

Enhancing Radar-Based Pedestrian Detection with Artificial Intelligence for Multipath Mitigation

Ingo Hoyer¹, Sebastian Böller¹, Karsten Seidl^{1,2}

¹*Fraunhofer IMS, 47057 Duisburg, Germany*

²*Department of Electronic Components and Circuits, University of Duisburg-Essen*

Abstract

Pedestrian safety in automated road traffic requires detection systems that function under complex environmental conditions. Camera-based systems may fail in fog, darkness, or occlusion, making radar an attractive alternative. This work investigates passive radar transponders integrated into pedestrian clothing or footwear, detected by a vehicle-mounted radar, to enable robust pedestrian localization. A key challenge is multipath propagation, which distorts the backscattered signal and degrades distance and angle estimation accuracy. To address this, an AI-based approach is proposed: a convolutional neural network (CNN) for distance estimation and a fully connected feedforward neural network (FC-FNN) for angle estimation. Both models are trained and evaluated on synthetically generated radar datasets covering distances up to 10 m and angles up to 90°, with scenarios ranging from a single reflection up to 50 multipath reflections, including a realistic case with a random number of reflections and added noise at 23 dB SNR. The AI-based approach is benchmarked against conventional signal processing algorithms. In the scenario with random number of reflections, distance and noise, the proposed models achieve a mean absolute error (MAE) of 0.29 m for distance and 7.50° for angle estimation, compared to 0.40 m and 8.19° for the conventional method—improvements of approximately 28 % and 9 %, respectively. In most tested multipath conditions, the AI-based approach outperforms the conventional baseline. Future work will focus on real radar measurement validation, hyperparameter optimization, and extension to higher distances and moving objects.

Keywords: Radar, AI, Multipath Mitigation, Signal Processing, Pedestrian Detection.

Introduction

In a future with fully automated road traffic, protecting pedestrians is crucial, as they are the most vulnerable traffic participants. Today, low visibility increases the risk of pedestrians being involved in a crash [1]. Detection and localization systems must therefore operate reliably under all weather and visibility conditions, including scenarios in which conventional camera-based artificial intelligence (AI) systems may fail due to fog, darkness, or optical obstructions. Radar is an attractive technology in this context because its sensing capabilities remain robust even under challenging environmental influences. A promising approach to enhance pedestrian safety involves integrating passive radar transponders based on [2] into clothing or shoes. These transponders can be detected by a vehicle-mounted radar and enable the reliable localization of pedestrians even in visually occluded situations, thereby supporting timely

identification of potentially dangerous events and improving overall traffic safety.

The transponder receives energy via an electromagnetic transmission link from the vehicle and returns a modulated backscatter signal. While clutter originating from static background reflections can largely be suppressed due to this modulation [2], multipath propagation remains a major challenge, as reflections from the environment may distort the backscattered signal and thereby reduce the accuracy of distance and angle estimation. AI techniques have recently shown promising results in radar signal processing tasks [3].

AI-based Approach

To address this challenge, in this paper the use of AI techniques to improve estimation robustness under multipath conditions is investigated. A convolutional neural network (CNN) is employed for distance estimation, whereas a fully connected feedforward neural

network (FC-FNN) is implemented for angle estimation. The two-stage pipeline architecture—CNN followed by FC-FNN—reflects the inherent structure of the estimation problem. Distance estimation requires extracting spectral peak information from high-dimensional FFT data containing hundreds of frequency bins, which motivates the use of convolutional layers for automatic feature extraction and dimensionality reduction. Angle estimation, in contrast, relies primarily on the phase relationship between the two antenna channels at a single spectral location, yielding a low-dimensional input for which a small fully connected network is sufficient. By conditioning the angle estimator on the predicted distance rather than the ground truth, the full pipeline can be deployed end-to-end at inference time without requiring prior knowledge of the target range. This design also means that errors in the distance estimate propagate into the angle estimation. However, the results in Tab. 1 demonstrate that the CNN achieves sufficient distance accuracy for the subsequent angle estimation to remain effective.

