FAST AND ACCURATE SCENE PARSING VIA BI-DIRECTION ALIGNMENT NETWORKS

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ABSTRACT

In this paper, we propose an effective method for fast and accurate scene parsing called Bidirectional Alignment Network (BiAlignNet). Previously, one representative work BiSiNeT [1] uses two different paths (Context Path and Spatial Path) to achieve balanced learning of semantics and details, respectively. However, the relationship between the two paths is not well explored. We argue that both paths can benefit each other in a complementary way. Motivated by this, we propose a novel network by aligning two-path information into each other through a learned flow field. To avoid the noise and semantic gaps, we introduce a Gated Flow Alignment Module to align both features in a bidirectional way. Moreover, to make the Spatial Path learn more detailed information, we present an edge-guided hard pixel mining loss to supervise the aligned learning process. Our method achieves 80.1% and 78.5% mIoU in validation and test set of Cityscapes while running at 30 FPS with full resolution inputs. Code and models will be available at https://github.com/jojacola/BiAlignNet.

Index Terms— Bidirectional Alignment Network, Fast and Accurate Scene Parsing

1. INTRODUCTION

Semantic Segmentation is a fundamental vision task that aims to classify each pixel in the images correctly. Some earlier approaches [4,5] use structured prediction operators such as conditional random fields (CRFs) to refine segmentation results. Recent methods for semantic segmentation are predominantly based on FCNs [6]. Current state-of-the-art methods [7,8,9] apply atrous convolutions [2] at the last several stages of their networks to yield feature maps with strong semantic representation while at the same time maintaining the high resolution, as shown in Fig. 1(a). Moreover, there are also several methods based on Feature Pyramid Network (FPN)-like [3][10][11] models which leverage the lateral path to fuse feature maps in a top-down manner. In this way, the deep features of the last several layers strengthen the shallow features with high resolution. Therefore, the refined features are possible to keep high resolution and meanwhile catch semantic representation, which is beneficial to the accuracy improvement, as shown in Fig. 1(b). However, both designs are not practical for real-time settings. The former methods [7,8] require extra computation since the feature maps in the last stages can reach up to 64 times bigger than those in FCNs. Meanwhile, the latter one [10] has a heavier fusion operation in their decoder. For example, under a single GTX 1080Ti GPU, the previous model PSPNet [7] has a frame rate of only 1.6 FPS for 1024 × 2048 input images. As a consequence,
this is very problematic for many time-critical applications, such as autonomous driving and robot navigation, which desperately demand real-time online data processing.

There are several specific designed real-time semantic segmentation models \([12, 13, 1, 14]\) handling above issues. However, these methods can not achieve satisfactory segmentation results as accurate models. The representative works BiSeNets \([1, 14]\) propose to use two different paths for learning spatial details and coarse context information respectively, shown in Fig. 1(c). However, they have not explored the interaction between two data flows explicitly. We believe such two data flows contain complementary content that can benefit each other. In this paper, we propose a new network architecture for real-time scene parsing settings. As shown in Fig. 1(d), two paths interact with each other through specific design modules before the fusion. Motivated by a recent alignment module \([15]\) which deforms the entire feature map using a learned flow field, we propose a Gated Flow Alignment Module to align features with each other. The original FAM \([15]\) is proposed to align adjacent features in the decoder. However, directly using such a module may lead to inferior results because of the huge semantic gap between the two paths. Thus, we plug a gate into the FAM to avoid the noises and highlight the important information. Suppose \(F_s\) is the source feature, and \(F_t\) can be features from the spatial path and context path respectively, and vice versa. The feature map that has a smaller size is bilinearly upsampled to reach the same size as the larger one. After flow field grid generation, we adopt a pixel-wise gate to emphasize the important part in current data flow:

\[
G = \sigma(\text{conv}(\text{cat}(F_s||F_t))),
\]

where \(F_s\) and \(F_t\) can be features from the spatial path and context path respectively, and vice versa. The feature map that has a smaller size is bilinearly upsampled to reach the same size as the larger one. After flow field grid generation, we adopt a pixel-wise gate to emphasize the important part in current data flow:

\[
\hat{G} = \sigma(\text{conv}(F_t)) \odot G,
\]

where \(\hat{G}\) is the gated flow field grid, \(\sigma\) means the sigmoid layer and \(\odot\) represents element-wise product.

