Real-Time Contactless WiFi Based Room Detection of Sitting and Standing Human Motions

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***Abstract*—In the field of healthcare, Human activity monitoring has recently been gaining widespread attention. The ability to monitor human activities is being applied to assist the care of vulnerable people. These monitoring systems can allow elderly people to live more independent lives within their own homes without residing in care facilities. The implementation of monitoring systems can relieve the strain on family members and/or caregivers from frequent visits to check on vulnerable people's well-being. The work of this paper proposes a contactless real-time monitoring system to detect if a person is sitting or standing. The contactless feature works by using machine learning to classify the propagation of RF signals as they travel through the atmosphere. The propagation data is collected using local devices and then uploaded to the cloud. A dashboard is used to download the data from the cloud and provide information on the output of the monitoring system. The system uses data filtering techniques to observe the patterns of propagation and establish if movements have taken place. If movements are detected then the data is passed to a trained AI model. The AI model will classify the movements as Sitting or Standing. The training of the AI model included applying 10-fold cross-validation to the training data to test performance. The Random Forest algorithm achieved an accuracy of 90.75 % and was used to build the AI model.**

***Index Terms*—Channel State Information, Real-time, Activities of Daily Living, Elderly Care, Machine Learning**

I. INTRODUCTION

The use of technology to monitor human movements has gained great interest in recent years. These monitoring systems are being implemented in the use of healthcare applications. They can provide vulnerable people such as elderly people to live more independent lifestyles without the need to have constant care monitoring from family members and/or caregivers [1]. Monitoring systems can allow for the detection of concerns and alert family members and/or caregivers in real-time. Concerns include falling instances where instead of waiting for family members and/or caregivers to check on the vulnerable person, assistance can be provided in a more reactive manner [2]. Falls in the home are a major concern in the healthcare of the elderly population [3, 4].

This paper implements a contactless solution for sensing human movements. This is achieved by using Radio Frequency (RF) signals to sense movements. WiFi systems already present in many homes are an example of RF technology. Therefore ambient RF signals already present in the home can be used to detect movements in the home environment. This allows for a cost-effective implementation of the monitoring system.

Monitoring with RF signals functions by observing the propagation of the signals through the atmosphere. As humans move, the RF signals are reflected from the human body. This causes a change in signal propagation. Machine learning can then be applied to recognise patterns associated with specific movements [5, 6]. The information concerning signal propagation is detailed in the Channel State Information (CSI). The CSI can be observed at the receiver side of the wireless link. The CSI describes signal frequency properties and effects of signal scattering, reflection and propagation [7, 8]. The CSI is in the format of a complex number. This complex number contains the amplitude and phase of the received signal [9, 10]. The amplitude is the absolute value of the complex number and the phase is the angel value of the complex number. The work of this paper focuses on the amplitude of the received signals and how specific human movements display similar effects on the amplitude. The system setup uses a

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transmitter and receiver placed in opposing corners of a room. As the signal travels the diagonal length of the room, human movements in the room affect the amplitude of the signal. Data filtering techniques are applied to decide if a movement is present. If movements are present then machine learning is used to compare changes to the amplitude of previously collected movements for sitting and standing, and provide a prediction for which action the human is performing.

The monitoring system implemented in this paper includes a web-based dashboard. This dashboard provides family members and/or caregivers with a visual representation of detected actions. Cloud computing is used to transfer locally collected data to the dashboard interface. The dashboard then observes the data from the cloud and processes for AI model classification of the data.

The contribution of this paper is the implementation of a real-time RF signal-based monitoring system which makes use of overlapping samples of data and data filtering techniques to ensure appropriate data is passed to a trained AI model. The data filtering techniques ensure that the AI model receives clear sitting or standing CSI data to allow for greater classification accuracy.

II. Methodology

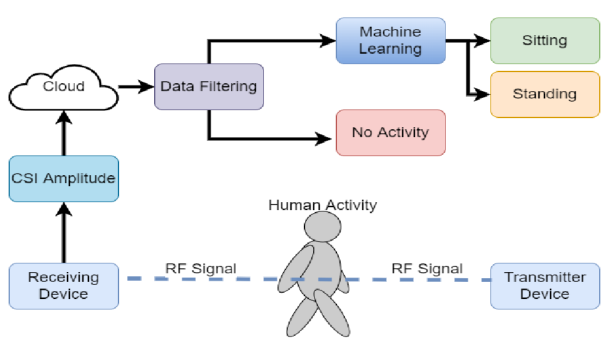

Figure 1. Complete Process of Proposed System

A. Experimental Setup

For wireless communication, this paper uses two Universal Software Radio Peripheral (USRP) devices. The models used are the X300 model. The devices are directly connected by Ethernet to individual PCs with i7 processors. Each PC is running Ubuntu Linux virtual machines with 12 GB RAM. GNU Radio is a free software package used to design a wireless link between the two USRP devices. The wireless link is set up to use the same 2.4 GHz centre frequency as WiFi [11]. GNU radio is also set up to collect CSI data of the transmission on the receiver. The receiver virtual machines capture the CSI data and store the information in a file buffer.

