RaLiBEV: Radar and LiDAR BEV Fusion Learning for Anchor Box Free Object Detection Systems

Yanlong Yang*, Jianan Liu†, Tao Huang‡, Senior Member, IEEE, Qing-Long Han, Fellow, IEEE, Gang Ma, and Bing Zhu, Member, IEEE

Abstract—In autonomous driving, LiDAR and radar play important roles in the perception of the surrounding environment. LiDAR provides accurate 3D spatial sensing information but cannot work in adverse weather like fog. On the other hand, the radar signal can be diffracted when encountering raindrops or mist particles thanks to its wavelength, but it suffers from large noise. Recent state-of-the-art works reveal that fusion of radar and LiDAR can lead to robust detection in adverse weather. The existing works adopt convolutional neural network architecture to extract features from each sensor data, then align and aggregate the two branch features to predict object detection results. However, these methods have low accuracy of bounding box estimations due to a simple design of label assignment and fusion strategies. In this paper, we propose a bird's-eye view fusion learning-based anchor box-free object detection system, which fuses the feature derived from the radar range-azimuth heatmap and the LiDAR point cloud to estimate possible objects. Different label assignment strategies have been designed to facilitate the consistency between the classification of foreground or background anchor points and the corresponding bounding box regressions. Furthermore, the performance of the proposed object detector is further enhanced by employing a novel interactive transformer module. The superior performance of the methods proposed in this paper has been demonstrated using the recently published Oxford Radar RobotCar dataset. Our system's average precision significantly outperforms the state-of-the-art method by 13.1% and 19.0% at IoU of 0.8 under 'Clear+Foggy' training conditions for 'Clear' and 'Foggy' testing, respectively.

Index Terms—ADAS, autonomous driving, anchor box free object detection, LiDAR, point cloud, radar, range-azimuth heatmap, label assignment, BEV fusion, interactive transformer, deep learning

I. INTRODUCTION

AUTONOMOUS driving systems typically employ sensors such as LiDAR, cameras, and radar to construct their perception functionality, which serves as the essential for the downstream tasks like trajectory prediction and ego motion planning [1, 2], etc. Such perception scheme has been widely demonstrated in numerous works, covering various aspects such as data collection/generation [3, 4], algorithm development [5], and real-world testing [6]. LiDAR, a key sensor used in Advanced Driver Assistance Systems (ADAS) and autonomous driving, offers rich semantic and geometric information for environmental perception tasks [7]. These tasks include object detection [8, 9], multi-object tracking [10, 11], ego localization [5, 12], and mapping [13]. To build a robust perception system for autonomous driving, recent works show that the fuse of LiDAR and camera at the raw data stream level can significantly improve the perception capability [14, 15]. However, the performance of either camera or LiDAR can severely drop in adverse weather, i.e., rain, snow, and fog [16, 17]. For instance, cameras can become blurred, the operating range of LiDAR might be significantly reduced, and the number of noise points might increase due to the impact of heavy snow or fog. As illustrated in Fig. 1(b), the number of noisy points around the ego vehicle increases while the far end LiDAR points disappear, compared to the LiDAR point cloud measured in clear weather, as shown in Fig. 1(a).

In contrast with cameras and LiDAR, radar can naturally...
avoid the influence of adverse weather since the millimeter wavelength signals can penetrate the rain, snow, and fog. Such characteristic makes radar a powerful complementary sensor in addition to either camera or LiDAR in ADAS and autonomous driving [18], and even in future cooperative perception [19]. The typical Frequency Modulated Continuous Wave (FMCW) radar, widely used in automotive systems, can accurately separate objects in range and speed dimension but has a low angular resolution due to the limited number of antennas in the compact space. Thus, radar can only provide many sparser detection points with ambiguity in angular information compared to the dense LiDAR point cloud. Such a drawback caused limitations on its performance when applied in the perception system [20–23].

To take full advantage of the robustness of radar in adverse weather, radar range-azimuth heatmap rather than detection points has been employed to fuse with LiDAR point cloud for vehicle detection in the recent proposed anchor box-based methods [24, 25]. However, their methods suffer from generalization issues since their approaches require predefined anchor boxes and they need to be carefully chosen according to the dataset. Moreover, these methods have been shown to have unsatisfactory performance, especially in the performance with high accuracy requirements.

To address these issues, we propose radar and LiDAR in Bird’s Eye View (BEV) fusion model, dubbed as RaLiBEV, for object detection. RaLiBEV introduces a novel object detection approach that fuses radar and LiDAR data in BEV in anchor boxes free scheme, intended for real-time application. The LiDAR point cloud is transformed into a structured data format in BEV, a process known as pillarization, while the radar range-azimuth heatmap naturally provides discrete sampling in BEV. These BEV feature maps from both radar and LiDAR are then separately extracted and combined to create an aggregated BEV feature map. This map is processed through the network’s backbone and then fed into a multi-scale detection head that doesn’t rely on anchor boxes to estimate the bounding boxes of vehicles.

Unlike the anchor box-based approach, the anchor box-free detection head first identifies representative pixels, or key points, in the predicted feature map. These key points are then used as positive samples to regress the remaining feature channels. However, this approach can lead to inconsistencies between the classification of foreground and background, and the regression problem. Specifically, a key point with a high classification score doesn’t necessarily result in better accuracy in bounding box regression. Another challenge lies in effectively fusing the rich feature information from the radar range-azimuth heatmap with the LiDAR feature map in a complementary manner, rather than simply concatenating them.

To address these issues, RaLiBEV incorporates innovative label assignment strategies to reduce the inconsistency between foreground-background classification and regression. Additionally, it employs interactive transformer-based BEV fusion techniques to better explore the interaction between radar and LiDAR feature maps. The experiment results demonstrate that our method outperforms the state-of-the-art method by 13.1% and 19.0% at IoU equals 0.8 in clear and foggy weather testing respectively.

