Jordan Walsh

Research Plan

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

A. Rationale:

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. A three-dimensional matrix of these vectors can be created, having the dimensions of the number of transmitting antennas × the number of receiving antennas × the number of subcarriers. 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.

B. Hypothesis(es), Research Question(s), Engineering Goal(s), and Expected Outcomes:

Research Question:

Can a statistical model using Wi-Fi Channel State Information (CSI) distinguish between the absence of human activity in a room, a human standing in a room, and a human walking in a room?

Engineering Goal:

Wi-Fi signals, like other radio waves, can be absorbed by and reflected off of objects, including humans. Water content and tissues of the human body contribute to its dielectric properties, making the human body an effective absorber of radio waves, especially those at frequency ranges commonly used in Wi-Fi systems (Melia, 2013). The presence of a human obstacle in between a wireless transmitter and receiver should produce a decrease in the measured amplitude of the Wi-Fi signal at the transmitter. Additionally, if a human is moving in a room, the amplitude and phase values should fluctuate over time due to the person's changing position.

Therefore, the goal of this project is to develop a statistical classification model that is able 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.

C. Procedures, Risk and Safety, Data Analysis, and Discussion of Results and Conclusions:

The experiment will be performed at New York Institute of Technology, Long Island Campus under the supervision of Dr. Batu Chalise.

(i) Procedures:

Collecting CSI Data

- CSI data for each of the three cases (no human activity, human standing, and human walking) will be collected to train and test the model.
- To collect the CSI data, a TP-Link AC1750 router connected to the university network through Ethernet will transmit the Wi-Fi signal. This signal will be 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) will be used on the Ubuntu 14.04.4 operating system to extract the CSI data from the Intel 5300.
- Data will be collected for a duration of approximately one hour for each case. To log the CSI data, the university network will be pinged from the Ubuntu terminal every second, with the measured amplitude and phase collected over every antenna-to-antenna connection and subcarrier every time. This will result in a 3 x 3 x 30 CSI data matrix being collected every second, with all of the matrices for each case (approximately 3,600, for every second in the hour) being logged to a specific file.

Processing CSI Data

- The Linux CSI tool generates a raw binary data file to store CSI and must be unpacked in Matlab before it can be processed ("FAQ, Things to Know, and Troubleshooting," n.d.). The matrices generated by the CSI tool can then be processed in Matlab, and tables of categorized amplitude and phase values will be created for the model. Matlab's

Classification Learner application will be used to determine the most accurate models to use for categorization based on CSI amplitude and phase data.

(ii) Risk and Safety:

- Walking back and forth for a long period of time while collecting the CSI data for that case could be physically exerting. If the experimenter is feeling fatigued, breaks will be taken from data collection.

(iii) Data Analysis:

- After unpacking, the CSI data in the file generated by the tool is stored as a set of 3 x 3 x 30 matrices, with one matrix for every second in which CSI will be logged. The modulus and argument can be taken of each complex number stored in the matrices, representing the signal's amplitude and phase (offset from a reference point), respectively, for that specific ping, antenna-to-antenna connection, and subcarrier.
- A categorical table will then be created, with a column for amplitude, a column for phase, and a category (like "LOS", "standing", and "walking") classifying the amplitude and phase as being collected from one of the three cases that are being tested (line-of-sight propagation, a human standing in the middle of the room, and a human walking, respectively). Matlab's Classification Learner can then be used to train and validate different supervised machine learning models and determine which are the most accurate at classifying data into the three specific cases based on CSI data.

D. Bibliography

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

NO ADDENDUMS EXIST