Adversarial Learning and Self-Teaching Techniques for Domain Adaptation in Semantic Segmentation

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Abstract—Deep learning techniques have been widely used in autonomous driving systems for the semantic understanding of urban scenes, however they need a huge amount of labeled data for training, which is difficult and expensive to acquire. A recently proposed workaround is to train deep networks using synthetic data, however the domain shift between real world and synthetic representations limits the performance. In this work a novel unsupervised domain adaptation strategy is introduced to solve this issue. The proposed learning strategy is driven by three components: a standard supervised learning loss on labeled synthetic data, an adversarial learning module that exploits both labeled synthetic data and unlabeled real data and finally a self-teaching strategy exploiting unlabeled data. The last component exploits a region growing framework guided by the segmentation confidence. Furthermore, we weighted this component on the basis of the class frequencies to enhance the performance on less common classes. Experimental results prove the effectiveness of the proposed strategy in adapting a segmentation network trained on synthetic datasets, like GTA5 and SYNTHIA, to real world datasets like Cityscapes and Mapillary.

I. INTRODUCTION

A key component of any autonomous driving system is the capability of understanding the surrounding environment from visual data. This is nowadays achieved using semantic segmentation techniques based on various deep learning strategies. Deep networks have shown impressive performance on this task but they have the key drawback that a huge amount of data is required for their training, especially in case recent highly complex architectures are used. In the case of road scenes this means that pixel-level information must be manually provided for a huge amount of frames acquired by cameras mounted on cars driving around and this requires a huge amount of work. Some recent papers [1], [2] introduced a workaround for this issue based on the idea of using computer generated data for training the networks. The realistic rendering models developed by the video game industry can be used to produce a large amount of high quality rendered road scenes [1]. However, despite the impressive realism of recent video games graphics, there is still a large domain shift between the computer generated data and real world images acquired by video cameras on cars. To be able to really exploit computer generated data in real world applications the domain shift issue needs to be addressed.

We present an unsupervised domain adaptation strategy for road driving scenes able to adapt an initial learning performed on synthetic data to the real world case. The domain adaptation strategy presented in this work is based on adversarial learning and is an extension of our previous work introduced in [3]: here we further improve the self-teaching strategy and we present a more robust experimental evaluation.

We focus on the training scenario where a large amount of annotated synthetic data is available but there are no labeled real world samples (or just a small amount that can be used for validation purposes but not sufficient for training the deep network). The proposed method exploits a segmentation network based on the DeepLab v2 framework [4] that is trained using both labeled and unlabeled data in an adversarial learning framework with multiple components. The first component that controls the training is a standard cross-entropy loss exploiting ground truth annotations used to perform a supervised training on synthetic data. The second is an adversarial learning scheme similar to the ones used in works (e.g., [5], [6]) dealing with semi-supervised semantic segmentation (i.e., for dealing with partially annotated datasets). In particular, we exploited a fully convolutional discriminator which produces a pixel-level confidence map distinguishing between data produced by the generator (both from real or synthetic data) and the ground truth segmentation maps. It allows to train in an adversarial setting the segmentation network using both synthetic labeled data and real world scenes without ground truth information. Finally, the third term is based on a self-teaching framework. This key component is based on the idea introduced in [5] that the output of the discriminator can be also used as a measure of the reliability of the network estimations to be exploited in a self-teaching framework. However, this component has been greatly improved in this work, both with respect to [5] and to [3]. First of all, the output of the discriminator has been considered as a weight to be applied to the loss function of the self-teaching component at each location (in place of the hard threshold used in previous work [3]). Then, a novel region growing scheme is introduced in order to extend and better represent the shape of reliable regions (the approaches of [3], [5] tend to almost always discard edge regions and small objects). Finally, since the various classes have different frequencies, we also weighted the loss coming from unlabeled data in proportion to the frequency of the various classes in the dataset thus obtaining a better balance of the results between the different classes and avoiding the dramatic drop in performance on less common classes (typically corresponding to small objects and structures that represent the critical elements for an autonomous vehicle).

The network has been trained on both synthetic labeled data (using the first and second component) and on unlabeled real world data (using the second and third component) and
we were able to obtain accurate results on different real world datasets even without using labeled real world data. In particular, we used the synthetic datasets SYNTHIA and GTA5 for the supervised part and the real datasets Cityscapes and Mapillary (the latter has been introduced in this journal extension) for the unsupervised components and then tested on the respective validation sets, achieving state-of-the-art results on the unsupervised domain adaptation task.

