WiFi Sensing Midterm Presentation

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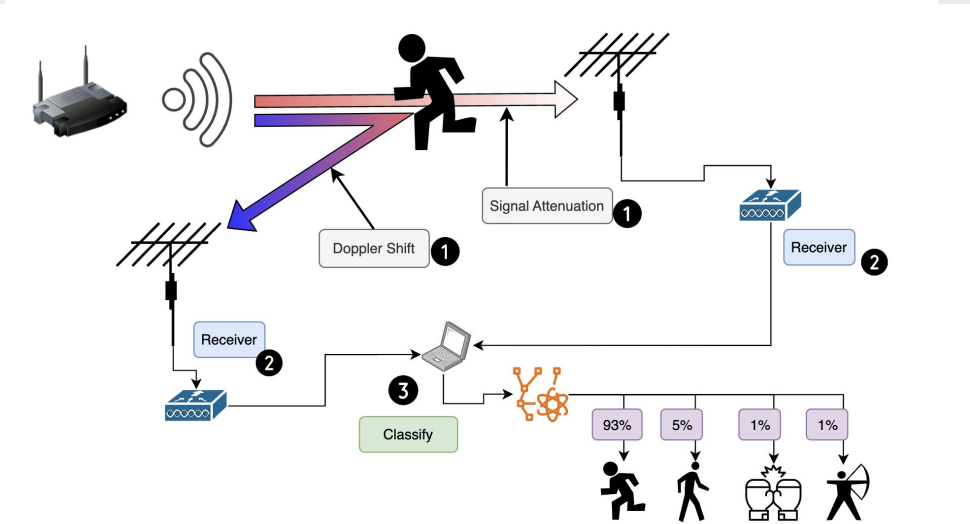
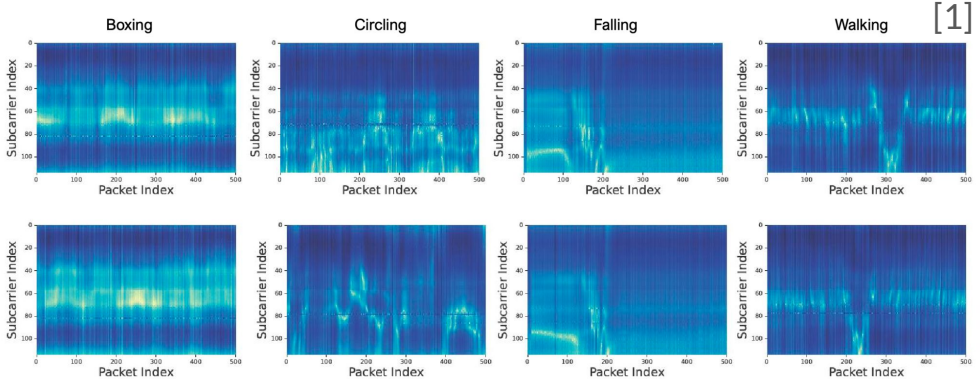
Background

- (1) Signal Propagates
- (2) Measure signal at some sampling rate
- (3) Process data and classify



[1]



[1] Yang, Jianfei, et al. "SenseFi: A library and benchmark on deep-learning-empowered WiFi human sensing." Patterns 4.3 (2023).

Motivation and Objectives

- We are exploring how the sampling rates will affect the performance of different WiFi Sensing applications/tasks
  - Across various datasets and models
- Being able to categorize and analyze different sampling rates over different datasets can help other researchers doing WiFi sensing
  - They would know what sampling rate they needed to collect their data and train their model at.
  - This would save them time and effort since collecting data can be a very time consuming process
- An categorical study on the effects of different sampling rates across different datasets (representing different activities) and models

Technical Approach and Novelty

- Currently, there is not one specific sampling rate that is claimed to be the best
  - Each research group uses what they consider the best in their case
  - This results in not having a standardized set to which new researchers can reference that would save them time and effort at the beginning of their research
- Our approach is to analyze and test different sampling rates on these datasets and using different models
  - The novelty of this approach is that there will now exist data on the effects of changing sampling rates
  - We will be able to show what sampling rate is ideal for certain activities and which models work best
- Additionally, if time permits, we will be exploring changing other parameters like subcarriers, bandwidth, etc.

Methods

- Algorithms currently being used include:
  - SenseFi [1]
  - SignFi [2]
- Datasets being used include:
  - NTU-Fi-HAR and NTU-Fi-HumanID
    - Developed by the SenseFi team
  - UT-HAR
    - S. Yousefi, H. Narui, S. Dayal, S. Ermon and S. Valaee, "A Survey on Behavior Recognition Using WiFi Channel State Information," in *IEEE Communications Magazine*
  - SignFi dataset
  - Widar
    - Zheng Yang, Yi Zhang, Guidong Zhang, Yue Zheng, December 26, 2020, "Widar 3.0: WiFi-based Activity Recognition Dataset", IEEE Dataport, doi: https://dx.doi.org/10.21227/7znf-qp86.
- Platform
  - Python
  - Matlab

[1]: Yang, Jianfei, et al. "SenseFi: A Library and Bench mark on Deep-Learning-Empowered WiFi Human Sensing." Patterns Journal 2023.
[2]: Ma, Yongsen, et al. "SignFi: Sign language recognition using WiFi." ACM IMWUT (2018).

Evaluation and Metrics

- The first thing we want to show is what happens to the model if we were to change the sampling rate
  - What happens to the accuracy?
  - Does it depend on the model used?
  - Does it depend on the dataset?
  - etc.
- We want to be able to categorize these details because many papers use different sampling rates to essentially do the same thing, identification over WiFi.

Current Status and Next Steps

- Have done control runs to replicate the results claimed in the several reference papers
- Have ran the following models across different datasets with different results and have seem some interesting results:
  - Multilayer Perceptron (MLP) model:
    - Datasets ran:
      - UT-HAR:
        - Downsampled from original 1 kHz to 5 Hz and saw about 2% decrease in accuracy
      - NTU-FI-HAR
        - Downsampled from original 500 Hz to 5 Hz and saw about 3% decrease in accuracy
      - NTU-FI-HumanID
        - Downsampled from original 500 Hz to 5 Hz and saw about 5% decrease in accuracy
      - Widar
        - Downsampled from original 1 kHz to 50Hz and saw about 50% decrease in accuracy
  - Convolutional Neural Network (CNN)
    - Datasets ran:
      - Signfi
        - Downsampled from original 200 Hz to 25 Hz and saw about 30% decrease in accuracy
- Next steps are to continue testing different models with these datasets and gather the results and analyze them