Real-time Fusion Network for RGB-D Semantic Segmentation Incorporating Unexpected Obstacle Detection for Road-driving Images

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Abstract—Semantic segmentation has made striking progress due to the success of deep convolutional neural networks. Considering the demand of autonomous driving, real-time semantic segmentation has become a research hotspot these years. However, few real-time RGB-D fusion semantic segmentation studies are carried out despite readily accessible depth information nowadays. In this paper, we propose a real-time fusion semantic segmentation network termed RFNet that efficiently exploits complementary features from depth information to enhance the performance in an attention-augmented way, while running swiftly that is a necessity for autonomous vehicles applications. Multi-dataset training is leveraged to incorporate unexpected small obstacle detection, enriching the recognizable classes required to face unforeseen hazards in the real world. A comprehensive set of experiments demonstrates the effectiveness of our framework. On Cityscapes, Our method outperforms previous state-of-the-art semantic segmenters, with excellent accuracy and 22Hz inference speed at the full 2048×1024 resolution, outperforming most existing RGB-D networks.

I. INTRODUCTION

Environment perception is a significant task for intelligent robots and systems in objects classification, autonomous driving and localization. In recent years, this field has made remarkable progress thanks to deep Convolutional Neural Networks (CNNs) based semantic segmentation methods [1] [2] [3]. As an environment perception method to be applied in autonomous driving, safety, accuracy and efficiency are the vital factors in semantic segmentation for upper-level navigational tasks. However, unexpected road hazards like debris, bricks, stones and cargos become the most dangerous and difficult elements to detect in autonomous driving imagery. According to AAA foundation for Traffic Safety, debris on the road led to more than 200,000 crashes on U.S. roadways between 2011 and 2014, resulting in approximately 39,000 injuries and more than 500 deaths [4]. These obstacles are generally small in size but not fixed in shape and type, making detecting them a challenging subject that has aroused interest among the robotics and computer vision community. For these reasons, it is desirable to investigate a semantic segmentation based method incorporating pixel-wise unexpected obstacle detection.

Compared to expensive 3D sensors like LIDAR, RGB camera is a much lower cost solution with higher resolution. Based on RGB stereo camera, there have been some attempts to detect small obstacles with the help of geometry cues and CNNs [5], but only relying on apparent information in RGB image alone is not sufficient for obstacle detection [6]. For example, manhole covers and small obstacles can both cause gradient changes on the image. The traversable areas and obstacles in the depth map vary vastly in depth maps. Depth maps contain more location and contour information that can be used as a critical indicator of objects in real-world driving scenarios. Consequently, appropriately combining of appearance and depth is promising to improve the performance based on multi-modal fusion schemes [6] [7] [8]. But most accuracy-oriented RGB-D semantic segmentation researches focus on indoor scenes [7] [9] [10], without assuring a fast inference speed that is necessary for autonomous vehicles.

On the other hand, the outstanding capacity of CNNs is based on a large amount of annotated data, especially...
for semantic segmentation tasks [11]. Current mainstream autonomous driving datasets generally assume only some fixed categories objects in the scene, ignoring unforeseen hazards like unexpected small obstacles in the real world. For instance, Cityscapes [12] only divides objects to 19 classes, without defining any unexpected class. Multi-source training has been proven to effectively increase recognizable semantics without having to relabel the dataset [13]. However, previous multi-source training framework has only considered the heterogeneity in the label hierarchies of RGB data, missing the opportunity to leverage complementary depth information from different sources.

