Rethinking of Radar’s Role: A Camera-Radar Dataset and Systematic Annotator via Coordinate Alignment

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Abstract

Radar has long been a common sensor on autonomous vehicles for obstacle ranging and speed estimation. However, as a robust sensor to all-weather conditions, radar’s capability has not been well-exploited, compared with camera or LiDAR. Instead of just serving as a supplementary sensor, radar’s rich information hidden in the radio frequencies can potentially provide useful clues to achieve more complicated tasks, like object classification and detection. In this paper, we propose a new dataset, named CRUW¹, with a systematic annotator and performance evaluation system to address the radar object detection (ROD) task, which aims to classify and localize the objects in 3D purely from radar’s radio frequency (RF) images. To the best of our knowledge, CRUW is the first public large-scale dataset with a systematic annotation and evaluation system, which involves camera RGB images and radar RF images, collected in various driving scenarios.

1. Introduction

Multi-modality data analytics is greatly involved in the autonomous or assisted driving systems [17, 36, 35] to improve the robustness of object perception [26, 31, 16, 37] in a variety of different driving scenarios. Among the common sensors, i.e., camera, LiDAR, radar, on the autonomous vehicles, the RGB images and point cloud data from cameras and LiDAR are relatively easy for human to understand since the semantic information they convey is obvious. For example, 2D and 3D bounding boxes are intuitive for human to annotate the objects from RGB images and LiDAR point clouds, respectively. Therefore, some large and well-labeled datasets [13, 8, 4, 3] have been released in the autonomous driving community to help develop and validate the machine learning algorithms. As an accurate 3D sensor for autonomous vehicles, LiDAR still faces the following critical limitations: 1) LiDAR is usually equipmental complex and computational expensive, so that not suitable for common industry use; 2) Laser transmitted by the LiDAR is not robust to occlusion or adverse weather scenarios. Radar, on the other hand, is a reliable and cost-efficient sensor capturing reliable 3D information even under adverse driving conditions, e.g., strong/weak lighting or bad weather. It is often used as supplement for other sensors due to its difficulty in parsing useful clues for semantic understanding. But this data unintuitiveness does not mean that radar has low potentials.

The use of the frequency modulated continuous wave (FMCW) radar in most autonomous driving solutions lies in its obstacle ranging and speed estimation. The capability of radar’s semantic understanding, e.g., object classification and detection, has not been well-exploited. The fea-

¹Dataset available at https://www.cruwdataset.org/.
performance of ROD, which pre-

In order to evaluate the performance of ROD, which pre-

sibility of achieving this semantic understanding owing to the hidden phase information inside the radio frequencies. Typically, radar’s amplitude is commonly used to estimate the distance and speed of the obstacles, while the phase information is usually not well-utilized because of its “non-intuitiveness”, making it difficult to be handled by the classical signal processing mechanisms. There are two kinds of data representations for the FMCW radar, i.e., radio frequency (RF) image and radar points (see examples in the supplementary document). RF image is a much denser and more informative data representation, which requires further processing to understand the contents, containing both amplitude and phase information, but the location and speed are implicit. Whereas radar points are a kind of handy representation, which are usually sparse (less than 5 points on a nearby car) [8, 12] and non-descriptive.

Therefore, to extract those hidden features from RF images for semantic understanding, some researchers start to take advantage of the recent deep convolution neural networks (CNNs) to explore the possibility of radar-only object detection [19, 10, 33], which usually require a large annotated dataset for training. However, radar data are very difficult to understand, making human annotations significantly expensive or sometimes impossible to obtain. Besides, due to the low angular resolution of the common FMCW radar sensors, resulting in unreliable object dimension information from radar, more specifically, the bounding boxes defined in camera-based object detection are rarely used in the RF images, especially when the absence of LiDAR. Consequently, people usually represent objects as points in the radar’s bird’s-eye view (BEV) coordinates instead [33]. These points are the reflection points of the radar signals from the obstacles in the radar’s field of view (FoV). All of the above make the large-scale dataset, annotation and performance evaluation for object detection in the RF images very challenging while critically needed.