II. RELATED WORK

Many different approaches for semantic segmentation of images have been proposed (see [7] for a recent review of the field). There are many different strategies for this task, but most current state-of-the-art approaches are based on encoder-decoder schemas and on the Fully Convolutional Network (FCN) model [8]. Some recent well-known and highly performing methods are DilatedNet [9], PSPNet [10] and DeepLab [4]. In particular the latter is the model employed for the generator network in this work. All the approaches for generic images can be applied also to road scenes, however since this is a very relevant application [11], [12] there has been a large effort both in the acquisition of datasets [13]–[15] and in the development of ad-hoc approaches [16]–[18].

These approaches show impressive performance but they all share the fundamental issue that a large amount of labeled data is needed for their training. They are typically trained on huge datasets with pixel-wise annotations (e.g., the Cityscapes [13], CamVid [19] or Mapillary [14]), whose acquisition is highly expensive and time-consuming. Recent research, as the proposed work, focuses on how to deal with this issue both by using only partially labeled data or by adapting the training done on a different set of data with slightly different statistics to the problem of interest.

The first family of approaches we consider is semi-supervised methods. They can be divided into methods exploiting weakly annotated data (e.g., with only image-wise labels or only bounding boxes) [20]–[27] or methods for which only part of the data is labeled while the other is completely unlabeled [5], [6], [21], [28], [29]. The work of [30] has opened the way to adversarial learning approaches for the semantic segmentation task while [21] to their application to semi-supervised learning. The approaches of [5], [6] are also based on adversarial learning but exploit a Fully Convolutional Discriminator (FCD) trying to discriminate between the predicted probability maps and the ground truth segmentation distributions at pixel-level. These works targeted a scenario where only part of the dataset is labeled but unlabeled data comes from the same dataset and shares the same domain data distribution of the labeled ones.

The work of [3] starts from [5] but instead proposes to tackle a scenario where unlabeled data refers to a different dataset with a different domain distribution, i.e., it deals with the domain adaptation task. A common setting for this task is domain adaptation from synthetic data to real world scenes. The development of advanced computer graphics techniques enabled the collect huge synthetic datasets for semantic segmentation purposes. Examples of synthetic semantic segmentation datasets for the autonomous driving scenario are the GTA5 [1] and SYNTHIA [2] datasets, which have been employed in this work. However, there is a cross-domain shift that has to be addressed when a neural network trained on synthetic data processes real-world images (in this case training and test data are not drawn i.i.d. from the same underlying distribution as usually assumed [16], [31]–[34]).

Some works propose to process the synthetic images to reduce the inherent discrepancy between real and synthetic domain distributions mainly using generative models based on Generative Adversarial Networks (GANs) [35]–[39].

The unsupervised domain adaptation has been widely investigated in classification tasks [40]–[43] but its application to semantic segmentation is less explored. The first work to deal with cross-domain urban scenes semantic segmentation is [44], where the adaptation is performed by aligning the features from the different during the adversarial training procedure. A curriculum-style learning approach is proposed in [16], where firstly the easier task of estimating global label distributions is learned and then the segmentation network is trained forcing that the target label distribution is aligned to the previously computed properties. Many other works addressed the domain adaptation problem with various techniques, including GANs [29], [45], cycle consistency [11], [46], output space alignment [47], [48], distillation loss [17], [49], class-balanced self-training [50], conservative loss [51], geometrical guidance [52], adaptation networks [53] and entropy minimization [54].

Region growing techniques have been recently applied to domain adaptation in semantic segmentation [26], [27]. In particular in [26] a semantic segmentation network is trained to segment the discriminative regions first and to progressively increase the pixel-level supervision by seeded region growing [55]. In [27] the authors propose a saliency guided weakly-supervised segmentation network which utilizes salient information as guidance to help weakly segmentation through a seeded region growing procedure. In [56] the region growing problem is defined as a Markov Decision Process.