The main contributions of this paper are concluded as below:

- A radar and LiDAR BEV fusion-based anchor box free object detector, RaLiBEV, is proposed. The RaLiBEV can generate accurate 2D bounding boxes in BEV by fusion of features extracted from the radar range-azimuth heatmap and the LiDAR point cloud.
- A novel label assignment strategy, Gaussian Area-based Consistent Heatmap and intersection over union (IoU) Cost Positive Sample Assignment (GACHIPS), is proposed to combat the inconsistency between the classification of key points and the corresponding bounding box regression tasks in the anchor box free object detector.
- A novel interactive query transformer-based fusion module, Dense Query Map-based Interactive BEV Fusion (DQMITBF), is proposed to fuse radar and LiDAR feature maps. With the introduction of dense learnable queries, the fusion module provides more flexibility to query the suitable features from both maps to fuse.
- The aforementioned object detector can achieve fairly accurate detection performance even in adverse weather, as shown in of Fig. 1(d) compared to the ground-truth bounding boxes illustrated in Fig. 1(c) which outperforms the state-of-the-art radar and LiDAR fusion-based object detector with a large margin in the popular Oxford Radar RobotCar (ORR) dataset [3].

The rest of this paper is organized as follows. Section II discusses the related works, including LiDAR-based perception methods, radar-based perception methods, and the methods which fuse radar and LiDAR for object detection. In Section III, the proposed radar and LiDAR fusion-based object detection approach, RaLiBEV, is introduced. In addition, the proposed label assignment strategies and interactive transformer-based fusion schemes are also described. Then, the experiment process and corresponding results on ORR datasets are explained and analyzed in Section IV. Finally, the conclusion and further work are drawn in Section V.

II. RELATED WORKS

A. LiDAR-based Object Detection

LiDAR is a widely used sensor in surrounding environment perception, and object detection is one of the most important missions in environment perception. The LiDAR object detection method based on deep learning can be divided into four categories according to the processing approach on the input point cloud.

The first approach is the point-based method. It implements a linear layer to extract features on unordered point cloud [26, 27]. The second approach is the grid-based method. This method discretizes the point cloud into 2D grids or 3D voxels, then applies CNN for further feature extraction [8, 9, 28, 29]. The third approach is the graph-based method, which transforms point cloud as graph data format [30]. The Graph Neural Network (GNN) is employed for extracting the feature and detecting the objects, where the points are defined as vertices.
and the relations between points are defined as edges. The fourth type is the combination method. One way is to combine features extracted from two different representations of the point cloud, such as points features and grid/voxel features [31]. Another way is to concatenate features from different views of 2D grids, such as range view and BEV, and decode concatenated features by 2D CNN afterward [32]. Although LiDAR can provide precise and dense 3D spatial information, the inherent problem of facing adverse weather still limits its performance.

B. Radar-based Object Detection

Radar, utilizing under-millimeter wave band electromagnetic signals, is capable of penetrating adverse weather conditions, making it effective for object detection under noise. Both conventional and deep learning methods are employed for this task.

Conventional methods, such as Constant False Alarm Rate (CFAR) algorithms [33] and clustering techniques [34], dynamically adjust the detection threshold based on noise levels and group detected points into objects. However, these methods may struggle with complex environments and overlapping objects. Deep learning methodologies initiate the processing of radar point clouds, employ semantic segmentation for categorization and utilize clustering techniques for the assembly of objects [35, 36]. This method provides detailed object detection but requires significant computational resources. More recent approaches, such as PointNet models [37, 38] and Graph Neural Networks (GNNs) [39, 40], process point cloud data directly. PointNet learns complex patterns for object detection and classification, while GNNs capture both local and global patterns for enhanced detection accuracy. These methods build a end-to-end points-based object detection pipeline for radar object detection. However both methods require substantial training data and computational resources. Lastly, range-azimuth heatmaps are used for radar object detection. One approach applies clustering and classification to the heatmap [41, 42], while another uses deep learning models to directly predict object presence and location from the heatmap [43–47]. Methods leveraging heatmap-based techniques possess the capability to extract the most comprehensive information, albeit at the cost of increased computational resources.

Despite its ability to penetrate adverse weather, radar’s limitations, such as susceptibility to multi-path propagation and lower resolution, hinder detailed object recognition. These drawbacks underscore the necessity of sensor fusion in autonomous driving systems. The fusion of radar and LiDAR data, leveraging LiDAR’s high-resolution point cloud data, can significantly enhance object detection and recognition capabilities.

C. Radar and LiDAR Fusion-based Object Detection

Radar and LiDAR both have their strength and weaknesses. Fusing the information from the two types of sensors can achieve a better surrounding perception [24, 25, 48]. Generally, sensor fusion can be performed at the result or feature levels.

In result-level fusion, each sensor is characterized as an individual detection union. Then the detected objects are collected to generate the final result. This method consumes less transmission bandwidth and has a fast operation speed. However, its performance is severely limited by each single sensor detector.

In feature-level fusion, it is essential to aggregate feature information from both sensors, providing rich and reliable data for end-to-end networks [49, 50]. General fusion strategies, such as concatenating or adding data from different sensors after CNN-based feature extraction, offer faster computational speeds but limited capacity in terms of weighted combination of feature information. Utilizing the attention mechanism proposed in transformers for information scraping has been demonstrated to be more effective [51]. However, previous works utilizing cross-attention, whether on different data channels or across different temporal data [24, 25, 52], suffer from certain effectiveness issues. This is because relying solely on attention to capture information without query limits the model’s flexibility to fit difficult samples. Bi-LRFusion [53] proposes a bidirectional LiDAR and radar feature fusion scheme, which uses a query-based approach guided by both elevation-view and bird’s-eye-view perspectives for fusing LiDAR and radar features. However, its utilization of sparse queries severely restricts its performance when handling dense radar range-azimuth heatmap data. To tackle this problem, we propose a dense, learnable query map-based transformer block that merges features from each sensor. This approach offers dense and adaptable attention weights for enhanced sensor fusion.

