Leveraging Heteroscedastic Aleatoric Uncertainties for Robust Real-Time LiDAR 3D Object Detection

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Abstract—We present a robust real-time LiDAR 3D object detector that leverages heteroscedastic aleatoric uncertainties to significantly improve its detection performance. A multi-loss function is designed to incorporate uncertainty estimations predicted by auxiliary output layers. Using our proposed method, the network ignores to train from noisy samples, and focuses more on informative ones. We validate our method on the KITTI object detection benchmark. Our method surpasses the baseline method which does not explicitly estimate uncertainties by up to nearly 9\% in terms of Average Precision (AP). It also produces state-of-the-art results compared to other methods, while running with an inference time of only 72 ms. In addition, we conduct extensive experiments to understand how aleatoric uncertainties behave. Extracting aleatoric uncertainties brings almost no additional computation cost during the deployment, making our method highly desirable for autonomous driving applications.

I. INTRODUCTION

A robust and accurate object detection system using on-board sensors (e.g. camera, LiDAR, radar) is crucial for the road scene understanding of autonomous driving. Among different sensors, LiDAR can provide us with accurate depth information, and is robust under different illumination conditions such as daytime and nighttime. These properties make LiDAR indispensable for safe autonomous driving. The recent Uber’s autonomous driving fatal tragedy could have been avoided, if the LiDAR perception system had robustly detected the pedestrian, or had timely informed the human driver to trigger the emergency braking because it was uncertain with the driving situation [1].

Recently, deep learning approaches have brought significant improvement to the object detection problem [2]. Many methods have been proposed that use LiDAR point clouds [3]–[6], or fuse them with camera images [7]–[12]. However, they only give us deterministic bounding box regression and use softmax scores to represent recognition probability, which does not necessarily represent uncertainties in the network [13]. In other words, they do not provide detection confidence regarding the classification and localization. For a robust perception system, we need to explicitly model the network’s uncertainties.

Towards this goal, in this work we build a probabilistic 2-stage object detector from LiDAR point clouds by introducing heteroscedastic aleatoric uncertainties - the uncertainties that represent sensor observation noises and vary with the data input. The method works by adding auxiliary outputs to model the aleatoric uncertainties, and training the network with a robust multi-loss function. In this way, the network learns to focus more on informative training samples and ignore the noisy ones. Our contributions can be summarized as follows:

- We model heteroscedastic aleatoric uncertainties in the Region Proposal Network (RPN) and the Faster-RCNN header (FRH) of a LiDAR 3D object detector.
- We show that by leveraging aleatoric uncertainties, the network produces state-of-the-art results and significantly increases the average precision up to 9\% compared to the baseline method without any uncertainty estimations.
- We systematically study how the aleatoric uncertainties behave. We show that the uncertainties are related with each other, and are influenced by multiple factors such as the detection distance, occlusion, softmax score, and orientation.

In the sequel, we first summarize related works in Sec. II and then describe our proposed method in detail in Sec. III. Sec. IV shows the experimental results regarding (1) the improvement of object detection performance by leveraging aleatoric uncertainties, and (2) an analysis on how the uncertainties behave. Sec. V summarizes the work and discusses future research. The video of this work is provided as a supplementary material.

II. RELATED WORKS

In the following, we summarize methods for LiDAR-based object detection in autonomous driving and uncertainty quantification in Bayesian Neural Networks.

A. LiDAR-based Object Detection

Many works process the LiDAR data in 3D space [3], [5], [6], [9], [10]. For example, Zhou et al. [5] propose a voxel feature encoding layer to handle discretized 3D point clouds. Li [3] employs a 3D fully convolutional neural network to predict an objectness map and a 3D bounding box map. Xu et al. [9] propose to directly process 3D LiDAR points without discretization via the PointNet [14]. Besides, other
works project 3D point clouds onto a 2D plane and use the 2D convolutional network to process LiDAR feature maps, such as front-view cylindrical images [4], [7], [15], camera-coordinate images [16], [17], and bird’s eye view (BEV) maps [18]–[20]. In addition to the LiDAR sensors, an autonomous driving car is usually equipped with other sensors such as cameras or radar sensors. Therefore, it is natural to fuse them for more robust and accurate object detection. For instance, Chen et al. [7] use LiDAR BEV maps to generate region proposals, and fuse the regional features from LiDAR BEV and front-view maps, as well as camera images for 3D car detection. Qi et al. [10] propose to generate 2D bounding boxes by an image object detector, and use the regional point clouds within these bounding boxes for 3D object detection. In this work, we build a LiDAR-only object detector using BEV representations. The network estimates 3D bounding boxes and object orientations.