B. Data Collection

The experimental setup is used to collect CSI data for training the AI models and collect new unseen data for classification by the trained AI models. The file buffer contains CSI for 64 subcarriers transmitted to the receiver. As this system is working in real-time, only one subcarrier is of interest. This allows for faster processing times as only one subcarrier needs to be processed rather than 64. The first step is to collect training data for the Sitting and Standing classifications. The training data is used to create an AI model which can be used to classify new unseen data. The training data is collected in real-time and the entire stream of real-time CSI is captured. During this real-time wireless communication, a person can sit and stand from a chair in various positions in the room. The entire stream of CSI data is stored in the file buffer. The amplitude data for a single subcarrier is extracted and stored in CSV file format. The CSV amplitude file is then normalised by taking the average value of all amplitude values captured during the transmission and then subtracting this average value from all of the captured amplitude values. The data is then divided into smaller overlapping CSI windows. The CSI windows contain 1500 amplitude values. Each CSI window is overlapping the previous 1200 amplitude values from the previous sample. Each new CSI window contains 300 new amplitude values in the 1500 CSI window size. This is done to create a sliding window effect on the streaming CSI data to identify start and end points [12]. The finalised system will work similarly to the training data collection methodology with the exception being that new CSI data is received during the ongoing transmission. It will create CSI windows as CSI data is fed into the receiving node. The real-time system will also not store the data in CSV format.

1) Data Filtering: Data filtering is applied to the CSI windows to filter out complete movements from CSI windows that contain no activity or partial activity. Data filtering is used on training data to find the complete movements observed in the CSI to train accurate AI models. The data filtering is used in the real-time system to decide if a CSI window contains a complete movement and can therefore be passed to the AI model which has been trained on complete movements. The data filtering techniques are applied by using Python rules looking at the amplitude values of the CSI window. The Python code analyses the CSI window in sections and takes the maximum and minimum amplitude values observed. The difference between the maximum and minimum values is reordered. When looking at the training data it can be seen that human movements cause large peaks in the amplitude values. Analysis of collected training data has shown that if the difference in maximum and minimum amplitude values is below 0.00449 dB, then no activity is occurring.

For the CSI window to be considered as a movement it must match 3 rules. The 3 rules are as follows:

1) The first 150 amplitude values must have a minimum and maximum amplitude difference of less than 0.00449 dB.
2) The last 150 amplitude values must have a minimum and maximum amplitude difference of less than 0.00449 dB.
3) Any group of 100 samples in the CSI window must be greater than 0.00449 dB

The first rule is used to detect if there is any partial activity taking place at the start of the CSI window. if there is partial activity at the start of the CSI window then this indicates that the start of the activity is not contained in this current CSI window. If there is no activity present as indicated by the difference between the maximum and minimum amplitude value being less than 0.00449 dB then rule 1 is set as true.

The second rule is used to detect if there is any partial activity taking place at the end of the CSI window. if there is partial activity at the end of the CSI window then this indicates that the end of the activity is not contained in this current CSI window. If there is no activity present as indicated by the difference between the maximum and minimum amplitude value being less than 0.00449 dB then rule 1 is set as true.

The third rule is used to detect if the entire CSI window is showing no movements. This is important as CSI windows showing no movements do not need to be used as training data or passed to the AI model. The rule works by dividing the CSI window into groups of 100 amplitude values and recording the difference between the maximum and minimum amplitude values. If any of the groups show a difference greater than 0.00449 dB then movement is detected in the sample and the rule is set as true.

The rules are applied to each CSI window stored in CSV format for training and each CSI window received during the real-time operation of the monitoring system. If all rules are true for a CSI window then the CSI window can be passed to training examples of movement or passed to the AI model to classify if the movement is Sitting or Standing.

Figure 2 shows overlapping windows and the values found when applying the rules to each window. Green CSI windows will be stored as movements and CSI windows defined as No Activity.

2) Training Data: The training data is collected with a person performing sit and stand actions from various areas within the room. The overlapping and data filtering techniques are applied to save CSI windows in CSV format. The accepted files are passed into folders for Sitting and Standing. Over 600 samples of Sitting and Standing are collected and compiled into a training dataset for the Sitting and Standing AI model.

C. Machine Learning

All training CSI windows with the data filtering rules as true are stored in separate folders for sitting training CSI windows and standing training CSI windows. There are over 600 training CSI windows for both sitting and standing. These CSI windows then have data processing techniques applied before machine learning takes place. The data processing techniques applied are noise reduction and feature extraction. For noise reduction, a low-pass Butterworth filter is applied. Then the features of the CSI window are extracted. The features extracted are the mean, maximum, minimum, kurtosis, skew, standard deviation, and the difference between the maximum and minimum values. These values are taken for the entire CSI window and 5 groups of the CSI window. The groups of the CSI windows are 0-500 amplitude values, 250-750 amplitude values, 500-1000 amplitude values, 750 - 1250 amplitude values and 1000 - 1500 amplitude values. This results in 42 features in total in the dataset. This dataset is used to create the AI model to classify new data. As shown in previous work of this nature [13], Random Forest has shown good results in the classification of CSI amplitude data. In the real-time system, the new CSI windows are passed through the same data filtering and data processing techniques as the training data. This way the new CSI window and the training CSI windows seen by the AI model previously are compatible.

