I ILLINOIS
Electrical & Computer Engineering
COLLEGE OF ENGINEERING

mmWave FMCW Radar-based Human Movement Classification from Micro-Doppler Signature & Multi-Object Signature Extraction

Edwin Pan (epan2), Jingning Tang (jtang10)

Introduction

The sensor suites needed for autonomous systems to function include varying assortments of sensing modalities. LiDAR and cameras are the go-to sensors. However, there are inherent issues with these sensors that make them unideal of some use-cases, and useless in other use-cases. Namely,

1. Camera based classification doesn't work well when FOV is dimly lit
2. Mechanical LiDAR systems are large and prone to mechanical wear-and-tear

Autonomous system safety could greatly improve if a different sensing modality could cover the areas where LiDAR and camera fails. Such a sensor should be able to:

1. Accurately classify common obstacles.
2. Separate objects that are close together in the sensor's FOV
3. Track objects as their move in the sensor's FOV

Our aim is to demonstrate that millimeter wave (mmwave) radars can cover these three areas. This classification problem is tackled using the mmwave radar micro-doppler (µDoppler) processing.

µDoppler Background

Radar is naturally sensitive to phase shift and therefore is superior in detecting the speed and micro-motion of the target. The micro-motion, commonly referred as the µdoppler signature of the target, can provide information that is useful for target classification.

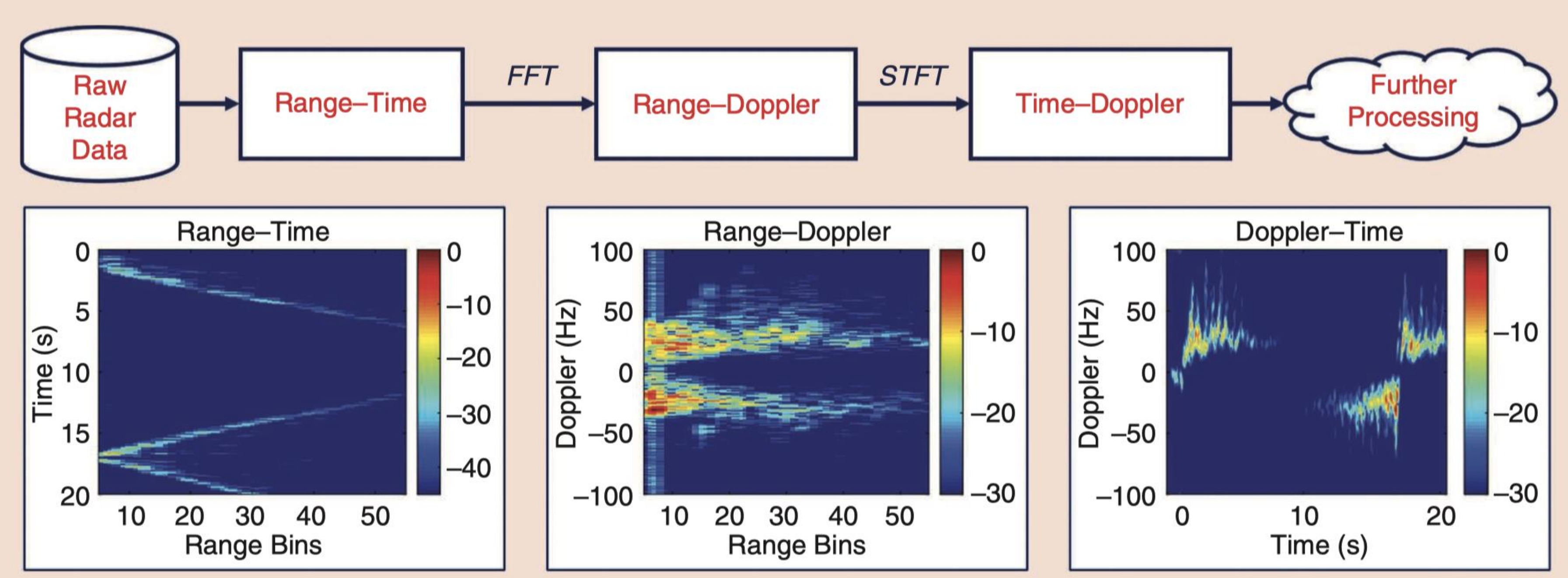


Figure 1: µdoppler signature extraction pipeline

When multiple objects are in the scene, their µDoppler signatures will overlap much like an audio spectrogram when two people are talking. This presents a problem when scans are taken in uncontrolled environments.