D. Label Assignment in Object Detection

The traditional label assignment design was initially proposed in anchor-based and anchor-free object detection frameworks. In these frameworks, fixed thresholds were used to determine whether a box or point is a positive sample, based on intuitive costs such as the IoU between anchor boxes and ground-truth boxes or whether an anchor point is inside a gt box. However, the biggest problem with these heuristic designs is that they ignore the issue of consistency between foreground-background classification and box regression [54], meaning that high-scoring anchor boxes or points may not always lead to the best box regression results. This gap can cause the model to select suboptimal boxes as output during inference, which lowers the model’s detection performance.

In anchor-based frameworks [55, 56], since all anchor boxes with an IoU greater than a certain threshold with the gt box need to calculate loss and regression, the loss is designed as a sum of foreground-background classification and box regression losses. The parallel loss design makes the two part independent of each other, leading to the aforementioned consistency problem. Similarly, in anchor-free frameworks [57–59], the fixed threshold label assignment uses some fixed anchor points inside the gt box as positive samples, such as center points or corner points. After calculating foreground-background classification loss and box regression loss separately and adding them together, there is still a numerical gap in regression. Again, the inconsistency problem prevails.
To address this problem, some works have attempted to focus on matching the predicted results and ground-truth by combining label assignment with model prediction, such as freeAnchor [60], ATSS [61], AutoAssign [62], PAA [63] and OTA [64]. These methods evolved the solution for assigning positive and negative samples from matching anchors and gt boxes to aligning predicted outcomes with ground-truth. This approach maximally reduces the consistency gap for bounding box decoding mentioned earlier.

However, these methods primarily concentrate on image-based object detection, addressing challenges such as varying object sizes, aspect ratios, and mutual occlusion by assigning multiple positive samples to individual gt targets. Nevertheless, incorporating multiple positive samples inevitably results in competition among them during the training process, as they all contribute to the gradient. This exacerbates the consistency gap during the inference phase.

III. PROPOSED METHOD

In this section, the framework of the proposed anchor box-free radar and LiDAR fusion-based object detector are first introduced. Then, two enhancements of RaLiBEV, one with label-assignment strategies and the other with interactive transformer fusion strategies, are described.

A. Anchor Box Free Object Detection

Following the idea of sensor fusion, aggregating features from each sensor under BEV representation is straightforward. Therefore, based on the YOLOv4 [65] backbone and neck, an anchor box-free radar and LiDAR BEV object detector, RaLiBEV, is proposed, as shown in Fig. 2. The corresponding LiDAR point cloud and radar range-azimuth heatmap are used as input data. Then the aggregated features are forwarded into the YOLOv4 backbone and neck for further processing. Finally, a multi-scale anchor box free detection head is employed to decode the 2D BEV rotating bounding boxes detection result.

For the radar data, the strength of the range-azimuth heatmap represents the possibility of object existence under the BEV space. Where the object exists, the energy of the heatmap would be greater than that of the empty area. The radar data is converted from polar to Cartesian coordinates by applying bilinear interpolation, so the final structure shape of the data shows as [\(W_r, H_r, C_r\)]. For LiDAR data, since the point cloud is an unordered 3D point set, the data needs to be structured before subsequent operations. Therefore the method of PointPillars [9] is applied to form the input LiDAR data into a fixed shape \([W_l, H_l, C_l]\) under BEV.

After the pre-processing, \(N\) convolution layers on each branch are applied to extract features without downsampling. Then two branch data are fused with an interactive transformer and sent into the YOLOv4 backbone and neck for further feature extraction.

A multi-scale anchor-free detection head is added at the end to decode the detection result. The first output channel of the detection head is a predicted heatmap, representing the object’s existence probability. The second to the last channel represents \(\Delta x, \Delta y,\) width, length, angle class, angle offset, and object class, respectively. \(\Delta x\) and \(\Delta y\) represents the predicted box center offset in x and y direction. Two channels are set to help angle regression. One is an angle classification channel, the other is an angle offset regression channel.

Following the state-of-the-art anchor-free detection paradigm, the anchor points of the feature map should be specified first, then start regression based on those locations. The 2D ground-truth label boxes generate a Gaussian distribution map as a supervision signal under each output head scale to train the network for heatmap estimation in a supervised manner. This method can be described by:

\[
G(X|\mu, \Sigma) = \frac{1}{2\pi|\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(X-\mu)^T \Sigma^{-1} (X-\mu)}, \tag{1}
\]

where the \(X\) is the 2D BEV spatial vector, \(d\) is the dimension of \(X\), \(\mu\) is the mean of \(X\), which is the center coordinates of ground-truth boxes. \(\Sigma\) is a covariance matrix of the distribution, which can be calculated by:

\[
\Sigma = E(X - E(X))(X - E(X))^T, \tag{2}
\]

where the four corners’ 2D coordinates of a box are used as \(x\), and the \(E(x)\) equals the center coordinates of the box. Iteration is done over all the ground-truth objects in one frame to generate the ground-truth Gaussian heatmap.

