PIDNet: A Real-time Semantic Segmentation Network Inspired from PID Controller

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Abstract

Two-branch network architecture has shown its efficiency and effectiveness for real-time semantic segmentation tasks. However, direct fusion of low-level details and high-level semantics will lead to a phenomenon that the detailed features are easily overwhelmed by surrounding contextual information, namely overshoot in this paper, which limits the improvement of the accuracy of existed two-branch models. In this paper, we bridge a connection between Convolutional Neural Network (CNN) and Proportional-Integral-Derivative (PID) controller and reveal that the two-branch network is nothing but a Proportional-Integral (PI) controller, which inherently suffers from the similar overshoot issue. To alleviate this issue, we propose a novel three-branch network architecture: PIDNet, which possesses three branches to parse the detailed, context and boundary information (derivative of semantics), respectively, and employs boundary attention to guide the fusion of detailed and context branches in final stage. The family of PIDNets achieve the best trade-off between inference speed and accuracy and their test accuracy surpasses all the existed models with similar inference speed on Cityscapes, CamVid and COCO-Stuff datasets. Especially, PIDNet-S achieves 78.6% mIOU with inference speed of 93.2 FPS on Cityscapes test set and 80.1% mIOU with speed of 153.7 FPS on CamVid test set.

1. Introduction

Proportional-Integral-Derivative (PID) Controller is a traditional concept proposed in last century and has been widely applied in modern dynamic systems or processes such as robotic manipulation [3], chemical process [25], power system [26]. Even though many advanced control strategies with better control performance have been developed in recent years, PID controller is still the first choice for most of the industry applications due to its simple but robust characteristics. A classic concept in one scientific area could be extended to many other areas. For example, the underlying methodology of PID controller were introduced to image denoising [32], stochastic gradient decent [1] and numerical optimization [49] and achieved great improvement over original methods. In this paper, we design a deep neural network architecture for real-time semantic segmentation tasks by employing the basic concept of PID controller and the performance of this novel model surpasses all the previous networks and thereby achieves the best trade-off between inference speed and accuracy as Figure 1 shows.

Semantic segmentation is a fundamental task for visual scene parsing and its objective is to assign a specific class label to each pixel in given images. With the gradual increasing of demand of intelligence, accurate semantic segmentation has become the basic perception component for many applications such as autonomous driving [17], medical imaging diagnosis [2] and remote sensing imagery [53]. Starting from FCN [31], who achieved great improvement over traditional methods, deep learning approaches gradually dominated the semantic segmentation field and many representative models were proposed [4, 7, 39, 47, 57, 58]. The development of these learning models indicates that a network architectures with satisfactory segmentation performance must possess the
we compare the performance of PIDNet with other state-
which is illustrated in Figure 2. To alleviate this problem, we
work were proposed and achieved state-of-art performance
was introduced as sacrifice, which significantly restricted
their application to real-time cases, such as autonomous ve-
vehicle [17] and robot-assisted surgery [43].
To satisfy the real-time or mobile requirements, re-
searchers came up with many efficient and effective models. Specifically, ENet [35] achieved great improvement on infer-
sence speed by adopting lightweight decoder and downsam-
pling the feature maps in early stages. ICNet [56] encoded the
small-size input in complex and deep path to parse the
semantics and utilized simple and shallow path to encode the
details from the large-size inputs. MobileNetv2 [41] replaced
the traditional convolutions with depthwise separable convo-
lutions to reduce the overall model complexity and proposed
an inverted residual block to alleviate regularization effect;
These earlier works made huge contribution to reducing the
latency and memory usage of segmentation models, but their
low accuracy significantly limits their real-world application.
Recently, some brilliant models based on two-branch net-
work were proposed and achieved state-of-art performance
regarding speed and accuracy [16, 22, 37, 38, 50, 51].
In this paper, we deeply analyze the basic architectures of
two-branch networks from the prospective of PID controller
and point out that the two-branch network is nothing but a
PI controller and suffers from the overshoot issue inherently,
which is illustrated in Figure 2. To alleviate this problem, we
establish a novel three-branch network architecture, namely
Proportional-Integral-Derivative Network (PIDNet), which
possesses one more branch for boundary detection. Then,
we compare the performance of PIDNet with other state-
of-art models on Cityscapes [13], CamVid [5] and COCO-
Stuff [6] benchmarks to demonstrate its superiority. Also,
ablation study and feature visualization is provided for better
understanding of the functionality of each elaborated mod-
ule. The code and pretrained models could be accessed via:
https://github.com/XuJiacong/PIDNet.
The main contribution of this paper is three-fold:
• We bridge a connection between deep learning mod-
els with PID controller and propose a family of three-
branch networks based on PID controller architecture.
• A selective-learning-based connection, a fast context
aggregation module and a boundary-guided fusion mod-
ule are proposed to boost the performance of PIDNets.
• Our models achieve the best trade-off between infer-
ence speed and accuracy among all the existed mod-
els. In particular, PIDNet-S achieves 78.6% mIOU
with speed of 93.2 FPS and PIDNet-L achieves 80.6%
mIOU (highest in real-time domain) with speed of 31.1
FPS on Cityscapes test set without acceleration tools.