In this paper, we propose a framework that combines RGB-D semantic segmentation and obstacle detection. RFNet, a real-time fusion network for RGB-D semantic segmentation is elaborately designed. With our multi-dataset training strategy, our framework is able to classify 19 categories in Cityscapes incorporating pixel-wise unexpected small obstacle detection (see Figure 1). An extensive set of experiments shows the effectiveness and efficiency of the proposed framework in the semantic segmentation task. The main contributions of our work are threefold:

- We propose RFNet, a real-time fusion network for RGB-D semantic segmentation incorporating detection of unexpected obstacle, which achieves higher accuracy with fast inference compared to other state-of-the-art methods on the Cityscapes dataset.
- Depth complementary features are efficiently extracted in the proposed network, which improves the accuracy compared to the single RGB-stream architecture.
- Multi-dataset training and the depth stream in the architecture enable the network to work remarkably effective in detecting unexpected small objects.

II. RELATED WORKS

A. RGB-D Semantic Segmentation

High quality dense depth maps from depth sensors like Kinect and RealSense boost the development of indoor semantic segmentation. Early attempt like [14] simply concatenates RGB and depth channels as a four-channel input, and feeds into a conventional RGB modal network. However, such methods cannot exploit complementary information from depth maps in most times [15]. In [9] and [10], RGB images and depth maps are fed into two separate neural network branches respectively, which are fused before the upsampling. In [16], depth maps are pre-processed as HHA features that encode horizontal disparity, height above ground and angle. [17] proposed a multilevel feature fusion scheme by introducing multi-modal feature fusion to the RefineNet blocks. ACNet [7] achieved a breakthrough by proposing an attention complementary module to exploit complementary depth information efficiently. These studies prove that RGB-D semantic segmentation can achieve better segmentation results than single RGB methods. The major reason for this is that compared to the single RGB images, depth maps contain more location and contour information that benefit the context-critical semantic segmentation.

B. Unexpected Obstacle Detection for Self-driving Cars

Detecting unexpected small but potentially hazardous obstacle on the road is a vital task for autonomous driving, and this subject has always been a research hotspot. Generally these methods for detecting and localizing generic obstacle are based on stereo cameras integrated on self-driving cars. Among these methods, most are based on generic geometric criteria. The Stixel algorithm [22] represents obstacles with a set of rectangular vertical obstacle segments, providing a robust representation of the 3D scene. Geometric point cluster methods like [23] and [24] exploit geometric relation between 3D points to detect and cluster obstacle points.

Because of the superiority in making use of visual appearance and context of images, CNNs are adopted in contemporary researches. [8] presented a principled Bayesian framework to fuse the semantic segmentation predicted from a convolutional neural network and stereo-based detection results from the Fast Direct Planar Hypothesis Testing (FPHT) method. [6] proposed a multi-stage training procedure involving weight sharing, separate learning of low and high level features from the RGB-D input and a refining stage which learns to fuse the obtained complementary features. But all these methods can only predict three main classes: free-space, obstacle and background. But to meet the demand of autonomous driving, we need a more universal approach that can enrich the detectable semantics beyond simple roads/obstacles separation. In this work, we address unexpected obstacle detection by incorporating it in a multi-source semantic segmentation framework to provide a unified pixel-wise scene understanding.

III. METHODOLOGY

A. Network Architecture

The entire network architecture of RFNet is shown in Figure 2. In the encoder part of the architecture, we design two independent branches to extract features for RGB and depth images separately—RGB branch as the main branch and Depth branch as the subordinate branch. In both branches, we choose ResNet-18 [25] as the backbone to extract features from inputs because ResNet-18 has moderate depth and residual structure, and its small operation footprint is compatible with real-time operation. After each layer of ResNet-18, the output features from depth branch are fused
to RGB branch after the Attention Feature Complementary (AFC) module. The spatial pyramid pooling (SPP) block gathers the fused RGB-D features from two branches and produces feature maps with multi-scale information. Finally, referred to SwiftNet [26], we design the efficient upsampling modules to restore the resolution of these feature maps with skip connections from the RGB branch.

**Attention Feature Complementary (AFC) module.** As discussed in the last part, the depth maps contain more contour and location information that benefit RGB semantic segmentation. In order to fuse RGB and depth information effectively, we design AFC module (shown in Figure 3) to make the network focus on learning more complementary informative features from RGB and depth branches. As shown in Figure 3 in the AFC module, we leverage a SE block as the channel attention method, which is inspired by Squeeze-and-Excitation Network [27].