As proof of concept, a dataset with only one reflection is generated first. Synthetic radar signals for two receiving antennas are computed using a mathematical model implemented in a Python script, covering distances up to 10 m and angles up to 90°. The dataset is split into 80 % for training, 10 % for validation, and 10 % for testing. Each antenna signal is preprocessed using a Fast Fourier Transform (FFT).

The CNN for distance estimation comprises three 1D convolutional layers with 6, 10, and 14 filters and kernel sizes of 9, 7, and 5, respectively. Each convolutional layer uses same-padding and ReLU activation. The first two convolutional layers are each followed by a MaxPooling layer with pool size 2, which progressively reduces the temporal dimension and encourages the network to learn increasingly abstract spectral features. The third convolutional layer is followed by a Global Average Pooling (GAP) layer, which collapses the remaining temporal dimension into a single feature vector, thereby reducing the number of trainable parameters and mitigating the risk of overfitting. The subsequent dense layers consist of 12 neurons with ReLU activation and a single linear output neuron. The target distance is normalized by a fixed scale of 10 m prior to training, so the network output lies approximately in the range [0, 1]. The Adam optimizer is used with a learning rate of 0.001, and early stopping with a patience of 5 epochs

monitors the validation loss to prevent overfitting. Training is conducted for 25 epochs with a batch size of 64. Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are used for evaluation.

The FC-FNN for angle estimation operates on a compact three-dimensional feature vector derived from the radar signals and the CNN output. First, the trained CNN predicts the normalized target distance, which determines the expected beat frequency. Around this beat frequency bin, the inter-antenna phase difference is computed using a magnitude-weighted circular mean over a window of ± 8 frequency bins. The sine and cosine of the resulting mean phase difference, together with the normalized predicted distance, form the input feature vector $[\sin(\Delta\varphi), \cos(\Delta\varphi), d_1]$. The FC-FNN itself consists of two hidden layers with 16 and 8 neurons, both using ReLU activation and L2 regularization ($\lambda = 10^{-4}$) to constrain the weights. The output is a single linear neuron predicting the normalized angle. Training uses the Adam optimizer with a learning rate of 0.001 for up to 30 epochs with a batch size of 64, with early stopping at a patience of 6 epochs. The architectures of both networks were based on preliminary experiments and their hyperparameters tuned empirically.

Evaluation and Comparison to Conventional Methods

To assess the robustness of the approach, additional datasets with different numbers of reflections (specifically 2, 5, 10, 20, and 50) are generated. In each evaluation step, the previously trained CNN and FC-FNN are retrained to improve their performance under increased multipath conditions. As in real-world scenarios the number of reflections is unknown, an additional dataset with a random number of reflections between 2 and 50 is created. Finally, additive noise with a signal-to-noise ratio (SNR) of 23 dB is applied.

For comparison, a conventional methodology for both distance and angle estimation is also implemented, serving as a non-learned baseline to quantify the performance gain achieved by the proposed AI-based estimators. For distance estimation, spectral peak detection is applied on the preprocessed beat signal spectrum. The beat frequency $f_b f_j$ is identified as the frequency corresponding to the maximum amplitude in the magnitude

spectrum, and the target range is obtained via the standard FMCW range equation

$$d = \frac{f_b c_0 T_{\text{FMCW}}}{2 B_{\text{FMCW}}}, \quad (1)$$

where c_0 denotes the speed of light, T_{FMCW} the chirp duration, and B_{FMCW} the sweep bandwidth. The parameters used in this work are

$$B_{\text{FMCW}} = 100 \text{ MHz} \quad \text{and}$$

$$T_{\text{FMCW}} = 10 \text{ ms}.$$

The theoretical minimum resolvable range therefore is

$$\Delta d = \frac{c_0}{2 B_{\text{FMCW}}} \approx 1.5 \text{ m}. \quad (2)$$

For angle estimation, the monopulse phase-comparison principle is applied. The inter-antenna phase difference is computed at the dominant beat frequency bin and a magnitude-weighted circular mean is taken over a window of ± 5 bins around the peak to improve robustness. The target angle is subsequently recovered by inverting the phase-angle relationship. Since the effective antenna baseline is approximately one half wavelength at 24 GHz, the maximum phase difference spans nearly one full cycle of 2π , introducing inherent ambiguity that limits angular accuracy.

