MVM3Det: A Novel Method for Multi-view Monocular 3D Detection

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Abstract—Monocular 3D object detection encounters occlusion problems in many application scenarios, such as traffic monitoring, pedestrian monitoring, etc., which leads to serious false negatives. Multi-view object detection effectively solves this problem by combining data from different perspectives. However, due to label confusion and feature confusion, the orientation estimation of multi-view 3D object detection is intractable, which is important for object tracking and intention prediction. In this paper, we propose a novel multi-view 3D object detection method named MVM3Det which simultaneously estimates the 3D position and orientation of the object according to the multi-view monocular information. The method consists of two parts: 1) Position proposal network, which integrates the features from different perspectives into consistent global features through feature orthogonal transformation to estimate the position. 2) Multi-branch orientation estimation network, which introduces feature perspective pooling to overcome the two confusion problems during the orientation estimation. In addition, we present the first dataset for multi-view 3D object detection named MVM3Det, Comparing with State-Of-The-Art (SOTA) methods on our dataset and public dataset WildTrack, our method achieves very competitive results.

I. INTRODUCTION

Object detection is a fundamental task for autonomous robot system, which has developed vigorously and has been widely deployed in perception systems. However, due to the lack of 3D information, 2D object detection is hard to provide sufficient information for decision-making and planning of autonomous robots. Therefore, a large amount of 3D object detection methods have been developed for 3D pose estimation, such as monocular-based methods [1], [2], LiDAR-based methods [3], [4], [5], and multi-sensor fusion methods [6], [7], [8]. However, these methods only use the sensor data obtained from a single perspective, and the mutual occlusion between objects causes serious information loss. Even for multi-sensor fusion methods whose relative positions between the sensors are close, the ability of these methods to alleviate blind spots in the field of view is limited.

Since almost current methods are based on a single view, the false negative caused by the occlusion has become one of the main problems in the application.

Multi-view 3D object detection is one of the possible solutions for this problem, which fuses the information from different perspectives to overcome detection failures caused by occlusion in single perspective scenarios, hence providing robust results and accurate pose estimation. However, estimating a unified 3D pose from sensor data captured from different perspectives is the main challenge of multi-view object detection, especially in the case of lack of depth information. Firstly, since the information from each view is different, how to effectively fuse multi-view information into unified global information is inevitable problem for 3D location estimation. Secondly, orientation is vital for trajectory tracking and intention prediction, but orientation estimation with multiple viewing information is intractable with two confusion problems: 1) label confusion and 2) feature confusion. The first problem is common in monocular 3D detection. Relative orientation labels are usually used to eliminate label ambiguity caused by different line of sight angles. However, since the relative orientation labels in each view are different, it is difficult to find a consistent relative orientation label for all different views in multi-view detection. The second problem is that due to the perspective transformation of multiple cameras, the global features of objects which have same orientation and different positions are different. At present, there is little work focusing on overcoming this feature confusion for accurate orientation estimation.

Another important factor restricting the development of multi-view 3D object detection methods is the lack of datasets. At present, although there are many datasets [9], [10] for monocular 3D object detection, these datasets are only limited to verifying the detection methods from a single perspective. Arnold et al. [11] uses LiDAR to collect roundabout data in the simulation environment to develop LiDAR-based multi-view 3D object detection method, but does not involve multi-view monocular data. The WildTrack dataset [12] is closest to the requirements of multi-view monocular 3D detection method. However, this dataset not only contains a small amount of data, but also has no orientation labels of objects. Therefore, the development of multi-view monocular 3D object detection method is largely limited to the lack of appropriate datasets.

In this paper, we propose a novel multi-view monocular 3D object detection method MVM3Det that simultaneously estimates the position and orientation. This method contains position proposal network which achieves the consistent
global features through feature orthogonal projection, and multi-branch orientation estimation network which alleviates features confusion problem with feature perspective pooling. In addition, we present the dataset MVM3D for multi-view 3D object detection, hoping to promote the development of multi-view 3D object detection methods. The main contributions of this paper are as follows.