B. Label Assignment Strategies

For an object detection problem, the total loss, in general, can be described as the sum of foreground-background classification loss and box regression loss, as shown here:

\[
\mathcal{L} = \mathcal{L}_{cls} + \mathcal{L}_{box}, \tag{3}
\]

where the \(\mathcal{L}_{cls}\) is the foreground-background classification loss implemented with focal loss [66], the \(\mathcal{L}_{box}\) is the box regression loss implemented with smooth \(L1\) loss. The focal loss is modified with Gaussian mixture distribution weight \(G\):

\[
\mathcal{L}_{cls} = \left\{ \begin{array}{ll}
- \sum_{i,j=0}^{M} G_{i,j} (1 - p_{i,j})^\gamma \log(p_{i,j}) & \text{if } G_{i,j} = 1, \\
- \sum_{i,j=0}^{M} G_{i,j} p_{i,j}^\gamma \log(1 - p_{i,j}) & \text{otherwise.}
\end{array} \right. \tag{4}
\]

The \(i, j\) range from 0 to feature map number of grid \(M, G_{i,j} \in [0, 1]\) specifies the supervision Gaussian mixture distribution heatmap generated from Eq. (1), \(p_{i,j} \in [0, 1]\) is the model’s estimated heatmap value for each anchor point in a feature map, and \(\gamma\) is a static parameter that balances the weight of positive and negative samples.

The box loss is consist of \(\Delta x, \Delta y,\) width, length and angle offset \(\Delta \theta\) loss, which are in the formulation of smooth \(L1\) loss. While for the angle classification loss, the cross-entropy loss \(I_{\theta}^c\) is applied:

\[
\mathcal{L}_{box} = \sum_{i,j=0}^{M} \alpha_{i,j} (I_{\Delta x}^reg + I_{\Delta y}^reg + I_{wl}^reg + I_{\theta}^c + I_{\Delta \theta}^reg). \tag{5}
\]
\( \alpha \) is binary mask matrix that controls the box regression loss in which each element \( \alpha_{i,j} \) is either 1 or 0. Typically, the binary mask matrix \( \alpha \) is utilized to control which anchor points on the feature map are selected for calculating the box loss, denoting by \( \alpha_{i,j} = 1 \). The chosen samples are referred to as positive samples, while the unselected ones are termed negative samples.

Because the box regression loss could only occur on the positive samples, while the foreground-background classification loss is computed upon every anchor point on the feature map. This leads to the problem that when decoding the predicted object, an anchor point with a higher foreground-background classification score does not always index the best bounding box regression result. This is known as the inconsistency problem in label assignments. A label assignment strategy with lesser inconsistency between foreground-background classification and box regression can decrease the model’s miss-detection rate and help achieve higher detection accuracy.

Typically, three strategies of label assignment could be applied, including bipartite matching, multi-positive label assignment, and single-positive label assignment. The ‘multi/single’ indicates how many anchor points can be chosen as the positive sample for one object.

1) Bipartite Matching Label Assignment: The typical bipartite matching label assignment is based on the Hungarian algorithm. This set-based label assignment builds a cost matrix of IoU between predicted and ground-truth boxes, where the predicted boxes are decoded from a predefined location. Then it finds the best matching positive samples by the Hungarian algorithm. The traditional bipartite matching process is based on anchors \([67]\), while DETR \([68]\) leveraging object query changes this matching art to a total end-to-end style. Using the Hungarian algorithm, DETR computes loss directly between predefined object queries and ground-truth object boxes. Then after training, the converged queries can be directly decoded into the final predicted box without Non-Maximum Suppression (NMS). However, the size of the query map in the proposed method is set to be the same as the size of the radar and LiDAR feature map. Such a large number of queries leads to massive computational consumption, which is not feasible when applying the Hungarian algorithm. Thus, such bipartite matching label assignment is not considered for our proposed method.

2) Multi-Positives Label Assignment: Following the idea that multiple positive anchor points may alleviate positive and negative sample imbalance problems in anchor-free detection architecture, a Gaussian area-based multi-positive label assignment is designed. Based on the ground-truth Gaussian mixture distribution heatmap \( G \) created in Section III-A, a static threshold is used to extract the specific region as the positive anchor points. foreground-background classification and box regression are then applied together on each positive anchor points. As Fig. 3(b) shows, all these dots with green and red colors overlapped are the selected positive samples. They are all located in the ground-truth Gaussian distribution orange-colored area, thus this approach is named as Gaussian Area-based Multi-Positives Sample assignment.

Nonetheless, the introduction of multiple positive samples inevitably leads to competition in training procedure among them because they all devote to the gratitude, exacerbating the consistency gap during the interference phase. The experiment result is shown later in Section IV-C1.

3) Single Positive Label Assignment: In order to prevent numerical regression conflicts caused by multiple positive samples, single positive sample allocation strategy has been designed. The fundamental characteristic of a single positive
sample is that, for each ground-truth object, there is only one positive anchor point corresponding to it, which contributes to the gradient of the loss in each training iteration. Four methods have been proposed successively to alleviate the inconsistency between foreground-background classification and box regression mentioned in the previous discussion. The experiment shows that abandoning the center prior can most effectively alleviate the consistency issue between object detection and regression.

The proposed four methods are Direct Index based Positive Sample (DIPS) assignment, Gaussian Area-based Heatmap cost Positive Sample (GAHPS) assignment, Gaussian Area-based Heatmap and IoU cost Positive Sample (GAHIPS) assignment and Gaussian Area-based Consistent Heatmap and IoU cost Positive Sample (GACHIPS) assignment. They share the same training framework as below:

1. Generate candidate anchor points: For each ground-truth object, create a set of candidate anchor points.
2. Design unique costs: Assign a unique cost to each candidate anchor point.
3. Select positive samples: Choose the most suitable candidate anchor points as positive samples.
4. Compute loss: Calculate the loss result based on the selected positive anchor points.

