Seeing Around Street Corners:  
Non-Line-of-Sight Detection and Tracking In-the-Wild Using Doppler Radar

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Abstract

Conventional sensor systems record information about directly visible objects, whereas occluded scene components are considered lost in the measurement process. Non-line-of-sight (NLOS) methods try to recover such hidden objects from their indirect reflections – faint signal components, traditionally treated as measurement noise. Existing NLOS approaches struggle to record these low-signal components outside the lab, and do not scale to large-scale outdoor scenes and high-speed motion, typical in automotive scenarios. Especially optical NLOS is fundamentally limited by the quartic intensity falloff of diffuse indirect reflections. In this work, we depart from visible-wavelength approaches and demonstrate detection, classification, and tracking of hidden objects in large-scale dynamic scenes using a Doppler radar which can be foreseen as a low-cost serial product in the near future. To untangle noisy indirect and direct reflections, we learn from temporal sequences of Doppler velocity and position measurements, which we fuse in a joint NLOS detection and tracking network over time. We validate the approach on in-the-wild automotive scenes, including sequences of parked cars or house facades as indirect reflectors, and demonstrate low-cost, real-time NLOS in dynamic automotive environments.

1. Introduction

Conventional sensor systems capture objects in their direct line of sight, and, as such, existing computer vision methods are capable of detecting and tracking only the visible scene parts [13, 15, 39, 38, 12, 23, 54, 30], whereas occluded scene components are deemed lost in the measurement process. Non-line-of-sight (NLOS) methods aim at recovering information of these occluded objects from their indirect reflections or shadows on visible scene surfaces, which are again in the line of sight of the detector. While performing scene understanding of occluded objects may enable applications across domains, including remote sensing or medical imaging, especially autonomous driving applications can benefit from a system which detects approaching traffic participants that are occluded.

Existing NLOS imaging methods struggle outside controlled lab environments, and they do not scale to large scale outdoor scenes and high-speed motion, as, e.g., in typical automotive scenarios. The most successful NLOS imaging methods send out ultra-short pulses of light and measure their time-resolved returns [47, 35, 14, 8, 46, 5, 34, 29]. In contrast to a conventional camera, such measurements allow to unmix light paths based on their travel time [1, 21, 32, 35], effectively trading angular with temporal resolution. As a result, pulse widths and detection at a time scale of < 10 ps is required for room-sized scenes, mandating specialized equipment which suffers from low photon efficiency, high cost, and slow mechanical scanning. As intensity decreases quartically with the distance to the visible relay wall, current NLOS methods are limited to meter-sized scenes even when exceeding the eye-safety limits for

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a Class 1 laser (e.g. Velodyne HDL-64E) by a factor of 1000 [28]. Moreover, these methods are impractical for dynamic scenes as scanning and reconstruction takes up minutes [29, 5]. Unfortunately, alternative approaches based on amplitude-modulated time-of-flight sensors [16, 18, 17] suffer from modulation bandwidth limitations and ambient illumination [25], and intensity-only methods [11, 43, 6] require highly reflective objects. Large outdoor scenes and highly dynamic environments remain an open challenge.

In this work, we demonstrate that it is possible to detect and track objects in large-scale dynamic scenes outside of the direct line-of-sight using automotive Doppler radar sensors, see Fig. 1. Departing from visible-wavelength NLOS approaches, that rely on diffuse indirect reflections on the relay wall, we exploit that specular reflections dominate on the relay wall for mm-wave radar signals, i.e. when the structure size is an order of magnitude larger than the wavelength. As such, in contrast to optical NLOS techniques, phased array antenna radar measurements preserve the angular resolution and emitted radio frequency (RF) power in an indirect reflection, which enables us to achieve longer ranges. Conversely, separating direct and indirect reflections becomes a challenge. To this end, we recover indirectly visible objects relying on their Doppler signature, effectively suppressing static objects, and we propose a joint NLOS detection and tracking network, which fuses estimated and measured NLOS velocity over time. We train this network in an automated fashion, capturing training labels along with data with a separate positioning system, and validate the proposed method on a large set of automotive scenarios. By using facades and parked cars as reflectors, we show a first application of non-line-of-sight collision warning at intersections.

