

CFTrack: Center-based Radar and Camera Fusion for 3D Multi-Object Tracking

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Abstract—3D multi-object tracking is a crucial component in the perception system of autonomous driving vehicles. Tracking all dynamic objects around the vehicle is essential for tasks such as obstacle avoidance and path planning. Autonomous vehicles are usually equipped with different sensor modalities to improve accuracy and reliability. While sensor fusion has been widely used in object detection networks in recent years, most existing multi-object tracking algorithms either rely on a single input modality, or do not fully exploit the information provided by multiple sensing modalities. In this work, we propose an end-to-end network for joint object detection and tracking based on radar and camera sensor fusion. Our proposed method uses a center-based radar-camera fusion algorithm for object detection and utilizes a greedy algorithm for object association. The proposed greedy algorithm uses the depth, velocity and 2D displacement of the detected objects to associate them through time. This makes our tracking algorithm very robust to occluded and overlapping objects, as the depth and velocity information can help the network in distinguishing them. We evaluate our method on the challenging nuScenes dataset, where it achieves 20.0 AMOTA and outperforms all vision-based 3D tracking methods in the benchmark, as well as the baseline LiDAR-based method. Our method is online with a runtime of 35ms per image, making it very suitable for autonomous driving applications.

I. INTRODUCTION

Multi Object Tracking (MOT) is the task of analyzing videos to identify and track objects belonging to certain categories, without any prior knowledge about the appearance or the number of targets [1]. Occlusions and interactions between objects with similar appearances are two main factors that make MOT a challenging task. Many algorithms have been developed in recent years to address these issues. The majority of these algorithms exploit the rich representational power of Deep Neural Networks (DNN) to extract complex semantic features from the input. Tracking-by-detection is a common approach used in these algorithms, where the tracking problem is solved by breaking it into two steps: (1) detecting objects in each image, (2) associating the detected objects over time. Recently, the Convolutional Neural Networks (CNN)-based object detection networks have been very successful in improving the performance in this task. As a result, many of the MOT methods adopt an existing detection method and focus more on improving the association step.

Object tracking is an important task in autonomous driving vehicles. Tracking of dynamic objects surrounding the vehi-

cle is essential for many of the tasks crucial to autonomous navigation, such as path planning and obstacle avoidance [2]. To increase reliability and accuracy, the perception system in an autonomous vehicle is usually equipped with multiple sensors with different sensing modalities such as cameras, radars and LiDARs. Incorporating the multi-modal sensory data into an object tracking framework for autonomous driving applications is not a trivial task. It requires an efficient, accurate and reliable fusion algorithm capable of utilizing the information embedded in different modalities in real time. Most multi-modal MOT methods use multiple sensing modalities in the detection stage, but only utilize features from one sensing modality in the association step. In addition, many existing MOT methods rely only on camera images [3], [4] or LiDAR point clouds [5], [6] for detection and tracking.

In recent years, radars have been widely used in vehicles for Advanced Driving Assistance System (ADAS) applications such as collision avoidance [7]. Radars are capable of detecting objects at much longer range compared to LiDAR and cameras, while being very robust to adverse weather conditions such as fog and snow. Additionally, radars provide accurate velocity information for every detected object. While objects' velocity information might not be necessary for object detection, it is extremely useful for the object tracking task as it can be used for predicting objects' path and displacement. Finally, compared to LiDARs, radar point clouds require less processing before they can be used as object detection results [7]. This is an important factor in real-time applications with limited processing power such as autonomous driving.

We propose an end-to-end MOT framework, utilizing radar and camera data to perform joint object detection and tracking. Our method is based on CenterFusion [7], a radar-camera sensor fusion algorithms for 3D object detection in autonomous driving applications. CenterFusion achieves state-of-the-art performance in 3D object detection using Radar and camera fusion and provides object velocity estimates that could be very helpful in the object tracking task. Our proposed network takes as input the current image frame and radar detections in addition to the previous frame and detected objects. The outputs are 3D object detection results and tracking IDs for the detected objects. Every detected object is also associated with an estimated absolute velocity in the global coordinate system.

