Human Activity Recognition using Wi-Fi Channel State Information (CSI)

Jordan Walsh

Commack High School

ABSTRACT

Channel State Information (CSI) describes the properties of a channel (i.e., the instantaneous amplitude and phase of a signal) in a wireless communications link. Transmitted Wi-Fi signals can travel through humans and objects, although there is an observed phase offset and decrease in amplitude at the receiver. The purpose of this project was to utilize collected CSI data to distinguish between three cases: (1) the absence of human activity within a room, (2) a stationary human standing in the middle of a room, and (3) a human continuously walking throughout a room. Whereas presently used detection methods, cameras and motion detectors, require specialized equipment to be installed, this CSI-based approach utilized existing Wi-Fi infrastructure already present in homes, schools, and public areas. Data was collected for one hour for each case, with CSI data over each antenna-to-antenna connection and subcarrier in a 3 x 3 MIMO Wi-Fi connection being logged every second. A linear support-vector machine (SVM) model in Matlab performed with 97.3% accuracy in a binary classification between case 1 (no activity) and case 2 (standing). When values from case 3 (walking) were introduced in a tertiary classification, the accuracy of the linear SVM decreased to 80.0%. This is likely because the distinguishing feature of the walking data was its amplitude and phase variance over time, which cannot be fully observed instantaneously. In the future, to improve accuracy in this tertiary classification, the variance of CSI values over a certain time period could be used by the classification model.

INTRODUCTION

Channel State Information (CSI) describes the properties of a channel in a wireless communications link (Aljumaily, 2016). For a given subcarrier at a certain frequency and time, a complex vector describes the amplitude and phase of the transmitted signal, in its modulus and argument, respectively. The purpose of this project was to create a classification model, utilizing collected CSI amplitude and phase values, to distinguish between the absence of human activity within a room, a stationary human standing in the middle of a room, and a human continuously walking throughout a room. The use of these cases is primarily a proof of principle, to establish how collected CSI data from Wi-Fi connections can be leveraged to detect and track the presence and movement of humans, in addition to other objects, within an area.

Previous studies have used machine learning to apply Channel State Information data to real-world problems including accurate indoor localization (Sanam and Godrich, 2019), keystroke recognition, and human gesture detection (Aljumaily, 2016). Channel State Information data can be collected using freely available tools developed for Intel Wi-Fi Wireless Link 5300 802.11n MIMO radios (Halperin, Hu, Sheth, and Wetherall, 2011) and Atheros WiFi NICs (Xie, Li, and Li, 2018). The use of CSI in human activity recognition has advantages over conventional methods—a recognition system can be integrated into existing Wi-Fi networks, making the cost to install expensive cameras and radar equipment unnecessary. For example, the top motion detection cameras on Amazon.com range in price from $30 to $60 (Amazon.com, 2019), while an aforementioned Intel 5300 MIMO radio can be purchased for $10 to $20 (Amazon.com, 2019). Additionally, a CSI-based approach is functional at a further distance than radar, and does not require the line-of-sight views needed with cameras.

CSI data collected by software is organized into a three-dimensional matrix, having the dimensions of the number of transmitting antennas × the number of receiving antennas × the number of subcarriers. Each CSI value is stored in this matrix as a complex number, with the observed amplitude stored in the modulus and the observed phase offset stored in the argument. CSI data was collected for a duration of one hour for each case, logged every second. Since the data was collected over a 3 x 3 MIMO Wi-Fi connection with 30 subcarriers, a total of 3,600 3 x 3 x 30 matrices were collected for each of the three cases. The amplitude and phase values can be extracted from these raw CSI values in Matlab, and organized into a categorical table to train classification models. The goal of this project is to develop a statistical classification model that is able to use these CSI values to detect, with high accuracy, that 1) higher, static amplitude values correspond to the absence of a human, 2) lower, static amplitude values correspond to a human standing, and 3) lower, fluctuating amplitude values and fluctuating phase values correspond to a human walking.