In this paper, we propose a platform, including a large-scale dataset, a systematic annotation system, and a set of evaluation metrics for ROD, as shown in Fig. 1. The proposed dataset contains about 400K synchronized camera-radar frames (3.5 hours) in various driving scenarios, i.e., parking lot, campus road, city street, and highway. As mentioned above, the radar data format is RF image with rich radio frequency information. The proposed object annotation method calculates the optimal camera-radar bilateral coordinate projection and aligns the detections between the two coordinates. Two different kinds of detections are fed into the system, including object detection from camera and peak detection from radar. Then, a coordinate alignment strategy is utilized based on the proposed bilateral coordinate projection between camera and radar, and the ground plane for each frame is optimized by the alignment cost. In order to evaluate the performance of ROD, which pre-
dicts objects as points, we introduce a point-based similarity metric, called object location similarity (OLS), to serve as a matching score between two points in an RF image. Based on OLS, to reasonably reflect the quality of the object detection results in the RF images, we introduce a series of evaluation metrics, considering object localization error, precision, and recall. Moreover, we define a new metric Detection Quality F1 Score (DQF1) that can jointly consider the above three metrics into a single metric to provide a comprehensive measurement of the detection performance. Unlike the widely used average precision (AP) and average recall (AR) defined for object detection tasks that emphasize classification, the proposed DQF1 focuses more on the localization accuracy.

Overall, the main contributions of this paper can be summarized as follows,

- A large-scale dataset with synchronized camera-radar frames in various driving scenarios, including RF images as the radar data format for radar semantic understanding tasks.
- An accurate and robust radar object annotator, that can systematically generate object labels for RF images, fusing the rich semantic information from a camera. It is also an object detector based on a camera-radar fusion manner in the normal driving scenarios.
- Derive the bilateral coordinate projection (BCP) between camera pixel coordinates and radar range-azimuth coordinates through the ground plane.
- Introduce a set of scoring metrics to evaluate the quality of ROD results comprehensively, including the proposed metrics, i.e., object location similarity (OLS) and detection quality F1 score (DQF1).

2. Related Works

Detectors. As mentioned in Section 1, radar-only object detection cannot reliably accomplish, especially the object-class identification, with sparse and non-descriptive radar points input. Therefore, most related research use the RF images as the input format. However, detecting objects from the radar RF data is very challenging because the inherent semantic information is not as obvious as that in the RGB images. Traditionally, peak detection algorithms are adopted to find the objects in the radar field of view (FoV), such as the widely used Constant False Alarm Rate (CFAR) detection algorithm [27]. A classifier is then appended to classify the object class [15, 5]. However, these algorithms usually result in a large number of false positives because it cannot distinguish the reflections of objects from that of background. Besides, it cannot reliably provide the object class. Moreover, one object may give multiple CFAR detections, which are confusing. Recently, some new techniques
for radar data are proposed. Major et al. [19] propose an automotive radar based vehicle detection method trained by LiDAR. However, they only consider vehicles as the target object class, and the scenarios are mostly highways without noisy obstacles. Palffy et al. [24] propose a radar based, single-frame multi-class object detection method. However, they only consider the data from a single radar frame, which does not involve the object motion information. Wang et al. [34] propose the RODNet with temporal inception layers to capture temporal features of different lengths, an M-Net is used to merge and extract Doppler information from multiple chirps, and temporal deformable convolution is used to handle object relative motion.