B. Uncertainty Quantification in Bayesian Neural Networks

A common way to estimate probabilities in deep neural networks is by Bayesian Neural Networks (BNNs), which assume a prior distribution of network weights and conduct inference in the posterior distribution over them [21]. There are two types of uncertainties we can model in BNNs [22], namely, the epistemic and the aleatoric uncertainty. The epistemic uncertainty shows the model’s uncertainty when describing the training dataset. It can be quantified through variational inference [23] or the sampling techniques [13], [24], and has been applied to active learning [25], [26], image semantic segmentation [27], [28], camera location estimation [29] or open-dataset object detection problems [30]. The aleatoric uncertainty, on the other hand, models the observation noises of input data. It has been modeled for geometry and semantic predictions in camera images [22], [31]. Recently, Ilg et al. [32] extract epistemic and aleatoric uncertainties in an optical flow problem, and we study how these uncertainties distinguish from each other in an object detector [18]. Unlike our previous method, in this work we focus on modelling the aleatoric uncertainties both in RPN and FRH, and systematically study how it improves the network’s robustness against the noisy LiDAR data.

III. METHODOLOGY

In this section, we present our method which leverages heteroscedastic aleatoric uncertainties for the robust LiDAR 3D object detection. We start with illustrating our network architecture, which is followed by a description of how to model the uncertainties. We end the section by introducing a robust multi-loss function that enables the network to learn the aleatoric uncertainties. The network architecture is shown in Fig. 1.

A. Network Architecture

1) LiDAR Point Clouds Transformation: In this work, we follow [7] to project the LiDAR 3D point clouds onto 2D grids, and use the bird’s eye view (BEV) feature maps as network inputs. These LiDAR feature maps comprise several height maps and a density map. To obtain height maps, we first divide point clouds along the vertical axis of the LiDAR coordinate frame (z axis) into several slices. We then discretize each slice into 2D grid cells, and encode the height information as the maximum height values of points within a cell. As for the density map, we assign the value \( \min(1, \log(N+1)) \) in each cell, where \( N \) refers to the number of points in a cell.

2) Two-stage Object Detector: We follow the two-stage object detection network proposed in [33]. The LiDAR BEV feature maps are fed into a pre-processing network based on VGG16 to extract high-level LiDAR features. After the pre-processing layers, a region proposal network (RPN) produces 3D region of interests (ROIs) based on predefined 3D anchors at each pixel on the feature map. The RPN consists of two task-specific fully connected layers, each with 256 hidden units. A ROI is parametrized by \([x_r, y_r, z_r, w_r, l_r, h_r, s_r]\), with \( x_r \) and \( y_r \) indicating the ROI
position in the bird’s eye view plane, $z_P$, its height, $w_P$, $l_P$, $h_P$ its dimensions, and $s_t$ the softmax objectness score (“Object” or “Background”). The anchor’s dimensions are determined by clustering the training samples into two clusters via the $k$-means algorithm. Its height is defined as the LiDAR’s height above the ground plane. Similar to [33], the RPN regresses the region proposals by the normalized offsets denoted as $t_r = [\Delta x_r, \Delta y_r, \Delta z_r, \Delta h_r, \Delta \theta_r]$ and predicts the objectness score $s_t$ by a softmax layer.

The Faster-RCNN head (FRH) with three fully connected hidden layers (2048 units for each layer) is designed to fine-tune ROIs generated by RPN. It produces multi-task outputs, including the softmax probability of the object classes and the background $s_v$, the 3D bounding box location, and the object orientation. We encode the location with four corner method introduced in [8]: $t_r = [\Delta x_r^{(1)} \ldots \Delta x_r^{(4)}; \Delta y_r^{(1)} \ldots \Delta y_r^{(4)}; \Delta h_r^{(1)} \Delta h_r^{(2)}]$, with $\Delta x_r$ and $\Delta y_r$ being the relative position of a bounding box corner in $x, y$ axes of the LiDAR coordinate frame, and $\Delta h_r^{(1)}, \Delta h_r^{(2)}$ being the height offsets from the ground plane. We also encode the orientation as $r_r = [\cos (\theta), \sin (\theta)]$, with $\theta$ being the object orientation in BEV. As explained in [8], explicitly modeling the orientation can remedy angle wrapping problem, resulting in a better object detection performance.