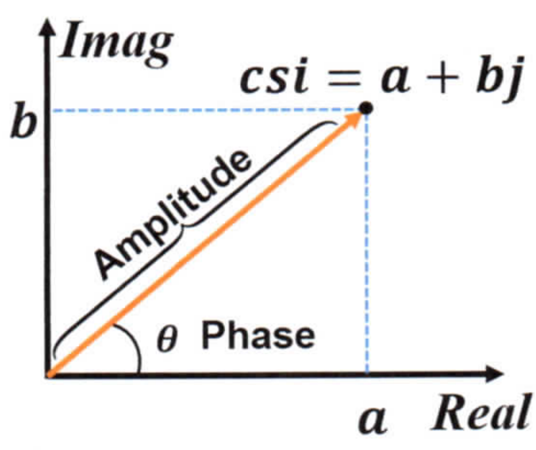

Figure 1: CSI complex vector (Xie, Li, and Li, 2018)

PROCEDURE

A TP-Link AC1750 router connected to a university network via Ethernet served as the transmitter in the Wi-Fi connection used for CSI data collection. The Wi-Fi signal was received by three Highfine 6 dBi Dual Band RP-SMA antennas, connected by pigtail U.FL to RP-SMA adapters to an Intel 5300 NIC. The Linux 802.11n CSI tool (Halperin, Hu, Sheth, and Wetherall, 2011) was used on the Ubuntu 14.04.4 operating system to extract the CSI data from the Intel 5300.

Figure 2. TP-Link router used as transmitter

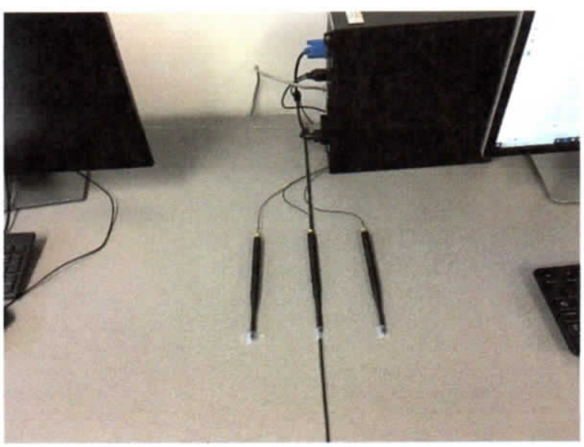

Figure 3. Highfine antennas connected to Intel 5300 used as receiver

For each of the three cases, CSI data used for training was collected for a duration of one hour. To log the CSI data, a ping command was sent to the network in the Ubuntu terminal every second, with the measured amplitude and phase collected over every antenna-to-antenna connection and subcarrier every time. This resulted in a 3 x 3 x 30 CSI data matrix being collected every second, with all of the matrices for each case (3,600, for every second in the hour) being logged to a specific file.

The Linux CSI tool generated a raw binary data file to store CSI and needed to be unpacked in Matlab before it could be processed ("FAQ, Things to Know, and Troubleshooting," n.d.). The matrices generated by the CSI tool could then be processed in Matlab, and tables of categorized amplitude and phase values were created for the model. Matlab's Classification Learner application was used to determine the most accurate models to use for categorization based on CSI amplitude and phase data.

RESULTS/DISCUSSION

Figure 4 shows a plot of the CSI amplitude and phase values observed over time for each case, specifically on the signal transmitted between the center transmitting antenna and the center receiving antenna, on subcarrier 16.