With the multi-branch architecture, we have the RGB input feature maps $X = [x_1, \ldots, x_C] \in \mathbb{R}^{C \times H \times W}$ and Depth input feature maps $Y = [y_1, \ldots, y_C] \in \mathbb{R}^{C \times H \times W}$. First we use global average pooling as a channel descriptor based on channel attention mechanism, then we add a $1 \times 1$ convolution layer with the same channels as input. This $1 \times 1$ convolution layer is able to excavate correlations between channels. The followed sigmoid function is applied to activate the convolution result and constrain the value of weight vector between 0 and 1. Next, we do outer product for the weight vector and input feature maps in both branches. Finally, by adding results from RGB and Depth branches, we have the resulted feature map $Z \in \mathbb{R}^{C \times H \times W}$, expressed as:

$$Z = X \otimes \sigma_1 [\phi_1 (X)] + Y \otimes \sigma_2 [\phi_2 (Y)] \quad (1)$$

Here $\phi$ denotes global pooling and $1 \times 1$ convolution. $\otimes$ and $\sigma$ denote outer product and sigmoid function respectively. By applying such attention mechanism in RGB-D fusion, more informative features obtain higher values of weights, which helps us exploit complementary information from depth maps more effectively.

**Spatial pyramid pooling.** In order to increase the receptive field to cover pixels of large objects while maintaining real-time speed, we adopt Spatial Pyramid Pooling (SPP) to average features over aligned grids with different granularities. Our SPP module is based on a simplified version of pyramidal pooling module from PSPNet [28]. PSPNet uses it to provide multi-scale context and to condition features for linear classification with only one convolution layer between the SPP and the predictions. In our case, we upsample the feature pyramid to the original resolution and concatenate them with input features, following by convolutions to obtain output feature maps. In RFNet, SPP features must pass through the whole decoder before getting classified. Thus, it acts as an instrument to enlarge the receptive field.

**Efficient upsampling module.** The purpose of the decoder is to upsample semantically rich visual features in coarse spatial resolution to the input resolution. We adopt a simple decoder contains 3 simple upsampling modules with skip connections from encoder. In the first two upsampling module, low resolution feature maps from former block are upsampled with bilinear interpolation to the same resolution as feature maps from skip connection, then these two streams of feature maps are element-wisely added and finally mixed as feature maps from skip connetcion, then these two streams of feature maps are element-wisely added and finally mixed with a $3 \times 3$ convolution. The third upsampling module is slightly different because we add a convolution layer and a $4$-times bilinear interpolation at last to restore to the same resolution as input. More precisely, the skip connection is routed before the second ReLU of the residual block because current study shows that skip connection from any other stage impairs the accuracy [26].

### B. Multi-Dataset Learning

As a data-driven technology, annotated labels are essential for semantic segmentation, but we can not annotate all classes in the real world. In order to utilize as much and diverse training data as possible and increase the number of recognizable classes from a few dozens to virtually anything that a scene can contain, multi-source learning is an effective method. However, simply mixing two or more datasets for training may cause some problems. As shown in Figure 4, the heterogeneity in the annotation type and samples amount may cause overfitting to one of the data source, leading to incomplete segmentation when simply mixing the datasets.

