Sensing the world using EM signals: using radar for Pedestrian and E-Scooter Detection and Classification

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Dear Professor Bialkowski,

In accordance with the requirements of the Master of Engineering (Electrical) in the School of Electrical Engineering and Computer Science, I submit the following thesis entitled

"Using mmWave Radar for Pedestrian and E-Scooter Detection and Classification."

The thesis was performed under the supervision of Dr Konstanty Bialkowski. I declare that the work submitted in the thesis is my own, except as acknowledged in the text and footnotes, and that it has not previously been submitted for a degree at the University of Queensland or any other institution.

Yours sincerely,

Haowen Jiang

Declaration by Author

This thesis is composed of my original work, and contains no material previously published, written by another person, or generated by artificial intelligence (AI), except where clearly referenced and acknowledged either in the main text or the preliminary pages of this thesis. I have clearly stated the contribution of others to jointly authored works that I have included in my thesis.

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Acknowledgments

Abstract

Small-wheeled e-scooters are popular on campuses but their design (small wheels, narrow platform, and forward centre of gravity) reduces stability and control, and throttle-initiated acceleration can be sudden, increasing collision risk with pedestrians[1]. Camera-based measures are also limited at night or in bad weather and raise privacy concerns[2]. This thesis proposes a millimetre-wave (mmWave) radar monitoring system that detects and classifies pedestrians and e-scooters in real time. Unlike cameras, mmWave radars work in bright light, darkness or fog and offer better range resolution. They measure only movement and position, so they help protect privacy.

The research starts with a review of radar-based road-user detection and explains why mmWave sensors are suitable for micro-mobility monitoring[3]. A prototype using a TI AWR1843 radar was built to collect data and process point clouds. Signal processing involved range and Doppler Fourier transforms and a constant false-alarm rate (CFAR) detector to extract moving targets. To remove static clutter, sliding-window and statistical models were compared. Point clouds were clustered using DBSCAN, and simple features such as speed and height were used to classify e-scooters and pedestrians. Early experiments show that the system can detect moving objects and estimate speeds; an e-scooter is flagged as dangerous if its speed exceeds 5.5 m/s. Future work will include micro-Doppler analysis, machine-learning classifiers and multi-target tracking to improve accuracy[4].

Contents

1. Introduction

Micro-mobility devices have become common in urban areas and university campuses. Electric scooters are convenient and low-carbon, but small wheel size, narrow deck and a higher/forward CoG reduce stability; throttle-based acceleration can be abrupt.When travelling on bicycle infrastructure, e-scooter speeds are comparable to conventional cyclists, which elevates conflict risk. Traditional measures such as signs or cameras are limited; cameras depend on lighting and may invade privacy[3]. Therefore there is a need for a privacy-preserving system that can detect and classify moving people and scooters and give early warnings[5].

Millimetre-wave radar offers several advantages. These sensors send frequency-modulated continuous-wave (FMCW) signals and receive echoes to estimate range, speed and angle. Because mmWave radars operate at high frequencies (24–77 GHz), they can resolve objects with centimetre accuracy. They work in bright light, darkness or bad weather and have good range and velocity accuracy with better penetration through rain or fog[6]. Unlike cameras, mmWave radars only measure movement and position instead of capturing images, helping to protect people's privacy.

This thesis aims to develop and evaluate a radar-based system that (1) detects and classifies pedestrians and e-scooters in real time, (2) analyses micro-Doppler signatures to recognise behaviours such as walking, running or riding, and (3) tracks multiple targets simultaneously. The work presented here focuses on the first stage of the project: building the data acquisition platform, processing radar point clouds, performing target detection and implementing preliminary classification based on physical features.

2. Literature Review

2.1 Active and Passive Radar Approaches

Radar sensing has long been used in automotive safety to detect obstacles and vulnerable road users. Active mmWave radars send chirps and measure reflections, giving range, speed and angle information even in bad light or weather[7]. Modern vehicles use 77 GHz FMCW radars to detect pedestrians and cyclists, showing the maturity of this technology[7]. By contrast, passive radars use ambient signals such as Wi-Fi. They can detect motion but suffer from lower signal quality and complex processing; passive systems have not been tested for e-scooter detection. Because of their higher resolution, this project adopts the active radar approach.