The object association step in our tracking framework is based on a simple greedy algorithm similar to CenterTrack [3]. While CenterTrack only uses the objects' 2D displace-

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ment in consecutive images to associate them, we propose a greedy algorithm based on a weighted cost function calculated from the object’s estimated depth and velocity in addition to their 2D displacement. This significantly improves the ability of the network to correctly associate occluded and overlapping objects, as the depth and velocity information provide valuable clues to distinguish these objects. Additionally, the proposed network uses the fused radar and image features to predict the objects’ displacement in consecutive frames, which makes these predictions more accurate compared to just using the visual information. We thus refer to the proposed MOT framework as CFTrack.

The main contributions of this paper are twofold. First, to the best knowledge of the authors, this study is the first to propose a radar and camera sensor fusion framework for 3D multi-object detection and tracking using a deep network trained end-to-end. Second, we propose a greedy algorithm that incorporates objects’ depth and velocity in addition to their 2D displacement for object association, resulting in more accurate object tracking.

Our experiments on the challenging nuScenes dataset [8] show that CFTrack outperforms all other image-based tracking methods on the nuScenes benchmark, as well as the nuScenes’ baseline LiDAR-based method AB3DMOT [9]. Our fusion-based object tracking algorithm achieves 20.0% AMOTA, outperforming CenterTrack [4] by a factor of 4, while running at 28 frames per second.

II. RELATED WORK

Object tracking methods have many applications in different computer vision tasks such as autonomous driving, surveillance and activity recognition. Most existing methods on MOT use the tracking-by-detection approach [4], [10], [11], relying on the performance of an underlying object detection algorithm [12], [13], [14] and focusing on improving the association between detections. One major drawback in this approach is that the association task does not utilize the valuable features extracted in the detection step. More recently, the *joint detection and tracking* approach is trending for MOT where an existing object detection network is converted into an object tracker to accomplish both tasks in the same framework [15], [16], [17]. Our method belongs to this category.

From another perspective, MOT algorithms can be split into batch and online methods. Batch methods use the entire sequence of frames to find the global optimal association between the detections. Most methods in this category are based on optical flow algorithms and create a flow graph from the entire sequence [18], [19]. Online methods, on the other hand, only use the information up to the current frame for tracking objects. Many of these algorithms generate a bipartite graph matching problem which is solved using the Hungarian algorithm [20]. More modern methods in this category use deep neural networks to solve the association problem [21], [22]. Our proposed algorithm is an online method and does not require any knowledge from future frames.

MOT methods can also be divided into 2D and 3D categories. Most 3D MOT methods are developed as an extension of existing 2D tracking models, with the distinction that input detections are in the 3D space rather than the 2D image plane. Some of the 3D MOT methods use LiDAR point clouds [23] or a combination of point clouds and images [24] as their inputs.

A. 2D Multi-Object Tracking

DeepSORT [25] uses an overlap-based association method with a bipartite matching algorithm, in addition to appearance features extracted by a deep network. In [15] authors use the current and previous frames as inputs to a siamese network that predicts the offset between the bounding boxes in different frames. Tracktor [16] exploits the bounding box regression of the object detector network to directly propagate the region proposals’ identities, which eliminates the need for a separate association step. Since it is assumed that the bounding boxes have a large overlap between consecutive frames, low frame-rate sequences would require a motion model in this approach. Zhu et al. [26] propose flow-guided feature aggregation, where an optical flow network estimates the motion between the current and previous frames. The feature maps from previous frames are then warped to the current frame using the flow motion and an adaptive weighting network is used to aggregate and feed them into the detection network. Integrated detection [27] proposes an early integration of the detection and tracking tasks, where the outputs of the object detector are conditioned on the tracklets computed over the prior frames. A bipartite-matching association method is then used to associate the bounding boxes.

B. 3D Multi-Object Tracking

Hu et al. [28] combine 2D image-based feature association and 3D LSTM-based motion estimation for 3D object tracking. Their method leverages 3D box depth-ordering matching and 3D trajectory prediction to improve instance association and re-identification of occluded objects. Weng et al. [23] propose a real-time MOT system called AB3DMOT that uses LiDAR point clouds for object detection and a combination of Kalman filter and the Hungarian algorithm for state estimation and data association. CenterTrack [3] takes a pair of images and detections from prior frames as input to a point-based framework, where each object is represented by the center point of its bounding box. The network estimates an offset vector from the center point of objects in the current frame to their corresponding center points in the previous frame, and uses a greedy algorithm for object association. Besides images and point clouds, some methods use map information to improve the tracking performance for autonomous driving applications. Argoverse [29] uses detailed map information such as lane direction, ground height and drivable area to improve the accuracy of 3D object tracking.