Datasets. Datasets are important to validate the algorithms, especially for the deep learning based methods. Since the release of the first complete autonomous driving dataset, i.e., KITTI [13], larger and more advanced datasets are now available [3, 4, 8]. However, due to the hardware compatibility and less developed radar perception techniques, most datasets do not incorporate radar signals as a part of their sensor systems. Among the available radar datasets (summarized in Table 1), some of them [8, 20, 7, 29] consider radar data in the format of radar points that do not contain the useful Doppler and surface texture information of objects. Later, researchers start to focus on RF images as the radar data format. More specifically, some manage to collect a dataset with camera, radar and LiDAR, and annotate the objects as 3D bounding boxes based on the dense point cloud from LiDAR [19, 10]. Others consider the camera-radar solution without a LiDAR [23, 24], whose annotation format is usually in pixel or point level. However, most of the datasets with RF images are not publicly available except CARRADA [23]. But CARRADA only contains one simple and easy scenario, i.e., parking lot, and is not suitable for practical usage.

Annotation methods. When LiDAR is not available to provide reliable object annotations, many people manage to fuse the semantic information from cameras. There are some camera-based techniques that are helpful for the radar object annotation task. Camera-based object detection [26, 14, 9, 25, 18, 11] aims to detect every object with its class and precise bounding box location from RGB images. Besides, some recent works try to infer 3D information from the 2D RGB images. Some methods [21, 22] localize vehicles by estimating their 3D structures using a CNN. Others [30, 6] try to develop a real-time monocular structure-from-motion (SfM) system, taking into account different kinds of cues. However, the above methods only work for the vehicles, which can satisfy the rigid-body structure assumption. To overcome this limitation, Wang et al. [32] propose an accurate and robust object 3D localization system, based on the detected and tracked 2D bounding boxes of objects, which can work for most common moving objects in the road scenes, such as cars, pedestrians, and cyclists. The limitation is its inability to reliably estimate the 3D location of objects due to the inaccurate depth maps and non-negligible car sizes. After that, [33] proposes a probabilistic camera-radar fusion (CRF) algorithm to jointly consider the object 3D localization results from both camera and radar. But this kind of late fusion methods may introduce the errors from the early stages nor consider the correlation between different objects in the same frame. Recently, Ouaknine et al. [23] propose a semi-automatic annotation approach on radar data of some simple parking lot scenarios. However, its sensitivity to tracking and clustering makes it not robust in complex driving scenarios. Therefore, in this paper, we propose an annotation system to overcome the above issues.

3. CRUW Dataset

3.1. Sensor System and Data Description

The sensor platform contains a pair of stereo cameras [1] and two perpendicular 77GHz FMCW mmWave radar antenna arrays [2]. The sensors are assembled and mounted together as shown in Fig. 2 (a). Some configurations of our sensor platform are shown in Table 2.

![Figure 2. The sensor platform and some sample driving scenarios.](image-url)

| Table 2: Configurations of CRUW Dataset |
|----------------------------------------|
| **Sensor Configuration**               |
| ---------------------------------------|
| Stereo Cameras                         |
| 77GHz FMCW mmWave Radar Antenna Arrays |
| **Scenarios**                          |
| Parking Lot                            |
| Highway                                |
| Urban Area                             |
| **Data Description**                   |
| RGB Images, RF Images, LiDAR Points     |
| **Annotation Method**                  |
| Camera-Radar                          |
| Semi-Automatic                        |
| Probabilistic CRF                      |
The proposed dataset contains 3.5 hours with 30 FPS (about 400K frames) of camera-radar data in different driving scenarios, including parking lot, campus road, city street, and highway. Some sample scenarios are shown in Fig. 2 (b). The data are collected in two different views, i.e., driver front view and driver side view, to validate different perspective views for autonomous or assisted driving. Besides, we also collect several vision-hard sequences of poor image quality, i.e., weak/strong lighting, blur, etc. These data are only used in the testing set for evaluation purpose.

### 3.2. Data Distribution

The data distribution is shown in Table 3 and Fig. 3. The object statistics in Fig. 3 only consider the objects within the radar’s field of view (FoV), i.e., 0-25m, ±90°, based on the current hardware capability. There are about 260K objects in CRUW dataset in total, including 92% for training and 8% for testing. The average number of objects in each frame is similar between training and testing data.