B. Modeling Heteroscedastic Aleatoric Uncertainties

As introduced in Sec. [1] the heteroscedastic aleatoric uncertainties indicate data-dependent observation noises in LiDAR sensor. For example, a distant or occluded object should yield high aleatoric uncertainties, since there are a few LiDAR points representing them. In our proposed robust LiDAR 3D object detector, we extract aleatoric uncertainties in both RPN and FRH.

Let us denote an input LiDAR BEV feature image as $x$, and a region of interest produced by RPN as $u$. The object detector predicts the classification labels $y$ with one-hot encoding from RPN and FRH, denoted by $y_r$ and $y_c$ respectively, i.e. $y \in \{y_r, y_c\}$. The detector also predicts the anchor positions $t_r$, object locations $t_c$, and orientations $r_c$, denoted as $l \in \{t, t_c, r_c\}$. Additionally, we refer $M$ to be the network weights and $f_M(\cdot)$ the noise-free network outputs both for classification and regression problems. Specifically, for classification $f_M(\cdot)$ indicates the network output logits before the softmax function.

We use multivariate Gaussian distributions with diagonal covariance matrices to model the observation likelihood for the regression problems $p(l|f_M(\cdot))$, including the anchor position $p(l_c|f_M(x))$, the 3D bounding box location $p(l_c|f_M(u))$ and the object orientation $p(r_c|f_M(u))$:

$$p(l|f_M(\cdot)) = \mathcal{N}(f_M(\cdot), \Sigma), \quad \Sigma = \text{diag}(\sigma_l^2),$$

(1)

with $\sigma_l^2 \in \{\sigma_1^2, \sigma_2^2, \sigma_3^2\}$ referring to the observation noise vectors. Each element in these vectors represents an aleatoric uncertainty scalar and corresponds to an element in $t_r$, $t_c$ and $r_c$. For instance, for the object orientation prediction which is encoded by $r_r = [\cos \theta, \sin \theta]$, we have $\sigma_{\theta_r}^2 = [\sigma_{\cos \theta}^2, \sigma_{\sin \theta}^2]$. In order to estimate those observation noises, we can add auxiliary output layers to regress their values. In practice, we regress $\log \sigma_l^2$ to increase numerical stability and consider the positive constraints. In this way, the regression outputs of RPN that model the aleatoric uncertainties can be formulated as $\hat{t}_r = [t_r, \log \sigma_{t_r}^2]$, and for FRH they are $\hat{r}_r = [r_r, \log \sigma_{r_r}^2]$, as illustrated by Fig. 1.

For the classification tasks, we assume that the network noise-free outputs are corrupted by the softmax function. Thus, the observation likelihood $p(y_r|f_M(x))$ and $p(y_c|f_M(u))$ can be written as:

$$p(y|f_M(\cdot)) = s = \text{softmax}(f_M(\cdot)),$$

(2)

with $y \in \{y_r, y_c\}$ and $s \in \{s_r, s_v\}$. Here, we do not explicitly model the aleatoric classification uncertainties, as they are self-contained from the softmax scores which follow the categorical distribution.

C. Robust Multi-Loss Function

In order to learn the aleatoric uncertainties, we incorporate $\sigma_1^2$, $\sigma_2^2$ and $\sigma_3^2$ in a multi-loss function for training the object detector:

$$\mathcal{L}(M, \sigma_1^2, \sigma_2^2, \sigma_3^2) = \frac{1}{2\sigma_{t_r}^2} \mathcal{L}(M, t_r) + \log \sigma_{t_r}^2 + \mathcal{L}(M, y_r)$$

