RF Based Real Time Human Motion Sensing

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***Abstract*—Recent research has shown that the propagation of Radio Frequencies signals is affected by human movements taking place between the RF transmitter and receiver antennas. Artificial intelligence has been widely used to classify the patterns of signal propagation. With the help of a universal software radio peripheral device, a system was developed based on a real-time machine learning classification algorithm to ensure alerts of incidents are received in a timely manner. The machine learning model was built to distinguish between "No Activity" and "Movement" status of a single human subject. The model recorded a high classification accuracy of 97.8 % which enabled an accurate classification of new data in real-time.**

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

I. Introduction

In recent years, healthcare monitoring technologies have started becoming a viable solution for providing vulnerable people with independence [1]. These monitoring systems can allow for care to be provided for vulnerable people within their own home in a reactive way rather than proactively. These types of systems can spare the vulnerable person from having to reside in a care home. Monitoring systems can be placed in the vulnerable person's home and provide real-time alerts if an incident requiring care takes place [2]. Allowing a carer to react to an incident and providing vulnerable people with Independence. Several technological approaches are used to extract information, known as features, that reflects human movement. Elderly people contribute to a large number of vulnerable people requiring care. The strain of care workers is on the increase due to the rising population of elderly people. This further contributes to the strain on care givers. Falling is an example of a serious incident which would impact elderly and vulnerable people. Falling can cause serious injuries to people and in some cases result in death. Therefore if a fall can be observed in real-time using technology, care givers can then react to this in a timely manner. Currently wearable devices can be used to achieve real-time monitoring of these vulnerable people [3]. However, these devices have number of disadvantages such as uncomfortably devices and users can potentially forget to wear the device, rendering the device as useless. A solution to this problem is to use non-contact methods where sensing can take place without users needing to wear a device. The use of Radio Frequency (RF) signals is an example of a non-contact method which has been used recently to detect human movements [4, 5]. This method works by using Machine Learning (ML) techniques to recognise signal propagation associated with movement taking place between the the RF transmitter and receiver. Channel State Information (CSI) describes how a signal propagates from the transmitter to the receiver. Movements will cause the signal propagation to change. This change can be detected by ML algorithms. The work presented in this paper develops a real time application using a Universal Software Radio Peripheral (USRP) device. The USRP is used to set up a communication link between the transmitter and receiver nodes and the CSI can be extracted for processing by ML. Training data is collected and used to build a ML model. This model can then provide real-time classifications on whether there is "Movement" or "No Activity" in newly received CSI. The paper is organized as follows. Section II discusses the methodology applied to achieve the system functionality; Section III presents the results obtained and discussion and finally Section IV concludes the paper.

II. Methodology

Firstly, the test bed is set by placing the USRP on a desk and the goal is to observe if the person in front of the desk is moving or not. The USRP communication is set up using the GNU radio software application, where a python script is produced which can initiate communication between the transmitter and receiver. The python script contains the parameters of communication such as sample rate (400khz), centre frequency (2 GHz) and gain values (20 dB for transmitter antenna and 10 dB for receiver antenna). Once the USRP is producing CSI, a python script processes it into readable format for ML to take place. Training data must be collected to train the model which is used for the classification. The "No Activity" training data is collected while the person does not move and the ”Movement” training data is collected while the person sits and stands in front of the desk. Figure 1 shows an example of the CSI detected while ”Movement” action takes place and Figure 2 shows an example of the CSI detected while ”No Activity” action takes place.

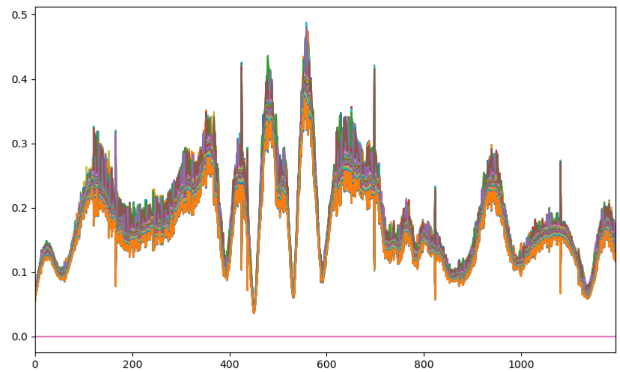

Figure 1. Channel State Information while Movement action takes place

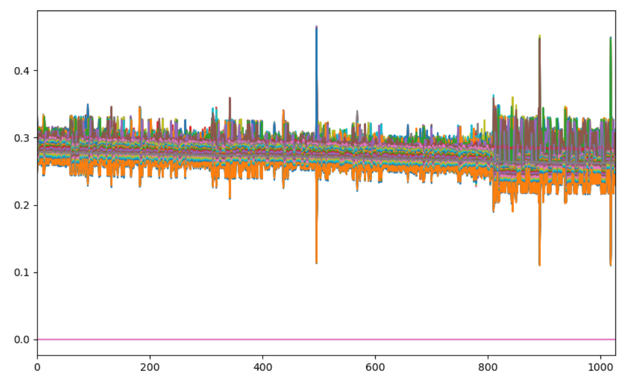

Figure 2. Channel State Information while No Activity action takes place

```
Random Forest
Confusion Matrix
[[490  10]
 [ 12 488]]
              precision    recall  f1-score   support

    Movement       0.98      0.98      0.98       500
  NoActivity       0.98      0.98      0.98       500

   micro avg       0.98      0.98      0.98      1000
   macro avg       0.98      0.98      0.98      1000
weighted avg       0.98      0.98      0.98      1000

Random Forest Accuracy 97.8 %
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Figure 3. Results of the training dataset

A complete training dataset is compiled with 500 samples of each activity. The Random Forest ML algorithm is used with 10 fold cross validation to measure the performance of the dataset. The results gave an accuracy score of 97.8 %. Figure 3 shows the confusion matrix, precision, recall, F1 score and the accuracy results. This accuracy shows that the algorithm is able to identify the difference between Movement and No Activity as seen in differences in amplitude in Figures 1 and 2. The complete dataset is then used to create the ML model for real-time classification.

III. Results and Discussion

The ML model was used in an experiment to test the real-time application of the system. The new unseen data was collected in real-time and compared to the created model, where a classification of ”No Activity” or ”Movement” was made. Demonstrations proved that the model successfully identify the change in signal propagation. A real life application of this concept can be implemented to observe movement within a vulnerable persons home. If there is no movement detected within an expected time frame this can raise a cause for concern.

IV. Conclusion

We have presented a working real-time application of human motion detection using RF signals. The work has collected a dataset of the Movement and No activity expected to be seen on the USRP device while classifying real-time data. The dataset is tested for performance by using 10 fold cross validation and achieved an accuracy score of 97.8 %. The complete dataset is used to create a model which is able to identify between samples of CSI in real-time. The next steps in this work would look to detect movements from different distances and to test the function of the system in different environments.

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