The four different driving scenarios, i.e., parking lot, campus road, city street, and highway, are shown in Table 3 with the number of sequences, frames and vision-hard percentages. From each scenario, we randomly select several complete sequences as testing sequences, which are not used for training. Thus, the training and testing sequences are captured at different locations and different time. For the ground truth needed for evaluation purposes, 10% of the visible and 100% of the vision-hard data are human-labeled by manually refinement on the results of the annotator introduced in Section 4.

### 4. Radar Object Annotation System

In this section, our proposed radar object annotation system (Fig. 4) will be introduced. First, the input data, both from camera and radar, are pre-processed and fed into our systematic annotation system for initialization. Second, the bilateral coordinate projection is derived to connect the camera and radar coordinates. Then, the detection alignment strategy with the ground plane optimization is applied to accurately detect and localize the objects in RF images. Overall, the radar detections are aligned and clustered by different instances, and the final object annotations are the centers of the resulting clusters.

#### 4.1. Notations

**Coordinates.** We first define two 2D coordinates used in our system: 1) Camera 2D pixel coordinates \((u, v) \in \mathcal{C};\) 2) Radar range-azimuth coordinates, i.e., bird’s-eye view...
The system takes two different kinds of detections from camera and radar, i.e., object detection from RGB images and peak detection from RF images, as the input, and manages automatic radar object annotation. The system takes detections from both RGB images and RF images, and optimizes the ground plane parameters. The ground plane parameters are initialized by the sensor calibration results. Specifically, for the CRUW dataset, \( \varphi_0 = 4^\circ, \gamma_0 = 0^\circ, h_0 = 1.65m \). Second, the density-based spatial clustering of applications with noise (DBScan) clustering algorithm [28] is implemented on the CFAR detections to obtain the initial detection clusters.

4.3. Bilateral Coordinate Projection

Consider the ground plane parameters defined in Section 4.1, we derive the camera-radar bilateral coordinate projection (BCP) for any point on the ground plane. We start from projecting a point \((r, \theta) \in \mathcal{R}\) to \(x^c = (x^c, y^c, z^c)\). After the data and detections are prepared, we need to initialize the systematic annotation system. First, the ground plane parameters are initialized by the sensor calibration results. Specifically, for the CRUW dataset, \( \varphi_0 = 4^\circ, \gamma_0 = 0^\circ, h_0 = 1.65m \). Second, the density-based spatial clustering of applications with noise (DBScan) clustering algorithm [28] is implemented on the CFAR detections to obtain the initial detection clusters.

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Finally, we project \( x^c \in \mathcal{W}^c \) to \( C \) by the camera intrinsic matrix \( K \). Put it together, we can project a point \((r, \theta) \in \mathcal{R}\) to \((u, v) \in C\) by the following \( \mathcal{R} \rightarrow C \) projection, denoted as \( P(\cdot) \),

\[
[u, v] = P(r, \theta),
\]

where

\[
\begin{align*}
    u &= f_x \frac{r \sin(\theta) + t_{cr,x}}{r \cos(\theta) + t_{cr,z}} + c_x, \\
    v &= f_y \frac{h - r \sin(\phi) - (r \sin(\theta) + t_{cr,x}) \tan(\gamma)}{r \cos(\theta) + t_{cr,z}} + c_y.
\end{align*}
\]

Here, \((f_x, f_y)\) represents the camera’s focal length; \((c_x, c_y)\) represents the camera center.

