AI-based Real-time Classification of Human Activity using Software Defined Radios

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***Abstract*—Real-time monitoring is an essential part in the development of healthcare monitoring systems. Research has shown that human movement affects the propagation of radio frequencies, as signals will reflect off the human body. Machine Learning techniques have been used in research to classify patterns observed in the signal propagation. This paper makes use of universal software radio peripheral devices to create a wireless communication link where the signal propagation data, known as channel state information, is collected while a user moves or remains still. A machine learning model which achieved an accuracy result of 93.25 % is used to classify between movement and no activity. Inference is then used to decide if the human position is sitting or standing and detected movements are used to differentiate between the two positions. The testbed implements cloud storage and a web-interface to present a visualisation of the human position.**

***Index Terms*—Real-Time, CSI, Human Motion Detection, RF Sensing**

I. Introduction

Recently healthcare monitoring systems are being researched as a viable means of providing independence to vulnerable people [1]. An efficient monitoring system can allow for care givers to react to the needs of individuals rather than scheduled visits [2]. This allows help to be given when needed and enables vulnerable people to reside in their own premises and not within a care home. Due to advancements in medical science, the elderly population is growing and this results in more vulnerable people requiring care contributing to increased strain on the care industry. Therefore, monitoring systems can allow for reducing the amount of care required as care can be delivered reactively.

An example of an incident impacting vulnerable people is falling within the home, which is extremely hazardous [3] resulting in injury and possible death. Falling is one of the key factors that justify the relocation to care homes where full time care is delivered. Permanent residence in a care home may not be preferable as a considerable amount of independence is removed from the persons life [4]. If a system can be used to detect falling or near falls in real-time, then individuals can reside in their own homes with the support of monitoring.

Current real-time systems make use of wearable devices [5, 6], however disadvantageous due to dependency on the user wearing the device. If the user finds the device uncomfortable they are more likely to remove them. This is a challenge of producing wearable devices to ensure comfort [7]. One of the main disadvantages is if users forget to wear the device, which is increased with elderly users as they may be suffering memory loss symptoms from pre-existing conditions. To resolve these issues, the implementation of non-contact methods is widely researched, where the position of the person can be determined by using sensors that are not connected to the body.

Radio Frequency (RF) signals have been implemented in research as a means to detect human movement [8, 9]. This method is supported by Machine Learning (ML) models which can recognise patterns in the propagation of radio signals as they travel through the atmosphere. As a person moves in the vicinity of these RF signals the signal propagation is affected. Channel State Information (CSI) is a feature of wireless communication that describes the signal propagation. This research exploits this information to detect movements while wireless communication is taking place.

This paper presents a novel real-time testbed that provides a proof of concept of how wireless communication can be used in a real-time application which can tell the position of a human being. Current research shows possibility of real-time systems [9, 10, 11] but our paper is the first to our knowledge to demonstrate a working system. The system works by first creating a machine learning model which detects the movement within CSI samples. The model is used to make classifications as real-time CSI data is feed through the system and define a movement. The system works on inference where the initial position of a person is defined as whether sitting or standing and then a movement will result in a change from the initial position. The model will therefore define if the position is sitting or standing and CSI information will dictate if the position changes. The sections of this paper are set as follows. Section II discusses the methodology adopted to achieve the system functionality; Section III presents the results obtained and discussion; Finally, Section IV concludes the paper and details plans for future work.

II. Methodology

The aim of this research is to develop a real-time testbed that can make use of radio frequency to decide if a single person is sitting or standing.

A. System Setup and Configuration

The testbed will seek to exploit CSI from RF communication to detect Movements. A Universal Software Radio Peripheral (USRP) is used to create OFDM communication in which CSI data can be extracted. USRP is selected due to the online support available for setting up initial communication. The testbed will make use of a single USRP with two omnidirectional antennas attached. One antenna is used as the transmitter and the second is used as the receiver. The wireless communication is configured to use a centre frequency of 2.4 GHz. The reason for this choice of centre frequency is to replicate Wi-Fi systems currently present in many homes using 2.4 GHz. During wireless communication, CSI values are stored in a text file which can be called for further processing.

