*Dehazing of Images using Dual Generative Adversarial Networks*

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***Abstract*—Images taken in unfavorable weather conditionsaffect systems that depend on image segmentation negatively. Our method to overcome this, especially in hazy or foggy conditions uses a Generative Adversarial Network that unlike conventional methods, does not estimate airlight or use a transmission map to get the clear or dehazed image from a haze containing image and is fast enough for real time deployment of dehazing frames in video feed with minimal to no artifact formation. We make use of a DualGAN[1] for our dehazing task, which is used for cross-domain image-to-image translation. We employ the DualGAN[1] to convert hazy images to dehazed images, and achieve satisfactory results in the process.**

***Keywords—Computer vision, Dehazing, GAN***

1. INTRODUCTION

There are two different types of haze that can occur in materials: Reflection haz**e** occurs when light is reflected from the surface of a material Transmission haze occurs when light passes through a material.

The light that passes through the transparent material can be affected by and scatter in different directions from the normal. In our project, we deal with negating the effect of scattering in images and traffic videos. Dehazing refers to the this task of removing haze from images and videos in order to improve quality.

The goal of using DualGAN[1] in dehazing is to get consistent dehazing results in outdoor conditions. The GAN is trained on synthetically generated haze images and their ground truth from the RESIDE [2] data set.

* 1. LITERATURE SURVEY

1. *Current Methods*

Current methods of single image dehazing estimate

airlight and use transmission maps or depth maps for dehazing and are physical models and not all are consistent and some lead to oversaturation and overexposure in some conditions.

Cai et. Al. [3] makes use of a deep CNN model to achieve the task of single image dehazing. DehazeNet takes a hazy image as input, and outputs its medium transmission map that is subsequently used to recover a haze-free image via atmospheric scattering model. DehazeNet adopts convolutional neural network-based deep architecture, whose layers are specially designed to embody the

established assumptions/priors in image dehazing. Specifically, layers of Max-out units are used for feature

extraction, which can generate almost all haze-relevant features. He et. Al. [4] makes use of a dark channel prior

based dehazing methodology. The dark channel prior is a kind of statistics of outdoor haze-free images. It is based on a key observation—most local patches in outdoor haze-free images contain some pixels whose intensity is very low in at least one color channel. Using this prior with the haze imaging model, the authors can directly estimate the thickness of the haze and recover a high-quality haze-free image.

Raj et. Al. [5] proposes a conditional GAN, that can directly remove haze from an image, without explicitly estimating transmission map or haze relevant features. The authors makes use of the pix2pix GAN, where the traditional U-Net generator network has been replaced with a Tiramisu network.



1. METHOD

*A. Pre-Processing*

We have developed a system for detecting if an image is hazy or not using horizontal variance and dominant color detection, with respect to road conditions before applying our dehazing method.

Another method of detection of hazy images we trialed is, the video is first split into frames, after which each frame of the video is classified as hazy or non-hazy according to the method described in Mao et. Al. [6].

Brightness, darkness and contrast matrices of the frames are considered to calculate the haze score of the respective frames. Brightness matrices are calculated by transferring the highest RGB channel value of a pixel to the corresponding black and white image. Darkness matrices are calculated by transferring the lowest RGB channel value of a pixel to the corresponding black and white image. Contrast matrices refer to the difference between the brightness matrix and darkness matrix of an image. The haze score obtained from the above calculations is used to classify an image as hazy or clear. A threshold value of 0.4 is set on the haze score. This means that, if an image has a haze score of less than 0.4, it is classified as hazy. If it is greater than 0.4, it is classified as clear.

*B. DualGAN[1] Model*

Given two sets of unlabeled and unpaired images sampled from domains U and V , respectively, the primal task of DualGAN[1] is to learn a generator GA : U → V that maps an image u ∈ U to an image v ∈ V , while the dual task is to train an inverse generator GB : V → U.