After the \( \mathcal{R} \rightarrow C \) projection is properly derived, we would like to consider the other direction, i.e., \( C \rightarrow \mathcal{R} \) projection. Since the projection in Eq. 6 is a 2D-to-2D projection without losing any degrees of freedom (DoF), it can be reversed. Therefore, we define the \( C \rightarrow \mathcal{R} \) projection as

\[
[r, \theta] = P^{-1}(u, v).
\]

Here, the \( C \rightarrow \mathcal{W}^c \) projection can be derived as

\[
\begin{align*}
    x^c &= \frac{h \hat{x}}{\sqrt{1 + \hat{x}^2 \sin(\phi) + \hat{x} \tan(\gamma) + \hat{y}}}, \\
    z^c &= \frac{h \hat{z}}{\sqrt{1 + \hat{x}^2 \sin(\phi) + \hat{x} \tan(\gamma) + \hat{y}}},
\end{align*}
\]

where

\[
\begin{align*}
    \hat{x} &= \frac{u - c_x}{f_x}, \\
    \hat{y} &= \frac{v - c_y}{f_y}.
\end{align*}
\]

4.4. Detection Alignment and Optimization

Based on the BCP, the connection between camera and radar is established through the ground plane parameters. To align these two coordinates, we come up with a detection alignment strategy by ground plane optimization.

**Detection alignment cost.** The alignment between \( \mathcal{R} \) and \( C \) is challenging because they are both 2D coordinates with significantly different perspectives. However, we find that the object height is very useful information during the alignment. The object will have very different heights at different distances in the RGB image due to the perspective. Thus, the object height is a special cue of its 3D location. In the alignment, we use the average height for each object class and project all the CFAR peak detections to RGB images by \( \mathcal{R} \rightarrow C \) projection with the object height. Each CFAR detection will be projected as a line segment in the RGB image, named as CFAR line. We define the detection alignment cost for a CFAR detection \( i \) to be

\[
\ell_i = \lambda_i \left( h_i - h_i^{\text{mask}} \right)^2 + (1 - \lambda_i) \left( h_i - h_i^{\text{bbox}} \right)^2,
\]

where \( h_i \) is the height of the projected CFAR detection in the RGB image; \( h_i^{\text{mask}} \) and \( h_i^{\text{bbox}} \) are the heights of the object mask and bounding box near the projected CFAR line, respectively. \( \ell_i \) is the combined cost from object mask and bounding box based on an adaptive weight \( \lambda_i \), where

\[
\lambda_i = e^{-\alpha z_i^c},
\]

which means \( \lambda_i \) is dependent on \( z_i^c \). The intuition behind is that, for nearby objects, 2D object masks can accurately describe the height of the objects, especially for the cars, whereas bounding boxes fail to do that. While for faraway objects, bounding boxes can perform better than the unreliable masks. Here, \( \alpha \) is a parameter to distinguish between nearby and faraway objects. During the experiment, we empirically find 10 meters is a good threshold, so that we set \( \alpha = 0.06 \) to make \( \lambda = e^{-10\alpha} \approx 0.5 \).

**Ground plane optimization.** After the detections are aligned between camera and radar, the ground plane parameters can be optimized accordingly. Here, we define the objective function as

\[
\min_{\phi, \gamma} \sum_i \frac{n_{\text{CFAR}}}{\sum_{i=1}^{n_{\text{CFAR}}}} (v_{i,t} - v_{i,t}^{\text{mask}})^2,
\]

where \( n_{\text{CFAR}} \) is the number of CFAR detections in the frame \( t \); \( v_{i,t} \) is the vertical pixel location of the CFAR detection, i.e., \( v \)-axis of the lower endpoint of the CFAR line;
\( v_{\text{mask}} \) is the bottom location of the object mask near the projected CFAR line.

When the ground plane is optimized for each frame, we can use the \( C \to R \) projection to project the detections in the RGB image that are not aligned. Here, we call this procedure \textit{supplementary projection}. Since the camera usually can detect more objects than radar, this projection can significantly improve the detection recall.