This is because classes in different datasets may conflict with each other. For example, the annotation type of these
classes are different, or certain class is a subclass of a class in another dataset. To facilitate multi-source learning with such heterogeneity, we design some training strategies. Formally, we have datasets \( D_1, \ldots, D_c, \ldots, D_n \). Class set \( A \) contains classes that are not conflict with each other, and class set \( B \) contains the rest. For these conflicted classes, we refer to dataset \( D_c \) as standard annotation. Let us denote an image by \( x \), and the corresponding human annotation for \( x \) is provided and denoted by \( y \), where \( y(m, n) \in 1, \ldots, C \) is the label of pixel \( (m, n) \), and \( C \) is the total number of classes. \( l \) denotes the total number of images in all datasets and \( \phi \) denotes the segmentation model. We train on the joint multi-datasets with the loss function shown below:

\[
\text{loss} = \frac{1}{l} \sum_{i=1}^{l} \left[ L_A(\phi(x_i), y_i) + \lambda L_B(\phi(x_i), y_i) \right]
\]

where \( L_A(\ldots) \) and \( L_B(\ldots) \) denotes cross entropy loss function for class set \( A \) and \( B \) respectively. \( \lambda \) is a hyperparameter balancing the weights of different classes, and in our work we set \( \lambda \) as following:

\[
\lambda = \begin{cases} 
1, & x_i \in D_c \\
0, & x_i \notin D_c 
\end{cases}
\]

For instance, in this work we leverage Cityscapes [12] and Lost and Found [5]. Note that Cityscapes has annotation of 19 classes except those unexpected small obstacles. We make some modifications to the loss function while training. Coarse annotated classes: free-space and background classes in Lost and Found belong to class set \( B \), and will not be counted in the loss function. In other words, loss values of these classes are ignored. With the presented multi-dataset training strategy, our RFNet learns to predict 19 classes from Cityscapes and the critical unexpected small obstacle class from the Lost and Found dataset.

Although unexpected small obstacle is a generalized conception, which is not limited to obstacle types in Lost and Found, the definition of this particular set of classes allows us to meet the demand by exploiting the power of deep learning methods. For example, learning that all kinds of obstacles have some common contextual property, being of small dimensions and surrounded at least partly by free-space. Thereby, the network is able to generalize far beyond its training data with the multi-source learning strategy when facing innumerable possible corner cases.

IV. EXPERIMENTS

A. Datasets

In this work, two RGB-D semantic segmentation datasets: Cityscapes and Lost and Found are exploited.

Cityscapes [12] is a large-scale RGB-D dataset that focuses on semantic understanding of urban street scenes. It contains 2975/500/1525 images in the training/validation/testing subsets, both with finely annotated labels on 19 classes. The images cover 50 different cities with a full resolution of 2048×1024.

The Lost and Found [5] dataset consists of 2014 annotated frames from 112 stereo video sequences, along with coarse annotations of free-space areas and fine-grained annotations of the small obstacles on the road. Among them, training set and validation set contain 814 and 1200 images with resolution of 2048×1024, covering different small obstacles present at long distance with non-uniform road textures/apparances and pathways with many non-obstacle class objects acting as distractors.

Both disparity images from Cityscapes and Lost and Found are obtained by using the semi-global matching algorithm [29], which is a sophisticated method for the estimation of a dense disparity map from a rectified stereo image pair.

B. Implementation Details

The models were implemented on a single 2080Ti GPU with CUDA 10.0, CUDNN 7.6.0 and PyTorch 1.1. Adam [30] is used for optimization with the learning rate set to \( 4 \times 10^{-4} \), where cosine annealing learning rate scheduling policy [31] is adopted to adjust learning rate with minimum value of \( 1 \times 10^{-6} \) in the last epoch. The weight decay is set to \( 1 \times 10^{-4} \). More precisely, we initialize the ResNet-18 in both RGB and Depth branches with pre-trained weights from Pytorch, and initialize the rest part of the model with kaiming initialization [32]. For pre-trained parameters, we update them with 4 times smaller learning rate and apply 4 times smaller weight decay. Because the left and bottom part of the disparity images are not applicable due to the restrictions of semi-global matching algorithm, we crop these pixels and resize images back to the original resolution with bilinear upsampling. Rest of the data augmentation operations consist of scaling with random factors between 0.5 and 2, random horizontal flipping and random cropping with an output resolution of \( 768 \times 768 \). We train all the models for 200 epochs with a batch size of 8.

