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.

1 Introduction

The problem of automatic detection and segmentation of objects in images can be encountered in many domains, from sports to medicine or physics (Rühle et al., 2021). Traditionally, one or more human experts would be required to perform live detection and give their expertise on the objects of interest location. Thus, automatizing this process was and still is considered of great value.

In this project we propose a general method for automatizing the process of segmentation of desired objects in an image, as displayed in Figure 1. Our method is based on Generative Adversarial Networks (GANs) (Goodfellow et al., 2014).

In recent years, the most successful methods for object segmentation were based on region proposal techniques such as R-CNN or Fast R-CNN (Girshick et al., 2015; Girshick, 2015). Even though such techniques achieve high performance on many benchmark datasets, they reveal two specific drawbacks. First, they tend to run slower than a simple FFNN, even after their training phase. Second, as most deep learning techniques, they need large training datasets.

We propose to treat the segmentation problem as a domain transfer task. The source domain is represented by the real images to be segmented and the target domain is represented by the segmentation masks. By doing so, we can adapt established techniques for image translation such as Conditional Generative Adversarial Networks (CGAN) and Cycle-Consistent Generative Adversarial Networks (CycleGAN) (Isola et al., 2017; Zhu et al., 2017) for segmentation masks generation.

By using GANs for learning how to generate a segmentation mask we seek to address both aforementioned issues of the region proposal techniques. First, since after the training phase we make use only of the GAN’s generator, the segmentation generation time is equal to that of a forward pass through a FFNN. Second, both the CGAN and the CycleGAN revealed favorable results on relatively small datasets, with under 1,000 samples, for example on the CMP Facades dataset, as shown in (Isola et al., 2017; Zhu et al., 2017).

2 Datasets

We seek to validate our methodology by testing it on two datasets. The first dataset *Particles* contains 40 images of particles acquired using electron microscopy (Rühle et al., 2021). Each image has an associated segmentation mask corresponding to the location of the particles. The second dataset *Bacteria* contains 366 images of the...
Spirochaeta bacteria acquired using darkfield microscopy\(^1\). The location of the bacteria is marked with a corresponding segmentation mask.

3 Experiments

We led experiments on both datasets using CGANs and CycleGANs. For all the experiments we splitted our datasets in train and test sets. For Particles, 35 samples for training and 5 samples for testing. For Bacteria, 320 samples for training and 46 samples for testing.

3.1 Conditional GAN

We have tested a CGAN composed of a U–Net \cite{ronneberger2015u} generator and a Convolutional Neural Network (2D-Conv) discriminator. The model was trained for 100 epochs. The last few epochs revealed stabilized values for the loss functions for both generator and discriminator. Thus, 100 epochs were enough for reaching a Nash Equilibrium between the generator and the discriminator on the analyzed datasets. We can see the CGAN results in Figure 2.

![Figure 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.](image)

3.2 Cycle GAN

We used the same U–Net generator and 2D-Conv discriminator when using the CycleGAN, as for the above mentioned experiments for the CGAN.

The image translation problem setting has two main changes when using a CycleGAN compared to using a CGAN. First, a CycleGAN does not need \((image, mask)\) pairs for the translation. It is enough to have a number of samples from a source Domain A and a number of samples from a target Domain B, whereas a CGAN requires perfect pairs between the two domains. Second, for a CycleGAN we have to train four discriminators and one generator. Thus the training procedure is more laborious.

We have observed that the results of a trained CycleGAN are inferior to those obtained by a trained CGAN as we can see in Figure 3. Since a CycleGAN does not take into account the \((image, mask)\) pairs, it is to be expected that the generations should be affected in quality.

![Figure 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.](image)

4 Conclusions and Future Work

We have shown in our preliminary experiments that indeed the segmentation problem can be treated as a domain transfer task and we proved our concept by using two types of generative networks, CGANs and CycleGANs on the Particles and Bacteria datasets.

In our future experiments we aim to compare established segmentation techniques against our method and compare them on multiple metrics, such as generator’s veracity when using a small training set, as well as segmentation generation speed.

Moreover, we wish to investigate the feasibility of the reverse problem. Mainly, the plausibility of generating true images from segmentation masks. There are multiple domains where the possibility of generating real images from categorical masks would represent a real asset.
References

Ross Girshick. 2015. Fast r-cnn. In Proceedings of the IEEE international conference on computer vision, pages 1440–1448.

Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. 2015. Region-based convolutional networks for accurate object detection and segmentation. IEEE transactions on pattern analysis and machine intelligence, 38(1):142–158.

Ian J Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative adversarial networks. arXiv preprint arXiv:1406.2661.

Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. 2017. Image-to-image translation with conditional adversarial networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 1125–1134.

Olaf Ronneberger, Philipp Fischer, and Thomas Brox. 2015. U-net: Convolutional networks for biomedical image segmentation. CoRR, abs/1505.04597.

Bastian Rühle, Julian Frederic Krumrey, and Vasile-Dan Hodoroaba. 2021. Workflow towards automated segmentation of agglomerated, non-spherical particles from electron microscopy images using artificial neural networks. Scientific reports, 11(1):1–10.

Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A Efros. 2017. Unpaired image-to-image translation using cycle-consistent adversarial networks. In Proceedings of the IEEE international conference on computer vision, pages 2223–2232.