Each position \(p\) in target feature \(F_t\) can be mapped to a position \(p'\), according to the values in gated flow field grid \(\hat{G}\). Note that the mapping result is not an integer, so the value at \(F_t(p')\) is interpolated by the values of the 4-neighbors \(N(p')\) (top-left, top-right, bottom-left, and bottom-right):

\[
\hat{F}_t(p) = \sum_{i \in N(p')} w_{p'} F_i(p'),
\]
where $w_p$ is the bilinear kernel weights estimated by the distance of warped grid, $F_t$ is the target feature aligned with information from source feature $F_s$. In BiAlignNet, we take both spatial feature and context feature as source features to align with each other bidirectionally. In this way, different pieces of information can complement each other, as shown in the orange box of Fig. 2.

### 2.3. Loss Function

The spatial path gives priority to spatial details while context path focuses on high-level semantic context. To force spatial path to focus on detailed information, we introduce an edge-guided hard pixel indicator $d$ to supervise the learning. $d$ is predicted from the spatial path feature and normalized by a sigmoid layer. Since most of the fine information are concentrated in the boundaries, the edge map $b$ is derived from the segmentation labels through algorithm [20] which retrieves contours from the binary image. We utilize the edge map $b$ to guide the prediction of indicator $d$. As for context path, we use cross-entropy loss with online hard example mining (OHEM) [16, 1]. We jointly supervise two paths with a loss function $L$:

$$L = L_{spatial}(d, b, s, g) + L_{context}(s, g),$$

where $s$ is the predicted segmentation output of the model and $g$ is the ground truth segmentation labels, and $L_{context}$ is the OHEM loss. $L_{spatial}$ is calculated from the following equation.

$$L_{spatial} = \lambda L_{bce}(d, b) + L_{hard}(s, g, d),$$

$$L_{hard} = \frac{1}{K} \sum_{i=1}^{N} \mathbb{1}[s_i, g_i < t_K \& d_i > t_b] \cdot \log s_i, g_i,$$

where $L_{bce}$ is the binary cross-entropy loss for edge-guided hard pixel indicator $d$, $L_{hard}$ mines the hard pixels with high probability in $d$ and calculate the cross-entropy loss. $N$ is the total number of pixels. $1[x] = 1$ if $x = 1$ otherwise 0. First Eq. 6 filters the positions that have a higher probability than threshold $t_b=0.8$ in $d$. Then it picks positions within top $K$ losses, where $t_K$ is the threshold for top $K$ loss. Empirically, we set $\lambda = 25$ to balance the losses in all experiments. In this way, the spatial path learns more detailed information during the training.

### 3. EXPERIMENT

#### 3.1. Datasets

We carry out experiments on Cityscapes and Camvid datasets. Cityscapes [17] is a large street scene dataset which contains 2,975 fine-annotated images for training, 500 images for validation and a testing set without annotations of 1,525 images. All images in this dataset have a high resolution of 1,024×2,048. CamVid [18] is another road scene dataset. This dataset contains 367 training images, 101 validation images and 233 testing images with a resolution of 720×960.

#### 3.2. Speed and Accuracy Analysis

**Implementation Details.** Our experiments are done with the PyTorch framework. We use stochastic gradient descent (SGD) with a batch size of 16 and a momentum of 0.9 and weight decay of 5e-4. The initial learning rate is 0.01 with a “poly” learning rate strategy in which the initial rate is multiplied by $(1 - \frac{\text{iter}}{\text{total iter}})^{0.9}$. As for data augmentation, we randomly horizontally flip the images and randomly resize them with a scale of [0.5, 2.0], and crop images to a size of 1024×1024 (720×720 for CamVid). We use the single scale inference and report the speed with one 1080Ti GPU.

**Result Comparison.** Table 1 compares our method compared to other state-of-the-art real-time methods. Our method with an input size of 768×1536 can get the best trade-off between accuracy and speed. When input with the whole image, BiAlignNet still runs in real time and gets 78.7% mIoU and 77.1% mIoU on val and test, which outperforms all the methods listed above. After pre-training on Mapillary [28] dataset, our BiAlignNet gains 1.4% improvement. We also apply our method with different light-weight backbones on CamVid dataset and report comparison results in Table 2. BiAlignNet also achieves state-of-the-art performance on the CamVid.