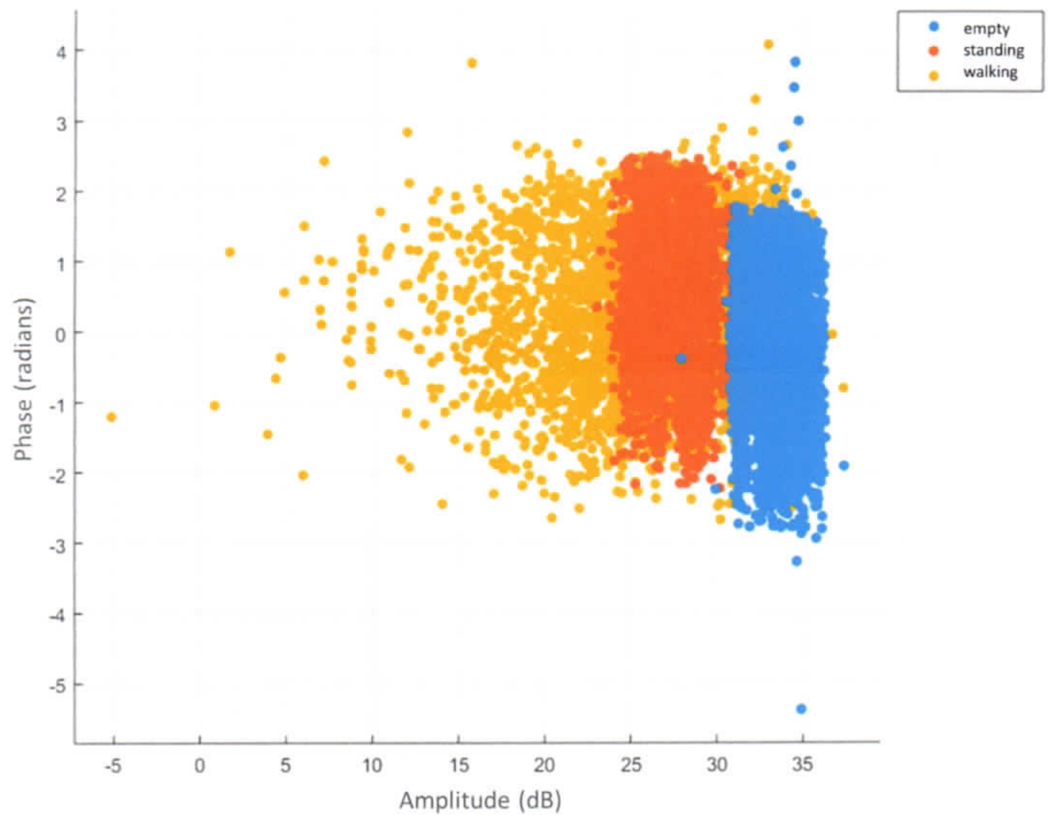

Figure 4. Amplitude-phase CSI plot for the three cases on Tx1-Rx1, subcarrier 16

There is a clear decrease in the observed amplitude values when a human is standing in between the transmitter and receiver, in addition to a slight phase offset. This supports that the Wi-Fi signal is slightly observed and reflected by the human body, causing attenuation of the signal in addition to the signal arriving at the receiver slightly later in time.

The CSI values observed when a human is continuously walking are much more varied in terms of amplitude over time. This supports that the human body's effect on the signal changes as its position within the room changes.