(3)

$$+ \frac{1}{2\sigma_{r_r}^2} \mathcal{L}(M, r_r) + \log \sigma_{r_r}^2 + \mathcal{L}(M, y_v)$$

where $\mathcal{L}(M, t_r), \mathcal{L}(M, t_c)$ and $\mathcal{L}(M, r_c)$ are the regression loss, and $\mathcal{L}(M, y_r)$ and $\mathcal{L}(M, y_v)$ the classification loss. Learning the aleatoric uncertainties via this multi-loss function has two effects. First, an uncertainty score $\sigma_l^2$ can serve as a relative weight to a sub-loss. Thus, optimizing relative weights enables the object detector to balance the contribution of each sub-loss, allowing the network to be trained more easily, as discussed in [31]. Second, aleatoric uncertainties can increase the network robustness against noisy input data. For an input sample with high aleatoric uncertainties, i.e. the sample is noisy, the model decreases the residual regression loss $\mathcal{L}(M, t_r), \mathcal{L}(M, t_c), \mathcal{L}(M, r_c)$ because $\frac{1}{2\sigma_l^2}$ becomes small. Conversely, the network is encouraged to learn from the informative samples with low aleatoric uncertainty by increasing the residual regression loss with larger $\frac{1}{2\sigma_l^2}$ term.
D. Implementation Details

We jointly train the RPN network and the Faster-RCNN head in an end-to-end fashion. The background anchors are ignored for the RPN regression loss. An anchor is assigned to be an object class when its Intersection over Union (IoU) with the ground truth in the BEV is larger than 0.5, and the background class if it is below 0.3. Anchors that are neither object nor background do not contribute to the learning. Besides, we apply Non-Maximum Suppression (NMS) with the threshold 0.8 on the region proposals to reduce redundancy, and keep 1024 proposals with the highest classification scores during the training process. We reduce the region proposals to 300 during the test time in order to speed up the inference. When training the Faster R-CNN head, a ROI is labeled to be positive when its 2D IoU overlap with ground truth in BEV is larger than 0.65, and negative when it is less than 0.55, suggested by [8]. We use the cross entropy loss for the classification problems, and the smooth $L_1$ loss for the regression problems, as it is more preferable than the $L_2$ loss in object detection tasks [33]. Correspondingly, we assume the observation likelihood follows the Laplacian distribution instead of Gaussian (Eq. [1]), similar to [22]. We train the network with Adam optimizer. The learning rate is initialized as $10^{-4}$ and decayed exponentially for every 30000 steps with a decay factor 0.8. We also use Dropout and $l_2$ regularization to prevent over-fitting. We set the dropout rate to be 0.5, and the weight decay to be $5 \times 10^{-4}$. We first train the network without aleatoric uncertainties for 30000 steps and then use the robust multi-loss function (Eq. [3]) for another 90000 steps. We find that the network converges faster following this training strategy.

IV. EXPERIMENTAL RESULTS

A. Experimental Setup

1) Dataset: We evaluate the performance of our proposed method on the “Car” category from the KITTI object detection benchmark [34]. KITTI provides 7,481 frames of data for training and another 7,518 frames for testing (test set). The dataset is classified into Easy, Moderate, and Hard settings. When evaluating our method on the test set, we train the network with all training data. As the ground truth for the test set is not accessible, we conduct the ablation study and extensive experiments for analyzing the aleatoric uncertainties on the training dataset. To this end, we follow [7] to split the training data into a train set and a val set (approximately 50/50 split). The network is trained on the train set and tested on the val set.

2) Input Representation: We use the LiDAR point cloud within the range length $\times$ width $\times$ height = $[0, 70] \times [-40, 40] \times [0, 2.5]$ meters in the LiDAR coordinate frame. The point clouds are discretized into 5 height slices along the z axis with 0.5 meters resolution and the length and width are discretized with 0.1 meters resolution, similar to [8]. After incorporating a density feature map, the input LiDAR point clouds are represented by the feature maps with size $700 \times 800 \times 6$.

