

GCC-GAN applications in Realistic Synthetic Traffic Sign Enhancement

Road images augmentation with synthetic traffic signs using neural networks

0. Abstract

- it talks about the fact that most of the well-research traffic sign recognition problem in computer vision uses frequent sign classes and the lack of rare traffic sign detection and classification.

1. Introduction

- it talks more about the subject and it resumes on what they will be focusing on

2. Related Work

- it talks about synthetic image generation and processing and why some basic solutions don't work that great and talks about what other authors proposed and what inspired them

3. Proposed methods

- they talk about processing of embedded traffic signs and they propose 3 approaches: a Pasted approach where an old traffic sign is inpainted, the image is put there and is enhanced with a GAN, a Cycled approach where the old traffic signed is inpained and the inpainted network is also trained at the same time, the same traffic sign is placed there and at the discriminator step is compared with the old traffic sign, and there are applied some losses to be sure the images look alike, and a Styled approach, where StyleGAN (a Progressive GAN with some additional features) is used to replace the traffic sign with a new one

4. Evaluation

- they talk about RTSD dataset (Russian traffic sign dataset) and some traffic sign recognition systems

5. Evaluation results

- they talk about their results on the proposed evaluation methods,

and comparing them with other approaches (KDE-only-synt, KDE-manystyled, NN-manystyled, KDE-additional, NN-additional)

6. **Conclusion**

- they talk a bit about what they've done and other things they tried but failed

7. **References**

Toward Realistic Image Compositing with Adversial Learning

0. **Abstract**

- they talk about the fact that compositing a realistic image is a challenging task and why it requires human supervision using professional image editing software, and how we can automate this task

1. **Introduction**

- they introduce us into the subject and why classic GANs and what the proposed novel GAN architecture (Geometrically and Color Consistent GAN) is proposed for

2. **Related Work**

- they talk about current solutions to Image Compositing, 3D Synthesis and the classic Generative Adversial Network

3. **Proposed Method**

- they talk about the system overview, the generative compositing model, the adversial learning, the geometric and color consistent GAN and the Implementation Details

4. **Experiments**

- they talk about image compositing and synthesized objects, importance of color consistency and some other qualitative results of different algorithms (Poisson Blending, Deep Harmonization and Pix2Pix)

5. **Conclusion**

- they resume what they've talked about and some failure cases

6. **References**

The mapillary traffic sign dataset for detection and classification on a global scale

0. Abstract

- they talk about the importance of such dataset for the self-driving cars

1. Introduction

- they talk about why a robust and accurate dataset would help detection and classification algorithms

2. Mappillary Traffic Sign Dataset

- they talk about how they collected the data in the dataset and where in the world the traffic signs are

3. Statistics

- they talk about image properties, traffic sign properties and annotator interactions

4. Traffic Sign Detection

- they talk about different metrics and they show some baseline and results for a classic network architecture in their dataset

5. Simultaneous Detection and Classification

- they show their results of current algorithms in their dataset

6. Conclusion

- they conclude and said that they would like to complete traffic sign taxonomy globally

7. References

Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks

0. Abstract

- they talk about how CNNs was adopted in various Computer Vision tasks and they introduce the new proposed class of CNNs, the deep convolutional generative adversarial networks

1. Introduction

- they talk about what contributions this paper will bring and how GANs will provide an attractive alternative to maximum likelihood techniques

2. Related Work

- they talk about other approaches to this kind of processes, such as representation learning from unlabeled data, generating natural images and how could we visualize the internals of CNNs (being considered some black-box methods with little understanding)

3. Approach and Model Architecture

- they talk about other GAN architecture (LAPGAN and other unsuccessful attempts to implement GANs with CNNs) and they describe the architecture of the proposed model, explaining how they've chosen each layer

4. Details of Adversial Training

- there they talk about how they trained the model on various datasets (LSUN, Deduplication, Human Faces, ImageNet-1K) and they show some of the results

5. Empirical Validation of DCGANs Capabilities

- they show where the components of the GAN (the generative model and the adversial model) would excel in various tasks such as classifying CIFAR-10 using GANs as a feature extractor and classifying SVHN digits using GANs as a feature extractor, showing the results compared with other models

6. Investigating and visualizing the internals of the networks

- there they explain what they've understood by exploring the landscape of latent space, and they tried to explain how they visualized the discriminator features and how they've manipulated the generator

7. Conclusion and Future Work

- there they concluded what they've proposed and talked about some flows (like the instability of the models, e.g. one learning faster than the other)

8. References

Semantic Image Inpainting with Deep Generative Models

0. Abstract

- they talk about how the image inpainting is a challenge and they talk about what they would propose in this article

1. Introduction

- they present the problem and they say that in this paper, they are more interested in more difficult tasks of semantic inpainting rather than just filling small holes in the image

2. Related Work

- they talk about GAN, Autoencoders, Variational Autoencoders, Context Encoder and about backpropagation to the input data.

3. Semantic Inpainting by Constrained Image Generation

- there they present about how they train the generator and the discriminator to perform this task, and they talk about some used losses such as importance weighted context loss and prior loss, after that they talk about how the inpainting is done and they talk a bit about the implementation details

4. Experiments

- they show some results and they evaluate it qualitatively and quantitatively, they also talk about the datasets that they did the experiments on (CelebA, SVHN, Stanford Cars Dataset) and the visual comparison using Nearest Neighbor Painting or the Context Encoder, they also talk about how the different mask placement would affect the algorithm

5. Conclusion

- they conclude what they've proposed in the paper and in which fields this model performed better than the other ones

6. References

Bibliography

- [1] Anton Konushin, Boris Faizov, and Vlad Shakhuro. “*Road images augmentation with synthetic traffic signs using neural networks*”. In: preprint arXiv:2101.04927 (2021), pp. 1-15.
- [2] Bor-Chun Chen and Andrew Kae. “*Toward Realistic Image Compositing with Adversial Learning*”. In: IEEE/CVF Conference on Computer Vision and Pattern Recognition (2019), IEEE pp. 8407-8416.
- [3] Christian Ertler, Jerneja Mislej, Tobias Ollmann, Yubin Kuang, Lorenzo Porzi and Gerhard Neuhold. “*The mapillary traffic sign dataset for detection and classification on a global scale*”. In: Computer Vision–ECCV 2020 Proceedings, Part XXIII 16. Springer. 2020, pp. 68–84.
- [4] Alec Radford, Luke Metz and Soumith Chintala. “*Unsupervised Representation Learning with Deep Convolutional Generative Adversial Networks*”. In: preprint arXiv:1511.06434 (2015), pp. 1–16.
- [5] Raymond A. Yeh, Chen Chen, Teck Yian Lim, Alexander G. Schwing, Mark Hasegawa-Johnson, Minh N. Do. “*Semantic Image Inpainting with Deep Generative Models*”. In: CVPR. (2017), pp. 5485–5493.