2.2 Pedestrian and Micro-Mobility Detection

Stationary radars at intersections have been used to monitor pedestrians and vehicles, providing real-time traffic information with little infrastructur. These studies emphasise radar’s robustness across different lighting and weather conditions. Micro-mobility detection mainly uses cameras, but visual algorithms may confuse e-scooters with pedestrians because they look similar[4]. This highlights the value of radar, which measures motion features that differ between riders and walkers.

2.3 Radar Classification of Vulnerable Road Users

Recent work has used mmWave radar to classify moving objects based on micro-Doppler signatures. Research shows that 77 GHz radar can distinguish pedestrians from cyclists by analysing frequency patterns from limb movement and wheel rotation[3]. These signatures are consistent across different heights and viewing angles, suggesting that they may also work for e-scooters. However, most previous studies were carried out on test tracks with single targets. Combining classification with real-time multi-target tracking remains an open problem.

2.4 Radar Principles

mmWave radars transmit FMCW chirps and measure the beat frequency between transmitted and received signals. The beat frequency encodes range, and phase differences across antennas encode angle. Because mmWave radars operate at 24–77 GHz, they achieve centimetre-level resolution. In this project, a TI AWR1843 sensor with three transmit and four receive antennas is used. It offers up to 4 GHz of bandwidth and includes digital signal processing and FFT accelerators on-chip.

Compared with cameras, mmWave radars are insensitive to lighting and weather and maintain privacy by measuring only distance and motion. According to TI application briefs, mmWave sensors suit e-bike and scooter safety because they penetrate fog and dust, reject static clutter and support long-range blind-spot detection[8].

2.5 Micro-Doppler Signatures

Beyond basic range and speed, radar returns show subtle frequency variations called micro-Doppler. These arise from internal movements such as arm or leg swings or wheel rotation. A pedestrian shows micro-Doppler patterns from swinging limbs, while an e-scooter rider's signature is dominated by wheel rotation and a relatively still torso. Research has shown that micro-Doppler signatures can differentiate between pedestrians and bicycles and that they vary with radar height[7]. This thesis does not yet use micro-Doppler classification but recognizing its potential guides future work.

3. Theory

4. Methodology

4.1 System Design and Data Collection

The experimental setup uses a TI AWR1843 mmWave radar mounted about 1.5 m above the ground at the edge of a campus walkway. The sensor's field of view covers roughly 120° and can monitor pedestrians and e-scooters approaching from both directions. Initial tests used the TI mmWave Demo Visualizer to configure the radar and view point clouds. To automate data collection, Python scripts connect to the radar via serial ports, send configuration files (.cfg) and stream the time-division multiplexed (TDM) radar data[9].

Data recorded in .dat format are converted to .csv using custom parsers. Early experiments found that many points in the exported .csv shared the same time stamp, preventing proper frame separation. By examining the detIdx (detection index) field—reset to zero at each frame—the frames are correctly segmented. This procedure lets the radar point clouds be replayed smoothly and synchronised with visualisation[9].

4.2 Signal Processing and Detection

Raw ADC samples undergo standard FMCW processing. Range FFTs convert the time-domain chirps into range bins, and Doppler FFTs compute speeds. A constant false-alarm rate (CFAR) detector identifies peaks corresponding to moving objects. Two CFAR variants—sliding-window averaging and statistical-model based—were implemented and compared. To suppress static clutter, background subtraction is performed using a sliding window of previous frames. Detections are represented as three-dimensional points with coordinates, radial velocity and radar cross-section (RCS) intensity.

4.3 Clustering and Preliminary Classification

CFAR outputs hundreds of points per frame. A DBSCAN algorithm groups points into clusters representing physical objects. The clustering parameters—epsilon (ε) and minimum number of points—were chosen empirically. For pedestrians, ε=0.5 m and at least three points yield stable clusters; e-scooters require slightly larger values due to their length. Cluster speed is computed from the mean absolute radial velocity. Objects with heights below 0.5 m and speeds above 3.5 m/s are classified as e-scooters; those with slower speeds and taller heights are considered pedestrians. These simple rules give preliminary classification without machine learning.

