Space-based ML Tracking and Identification in Nanosatellite Clusters with Low-Cost Radar

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List of Acronyms

RADAR ***Ra***dio ***D***etection ***A***nd ***R***anging.

List of Symbols

ΔR	Range Resolution
λ	Wavelength
σ_S	Radar Cross Section
B	Bandwidth of a Pulse
c	Speed of Light
E	Energy
f	Frequency
f_{re}	Reflected Frequency
f_{tx}	Transmitted Frequency
G	Antenna Gain
P	Power
P_r	Receive Power
P_t	Transmit Power
R	Distance
r	Range
t	Time
v_{target}	Target Velocity

1 Methodology

1.1 FMCW Dataset

1.1.1 Hardware Configuration

This study utilized the Analog Devices CN0566 Phased Array Development Platform for radar data acquisition. The platform incorporated an EVAL-CN0566-RPIZ board integrated with a Raspberry Pi 4 for input/output control and an ADALM-Pluto Software Defined Radio for analog-to-digital conversion. The radar hardware comprised an ADL8107 Low Noise Amplifier (6-18 GHz, 1.3 dB NF, 24 dB gain), an ADAR1000 beamformer (8-16 GHz, 4-channel, 360° phase adjustment with 2.8° resolution), and an LTC5548 mixer configured for 2.2 GHz output. The system operated at a center frequency of 550 MHz with the output frequency established at 10 GHz.

To optimize radar beam formation, a Blackman taper configuration was implemented with gain values [8, 34, 84, 127, 127, 84, 34, 8] across the array elements. This configuration provided enhanced sidelobe suppression while maintaining appropriate main beam width for target detection applications.

1.1.2 FMCW Configuration and Chirp Synchronization

The radar system was configured to operate in Frequency Modulated Continuous Wave (FMCW) mode with chirp synchronization. A sample rate of 522 kHz and chirp bandwidth of 1000 MHz were selected, providing a theoretical range resolution of 15 cm according to:

$$\Delta R = \frac{c}{2B} \tag{1}$$

where ΔR is range resolution, c is the speed of light, and B is bandwidth.

Chirp synchronization was implemented using the Pluto TDD (Time Division Duplex) engine to mitigate non-linearities typically present at the beginning and end of each frequency chirp. This technique synchronized data acquisition to capture only the linear portion of the transmitted waveform. The ramp time was established at 450 μs with the initial 10% of each chirp discarded to ensure data quality.

1.1.3 Data Collection Procedure

Data collection was conducted using a modified version of Jon Kraft's CFAR Radar Waterfall Chirp Sync Python script. For each acquisition, carboard boxes covered in aluminum foil of various dimensions (approximately $X \times Y \times Z$ cm, $X \times Y \times Z$ cm, $X \times Y \times Z$ cm, and $X \times Y \times Z$ cm) were positioned from the radar within predetermined range bins at three different positions. The three positions were the front, middle, and back of the respective range bin. Each range bin spanned 15 cm, corresponding to the radar's range resolution, with 15 cm separation between consecutive bins. The range bins were positioned at 0.37-0.52 m, 0.67-0.82 m, 0.97-1.12 m, 1.27-1.42 m, and 1.57-1.72 m from the radar apparatus.

The data collection protocol followed a systematic procedure:

1. Position one box at a specific location within a range bin (front, middle, or back)
2. Execute the data collection program
3. Monitor collection until program displayed "Image [n] samples gathered" notification
4. Rotate the box approximately 15° to capture different radar reflections

5. Repeat the procedure until 25 samples were collected per box at each position and the program auto shut down

This methodical approach ensured comprehensive representation of different object orientations and positions within each range bin. Additionally, data for an "empty" class with no objects present was collected to establish baseline ambient conditions.

1.1.4 Dataset Construction

The collection procedure generated a structured dataset which comprised of 6 classes (5 range bins plus 1 empty bin), 300 samples per class (25 samples $\times$ 4 boxes $\times$ 3 positions), and a total dataset size of 1,800 samples.

Each sample was preserved in two formats. The first was a CSV containing time, frequency values, magnitude measurements, and calculated range estimates. The second was processed spectrograms of 56×56 pixel resolution utilizing a Viridis colormap.

The CSV data captured the time-frequency representation of radar returns with thousands of data points per sample. The spectrograms visualized this time-frequency data, providing distinct electromagnetic signatures for objects at different distances. Each image was labeled using a standardized nomenclature containing acquisition timestamp, true distance (measured physically), calculated distance (determined through signal processing), range bin classification, and image sequence identifier.

The dataset was organized hierarchically with range bins as primary classification criteria and separate subdirectories for raw data and processed spectrograms. This organization facilitated subsequent machine learning investigations for range estimation and object detection applications.

1.1.5 ML Magic

Andrew did magic and made the computer understand the pictures

References

Appendix

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