The four label assignment strategies contribute different innovations in the pipeline. The details are elaborated below:

The first step is generating candidate anchor points. This step is the common procedure for all four label assignment strategies. According to Eq. (1), a Gaussian distribution \( \{ G_k, k = 1, ..., n \} \) is generated for each ground-truth object, and the multiple objects form a Gaussian mixture distribution \( \mathcal{G} \). By setting a fixed threshold, the anchor points inside each Gaussian distribution can be obtained, which are called candidate anchor points. This step can be described as:

\[
A^G_k = A \cap G_k, \quad (6)
\]

where \( A^G_k \) represents the set of candidate anchor points in the \( k \)-th ground-truth Gaussian distribution, \( A \) represents the set of all anchor points on the BEV grid, and \( \cap \) represents the intersection operation.

The second and third steps are to design unique cost for these candidate anchor points and then select one as positive sample. In this two steps, the first three label assignment strategies make improvements rely on different design:

- The first design is Direct Index based Positive Sample (DIPS) assignment. As Fig. 3(c) shows, DIPS treats the label center locations as the positive anchor points, then applies foreground-background classification and box regression on these anchor points. The DIPS sample assignment is a standard design of CenterPoint [8] whose cost and selection are described as:

\[
a_k = \text{computeCenter}(A^G_k). \quad (7)
\]

The process begins by determining if a candidate anchor point is positioned at the center of \( A^G_k \). This is calculated and represented as \( a_k \) according to Eq. (7). Following this, a binary mask, symbolized as \( \alpha \), is used to indicate
the selection of positive samples. This mask is assigned a value of 1 in accordance with:

$$\alpha(a_k) = 1. \quad (8)$$

After the establishment of \( \alpha \), the location for the box regression loss is pinpointed. Subsequently, the final loss is then calculated based on Eq. (3), which is summation of two values obtained from Eq. (4) and Eq. (5) for all the positive samples.

- The second approach is termed as the Gaussian Area-based Heatmap cost Positive Sample (GAHPS) assignment. In this method, we substitute the cost calculation from determining the centers of ground-truth labels to assessing the maximum predicted heatmap value for each anchor point. The remaining steps, including the first and the fourth, are kept unchanged. Firstly, the model infers predicted heatmap \( P_{cls}^k \) and boxes \( P_{box}^k \) follows Eq. (9). As illustrated in Fig. 3(d), the red fading ellipses in Fig. 3(d) represents the predicted Gaussian distribution heatmap. This step is described as:

$$P_{cls}^k, P_{box}^k = \text{Decode}(F, A_G^k). \quad (9)$$

The decoding function, denoted as \( \text{Decode}(\cdot) \), takes two inputs: the feature map \( F \) and the anchor points in \( k \)-th Gaussian distribution \( A_G^k \). Then, different from DIPS, the cost is designed as predicted heatmap as shown in:

$$C_a^k = P_{cls}^k. \quad (10)$$

The anchor point with highest predicted heatmap value are chosen as the positive sample \( a_k \) as shown in:

$$a_k = \text{argmax}(C_a^k). \quad (11)$$

The Eqs. (9), (10), and (11) are utilized to substitute Eq. (7). Following this, the binary mask \( \alpha \) is computed using Eq. (8). Similar to the first DIPS strategy, the final loss is also calculated using Eq. (3), (4) and (5). However, the final loss is determined based on the established \( \alpha \) here in this design.

- The third approach is termed as the Gaussian Area-based Heatmap and IoU cost Positive Sample (GAHIPS) assignment. In this method, we go beyond merely substituting the cost with the predicted heatmap value. Instead, we replace it with the sum of the predicted heatmap value and the IoU value between the predicted box and the ground-truth box. Therefore, the first step is to calculate the IoU score of predicted bounding box and ground-truth box.

The decoded \( P_{box}^k \) derived from Eq. (9) is utilized to compute the IoU scores \( S_{IoU}^k \) in relation to the ground-truth bounding boxes \( G_{box}^k \) as depicted in:

$$S_{IoU}^k = \text{computeIoU}(P_{box}^k, G_{box}^k). \quad (12)$$

Following this, the sum of the predicted heatmap values and IoU scores, represented as \( C_a^k \), is employed as the new cost, as indicated in:

$$C_a^k = P_{cls}^k + S_{IoU}^k. \quad (13)$$

The positive anchor point \( a_k \) is then selected using Eq. (11), and the binary mask \( \alpha \) is also determined by Eq. (8). Lastly, same as aforementioned strategies, the final loss is still calculated using Eq. (3), which is a combination of Eq. (5) and Eq. (4). To be noted that, although the processes of determining \( \alpha \) are different in DIPS, GAHPS and GAHIPS, the ways of computing final loss are same. However, because the foreground-background classification loss and box regression loss are independent of each other, such definition of final loss leads to a consistency gap between the two loss above. To address this issue, the fourth design is proposed.

The fourth design is Gaussian Area-based Consistent Heatmap and IoU cost Positive Sample (GACHIPS) assignment, which is a divergence of the GAHIPS. GACHIPS follows the previous three steps as the GAHIPS, but modifies the final step of loss computation. All the previous designs conceal a fact that the positive sample position of foreground-background classification is designed to converge to the center of the ground-truth box. Meanwhile, the box regression positive sample position moves with the it when training iteration by iteration. Those strategies build a weak relation between the two loss part. However, the position of positive samples is not necessarily required to be at the center of the ground-truth bounding box. Therefore, the foreground-background classification loss should performs after the positive sample positions are set together with box regression loss. This means though the other steps are exact same as GAHIPS, the former foreground-background classification loss function which is shown in Eq. (4), should be replaced by:

$$\mathcal{L}_{cls} = \begin{cases} 
- \sum_{i,j=0}^M \alpha_{i,j} \gamma (1 - p_{i,j}) \log(p_{i,j}) & \text{if } \alpha_{i,j} = 1, \\
- \sum_{i,j=0}^M p_{i,j} \gamma \log(1 - p_{i,j}) & \text{otherwise.}
\end{cases} \quad (14)$$

In the end, a toy visualization of aforementioned label assignment strategies is shown in Fig. 3.