| Method          | $AP_{3D} (%)$ | $AP_{BEV} (%)$ |
|-----------------|---------------|----------------|
|                 | Easy | Moderate | Hard | Easy | Moderate | Hard |
| 3D FCN [3]      | 66.77 | 52.73 | 51.31 | 69.94 | 62.54 | 55.94 |
| MV3D (BV+FV) [7]| 71.19 | 56.60 | 55.30 | 88.16 | 77.32 | 76.33 |
| PIXOR [20]      | 69.50 | 62.30 | 59.73 | -     | -     | -     |
| VoxelNet [5]    | 81.97 | 65.46 | 62.85 | 89.60 | 84.81 | 78.57 |
| Baseline        | 73.92 | 62.63 | 56.77 | 85.91 | 76.06 | 68.75 |
| Ours            | 78.81 | 65.89 | 65.19 | 87.03 | 77.15 | 76.95 |

TABLE I: Comparison with state-of-the-art methods on KITTI test set. Compared to the baseline method, Ours simply models the aleatoric uncertainties in both RPN and FRH, without further tuning any hyper-parameters.

B. Comparison with State-of-the-art Methods

We first compare the performance of our proposed network (Ours) with the baseline method which does not explicitly model aleatoric uncertainties, as well as other top-performing methods (see Tab. I and Tab. II). Compared to the baseline method, we only add auxiliary output layers to regress aleatoric uncertainties, without further tuning any hyper-parameters. For a fair comparison, we only consider LiDAR-only methods. We use the 3D Average Precision for 3D detection ($AP_{3D}$) and the bird’s eye view Average Precision for 3D localization ($AP_{BEV}$). The AP values are calculated at the Intersection Over Union IOU=0.7 threshold introduced in [34] unless mentioned otherwise.

Tab. I shows the performance on KITTI test set. We compare against 3D FCN [3], MV3D(BV+FV) [7] (using birds’ eye view and front view LiDAR representation as inputs), PIXOR [20] and VoxelNet [5]. In the table, we can see that the baseline method performs similarly to the MV3D(BV+FV) network. By leveraging aleatoric uncertainties, our method largely improves the baseline method up to 7.15% in $AP_{3D}$, while achieving on-par performance in $AP_{BEV}$. Furthermore, our method produces results comparable to PIXOR [20] and VoxelNet [5] which are strong state-of-the-art methods on the KITTI leaderboard. Tab. II shows the detection performance on KITTI val set with the same train-val split introduced in [7]. Besides PIXOR and VoxelNet, we include VeloFCN [4] and Frustum PointNet (LiDAR) [10] for comparison. Unlike the original Frustum PointNet which takes 2D region proposals predicted by a RGB image detector, we use LiDAR BEV feature maps to generate proposals, as described in [10]. Tab. II illustrates that our method improves the baseline method up to nearly 9% by modeling aleatoric uncertainties. It also outperforms all other methods in $AP_{3D}$ for the moderate and hard settings. It is noteworthy to mention that both PIXOR and VoxelNet use the data augmentation tricks to enrich the training data and prevent over-fitting. For example, VoxelNet employs...
perturbation, global scaling and global rotation when training the network [5]. In contrast, we do not employ any data augmentation. The performance gain is purely from modeling the aleatoric uncertainties. We expect further improvements if we augment the training data during the training process. To sum up, the experiments show that we can leverage aleatoric uncertainties to boost the detection performance.

C. Ablation Study

We then conduct an extensive study regarding on where to model the uncertainties, the network speed and memory, as well as a qualitative analysis. Here, all networks are trained on the train set and evaluated on the val set.

1) Where to Model Aleatoric Uncertainties: In this experiment we study the effectiveness of modeling aleatoric uncertainties in different sub-networks of our LiDAR 3D object detector. In this regard, we train another two detectors that only capture uncertainties either in RPN (Aleatoric RPN) or FRH (Aleatoric FRH), and compare their 3D detection performance with the baseline method (Baseline) and our proposed method (Ours) that models uncertainties in both RPN and FRH. Tab. III illustrates the AP values and their improvements for Baseline on KITTI easy, moderate, and hard settings. We find that modeling the aleatoric uncertainties in either RPN, FRH or both can improve the detection performance, while modeling the uncertainties in both networks brings the largest performance gain in moderate and hard settings. Furthermore, we evaluate the detection performance on different LiDAR ranges, shown by Tab. IV. Again, our method consistently improves the detection performance compared to Baseline. Modeling the uncertainties in both RPN and FRH shows the highest improvement between ranges 20 – 70 meters, indicating that the aleatoric uncertainties in both networks can compensate each other. As we will demonstrate in the following section (Sec. IV-D), our proposed network handles cars from easy, moderate, hard, near-range or long-range settings differently. It learns to adapt to noisy data, resulting in improved detection performance.

