Image De-hazing using Generative Adversarial Network

A DISSERTATION

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Submitted by:

MADHAV KAPOOR

2K17/SPD/06

Under the supervision of

PROF. S. INDU

DEPARTMENT OF ELECTRONICS AND COMMUNICATION
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi College of Engineering)
Bawana Road, Delhi-110042

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CANDIDATE'S DECLARATION

I, Madhav Kapoor, 2K17/SPD/06, of M.Tech hereby declare that the project Dissertation Titled "Image De-hazing using Generative Adversarial Network" which is submitted by me to the Department of Electronics and Communication, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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I hereby certify that the Project Dissertation titled "Image De-hazing using Generative Adversarial Network" which is submitted by Madhav Kapoor, Roll No 2K17/SPD/06, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: Delhi

Date:

PROF. S. INDU

Head of Department

Department of Electronics and communication

Delhi Technological University, Delhi

SUPERVISOR

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………………………
MADHAV KAPOOR

ABSTRACT – IMAGE DE-HAZING USING GENERATIVE ADVERSARIAL NETWORK

Image de-hazing is the phenomena in which images captured in hazy or mist weather conditions is degraded by scattering of atmospheric particles in the environment, which reduces the disparity, changes the color of an image, and makes the object features tough to identify by humans being's vision and by almost some outdoor computer vision systems. Therefore, image de-hazing is a very crucial and an important issue and has been widely researched by many of researchers in the field of computer vision. The purpose of image de-hazing is to eradicate the influence of weather conditions and factors that are affecting the image in order to improve the visual effects of an image. Image de-hazing is a challenging problem in today's time as haze removal or de-hazing of an image is highly required in many applications like computational photography, face recognition, saliency detection, etc.

In this thesis, we study the image de-hazing using self-attention based Progressive Generative Adversarial Network (PAGN) which consists of residual encoder-decoder network and a Self-attention based progressive Generative network in a cascaded form to perform the de-noising and de-hazing of the image to give better results. Following illustrative points are made to describe the thesis in a nutshell which will later to be discussed in detail.

Firstly, we pass the noisy de-hazed image to Residual encoder decoder network which is a fully convolutional network consisting of the encoder section and the decoder section along with use of skip connections for removing the noise from the hazy image.

Now, the de-noised image is passed through Self-attention based Progressive Generative Adversarial Network consisting of a generator network and a discriminator network.

The generator architecture is inspired by UNet having the typical architecture of a convolutional network which consists of a contracting path and an expansive path used for down-sampling and up-sampling respectively.

Further, the generator network is trained progressively to increase the pace of training and proper generalization of features the network is trained using two

losses, the VGG-16 based content loss and secondly, hinge adversarial loss from the critic.

(v)

The discriminator network is a simple convolutional neural network consisting of five convolution layers. We have used various techniques like spectral normalization, dropout, leaky ReLU, self-attention mechanism, Adam optimizer for getting visually pleasing results.

In a nutshell, this project has used various different architectures to generate best results possible. These adopted criteria significantly contributed to show perceptual results on noisy de-hazed images.

To describe it briefly the project consists of following five subsections-

1. Residual encoder decoder network

2. Self-attention based Progressive Generative Adversarial Network

3. Spectral Normalization

4. Two Time Update Rule

5. Progressive Growing of Input Channel

CONTENTS

LIST OF FIGURES

LIST OF SYMBOLS & ABBREVIATIONS

1 – Wide-Angle Scattering (WAS)

2 – Narrow-Angle Scattering (NAS)

3 - Line of Sight (LOS)

4 – Adaptive Histogram Equalization (AHE)

5 – Markov Random Fields (MRF)

6 – Artificial Neural Networks (ANN)

7 - Convolutional Neural Networks (CNN)

8 – Rectified Linear Unit (ReLU)

9 – Bilateral Rectified Linear Unit (BReLU)

10 – Multi-Scale Convolutional Neural Networks (MSCNN)

11 – All-in-One De-hazing Network (AOD-Net)

12 – Region Convolutional Neural Networks (RCNN)

13 – White Balance (WB)

14 – Contrast Enhancing (CE)

15 – Gamma Correction (GC)

16 – Gated Fusion Network (GFN)

17 – Generative Adversarial Network (GAN)

18 – Residual Encoder-Decoder Network (REDNet)

19 – Self-attention based Progressive-Generative Adversarial Network (SP-GAN)

20 – Inception Score (IS)

21 – Frechet Inception Distance (FID)

22 – Two Time-scale Update Rule (TTUR)

Madhavthesis

by Madhav Madhav

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CHAPTER 1: INTRODUCTION – IMAGE DE-HAZING USING GENERATIVE ADVERSARIAL NETWORK

Nowadays, we see so many atmospheric changes in our surroundings. The most common phenomena we observe is the “haze”. The haze refers to the natural atmospheric phenomena in which the amount of visibility to the high sky is obscured by dust, mist, smoke and other tiny particles. Also, the department of meteorology have classified the darkness pervading in all directions into multiple categories such as fog, fog with steam, small mist particles, haze effect, smoke particles mixed with the air, ash coming out from volcanoes, dust particles, sand, snow etc. Also, the farming when done in moist weather, increasing traffic, pollution from many industries and wildfires are the main sources for haze particles. Also, to highlight here, the major causes stopping the ongoing developments is certainly because of unfeasibility to clear if the de-hazing action of an algorithm is because of the lack of presence of reference images which are haze-free. To record both the images with similar scene illumination is one of the main problem in accumulating the images which have hazy and haze-free effects both.