Specifically, we make the following contributions:

- We formulate an image formation model for Doppler radar NLOS measurements. Based on this model, we derive the position and velocity of an occluded object.

- We propose a joint NLOS detection and tracking network, which fuses estimated and measured NLOS velocity over time. To tackle the labeling of occluded objects, we acquire training data with an automated positioning system.

- We validate our system experimentally on in-the-wild scenarios, and, as a first application of this new imaging modality, demonstrate collision warning for pedestrians and cyclists before seeing them with the direct line-of-sight sensors.

- The experimental training and validation data sets and models will be published for full reproducibility.

2. Related Work

Optical Non-Line-of-Sight Imaging A growing body of work explores optical NLOS imaging techniques [35, 47, 14, 18, 34, 46, 5, 36, 33, 51, 29]. Following Kirmani et al. [21], who first proposed the concept of recovering occluded objects from time-resolved light transport, these methods directly sample the temporal impulse response of a scene by sending out pulses of light and capturing their response using detectors with high temporal precision of $< 10\text{ps}$, during which the pulses travels a distance of $3\text{mm}$. While early work relies on costly and complicated streak camera setups [47, 48], a recent line of work uses single photon avalanche diodes (SPADs) [8, 33, 29]. Katz et al. [20, 19] demonstrate that correlations in the carrier wave itself can be used to realize fast single shot NLOS imaging, however, limited to scenes at microscopic scales [19].

Non-Line-of-Sight Imaging Tracking and Classification Several recent works use conventional intensity images for NLOS tracking and localization [22, 9, 10, 6, 11]. The ill-posedness of the underlying inverse problem limits these methods to localization with highly reflective targets [6, 11], sparse dark background, or only scenes with additional occluders present [43, 6]. Unfortunately, recent acoustic methods [27] are currently limited to meter-sized lab scenes and minutes of acquisition time. All of these existing methods have in common that they are impractical for large and dynamic outdoor environments.

Radio Frequency Non-Line-of-Sight Imaging A further line of work has explored imaging, tracking, and pose estimation through walls using RF signals [2, 3, 4, 40, 50, 53]. However, RF signals are not reflected when traveling through typical interior wall material, such as drywall, drastically simplifying through-the-wall vision tasks. As a result, only a few works have explored NLOS radar imaging and tracking [45, 37, 52]. These methods back-propagate raytraced high-order-bounce signals, which requires scenes with multiple known (although they are occluded) hidden relay walls. For the in-the-wild scenarios tackled in this work without prior scene knowledge, only third-bounce measurements, and with imperfect relay walls, e.g., a parked sequence of vehicles, these methods are impractical. Moreover, the proposed traditional filtering and backprojection estimation suffers from large ambiguities at more than $10\text{m}$ in the presence of realistic measurement noise [37]. However, existing automotive radar systems often suffer from severe clutter. In this work, we address this challenge with a data-driven joint detection and tracking method, allowing us to demonstrate practical NLOS detection in-the-wild using radar systems which have the potential for low cost mass market production in the near future.
3. Observation Model

When a radar signal gets reflected of a visible wall to a hidden object, some of the signal is scattered and reflected back to the wall where it can be observed, see Fig. 2. Next, we derive a forward model including such observations.

3.1. Non-Line-of-Sight FMCW Radar

Radar sensors emit electromagnetic (EM) waves, traveling at the speed of light \( c \), which are reflected by the scene and received by the radar sensors. In this work, we use a frequency-modulated continuous-wave (FMCW) Doppler radar with multiple input multiple output (MIMO) array configuration, which can resolve targets in range \( r \), azimuthal angle \( \phi \), and radial Doppler velocity \( v_r \). Instead of a single sinusoidal EM wave, our FMCW radars send out linear frequency sweeps [7] over a frequency band \( B \) starting from the carrier frequency \( f_c \), that is

\[
g(t) = \cos \left( 2\pi f_c t + \pi \frac{B}{T_m} t^2 \right),
\]

with \( T_m \) being the sweep rise time. The instantaneous frequency of this signal is \( \frac{1}{2\pi} \frac{d}{dt} \left( 2\pi f_c t + \pi \frac{B}{T_m} t^2 \right) = f_c + \frac{B}{T_m} \omega, \) that is a linear sweep varying from \( f_c \) to \( f_c + B \) with slope \( \frac{B}{T_m} \), which is plotted in Fig. 3.