2) Runtime and Number of Parameters: We use the runtime and the number of parameters to evaluate the computational efficiency and the memory requirement. Tab. V shows the results of our method relative to the baseline network. We only need additional 2 ms and 26112 parameters to predict aleatoric uncertainties during the inference, showing the high efficiency of our proposed method.

### TABLE III: Ablation study - Comparison of 3D car detection performance for easy, moderate, and hard settings on KITTI val set. We mark the highest performance gain in bold.

| Method      | Easy   | Moderate | Hard   |
|-------------|--------|----------|--------|
| Baseline    | 71.50  | 63.71    | 57.31  |
| Aleatoric RPN | 72.92 (+1.42) | 65.84 (+0.13) | 58.61 (+1.30) |
| Aleatoric FRH | 81.07 (+9.57) | 65.51 (+1.80) | 65.09 (+7.78) |
| Ours        | 78.81 (+7.31) | 65.89 (+2.18) | 65.19 (+7.88) |

### TABLE IV: Ablation study - Comparison of 3D car detection performance for data within different distances from KITTI val set. We use IOU=0.5 threshold in this experiment. We mark the highest performance gain in bold.

| Method      | 0-20 (m) | 20-35 (m) | 35-50 (m) | 50-70 (m) |
|-------------|----------|-----------|-----------|-----------|
| Baseline    | 72.42    | 78.96     | 57.87     | 26.17     |
| Aleatoric RPN | 80.86 (+8.44) | 79.72 (+0.76) | 65.44 (+7.57) | 30.54 (+4.37) |
| Aleatoric FRH | 79.10 (+6.68) | 83.89 (+4.93) | 61.98 (+4.11) | 29.67 (+3.50) |
| Ours        | 80.78 (+8.36) | 84.75 (+5.79) | 66.81 (+8.94) | 34.07 (+7.90) |

### TABLE V: A comparison of the runtime and the number of parameters. The runtime is measured by averaging the predictions over all KITTI val set on a TITAN X GPU.

| Method      | Number of parameters | Runtime          |
|-------------|----------------------|------------------|
|             | Data pre-processing  | Inference        |
| Baseline    | 3619217/1           | 97 ms (+0.07%)    |
| Ours        | +26112 (+0.07%)      | 70 ms (+2 ms (+2.86%)) |

### D. Understanding Aleatoric Uncertainties

We finally conduct comprehensive experiments to understand how aleatoric uncertainties behave. We use the scalar Total Variance (TV) to quantify aleatoric uncertainties introduced in [18]. A large TV score indicates high uncertainty. We also use Pearson Correlation Coefficient (PCC) to measure the linear correlation between the uncertainties and the factors that influence them. We study the RPN uncertainties and the FRH uncertainties. The RPN uncertainties indicate observation noises when predicting anchor positions, while the FRH uncertainties consists of the FRH location uncertainties for the bounding box regression and the FRH orientation uncertainties for heading predictions. We evaluate all predictions with a score larger than 0.5 from the KITTI val set unless mentioned otherwise.

1) Relationship Between Uncertainties: Fig. 3(a) and Fig. 3(b) show the prediction distribution of FRH uncertainties with RPN uncertainties, as well as FRH location uncertainties with orientation uncertainties, respectively. The uncertainties are highly correlated with each other, indicating that our detector has learned to capture similar uncertainty information at different sub-networks and prediction outputs.

2) Orientation Uncertainties: Fig. 4(a) illustrates the prediction distribution of FRH orientation uncertainties (radial axis) w.r.t. angle values θ (angular axis) in the polar coordinate. Most predictions lie at four base angles, i.e. θ = 0°, 90°, 180°, 270°. Fig. 4(b) shows the average orientation uncertainties with the orientation difference between the predicted angles and the nearest base angles. They are highly
Fig. 2: Some car detection examples on KITTI val set within the range \( \text{length} \times \text{width} = [0,70] \times [-40,40] \) meters. The LiDAR points which are out of camera front view are not evaluated. The predictions from our proposed network (Ours) are visualized in blue, the predictions from baseline method in red, and the labeled samples in green. Better view by magnificence.