To realize this, the authors employ two GANs, the primal GAN and the dual GAN. The primal GAN learns the generator GA and a discriminator DA that discriminates between GA’s fake outputs and real members of domain V . Analogously, the dual GAN learns the generator GB and a discriminator DB.

As shown in Fig. 1, image u ∈ U is translated to domain V using GA. How well the translation GA(u, z) fits in V is evaluated by DA, where z is random noise, and so is z ′ that appears below. GA(u, z) is then translated back to domain U using GB, which outputs GB(GA(u, z), z′ ) as the reconstructed version of u. Similarly, v ∈ V is translated to U as GB(v, z′ ) and then reconstructed as GA(GB(v, z′ ), z). The discriminator DA is trained with v as positive samples and GA(u, z) as negative examples, whereas DB takes u as positive and GB(v, z′ ) as negative. Generators GA and GB are optimized to emulate “fake” outputs to blind the corresponding discriminators DA and DB, as well as to minimize the two reconstruction losses kGA(GB(v, z′ ), z)−vk and kGB(GA(u, z), z′ ) − uk.

*C. Dehazing Model*

We make use of a DualGAN, as described in Yil et. Al [1], to achieve the task of single image dehazing. The architecture of the model consists of two generator networks and two discriminator networks. Both the generators are identical in structure. In the original DualGAN paper, Fully Convolutional Networks with 8 convolutional layers and 8 deconvolutional layers were used as generator networks. In order to better suit the task of dehazing larger resolution images, an additional convolution and deconvolution layer were added.

The discriminators used in the original paper consisted of 5 convolutional layers. In the task of single image dehazing, we add an additional convolutional layer to the network to improve accuracy.

DualGAN is utilized for unpaired image to image translation between two domains. However, as the RESIDE OTS dataset that was utilized to train the model consists of pairs of ground truth and hazy images, it was optimal in our task, to perform paired image translation.

We have modified the DualGAN generative network to allow for more detail retention when dehazing images greater than 256 x 256 size.

We have trialed the modification of the loss functions based on the PSNR function and have trialed thresholding of loss to prevent the discriminator’s loss to reach zero which would stagnate learning of the model.

A screenshot of a cell phone

Description automatically generated

Fig. 1 : The DualGAN Model

To improve accuracy of the model we have modified the original model to train data in a pairwise flow of ground truth clear images and hazy images.

IV. RESULTS

*A.. Benchmarking*

Current methods of single image dehazing estimate airlight and use transmission maps or depth maps for dehazing and are physical models and not all are consistent and some lead to oversaturation and overexposure in some conditions.

Two key metrics are used to indicate the quality of dehazing, PSNR and SSIM. PSNR refers to Peak Signal to Noise Ratio. It is calculated as,

PSNR = 10 \*

= 20 \*

= 20 \*

A higher PSNR value indicates that the amount of noise present in the dehazed image is low, which is optimal in the case of dehazing.

SSIM refers to Structural Similarity. It is based on the percieved change in the structural information between the ground truth image and the dehazed image. It is calculated as,

Higher value of SSIM indicates better quality of dehazing.

B. *Comparison*

*A picture containing photo, window, indoor, building

Description automatically generated*

We compared our model with other state of the art models, and were able to achieve reasonable results, as can be seen above. As can be seen above, our model works well in estimating the colours of the pixels in the image, and does not oversaturate the colours.

*A screenshot of a cell phone

Description automatically generated*

The table above showcases the average PSNR and SSIM scores of various models on our test images.

1. CONCLUSION

We introduce a novel approach to image and video dehazing which utilizes DualGAN model.

Dehazing results have a high structural similarity of 0.854 and PSNR of 23.782, which is on par with the deep learning methods that have been utilized for this purpose in recent times. Our model works well for images with light or intermediate haze score. However, for images with dense haze, it does not work optimally. Additionally, in some cases, the model tends to add blur to the dehazed result. We look to work upon these aspects in the future.

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