The emitted signal \( g \) propagates through the visible and occluded parts of the scene, that is, this signal is convolved with the scene’s impulse response. For a given emitter position \( l \) and receiver position \( w \) the received signal becomes

\[
s(t, l, w) = \int_{\Lambda} \alpha(x) \rho(x - w, w - x) \cdot
\frac{1}{(r_{lw} + r_{ww})^2} \frac{1}{r_{lw} + r_{ww}} \frac{g(t - \frac{r_{lw} + 2r_{lw} + r_{ww}}{c})}{dx},
\]

see Fig. 2, with \( x \) being the position on the hidden and visible object surface \( \Lambda \), \( \alpha \) as the abledo, and \( \rho \) denoting the bidirectional reflectance distribution function (BRDF), which depends on the incident direction \( \omega_i = x - w \) and outgoing direction \( \omega_o = w - x \). The distance \( r \) describes here the distance between the subscript position and its squared inverse in Eq. (2) models the intensity falloff due to spherical travel, which we approximate as not damped by the specular wall, and diffuse backscatter from object back to the receiver \( c \).

Reflection Model The scattering behavior \( \rho \) depends on the surface properties. Surfaces that are flat, relative to the wavelength \( \lambda \) of \( \approx 5 \) mm for typical 76 GHz-81 GHz automotive radars, will result in a specular response. As a result, the transport in Eq. (2) treats the relay wall as a mirror, see Fig. 2. We model the reflectance of the hidden and directly visible targets following [11] with a diffuse and retroreflective term as

\[
\rho(\omega_i, \omega_o) = \alpha_s \rho_d (\omega_i, \omega_o) + \alpha_s \rho_s (\omega_i, \omega_o),
\]

In contrast to recent work [11, 27], we cannot rely on the specular component \( \rho_s \), as for large standoff distances, the relay walls are too small to capture the specular reflection. Indeed, completely specular facet surfaces are used to hide targets as “stealth” technology [31]. As retroreflective radar surfaces are extremely rare in nature [40], the diffuse part \( \rho_d \) dominates \( \rho \). Note that \( \alpha(x)\rho(x - w, w - x) \) in Eq. (2) is known as the intrinsic radar albedo, describing backscatter properties, i.e., the radar cross section (RCS) [42].

Range Measurement Assuming an emitter and detector position \( c = 1 = w \) and a static single target \( \xi \) at distance \( r = |c - x| \) with roundtime reflection \( \tau_r = \frac{2r}{c} \), Eq. (2) becomes a single sinusoid

\[
s_\xi(t) = \alpha_\xi g(t - \tau_r),
\]

where \( \alpha_\xi \) describes here the accumulated attenuation along the reflected path. FMCW radars mix the received signal \( g \), resulting in a signal \( p_\xi \) consisting of the sum and a difference of frequencies:

\[
p_\xi(t) = s_\xi(t) \cdot g(t) \approx \frac{\alpha_\xi}{2} \cos \left( 2\pi f_{\text{beat}}t + 4\pi \frac{f_c r}{c} \right),
\]

The sum is omitted in Eq. (5) due to low-pass filtering in the mixing circuits. In contrast, the difference does not vanish due to the time difference between transmitted and received chirp signal, see Supplemental Material, resulting in a frequency shift with beat frequency

\[
f_{\text{beat}} = \frac{B}{T_m} \frac{2r}{c}, \quad \text{and} \quad r = c \frac{f_{\text{beat}} T_m}{2B}.
\]
For this angle estimation, a single transmitter antenna illuminates and all receiver antennas listen. A frequency analysis on the sequence of phasors corresponding to peaks in the 2D range-velocity spectrum assigns angles, resulting in a 3D range-velocity-angle data cube.

