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RSSI Based Uncooperative Direction Finding

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Outline

- Problem Definition
- Applications
- Data Collection
  - Software Defined radio
  - Direction Antenna
- Feature Engineering
- Feature Selection
- Algorithms & Results

Why Machine Learning with SDR (RF)

- ML and RF: very little communication
- ML and RF: sometimes misunderstanding persists
- SDRs can produce lots of data
- Machine Learning needs lots of data
- We hope to start building the bridge

Direction Finding: Problem

Direction Finding

Using single receiver find the direction of one or more transmitters

- Both directional and omni-directional transmitters
- Transmitters must be at different frequencies
- Several hardware solutions exist
- Generally very expensive ($100,000 & above)

Direction Finding: Applications

- Studied from the time of first World War
- Lots of military applications
  1. Finding beacons
  2. Finding lost soldiers
  3. Finding enemy transmitters
- Lots of civilian applications
  1. Rescue at sea
  2. Tracking stolen cars
- Hardware based solutions (Mostly EE principles)

Our Setup

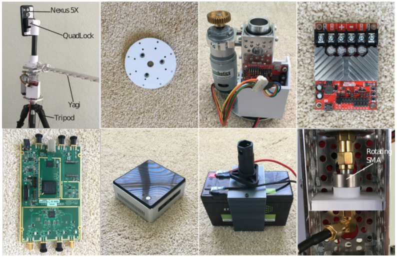

Figure 1: Equipment Setup

Direction Finding

Can we solve this problem using Machine Learning Techniques ?

- Single transmitter
- Directional & Omni-directional
- Transmission @ 2.4 GHz
- Single rotating directional receiver

Our Setup

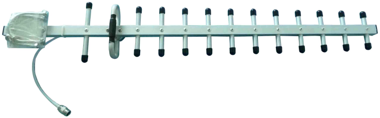

Figure 2: WiFi Yagi Antenna

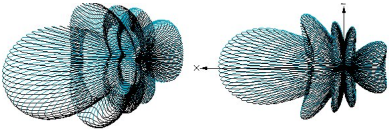

Figure 3: Antenna Characterization for Yagi Antenna

- Left: Actual 3D pattern
- Right: 2 D pattern
- Assumes no multi-path
- Looks Nice !

Sample Data

Rotations

Tuples: (angle,power) for each rotation

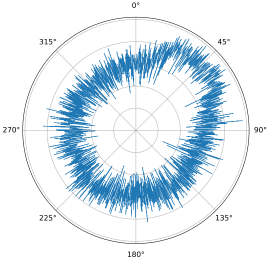

Figure 4: Data Collected Indoors

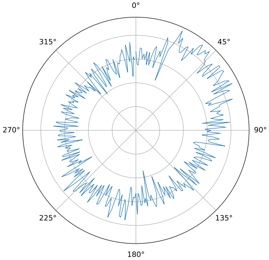

Figure 5: Normalized Data for 360 points

Sample Data

Rotations

Tuples: Average 2200 tuples per rotation

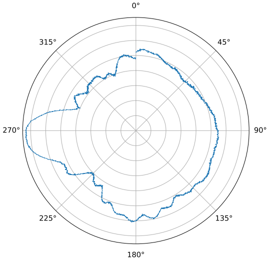

Figure 6: Data Collected Indoors

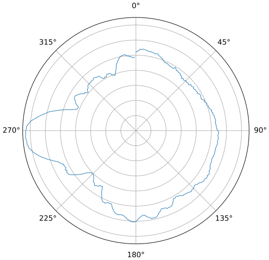

Figure 7: Normalized Data for 360 points

Sample Data

Rotations

Tuples: Normalized to 360 data points per rotation

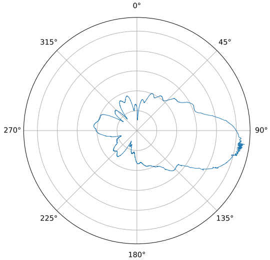

Figure 8: Data Collected Outdoors

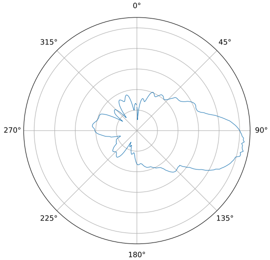

Figure 9: Normalized Data for 360 points

Data Collection

- Omni-/Directional transmitter & receiver
- Initialize receiver to fixed orientation ($\theta = 0$)
- Start rotation using motor and rotate fixed number of times
- Record RSSI values corresponding to motor "ticks"
- Reset angle to 0 after full rotation
  - Angles computed using motor encoder
  - Encoder "slips" over a run (many rotations)
  - Need to correct for "slip" before getting rotations