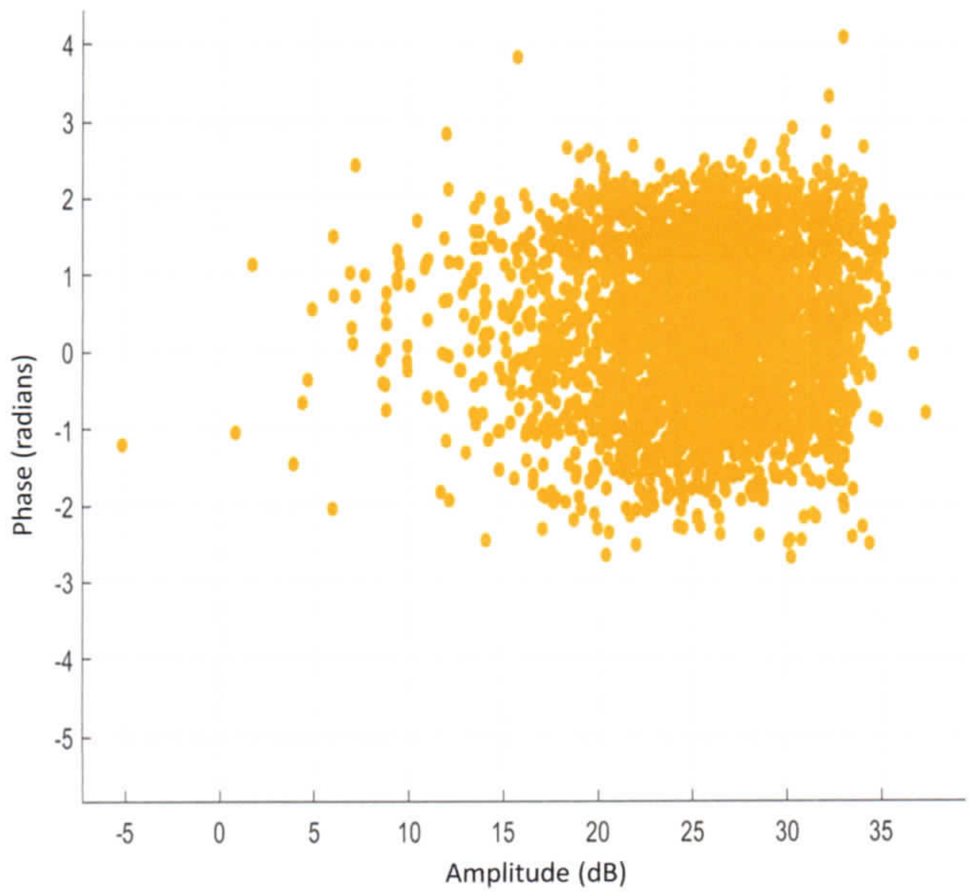

Figure 5. Amplitude-phase CSI plot for case 3 (walking) on Tx1-Rx1, subcarrier 16

When this data was inputted into Matlab, the linear support-vector machine (SVM) model performed the best in a binary classification between the data from cases 1 and 2, classifying instantaneous data with 97% accuracy. When the data from case 3 was introduced, the model's accuracy decreased to 80%. This is likely because the walking data is characterized by its variation in amplitude over time, as the body's position changes. Therefore, it is difficult to tell at a single point in time whether the person is walking, since the context (previous and future measurements) is unknown. Other models showed a decrease in accuracy as well when case 3 was introduced.

Table 1. Comparison of model performance in binary empty vs. standing classification and tertiary empty vs. standing vs. walking classification

Model	Binary Accuracy	Tertiary Accuracy
Linear SVM	97%	80%
Naive Bayes	80%	73%
Fine Tree	79%	70%

The proof of principle was successful. Common personal desktop computers can be modified to collect and process channel state information data from a Wi-Fi connection. Expensive specialized equipment, such as cameras and motion sensors, are not necessary to implement an effective human monitoring and security system. This CSI-based system can be implemented within existing home, school, and business Wi-Fi systems. In addition, since other objects display similar reflection and absorption of Wi-Fi signals seen with the human body, this system could be extended to track things like packages as well.

REFERENCES

Aljumaily, M. (2016). A survey on WiFi Channel State Information (CSI) utilization in Human Activity Recognition. doi: 10.13140/RG.2.1.4383.5121

Amazon.com: Motion detection camera. (2019). *Amazon.com*. Retrieved October 28, 2019, from https://www.amazon.com/s?k=motion+detection+camera

Amazon.com: Intel WiFi Link 5300. (2019). *Amazon.com*. Retrieved October 28, 2019, from https://www.amazon.com/s?k=intel+wifi+link+5300

FAQ, Things to Know, and Troubleshooting. (n.d.). *Linux 802.11n CSI Tool -- FAQ, Things to Know, and Troubleshooting*. Retrieved June 30, 2019, from https://dhalperi.github.io/linux-80211n-csitool/faq.html

Halperin, D., Hu, W., Sheth, A., and Wetherall, D. (2011). Tool Release: Gathering 802.11n Traces with Channel State Information. *ACM SIGCOMM CCR, 41*(1), 53.

Ma, Y., Zhou, G., and Wang, S. (2019). WiFi Sensing with Channel State Information: A Survey. *ACM Computing Surveys*, *52*(3), 46:1-46:36.

Melia, G.C.R. (2013). *Electromagnetic Absorption by the Human Body from 1 to 15 GHz*. York, UK: University of York.

Qian, K., Wu, C., Yang, Z., Liu, Y., and Zhou, Z. (2014). PADS: Passive Detection of Moving Targets with Dynamic Speed using PHY Layer Information. *2014 20th IEEE International Conference on Parallel and Distributed Systems (ICPADS)*, 1-8.

Sanam, T.F. and Godrich, H. (2019). FuseLoc: A CCA Based Information Fusion for Indoor Localization Using CSI Phase and Amplitude of Wifi Signals. *ICASSP 2019 – 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 7565-7569. doi: 10.1109/ICASSP.2019.8683316

Xie, Y., Li, Z., and Li, M. (2018). Precise Power Delay Profiling with Commodity Wi-Fi. *IEEE Transactions on Mobile Computing*, *18*(6), 1342-1355. doi: 10.1109/TMC.2018.2860991