HOME PRESENCE DETECTION AND LOCALIZATION USING WI-FI CSI

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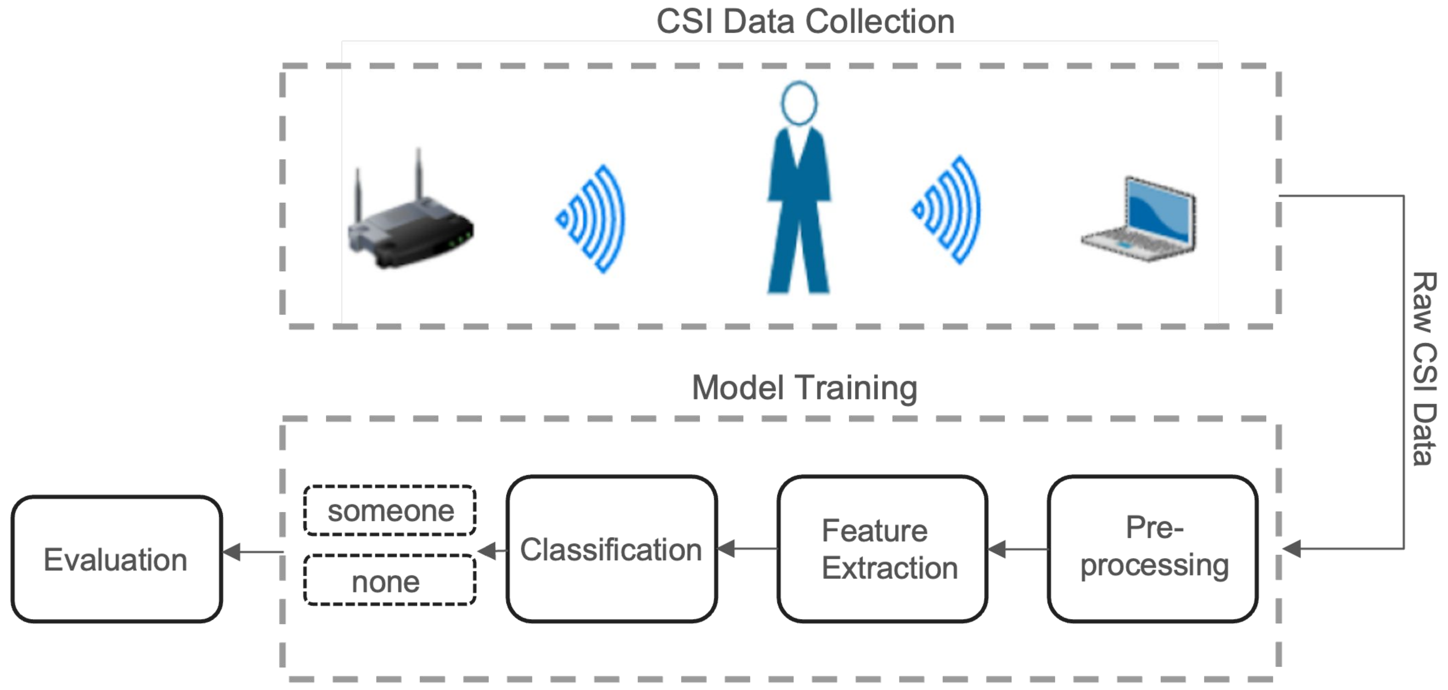
Wi-Fi Sensing with CSI Data

- Wi-Fi sensing using Channel State Information (CSI) is an innovative approach that leverages the characteristics of wireless signals to detect and analyze environmental changes
- CSI data provides detailed information about the physical layer of a wireless connection, capturing the state of the channel, including the amplitude and phase of the signal at each subcarrier
- This information allows for precise insights into the signal's propagation environment, enabling the detection of various activities and changes within a space

Objectives

- **Presence Detection:** Detect human presence in a home using commodity Wi-Fi CSI devices
- **Presence Localization:** Localize human presence, determining whether a person is near the access point (AP) or near the device
- **Generality:** Develop a solution that is generalizable to any RF environment, ensuring broad applicability and robustness across different settings



