sits.

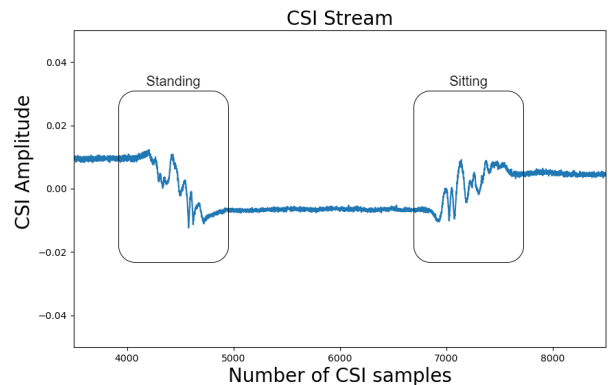


Fig. 1. CSI stream Showing the Standing and Sitting Variations

The training data is then constructed into a dataset which can be passed to a ML algorithm. The Random Forest ML algorithm is selected [3]. In total there are over 300 samples each collected for both sitting and standing. Data processing is used to apply a low pass filter to the data and then features are extracted. The features extracted are the mean, maximum, minimum, kurtosis, skew, standard deviation, and the difference between the maximum and minimum values. The dataset contains the label of the action sitting or standing and then the values of the extracted features.

### III. RESULTS AND DISCUSSION

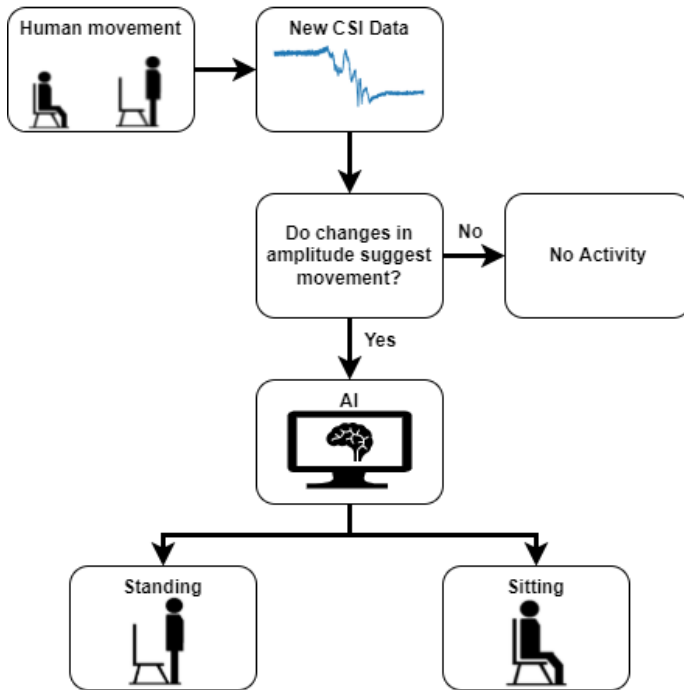


Fig. 2. Flowchart of the Real-time System

The dataset is used with the random forest ML algorithm using 10-fold cross-validation which produced an accuracy of 94.63 %. An AI model is then created using the random forest classifier and is carried forward for the real-time application. Software is set up to run the USRP communication and save the output similar to the collection of training data. The amplitude of the new data is extracted from the software output and movement samples are filtered out. If no movement is detected then the system will output "No activity". If movement is detected then the data will be passed to the AI model which will establish if the activity is sitting or standing. The system will then output the value of "Sitting" or "Standing" depending on the prediction of the AI model. The system is tested and is able to perform real-time classifications. The system is additionally tested in multiple office environments and the system was still able to perform correct classifications in real-time. This is because the action of sitting or standing still produces similar propagation patterns in the CSI of the RF

signals. Figure 2 presents a flow chart of the real-time system. New CSI data is passed into the system and if activity is detected then the AI model is used to differentiate between sitting and standing movements. Future work will seek to implement activity detection for greater distances by making use of multiple devices to serve as separate transmitter and receiver nodes which can be placed further apart.

### IV. CONCLUSION

This paper has presented a real-time system which can classify different human movements in real-time using contactless sensing. The system is able to determine if a person is sitting or standing by analysing the signal propagation of RF signals. A real-time data stream is collected while a person sits and stands from a chair and the movement samples are extracted from the stream. The movement samples are then compiled and features extracted to create a dataset which is used to create an AI model which is used in the real-time system. The real-time system was able to identify if the person is sitting or standing within multiple environments. Future work will seek to extend the number of actions detected and allow for real-time classifications within larger areas such as an entire room.

### V. ACKNOWLEDGEMENT

William Taylor's studentship is funded by CENSIS UK through the Scottish funding council in collaboration with British Telecom. This work is supported in parts by EPSRC EP/T021020/1 and EP/T021063/1

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