
Summer2Rainy: Using CycleGAN for Image-to-Image Translation

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Abstract

1 Introduction

Experiments on self-driving cars have been conducted since at least the 1920's [7] and the first truly autonomous cars appeared in the 1980's, with Carnegie Mellon University's Navlab [8]. Waymo, a subsidiary of Alphabet, began their self driving car project in 2009. Waymo uses deep learning to interpret, predict and respond to data collected from it's 6 million miles driven on public roads and 5 billion driven in simulation [9]. The way an autonomous car reacts to a situation is hugely dependent on the weather conditions of the environment it is in. For example, a self-driving car would drive slower and more cautiously during the monsoon season than during the summer time due to various environment factors such as lack of visibility and slippery roads. Training the deep learning model for self-driving cars on simulations of different weather conditions can be a daunting task as weather conditions are seasonal and can immensely delay the time needed for data collection and training.

We propose a novel method of translating frames/images of environments taken in the summer season to the monsoon season and back. This would allow the data collected by researchers during summer to transform into monsoon conditions and train their models on both these environments simultaneously thereby decreasing the time needed for data collection and training.

To solve this, we plan to use CycleGAN, which performs image to image translation, by learning the mapping between input image and output image using a training set of unpaired image pairs [1]. CycleGAN captures the special characteristics of one domain and finds out how these characteristics could be translated into the other domain, all in the absence of any paired training examples. In our research, one image collection would be of images taken in during the summer season and the other during the monsoon season. We will discuss this in greater detail in Section 5.

There are various other applications of our research, which include solving the problem of de-raining and helping the film industry (Hollywood) capture the essence of Monsoon, off-season. There has been various research done on de-raining, as discussed in Section 6 and we believe that our proposed model would be able to solve the problem by training it to transform rainy images to summer.



Figure 1: Taken from nvidia paper. Goal of this project is to do better than this using cycle gan

2 Implementation

3 Results

4 Limitation & Discussions

5 Research Plan and Expected Outcome (ARCHIVE)

For this project we will train the implementation cycleGAN provided by the authors of [1] on our dataset. Both Pytorch and Torch implementations are available. Our dataset consists of 2 sets of images: summer images and rainy images. There is no one-to-one correspondence between the two sets. We will first search for the image datasets and if we do not find any, we plan to scrape images of summer and rainy season from the web and scale them to same size (say 256 x 256). Since the cycleGAN assumes some underlying relationship between the images from two sets, our first attempt will be to obtain images of the same place corresponding to the two seasons and divide them into train and test datasets. The images can be obtained using google or Flickr API for a particular place and categorize into summer vs rainy based on the time of the year the pictures were taken. If the model works well on this dataset, we will attempt to train the model on datasets where the images in each set can be unrelated.

The first obvious expected outcome of our project is that the training error of our model converges and we are able to train the model. In that case, we will evaluate if the model works well on the test dataset and is able to produce images that are able to fool the human eyes. We will also quantitatively evaluate the results. The first measure is the cycle loss that is the difference between the original image and the one obtained after complete cycle. For example, give a test image from the summer dataset, we first convert it to rainy and then back to summer and measure how different it is from the original image. Although this is not a very good measure of what we are trying to achieve because any translation that can be reversed will have a low cycle loss but it definitely is a sanity check for the results.

If our model trains and tests well on images of the same place, we will evaluate the performance of the model on images that may be from different places. We plan to compare our results with existing approaches that solve the problem of image to image translation or image de-raining.

Generative networks are considered much harder to train than discriminative networks. Similarly GANs are difficult to train and require a balance between the discriminator and generator networks for the training loss to converge. GANs are also highly sensitive to hyperparameters. As a part of this project, we also plan to evaluate the impact of hyperparameters on training the cycleGAN network. We aim to study and experiment methods suggested by the authors of CycleGAN to mitigate the model parameters oscillation.

6 Related Work

In this section, we briefly review works related to Image-to-Image translation and single image deraining.

6.1 Image-to-Image translation

Generative Adversarial Networks (GANs) [2] were introduced by Ian Goodfellow in 2014 and have been very successful in image-to-image translations. GANs have one neural network that generates

data while the other discriminates between real and fake (generated) data. Over time both networks get better at their tasks and the generator is now able to mimic the distribution of the real world. GAN was used for a variety of applications and it also paved way for a series of GAN-family work for different applications. As stated before, the work that we will be exploring in this paper is CycleGAN [1]. If we have two domains, X and Y , and two generators $G : X \rightarrow Y$ and $F : Y \rightarrow X$ then we try to achieve a cycle-consistency such that $F(G(X)) \approx X$ and $G(F(Y)) \approx Y$.

There is also other work done in the domain of image-to-image translation. The authors of CycleGAN previously proposed pix2pix [5] which used Conditional GANs. pix2pix also has multiple applications but one of the constraints is that pix2pix needs paired data. This is sometimes impossible or a really difficult task. For example in our case we would need images taken from the same exact location in 2 different seasons for our dataset. Some related work on image-to-image translation is also done by Nvidia using coupled GAN [3]. Concurrent to the work done in CycleGAN, Yi et al [6], published a paper on dual-GAN.

6.2 Single Image deraining

Single image deraining is a difficult problem to solve due to its ill-posed nature and unlike video based methods, images do not provide any temporal information. Traditionally it has been approached as considering an image y to be the sum of rain streak r and background image x

$$y = x + r$$

So most works try to decompose the image into a background image and rain streak image using various approaches. One of the earliest methods is sparse coding based [a] where image is decomposed using learned dictionary atoms that can sparsely represent two components clearly. Gaussian mixture models based priors [c] have also been used in image decomposition frameworks that can capture different orientations and scales of rain streaks. CNNs have also been employed to directly learn non linear mapping between synthesized images and ground truths successfully for image deraining [d] [e] [f].

Conditional GANs are also used to achieve de-raining [4]. The work in this, and other papers on de-raining, doesn't completely solve the problem as they only remove rain from the image but some aspects of the image still look the same as the sky will still look cloudy and the roads will look wet even after removing the rain. These models only work on monsoon to summer translations but not vice versa.

7 Conclusion & Future Work

We have employed the CycleGAN model for the purpose of translating images from summer to monsoon and vice-versa. We were successfully able to train the model to minimize the proposed loss function on our final dataset collected from various sources. We conducted a survey to see if users can identify fake images as real and achieved comparable results to the CycleGAN work. We also employed CycleGAN to derain the images as well as add rain to images and evaluated the results based on SSIM scores and compared to some of the previous works.

In future, we want to explore the model used in [3] that involves shared latent space and believe that it would give better results than our current model. In our model the generator loss did not converge but overall loss did and that is something we are keen on analyzing. The loss proposed in CycleGAN is weighted sum of different losses and we believe that these weights can be tuned to achieve even better results.

References

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