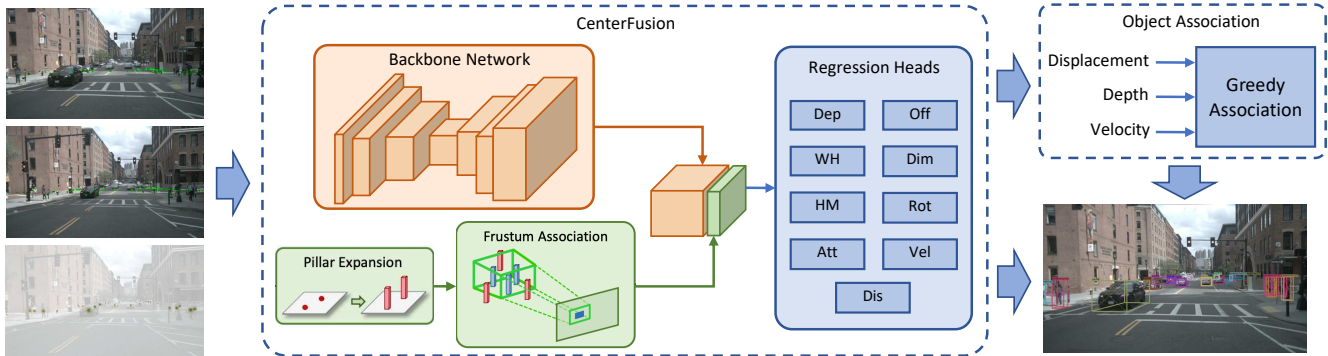


Fig. 1. CFTrack network architecture. The inputs to the network are shown on the left which includes the current image and radar point clouds (top), the previous image frame and radar point clouds (middle) and the previous detection results in the form of class-agnostic heatmaps (bottom). The radar point clouds are shown on the input images. An additional regression head (“Dis”) is added to the model, which uses the fused radar and image features to predict objects displacement in consecutive frames. The greedy algorithm in the association step uses the displacement, depth and velocity of each object to associate it to previous detections. The output is 3D bounding boxes and track IDs for all detected objects.

III. PRELIMINARIES

Our proposed 3D tracking algorithm is based on the CenterFusion 3D object detection algorithm [7]. CenterFusion takes an image $I \in \mathbb{R}^{W \times H \times 3}$ and a set of radar detections $P_i = (x^i, y^i, z^i, v_x^i, v_y^i)$ where (x^i, y^i, z^i) are the coordinates of the point i in the radar point cloud, and (v_x^i, v_y^i) are the radial velocities in the x and y directions, respectively. These coordinates are according to the vehicle coordinate system, where x is forward, y is to the left and z is upward from the drivers point of view.

CenterFusion first uses a center point detection method called CenterNet [30] to detect the centerpoint of objects by estimating a heatmap $\hat{Y} \in [0, 1]^{\frac{W}{R} \times \frac{H}{R} \times C}$ where R is the down-sampling factor and C is the number of object categories in the dataset. The local maxima in the estimated heatmap \hat{Y} correspond to the centers of detected objects in the image. The ground truth heatmap Y is generated by rendering a Gaussian-shaped peak at the center points of each object, calculated as the center point of their corresponding bounding box.

The network uses regression layers to generate preliminary 3D bounding boxes for all objects, then associates the radar detections to these preliminary 3D detections using a frustum-based association method. To do this, the radar detections are first expanded into pillars with predefined dimensions. A frustum is then formed around each detected object, and radar pillars inside the frustum are associated with that object. If there are multiple radar pillars inside the frustum, the closest one is kept and others are discarded.

Based on the association results, the depth and velocity of the radar detection are mapped to their corresponding objects on the image. These values are represented as separate heatmap channels and are concatenated to the image-based features. These fused features are then used to improve the preliminary detection results by re-calculating the depth, size, orientation and other object attributes. Additionally, a velocity vector is estimated for every detected object.