5. Point-based Detection Evaluation

As mentioned in Section 1, the common datasets with the FMCW radar \([8, 7, 23, 29, 33]\) usually use points to represent detections, we propose an evaluation system for point-based detection without any bounding box.

5.1. Point-based Similarity

Before introducing the evaluation metrics, the matching strategy between the generated annotations and the ground truth needs to be explained. We propose the object location similarity (OLS) to represent the similarity between a detection \( i \) and a ground truth \( j \) to be

\[
\text{OLS}(i, j) = \exp \left( -\frac{d_{ij}^2}{2(s_j \kappa_{\text{cls}})^2} \right),
\]

where \( d \) is the distance (in meters) between the two points in an RF image; \( s \) is the object distance from the sensors; and \( \kappa_{\text{cls}} \) is a per-class constant that represents the error tolerance for class \( \text{cls} \), which can be determined by the object average size of the corresponding class.

5.2. Scoring Metrics

The quality of the radar object detection includes two aspects: 1) The location accuracy of the object detections; 2) The object-class correctness in the radar’s FoV.

Typically, to evaluate the location accuracy, the mean absolute error (MAE) is used to calculate the absolute localization error in meters. But MAE cannot reflect the false positives or false negatives, i.e., wrong or missing detections. Therefore, we also include \textit{precision} and \textit{recall} into our evaluation metrics.

Moreover, to better describe the quality of the detections, we define a new evaluation metric called \textit{Detection Quality F1 Score} (DQF1), that aims to jointly consider MAE, precision and recall into one single number of measurement. Considering the F1 score that is frequently used to combine precision and recall into one single number of measurement. Overall, the DQF1 score of our system can achieve over 40% for both the precision and recall. Overall, the DQF1 score of our system outperforms CO \([32]\) by about 15%. Comparing with CRF algorithm \([33]\), the MAE and precision are similar but the recall of CRF is much worse, which means that CRF has a number of false negatives. These false negatives may be due to the large errors from the results of the CO method. Overall, our annotator improves the DQF1 performance by around 6%, compared with CRF. The qualitative results are shown in Fig. 7, where the objects are accurately annotated even if they are not detected by the radar.

We also use different time window sizes \( t \) in the ground plane optimization (Eq. 13) and evaluate the performance

6. Baseline Evaluation

6.1. Evaluation on Radar Object Detection

We first evaluate the radar-only object detection performance of the state-of-the-art method, called RODNet \([33, 34]\), using our proposed evaluation system. Vanilla, Hourglass (HG), and Full are three different network configurations mentioned in the original paper. The evaluation scores are shown in Table 4. The comprehensive metrics for radar object detection include AP, AR, and the proposed DQF1. AP and AR used in the original paper are classical metrics for object detection, while DQF1 focuses more on localization accuracy instead of classification.

It is obvious that the localization accuracy of the RODNet is very promising since it considers radar data as the only input. Therefore, the DQF1 scores are also a little bit higher than the original AP and AR, which shows the property of DQF1 that emphasize more on localization. Overall, with AP, AR, and DQF1, we can have an overall impression of the point-based detection performance from both classification and localization.

6.2. Radar Object Annotation Comparison

We use our proposed annotation system to automatically generate object annotations on CRUW dataset and evaluate the annotation quality by the evaluation metrics mentioned in Section 5.2, on the selected crowded training set. Note that the MAE is evaluated by both mean and standard deviation of the localization errors.

We compare the proposed annotation system with a camera-only (CO) object 3D localization method \([32]\) and CRF algorithm \([33]\). Comparing with CO, the MAE achieved by our proposed annotator can be decreased by as much as 40% after taking radar into consideration. Besides, our system can achieve over 90% for both the precision and recall. Overall, the DQF1 score of our system outperforms CO \([32]\) by about 15%. Comparing with CRF \([33]\), the MAE and precision are similar but the recall of CRF is much worse, which means that CRF has a number of false negatives. These false negatives may be due to the large errors from the results of the CO method. Overall, our annotator improves the DQF1 performance by around 6%, compared with CRF. The qualitative results are shown in Fig. 7, where the objects are accurately annotated even if they are not detected by the radar.