III. ARCHITECTURE OF THE PROPOSED APPROACH

Our target is to train a semantic segmentation network (we name it $G$ in this paper since it has the role of the generator in the adversarial training framework) in a supervised way on synthetic data and to adapt it in unsupervised way to real data. A supplementary discriminator network $D$ is used to evaluate the reliability of $G$’s output. This information can be employed to guide the adaptation of $G$ to unlabeled real data. In this section, we detail the CNN architectures and the training procedure implementing the unsupervised domain adaptation. Our approach is independent of the $G$ architecture and in general any semantic segmentation network can be used, however in our experiments $G$ is a DeepLab v2 network [4]. This widely used model is based on the ResNet-101 backbone whose weights were pre-trained [57] on the MSCOCO dataset [58].

Figure [1] shows the architecture of the proposed training framework. The optimization of the network is driven by the minimization of three loss functions. The first loss function
is a standard multi-class cross-entropy ($\mathcal{L}_{G,1}$). $G$ is trained to estimate for each input pixel the probability that it belongs to a class $c$ inside the set of possible classes $\mathcal{C}$. It is optimized only on labeled synthetic data since the ground truth is required. By defining as $G(X_n^s)$ the output of the segmentation network on the $n$-th input image, $X_n^s$, from the source (synthetic) domain and with $Y_n^s$ its one-hot encoded ground truth segmentation, the loss $\mathcal{L}_{G,1}$ is formulated as:

$$\mathcal{L}_{G,1} = - \sum_{p \in X_n^s} \sum_{c \in \mathcal{C}} Y_n^s(p)[c] \cdot \log \left(G(X_n^s)(p)[c]\right)$$ (1)

where $p$ is the index of a pixel in the considered image, $c$ is a specific class belonging to $\mathcal{C}$ and $Y_n^s(p)[c]$ and $G(X_n^s)(p)[c]$ are the values relative to pixel $p$ and class $c$ respectively in the ground truth and in the generator ($G$) output. As mentioned above, this loss can be computed only on the source (synthetic) domain where the semantic ground truth is available.

The second and the third loss functions, minimized during the $G$ training, aim at adapting the semantic segmentation CNN $G$ to real data without using ground truth labels for real data. These loss functions are implemented by means of the discriminator network $D$, that is trained to distinguish segmentation maps produced by the generator from the ground truth ones. The peculiarity of this discriminator network is that it produces a per-pixel estimation, differently from traditional adversarial frameworks where the discriminator outputs a single binary value for the whole input image. The discriminator $D$ is made of a stack of 5 convolutional layers each with $4 \times 4$ kernels with a stride of 2 and Leaky ReLU activation function. The number of filters (from the first layer to the last one) is 64, 64, 128, 128, 1 and the cascade is followed by a bilinear upsampling to match the original input image resolution. The discriminator is trained by minimizing the loss function $\mathcal{L}_D$ that is a standard cross-entropy loss between $D$ output and the one-hot encoding indicating if the input is produced by $G$ (class 0) or if it is the ground truth one-hot encoding semantic segmentation (class 1). $\mathcal{L}_D$ can be formulated as:

$$\mathcal{L}_D = - \sum_{p \in X_n^{s,t}} \log(1 - D(G(X_n^{s,t}))(p)) + \log(D(Y_n^s)(p))$$ (2)

Please notice that the class 0, associated to $G$ output, can be produced both from an input $X_n^s$ coming from the source domain and from a real world input $X_n^t$. This means that $D$ can be trained on both synthetic and real data, trying to discriminate between generated data from ground truth one. Segmented source and target datasets share a similar statistic, since low level features of the color images are elaborated to leave place to the class statistic, and for this reason the training of $D$ on real and synthetic data is possible. Another possible source of errors during the training procedure could be related to the well distinguishable Dirac distributed segmentation ground truth data from other distributions generated by $G$. We have investigated this issue and in general $G$ produces segmentation maps very close to the Dirac distribution and this forces $D$ to capture also other statistical properties of the two different types of input data. Notice that this issue has been investigated also in [3], [5] with similar conclusions. The discriminator $D$ is used to implement the second loss function for the training of $G$, $\mathcal{L}_{G,2}^{s,t}$. This loss function is an adversarial loss since $G$, the generator in the traditional adversarial training scheme, is updated in order to create an output that has to look similar to ground truth data from the $D$ viewpoint. On a generic image $X_n^{s,t}$ this loss function can be formulated as:

$$\mathcal{L}_{G,2}^{s,t} = - \sum_{p \in X_n^{s,t}} \log(D(G(X_n^{s,t}))(p))$$ (3)