CenterFusion uses an objective function based on the focal loss, defined as:

$$L_i = \frac{1}{N} \sum_{xyc} \begin{cases} (1 - \hat{Y}_{xyc})^\alpha \log(\hat{Y}_{xyc}) & Y_{xyc} = 1 \\ (1 - Y_{xyc})^\beta (\hat{Y}_{xyc})^\alpha \log(1 - \hat{Y}_{xyc}) & \text{otherwise} \end{cases},$$

where N is the number of objects, $Y \in [0, 1]^{\frac{W}{R} \times \frac{H}{R} \times C}$ is the annotated objects’ ground-truth heatmap and α and β are the hyper-parameters of the focal loss. After detecting objects’ center point, different regression heads are used to regress to size, orientation, depth and velocity of the detected objects.

IV. CFTRACK

We follow CenterTrack [3] and approach the tracking problem from a local perspective, where an object’s identity is preserved across consecutive frames without re-establishing associations if the object leaves the frame. We use both camera and radar data from the previous frame to improve the ability to track occluded objects in the current frame. CFTrack uses the fused radar and image features to estimate objects’ displacement in consecutive frames, which is used for object association through time. In the association step, a greedy algorithm is proposed that leverages objects’ velocity and depth information in addition to their 2D displacement for accurate association through time.

The next section presents our problem formulation. Section IV-B describes the underlying detection network CenterFusion, which is modified to use the previous frame as an additional input and also estimate objects’ displacements between consecutive frames. Finally, Section IV-C discusses the greedy algorithm used to associate detected objects.

A. Problem Formulation

The inputs to CFTrack are the current and previous image frames $I^{(t-1)}, I^{(t)} \in \mathbb{R}^{W \times H \times 3}$, the current and previous radar detections $P^{(t-1)}, P^{(t)} \in \mathbb{R}^{N \times 5}$ where N is the number of radar detections, and the tracked objects from the previous frame $T^{(t-1)} = \{b_0^{(t-1)}, b_1^{(t-1)}, \dots\}$. The tracked objects are represented by $b = (p, d, v, w, id)$ where $p \in \mathbb{R}^2$ is the object’s center location, $d \in \mathbb{R}$ is the object’s depth, $v \in \mathbb{R}^2$ is object’s velocity, $w \in [0, 1]$ is the detection

confidence and id is an integer representing the unique identity of the tracked object. For every frame, the goal is to detect and track objects $T^{(t)} = \{b_0^{(t)}, b_1^{(t)}, \dots\}$ and assign a consistent id to the objects in consecutive frames. The detection and association of objects are done in a single deep network trained end-to-end.

B. Detection Network

The overall network architecture is shown in Fig. 1. The CenterFusion network is modified to take as input the current image frame $I^{(t)}$ and radar detections $P^{(t)}$, in addition to the previous image frame $I^{(t-1)}$, radar detections $P^{(t-1)}$ and detected objects. The outputs are 3D bounding boxes for all detected objects and an absolute velocity for each object, reported in the x and y directions in the vehicle’s coordinate system. The previous detections are represented as a single channel heatmap using a 2D Gaussian kernel. Including the previous image, radar detections and detected objects helps the network to better estimate the location of objects in the current frame. The radar information from previous frame further improves the ability of network to detect objects even if the visual evidence is not present due to occlusion.

Besides the object detection results for the current frame, the modified network also estimates the 2D displacement of the detected objects between the current and previous frames, using the concatenated radar and image features. Having the radar depth and velocity information in addition to the image features from the current and previous frames helps the network to generate more accurate object displacement predictions.

C. Object Association

We use a greedy algorithm to associate the detected objects over time. The detected objects are represented by $a = (p, d, v, c)$ where $p \in \mathbb{Z}^2$ is the object’s center in pixels, $d \in \mathbb{R}$ is the object’s depth, $v \in \mathbb{R}^2$ is the object’s velocity, and $c \in C$ is the object’s category. Similar to [3], the displacement is calculated by a regression layer in the form of two output channels $\hat{D}^{(t)} \in \mathbb{R}^{\frac{W}{R} \times \frac{H}{R} \times 2}$ representing the displacement of the center of the objects on the image, as shown in Fig. 2. Similar to the other regression heads, the L1 loss is used as the objective function to train this layer.