3.2. Sensor Post-Processing

The resulting raw 3D measurement cube contains $1024 \times 512 \times 64$ bins for range, angle, and velocity, respectively. For low reflectance scenes, noise, and clutter, this results typically in tens of millions of non-zero reflection points. To tackle such measurement rates in real-time, we implement a constant false alarm rate filter following [41], see Supplemental Material. After compensating all velocity for ego-motion, we retrieve a radar pointcloud $\tilde{U}$ with less than $10^4$ points, allowing for efficient inference. That is,

$$\tilde{U} = \{(\hat{\phi}, \tilde{r}, \tilde{v}, \tilde{\alpha}) | 1 \leq i \leq R\} \quad \text{with} \quad R < 10^4. \quad (10)$$

See Supplemental Material for details on post-processing.

4. Joint NLOS Detection and Tracking

In this section, we propose an artificial neural network for the detection and tracking of hidden objects from radar bird’s eye view (BEV) measurements.

4.1. Non-Line-of-Sight Detection

The detection task is to estimate oriented 2D boxes for pedestrians and cyclists, given a BEV point cloud $\tilde{U}$ as input. The overall detection pipeline consists of three main stages: (1) input parameterization that converts a BEV point cloud to a sparse pseudo-image; (2) high-level representation encoding from the pseudo-image using a 2D convolutional backbone; and (3) 2D bounding box regression and detection with a detection head.

Input Parameterization We denote by $u$ a $d$-dimensional ($d = 4$) point in a raw radar point cloud $\tilde{U}$ with coordinates $x, y$ (derived from the polar coordinates $\hat{\phi}, \tilde{r}$), velocity $\tilde{v}$, and amplitude $\tilde{\alpha}$. We first preprocess the input by taking the logarithm of the amplitude $\tilde{\alpha}$ to get the intensity value $s = \log \tilde{\alpha}$. As a first step, the point cloud is discretized into an evenly spaced grid in the $x$-$y$ plane, resulting in a pseudo-image of size $(d, H, W)$ where $H$ and $W$ indicate the height and width of the grid, respectively.

High-level Representation Encoding To efficiently encode high-level representations of the hidden detections, the backbone network contains two modules: a pyramid network and a zoom-in network. The pyramid network contains two consecutive stages to produce features at increasingly small spatial resolution. Each stage downsamples its input feature map by a factor of two using three 2D convolutional layers. Next, a zoom-in network upsamples and
concatenates the two feature maps from the pyramid network. This zoom-in network performs transposed 2D convolutions with different strides. As a result, both upsampled features have the same size and are then concatenated to form the final output. All (transposed) convolutional layers use kernels of size 3 and are interlaced with BatchNorm and ReLU, see Supplemental Material for details.

**Detection Head** The detection head follows the setup of Single Shot Detector (SSD) [26] for 2D object detection. Specifically, each anchor predicts a 3-dimensional vector for classification (background / cyclist / pedestrian) and a 5-dimensional vector for bounding box regression (center, dimension, and orientation of the box).

**Third-Bounce Geometry Estimation** Next, we derive the real location $x$ of a third-bounce or virtual detection $x'$, for reference see Fig. 2 and Fig. 5. In order to decide whether a point is a virtual detection, we first derive its intersection $w$ with the relay wall $p = p_2 - p_1$ represented by its two endpoints $p_1$ and $p_2$, that is

$$w = c + \frac{(p_1 - c) \times p}{(x' - c) \times p} (x' - c).$$

(11)

For a detection $x'$ to be a third bounce detection, we have two criteria. First, $x'$ and the receiver $c$ must be on opposite sides of the relay wall. We define the normal $n_w$ of the relay wall in such way, that it points away from the receiver $c$. Second, the intersection $w$ must be between $p_1$ and $p_2$, both expressed as

$$n_w \cdot (x' - p_1) \geq 0 \land \left| w - p_1 \right| \leq \left| p \right| \land \left| w - p_2 \right| \leq \left| p \right|. $$