To recognise behaviours, the system logs cluster bounding boxes and velocity time series. Overspeed thresholds are set—3.5 m/s for pedestrians and 5.5 m/s for e-scooters. Clusters exceeding these limits are labelled “dangerous scooters.” When no cluster meets the criteria, the system displays “no target detected.” Micro-Doppler spectra will be extracted in future to distinguish walking, running and riding.

4.4 Software and Visualisation Platform

The data acquisition and processing pipeline is written in Python using libraries such as NumPy, PySerial and Open3D. A PyQt graphical user interface shows real-time point clouds and bounding boxes. A timer updates frames based on the reconstructed timeline, ensuring smooth playback. The interface supports recording and replaying data for offline analysis. To achieve real-time performance, this project will offload FFT and clustering to a GPU; prior work shows GPUs significantly speed up radar preprocessing and FFT to real-time, though CPU-side post-processing can become a bottleneck[10], [11].

5. Preliminary Results and Discussion

5.1 Data Acquisition and Parsing

Over several months, multiple data sets were collected. Early sessions focused on connecting the sensor, analysing configuration files and verifying theoretical range and velocity resolutions. Once the scripts were stable, recordings were made in indoor corridors and outdoor pathways. A key lesson was that parsing .dat files depends on radar configuration. The parser was generalised to read chirp parameters from the .cfg file and decode the data stream. Frame reconstruction using the detIdx field allowed correct separation of frames and smooth playback. Without this correction, frames would overlay at the first time stamp and the animation would not show movement.

5.2 Clustering and Speed Estimation

Point cloud clustering using DBSCAN grouped detections into distinct objects. Parameter sweeps showed that $\varepsilon \approx 0.55$ m and min_samples=3 balanced sensitivity and noise rejection. Clusters were tracked over time by correlating their centres and velocities. When a cluster disappeared for a few frames (e.g., due to occlusion), its trajectory was extrapolated using a constant-velocity model. In recordings of pedestrians walking along the footpath, speeds ranged between 0.5–2 m/s, consistent with typical campus walking/running envelopes reported in transport-safety syntheses[12]. Slow walkers (<0.3 m/s) sometimes failed to form clusters and were classed as static or noise.

For e-scooter recordings, DBSCAN parameters were adapted to account for the scooter's longer footprint. Clusters showed average speeds from 4–7 m/s, with some runs reaching 9 m/s. When speed exceeded 5.5 m/s, the system flagged a "fast scooter" event and coloured the bounding box red. These preliminary tests demonstrate that the system can identify dangerous riding without false alarms.

However, relying only on speed and height can misclassify joggers as scooters when they run faster than 4 m/s. Integrating micro-Doppler features and deep-learning classifiers is therefore important for improved accuracy[13].

5.3 Challenges and Lessons Learned

Several issues emerged during the project. First, the mmWave sensor produces large amounts of data, and managing the serial stream requires careful buffer sizes and parity settings. Any mismatch can result in blank .csv files. Second, clustering performance depends on point density; sparse point clouds at long range reduce DBSCAN reliability[14]. Third, the low frame rate of the radar configuration (1–2 fps) makes it hard to capture high-speed scooters. Increasing frame rate or combining multiple sensors may help. Finally, the current classification uses hand-crafted thresholds; a machine-learning model trained on labelled data should generalise better to different situations.

5.4 Conclusion and Future Work

This thesis reports the initial stages of developing an mmWave radar system for real-time detection and classification of pedestrians and electric scooters. The review of existing work notes the limits of camera-based monitoring and the benefits of active mmWave radar. A prototype using a TI AWR1843 sensor was built, and a complete processing pipeline was developed. Key contributions include: (1) generalising the data parser to support different radar settings; (2) reconstructing frame timelines using the detIdx field; (3) implementing CFAR detection and DBSCAN clustering; and (4) creating simple rules for preliminary classification and speed warnings. Early experiments show that the system can detect moving targets and estimate their speeds, but they also highlight challenges such as sparse point clouds and low frame rates[15].

Future work will integrate micro-Doppler feature extraction and machine-learning classifiers to better distinguish pedestrians, joggers and scooters. GPU acceleration will be explored to achieve real-time processing, and multi-target tracking algorithms will be implemented to maintain object identities. Field tests on campus will evaluate system performance under varying conditions and refine detection rules. The ultimate goal is to deploy an intelligent, privacy-preserving monitoring system that improves campus safety by providing timely alerts and data for risk assessment[16].

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