When we see some objects from a far distance (e.g. an aircraft coming towards us) , then considering the direction in which it will fly in reference to sun, we could observe the haze to appear dark (brownish/bluish), however the mist to appear a little bluish grey. We can also define haze as a phenomena having less moist air whilst the formation of mist to be a phenomena of less moist air. We can also sum up the subsequent formation of mist droplets as a result of many particles of haze undergoing condensation. These different haze types are called "wet haze." When the air has pollution in large amount, it could result in haze too. In meteorological history, the moist aerosols which hamper the visibility can also be denoted as “haze” and the complex chemical reactions lead to generation of such aerosols. The existence of sunlight, large amount of humidity and constant flow of air enhances haze. Many trees such as terpenes lead to generation of very less components of aerosols of the wet-type. Due to mentioned reasons, wet type of haze is referred as an amiable-season phenomena. Under the favorable conditions during summers, the haze can be produced over large areas covering large distances.

When the small floating particles leading to reduction in the clarity of far objects because of scattering of light along with attenuation, it leads to haze which leads to the dropping of the contrast of far away objects. It also leads to images with noise being added to them. The challenging issue which has grabbed much attention and concern in the past years is image de-hazing.

The two types for haze which are found inside the different matters/materials are:

- Reflection haze - it happens when the surface of a material reflects the light
- Transmission haze - it happens when material allows the light to pass through it

To ensure an optimum quality, acceptability or suitability for the product-purpose, the quantification and restriction for both haze types in the manufacture has much importance. For instance, in automotive manufacturing, with low reflection haze and high contrast, a high quality reflective appearance is desirable. While in packaging, for the contents and foods etc to be clearly observed, the clear-low haze and highly transmittable films can fulfill the requirement.

1.1 REFLECTION HAZE

The phenomenon which can optically get directed and linked to the glossy surface is called Reflection Haze which can affect the quality of the appearance. Due to several surface imperfections because of presence of microscopic textures matching wavelength ≈ 0.01 mm, the reflection can result in a milky/hazy appearance which lowers the overall quality appearance. Also, the reflection produced from any ideal glossy surface needs to be visible and vibrant.

This type of haze can be because of many pointers –

- The dispersion could be poor
- Methods used to apply the new coats/layers
- Variations produced in several processes like drying, baking or curing
- Different materials that are used for formulation
- Abrasion and polishing

The estimation of reflection bases haze nowadays is restricted to high amount of glossy paints, coatings and metals which are polished many times. The measurement method for films is little successful, however we cannot completely depend on it because of variation caused due to varying thickness of the film and the variations in refractions and the color in background needs to be selected with caution as the sample of the film has to be placed on it.

1.2 TRANSMISSION HAZE

The following interactions occur when the surface of transparent material is striked by light-

- The front surface of the material reflects the falling light on it
- For some materials (thickness-based), the light gets refracted inside and gets reflected back from the other surface
- When the incidence of light is at some angle (that can be calculated with help of material's refractive index and illumination angle).

Such irregularities within the material affects the amount of light which passes through transparent material. These involve the particles which are dispersed poorly, impurities such as particles of dust and the spaces of air. Due to its presence, light gets scattered in various directions wrt normal and its inclination/intensity depends on the number or size of the present irregularities. Light tends to get scattered and spread in various directions due to the small irregularities. However, the light gets scattered in the forward direction in a narrow cone shape due to the large particles. These scattering-type behaviors can be called Wide-Angle Scattering (WAS) leading to the haze which occurs because of the contrast loss in transmission. Also, the Narrow-Angle Scattering (NAS) is a way to measure the clarity/"see through quality" of the materialistic objects based on the variation in sharp effect.

Thus, the below mentioned factors prove useful and are required for classifying various forwarding/allowing properties for any clear material-

- Transmission –the material which allows the light to pass through it without getting it dispersed/deviated
- Haze – light categorized under the Wide-Angle Scattering passing with angle measure more than 2.5° wrt normal
- Clarity – light which refers to Narrow-Area Scattering passing with angle measure less than 2.5° wrt normal

So, image de-hazing is the phenomena in which sample images getting clicked in blurry or mist conditions of weather is lowered in quality due to the particles in the atmosphere which are scattered that cause many problems like lowering the disparity, changing the color of an image and making the object features tough to identify by normal vision. Therefore, image de-hazing is a very important issue and is being widely researched by many researchers in field of computer vision.