2. Related Work
Since the network design philosophies for real-time and
ordinary cases are quite different, we provide a concise intro-
duction to some representative architectures in both cases.
2.1. High-accuracy Semantic Segmentation
Most of the early deep learning approaches for seman-
tic segmentation were based on encoder-decoder architec-
ture [4, 31, 39], where the encoder gradually enlarges its
receptive field by cascading strided convolutions or pooling
operations and the decoder recovers the detailed informa-
tion from high-level semantics using deconvolutions or up-
sampling. However, spatial details could be easily ignored
in the process of downsampling for encoder-decoder net-
work. Towards this issue, dilated convolution [52] was pro-
posed, which could enlarge field-of-view without reducing the
spatial resolution. Based on this, DeepLab series [8–10]
achieved great improvement over previous works by integrat-
ing the dilated convolutions with different dilation rates in
the network. A critical problem for DeepLabs is that the di-
lated convolution is not suitable for current hardware due to
its numerous non-contiguous memory accesses. To mitigate
this problem, PSPNet [57] introduced a Pyramid Pooling
Module (PPM) to parse multi-scale context information and
HRNet [47] adopted multiple paths and bilateral connections
to learn and fuse different scale representations. Inspired
from the context aggregation power of self-attention mecha-
nism [46] in machine translation, non-local operation [48]
was introduced into computer vision and triggered many
meaningful works for semantic segmentation [18, 24, 54].
2.2. Real-time Semantic Segmentation
To achieve the best trade-off between inference speed and
accuracy, researchers contributed lots of effort to redesign
the network architectures, which could be summarized as:
lightweight encoder and decoder (convolution factorization

Figure 2. Overshoot issue for dynamic system (left |) and image
segmentation (| right). Left |: Step responses of PI and PID con-
trollers for a second-order system; | Right: From the first row to
the last row, the images are cropped from ground truth, outputs of
DDRNet-23 [22] and ADB-Bag-DDRNet-23 (ours), respectively.
or group convolution), multi-scale input and two-branch network. Specifically, SwiftNet [34] employed one low-resolution input to obtain the high-level semantics and another high-resolution input to provide sufficient details for its lightweight decoder. DFANet [28] introduced a light-weight backbone by modifying the architecture of Xception [12], which was based on depth-wise separable convolution, and reduced the input size for faster inference speed. ShuffleSeg [19] adopted ShuffleNet [55], which combined channel shuffling and group convolution, as its backbone to reduce computational cost. However, most of these networks are still in the form of encoder-decoder architecture and require the information flow go through the deep encoder and then reverse back to pass the decoder, which introduces much latency for these models. Besides, since the optimization for depthwise separable convolution on GPU is not mature, traditional convolution presents faster speed even though it has more FLOPs and parameters [34].

