

# Real-time Domain Adaptation in Semantic Segmentation\*

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1<sup>st</sup> Berardo Nicholas  
dept. Computer Engineering  
Politecnico di Torino  
Turin, Italy  
s319349@studenti.polito.it

2<sup>nd</sup> Cardona Riccardo  
dept. Computer Engineering  
Politecnico di Torino  
Turin, Italy  
s319441@studenti.polito.it

3<sup>rd</sup> De Marco Alessandro  
dept. Computer Engineering  
Politecnico di Torino  
Turin, Italy  
sXXXXXXX@studenti.polito.it

**Abstract**—We use an efficient structure named Short-Term Dense Concatenate network (STDC network) for the semantic segmentation task. This structure reduces the dimension of feature maps and uses the aggregation of them for image representation, then uses a Detail aggregation module for producing the low-level features. Finally, these two are merged to produce the segmentation result. We test this model on Cityscapes and GTA V, following the evaluation of the domain shift between GTA V and Cityscapes and finally we implement an unsupervised adversarial domain adaptation method used for reducing the domain shift. We also show the result for the STDC network in terms of mIoU and the result for the domain adaptation.

## I. INTRODUCTION

Semantic Segmentation is a topic in computer vision that aims at assigning a label to each pixel of the image. This is used in many fields such as autonomous vehicle, video surveillance and robot sensing. There are a lot of models that can achieve good accuracy. For real-time semantic segmentation, some models choose lightweight backbones for having an increase of performance but with an acceptable loss in accuracy. For this reason, some new methods were investigated, like feature fusion or aggregation modules. Other models reduce the input image size but this can result in a bad accuracy around boundaries and small objects.

STDC net [1] uses the first approach. Fig. 1 shows how the image is encoded in different scales. The kernel size is also reduced to speed up the performance but with an acceptable loss in accuracy. Then a Detail Guidance is used to learn the space details instead of using a Spatial Path as in BiSeNet [2].

The next step is domain adaptation. A model trained on a certain dataset may not generalize on an unseen dataset ending in poor performance. This is caused by the domain shift between the source (training) and target (test) dataset, for example different cities, weather and lighting conditions. Domain adaptation methods are used to close the gap between source and target domains. In this paper, we use an adversarial domain adaptation method [3] that is composed of a segmentation model to predict the output and a discriminator to predict if the input is from the source or target domain. The goal is to generate a segmentation output from the segmentation

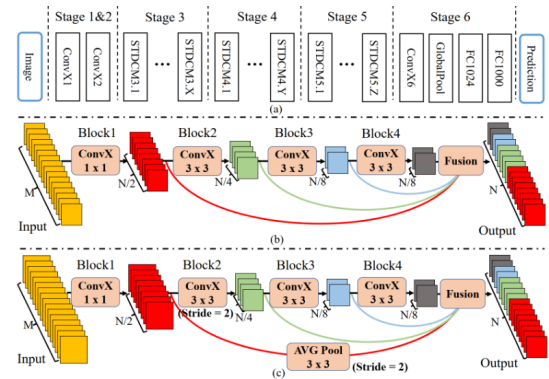


Fig. 1. STDC network.

part that fools the discriminator, meaning that the segmentation output is similar between source and target domains. We show experiments done on the adaptation between GTAV and Cityscapes.

Our contributions can be summarized as follows: First we build the STDC network and train it on Cityscapes and test it again on Cityscapes. Second we repeat the same idea over the GTAV dataset, so train on GTAV and test on GTAV. Third we compute the domain shift between GTAV (source) and Cityscapes (target) domains firstly in vanilla, then with some augmentation on GTAV. Fourth we implement the adversarial domain adaptation method and test it with GTAV as source domain and Cityscapes as target domain. Lastly we apply some real-time semantic segmentation method to our discriminator function in order to make it faster.

## II. RELATED WORK

Chiedere cosa mettere

## III. METHODS

We first introduce the Short-Term Dense Concatenate network (STDC network) and how we used it with BiSeNet [2], then the unsupervised adversarial domain adaptation method.

STDC network [1] is represented in Fig. 1 (a). Stage 3,4 and 5 have a number of Short-Term Dense Concatenate Module (STDCM) where each module is composed of ConvX blocks Fig. 1 (b)(c). Each  $ConvX_i$  is a block composed of one convolutional layer, one batch normalization layer and one ReLU activation layer. The ConvX layers filter the input into  $N/2$ , where N is the channel number of the STDC module. At the end we concatenate the output of each ConvX block as follow:

$$x_{output} = F(x_1, x_2, \dots, x_n)$$

where  $x_{output}$  is the STDC module output,  $F$  is the fusion operation, that in our case is the concatenation and  $x_1, x_2, \dots, x_n$  are the output of each  $ConvX_i$  block.

This STDC network is then used as backbone for the context path of BiSeNet, in particular we use stage 3,4 and 5 to reduce the feature map to obtain large receptive field. Then a global average pooling is added on the tail of the context path. We also use Attention Refine Module (ARM) on Stage 4 and 5. Finally a Future Fusion Model (FFM) is used to fuse the 1/8 feature from Stage 3 with this last part.