To associate objects across time, we define a cost function based on the objects’ depth, velocity and displacement on the image. This cost function is defined as:

$$Cost_{t,t-1} = \begin{cases} \alpha \cdot \mathcal{L}_{pixel} + \beta \cdot \mathcal{L}_{depth} + \delta \cdot \mathcal{L}_{velocity} & c_t = c_{t-1} \\ \infty & c_t \neq c_{t-1} \end{cases}$$

$$\mathcal{L}_{pixel} = (x_t - x_{t-1})^2 + (y_t - y_{t-1})^2$$

$$\mathcal{L}_{depth} = (d_t - d_{t-1})^2$$

$$\mathcal{L}_{velocity} = (vx_t - vx_{t-1})^2 + (vy_t - vy_{t-1})^2$$

where x, y is the object’s center, d is the object’s depth, and vx, vy are the velocity of the object in x and y directions respectively. $\alpha, \beta, \delta \in \mathbb{R}^+$, are tunable parameters.

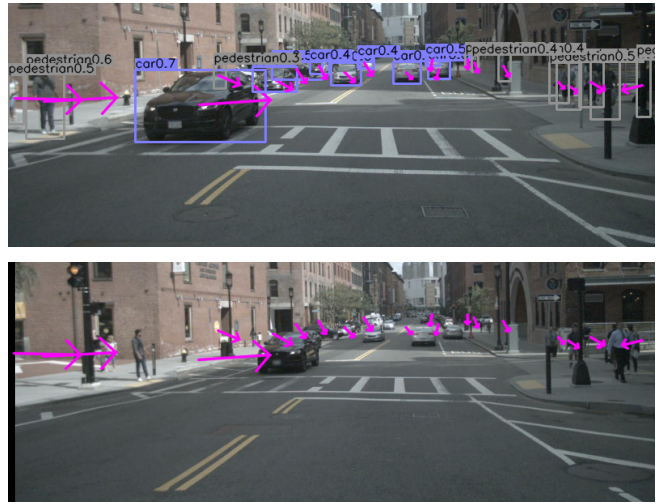


Fig. 2. Top: Object displacement from the previous frame, represented by arrows pointing from the center of each object in the current frame to the estimated center of the same object in the previous frame. Bottom: Previous frame. Displacement arrows re-drawn for comparison.

For every detected object at position p , we look for prior detections within a radius r from $p - D_p$. If there are unmatched prior detections at that position, we calculate the above cost function to determine the distance between these detections, and match the object with the previous detections with the lowest cost. For every unmatched detection, a new track is created.

V. EXPERIMENTS

A. Dataset and Evaluation Metrics

We evaluate our method on the nuScenes dataset [8], a large-scale dataset for autonomous driving with annotations for 3D object detection and tracking containing camera, radar and LiDAR data. It provides 1000 different sequences from which 700 sequences are used for training, 150 sequences for validation and 150 sequences for testing. Each sequence is comprised of 40 annotated frames, each containing camera, radar and LiDAR samples. Samples are obtained from 6 different cameras and 5 different radars.

The main evaluation metric used in the nuScenes benchmark, AMOTA, is a weighted average of the recall-normalized Multi-Object Tracking Accuracy (MOTA) metric at different recall thresholds:

$$MOTAR = \max(0, 1 - \frac{IDS_r + FP_r + FN_r - (1 - r) * P}{r * P})$$

$$AMOTA = \frac{1}{n - 1} \sum_{r \in \{\frac{1}{n-1}, \frac{2}{n-1}, \dots, 1\}} MOTAR$$

where r is the recall threshold, IDS_r is the number of identity switches, FP_r is the number of false positives, FN_r is the number of false negatives and P is the total number of annotated objects in all frames.

TABLE I

EVALUATION ON THE nuSCENES TEST SET. WE COMPARE TO PUBLISHED WORKS ON THE nuSCENES BENCHMARK, INCLUDING VISION-BASED AND LiDAR-BASED METHODS. AMOTA IS THE MAIN METRIC USED IN THE nuSCENES BENCHMARK. OTHER METRICS ARE DEFINED IN [8].

