

Topic K - Image manipulation with generative adversarial networks (GANs)

Project Proposal

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1. Introduction

A new technique, SinGAN [1] which proposes to train a series of GANs¹ from a single image in order to synthesize its variations was recently published. Each of those GANs is used to capture the specificity of the input image at a specific scale. Then, by combining more or less scales, we can generate images similar to the input one. In this project, we want to explore this technique for an inpainting task. Our aim is to explore *how to remove an element from an image, coherently filling its space with SinGAN ?*

2. Plan of work

2.1. Deep understanding of the paper

First of all, we will do an in-depth reading of the paper. The main results of the paper such as *random sampling at arbitrary sizes*, *Animation from a single image*, *Harmonization* and *Super Resolution* will also be reproduced using the available code and images provided by the authors at [2].

2.2. Inpainting task with SinGAN

The inpainting functionality is not natively present in SinGAN, but can be a consequence of it. Indeed, inpainting is the coherent filling of a well-defined removed region, and the "Editing" function of SinGAN can approximate such a filling. From what the original paper shows, it suffices to fill the target area with a naive approximation (see Fig 12 in the paper), and SinGAN will fill this space coherently. We will explore 2 factors of the inpainting quality : the precision of the region delimitation (the simplest one will be just a box; the most precise one will use Mask R-CNN [3]) and the quality of the naive filling.

2.3. Related work for comparison

2.3.1 Learning-based baseline

A classic paper of inpainting paper using deep convolutional neural networks as adversarial networks is [4]. This

method uses one generator and two discriminators. The global discriminator network takes the entire image as input, while the local discriminator network takes only a small region around the completed area as input.

2.3.2 Non learning-based baseline

A comparison will be done on [5] which uses similar patches found in the image to fill the missing region. An online demo is available on the IPOL website. The comparison here is more fair because this algorithm uses only a single image, just like SinGAN.

2.3.3 Mixed baseline

Finally, the paper [6] makes the most of the two previous baselines. We will incorporate this state of the art approach to our evaluation process.

2.4. Evaluation process

We will use an evaluation process similar to the original paper. We will present to some people images for a restricted amount of time and ask whether it is fake. Different inpainted images will be presented using the previous mentioned algorithms, including our SinGAN method. The quiz will be held on an online survey tool such as *Google Form*.

References

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- [4] S. Iizuka, E. Simo-Serra, and H. Ishikawa, "Globally and locally consistent image completion," *ACM Transactions on Graphics (ToG)*, vol. 36, no. 4, pp. 1–14, 2017. [1](#)
- [5] A. Newson, A. Almansa, Y. Gousseau, and P. Pérez, "Non-Local Patch-Based Image Inpainting," *Image Processing On Line*, vol. 7, pp. 373–385, 2017. <https://www.ipol.im/pub/art/2017/189/>. [1](#)
- [6] J. Yu, Z. Lin, J. Yang, X. Shen, X. Lu, and T. S. Huang, "Generative image inpainting with contextual attention," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 5505–5514, 2018. [1](#)

¹Generative Adversarial Networks