Results and Discussion

The results, summarized in Tab. 1, indicate strong performance across all tested scenarios. While the models perform best with only one reflection, their estimations for datasets with a random number of reflections (between 1 and 50) and added noise remain sufficiently accurate for the intended application. In the noisy scenario, the models achieve an MAE of 0.29 m for distance estimation and 7.50° for angle estimation.

Fig. 1 and Fig. 2 illustrate the prediction accuracy for the simplest scenario with a single reflection and no noise. For distance estimation (Fig. 1), the AI-based CNN predictions closely follow the ideal $y = x$ line across the full range from 0 to 10 m, with only minimal scatter. The conventional peak-detection method, by contrast, exhibits a visibly stepped pattern attributable to the limited range resolution of $\Delta d \approx 1.5 \text{ m}$, which prevents it from resolving closely spaced distance values. This fundamental limitation explains the large baseline MAE of

0.34 m even in the absence of multipath interference. For angle estimation (Fig. 2), both methods perform well in the single-reflection case, with the AI-based FC-FNN achieving an MAE of 0.06° compared to 3.18° for the phase-comparison method.

The more realistic scenario with a random number of reflections and additive noise is depicted in Fig. 3 and Fig. 4. For distance estimation (Fig. 3), the AI-based CNN maintains a concentrated scatter around the ideal line, whereas the conventional method shows broader dispersion, particularly at shorter distances where multipath reflections can shift the dominant spectral peak. For angle estimation (Fig. 4), both methods exhibit increased scatter compared to the single-reflection case, which is expected given the higher complexity introduced by multipath propagation and noise. Nevertheless, the AI-based FC-FNN produces a tighter distribution around the diagonal than the conventional phase-comparison approach, especially in the mid-angle range between 20° and 60° .

A comparison between the AI-based approach and the conventional baseline (Tab. 2) reveals that the proposed models consistently outperform the traditional methods across nearly all multipath scenarios. For distance estimation, the AI-based CNN achieves substantially lower MAE already from a single reflection (0.06 m vs. 0.34 m), a difference that is attributable to the fundamental range resolution limit of $\Delta d_1 \approx 1.5 \text{ m}$ inherent to the spectral peak detection method. Notably, the conventional distance estimator remains relatively stable across increasing reflection counts, as the peak-detection error is dominated by the resolution limit rather than by multipath distortion. The CNN, while starting from a much lower error, shows a gradual increase in MAE with more reflections, reaching 0.61 m at 50 reflections—a regime where the spectral shape is heavily distorted by overlapping multipath components.

For angle estimation, the conventional phase-comparison method performs comparably to the FC-FNN at low reflection counts, but degrades more rapidly with increasing multipath interference, consistent with the phase ambiguity introduced by the 2π constraint. In the most realistic scenario—random multipath reflections with added noise—the AI-based models achieve MAE improvements of approximately 28 % for distance (0.29 m vs. 0.40 m) and 9 % for angle (7.50° vs. 8.19°), demonstrating the practical advantage of the

learned approach under real-world-like conditions. The improvement observed when adding noise to the random-reflections dataset (MAE decreasing from 0.37 m to 0.29 m for distance and from 8.29° to 7.50° for angle) suggests that the models benefit from training on the larger combined dataset, which effectively provides a form of data augmentation that improves generalization.

Conclusion and Outlook

Notably, the neural network weights were not reset between experiments involving increasing numbers of reflections. The improvement when adding noise suggests that the models benefit from training with a larger dataset. Future work will focus on validating the approach using real-world radar measurement to determine whether the findings can be transferred to practical traffic situations.

Further analysis will be considered for the approach, e.g. how the final model performs for low numbers of reflections, how further hyperparameter tuning might impact the model, how further restricting the angle improves performance, how the performance develops for higher distances relevant to road traffic scenarios and how moving objects may impact the model. Finally, a validation with real data is planned.