B. Experimental Setup

The experiment is set up on a desk environment. The USRP is placed on the desk in front of a chair. The subject sits and stands from the chair. Ethical approval was obtained for subjects in this study. Python scripts are configured to extract the CSI data from the CSI text file. The CSI data is in the format of complex numbers. The Numpy Python package is used to calculate the CSI amplitude by obtaining the absolute value of the complex numbers. When a person moves during the wireless communication this affects the amplitude of the signals and this can be observed in the CSI. This is exploited in this experiment.

III. Results and Discussion

This section displays the results of the processes described in II in the application of a real-time testbed for detecting sitting and standing. Discussion of how these methods can work as a real life application is also given.

A. Machine Learning

The testbed makes use of ML to classify if CSI samples contain movement. A Machine Learning model is created to classify real-time CSI data. To train this model, 200 samples of both Movement and No Activity are collected. The Movement action includes sitting and standing from the chair. The No Activity samples include sitting still on the chair and standing still in front of the chair. The samples are then all combined into a complete dataset and used to create a model which can be recalled to classify new data from the testbed. Various Machine learning algorithms were tested on the dataset using 10-fold cross validation [9]. Random Forest produced the best results of 93.25% Accuracy during testing. Therefore Random Forest was used to create the machine learning model.

B. Real-Time Testbed

This section describes how the real-time testbed is developed to utilise the results of the model. For the real-time testbed, the USRP is run similar to collecting the testing data however in this case the data is not saved. The CSI data is collected in the text file and when 1000 CSI samples are collected to match the size of the training CSI samples then it is passed through the model. The model classifies whether this data is "Movement" or "No Activity". The process then repeats constantly as the CSI data is received. This then provides real-time classification to the CSI being output by the USRP in real-time. Figures 1 and 2 show how the CSI appears as it is passed through the model. It can be clearly seen how "No Activity" shows almost no variations and how "Movement" disturbs the signal's propagation.

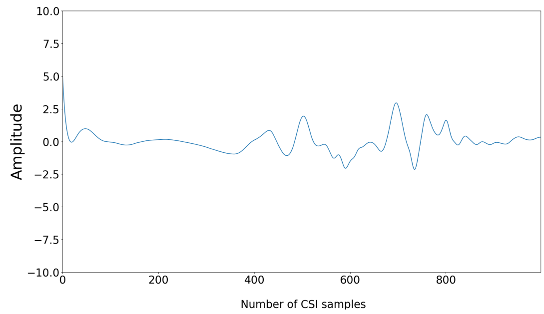

Figure 1. Movement CSI sample

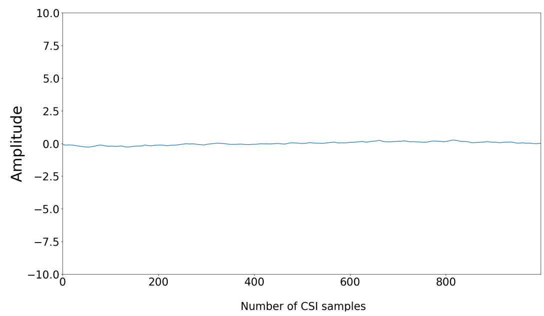

Figure 2. No activity CSI sample

The real-time model is able to identify when the user moves with the use of the ML model. In order to differentiate between sitting and standing the testbed will work on inference. The reasons for implementing this strategy is due to the real-time nature of the testbed. As samples come in at a fixed size of 1000 packets, the human movement is likely to occur between samples therefore separating the activity between multiple samples. This testbed works on the inference that the user is sitting at the desk as the start position. Then as the person stands they will cause the disturbance in the signal propagation and create a movement classification from the CSI data. Initially the Position is set to sitting. When a movement classification occurs the position is then changed to standing. Then when another movement occurs then the position will revert back to sitting. However as explained before there is a high chance that a movement occurrence in the CSI can stretch over 2 samples. If this is the case then the position will change standing and then back to sitting almost instantaneously. To resolve this issue, python coding is used to create if statements. Where the last 3 machine learning classifications are stored in a list. Then the position will not be changed unless there is a no activity classification recorded between the movement classifications. This allows for a transition period before the position can be changed. Figure 3 Shows the process of how the real-time testbed works.