As for the training of $D$ (Eq. 2), $\mathcal{L}_{G,2}^{s,t}$ can be optimized both on the source and on the target data. In case the input is coming from the source dataset we will refer to Eq. 2 with $\mathcal{L}_{G,2}^{s,t}$, otherwise in case of target data as input we will use $\mathcal{L}_{G,2}^{t}$. Notice that by minimizing $\mathcal{L}_{G,2}^{s,t}$ the generator is forced to adapt to the target real domain in an unsupervised way. $G$ is forced to produce data similar to what $D$ considers ground truth also on real data, for which a true ground truth is not considered in the training phase.

The third loss function starts from the work of Hung et al. [5]. The idea is to interpret the output of the discriminator $D$ as a measure of the reliability of the output of $G$ in case of synthetic and real data. This reliability measure is used
to realize a self-training on real data. The predictions of $G$ are converted to the one-hot encoding and are used as a self-taught ground truth to train $G$ on unlabeled target real data. This loss can be formulated as

$$L_{G,3} = - \sum_{p \in X_n} \sum_{c \in C} D_R(X_n^t(p)) \cdot W_c \cdot \tilde{Y}_n[p][c] \cdot \log(G(X_n^t(p))[c])$$

(4)

where $\tilde{Y}_n$ is the one-hot encoded ground truth derived from the per-class argmax of the generated probability map $G(X_n)$. Each contribution to the loss is weighted by two terms. The first ($D_R$) is a weighting term dependent on the output of the discriminator refined by a region growing procedure that exploits pixel aggregation to improve the confidence estimation. The second ($W_c$) is a weighting function proportional to the class frequency on the source domain.

More in detail, the first term locates the reliable locations and assigns to them a weight using the following procedure. First of all, a region growing module $D_R(\cdot)$ takes in input a real image $X_n$ and starts from computing a mask $m_{T_u}$ selecting confident points by applying a threshold $T_u$ to the output of the discriminator at each location (i.e., the discriminator output is interpreted as a confidence map related to the segmentation map estimated on $X_n^t$). Formally,

$$m_{T_u} = \begin{cases} 1 & \text{if } D(G(X_n^t(p))^t(p) > T_u \\ 0 & \text{otherwise} \end{cases}$$

(5)

In the second step, for a generic confident pixel $p$ in $m_{T_u}$, the algorithm expands the confident region to a generic adjacent pixel $p' \in X_n^t$ if the output of the segmentation network for the class $c^*$ selected for point $p$ is greater than a threshold $T_R$ at location $p'$, i.e., $G(X_n^t(p'))[c^*] > T_R$. We will denote with $m_{R_u}^c$ the mask obtained by applying this region growing process to the original mask $m_{T_u}$. Finally, for each location $p^R$ selected by the updated mask $m_{R_u}^c$, the weight is given by the corresponding output of the discriminator $D(G(X_n^t))(p^R)$, so the resulting weights $D_R(X_n^t)$ are:

$$D_R(X_n^t) = m_{R_l}^c \cdot D(G(X_n^t)))$$

(6)

i.e., the weight is equal to the discriminator output for points selected by $m_{R_u}^c$, and to 0 for points not selected by the mask. Empirically we set $T_u = 0.2$ and $T_R = 1 - 10^{-5}$ thus achieving high reliability when expanding the confidence map.

The second weighting function is related to the class frequency on the source domain ($W_c$) and is defined as:

$$W_c = 1 - \frac{\sum_{p \in \mathbb{N}_n \land p \in c}}{\sum_{p \in \mathbb{N}_n}}$$

(7)

where $\cdot$ is the cardinality of the considered set.

This weighting function balances the overall loss when unlabeled data of the target set are used, avoiding that rare and tiny objects (e.g., traffic lights or pole) are forgotten and replaced by more frequent and large ones (such as road, building). Notice that $W_c$ is estimated on source data since the ground truth of the target data is assumed to be unknown during the training phase. Furthermore, $W_c$ does not change during the training process and so it is computed only once.

Finally, the overall loss function for the training of $G$ is a weighted average of the three losses, i.e.:

$$L_{full} = L_{G,1} + w^s \cdot L_{G,2} + w^t L_{G,3}$$

(8)

We empirically set the weighting parameters as $w^s = 10^{-2}$, $w^t = 10^{-3}$ and $w^t = 10^{-1}$.

