GCC-GAN applications in Realistic Synthetic Traffic Sign Enhancement

I. Sketch

0. Abstract

- there I will talk about why realistic synthetic traffic sign enhancement is an important step towards generating data with some “rare” traffic signs and why this is an important step towards self-driving cars

1. Introduction

- there I will talk firstly a bit about Deep Convolutional Neural Networks and how they influenced Computer Vision, then about GANs [4] in general and why we need a more fine-tuned model in this specific field, rather than some general purposed ones and why good data generation will help self-driving algorithms do better (because the data is distributed however we train it, so a sufficient enough dataset will cover most of the cases most of the drivers will encounter), and I briefly talk about the causes the lack of data [3]

2. Related Work

- there I will talk about the current approaches and their flaws, so a simple GAN approach [4], Conditional GANs [10] (for labelling what kind of traffic signs we want to generate) the approaches proposed in [1] (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 [8] is used to give the style of the

synthetic traffic sign, but its hard to train and depends hardly on the dataset)

3. Approach

- in the proposed approach the images will be inpainted like in the old approaches, and we will apply the mask on the image wherever we want the synthetic sign to be applied (an advantage in face of the other approaches will be that we can also rotate or apply different kind of transformations to the mask, the used model knows in most of the cases how to apply it), then this and the synthetic traffic sign will pass through the Geometrical and Color Consistent GAN [2], after that it will be described why is a better approach in terms of retaining some features the old approaches weren't aware of

4. Results

- there I will present some visual results compared with the other approaches, preferably showcasing the big advantages of this model in comparison with the other ones (which I previously talked about), then I will use a WideResNet classifier to try to predict the rare traffics signs generated by the proposed algorithm and display the results, these could be compared with the ones shown at [1] and some of the ones shown at [13]

5. Conclusions and Future Considerations

III. Research Plan

Hypothesis:

The hypothesis of this research is that the application of Geometrical and Color Consistent GAN (GCC-GAN) in generating realistic synthetic traffic sign enhancements will outperform existing methods, providing more accurate and diverse data for training self-driving algorithms. This hypothesis is based on the belief that GCC-GAN's ability to maintain

geometric and color consistency will result in more convincing and informative synthetic traffic signs.

Methodology:

Data Collection:

- gather a diverse dataset of real traffic sign images, ensuring representation of rare and less common signs.

Model Architecture:

- implement the proposed approach, integrating the GCC-GAN [2] with a traffic sign inpainting mechanism [14].

- fine-tune the architecture to handle variations in traffic sign appearance and background scenarios.

Training:

- train the model on the augmented dataset, optimizing for the preservation of key features in synthetic traffic signs.

- monitor and adjust hyperparameters to achieve optimal results.

Evaluation:

- evaluate the model using both qualitative and quantitative measures.

Comparison with Existing Approaches:

- compare the proposed approach with previous methods, specifically the ones mentioned in [1].

- highlight advantages such as improved realism, diversity, and applicability to rare traffic signs.

IV. Contributions to Research State

This work will contribute to the current research state of the field by:

Advancing Realism in Synthetic Data:

→ pushing the boundaries of realism in synthetic data generation for traffic signs, enhancing the authenticity of generated content. This advancement is crucial for training algorithms to recognize and respond to a wide array of real-world traffic scenarios.

Overcoming Limitations of Previous Approaches:

→ addressing the limitations of prior methods, such as potential loss of geometric or color details, and offering a more comprehensive solution through the integration of GCC-GAN. This contributes to the refinement of traffic sign synthesis techniques.

II. Bibliography

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