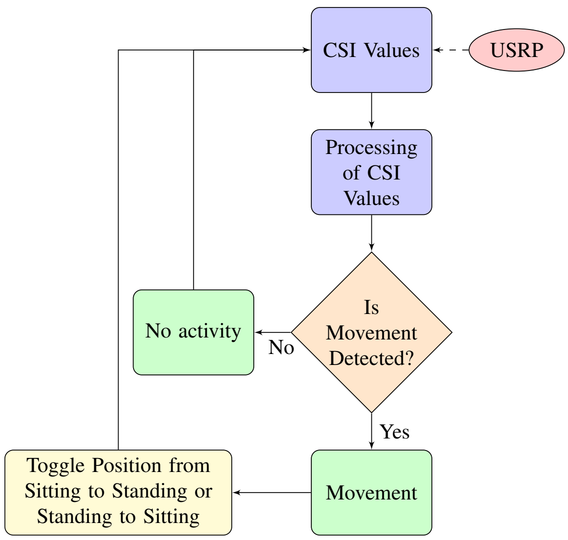

Figure 3. Process of Real-Time testbed

C. *Web-Interface*

The testbed makes use of a web-interface and the cloud. The web-interface provides a dashboard that can be used to observe position of the subject. The cloud is implemented to store the most current CSI sample collected. Cloud implementation demonstrates how data can be collected on site with the devices and classification can occur on the web-server side. This could be implemented in a centralised care system in the application of home monitoring of vulnerable people. The web-interface then downloads the samples and applies the machine learning model to the data. The web-interface then obtains the position from the classification and displays a figure of the position on the web page. Additionally the web page also presents the figure generated from the CSI amplitude data. Figures 4 and 5 shows the web-interface for position sitting and standing respectfully.

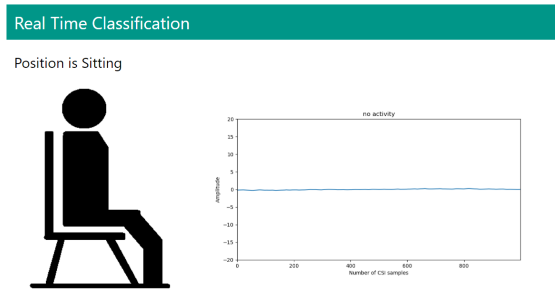

Figure 4. Dashboard displaying initial Sit position and ”No Activity” CSI

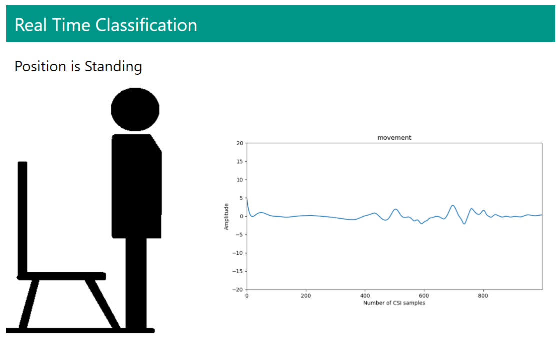

Figure 5. Dashboard displaying toggle to Stand position with ”Movement” CSI sample

IV. Conclusion

This paper describes the process used to create a real-time testbed which can detect if a human is sitting or standing. The testbed works on an inference method where the detection of movements, due to standing or sitting, are used to establish a change in the position. The testbed makes use of a web-interface, serving as a dashboard, to visualise the position and incoming data. The testbed also implements the use of the cloud system where real-time data is uploaded from the device and classifications can be applied at the web server side. This can used for a centralised system for activity monitoring in the application of elderly care. The results show that the system can use real-time RF signals to classify if a user is moving or not and can therefore be used to make inferences based on what type of activity is expected. This can be useful for ensuring that vulnerable people are behaving as expected within their homes and inconsistencies can be flagged up to care givers, instantly. Future work will seek to advance the testbed by including more classifications which can increase the realism and applicability of the system. These additional classifications will seek to include empty room, walking, and others. These additional classifications will enable observing when users are not present in the monitored room and when they walk away or towards the area of monitoring.

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