1) In order to estimate unique position of the object with multi-view information, we propose feature orthogonal projection and construct a position proposal network. This network generates the consistent global features from multi-view cues.

2) We design multi-branch orientation estimation network with feature perspective pooling to estimate the corresponding relative orientation for each perspective. This network alleviates features confusion problem during orientation estimation. Based on above modules, a multi-view 3D detection method is proposed. It is worth mentioning that our method is the first method that estimates the orientation and position simultaneously with multi-view monocular information.

3) We present the first multi-view 3D object detection dataset named MVM3D. Compared with the SOTA methods on our dataset and public dataset WildTrack, the proposed method achieves very competitive results. On MV3D dataset, our method achieves 95.9% MODA, an 1.1% increases over SOTA method. Our method achieves 49.0% AP3D, an 9.7% increases over monocular-based 3D detection method.

II. RELATED WORK

A. Monocular based detection

There are severval monocular based 3D detection methods for autonomous robots. Due to the lack of depth information in the image, some assumptions are usually required to restore the 3D pose of the object from the image. For example, objects are assumed to have the same altitude [13]. This assumption cannot be satisfied in many automatic driving scenes. Therefore, OFTNet [1] realizes orthogonal feature transformation within a certain height range to weaken the previous assumption. In addition, some methods [14], [15], [16] abandon the altitude hypothesis. They use the 2D bounding boxes obtained by the 2D object detection method, and predict the size and orientation of the object. Finally, the spatial position of the object is estimated by solving perspective N – points problem. These methods are sensitive to the prediction accuracy of object size and orientation. Another kind of methods is based on monocular depth estimation [17], [18], [19]. This kind of methods needs to pre-train the depth estimation network, and then estimate the 3D pose of the object combined with the 2D detection frame.

B. Multi-view based detection

Monocular based methods confront the false negative problem caused by the occlusion, especially when the objects are crowded. In the past two years, some multiple perspectives based methods have been developed to overcome the occlusion problem by capturing information from multiple perspectives. Fleuret et al. [20] propose probabilistic occupancy map method which estimates the probabilities of occupancy on the ground plane with multi-view information. Peng et al. [21] builds a multi-view network which combines multiple Bayesian networks from per view and predicts the localization of the objects. Baque et al. [22] fuses the results of 2D target detection and used convolutional neural network and conditional random field to estimate pedestrian occupancy jointly. Hou et al. [23] chooses an efficient anchor free feature aggregation method to regress pedestrian occupancy as a Gaussian distribution. However, these methods only realize position estimation for pedestrian detection, and do not estimate the orientation of objects. In this paper, a novel multi-view 3D object detection method is proposed, which estimates the position and orientation simultaneously.

III. METHOD

In this paper, we propose a novel multi-view 3D object detection method. This method simultaneously estimates 3D position and orientation from multi-view monocular information, and effectively alleviate the problem of false negative caused by the occlusion. This method mainly consists of two parts: position proposal network and multi-branch orientation estimation network. Position proposal network obtains the consistent global features from data of different perspectives, and uses anchor-based method to estimate the spatial position of objects. Multi-branch orientation estimation introduces feature perspective pooling to realize orientation estimation from different perspectives according to the previous position, so as to alleviate the confusion problem. The network structure is shown in Fig. 1.

A. Position proposal network

The purpose of Position Proposal Network (PPN) is to estimate the possible 3D spatial position of objects according to the data obtained from different perspectives. Different from the classical Region Proposal Network (RPN), PPN includes three processes: feature extraction, feature fusion and position proposal. In this paper, the monocular camera is used for each view to monitor the objects. Considering the great breakthrough of deep convolutional networks in the field of image processing, we employ ResNet-18 [24] as the feature extractor of the image in each perspective to capture deep features.