Fig. 3: (a) The distribution of uncertainties in FRH (x axis) and in RPN (y axis). Each scatter represents a prediction. (b) The distribution of uncertainties for FRH location (x axis) and orientation prediction (y axis).

Fig. 4: (a) The prediction distribution of FRH orientation uncertainties w.r.t angle values \( \theta \) (angular axis). (b) The average orientation uncertainties with orientation difference between predicted angles and the nearest base angles.

correlated with PCC=0.99, showing that the network produces high observation noises when predicting car headings that are different from the base angles. We assume that this is because most car headings in the KITTI dataset lie at four base angles, so that the network cannot be equally trained with various car headings.

3) Relationship Between Softmax Score, Detection Distance and Uncertainties: In Fig. 5(a) we plot the average RPN and FRH uncertainties with the increasing softmax scores for anchor and final object classification. We find a strong negative correlation between them. As introduced by Eq. \( 1 \), the softmax scores can be regarded as aleatoric uncertainties for classification. This indicate that our network has learned to adapt the uncertainties in regression tasks (i.e. anchor position, bounding box location and orientation) to that in the classification, i.e. the uncertainties increase as the softmax score reduces. Fig. 5(b) shows that the average RPN and FRH uncertainties become larger as the detection distance increases. This is because the LiDAR sensor measures fewer reflections from a distant car, which yields high observation noises.

4) Uncertainty Distribution for Easy, Moderate, and Hard Settings: We finally evaluate the FRH uncertainty distribu-
tion for easy, moderate, and hard objects, demonstrated in Fig. 6. The uncertainty distributions vary: for easy setting there are more predictions with lower uncertainties, whereas for hard objects which have larger occlusions, truncations, and detection distances, the network estimates higher uncertainties. The result indicates that the network has learned to treat objects from these three settings differently.

5) Qualitative Observations: In Fig. 7 we visualize nine exemplary detections whose uncertainties are equally distributed at the log scale, ranging from -3 to -1. We observe: (1) The uncertainties are influenced by occlusion, detection distance, orientation as well as softmax score, as discussed above. (2) The network shows higher aleatoric uncertainties if there are fewer points around the car. The results show that our network has captured reasonable LiDAR observation noises.

V. DISCUSSION AND CONCLUSION

We have presented our robust LiDAR 3D object detection network that leverages heteroscedastic aleatoric uncertainties in both the Region Proposal Network and the Faster-RCNN to significantly improve detection performance. Trained with a multi-loss function which incorporates aleatoric uncertainties, our method learns to adapt to noisy data and increases the average precision up to 9%, producing state-of-the-art results on KITTI object detection benchmark. Our method only requires to modify the cost function and output layers with only 2 ms additional inference time. This makes our method suitable for real-time autonomous driving applications.

We have qualitatively analyzed how the network learns to deal with noisy data in Sec. IV-C. The network tends to predict high uncertainties for detections that are highly occluded (Fig. 7), far from the ego-vehicle (Fig. 5(b)), with different orientations from the base angles (Fig. 4(b)) or with low objectness score (Fig. 5(a)). Therefore, our network learns less from the noisy samples during the training process by penalizing the multi-loss objective with the $\frac{1}{2}$ terms (Eq. 2). Conversely, the netowrk is encouraged to learn more from the informative training samples with more LiDAR reflections. In this way, its robustness against noisy data is enhanced, resulting in improved detection performance for data from easy, moderate, hard settings (Tab. III), or at different distances (Tab. IV). Note that this effect is because we explicitly model the observation noises rather than an ad-hoc solution.

Compared to the Focal Loss [35] which incorporates prediction probability in the loss function to tackle the positive-negative sample imbalance problem, our proposed method works in an opposite way: it depreciates “outliers” with high aleatoric uncertainties, and encourages the network to learn from the training samples with small errors. It is an interesting future work to investigate how a network behaves with the Focal Loss and our proposed method.

In the future, we intend to improve PIXOR [20] and VoxelNet [5] by incorporating aleatoric uncertainties. We also intend to evaluate our method on non-motorized objects (e.g. pedestrian) using our own test vehicles and dataset.

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