For real-world scenarios, fast computation is critical. Therefore an implementation may require hardware accelerators. Generating hardware accelerators using a high level synthesis tool (HLS) such as tinyHLS is one feasible approach [4].

Acknowledgement

This manuscript was edited with the assistance of a generative AI model to enhance clarity, readability, and consistency. All suggestions were critically reviewed and accepted or modified by the authors, who take full responsibility for the final content. No AI tools were used to create, alter, or manipulate original research data or results.

This research has been funded in the project *SafeMe* by the German ministry for research, technology and space under grant no. 16ME0887.

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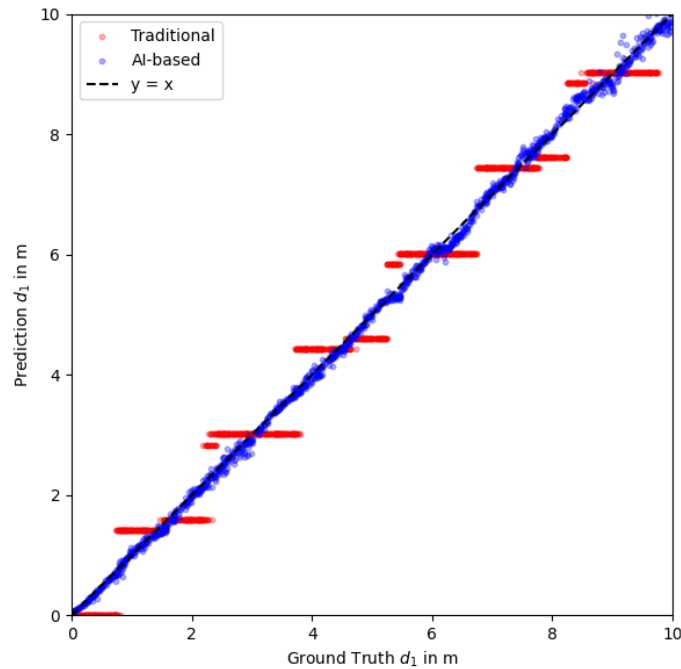
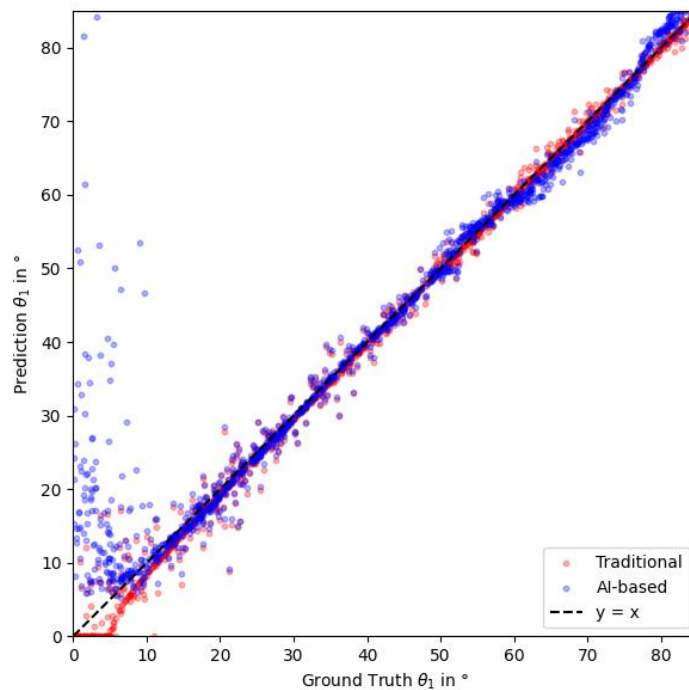
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Tab. 1: Test MAE for different numbers of reflections using the proposed AI-based approach.

Reflections	1	2	5	10	20	50	Random	Noise
Distance in m	0.0643	0.1432	0.3188	0.2137	0.4963	0.6117	0.3745	0.2869
Angle in °	0.0600	2.31	3.79	5.83	6.93	10.97	8.29	7.50

Tab. 2: Test MAE for different numbers of reflections using traditional algorithms.