Data Collection

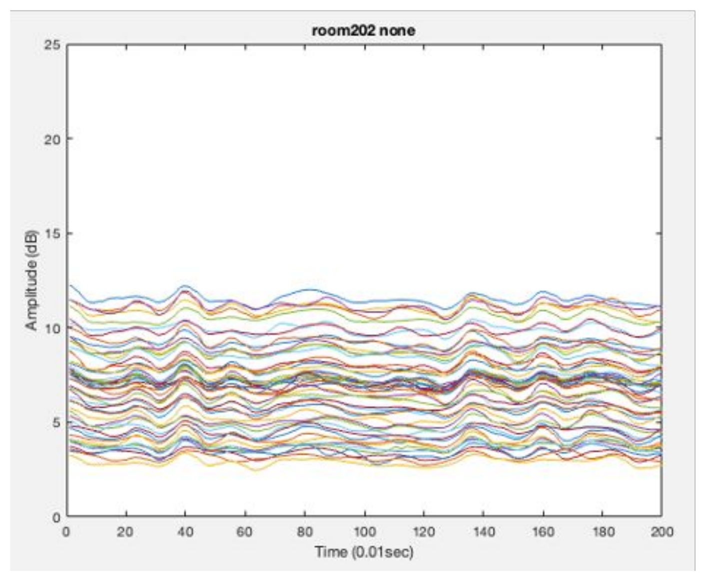
Devices Setup
- 2 ESP32-S3 chips (Tx and Rx), Espressif ESP CSI toolkit
- Bandwidth: 802.11n, 20 MHz
- Subcarriers: 52
- Send Frequency: 100 packets/second

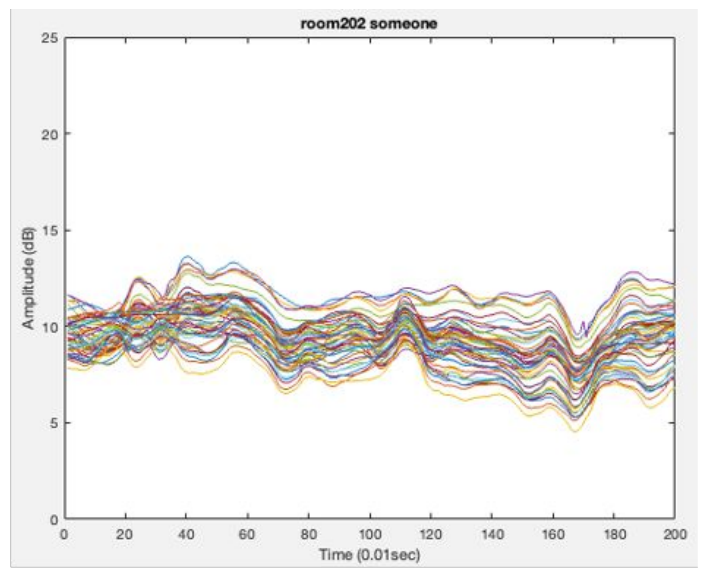
Room Selection (25 rooms total)
- 10 rooms (near AP/near device)
- 10 rooms(Positional Point: 0-1m, 1-2m, 2-3m, 3-4m)
- 5 rooms (random configurations for human presence)

Environments
- Study rooms, lab rooms, living rooms
- Data Classification
- No one present/Someone near transmitter/Someone near receiver

Presence Detection

- Apply a 3-level wavelet transform to CSI data to capture sharp transitions and intrinsic properties
- Utilize a Recurrent Neural Network (RNN) for home presence detection, configured with input dimensions of 200 and a hidden layer of 64 units
- Optimize the RNN model for analyzing time-variant CSI signals in a sequential manner, enabling effective extraction of temporal patterns
- Apply layer normalization to the final hidden state and map the processed temporal features to a binary outcome for presence detection via a fully connected layer