The discriminator is trained minimizing $L_D$ (Eq. 3) on ground truth labels and on the generator output computed on a mixed batch composed by both source and target data. During the first 5000 steps, $L_{G,3}$ is disabled, setting $w^t = 0$, allowing the discriminator to learn how to produce higher quality confidence maps before using them. After this initial phase, all the three components of the loss are enabled and the training ends after 20000 steps.

IV. Datasets

The proposed unsupervised domain adaptation framework has been trained and evaluated using 4 different datasets. Recall that the target is to train the semantic segmentation network using labeled synthetic road scenes while no labels are available for real world data. The supervised synthetic training exploits two publicly available datasets, i.e., GTAS [1] and SYNTHIA [2]. The real world datasets used for the unsupervised adaptation and for the result evaluation are instead Cityscapes [15] and Mapillary [14]. Notice that the evaluation scenario is the same of recent competing approaches as [16], [29], [44] in order to allow for a fair comparison. During the training stage all the images have been resized and cropped to 750 x 375 px for memory constraints. The testing on the real datasets, instead, has been carried out at their original resolution.

The GTA5 dataset [1] contains 24966 synthetic images with pixel level semantic annotation. The images have been rendered using the open-world video game Grand Theft Auto 5 and are all from the car perspective in the streets of American-style virtual cities. The images have an impressive visual quality and are very realistic since they come from a high budget commercial production. We used 23966 images for the supervised training while the last 1000 have been taken out for validation purposes. There are 19 semantic classes which are compatible with the ones of the exploited real world datasets.

The SYNTHIA-RAND-CITYSCAPES subset of the SYNTHIA dataset [2] contains 9400 synthetic 1280 x 760 px images with pixel level semantic annotation. The images have been rendered with an ad-hoc engine, allowing to obtain a large variability of street scenes (in this case they come from virtual European-style towns in different environments under various light and weather conditions). On the other hand, the visual quality is not the same of the commercial video game GTA5. The semantic labels are compatible with 16 of the 19 classes of Cityscapes (for the evaluation on the Cityscapes dataset, only the 16 classes contained in both datasets are taken into consideration). We used 9300 images for the supervised training while 100 have been taken out for validation purposes.

The Cityscapes dataset [15] contains 2975 color images of 2048 x 1024 px captured on the streets of 50 European cities. They have pixel level semantic annotation with 34 classes
overall (we used the labels only for experimental evaluation, since the domain adaptation procedure is unsupervised). The original training set (without the labels) has been used for unsupervised adaptation, while the 500 images in the original validation set have been used as a test set (as done by competing approaches since the test set labels are not available).

The Mapillary dataset [14] contains 20000 high resolution images taken from different devices in many different locations. The variability in classes, appearance, acquisition settings and geo-localization makes the dataset the most complete and of highest quality in the field. As for Cityscapes we used this dataset for unsupervised domain adaptation and testing. The semantic annotations have been re-conducted to the labels of the Cityscapes dataset following the mapping in [18]. We exploited the 18000 training images (without the labels) for unsupervised training and the 2000 images in the original validation set as test set (as done by competing approaches).

V. EXPERIMENTAL RESULTS

The target of the proposed approach is to adapt a deep network trained on synthetic data to real world scenes. To evaluate the performance on this task we used the 4 different datasets introduced in Section IV. We started by evaluating the performance on the validation set of Cityscapes. In the first experiment, we trained the network using the scenes from the GTA5 dataset to compute the supervised loss $L_{C,1}$ and the adversarial loss $L_{G,2}$ while the training scenes of the Cityscapes dataset have been used for the unsupervised domain adaptation, i.e., to compute the losses $L_{G,2}$ and $L_{G,3}$. Notice that no labels from the Cityscapes training set have been used. In the second experiment, we performed the same procedure but we replaced the GTA5 dataset with the SYNTHIA one.

Then we switched to the Mapillary dataset and we repeated the two experiments using this dataset: we performed the supervised training with GTA or SYNTHIA and we used the training set of Mapillary (again only the images without any label) for the unsupervised domain adaptation. Finally we evaluated the results on the validation split of Mapillary.