During inference procedure, the key step is to extract peaks from the predicted heatmap. We set a static threshold to pick every anchor point to generate the corresponding box, then NMS is applied to discard other boxes that overlap with the higher confidence box by a certain size. Beware that NMS can still filter out a certain amount of overlapping bounding boxes estimated from three branches in multiple scales. However, the estimated bounding boxes rarely overlap in a single scale branch since the anchor box-free approach with a single positive label assignment strategy is employed.

C. Interactive Transformer for Fusion of Radar and LiDAR in BEV

In the pursuit of enhancing the performance of sensor fusion in autonomous driving systems, we propose a novel approach
that transcends the conventional method of simply concatenating features from each sensor. The traditional approach, while straightforward, is inherently limited in its ability to effectively weigh the features from each sensor. To address this limitation, we have designed an innovative interactive transformer-based BEV Fusion block. This block leverages modifications to the standard transformer, as described in [51], to fuse data from the two sensor branches more effectively. Fig. 4 provides a visual representation of two distinct fusion logics that we have developed.

The first approach Direct Interactive Transformer for BEV Fusion, depicted in Fig. 4(a), employs a direct interactive BEV fusion. This method utilizes one sensor branch feature map as the query and the other as the key and value. The weight matrix is computed through matrix multiplication of the query and key, which is subsequently normalized using a softmax function. The final output is the dot product of the weight and value, where the value is the LiDAR feature map. This process can be mathematically represented as follows:

$$X_{out} = \sigma(X_{s_0}X_{s_1}^T) \odot X_{s_1} + X_{s_1}.$$  

In this equation, $X$ represents the feature map, $\sigma(\cdot)$ denotes the softmax function, and $s_0$, $s_1$ are different sensors serving the roles of query and key.

Our second approach shown in Fig. 4(b), Dense Query Map-based Interactive Transformer for BEV Fusion (DQMITBF), shares the core concept with the first approach but introduces a variation in the query definition. In this method, we define a randomly initialized learnable query that shares the same size as the input key feature map. The interactive attention is computed between this learnable query and the concatenated radar and LiDAR feature map, which is treated as the key. This process can be mathematically expressed as:

$$X_{out} = \sigma(X_QX_C^T) \odot X_C + X_C.$$  

In this equation, $X_Q$ is the randomly initialized learnable query, and $X_C$ is the concatenated feature map of radar and LiDAR.

These innovative approaches to sensor fusion offer a more effective way to weigh and combine features from different sensors, thereby enhancing the performance of autonomous driving systems.

IV. IMPLEMENTATION AND RESULTS

A. Dataset and Evaluation Metrics

The ORR dataset [3] is selected because it provides a synchronized LiDAR point cloud, radar range azimuth heatmap, car motion pose parameters, etc. The LiDAR point cloud was captured by two Velodyne HDL-32E LiDARs, each designed to cover one side of the car. On the top of the car locates a NavTech CTS350-X radar, which has a 360° field of view in the fashion of a mechanical scan. The angle resolution of radar data is 0.9° every 400ms, while LiDAR data angle resolution is 0.33° every 20ms.

The synchronization issue between LiDAR data and radar data and the annotation generation was solved by interpolation with the help of ego vehicle pose [24]. Specifically, the pose parameters compensated for the misalignment between the LiDAR point cloud and radar range-azimuth heatmap. Utilizing the timestamps as a reference, [24] computes the motion
between LiDAR point cloud and radar heatmap, then transfer every point to radar coordinate. The annotation bounding boxes are also created by [24] every 20 frames. The remaining frames’ annotations were also generated by interpolation. For testing in a foggy scenario, MVDNet relocates the LiDAR point cloud with the method of DEF [48]. According to the fog model in DEF, MVDNet sets the fog probability to 0.5 to recompute a maximum visible range for every point. If the current point range is greater than the maximum foggy range, this point would be set rather lost or relocated as a scatter point. Following the same operations on data in MVDNet, the 2D label bounding boxes are used as supervision. Corresponding radar and LiDAR data in 8862 number frames are split into 7071 for training and 1791 for testing.

To evaluate the prediction result of the model, the 2D rotated bounding box average precision (AP) under different IoU thresholds is employed as a final evaluation metric. This metric simultaneously evaluates the precision and recall performance of the model under the test dataset. A higher AP value represents better prediction precision of the bounding box and a smaller missing detection rate of the objects. Prediction boxes can be defined as True Positive (TP) objects, which overlap with the ground-truth objects over the IoU threshold, or False Positive (FP) objects which overlap with ground-truth objects lesser than the IoU threshold. The Table I shows an example of how the AP is calculated by setting the IoU threshold as 0.5. Assuming no miss-detected objects exist, all these predicted objects represented in the column are sorted by their scores. Precision and recall are computed according to Eq. (17) in each column. It is worth mentioning that the precision result drops and the recall increase, along with the decrease of the object’s scores. The AP@IoU=0.5 is then defined as the area value enclosed under the precision-recall curve accordingly to reflect the trend of the precision-recall curve as a performance metric. The greater the AP value is, the better model performs.

| Scores  | 0.98 | 0.97 | 0.96 | 0.95 | 0.94 | 0.92 | 0.91 |
|---------|------|------|------|------|------|------|------|
| Prediction Objects | TP | TP | FP | TP | FP | TP | FP |
| Precision | 1 | 1 | 1/3 | 3/4 | 4/5 | 5/6 | 5/7 |
| Recall | 0/5 | 2/5 | 2/5 | 3/5 | 4/5 | 1 | 1 |