Method	Modality			Time(ms)	AMOTA	AMOTP	MOTAR	MOTA	MOTP	Recall
	Cam	Rad	LiDAR							
AB3DMOT [9] + Mapillary			✓	-	0.018	1.790	0.091	0.020	0.903	0.353
AB3DMOT [9] + PointPillars			✓	-	0.029	1.703	0.243	0.045	0.824	0.297
AB3DMOT [9] + Megvii			✓	-	0.151	1.501	0.552	0.154	0.402	0.276
CenterTrack [3]	✓			45	0.046	1.543	0.231	0.043	0.753	0.233
CenterTrack [3] + Megvii	✓		✓	45	0.108	0.989	0.267	0.085	0.349	0.412
Ours	✓	✓		35	0.200	1.292	0.353	0.151	0.766	0.420

TABLE II

PER-CLASS AMOTA RESULTS.

Method	Modality			AMOTA						
	Cam	Rad	LiDAR	Car	Truck	Bus	Trailer	Pedest.	Motor.	Bicycle
AB3DMOT [9] + Mapillary			✓	0.125	0.000	0.000	0.000	0.000	0.000	0.000
AB3DMOT [9] + PointPillars			✓	0.094	0.000	0.066	0.000	0.039	0.000	0.000
AB3DMOT [9] + Megvii			✓	0.278	0.013	0.408	0.136	0.141	0.081	0.000
CenterTrack [3]	✓			0.202	0.004	0.072	0.000	0.030	0.011	0.000
CenterTrack [3] + Megvii	✓		✓	0.341	0.012	0.256	0.000	0.142	0.005	0.000
Ours	✓	✓		0.546	0.000	0.107	0.075	0.346	0.206	0.114

B. Implementation Details

Following CenterFusion [7], we use an input resolution of 800×448 and apply horizontal flipping and random shifts for regularization. The Deep Layer Aggregation (DLA) network is used as the backbone for extracting image features, optimized with the Adam [31]. The CFTrack network is trained for 60 epochs with a batch size of 24 and a learning rate of $1.2e-4$, starting from a pre-trained CenterFusion network trained for 170 epochs. We train on a machine with an Intel Xeon E5-1650 CPU and two Quadro P5000 GPUs. The reported tracking runtime is obtained on a machine with an Intel Xeon E5-1607 CPU and a TITAN X GPU. We reimplement the Frustum Fusion algorithm in CenterFusion to run in parallel and improve the overall runtime of the detection network.

VI. RESULTS

Table I compares our method with some of the other published methods in the nuScenes object tracking benchmark. Specifically, we compare our method with the CenterTrack [3] algorithm using both image-based and LiDAR based detection results, as well as the AB3DMOT [9] with three different LiDAR-based object detection algorithms. According to the table, CFTrack outperforms both methods by achieving an AMOTA score of 20.0%, improving the vision-based CenterTrack algorithm by about 15% (by a factor of 4) and the LiDAR-based CenterTrack algorithm by 9.2%. CFTrack also outperforms CenterTrack in the MOTAR, MOTA, MOTP and Recall metrics.

Given the similarity of the tracking algorithms in CFTrack and CenterTrack, these results demonstrate the effect of utilizing radar data in both detection and tracking stages. Both methods use a greedy algorithm for associating objects, but CFTrack also takes advantage of the depth and velocity of the detected objects to better associate them through time. Additionally, the velocity data provided by the radar enables

the network to predict the objects' displacement in the image more accurately, further improving object association.

Table II shows AMOTA for each class. According to the results, CFTrack significantly outperforms all the other methods in the Car, Pedestrian, Motorcycle and Bicycle categories, while AB3DMOT with the Megvii detector performs better in the Truck, Bus and Trailer categories. Note that all categories where CFTrack is outperformed are large objects, namely Truck, Bus and Trailer. One explanation could be the fact that it is more difficult for the underlying fusion algorithm to correctly associate many radar detections obtained from these large objects to their corresponding 3D bounding boxes, resulting in lower accuracy in estimated depth and velocity for these objects.

On average, our method achieves a runtime of 35ms per image (28 fps), which makes it suitable for the real-time autonomous driving applications.

VII. CONCLUSIONS

In this work, we presented an online and end-to-end object detection and tracking method based on radar and camera sensor fusion. The proposed method uses the fused radar and image features to detect objects and also estimate their displacement from the previous frame. To associate objects across time, we proposed a greedy algorithm that uses a cost function incorporating objects' depth, velocity and displacement, which makes our tracking algorithm very robust to overlapping and occluded objects. Our proposed method is currently the only tracking algorithm based on radar and image information on the nuScenes tracking benchmark, outperforming all published vision-only methods as well as the nuScenes' baseline LiDAR-based method.

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