Amplifying the Anterior-Posterior Difference via Data Enhancement - A More Robust Deep Monocular Orientation Estimation Solution

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Abstract—Existing deep-learning based monocular orientation estimation algorithms faces the problem of confusion between the anterior and posterior parts of the objects, caused by the feature similarity of such parts in typical objects in traffic scenes such as cars and pedestrians. While difficult to solve, the problem may lead to serious orientation estimation errors, and pose threats to the upcoming decision making process of the ego vehicle, since the predicted tracks of objects may have directions opposite to ground truths. In this paper, we mitigate this problem by proposing a pretraining method. The method focuses on predicting the left/right semicircle in which the orientation of the object is located. The trained semicircle prediction model is then integrated into the orientation angle estimation model which predicts a value in range $[0, \pi]$. Experiment results show that the proposed semicircle prediction enhances the accuracy of orientation estimation, and mitigates the problem stated above. With the proposed method, a backbone achieves similar state-of-the-art orientation estimation performance to existing approaches with well-designed network structures.

Index Terms—Orientation Estimation, Convolutional Neural Network (CNN), Monocular Camera, Anterior-Posterior Similarity, Data Enhancement

I. INTRODUCTION

Obstacle avoidance is a significant step in autonomous driving and intelligent vehicle design. In complex traffic environments, moving objects such as cars and pedestrians are harder to detect and localize, and are yet more threatening obstacles than stationary objects. In such environments, perception modules with orientation estimation are better at satisfying the needs for safety than those with pure object detection. Orientation estimation modules play the important role of predicting the heading directions and short-term tracks $[1]$ of the surrounding objects, which serve as references to a set of safety measures determined and carried out by the ego vehicle, such as path planning, speed control and risk assessment $[2]–[4]$. Therefore, as one fundamental step of track prediction, orientation estimation is a vital ability of modern perception modules in autonomous vehicles $[5]$.

From the characteristics and applications of orientation estimation, it is more suitable and more important in monocular occasions, since the information the monocular cameras can obtain is much more scarce than other types of sensors. With the depth information unknown, orientation becomes the only information for tracking. From another perspective, monocular solutions are more resource-saving with less complexity, and are vital in occasions with LiDAR not available or suitable $[6]$. Therefore, monocular orientation estimation attracts much research interest in autonomous driving $[1]$, $[3]$, $[6]$, $[7]$. Since orientation estimation is based on object localization, solutions to the problem are mostly attached to classic object detection methods. However, apart from difficulties in object localization, orientation estimation faces several more problems, with the main ones listed as follows:

First, More and deeper features required: Object localization models have the ability of extracting object-level features. On the contrary, orientation estimation requires more component-level features, since orientation is estimated with advantage of relative positions of specific components to the whole object.

Second, Lack of prior information: There are much less prior knowledge available for orientation estimation than object localization (e.g. exclusion of obviously irrational locations of cars and pedestrians). All directions are reasonable for any objects.

Third, Confusion between the anterior and posterior parts of objects: The anterior and posterior parts have similar component-level features (e.g. similar light, license plate and window positions, etc), which may confuse the orientation estimation methods to output results just opposite to the truth. The problem is more severe in pedestrian orientation estimation, since the most notable face characteristics cannot be used for orientation estimation (face orientation is not necessarily equal to body orientation).

Such problems are especially tough for monocular solutions: First, depth information of objects is not available for them; second, the anterior and posterior parts of objects cannot both be visible without occlusion at the same time in monocular images, making the third problem even harder to solve. In most existing orientation estimation solutions, object localization and orientation estimation share one feature extractor, indicating that the features of objects are still scarce in the orientation estimation process. In the meantime, little existing research focus on the second and the third problem. Therefore, the above three problems still exist in orientation estimation.

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We focus on the third problem stated above in monocular orientation estimation, and propose a monocular pretraining method to enhance performance of the orientation estimation model, while in the meantime, partially solving the first and the second problem. The pretraining method predicts the left/right semicircle in which the orientation of the object is located. With the pretraining method, the original orientation estimation problem is converted to estimation of an absolute orientation value in range $[0, \pi]$. We implement the method in both supervised and semisupervised manners, and test their performance in typical traffic scenarios. Experiment results with the KITTI [8] dataset show that the proposed pretraining method effectively improves the accuracy of orientation estimation. A backbone model achieves state-of-the-art orientation estimation performance with the proposed method, similar to existing approaches with well-designed network structures. Our contributions are summarized as follows: first, we propose a novel pretraining method in orientation estimation and achieve state-of-the-art performance; second, we offer a new perspective of features available for orientation estimation, with the proposed method being a way of feature mining and augmentation.