Since the information observed from each perspective is different, it is meaningless to directly fuse the deep features obtained by ResNet in image space. Therefore, the premise of feature fusion is to align the features captured from different perspectives in a unified feature space. In this paper, we assume that the altitude of the objects is approximately distributed on a horizontal plane, then we introduces the feature orthogonal transformation to project the deep features from different perspectives into a Birds-Eye-View (BEV) space. Similar to [1], [23], [25], when the altitude of the distribution plane of the objects is known, we calculate
the position of each pixel from deep features in the BEV space by orthogonal transformation.

\[ \Gamma = \tau(R^{-1}K^{-1}U + R^{-1}T). \]

Here \( \Gamma \) is 3D position, and \( U \) is the homogeneous coordinates of the pixel in the camera image. \( K \) is the camera matrix. \( R \) and \( T \) are the rotation matrix and translation vector of the camera, respectively. \( \tau \) is scale factor which is estimated by

\[ \tau = \frac{(R^{-1}K^{-1}U + R^{-1}T)}{z^P}. \]

\( V|_z \) means the \( z \) axis value of the vector \( V \). \( z^P \) is the altitude of the objects. For each deep feature of each view, the above orthogonal transformation is used to convert image features to the BEV space. We stack the projected features with coordinate maps and fuse them in the BEV space by the convolutional network, so as to obtain consistent global features.

Based on the global features, we introduce anchor-based method for location estimation. Similar to RPN, the global feature is input into the fully convolutional network to predict the probability of an object at the corresponding position of each anchor and the offset of the object center relative to the anchor center. During the training process, the prediction bounding box whose Intersection over Union (IoU) with the ground truth is greater than 0.7 is taken as the positive sample, and the prediction bounding box whose IoU is less than 0.3 is taken as the negative sample. During the inference process, the confidence threshold and Non-Maximum Suppression (NMS) [26] are applied to predict the possible position.

**B. Multi-branch orientation estimation network**

Orientation estimation is an essential part of 3D object detection. However, there are several challenges to estimate orientation with multi-view monocular information. Similar to the monocular 3D object detection methods, multi-view orientation estimation also faces the same label confusion problem. This problem means that the different line of sight relative to the camera makes the observed states various when the object orientation is fixed, resulting in the same label corresponding to different states, as shown with 2, 4 and 5 in Fig. 2. The usual solution is to redefine the label according to the line of sight angle to eliminate this ambiguity. When objects with the same orientation are in the same line of sight, there is no label confusion problem, but due to the influence of the feature orthogonal projection, the previous consistent global features face another confusion problem. This is due to the altitude assumption, which causes the streak near the projection center. This streak leads to the global features of object at different positions are quite different, even though they have the same orientation on the same line of sight angle. This phenomenon is called feature confusion, as shown with 1, 2 and 3 in Fig. 2.

Since feature confusion is caused by the orthogonal transformation of features, the global features are not suitable for orientation estimation. Here we propose **feature perspective pooling** which combines features from each perspective and the position proposals. Firstly, according to the position obtained by PPN, the pool region corresponding to the 3D position in the image of each view is calculated through perspective transformation. Specifically, 8 vertices of the bounding box are obtained according to the estimated center position of the object and the predefined orientation. According to the parameters of the camera, the position of each vertex in the image is calculated by perspective transformation. We obtain the Region Of Interest (ROI) by calculating the minimum outer rectangle of the 8 projection vertices. Then, ROI pooling is used to obtain the features.
we adopt a phased training method: first train the PPN, and then train the multi-branch orientation estimation network.

for orientation prediction under each perspective. During the perspective pooling process, we assume the altitude and height of the object are known. Similar to [14], we do not directly regress the orientation, but divide the value into $N$ intervals. Each branch network predicts the confidence of the object included in the ROI, the probability that the object angle falls in region $[\frac{i-1}{N}, \frac{i}{N}]$, $i \in \{1, 2, \cdots, N\}$, and the offset of the object angle relative to the center value of the region. During training, the label of offset $o_i$ is calculated as follows

$$o_i = \beta - \frac{\pi}{N}(2 \ast i - 1), \text{ where } i \in \{1, 2, \cdots, N\},$$

where $\beta$ is the ground truth of the orientation. In order to eliminate label confusion, the value is the angle relative to the line of sight. Since the multi-branch method predicts the orientation of the object in each perspective, each object may have multiple prediction bounding boxes with different orientation. During the inference, we first rank the boxes according to the confidence, and then apply NMS to determine the final prediction result.