The proposed deep learning scheme has been implemented using the TensorFlow framework. The generator network $G$ (that is a Deeplab v2 network) has been trained as proposed in [4] using the Stochastic Gradient Descent (SGD) optimizer with momentum set to 0.9 and weight decay to $10^{-4}$. The discriminator $D$ has been trained using the Adam optimizer. The learning rate employed for both $G$ and $D$ started from $10^{-4}$ and was decreased up to $10^{-6}$ by means of a polynomial decay with power 0.9. We trained the two networks for 20000 iterations on a NVIDIA GTX 1080 Ti GPU. The longest training inside this work, i.e., the one with all the loss components enabled, took about 20 hours to complete.

A. Evaluation on the Cityscapes Dataset

We started the experimental evaluation from the Cityscapes dataset. The performances have been computed by comparing the predictions on the Cityscapes validation set with the ground truth and measuring the mean Intersection over Union (mIoU), as done by competing approaches ([17], [44], [47]). Table I refers to the first experiment (i.e., using GTA5 for the supervised training). It shows the accuracy obtained with standard supervised training, with the proposed approach and with some state-of-the-art approaches. By simply training the network in a supervised way on the GTA5 dataset and then performing inference on real world data from the Cityscapes dataset a mIoU of 27.9% can be obtained. The proposed unsupervised domain adaptation strategy allows to enhance the accuracy to 33.3% with an improvement of 5.4%. By looking more in detail to the various class accuracies, it is possible to see that the accuracy has increased on almost all the classes (only on two of them the accuracy has slightly decreased), there is a large improvement on the most common classes corresponding to large structures, since the domain adaptation strategy allows to better learn their statistic in the new domain. At the same time the performance improves also on less frequent classes corresponding to small objects. Notice that in the third loss component, related to the self-teaching, the class weights $W_c$ have been taken into account, without this provision the performance on uncommon classes and small objects is much more unstable. By comparing the proposed framework with other state-of-the-art approaches, it is possible to see that the method of Hung et al. [5], based on a similar framework, achieves an accuracy of 29%, lower than our approach mostly because it struggles with small structures and uncommon classes. The method of [16] has similar performance, while the one proposed in [44] has lower performance. However, it is also based on a different loss performing generator network (i.e., the generator proposed in [4]). The older version of our method, introduced in [5], achieves an accuracy of 30.4%, with a gap of almost 3% w.r.t. the proposed approach, proving that the newly introduced elements (i.e., the weighting in the self-teaching and the region growing strategy) have a relevant impact on the performance.

Figure 2 shows the output of the supervised training of the methods of [5] and [3] and of our approach on some sample scenes, using the GTA5 dataset as source dataset and the Cityscapes as target one. The supervised training leads to reasonable results, but some small objects get lost or the object contours are badly captured (e.g., the rider in row 1 or the poles in row 3). Furthermore, some regions of the street are corrupted by noise (e.g., see rows 1 and 2). The approach of [5] seems to lose some structures (e.g., the terrain in the third row) and presents issues with small objects (the poles in row 3 get completely lost) as pointed out before. The old version of the approach [3] has better performance, for example in the images of Figure 2 the people are better preserved and the structures have better defined edges but there are still artifacts like the road surface in row 2 and 3. Finally the proposed method has the best performance showing a good capability of detecting small objects and structures and at the same time a reliable recognition of the road and of the larger elements in the scene. We can confirm this by looking at the proposed images: all of them have a cleaner representation of the road than previous approaches removing the sidewalk class where is not present but the same class is correctly localized in the second row differently from the other methods. Similar discussion holds also for the terrain class in row 3 and for the pole class whose
detection has been highly improved w.r.t. [5].

By using the SYNTHIA dataset as source dataset, the domain adaptation task is even more challenging w.r.t. the GTA5 case since the computer generated graphics are less realistic. By training the network \( G \) in a supervised way on the SYNTHIA dataset and then performing inference on the real world Cityscapes dataset, a mIoU of 25.4% can be obtained (see Table I). This value is smaller than the mIoU of 27.9% obtained by training \( G \) on the GTA5 dataset. The performance gap confirms that the GTA5 dataset has a smaller domain shift with respect to real world data, when compared with the SYNTHIA dataset (GTA5 data, indeed, have been produced by a more advanced rendering engine with more realistic graphics). By exploiting the proposed approach an accuracy of 31.3% can be obtained. The improvement is very similar to the one obtained using GTA5 as source dataset, proving that the approach is able to generalize to different datasets. In this case, there is a larger variability among different classes, however notice the very large improvement on the road and building classes. The previous version of the method [3] has an accuracy of 30.2%, again lower than the new version even if in this case the gap is more limited.