The paper is organized as follows: we introduce some related work in orientation estimation in Section II, introduction and details of the semicircle pretraining method are stated in Section III, experiments are conducted in Section IV to validate the effectiveness and performance of the proposed method, we conclude the paper in Section V.

II. RELATED WORK

Although with equally much importance, orientation estimation attracts much less attention than object detection, according to recent studies and researches in the related field. The orientation estimation module in most existing monocular methods [9]–[14] is basically a prediction branch connected to the feature extractor of a well-designed object detection model. Some work pays special attention to orientation estimation and makes related improvements: In [7], the authors proposed the Multibin mechanism, to divide the orientation domain into several sectors, converting the problem into a high-level classification and low-level residual regression; another discretized method similar to Multibin is proposed in [13]; 3D modelling is adopted in [16], and the problem is solved in an unsupervised manner using GAN and the 3D models; the authors in [6] introduce the relationship between 2D/3D dimensions and orientation angles of objects to orientation estimation as supplementary prior knowledge.

While having accuracy improvements on object orientation estimation to some extent, the methods above may not be qualified for complex orientation estimation problems. As stated above, orientation estimation and object detection require different levels of features, indicating that one feature extractor may not be qualified for solving both problems. The same problem happens on the Multibin classifier. Besides, since object features with different orientations may appear to be rather similar (e.g. features of exactly opposite orientations), the sector-classification solution may be confused of feature-similar orientations. The anterior-posterior-similarity problem still exists in [6] in which 2D and 3D dimensions are independent from anterior and posterior features. In the meantime, the method proposed in [16] relies heavily on the predetermined 3D model, thus restricted to simple scenarios with available 3D models of all objects.

In this paper, we propose a method specially intended for orientation estimation. We focus on the neglected anterior-posterior-similarity problem and propose a novel pretraining method to solve it.

III. PREDICTION OF ORIENTATION SEMICIRCLE AS PRETRAINING

A. Definition and Choice of Orientation Semicircles

To strengthen the ability of anterior-posterior classification of the orientation estimation model, we connect a classification branch to the feature extractor of the original model, and train the feature extractor and the branch firstly. The anterior-posterior classification is a coarse pretraining step yet helpful to better orientation estimation.

Inspired by the sector classification spirit of Multibin, the proposed method first divides the orientation domain into several sectors. With the aim of amplifying the differences between the anterior and posterior parts, the number of sectors is set 2 to make the target of the pretraining process a pure anterior-posterior classification. In consideration of dataset enhancement, locations of the two sectors are set left and right instead of front and back. With the left/right location settings, dataset is enhanced by simple flip of images, and each object forms a pair of data with different semicircle classification labels. Choice of the semicircles and related dataset enhancement are shown in Fig. 1.

B. Supervised Orientation Estimation with Semicircle Prediction as Pretraining

The semicircle prediction serves as a pretraining step, and is combined with the main orientation estimation process.

The network structure of the whole orientation estimation model is shown in Fig. 2. The network adopts the ResNet18
The proposed method solves the third problem and partially solves the first and second problems stated in Section I with the following reasons:

- (to problem 1) Features of orientation semicircles are closely related to the final orientation results, thus serving as supplementary information in orientation estimation.
- (to problem 2) The following prior information is introduced to orientation estimation: the semicircle label of an image is opposite to that of the corresponding horizontal-flipped image.
- (to problem 3) The semicircle classification has no essential difference from the anterior-posterior classification. An effective solution to the former problem will be equally effective to the latter one.

### C. Semisupervised Orientation Estimation with Unsupervised Semicircle Prediction

The method can also be implemented in a semisupervised way with the first step unsupervised.

As stated in Section III-A, each object forms a pair of data with different semicircle classification labels with a simple horizontal flip of the image. Choices of locations of the semicircles as left and right enable not only dataset enhancement, but also unsupervised training, since the unsupervised criterion can be set the difference between prediction results of the elements in each pair. The unsupervised criterion is shown in (4), in which $x_1$ and $x_2$ are respectively the original and flipped image:

$$L_u = L_{CE}(C(F(x_1)), C(F(x_2)))$$

(4)

$C(F(x_1))$ (result of the original image) and $C(F(x_2))$ (result of the flipped image) are ‘considered’ the output and the label of the semicircle classification (although the correctness of them remains undetermined).