B. Implementing Details

The preprocess of LiDAR data is based on PointPillars [9], where we set 0.2m × 0.2m as our BEV spatial resolution. It transforms the disordered LiDAR point cloud to a 320×320×9 structured matrix. Meanwhile, the input radar data is in the format of 320 × 320 × 1 under BEV, naturally. As Fig. 2 shows, the subsequent convolution block consists of a 3 × 3 convolution layer, a batch norm layer, and a leaky ReLu layer. The replication N of it is set as 3. The inference procedure decodes the predicted boxes from three scale output anchor-free heads. The static threshold is set to 0.1 to extract peaks (as key points among all anchor points) from the predicted heatmap. After generating boxes from three scale output feature maps, the NMS method is applied for deleting extra boxes, whose threshold is set as 0.2.

When training, the batch size is set to 32, and 4 Nvidia Tesla V100S GPUs are used. The first two epochs are used as a warming up. The learning rate linearly increases from 0 to 0.01 after 2 epochs’ iterations and then decreases by a ratio of 0.1 every 10 epochs. ADAM optimizer is used in the training process.

C. Experimental Results and Analysis

1) Ablation Study on Label Assignment Strategies: Experiments on Oxford Radar RobotCar dataset are performed to evaluate the effectiveness of the proposed strategies. Since the annotation has only one type of labeled car class, the AP is used only for cars. The evaluation metrics of AP at IoU 0.5, 0.65, and 0.8 are chosen to demonstrate changes in performance.

Table II presents the experiment results of different label assignment strategies and interactive transformer fusion architectures of our proposed RaLiBEV. It is noted that the performance of the Gaussian Area-based Multi-Positive Sample Assignment strategy serves as a solid baseline thanks to the use of YOLOv4 backbone and neck in our RaLiBEV framework, which is similar to the core design of PillarNeXt [69]. The AP of IoU of 0.5 and 0.65 is 95.4% and 94.2%, both improve 2.2%, but show a 5.8% drop of AP at IoU of 0.8, falling down to 75.7% compared to the ST-MVDNet++ [52]. The AP performance of the state-of-the-art ST-MVDNet++ [52] at IoU 0.5, 0.65, and 0.8 are 93.2%, 92.0%, and 81.5%, respectively.

The second type of label assignment strategy is DIPS Assignment. This strategy presents improvement not much at the low precision AP result at IoU of 0.5 and 0.65, about 0.7% - 0.9%. Still, better performance at high precision AP at IoU of 0.8 results about 6% compares to the first strategy above. The result of the third strategy illustrates the effectiveness of choosing a more appropriate positive-sample strategy. Compared to the previous strategy, the performance of GAHIPS Assignment shows another performance improvement of about 5% in high precision, which reaches 89.5% AP at IoU of 0.8. Following this idea, heatmap plus IoU cost design are implemented to upgrade the previous strategy. In GAHIPS Assignment, the performance at IoU of 0.5 maintains almost the same as the previous strategy, while the most notable change is on AP at
The above single positive label assignment strategies are based on propelling the regression loss to approach the classification loss. These type of ideas shows great validity. In this way, the strong binding strategy has been experimented with. The Gaussian Area-based Multi-Positives Sample Assignment, which employs fusion of radar and LiDAR-, shows great improvement over the baseline. The introduction of more positive sample points makes the model better distinguish the target and the background. The experimental results show that the prediction regression results of many key points identified as positive samples have a small overlap with the ground-truth box. They are located far from the center point of the ground-truth box and have prediction boxes of the same size as the ground-truth box, but there is a larger offset. The performance of this point in statistics indicates that the low-precision AP results are not much different, while the high-precision AP@IoU=0.8 result is 18.2% lower than GACHIPS. This indicates that these positive sample points have a large deviation in the loss of $l_{reg}$ and cannot continue to optimize. This is because the offset supervision values of multiple positive samples at different key point positions are variant. The farther away from the center point, the larger the offset supervision value is. These positive sample points of the same target provide a great improvement of 10.5% compared to 81.5% of state-of-the-art ST-MVNet++.

The multi-positive sample strategy designed in image object detection is actually to solve problems such as missed detection. The introduction of more positive sample points makes the model better distinguish the target and the background. However, the bounding boxes belonging to different targets do not overlap in the BEV perspective detection problem. Therefore, there is no problem that some targets have fewer pixels and are difficult to identify as foreground due to overlapping targets. Introducing multiple positive samples into BEV object detection does not consider the problems it brings to the regression, that is, the reduction of regression accuracy over the baseline. The final result shows further improvement at AP of IoU 0.5 and 0.8, which increased to 97.4% and 93.9%, respectively.

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the overall loss with different gradient values. However, the gradient descent algorithm can only regress each channel of each positive sample point to the same numerical level. Positive sample points with larger offset positions need higher weights to make their predicted values closer to the ground-truth value. However, to solve such problems introduced by the multi-positive sample design, the benefits are not as good as directly using the single-positive sample point design because focal loss can solve the problem of foreground-background classification in the current scene.

