Semantic Segmentation Alternative Technique: Segmentation Domain Generation

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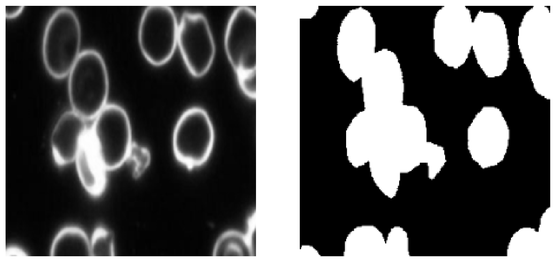
Abstract

Detecting objects of interest in images was always a compelling task to automate. In recent years this task was more and more explored using deep learning techniques, mostly using region-based convolutional networks. In this project we propose an alternative semantic segmentation technique making use of Generative Adversarial Networks. We consider semantic segmentation to be a domain transfer problem. Thus, we train a feed forward network (FFNN) to receive as input a seed real image and generate as output its segmentation mask.

Introduction

Motivation: The problem of automatic detection and segmentation of objects in images can be encountered in many domains, from sports to medicine or physics [RKH21]

Approach: We propose a general method for automating the process of segmentation of desired objects in an image, as displayed in Figure 1, based on Generative Adversarial Networks (`GANs`) [Goo+14].



(a) Source image (b) Segmentation mask

Fig. 1: Problem description: given a dataset labeled for a segmentation task, the goal is to train a `GAN` to be able to transform (a) the source image into its corresponding (b) segmentation mask.

Methods: We experiment with two relatively small datasets and adapt the following architectures: Conditional Generative Adversarial Networks (`CGAN`) and Cycle-Consistent Generative Adversarial Networks (`CycleGAN`) two relatively small datasets

Datasets

The methodology was tested on the following two datasets:

- `Particles` contains 40 images of particles acquired using electron microscopy [RKH21].
- `Bacteria` contains 366 images of the *Spirochaeta* bacteria acquired using darkfield microscopy [Ngu20].

Both datasets have an associated segmentation mask corresponding to the location of the particles and the location of the bacteria.

Experiments

We led experiments on both datasets using `CGANs` and `CycleGANs`. The datasets were splitted in the following manner:

- `Particles`, 35 samples for training and 5 samples for testing.
- `Bacteria`, 320 samples for training and 46 samples for testing.

Conditional GAN composed of a `U-Net` [RFB15] generator and a Convolutional Neural Network (`2D-Conv`) discriminator. The model was trained for 100 epochs. The results for the `CGAN` are shown in Figure 2.

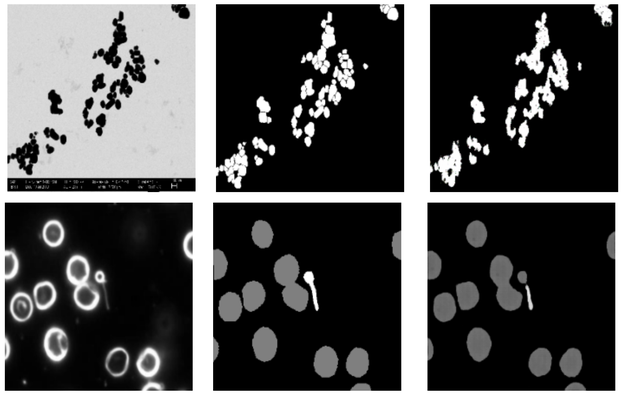


Fig. 2: Segmentation masks generated using `CGANs`. On each row we can see, from left to right: the real image, the ground truth segmentation mask and the generated segmentation mask. On the first and second row we can see examples from the `Particles` and `Bacteria` datasets respectively.

Cycle GAN composed out of the same generator and discriminator architectures as for the above mentioned experiments for the `CGAN`.
There are two main changes in this case from the previous one:

- `CycleGAN` does not need *(image, mask)* pairs for the translation.
- for a `CycleGAN` we have to train four discriminators and one generator.

The results for the `CGAN` are shown in Figure 3.

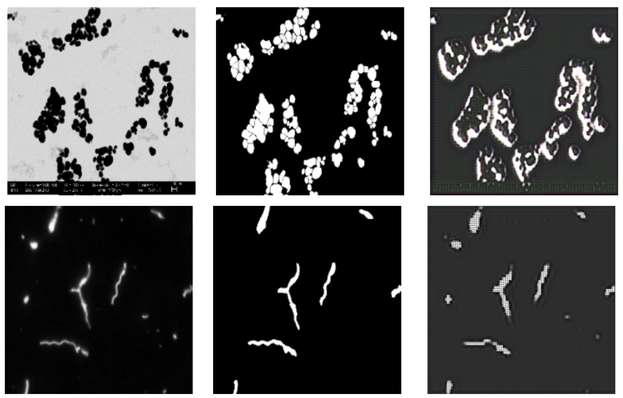


Fig. 3: Samples of segmentation masks generated using `CycleGANs`. On each row we can see, from left to right: the real image, the ground truth segmentation mask and the generated segmentation mask. On the first and second row we can see examples from the `Particles` and `Bacteria` datasets respectively.

Proof of concept

For validating our results, we projected our test images from the `Particles` dataset as 2D data-points for both model architectures using T-SNE visualization technique [VH08]. The results are illustrated in Figure 4.

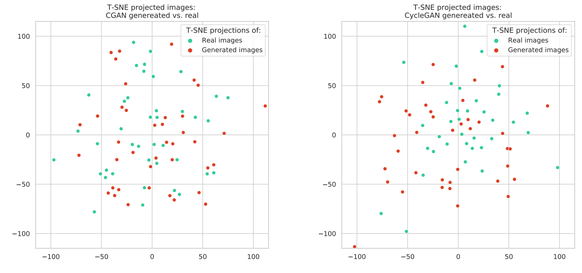


Fig. 4: T-SNE 2D representation of the original and generated images for both CGAN (left) and CycleGAN (right).

Conclusions

Results. We have shown in our experiments that the segmentation problem can be treated as a domain transfer task using the `Particles` and `Bacteria` datasets. We have observed that the results of a trained `CycleGAN` are inferior to those obtained by a trained `CGAN` both from our generated samples and from the T-SNE plots.

Future work.

- Compare established segmentation techniques against our methods.
- Investigate the feasibility of the reverse problem (i.e. generating true images from segmentation masks).

References

[Goo+14] Ian J Goodfellow et al. "Generative adversarial networks". In: *arXiv preprint arXiv:1406.2661* (2014).

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