Reflections	1	2	5	10	20	50	Random	Noise
Distance in m	0.3448	0.3451	0.3400	0.3594	0.3673	0.5871	0.4276	0.4019
Angle in °	3.18	2.16	4.28	6.86	8.02	12.28	8.35	8.19

**Fig. 1:** Distance prediction vs. ground truth on the test set for the ai-based method (blue) and conventional method. The dataset features only one reflection and without noise.**Fig. 2:** Angle prediction results vs. ground truth on the test set for AI-based method (blue) and conventional method (red). The dataset features only one reflection without noise.

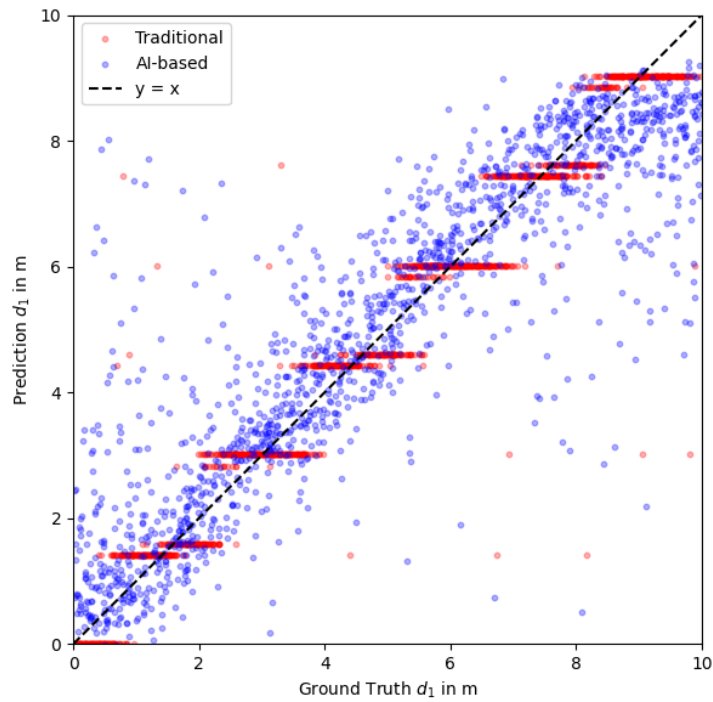


Fig. 3: Distance prediction results from the test dataset with random number of reflections and noise of a standard deviation of 0.05 for the traditional and AI-based methodology.

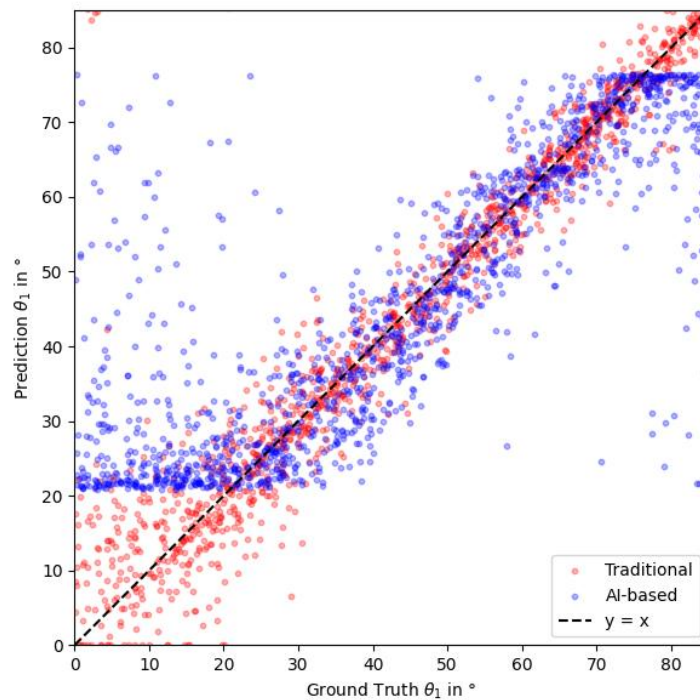


Fig. 4: Angle prediction results from the test dataset with random number of reflections and noise of a standard deviation of 0.05 for the traditional and AI-based methodology.