**Visualization.** In Fig. 3, we visualize flow fields from two

| Method                  | $\gamma$ | Backbone | mIoU (%) | #FPS | #Params |
|-------------------------|----------|----------|----------|------|---------|
| ENet [21]               | 0.5      | -        | 58.3     | 60   | 0.4M    |
| ESPNet [22]             | 0.5      | ESPNet   | 60.3     | 132  | 0.4M    |
| ESPNet2 [23]            | 0.5      | ESPNet2  | 66.4     | 66.2 | 0.8M    |
| ERFNet [24]             | 0.5      | -        | 70.0     | 68.0 | 41.9    |
| BiSeNetv1 [16]†         | 0.75     | Xception39 | 69.0    | 68.4 | 175     |
| ICNet [12]              | 1.0      | PSPNet50 | 69.5     | 34   | 26.5M   |
| CellNet [13]            | 0.75     | -        | 70.5     | 108  |        |
| DFANet [13]             | 1.0      | Xception A | 71.3    | 100  | 7.8M    |
| BiSeNetv2 [16]†         | 0.5      | -        | 73.4     | 72.6 | 28      |
| DF1-Seg [19]            | 1.0      | DFNet1   | 73.0     | 100  | 8.55M   |
| BiSeNetv1 [17]          | 0.75     | ResNet18 | 74.8     | 74.7 | 35      |
| DF2-Seg [19]            | 1.0      | DFNet2   | 74.8     | 68   | 18.8M   |
| SwiftNet [20]           | 1.0      | ResNet18 | 75.4     | 75.8 | 39.9    |
| FC-HarDNet [22]         | 1.0      | HarDNet  | 77.4     | 76.0 | 35      |
| SwiftNet-ens [25]       | 1.0      | -        | 76.5     | 18.4 | 24.7M   |

†Mapillary dataset used for pretraining.
Table 2. Comparison on the CamVid test set with previous state-of-the-art real-time models.

| Method        | Backbone  | mIoU (%) | #FPS |
|---------------|-----------|----------|------|
| DFANet B [13] | -         | 59.3     | 160  |
| SwiftNet [26] | ResNet18  | 63.33    | -    |
| DFANet A [13] | -         | 64.7     | 120  |
| ICNet [12]    | ResNet-50 | 67.1     | 34.5 |
| BiSeNetv1 [1] | ResNet18  | 68.7     | 60   |
| BiSeNetv2 [14]| -         | 72.4     | 60   |
| BiSeNetv2*    | -         | 76.7     | 60   |

BiAlignNet DFNet1 68.9 85
BiAlignNet DFNet2 72.3 65
BiAlignNet* DFNet2 77.1 65

* Cityscapes dataset used for pretraining.

Fig. 3. Visualization of learned flow field and segmentation output. Column (a) lists three exemplary images. Column (b) and (c) show the flow field in two directions, spatial to context and context to spatial correspondingly. Column (d) and (e) show the comparison between BiAlignNet and BiSeNet. Best viewed on screen and zoom in.

directions. Flow from the spatial path to the context path (Column b) contains more detailed information and Column c that is from the context path, includes more high-level information. Thus, different features are aligned to each other under the guidance of learned flow field. Fig. 3(d) shows that BiAlignNet outperforms BiSeNet (Column e) on boundaries and details. Fig. 3 gives more insights into the proposed GFAM module and the hard pixel mining supervision. As shown in Column b, gates from the spatial path assign higher scores on image details. It confirms that the gate in GFAM can filter the noise and highlight the significant part in the flow field. Fig. 3(c) and (d) visualize hard pixels used in $L_{hard}$ and the predicted indicator map by the spatial path. They are consistent with the fact that edge-guided hard pixel mining pays more attention to fine-grained objects and edges that are difficult to separate.

3.3. Ablation Study

We carry out ablation studies on each component of BiAlignNet in this section. As shown in Table 3, our proposed module only introduces a very small amount of computation.

Ablation for bidirectional alignment. We argue that insufficient feature fusion leads to low performance in previous BiSeNet. As we can see in Table 3, compared to the baseline that simply concatenates two feature maps, bidirectional alignment with GFAM can improve performance by 2.4%. Moreover, the alignments in two directions show the synergistic effects with each other. The performance increase brought by bidirectional alignment is more than the two one-way models. Also, the simple gate mechanism in GFAM results in a 0.8% performance increase.

Ablation for the spatial loss. We expect two paths to learn different contents from the input, especially the spatial path. Thus, we enhance the detail supervision in the spatial path through the specially designed spatial loss with a hard pixel mining indicator. After adding the spatial loss, the performance has improved by 0.9%. This proves the effectiveness of the designed spatial loss function.

4. CONCLUSION

In this paper, we propose a Bidirectional Alignment Network (BiAlignNet) for fast and accurate scene parsing. With the bidirectional alignment and specific supervision in each pathway, the low-level spatial feature can be deeply fused with the high-level context feature. Comparative experiments are performed to show the effectiveness of our proposed components over the baseline models. BiAlignNet also achieves a considerable trade-off between segmentation accuracy and the inference speed.
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