2.3. Two-branch Network Architecture

As the discussion in previous sections, contextual dependency could be extracted by large receptive field, and spatial details are vital for precise boundary delineation and small-scale object recognition. With this consideration, BiSeNet [51] proposed a two-branch network architecture, which contains two branches with different depths for context embedding and detail parsing along with a Feature Fusion Module (FFM) to fuse the context and detailed information. Then, several works based on this architecture were proposed to boost its representation ability or reduce the model complexity [37, 38, 50]. Especially, DDRNet [22] introduced bilateral connections to enhance the information exchange between context and detailed branches and achieved the state-of-art result in real-time semantic segmentation. Nevertheless, the output size for detailed branch is 8 times of context branch in DDRNet (4 times in BiSeNet) and direct fusion of them will inevitably leads to a phenomenon that the object boundary are easily corroded by its surrounding pixels and the small-scale object could be overwhelmed by its adjacent large objects, namely overshoot in this paper, which is shown in Figure 2. To alleviate the overshoot issue, we borrowed the PID concept from automation engineering field and proposed a three-branch network architecture: PIDNet, which simply supplements an additional branch for boundary extraction and leverages the boundary to supervise the fusion of context and detailed features.

3. Method

PID controller contains three components with complementary capabilities: Proportional (P) controller represents current error, Integral (I) controller accumulates previous error and Derivative (D) controller predicts future change of error, as shown in Figure 3. Thus, the output of PID controller is generated based on the error in the entire time domain. Usually, PI controller could satisfy most of setpoint control scenarios but it suffers from the overshoot issue inherently [15]. For better dynamic response, researchers introduced Derivative controller to make prediction and adjust the control output before overshoot happens. In two-branch network, the context branch constantly aggregate the semantic information from local to global area by cascading strided convolution or pooling layers to parse the long-range dependencies between pixels, while the detailed branch maintains high-resolution feature maps to preserve the semantic and localization information for each individual pixel. Thus, the detailed and context branch could be seen as Proportional and Integral controllers in spatial domain, which explains the underlying reason for the overshoot issue of segmentation.

3.1. PIDNet: A Novel Three-branch Network

To mitigate the overshoot issue, we propose to provide an Auxiliary Derivative Branch (ADB) for two-branch network and fully mimic the PID controller in spatial domain. The semantics for pixels inside each object are consistant and only become inconsistent along the boundary of adjacent objects, so the derivative of semantics is nonzero only at the object boundary and the function of ADB should be boundary detection. Accordingly, we establish a new three-branch real-time semantic segmentation architecture, namely Proportional-Integral-Derivative Network (PIDNet), which is shown in Figure 4. PIDNet possesses three branches with complementary responsibilities: Proportional (P) branch parses and preserves the detailed information in its high-resolution feature maps; Integral (I) branch aggregates context information locally and globally to parse long-range dependencies; Derivative (D) branch extracts the high-frequency features to predict the boundary regions. The entire network are de-
Figure 4. An overview of the basic architecture of our proposed Proportional-Integral-Derivative Network (PIDNet). S and B denote semantic and boundary, and Add and Up refer to element-wise summation and bilinear Upsampling operation, respectively; BAS-Loss represents the boundary-awareness CE loss [45]. Dashed lines and associate blocks will be ignored in inference stage.

Developed following [22], which adopted cascaded residual blocks [21] as backbone, for hardware-friendly architecture. Besides, the depths for P, I and D branches are scheduled to be moderate, deep and shallow for efficient implementation considering the complexity for corresponding task. Also, a family of PIDNets (PIDNet-S, PIDNet-M and PIDNet-L) are generated by deepening and widening the model.