(12)

Figure 5: NLOS geometry and velocity estimation from indirect specular wall reflections. The hidden velocity $v$ can be reconstructed from the radial velocity $v_r$, by assuming that the road user moves parallel to the wall, i.e., on a road. The first term is the signed distance, indicating whether $x'$ and $c$ are on opposite sides of the wall and the other terms determine whether $w$ lies between $p_1$ and $p_2$. If Eq. (12) is true, $x'$ is a third bounce detection, we reconstruct the original point $x$ as

$$x = \frac{(w - c - 2 (n_w \cdot (w - c)) n_w) \cdot (w - x')}{\left| w - c \right|}.$$  

(13)

**Third-Bounce Velocity Estimation** After recovering $x$, we estimate the real velocity vector $v$ under the assumption that the real velocity is parallel to the relay wall, see Fig. 5. Specifically, it is

$$v = \left| v \right| \frac{\text{sgn}(v_r) \cdot \text{sgn} (\gamma_{x'} - \gamma_w) p}{\left| p \right|}.$$  

(14)

Here, $\gamma_{x'}$ and $\gamma_w$ are the angles of $x' - c$ and $n_w$ relative to the sensor’s coordinate system. In (14), the sign
of \(v_r\) distinguishes approaching and departing hidden object targets, while \(\text{sgn}(\gamma_w - \gamma_w')\) determines the object’s allocation to the left or right half-plane with respect to the normal \(\mathbf{n}_w\). By convention, we define that \(\mathbf{p}\) is rotated \(\frac{\pi}{2}\) anti-clockwise relative to \(\mathbf{n}_w\). Using the measured radial velocity \(v_r = \|\mathbf{v}\| \cdot |\cos \varphi|\), we get
\[
\mathbf{v} = \text{sgn}(v_r) \cdot \text{sgn}(\gamma_w' - \gamma_w) \cdot \frac{|v_r|}{|\cos \varphi|} \cdot \frac{\mathbf{p}}{||\mathbf{p}||},
\]
see the Supplemental Material for detailed derivations.

**Relay Wall Estimation** We use first-response pulsed lidar measurements of a separate front-facing lidar sensor to recover the geometry of the visible wall. Specifically, we found that detecting line segments in a binarized binned BEV is robust using \([49]\), where each bin with size \(0.01\) m is binarized with a threshold of 1 detection per bin. We filter out segments with a length shorter than \(1\) m, \(1\) frames at different scales, the model is allowed to capture both low-level features and high-level motion features. We refer to Fig. 4 for an illustration of our architecture.

### 4.2. Non-Line-of-Sight Doppler Tracking

Our model jointly learns tracking with future frame prediction, inspired by Luo et al. \([30]\). At each timestamp, the input is from the current and its \(n\) preceding frames, and predictions are for the current plus the following \(n\) frames.

One of the main challenges is to fuse temporal information. A straightforward solution is to add another dimension and perform 3D convolutions over space and time. However, this approach is not memory-efficient and computationally expensive given the sparsity of the data. Alternatives can be early or late fusion as discussed in \([30]\). Both fusion schemes first process each frame individually, and then start to fuse all frames together.

Instead of such one-time fusion, our approach leverages the multi-scale backbone and performs fusion at different levels. Specifically, we first perform separate input parameterization and high-level representation encoding for each frame as described in Sec. 4.1. After the two stages of the pyramid network, we concatenate the \(n + 1\) feature maps along the channel dimension for each stage. This results in two feature maps of sizes \(((n + 1)C_1, \frac{H}{4}, \frac{W}{4})\) and \(((n + 1)C_2, \frac{H}{4}, \frac{W}{4})\), which are then concatenated as inputs to the two upsampling modules of the zoom-in network, respectively. The rest of the model is the same as before. By aggregating temporal information across \(n + 1\) frames at different scales, the model is allowed to capture both low-level per-frame details and high-level motion features. We refer to Fig. 4 for an illustration of our architecture.