Most current literature deals with more than one objects by creating additional classes as the mixture of classes (e.g. pedestrian, bicyclist and pedestrian + bicyclist). However, n targets in the scene will require n different classes. This is impractical, especially for applications where individual target's signature is required. Therefore, we explored the feasibility of extracting multi-object µDoppler signature.

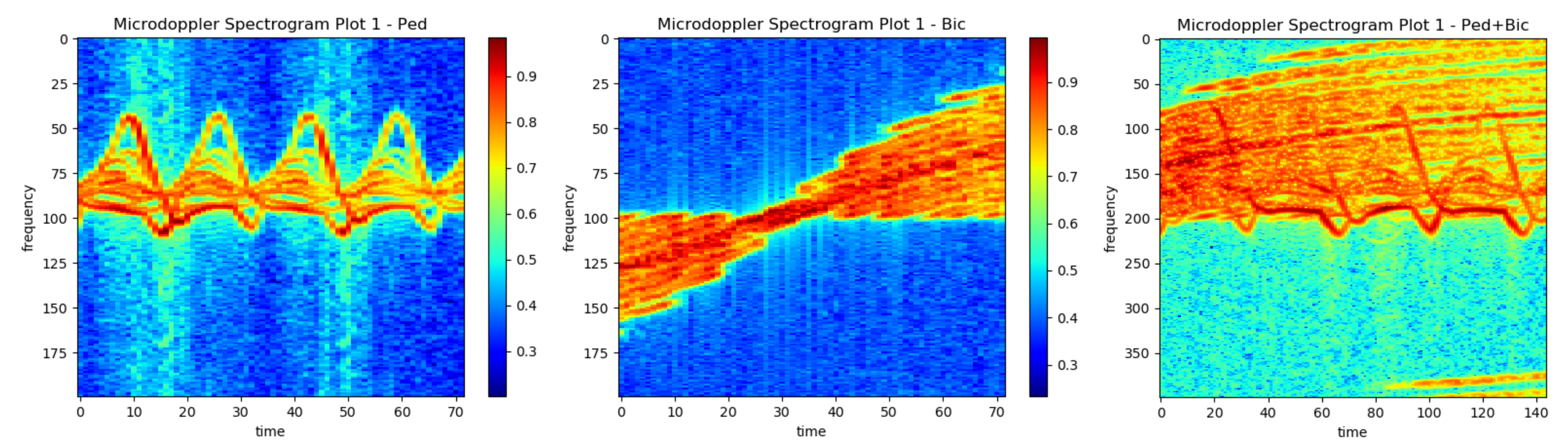


Figure 2: µdoppler sig., (1) One pedestrian, (2) One bicycle, (3) One pedestrian & one bicycle

Our Goal & Plan

In this project, we aim to show that accurate classification of targets is achievable with no prior assumptions on the location or number of targets in the radar FOV.

The processing stack can to thought of as two mutually exclusive tasks.
1. µDoppler signature extraction
2. µDoppler signature classification

We do this using the following processing stack.
1. Use the MIMO sensor arrays to determine angle of arrival from radar data cube (RDC)
2. Cluster detections using DBSCAN and CFAR
3. Track detected targets using Extended Kalman Filter (EKF) with constant acceleration
4. Stitch together µdoppler signatures from range-doppler plots for each tracked object
5. Classify tracked object as either pedestrian or bicycle.

Micro-Doppler Signature Extraction

1. Clustering-based extraction:

ADC Data → DSP → Clustering → Tracking

- Grid-Based DBSCAN
- Track objects to continuously extract µdoppler
  - Association between frames.
  - Kalman Filter on cluster center.

2. Clustering-free extraction:

ADC Data → DSP → CFAR → Tracking

- Kalman-Filter performs a "soft" clustering in data association
- CFAR may filter out part of the object.

µDoppler Signature Classification

The µDoppler classification problem is limited to discerning between pedestrians and bicycles; two common roadway obstacles that are hard to classify.