Following [22, 29, 50], we place a semantic head at the output of the first Pag module to generate the extra semantic loss \(l_0\) for better optimization of entire network. Instead of dice loss [14], weighted binary cross entropy loss \(l_1\) is adopted to deal with the imbalanced problem of boundary detection since coarse boundary is preferred to highlight the boundary region and enhance the features for small objects. \(l_2\) and \(l_3\) represents the CE loss, while we utilize the boundary-awareness CE loss [45] for \(l_3\) using the output of Boundary head to coordinate semantic segmentation and boundary detection tasks and enhance the function of Bag module, which could be written as:

\[
l_3 = -\sum_{i,c} \{1 : b_i > t\} \left(s_{i,c} \log \hat{s}_{i,c}\right)\]  

where \(t\) refers to predefined threshold and \(b_i, s_{i,c}\text{ and }\hat{s}_{i,c}\) are the output of boundary head, segmentation ground-truth and prediction result of the \(i\)-th pixel for class \(c\), respectively. Therefore, the final loss for PIDNet could be summarized as:

\[
Loss = \lambda_0 l_0 + \lambda_1 l_1 + \lambda_2 l_2 + \lambda_3 l_3
\]

Empirically, we set the parameters for the training loss of PIDNet as \(\lambda_0 = 0.4, \lambda_1 = 20, \lambda_2 = 1, \lambda_3 = 1\) and \(t = 0.8\).

3.2. Pag: Selective Learning High-level Semantics

The lateral connection utilized in [22, 34, 47] enhances the information transmission between different feature maps and improves the representation ability of their models. In PIDNet, the rich and accurate semantic information provided by I branch is crucial for detail parsing of P branch, which contains relatively less layers and channels. Thus, we could treat I branch as the backup for other two branches and enable it to provide required information to them. Different from D branch that directly adds the provided feature maps, we introduce a Pixel-attention-guided fusion module (Pag), which is shown in Figure 5, for P branch to selectively learn the useful semantic features from I branch without being overwhelmed. Basically, the underlying concept for Pag is...
borrowed from self-attention mechanism [46] but Pag computes the attention locally for real-time requirement. Define the vectors for the corresponding pixels in feature maps provided by P branch and I branch as $\vec{v}_p$ and $\vec{v}_i$, respectively, then the output of Sigmoid function will become:

$$\sigma = \text{Sigmoid}(f_p(\vec{v}_p) - f_i(\vec{v}_i))$$  \hspace{1cm} (3)$$

where $\sigma$ represents the possibility of these two pixels are from the same object. If $\sigma$ is high, we trust $\vec{v}_i$ more since I branch is semantically accurate, and vice versa. Thus, the output of the Pag module could be written as:

$$\text{Out}_{\text{Pag}} = \sigma \vec{v}_i + (1 - \sigma) \vec{v}_p$$ \hspace{1cm} (4)$$

3.3. PAPPM: Fast Aggregation of Contexts

For better global scene prior construction, Spatial Pyramid Pooling (SPP) [20] was adopted in SwiftNet [34] to parse the global dependencies. Also, PSPNet [57] introduced a Pyramid Pooling Module (PPM), which concatenates multi-scale pooling maps before convolution layer to form local and global context representations. Deep Aggregation PPM (DAPPM) proposed by [22] further improved the context embedding ability of PPM and showed superior performance.

However, the computation of DAPPM cannot be parallelized regarding its depth, which is time-consuming and DAPPM contains too many channels for each scale, which surpasses the representation ability of lightweight models. Thus, we slightly change the connections in DAPPM to make it parallelized, which is shown in Figure 6, and reduce the number of channels for each scale from 128 to 96. This new context harvesting module is called Parallel Aggregation PPM (PAPPM) and is applied in PIDNet-M and PIDNet-S to improve their speeds. For our deep model: PIDNet-L, we still choose the DAPPM considering its depth but change its number of channels for each scale from 128 to 112.

3.4. Bag: Balancing the Details and Contexts

Given the boundary features extracted by ADB, our proposal is to employ the boundary attention to guide the fusion of detailed (P) and context (I) representations. Therefore, we design a Boundary-attention-guided fusion module (Bag) to fuse the features provides by three branches. Note that the context branch is semantically rich and could presents more accurate semantics but it loses too much spatial and geometric details especially for the boundary region and small object. Thanks to the detailed branch, which preserves the spatial details better, we force the model to trust the detailed branch more along the boundary region and utilize the context features to fill the area inside object, which could be accomplished by Bag in Figure 7. Define the vectors for the corresponding pixels in the output of P, I and D branches as $\vec{v}_p$, $\vec{v}_i$ and $\vec{v}_d$, respectively, then the outputs of Sigmoid, Bag and Light-Bag could be represented as:

$$\sigma = \text{Sigmoid}(\vec{v}_d)$$ \hspace{1cm} (5)$$

$$\text{Out}_{\text{Bag}} = f_{\text{out}}((1 - \sigma) \otimes \vec{v}_i + \sigma \otimes \vec{v}_p)$$ \hspace{1cm} (6)$$

$$\text{Out}_{\text{Light}} = f_{\text{Light}}((1 - \sigma) \otimes \vec{v}_i + \vec{v}_p) + f_{i}(\sigma \otimes \vec{v}_p + \vec{v}_i)$$ \hspace{1cm} (7)$$

where $f$ refers to the composition of convolutions, batch normalizations and ReLUs. Even though we replaced the $3 \times 3$ convolution in Bag by two $1 \times 1$ convolutions in Light-Bag, the functionalities of Bag and Light-Bag are similar, that is when $\sigma > 0.5$ the model trusts more on detailed features, otherwise context information is preferred.

4. Experiment

To validate the superiority of our proposed methods, we train our models on Cityscapes, CamVid and COCO-Stuff benchmark datasets and compare their test accuracy and inference speed with other state-of-art real-time networks.

4.1. Datasets

Cityscapes. Cityscapes [13] is one of the most well-known urban scene parsing datasets, which contains 5000 fine annotated images collected from the car perspective in different
cities. These images are divided into sets with numbers of 2975, 500, and 1525 for training, validation and test. The annotation contains 30 classes but only 19 of them are utilized for semantic segmentation. The image size for all the data is 2048×1024, which is challenging for real-time segmentation. Here, we only use the fine annotated dataset to train our models for fair comparison with other networks.

**CamVid.** CamVid [5] provides 701 images of driving scenes, which is partitioned into 367, 101 and 233 for training, validation and testing. The image resolution is of 960×720 and the number of annotated categories is 32, of which 11 classes are used for semantic segmentation. Pixels outside these 11 classes are ignored for fair comparison with others.

**COCO-Stuff.** We choose the 10K version of the COCO-Stuff [6] dataset, which is also exploited in [22, 50]. This dataset consists of 10K densely annotated images and is divided into 9K for training and 1K for testing. The complex categories of COCO-Stuff is challenging for every segmentation model, which includes 91 thing and 91 stuff classes.

### 4.2. Implementation Details

**Pretraining.** Before training our models on three datasets, we firstly pretrain these models by ImageNet [40] considering pretraining is crucial for lateral connections in [22, 34]. We remove the D branch and follow the same merging method as DDRNet [22] in finally stage to construct the classification models. The total number of training epochs is 90 and the learning rate is scheduled to be 0.1 initially and multiplied by 0.1 at epoch 30 and 60. CE loss and SGD with momentum of 0.9 and weight decay of 1e-4 are used to optimize the networks. The images are randomly cropped into 224×224 and flipped horizontally for data augmentation.

**Training.** For fair comparison, our training protocols are almost the same as previous works [16, 22, 50, 51]. Specifically, we adopt the poly learning rate strategy to update the learning rate in each iteration. Also, random cropping, random horizontal flipping and random scaling in the range of [0.5, 2.0] are employed for data augmentation. The number of training epochs, the initial learning rate, weight decay, cropped size and batch size for Cityscapes, CamVid and COCO-Stuff could be summarized as [484, 1e-2, 5e-4, 1024×1024, 12], [200, 1e-3, 5e-4, 960×720, 12] and [180, 5e-3, 1e-4, 640×640, 16], respectively. Following [22, 50], we finetune the models pretrained by Cityscapes for CamVid and early stop training process to avoid overfit.