In the single positive sample design, a classification-guided regression strategy and classification-regression binding strategy are adopted to synchronize the contribution of classification and regression to the model’s gradient. Experiments show that the original DIPS strategy defines a set of optimal positive sample points for classification and regression through artificial methods. The classification and regression of positive samples are at the center of the supervision frame. This set of artificial positive points circumvents the sample assignment operation but suffers from limited performance. Based on classification-guided regression, the GAHPS and GAHIPS experiments show better performance. Based on the training classification results of the current round, the two strategies define the position of the regression positive sample points. As the training progresses, the regression of positive sample points of the model will gradually approach the positive sample points of classification. Unlike DIPS, because the model will regress key points other than the center point during the training process, the model has an ideal situation where the classification does not completely converge to the target center point. In other words, the classification score of the center point is not necessarily the highest. Therefore, after certain epochs of training, the model will infer the current best prediction bounding box based on the current results in the testing stage, which has the highest classification score and the smallest regression bias. In addition, it is found from the GAHIPS experimental results that when the regression prediction results are involved in sample assignment, the high-precision performance of the model is further improved. This indicates that the rotation IOU participates in model training guidance through sample assignment, further improving the model’s performance. Based on this, we believe that the center point assumption should be discarded, and the allocation search of positive and negative samples in training should be carried out in a completely free manner. GACHIPS takes the sum of the heatmap and IOU decoded by each candidate point in the Gaussian region as the cost and finds the best candidate point as the positive sample point of the current target to guide the model training and maximize the consistency of classification and regression. Experiments show that this method further improves the model’s overall performance and achieves a 1.9% improvement in high-precision performance.

2) Ablation Study on Interactive Transformer-based BEV Fusion Approaches: To illustrate the effectiveness of interactive transformer-based BEV fusion approaches, the fusion module is inserted into the basic network framework with DIPS label assignment. Table II presents the results of transformers as well. In the Direct Interactive Transformer for BEV Fusion, the performance rapidly reached the same level as GACHIPS with only slightly lower performance, around 1.6% in high precision IoU of 0.8. The DQMITBF exhibits stronger performance. All three indicators exceed GACHIPS.
in an all-around way. This brings the AP result of IoU 0.5, 0.65, and 0.8 to 98.8%, 97.7%, and 94.8%, respectively.

To highlight the benefits of multi-modality fusion, Table IV presents a comparison of performance metrics between the LiDAR-only approach and the fusion of radar and LiDAR. It is evident from the comparison that neither RaLiBEV with LiDAR only nor PointPills can match the performance levels achieved by the fusion of radar and LiDAR. This performance enhancement is particularly noticeable in foggy testing scenarios. When the model is trained on a “Clear+Foggy” dataset, RaLiBEV, in the radar and LiDAR fusion modality (denoted as “R+L”), exhibits exceptionally high performance, especially under the stringent requirements of a 0.8 IoU in “Foggy” test scenarios.

The results of this experiment show that a reasonable fusion logic would significantly enhance the performance of our RaLiBEV. Simple cross-attention between feature maps can increase performance. Still, query-based ideas can result in better effects depending on the flexibility of weights brought in by the learnable query.

3) Performance Comparison with State-of-the-Art Methods on Different Weather Conditions: Following MVDNet [24], model performance in different weather is tested in this paper as described in Table III. The simulated foggy LiDAR data is generated by the code provided by MVDNet. This experiment is set as training using clear-only and clear plus foggy LiDAR and radar data, then testing under both clear and foggy data. Two peak performance models are chosen to prove their capability under this condition. One is RaLiBEV with GACHIPS, the other is RaLiBEV with DQMITBF. The performance of GACHIPS training under clear-only data and testing under the foggy scenario is better than DQMITBF’s. The performance of the horizontal comparison model after data enhancement is about 10%. GACHIPS increases from 84.6%, 82.4%, and 73.8% to 97.8%, 96.7%, and 93.7% under the foggy test. This result exceeds the ST-MVDNet [25] over 20% at clear plus foggy training and foggy test scenario. Compared to the newest work Bi-LRFusion [53], RaLiBEV outperforms a large margin of 20.7% in IoU 0.8 requirement. Meanwhile, according to the results of the state-of-art work ST-MVDNet++ [52], RaLiBEV has made progress of 4.4%, 7.8% and 19.0% in IoU 0.5, 0.65 and 0.8 under “Clear+Foggy” training. “Foggy” test. This result represents that RaLiBEV is able to perform better accuracy in adverse weather such as fog. The fusion logic and label assignment strategy help the detector achieves higher precision.

Fig. 5 shows the ground-truth, the estimation from MVDNet in clear weather, the estimation from RaLiBEV in clear weather, and the estimation from RaLiBEV in foggy weather, at the 3332th and 4103th frame of test dataset. The ground-truth bounding boxes are decorated with yellow color, and the predicted boxes by each model are shown with red color. All boxes use green lines to indicate the heading of the object. It is easy to find out that the estimations of MVDNet have 3 miss detection and 4 predicted boxes with reversed heading direction in the top row figure, and 1 false alarm and 2 reversed predicted boxes in the bottom row figure, though the weather is clear. In contrast, The RaLiBEV shows perfect detection results in clear weather, and only gives one false detection and no reversed heading estimation in both time frame under foggy weather.

V. CONCLUSION

In this paper, we introduce RaLiBEV, an innovative method for fusing LiDAR and radar data. According to the experiment results, this method effectively showcases the significant role that radar can play in fusing autonomous driving perception technology, especially in adverse weather. To enhance the performance of the model, especially for high-precision detection, novel label assignment and transformer-based fusion strategies are proposed. Specifically, the GACHIPS strategy is proposed to dynamically adjust the classification and regression positive sample position, to solve the inconsistency problem in the loss procedure. Meanwhile, the DQMITBF is proposed to aggregate more aligned features from different sensor data. Due to the introduction of the dense learnable query in the fusion module, RaLiBEV can fuse the features from radar and LiDAR in a more flexible way. It’s noteworthy that by incorporating the GACHIPS label assignment into a simple fusion architecture, the model can attain performance on par with the more intricate transformer fusion. The experiments with ORR dataset show that RaLiBEV exceeds all existing state-of-the-art approaches by a large margin.

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