Furthermore, our domain adaptation framework outperforms all the compared state-of-the-art approaches. The method of Hung et al. [5], that exploits the same generator architecture of our approach, obtains a mIoU equal to 29.4%, lower than our method. The approach of [16] has an even lower mIoU of 29.0%. The method of [44] is the less performing approach and in this comparison it is even less accurate than our synthetic supervised trained network, but recall that it employs a different segmentation network.

The fourth, fifth and sixth row of Figure 2a shows the output on the same sample scenes as the ones discussed above in case that the SYNTHIA dataset is used as source. The first thing that stands out when looking at the qualitative results of the synthetic supervised version is that by training on the SYNTHIA dataset some very common classes as sidewalk and road are highly corrupted. This is caused by the not very realistic textures used for streets and sidewalks in the SYNTHIA dataset. Furthermore, while the positioning of the camera in the Cityscapes dataset is always fixed and mounted on-board inside the car, in SYNTHIA images the camera can be placed in different positions. For example, the pictures can be captured from inside the car, from cameras looking from the top or from the side of the road. Thus, it is evident that a standard supervised training starting using this dataset leads to a segmentation network that can not be used in a real world autonomous vehicle scenario.

The approach of Hung et al. [5] is able to correctly recognize the class road, correcting the noise present in the synthetic supervised training, but as mentioned in the previous section it suffers on small classes where it tends to lose small objects and to produce not very precise shapes for the recognized ones. The method of [3] and the proposed one have slightly better performance and the last two columns of Figure 2a show how the unsupervised adaptation and the self-teaching component of the third loss allow to avoid all the artifacts on the road surface by reinforcing the segmentation network to capture the real nature of this class in the Cityscapes dataset. At the same time our method is able to locate a bit more precisely small classes as person and vegetation. However, in this setting the difference between the old and new version of the proposed method is limited.

### B. Evaluation on the Mapillary dataset

To ensure that our approach can generalize to other real datasets, we performed the same experimental evaluation procedure also on the Mapillary dataset. We started by using the GTA5 dataset for the supervised training as before. By simply performing a supervised training on GTA5 and then...
| road | sidewalk | building | wall | fence | pole | traffic light | traffic sign | vegetation | terrain |
|------|----------|----------|------|-------|------|--------------|--------------|------------|---------|
| sky  | person   | rider    | car  | truck | bus  | train        | motorcycle   | bicycle    | unlabeled |

Fig. 2: Semantic segmentation of some sample scenes extracted from the Cityscapes (a) and Mapillary (b) validation datasets. The first group of six rows is related to the Cityscapes dataset, the last six to the Mapillary dataset. For each group, the first three rows are related to the experiments in which the GTA5 dataset is used as source. The last three rows are related to the case in which the SYNTHIA dataset is used as source (best viewed in colors).
testing on the Mapillary dataset a mIoU of 32.7% can be obtained. The proposed approach allows to obtain a much more accurate classification with a mIoU of 38.5%. Notice that the gain of almost 6% is consistent with the results obtained on the Cityscapes dataset, proving that the performance of the approach are stable across different datasets. The improvement can also be appreciated on both small and large classes, the mIoU values of 14 out of 19 classes show a clear gain. This is also visible in the qualitative results depicted in Figure 2b, where most of the artifacts on the road surface present in the synthetic trained network disappear and the shape of the small objects is more accurate. The results of [44] and [16] are not available for this dataset, however notice how the approach outperforms by a large margin both [5] and the old version of the approach [3] that are able to reduce only partially the artifacts on the road surface (visible in all the images), on the cars (row 1) and on the buildings (row 3).