C. Multi-view based 3D object detection

Based on the PPN and multi-branch orientation estimation network, we propose a multi-view 3D detection method MVM3Det. This method takes the monocular image from multiple perspectives as the input and extracts the features through the sharing ResNet-18, then obtains the consistent global feature through the feature orthogonal transformation, and applies the anchor based method to estimate the possible spatial position of the object. After confidence threshold and NMS, the estimated position is combined with feature perspective pooling to obtain the features of ROI in each perspective and estimates the orientation of the object in each perspective. Finally, the bounding boxes are obtained by NMS. In the training process, considering that the orientation estimation network is based on accurate position estimation, we adopt a phased training method: first train the PPN, and then train the multi-branch orientation estimation network.

1) Position proposal network loss: PPN loss $\mathcal{L}^{PPN}$ consists of two parts

$$\mathcal{L}^{PPN} = \frac{1}{N_{conf}} \sum_i \mathcal{L}_{conf}(\hat{p}_i, p_i) + \lambda D^{PPN} \frac{1}{N_{val}} \sum_i p_i \mathcal{L}_{offset}(\hat{t}_i^{BEV}, \hat{t}_i^{BEV})$$

(1)

where the first part represents the loss of predicted confidence of each anchor. $\hat{p}_i \in \{0, 1\}$ and $p_i$ are the ground truth label and predicted confidence, respectively. $N_{conf}$ represents the total number of anchors. The second part represents the offset loss of anchor in BEV space, $\hat{t}_i^{BEV}$ represents the offset between the true position and anchor, and $t_i^{BEV}$ represents the predicted offset. Here, only offset loss of anchor involving objects are considered. $N_{val}$ represents the number of the validate anchors which involve objects. The last part is multi-brach regression loss which represents the offset loss of 2D bounding box in the image space under the different view $v$. The box is projected from the BEV position prediction. Experiments show that this loss function improves the accuracy of position estimation. Softmax loss and smooth L1 loss are adopted for $\mathcal{L}_{conf}$ and $\mathcal{L}_{offset}$ respectively. We follow [27] to encode $t_i^{BEV}$ and $t_i^{BEV}$, $\lambda D^{PPN}$ and $\lambda 2D^{PPN}$ are balance parameters.

2) Multi-branch orientation estimation network loss: For multi-branch orientation estimation network, we predict three parts: 1) the confidence of object existence, 2) the orientation interval classification probability and 3) the orientation offsets. Therefore, the loss function also consists of three parts.

$$\mathcal{L}^{MBON} = \sum_v \frac{1}{N_{conf}^v} \sum_i \mathcal{L}_{conf}(\hat{p}_i^v, p_i^v) + \frac{1}{N_{val}^v} \sum_i p_i^v \mathcal{L}_{cls}(\hat{b}_i^v, b_i^v)$$

(2)

$$+ \lambda^{MBON} \frac{1}{N_{val}^v} \sum_i p_i^v \mathcal{L}_{ori}(\hat{o}_i^v, o_i^v)$$

where $p_i^v$ represents the true label of the $i$-th predicted bounding box in the $v$-th perspective. Second part $\mathcal{L}_{cls}$ is multi-bin classification loss which calculates distribution distance between the one-hot label and predicted probability distribution. Here softmax loss is used for this loss. $\hat{b}_i$ represents the probability distribution of the $i$-th box over orientation intervals, and $o_i$ represents the offset between the orientation and the interval center. $N_{conf}^v$ is the total number of the predicted bounding boxes in view $v$, $N_{val}^v$ is the number of the validate boxes. Considering the periodicity of the orientation, we employ the cosine function to encode the offset prediction error as the offset prediction loss $\mathcal{L}_{ori}$, which is same as [14].

IV. EXPERIMENT

In order to verify the performance of the proposed multi-view 3D detection method, we present a multi-view monoc-
IoU thresholds and employed to select positive samples and size \([120, 160]\). During training PPN, 0.7 and 0.3 are the work. The features in BEV space are interpolated into a fixed size. Similar to [23], ResNet-18 is applied as the backbone network. During training, random brightness, random contrast and random saturation are used for image augmentation.