The main idea of the unsupervised adversarial domain adaptation method [3] is to create a segmentation network that classify the source image (that as a label) and the target image (without annotations). Then those two predictions are given to the discriminator that has to distinguish whether the input is from source or target domain. To do so we need a loss from the discriminator to the segmentation network which encourage the segmentation to generate similar predictions. We use as segmentation network the BiSeNet developed above. The loss is

$$L(I_s, I_t) = L_{seg}(I_s) + \lambda_{adv} * L_{adv}(I_t)$$

where  $L_{seg}$  is the cross entropy loss for the prediction of the source domain,  $\lambda_{adv}$  is the weight used to balance the  $L_{adv}$  that is a BCEWithLogitLoss. We first forward  $I_s$  to the segmentation network to get the prediction  $P_s$  and the loss  $L_{seg}$  using the label of  $I_s$ . Then forward  $I_t$  to the segmentation network to get the prediction  $P_t$  and feed  $P_s$  to the discriminator and get the  $L_{adv}$  and optimize the segmentation network. Now let's optimize the discriminator computing first the loss on the GTA5 image with label 1 and finally computing the loss on the Cityscape image, with label 0.

Finally we also tried to apply some real-time semantic segmentation method to our discriminator to make it lighter and faster. We build a discriminator using depthwise separable convolutions, following MobileNets [4]. These are composed of two part: depthwise convolutions and pointwise convolutions. Depthwise convolutions are used to filter each input channel, but they can only filter so we use pointwise convolutions (1 x 1 kernel size) to generate new features. Now our discriminator is based on blocks of depthwise convolution layer, leaky ReLU, pointwise convolution and again leaky ReLU.

#### IV. EXPERIMENTS

We have done the following experiments: (1) train on Cityscapes and test on Cityscapes, (2) train on GTA5 and test

TABLE I  
TRAIN ON CITYSCAPES TRAIN SET AND TEST IT CITYSCAPES VAL SET

Cityscapes -> Cityscapes		
Accuracy (%)	mIoU (%)	Train time (avg per-epoch)
81.1	58.6	2.5 minutes

on GTA5, (3) train on GTA5 and test on Cityscapes without domain adaptation, (4) train on GTA5 and test on Cityscapes without domain adaptation with some augmentation on GTA5, (5) train on GTA5 and test on Cityscapes with domain adaptation and (6) train on GTA5 and test on Cityscapes with domain adaptation with a lighter discriminator. We use as optimizer the SGD (Stochastic Gradient Descent) with momentum set at 0.9 and weight decay at  $5e^{-4}$ . We use a batch size of 2 and poly learning rate where the learning rate is updated as follow  $lr = init\_lr * (1 - \frac{iter}{max\_iter})^{power}$ , where  $init\_lr$  is 0.01,  $iter$  is the actual epoch,  $max\_iter$  is the number of epochs and  $power$  is 0.9. Data augmentation, when used, contains Color Jitter, Random Horizontal Flip, Random Crop and Normalization. The discriminator for the domain adaptation part is trained using Adam with a poly learning rate with the same parameter as before. We perform our experiments with those versions: **TODO!!!!!!!!!!**

(1) Here we trained our model on Cityscapes train set and test it on Cityscapes validation set. Here there's no domain adaptation, so we expect to have high results. Table I shows the results.

(2) We train our model on GTA5 train set and test it on GTA5 validation set. Again we expect high results. Table II shows the results.

(3) Here we evaluate the domain shift between GTA5 and Cityscapes. We train on GTA5 train set and test on Cityscapes validation set. Here we don't have any domain adaptation method, so we expect bad results. Table III shows the results. We can see that the mIoU is low, this because the source domain and target domain are different.

(4) Again we evaluate the domain shift between GTA5 and Cityscapes, but this time with some augmentation on GTA5. Table IV shows the results and again the mIoU is low because of the domain shift, but higher than step (3). This thanks to the augmentation done on GTA5.

(5) Here we have domain adaptation [3]. So we train on GTA5 and test on Cityscapes, but this time we train also the discriminator with the segmentation network. Table V shows the results. We can see a slight improvement of performance in the mIoU of 3% with respect to (4).

(6) Finally we implement depthwise separable convolutions in the discriminator. Again same thing as (5) but with a lighter discriminator. Table VI shows the results.

#### V. CONCLUSION

#### ACKNOWLEDGMENT

The preferred spelling of the word "acknowledgment" in America is without an "e" after the "g". Avoid the stilted expression "one of us (R. B. G.) thanks ...". Instead, try

TABLE II  
TRAIN ON GTA5 TRAIN SET AND TEST IT GTA5 VAL SET

GTA5 -> GTA5		
Accuracy (%)	mIoU (%)	Train time (avg per-epoch)
80.82	62.36	3,4 minutes

TABLE III  
TRAIN ON GTA5 TRAIN SET AND TEST IT CITYSCAPES VAL SET WITHOUT ADAPTATION

GTA5 -> Cityscapes		
Accuracy (%)	mIoU (%)	Train time (avg per-epoch)
60.1	24.6	???

“R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

#### REFERENCES

Please number citations consecutively within brackets [1]. The sentence punctuation follows the bracket [2]. Refer simply to the reference number, as in [3]—do not use “Ref. [3]” or “reference [3]” except at the beginning of a sentence: “Reference [3] was the first . . .”

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TABLE IV  
TRAIN ON GTA5 AUGEMNTED TRAIN SET AND TEST IT CITYSCAPES VAL SET WITHOUT ADAPTATION

GTA5 -> Cityscapes		
Accuracy (%)	mIoU (%)	Train time (avg per-epoch)
71	30	5.37 minutes

TABLE V  
TRAIN ON GTA5 AUGEMNTED TRAIN SET AND TEST IT CITYSCAPES VAL SET WITH ADAPTATION

GTA5 -> Cityscapes		
Accuracy (%)	mIoU (%)	Train time (avg per-epoch)
74	33	4.55 minutes

TABLE VI  
TRAIN ON GTA5 AUGEMNTED TRAIN SET AND TEST IT CITYSCAPES VAL SET WITH LIGHTER ADAPTATION

GTA5 -> Cityscapes		
Accuracy (%)	mIoU (%)	Train time (avg per-epoch)
73	32.5	4.5 minutes

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