With the randomly decided semicircle label in training, the semicircle classifier may not be absolutely accurate. As a result, parameters of the classifier will not be frozen, and the second step is deleted from semisupervised training. Training details of the third step are similar to the supervised training frame.

### IV. EXPERIMENTS

Both supervised and semisupervised training are experimented with results and analyses. Experimental comparisons with the plain model and with state-of-the-art baselines are conducted.

#### A. Experiment Setup

The dataset of KITTI Object Detection and Orientation Estimation Evaluation benchmark is used. We conduct orientation estimation experiments on both cars and pedestrians. Hyperparameters in training are shown in Table II.

| step | F | C | R | loss\(_{CE}\) | loss\(_{MSE}\) |
|------|---|---|---|-------------|-------------|
| 1    | ✓ | ✓ | ✓ | ✓           | ✓           |
| 2    | ✓ | ✓ | ✓ | ✓           | ✓           |
| 3    | ✓ | ✓ | ✓ | ✓           | ✓           |
TABLE II: Hyperparameters in supervised and semisupervised training in the proposed method.

| Hyperparameter        | Value                  |
|-----------------------|------------------------|
| image size            | step1: 224 x 224, step2: 224 x 224, step3: 224 x 224 |
| learning rate         | step1: $10^{-5}$, step2: $10^{-5}$, step3: $5 \times 10^{-6}$ |
| number of iterations  | step1: 250K, step2: 150K, step3: 100K |
| batch size            | 16                     |

![Fig. 3: The mean squared orientation error of the plain model.](image)

**B. Results of Vanilla Training on Backbone**

We first conduct vanilla training on the backbone to prove that the anterior-posterior problem does exist.

After the identical training process without the semicircle classifier, the backbone has the mean squared orientation error shown in Fig. 3. From the experiment results, it is obvious that the backbone is weak at classifying the anterior and posterior parts of objects, resulting in the two error peaks (0 and $\pi$) shown in Fig. 3. Therefore, the anterior-posterior problem is an existing urgent problem.

**C. Results of Supervised Training on Backbone with Semicircle Classifier**

In training of the first step, the loss convergence and accuracy increase of the semicircle classifier with both car and pedestrian objects are shown in Fig. 4. From the results, it is obvious that the semicircle classification method is effective and accurate. The classifier reaches about 95% and 90% accuracy on cars and pedestrians.

![Fig. 4: The loss convergence and accuracy increase of the semicircle classifier in the first step.](image)

![Fig. 5: The loss convergence and error decrease in the second step.](image)

In training of the second step, the classification loss of the semicircle classifier is shown in Fig. 5a. Although facing slight oscillations, loss of the classifier converges to a satisfactory level with a fast speed. At the beginning of the second step, the loss value is much smaller than that at the beginning of the first step, indicating the effectiveness of the pretraining method. The loss convergence and error decrease of the orientation regressor are shown in Fig. 5b. The average orientation error can be converged to 0.4 (0.12 $\pi$) in cars and 0.7 (0.22 $\pi$).

![Fig. 6: The loss convergence and error decrease of the joint model in the final step.](image)

In training of the final step, neither of the losses and average errors have large-amplitude changes, as shown in Fig. 6. Comparison on the mean squared orientation error of the proposed model and the plain model after identical training is shown in Fig. 7. From the comparison, it is obvious that the pretraining method effectively mitigates the anterior-posterior-similarity problem raised in Section I.

Examples of orientation estimation results with full-view monocular images are shown in Fig. 8. Note that in Fig. 8, the 2D object detection results are the truth labels provided in the dataset.

**D. Results of Semisupervised Training on Backbone with Semicircle Classifier**

Fig. 9 shows the comparison of the supervised and semisupervised methods at the final step. From the comparison, the semisupervised method fails to train a qualified backbone for orientation estimation. Possible reasons are listed as follows:

- Uncertainty of semicircle labels. In semisupervised training, the labels are set the prediction results of the original...
Table III: Comparisons between the proposed method and state-of-the-art baselines.