We also use different time window sizes \( t \) in the ground plane optimization (Eq. 13) and evaluate the performance
### Table 4. Performance evaluation using our proposed scoring metrics for a radar-only object detection method (RODNet) on the testing set under different driving scenarios.

| Method                  | Scenario     | MAE     | Precision | Recall | AP     | AR     | DQF1   |
|-------------------------|--------------|---------|-----------|--------|--------|--------|--------|
| RODNet (Vanilla) [33]   | Overall      | 0.31 ±0.26 | 95.90%    | 78.03% | 74.29% | 77.85% | 81.02% |
|                         | Parking Lot  | 0.26 ±0.19 | 98.29%    | 87.76% | 85.33% | 86.76% | 89.33% |
|                         | Campus Road  | 0.42 ±0.30 | 89.49%    | 53.02% | 42.67% | 49.03% | 56.03% |
|                         | City Street  | 0.48 ±0.39 | 88.88%    | 73.42% | 59.79% | 67.23% | 71.15% |
| RODNet (HG) [33]        | Overall      | 0.31 ±0.23 | 96.02%    | 88.56% | 83.76% | 85.62% | 86.64% |
|                         | Parking Lot  | 0.26 ±0.16 | 98.26%    | 96.94% | 93.60% | 94.98% | 93.63% |
|                         | Campus Road  | 0.40 ±0.26 | 92.16%    | 68.76% | 50.34% | 57.23% | 70.28% |
|                         | City Street  | 0.48 ±0.39 | 91.53%    | 81.27% | 64.54% | 70.47% | 75.55% |
| RODNet (Full) [34]      | Overall      | 0.31 ±0.25 | 95.93%    | 88.86% | 85.98% | 87.86% | 87.82% |
|                         | Parking Lot  | 0.27 ±0.21 | 98.49%    | 97.98% | 95.79% | 96.85% | 94.62% |
|                         | Campus Road  | 0.36 ±0.26 | 92.08%    | 69.40% | 57.06% | 62.08% | 73.62% |
|                         | City Street  | 0.49 ±0.37 | 91.59%    | 76.37% | 62.83% | 70.41% | 74.65% |

### Table 5. Performance evaluation of different annotation methods on the selected training set (campus road and city street).

| Methods | MAE     | Precision | Recall | DQF1   |
|---------|---------|-----------|--------|--------|
| CO [32] | 1.21 ±1.05 | 81.10%   | 96.11% | 55.16% |
| CRF [33] | 0.68 ±0.72 | 93.02%   | 70.11% | 64.14% |
| Ours    | 0.72 ±0.78 | 90.57%   | 95.35% | 70.36% |

### Table 6. The performance using different time window sizes evaluated on the selected training set (campus road and city street).

| Window t | MAE     | Precision | Recall | DQF1   |
|----------|---------|-----------|--------|--------|
| 1        | 0.69 ±0.77 | 90.78%   | 91.03% | 65.39% |
| 5        | 0.71 ±0.79 | 90.70%   | 92.88% | 66.22% |
| 10       | 0.72 ±0.80 | 91.06%   | 93.47% | 67.33% |
| 50       | 0.72 ±0.78 | 90.57%   | 95.35% | 70.36% |
| 100      | 0.73 ±0.79 | 90.34%   | 95.87% | 70.35% |

7. Conclusion

In this paper, we proposed a novel radar object detection platform for adverse driving scenarios, including a large-scale dataset, annotation and evaluation system. This platform is potentially valuable to the autonomous driving community for the deep learning based radar semantic understanding tasks, e.g., detection, segmentation, tracking, etc. It is also an inspiration for a new autonomous vehicle solution using a camera-radar sensor system for all-weather conditions.

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