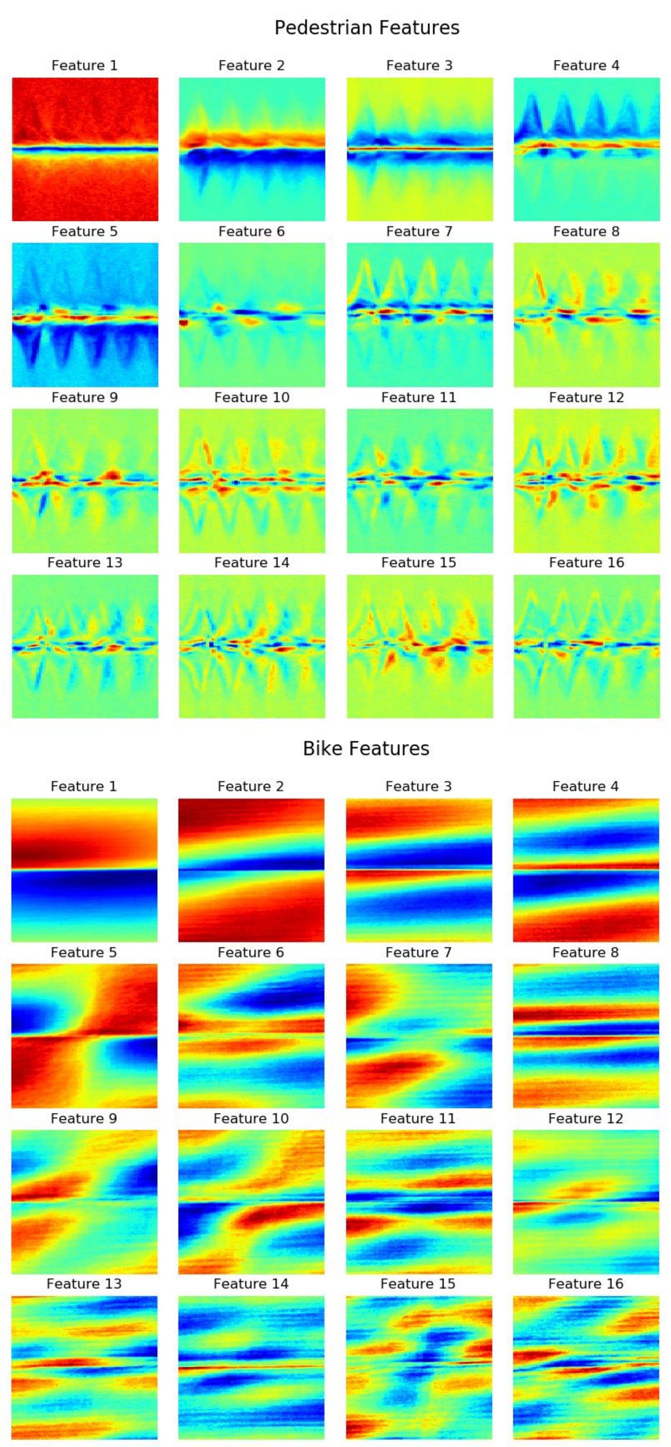
Classification is done assuming targets have been source separated. Additionally, we treat each spectrogram as an image, rather than a frequency varying time series. We can achieve excellent accuracy without considering temporal changes.

Two methods of image classification were used:
1. Gaussian Mixture Model (GMM)
2. Convolutional Neural Network (CNN)

The data used for training and testing was a mixture of single target scans taken using the Texas Instruments 1843 mmwave radar system, as well as simulated data using the Phased Array System Toolbox.

Dataset: 5000 data samples. 1:4 training vs. testing, 1:1 pedestrian vs bicycle

Images were down sampled using running average to decimation to allow moderate anti-aliasing.



µDoppler Classification Results

Classification Method	Hidden Test Set Accuracy
Gaussian Mixture Model	95.215%
Convolutional Neural Net	

Reference

1. *Pedestrian and Bicyclist Classification Using Deep Learning - MATLAB & Simulink.* [Online]. Available: https://www.mathworks.com/help/phased/examples/pedestrian-and-bicyclist-classification-using-deep-learning.html.
2. M. O. Padar, A. E. Ertan and Ç. ğ. Candan, "Classification of human motion using radar micro-Doppler signatures with hidden Markov models," *2016 IEEE Radar Conference (RadarConf)*, Philadelphia, PA, 2016, pp. 1-6. doi: 10.1109/RADAR.2016.7485201
3. T. Wagner, R. Feger and A. Stelzer, "Radar Signal Processing for Jointly Estimating Tracks and Micro-Doppler Signatures," in *IEEE Access*, vol. 5, pp. 1220-1238, 2017. doi: 10.1109/ACCESS.2017.2667720
4. D. Kellner, J. Klappstein and K. Dietmayer, "Grid-based DBSCAN for clustering extended objects in radar data," *2012 IEEE Intelligent Vehicles Symposium*, Alcala de Henares, 2012, pp. 365-370. doi: 10.1109/IVS.2012.6232167

CS 598: Machine Learning for Signal Processing

Contact Information
Edwin Pan, epan2@Illinois.edu
Jingning Tang, jtang10@illinois.edu