| Name            | AOS (car) | Rank (car) | AOS (ped) | Rank (ped) | Time | 3D info |
|-----------------|-----------|------------|-----------|------------|------|---------|
| Mono3D          | 87.28%    | 8th        | 58.66%    | 3rd        | 4.2s | ✓       |
| Deep3DBox       | 89.88%    | 1st        | 66.70%    | 1st        | 1.5s | ✓       |
| SubCNNS         | 93.31%    | 2nd        | 61.70%    | 2nd        | 0.23s| ✓       |
| MVRA            | 94.46%    | 1st        | 54.65%    | 3rd        | 0.18s| ✓       |
| Deep MANTA      | 93.31%    | 2nd        | 61.70%    | 2nd        | 0.7s | ✓       |
| MonoPSR         | 87.47%    | 6th        | 46.56%    | 5th        | 0.2s | ✓       |
| Shift R-CNN     | 87.47%    | 6th        | 46.56%    | 5th        | 0.25s| ✓       |
| Ours (Supervised)| 90.63%    | 3rd        | 61.70%    | 2nd        | 0.23s| ✓       |

In [13] to be the 2D object detector of the proposed method. The proposed supervised method gets 4th in cars and 2nd in pedestrians among state-of-the-art monocular orientation estimation models on the KITTI Object Detection and Orientation Estimation Evaluation scoreboard, with the detailed results shown in Table III. AOS on moderate-difficulty-level images is used as metric. From the baseline comparisons, it is proved that the proposed method makes a simple backbone reach the state-of-the-art performance in orientation estimation.

F. Discussions

In this section, two main parts are discussed: first, the core advantages of the proposed method over baselines; second, the effectiveness of the proposed method from a hypothetical perspective.

From Table III, one major difference between the proposed method and baselines is that the proposed method does not rely on 3D information of the environment in training. In terms of applications, monocular cameras are more suitable in occasions without 3D sensors, as stated in Section I. Moreover, with 3D information, there are better ways with better devices to make intention predictions, such as LiDAR-based object tracking. Therefore, our monocular method is more suitable in monocular occasions.

The proposed method is also less complex than most baselines. The semicircle classifier can be integrated into other orientation estimation models, indicating that it is a universal method not repelling to baselines. In contrast, the baselines for comparison mostly require special designs (such as well-designed 3D object detection head) or additional materials (such as 3D labels and premade 3D models). This is another advantage of the proposed method.

The state-of-the-art performance with a simple network structure is achieved by more precise network training caused by semicircle prediction.

A manifold of optimization of orientation estimation is shown in Fig. 10a. An ideal model (i.e., oracle) can reach optimal with the ideal iteration direction. A well-trained model may fail to reach optimal because of anterior-posterior-similarity, shown in Fig. 10a that the iteration direction is different from the oracle. To be more accurate, the model should continue the iterations until it covers this difference. The rest of the iterations should be guided with a criterion closely related to the similarity problem, which, in this paper, is the semicircle classification loss.
With the semicircle classifier, such iterations are started at the beginning of the training process (i.e. as pretraining), with the whole iteration process shown in Fig. 10b. With the semicircle classifier, the anterior-posterior-similarity problem is mitigated, and the model reaches better performance. Due to the differences of models, the iteration direction of the proposed model in joint training is slightly different from the original plain model.

However, with the semicircle label unknown and ‘randomly’ decided, the iteration direction in semisupervised training is different from that in supervised training. The supervised criterion is a stronger restriction to the network than the semisupervised criterion, which is presented in (5).

\[
(C(F(x_1)) = y) \cap (C(F(x_2)) = \overline{y}) \rightarrow C(F(x_1)) = C(F(x_2))
\]

Therefore, any direction can be the iteration direction of semisupervised training if it has a component with the same direction as the supervised pretraining direction (the red arrow in Fig. 10b):

\[
d_{\text{supervised}} \cdot d_{\text{semisupervised}} > 0
\]

An instance is shown in Fig. 10c with the semisupervised pretraining direction satisfying all conditions but having huge difference from the supervised direction. This may severely reduce the performance of the joint model, since the flawed classifier acts as a misleading factor of the feature extractor in joint training. The semisupervised model in this paper is an example of, but not limited to, this instance.

V. CONCLUSION

We propose a pretraining method to enhance the robustness of orientation estimation models. We pretrain the model to classify the semicircle in which the orientation angle is located, to develop its ability of classifying the similar anterior and posterior parts of objects and extracting basic orientation features in the image. The supervised and semisupervised versions of the method are both proposed, analyzed, and experimented. Experiments show that the pretraining step contributes to the accuracy and robustness of orientation estimation. The proposed method enhances the accuracy of orientation estimation models, and mitigates the serious safety threats in autonomous driving to a certain extent.

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