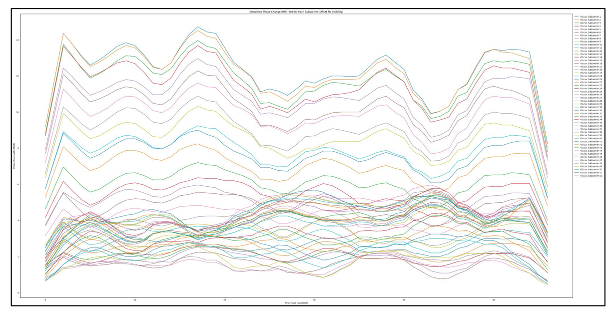


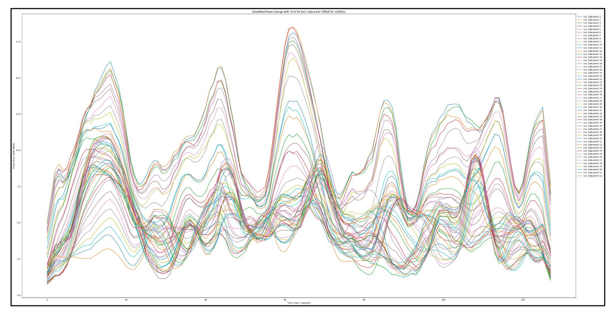


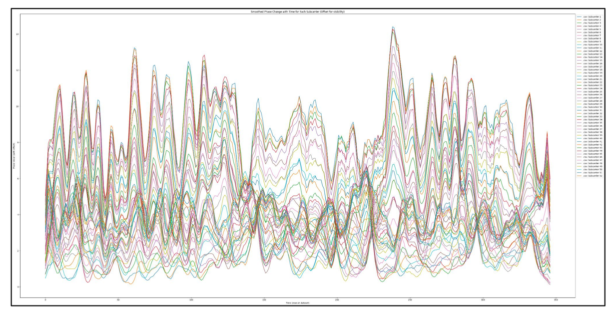
Presence Localization

Near AP - Near device localization
- Each room is a test set once (leave-one-room-out cross-validation) to ensure generalization. Data is reshaped and labeled.
- The model uses a pre-trained ResNet50 base with custom layers, trained for 20 epochs, batch size 16, Adam optimizer, and sparse categorical cross entropy loss. Learning rate adjustments are managed by a scheduler.
- Highest validation accuracy for each room is recorded, showing the model's ability to detect and localize human presence.

Positional Point Classification (Line of Sight)
- Localization from specific points to device distance ranges (0-1m, 1-2m, 2-3m, 3-4m)
- Utilized LSTM and RNN models trained on 1,896 samples and tested on 200 samples. Training set included samples from 9 rooms, while the test set focused on a single room