C. Results and Analysis

Ablation Study. We perform the ablation study on our RFNet to explore the influence of different architecture variants and fusion schemes on the network accuracy where the results are shown in Table I. All the results in this section are obtained by evaluating on the blended validation set of Cityscapes and Lost and Found, which includes all images from both validation datasets.
In the table, the single RGB method only exploits the RGB branch of RFNet, and it is a control group to determine if the depth information helps improve the accuracy, which achieves a mean Intersection over Union (mIoU) of 70.41%. In RGB-D-Stack method, we stack depth maps with respective RGB image to form a 4-channel input to the single branch of RFNet. The low accuracy of the method (65.20% in mIoU) proves that depth information is not exploited effectively in this way. We also design RGB-D-Fusion (concatenation), where the only difference of this method to the RGB-D-Fusion (element-wise add) in our RFNet is that RGB feature maps and depth feature maps are concatenated to a higher dimension feature maps and restore RFNet is that RGB-D fusion networks (ERFNetEnc) [20]. Our RFNet is both more accurate and faster than these multimodal networks. Overall, rare multi-modal semantic segmentation method meets the real-time prediction speed, while our method achieves the highest accuracy on the validation set of Cityscapes to the best of our knowledge that meets both demands including real-time inference, highly qualified accuracy, and capacity to leverage complementary features in cross-modal imagery.

**Qualitative Performance Study.** We present the qualitative examples in Figure 5 and Figure 7. In this paper, the main purpose of exploiting depth information is to enhance the segmentation accuracy in classes which are difficult for
RGB method, including small obstacles. The appearance and surface texture of the small obstacles are not fixed, and it is easy to be confused with graffiti, manhole covers, zebra crossings on the road. Comparatively, in the depth map where texture is ignored, the contour of small obstacles is clear. Graffiti, manhole covers are flat, making it part of the road surface in the depth map. All these features of depth maps enable to reduce the chance of false alarm in detecting small obstacles. We compare our RFNet with SwiftNet [26], which has a similar network architecture with RFNet, where Figure 7 shows representative contrast results from two networks. As a purely RGB-based method, SwiftNet predicts manhole cover as small obstacle, while RFNet correctly classifies the manhole as part of the road, which demonstrates the superiority of our method for safety-critical road sensing. RFNet also performs better in large-scale objects like bus and truck because contours of these classes are much clearer in depth maps compared to RGB images.

Furthermore, Figure 6 shows the feature maps after the second block from RFNet, in which the first two are feature maps from RGB and depth branch respectively, and the merged feature maps are from the output part of the AFC module. As it can be clearly seen, compared to RGB feature maps, small obstacle is much more clear and manhole cover disappears in depth feature maps, while the feature map after AFC module takes the advantages of both branches. In summary, the AFC module enables RFNet to effectively exploit the depth features in a complementary way, improving the accuracy of obstacle detection evidenced by both numerical and qualitative results.

V. CONCLUSION

In this study, we propose a RFNet, a real-time fusion network for RGB-D semantic segmentation on road-driving images. With the designed Attention Feature Complementary module, RFNet exploits complementary depth information effectively, and significantly improves the accuracy over purely RGB-based method. With the presented multi-source training strategy, RFNet can also detect unexpected small obstacle, enriching the recognizable classes required to face the real world with unforeseen hazards. More importantly, RFNet operates at 22Hz with full resolution Cityscapes images and 41.6Hz with half resolution on a single Nvidia GTX2080Ti GPU, which make it ideally suitable for autonomous driving applications. Our RFNet outperforms state-of-the-art RGB-D fusion methods in terms of accuracy and speed. In the future, we plan to further streamline RFNet and deploy it to portable TPU devices with robustness augmented. The source code of our RFNet is available at https://github.com/AHupuJR/RFNet.

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Fig. 7. Qualitative semantic segmentation results from SwiftNet and the proposed RFNet that exploits both RGB and depth information.

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