### 4.3. Loss Functions

Our overall objective function contains a localization term and a classification term and the hidden vulnerable road users.

\[
L = \alpha L_{\text{loc}} + \beta L_{\text{cls}},
\]

The localization loss is a sum of the localization loss for the current frame \(T\) and \(n\) frames into the future:
\[
L_{\text{loc}} = \sum_{t=T}^{T+n} L_{\text{loc}_t} \quad \text{with} \quad L_{\text{loc}_t} = \sum_{u \in \{x,y,w,l,\theta\}} |\Delta u|,
\]
where \(\Delta u\) is the localization regression residual between ground truth \((gt)\) and anchors \((a)\) defined by \((x, y, w, l, \theta)\):

\[
\begin{align*}
\Delta x &= x_{gt} - x_a, \quad \Delta y = y_{gt} - y_a, \\
\Delta w &= \log \frac{w_{gt}}{w_a}, \quad \Delta l = \log \frac{l_{gt}}{l_a}, \quad \Delta \theta &= \sin(\theta_{gt} - \theta_a).
\end{align*}
\]

We do not distinguish the front and back of the object, therefore all \(\theta\)’s are within the range \([-\frac{\pi}{2}, \frac{\pi}{2}]\).

### 5. Data Acquisition and Training

**Prototype Vehicle Setup** The observation vehicle prototype is shown in Fig. 6. We use experimental FMCW radar prototypes, mounted in the front bumper, with frequency band 76 GHz to 77 GHz and chirp sequence modulation, see Sec. 3. We use a mid-range configuration with 153 m maximum range and FoV of 140°, i.e., for urban scenarios or intersections. A single measurement takes 22.6 ms, with a resolution of 0.15 m, 1.8°, and 0.087 m s\(^{-1}\). Similar sensors are available as development kits for a few hundred USD, e.g. Texas Instruments AWR1642BOOST; the mass-produced version costing a small fraction. The radar sensors are complimented by an experimental 4-layer scanning lidar with 0.25° and 0.8° resolution in azimuth and elevation. With a wide FoV of 145°, a single sensor installed in the radiator grill suffices for our experiments. We use a GeneSys ADMA-G PRO localization system consisting of a combined global navigation satellite system (GNSS)
Automated Ground-Truth Estimation Unfortunately, humans are not as accustomed to annotate radar measurements as to visual image data, and NLOS annotations become even more challenging. We tackle this problem by adopting a variant of the tracking device from [44]. We equip vulnerable road users, i.e., occluded pedestrians or bicyclists, with a hand-held GeneSys ADMA-Slim tracking module synced with the capture vehicle via Wi-Fi, see Fig. 6. In contrast to [44] we do not purely rely on GNSS data, but instead use the IMU for a complete pose estimation of the hidden object. For both training and validation sets, where the validation set consists of four scenes with 20 sequences and 3063 frames.

6. Assessment

Evaluation Setting and Metrics For both training and validation, the region of interest is a large area of 60 m × 80 m. We use resolution 0.1 m to discretize both x, z axes into a 600 × 800 grid. We assign each ground truth box to its highest-overlapping predicted box for training. The hidden classification and localization performance are evaluated with Average Precision (AP) and average distance between the predicted and ground truth box centers, respectively.

6.1. Qualitative Validation

Fig. 8 shows results for realistic automotive scenarios with different wall types. Note that the size of ground truth bounding box varies due to the characteristics of radar data. The third row shows a scenario where no more than three detected points are measured for the hidden object, and the model has to rely on velocity and orientation of these sparse points to make a decision on box and class prediction. Despite such noise, we do observe that the model outputs stable predictions. As illustrated in the fourth row, predicted boxes are more consistent in size and orientation across frames than the ground truth. The first frame in the fourth row shows a detection where a hidden object became visible by lidar but not radar. Note that all other scenes have occluder geometries visible in the lidar measurements. While the predicted box seemingly does not match the ground truth well due to jitter of the ground truth acquisition system in this particular frame, it is, in fact, detected correctly by reasoning about sequences of frames instead of a single one, validating the proposed joint detection and tracking approach. Fig. 9 shows qualitative tracking trajectories for two different scenes. The model is able to track an object only with occasional incorrect ID switch.