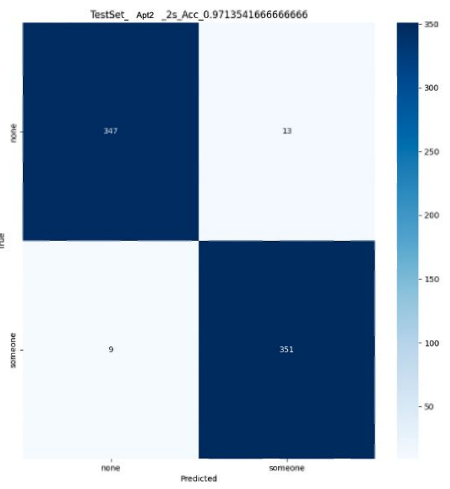

CSI Magnitude V. Subcarriers Plot for No Presence

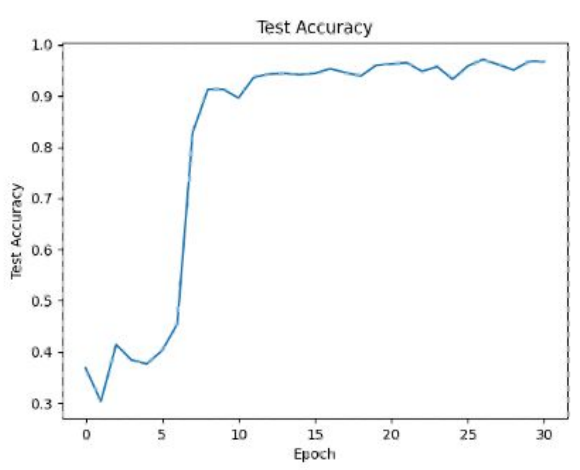

CSI Magnitude V. Subcarriers Plot for Presence near AP


CSI Magnitude V. Subcarriers Plot for Presence nead device

Results

Presence Detection
- Detect human presence in a home with >90 % True Positive rate with commodity WiFi CSI device

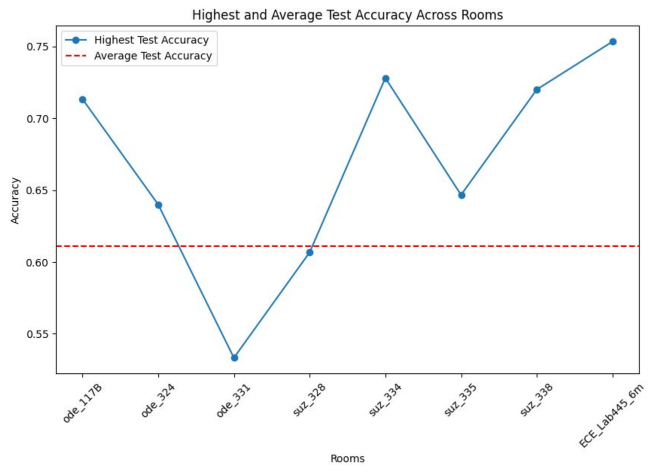


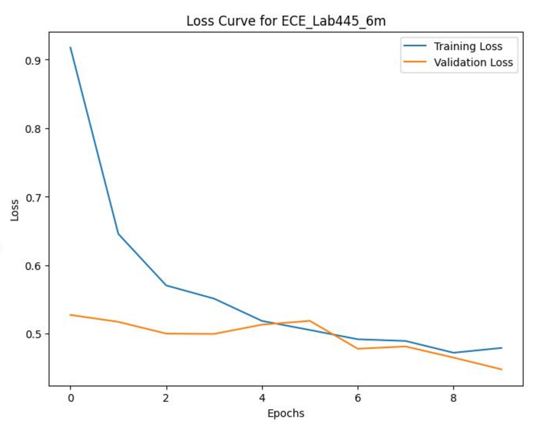


Test Set	Accuracy(%)
Apartment1	97.1
Apartment2	96.24
StudyRoom324	98.93
StudyRoom333	92.84

Presence Localization

Room	Accuracy (%)	True Positive Rate (%)
Suz_334	73	66
Lab445	75	78
Suz_338	72	61
Ode_117B	71	69





RNN Model Result For Positional Point

	precision	recall	f1-score	support
Class: 0-1	0.43	0.24	0.31	80
Class: 1-2	0.46	0.82	0.59	80
Class: 2-3	0.67	0.20	0.31	40
Class: 3-4	0.00	0.00	0.00	0

Limitations for Model Performance:
- Different collection methods and environmental factors can significantly impact dataset consistency
- Limited Data Size: Insufficient data collected from each environment

Challenges:
- Model Generalization Across Environments: Environmental diversity (e.g., room size, furniture, ambient noise) affects WiFi signal propagation

Future Work, References, and Acknowledgments

- Expanding Data Collection: gather data from a wider range of environments to improve model robustness.
- Enhanced Generalization: Explore the potential of transfer learning to improve model adaptability across different environments.

[1] Chen X. xyanchen/WiFiCSISensingBenchmark [Internet]. 2022. Available from: https://github.com/xyanchen/WiFiCSISensingBenchmark ?tab=MIT1ovfile
[2] Zhan Z. zhanchaocheng/ESPCSI [Internet]. 2023. Available from: https://github.com/espressif/espcsi

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