Furthermore, we can appreciate that also on the Mapillary dataset the accuracy is lower when the SYNTHIA dataset is used for supervised training leading to a mIoU of 26.6% only. As for Cityscapes the road and the sidewalk classes have an extremely low accuracy due to the poor texture representation (the visual results are reported in the last 3 rows of Figure 2b). By exploiting the proposed unsupervised domain adaptation strategy the average mIoU increases to 32.0% with an improvement of 5.4%, again consistent with the other experiments. In this case, the performance is more unstable across the various classes but it is noticeable the large gains on the road and building classes. This is also confirmed by the qualitative results, for example we can appreciate that the proposed approach is the only one able to achieve an accurate and reliable recognition of the road on all the 3 presented images. The method of Hung et al. [5] achieves a mIoU of 27% with a very limited improvement w.r.t. the synthetic supervised training. It is strongly penalized by the poor performance on the small and uncommon classes. The approach of [3] has slightly better performance (28.4%), but it has a quite large gap with respect to the proposed method. The weighting scheme and the region growing strategy introduced in this work allowed to obtain a very large improvement in this setting.

### C. Ablation Study

In this section, we are going to analyze the contributions of the various components of the proposed loss function. We focus on the use of Cityscapes as target dataset for this study. The results of this analysis are shown in Table II. By training the generator with a synthetic supervised approach, i.e., using only $L_{G,1}$, it is possible to obtain a mIoU of 27.9% when GTA5 is the source dataset and 25.4% when SHYNTHIA is the source dataset. As mentioned in the previous sections, this is the less performing training approach. A slight improvement can be obtained by adding the adversarial term $L_{G,2}$ in the loss function. In this case, the mIoU increases of 1.5% and 2% when the source datasets are GTA5 and SYNTHIA respectively. The use of the self-teaching loss $L_{G,3}$ is particularly useful when exploiting the SYNTHIA dataset, obtaining an improvement of almost 3%, probably because the domain shift from this dataset is larger.

In the case of GTA5, the improvement is smaller but still significant. Moving to the new elements introduced in this work, the region growing strategy (i.e., masking with $m_{T}^R$) allows to a further performance enhancement, especially when using GTA5 with a 2.2% increase, mostly due to the improved handling of medium and large size objects. When starting from SYNTHIA the gain is more limited but still noticeable (almost 1%). The usage of the discriminator soft output, not masked with $m_{T}^R$, as a weighting factor has a more unstable behavior. This leads to a very good improvement of 2.4% when starting from GTA5 but having almost no impact when employed alone in the SYNTHIA case. Finally notice how the complete version of our approach, where all the aforementioned components are taken in consideration, has the best performance. In particular notice how the discriminator-based weighting on the SYNTHIA dataset, that alone had
a limited impact, is instead useful when combined with the region growing scheme.

| $\mathcal{L}_{G,1}$ | $\mathcal{L}_{G,2}$ | $\mathcal{L}_{G,3}$ | RG | DW | mIoU GTA | mIoU SYNTHIA |
|------------------|------------------|------------------|-----|-----|---------|-------------|
| ✓                | ✓                | ✓                | ✓   | ✓   | 27.9    | 25.4        |
| ✓                | ✓                | ✓                | ✓   | ✓   | 29.4    | 27.4        |
| ✓                | ✓                | ✓                | ✓   | ✓   | 30.4    | 30.2        |
| ✓                | ✓                | ✓                | ✓   | ✓   | 32.6    | 31.0        |
| ✓                | ✓                | ✓                | ✓   | ✓   | 32.8    | 30.2        |
| ✓                | ✓                | ✓                | ✓   | ✓   | 33.3    | 31.3        |

TABLE V: Ablation study on the Cityscapes validation set.

VI. CONCLUSIONS

In this paper, a complex scheme to perform unsupervised domain adaptation from synthetic urban scenes to real world ones has been proposed. Two different strategies have been used to exploit unlabeled data: firstly an adversarial learning framework, based on a fully convolutional discriminator, and secondly a soft self-teaching strategy, based on the assumption that predictions labeled as highly confident by the discriminator are reliable. Additionally, we improved this approach with a region growing module that further refines the confidence maps on the basis of the segmentation output on real-world images. Experimental results on the Cityscapes and Mapillary datasets prove the effectiveness of the proposed approach. In particular, we obtained good results both on large sized classes, thanks to the region growing procedure, and on particularly challenging small and uncommon ones, thanks to the class frequency weighting of the self-teaching loss.

Further research will be devoted to test the proposed framework with different backbone networks and to the exploitation of generative models to produce more realistic and refined synthetic training data to be fed to the framework.

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