6.2. Quantitative Validation

Detection Results We report AP at IoU thresholds 0.1, 0.25 and 0.5 for cyclist/pedestrian and Object. We also list the mean AP of predicting object/non-object by merging radar systems. We split the dataset into non-overlapping training and validation sets, where the validation set consists of four scenes with 20 sequences and 3063 frames.

| Class       | Cyclist | Pedestrian | Object |
|-------------|---------|------------|--------|
| AP          | @0.5   | @0.25     | @0.1          |
| Ours        | 23.06  | 49.06     | 55.47  |
| SSD [26]    | 7.21   | 32.92     | 48.25  |
| PointPillars [24] | 2.02   | 15.02     | 28.00  |

Table 1: Detection classification (AP) comparison. We compare our model to an SSD detector and the PointPillars [24], details in Supplementary Material.
Building Wall Cyclist Warehouse Wall Cyclist Marble Wall Pedestrian Parked Cars Cyclist

Figure 8: Joint detection and tracking results for automotive scenes with different relay wall type and object class in each row. The first column shows the observer vehicle front facing camera view. The next three columns plot BEV Radar and Lidar point clouds together with bounding box ground truth and predictions. NLOS velocity is plotted as line segment from the predicted box center: red and green corresponds to moving towards and away from the vehicle.

The first column shows the observer vehicle front facing camera view. The next three columns plot BEV Radar and Lidar point clouds together with bounding box ground truth and predictions. NLOS velocity is plotted as line segment from the predicted box center: red and green corresponds to moving towards and away from the vehicle.

| Localization (Box Center Distance) | Model | Visibility | MOTA | MOTP |
|-------------------------------------|-------|------------|------|------|
| Tracking (w, v)                    |       | NLOS       | 0.26 | 0.94 |
| Tracking (w/o. v^2)                |       | LOS        | 0.77 | 0.90 |
| Tracking (w, v)                    |       | NLOS       | 0.14 | 0.94 |
| Tracking (w/o. v^2)                |       | LOS        | 0.61 | 0.84 |

Table 2: Localization and tracking performance on NLOS and LOS data, with MAE (Mean Absolute Error) and MSE (Mean Squared Error) in meters.

cyclist/pedestrian labels. We also compare our model with a simplified SSD and original PointPillars for BEV point cloud detection, see Supplemental Material. Since most bounding boxes in our collected data are challenging small boxes with sizes smaller 0.5 m × 0.5 m, a very small offset may significantly affects the detection performance at a high IoU threshold. However, in practice, a positive detection with an IoU as small as 0.1 is still a valid detection for collision warning applications. Combined with the high localization accuracy shown in Tab. 1 (right), we validate that the proposed approach allows for long-range detection and tracking of hidden object in realistic automotive scenarios, even for small road users as pedestrians and bicycles.

Tracking Results Tables 1 and 2 list the localization and tracking performance of the proposed approach. Relying on multiple frames and measured Doppler velocity estimates, the proposed method achieves high localization accuracy of almost 10 cm in MSE despite measurement clutter and small diffuse cross section of the hidden pedestrian and bicycle objects. We evaluate the tracking performance on NLOS and visible line-of-sight (LOS) frames separately in Tab. 2. For challenging NLOS data, while the number of unmatched object (MOTA) increases, the model is still able to precisely locate most of the matched objects (MOTP). These tracking results validate the proposed joint NLOS detector and tracker for collision avoidance applications.
7. Conclusion

In this work, we introduce a non-line-of-sight method for joint detection and tracking of occluded objects using automotive Doppler radar. Learning detection and tracking end-to-end from a realistic NLOS automotive radar data set, we validate that the proposed approach allows for collision warning for pedestrians and cyclists in real-world autonomous driving scenarios – before seeing them with existing direct line-of-sight sensors. In the future, detection from higher-order bounces, and joint optical and radar NLOS could be exciting next steps.

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