D. Dashboard and Cloud Computing

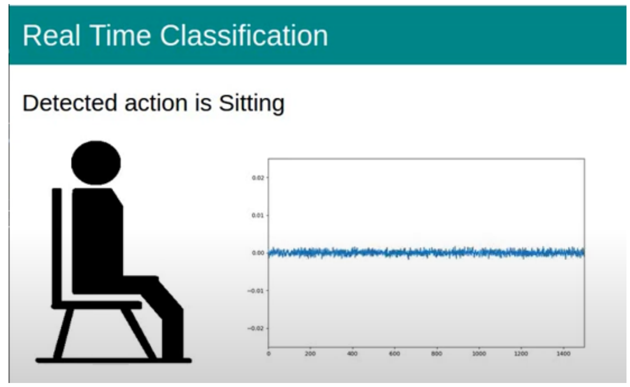

Figure 3. Dashboard Layout when the System Detects User is Sitting

For classifying new CSI windows a dashboard interface is implemented in this paper. The dashboard interface is designed to be used by family members and/or caregivers to observe what activities are occurring in the vulnerable person's home. The dashboard uses the flask python package to implement a web interface. The python package allows for the dashboard to apply the data filtering and data processing techniques used to train the AI models which are python based. The dashboard also contains the trained AI model to classify the data. The CSI windows are transferred from the local system to the dashboard by using cloud computing. When the local system collects new CSI windows, they are uploaded to the cloud. The dashboard then retrieves the CSI window from the cloud and can perform the required actions to gain a prediction for the CSI window. The dashboard then displays the prediction and a graphical representation of either sitting or standing. The dashboard will also display the CSI window in the form of a line graph, showing the amplitude values for all 1500 CSI amplitude values contained in the CSI window. Figure 3 shows the layout of the dashboard. The Figure shows the last AI prediction in text format, The graphical representation and the current CSI amplitude data.

III. RESULTS AND DISCUSSION

The following section describes the results of the proposed system. The training data collected is tested by using 10-fold cross-validation with Random Forest. The 10-fold cross-validation results can indicate how an AI model built using this training data will perform when looking at new unseen data. If the results are good then an AI model can be built using

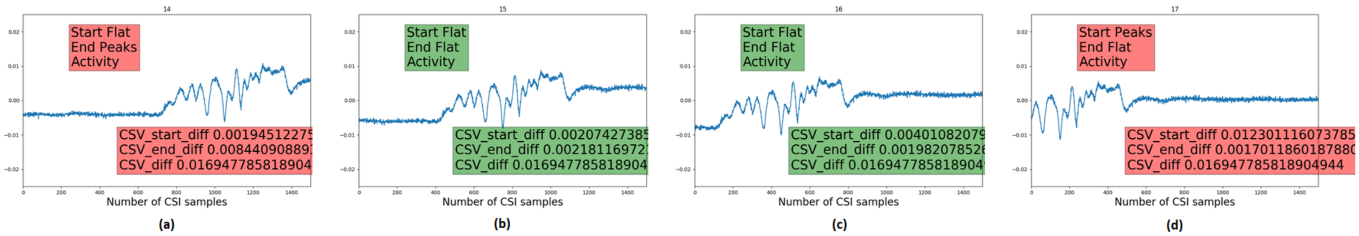

Figure 2. CSI Window Images Showing the Observed Values Following Data Filtering. a) CSI Window Rejected as Rule 2 is False, b) and c) are Accepted as all Rules are True, d) is Rejected as Rule 1 is False

Random Forest and added to the dashboard for classifying new unseen data. The dataset achieved an accuracy score of 90.75 %. Table I shows the confusion matrix of the classifications.

Table I
CONFUSION MATRIX OF TRAINING DATA SET

	Actual Sitting	**Actual Standing**
Predicted Sitting	540	60
Predicted Standing	51	549

A. *Classification of real-time data*

The AI model is created using the Random Forest algorithm and stored for making predictions on new unseen data. Only CSI windows are passed to the AI model for classification if all of the data filtering rules are set to true. if any of the rules are false then ”no activity” is output without using AI. Testing of the AI model included having RF communication take place with the system running. Results found that the system could recognise when a person performed sitting or standing actions. The system also recognised the sitting and standing motions throughout the room. This is to be expected due to the results achieved when applying 10-fold cross-validation to the training data.

IV. CONCLUSION

The work of this paper has presented a real-time human activity monitoring system using RF signals. Machine learning has been applied using the Random Forest algorithm to distinguish between different patterns of signal propagation of the RF signals to classify them as specific human movements. The specific movements the system is trained to detect are Sitting and Standing. This is accomplished by training an AI model. The AI model was able to achieve an accuracy score of 90.75 %. Future work will seek to improve the overall accuracy of the system and implement additional activities.

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