### C. Implementation details

During experiments, random brightness, random contrast and random saturation are used for image augmentation. Similar to [23], ResNet-18 is applied as the backbone network. The features in BEV space are interpolated into a fixed size \([120, 160]\). During training PPN, 0.7 and 0.3 are the IoU thresholds and employed to select positive samples and negative sample, respectively. \(\lambda^{PPN}\) is 3, and \(\lambda^{2D}_{MBON}\) is 1. During training multi-branch orientation estimation network, we select 128 samples from PPN with IoU greater than 0.5 to train the network. \(\lambda^{MBON}\) is 0.4. We use Adam optimizer with learning rate \(0.15 \times 10^{-5}\) to train the networks for 15 epochs, and batchsize is set to 1.

### D. Localization performance

1) **Results on WildTrack dataset:** On WildTrack dataset, we compare the proposed method with the current SOTA methods, and the results are shown in Table I. The results show that MVDet is the best positioning method at present. Compared with that, the proposed method is slightly better than MVDet in MODP, and the results of other metrics are close. Compared with anchor free method MVDet, location estimation of MVM3Det is an anchor based method. Due to the limitation of anchor, the recall of this method is lower than that of anchor free method when the objects are dense, so the MODA also is lower. Compared with the remaining methods, our method has obvious advantages in positioning performance.

2) **Results on MVM3D dataset:** Compared with WildTrack dataset, MVM3D dataset is larger and the illumination changes are richer. Moreover, due to the existence of obstacles, the occlusion situation is more complex. It should be noted that although the MVM3D dataset is larger than WildTrack dataset, the density of objects in each frame is less than that of WildTrack. This is also the reason why MVM3Det has high recall on this dataset. With close recall, anchor based method MVM3Det has better precision, and higher MODA than MVDet, as shown in Table II. The visualization of results on MVM3D dataset are shown in Fig 3. It can be seen from the results in the figure that our proposed method can accurately estimate the position and orientation of the object even when it is seriously blocked by obstacles.

### E. Ablation studies for localization

We set up several ablation experiments for the proposed method on MVM3D to analyze the localization performance. The results are shown in Table III.

#### 1) Basic monocular model: The simplest baseline model is to project the original image into BEV space by feature

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**TABLE I: Comparison on WildTrack**

| Methods               | MODA (%) | MODP (%) | Prec. (%) | Recall (%) |
|-----------------------|----------|----------|-----------|------------|
| RCNN & clustering [28] | 11.3     | 18.3     | 68        | 43         |
| POM-CNN [20]          | 23.2     | 30.5     | 75        | 55         |
| DeepMCD [29]          | 67.8     | 64.2     | 85        | 82         |
| Deep-Occlusion [22]   | 74.1     | 53.8     | 95        | 80         |
| MVDet [23]            | 88.2     | 75.7     | 94.7      | 93.6       |
| MVM3Det(Ours)         | 84.0     | 75.8     | 93.6      | 90.2       |

**TABLE II: Comparison on MVM3D**

| Methods               | MODA (%) | MODP (%) | Prec. (%) | Recall (%) |
|-----------------------|----------|----------|-----------|------------|
| MVDet [23]            | 94.8     | 87.7     | 97        | 98.2       |
| MVM3Det(Ours)         | 95.9     | 83.2     | 99.2      | 95.8       |

**TABLE III: Ablation studies on MVM3D**

| Methods              | 1 | 2 | 3 | 4 | 5 |
|----------------------|---|---|---|---|---|
| MODA (%)             | 12.7 | 69.0 | 27.9 | 94.7 | 95.9 |
| MODP (%)             | 43.2 | 76.2 | 69.3 | 80.6 | 83.2 |
| Prec. (%)            | 50.6 | 90.4 | 91.8 | 96.6 | 99  |
| Recall (%)           | 22.0 | 56.3 | 30.6 | 99  | 95.8 |

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**Website:** https://github.com/DRL-CASIA/MVM3D

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The collection of datasets is completed in an 8m×4.5m site. A pair of monocular cameras are erected diagonally on the site to capture images of the site. There are some obstacles with different heights and moving objects in the site. In MVM3D dataset, the object to be detected is mobile robot. The orientation distribution of labels in the dataset is very important for orientation estimation. The WildTrack dataset is the most similar to our proposed dataset, but it only contains 400 samples and does not provide the orientation label of the object. Therefore, it is unable to verify the orientation estimation performance of the methods. Our proposed dataset contains 4330 pairs monocular images collected from multiple perspectives and a large number of bounding boxes including position and orientation.