**Inference.** Before being evaluated on test set, our models are trained by both train and validation set for Cityscapes and CamVid. We measure the inference speed on the platform consists of single RTX 3090, PyTorch 1.8, CUDA 11.2, cuDNN 8.0 and Anaconda environment. Using the speed measurement protocol proposed by [11] and following [22, 34, 44], we integrate the batch normalization into the convolutional layers and set the batch size to be 1 and the input image size to be 2048×1024, 960×720 and 640×640 for Cityscapes, CamVid and COCO-Stuff, respectively.

### 4.3. Ablation Study

**ADB for Two-branch Networks.** To demonstrate the effectiveness of ADB, we borrow the ADB and Bag from PIDNet and combine them with existed models. Here, two representative two-branch networks: BiSeNet [51] and DDRNet [22] equipped with ADB and Bag are implemented and achieve higher accuracy on Cityscapes val set compared with their original models, which is shown in Table 1. However, additional computation significantly slow down their inference speed, which then triggers us to establish PIDNet.

| Model               | ADB-Bag | mIOU  | FPS  |
|---------------------|---------|-------|------|
| BiSeNet(Res18)      | ✓       | 75.4  | 63.2 |
|                     | ✓ ✓ ✓   | 76.7  | 52.1 |
| DDRNet-23           | ✓ ✓ ✓   | 79.5  | 51.4 |
|                     | ✓ ✓ ✓   | 80.0  | 39.2 |

Table 1. Ablation study of ADB-Bag for BiSeNet and DDRNet.

**Collaboration of Pag and Bag.** Element-wise summation is a traditional way to merge features in lateral connection. Instead of direct adding up the feature maps, we provided P branch with the Pag module to assist it to learn useful information from I branch without being overwhelmed. Besides, the Bag module was introduced to guide the fusion of detailed and context features using boundary attention in the final stage. As Table 2 shows, lateral connection could significantly improve the model accuracy and pretraining could further boost its performance. In our scenario, the combinations of Add lateral connection and Bag fusion module or Pag lateral connection and Add fusion module make little sense since preservation of details should be consistent in the entire network. Thus, we only need to compare the performance of Add + Add and Pag + Bag and the experimental results in Table 2 and 3 demonstrate the superiority.

| IM | Lateral | Add | Pag | Fusion | mIOU |
|----|---------|-----|-----|--------|------|
|    | None    | ✓   | ✓   |        | 79.3 |
| ✓  |         | ✓   | ✓   |        | 78.1 |
| ✓  |         | ✓   | ✓   |        | 80.0 |
| ✓  |         | ✓   | ✓   |        | 80.7 |
| ✓  |         | ✓   | ✓   |        | 80.5 |
| ✓  |         | ✓   | ✓   |        | 80.5 |
| ✓  |         | ✓   | ✓   |        | 80.9 |

Table 2. Ablation study of Pag and Bag on PIDNet-L. IM refers to ImageNet [40] pretraining, Add represents the element-wise summation operation and None means there is no lateral connection.
Figure 8. Feature visualization of Pag module. The maps in the first row from left to right are the original input image, P input, I input and output of Sigmoid function for the first Pag; The maps in the second row are groundtruth, P, I inputs and Sigmoid output for the second Pag; The third and fourth rows are for another image.

of the collaboration of Pag and Bag (or Light-Bag). The visualization of feature maps in Figure 8 shows that the small objects become much darker compared with large objects in the Sigmoid map for second Pag, where I branch loses more detailed information. Also, the features in boundary regions and small objects are greatly enhanced in the output of Bag module, which is illustrated in Figure 9 and explains the reason why we choose coarse boundary detection.

| Efficient of PAPPM. For real-time models, a heavy context aggregation module could drastically slow down the inference speed and may surpass the representation ability of the network. Thus, we proposed the PAPPM, which is constituted by parallel structure and small number of parameters. The experimental results in Table 3 show that PAPPM achieves the same accuracy as DAPPM [22] but presents a speed-up of 9.5 FPS for our light-weight model. |
| Extra Loss | OHEM | mIOU |
| l₀ | l₁ | l₃ |
| ✓ | ✓ | 78.6 |
| ✓ | 78.8 |
| ✓ ✓ ✓ | 80.5 |
| ✓ ✓ ✓ ✓ | 80.9 |