Orientation

We use the magnetic North as the fixed orientation of the Yagi

System Design

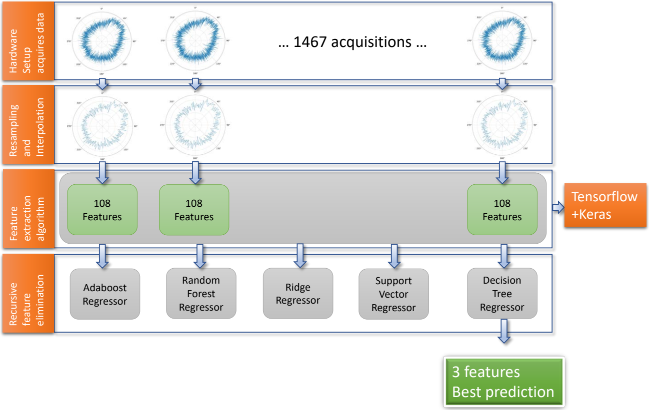

Figure 10: Direction Finding System Architecture

GNU Radio Flowgraph

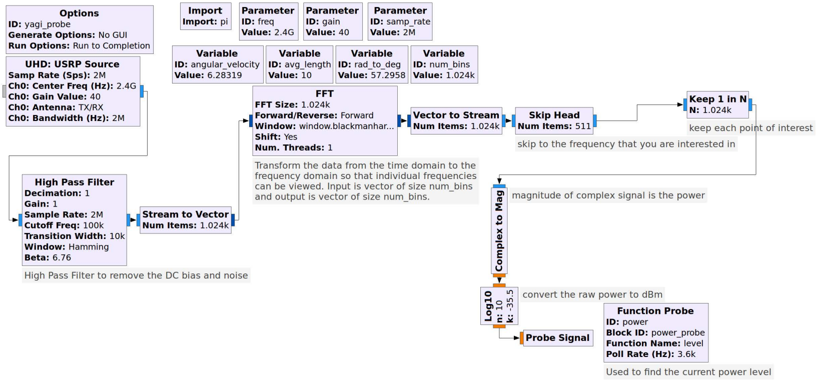

Figure 11: GNU Radio Flowgraph for Data Collection

Max RSSI

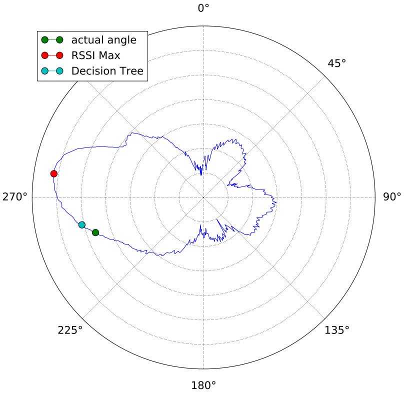

Figure 12: Failure with Max RSSI

Feature Engineering

Intuition

Rotations can be treated as time series data

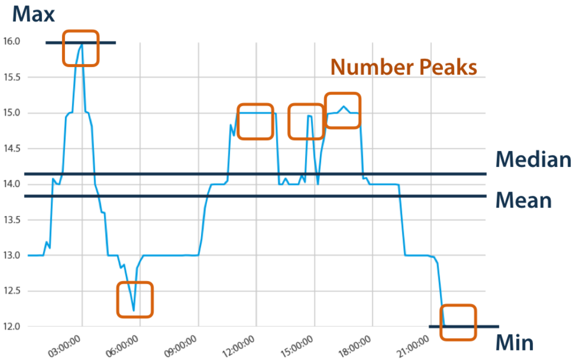

Figure 13: Example: time series features

Feature Engineering

Moving Average Max Value (MAMV)

Index (angle) at which max RSSI is obtained after applying *Moving Average Filter*

Moving Average

Moving Average Filter at index i with a window of d is defined as:

$$MA(i, d) = \frac{\sum_{j=i-d}^{i+d} RSSI(j)}{2d + 1}$$

- Total 86 features for time series features
- Total 22 features for MAMV; ($d = 3, 5, \ldots, 45$)

Algorithms

Regression Problem

As *bearing* of transmitter is a *continuous variable* we use *regression*

- Support Vector Regression with ϵ-insensitive loss function
- Kernel Ridge Regression with squared loss
- Decision Tree regression
- ADA Boost with Decision Tree

Feature Selection

Intuition

Total 108 features. Not all may be important.

	SVR	KRR	DT	AB
Avg. Error	26.4°	55.2°	16.2°	22.1°

Table 1: Errors with all features, random 50-50 test/train split

- Feature Selection through pruning using ranking function
- Feature selection through *Recursive Feature Extraction and Cross Validation* (RFECV)

Feature Ranking Profile

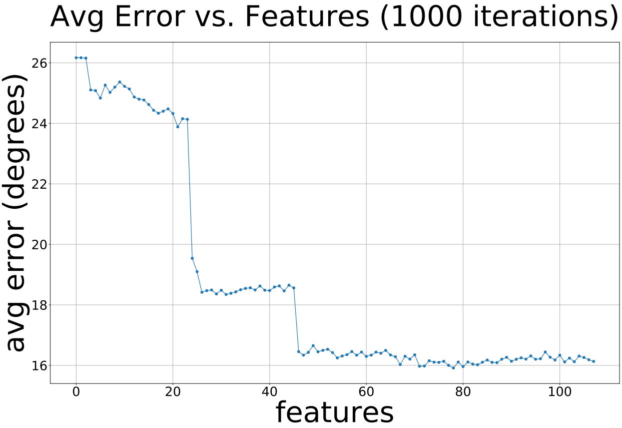

Figure 14: Feature Profile for Ranking Based Selection

Feature Selection

- Use MAMV-41, selected as best feature by ranking for prediction
- Use MAMV-41 with Decision Tree Regression
- Use "feature profile" from ranking (78 features) with Decision Tree Regression
- Use RFECV features (only selects 3 features MAMV-23, MAMV-41 and second co-efficient of Welch's Transform) with Decision Tree Regression
- Neural net (NN) was used with all features and four layers

	MAMV-41	MAMV-41 (DT)	Rank	RFECV	NN
Avg. MAE	$\pm 57.1°$	$\pm 25.9°$	$\pm 15.7°$	$\pm 11.0°$	$\pm 15.7°$

Thank You