The results are shown in Table III. In MVM3D dataset, the object to be detected is mobile robot. The orientation distribution of labels in the dataset is very important for orientation estimation. We try our best to ensure that the number of samples is distributed uniformly in each angle interval. More information about dataset can be found [https://github.com/DRL-CASIA/MVM3D](https://github.com/DRL-CASIA/MVM3D).
orthogonal transformation, and then uses ResNet-18 as feature extractor to predict the position of objects in BEV space. The results are shown in the 1-th row of Table III.

2) **Feature orthographic transformation (FOT):** The baseline model of the 2-th row is modified based on the model of the 1-th row. Specifically, the model applies ResNet-18 to extract features in image space, and then uses feature orthogonal transformation to obtain the features in BEV space and predict the spatial position of the object. Compared with the results in the 1-th row, it is noticeable that the pre-trained ResNet-18 model has better performance in the original image space.

3) **Multi-view image fusion:** Based on first baseline model, the model in the 3-th row adds the input from multiple perspectives. Images projected from multiple perspectives into the BEV space are stacked as the input to ResNet-18. Compared with the results in the 1-th row, it can be seen that multi-view information increases the location performance to a certain extent.

4) **Multi-view feature fusion:** The model of the 4-th row is based on the 3-th row, which employs ResNet-18 to extract the deep features from the original perspective, and then uses the feature orthogonal transformation to obtain the features in the BEV space. This model is trained with first two part of PPN loss. The results in the 2-th and 4-th rows show that feature fusion under multi-view greatly reduces the false negatives and improves the performance of the method.

5) **Multi-branch regression (MBR):** The last line is the multi-view 3D object detection method proposed in this paper, which adds a multi-branch 2D bounding box regression loss. Compared with the results in the 4-th and 5-th rows, it can be seen that the joint BEV space loss and multi-branch regress loss increases the position estimation accuracy to a certain extent.

### TABLE IV: Orientation performance on MVM3D

| Methods | $\text{IoU} = 0.25$ | $\text{IoU} = 0.5$ |
|---------|---------------------|-------------------|
|         | $A_{3D}$ | $A_{OS}$ | $O_{OS}$ | $A_{3D}$ | $A_{OS}$ | $O_{OS}$ |
| Monocular | 77.2%  | 67.1% | 0.87 | 30.3% | 26.6% | 0.88 |
| MVM3Det   | 90.2%  | 82.6% | 0.91 | 49.0% | 45.5% | 0.92 |

### F. Orientation performance

As far as we know, there is no method to realize orientation estimation with multi-view monocular information. However, orientation is necessary to monocular 3D detection. The baseline model compared here is a degraded model based on our proposed method, which only uses single view information. It can be seen from the results in Table IV that multi-view fusion greatly improves the accuracy of orientation estimation.

### V. CONCLUSIONS

In this paper, a novel multi-view monocular 3D object detection method is proposed, which overcomes false negatives caused by the occlusion and the confusion problem of orientation estimation under multiple perspectives. This method is mainly composed of PPN and multi-branch orientation estimation network. PPN fuses the data from different perspectives through the feature orthogonal transformation to estimate the spatial position of the objects. Multi-branch orientation estimation introduces feature perspective pooling to realize orientation estimation from various perspectives, so as to alleviate the problems of label confusion and feature confusion in orientation estimation. In addition, in order to promote the development of multi-view 3D object detection, we present the first multi-view monocular 3D dataset MVM3D, covering different illumination and complex occlusion scenes. Through the experiments on our dataset and public dataset, the proposed method achieves competitive results to the current SOTA in position estimation, and realizes orientation estimation for the first time.