Table 4. Ablation study of extra losses and OHEM for PIDNet-L.

| Effectiveness of Extra losses. Three extra losses were introduced to PIDNet to boost the optimization of entire network and emphasize the functionality for each components. According to Table 4, boundary loss l₁ and boundary-awareness loss l₃ are necessary for better performance of PIDNet, especially the boundary loss (+1.1% mIOU), which strongly proves the necessity of D branch, and Online Hard Example Mining (OHEM) [42] further improves the accuracy. |
| Model | mIOU | #FPS | GPU |
| MFNet [44] | 75.4 | 91.0 | GTX 2080Ti |
| PP-LiteSeg-T [36] | 75.0 | 154.8 | GTX 1080Ti |
| TD2-PSP50 [23] | 76.0 | 11.0 | TITAN X |
| BiSeNetV2† [50] | 76.7 | 124.0 | GTX 1080Ti |
| BiSeNetV2-L† [50] | 78.5 | 33.0 | GTX 1080Ti |
| HyperSeg-S [33] | 78.4 | 38.0 | GTX 1080Ti |
| HyperSeg-L [33] | 79.1 | 16.6 | GTX 1080Ti |
| DDRNet-23-S†* [22] | 78.6 | 182.4 | RTX 3090 |
| DDRNet-23†* [22] | 80.6 | 116.8 | RTX 3090 |
| PIDNet-S† | 80.1 | 153.7 | RTX 3090 |
| PIDNet-M† | 82.0 | 85.6 | RTX 3090 |

Table 5. Comparison of speed and accuracy on CamVid. The models pretrained by Cityscapes [13] are marked with †; The inference speeds for models marked with * are tested on our platform. The accuracy of our lightweight models exceeds 80% mIOU and PIDNet-M achieves the highest accuracy with a big margin ahead of previous models, which strongly demonstrates the superiority of our models. Besides, the accuracy of PIDNet-
Table 6. Comparison of speed and accuracy on Cityscapes. The models pretrained by other segmentation datasets are marked with †; The inference speeds for models marked with * are tested on our platform. The GFLOPs for PIDNet is derived based on input size of 2048 × 1024.

Table 7. Comparison of speed and accuracy on COCO-Stuff. The speeds for models marked with * are tested on our platform.

S surpasses previous state-of-art model: DDRNet-23-S by 1.5% mIOU with only around 1 ms latency increase.

Cityscapes. Previous real-time works treat Cityscapes [13] as the standard benchmark. As shown in Table 6, only SFNet and DDRNet present similar accuracy with our models, so we test their speeds on the same platform as PIDNets for fair comparison. The experimental results shows that PIDNets achieve the best trade-off between inference speed and accuracy. Specifically, PIDNet-L surpasses SFNet(ResNet-18) and DDRNet-39 in terms of speed and accuracy and becomes the most accurate model in real-time domain by rising the test accuracy from 80.4% to 80.6% mIOU. PIDNet-M and PIDNet-S also provide much higher accuracy compared with the models with similar inference speeds. Especially, PIDNet-S becomes the fastest one amongst all the models with accuracy higher than 77.5% mIOU, which will satisfy most of the applications with strict latency and accuracy requirements. See Figure 10 for actual performance.

COCO-Stuff. The (17,8)-Avg-pooling path in PAPPM is removed since the image size is too small in COCO-Stuff [6]. Even though the annotations for COCO-Stuff along the boundary region are not as precise as previous two datasets, our models still achieve competitive performance regarding efficiency compared with others, as shown in Table 7.

5. Conclusion

This paper proposes a series of three-branch networks: PIDNets for real-time semantic segmentation tasks. PIDNets achieve the best trade-off between inference time and accuracy, which is demonstrated by extensive experiments. However, since PIDNets utilize the boundary prediction to balance the detailed and context information, precise annotation around boundary is required for better performance.
Figure 10. An illustration of the segmentation performance of PIDNets on Cityscapes Val set. The four columns from left to right refer to input images, predictions of PIDNet-S and PIDNet-L and ground truth, respectively.

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