The main reason for the de-hazing of image is the removal of influenced conditions of weather. Also, the different factors due to which many visual effects an image can have can be improved. Since the haze removal/de-hazing of an image is mandatorily required in applications like computational photography, face recognition, etc., de-hazing of image poses a challenging issue in today's era.

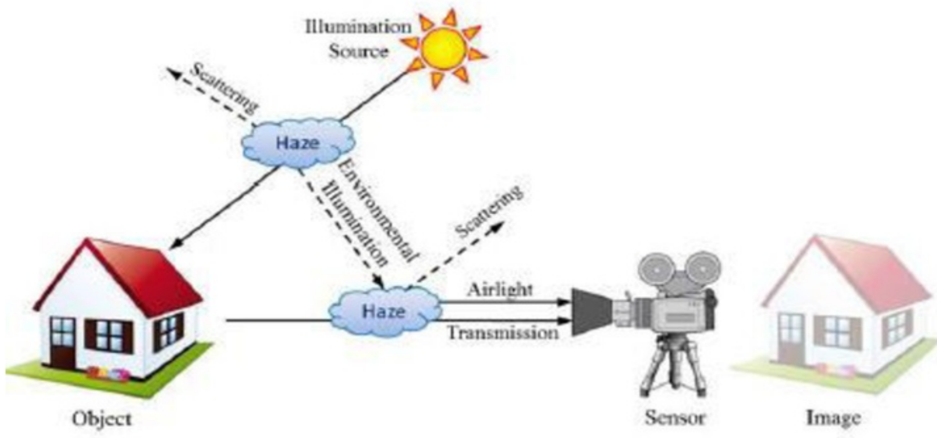

Fig1: Imaging in hazy weather conditions

Because of availability of multiple particulates and droplets of water in environment, the images of the indoor and outdoor scenes get degraded. There are multiple atmospheric phenomenon's leading to absorption in atmosphere along with scattering such as haze, fog, smoke, etc exist. While capturing one scene in the camera in a terrible condition of weather, the irradiance camera could receive from observation point is lost following the LOS. Depending on varying distance between observation points and the camera, the amount of light gets highly scattered. Due to this, the contrast varies and image that has been captured gets degraded.

Due to haze present, the image degradation (atmospheric scattering model as represented in figure 2) is calculated below:

$$I(z) = J(z).t(z) + A(z).(1 - t(z)) \quad (1.1)$$

Here 'I' - hazy image observed, 'J' – radiance of true scene, 'A' – light which indicates intensity of bright light in atmosphere, 't' - transmission map and 'z' – location of pixel. Here, the transmission-map is one of factors which depend on distance and alters the light fraction that can reach to sensor of the camera.

(4)

When homogeneity is observed in light passing in random directions marked as ‘A’, the expression for transmission-map is:

$$t(z) = \exp(-b.d(z)) \quad (1.2)$$

Here ‘b’ - attenuation coefficient in atmosphere, ‘d’ – depth of the scene. The main purpose is to calculate J, when I is given.

We observe from equation 1.1 that here exists the important features in process of de-hazing:

(1) Estimating the accuracy for transmission-map

(2) Estimating the accuracy for light in atmospheric

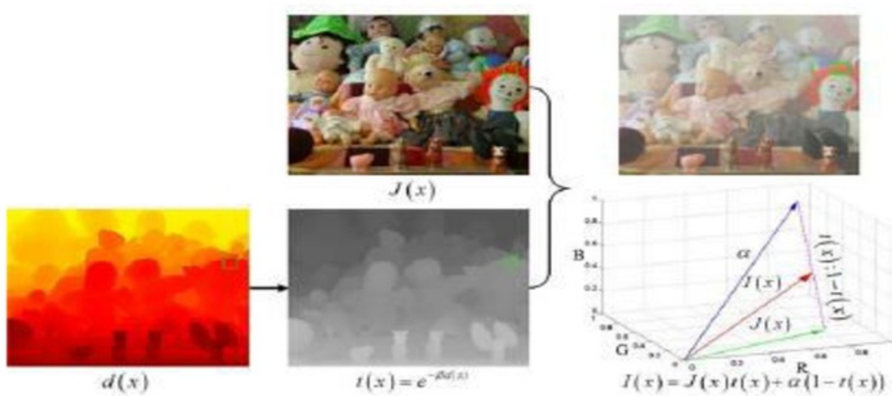

Fig 2: Atmospheric Scattering Model

There are several tasks which focus on calculating the amount of atmospheric light. Many algorithms lay their pointers for estimating accuracy of transmission-map and using the actual rule/method in calculating light present in atmosphere. The main reason here is for good and fairly estimating the transmission-map which results in improved de-hazing. As soon as transmission-map and light in atmosphere get estimated, we can recover the de-hazed as shown below:

$$\hat{J}(z) = [I(z) - \hat{A}(z).(1 - \hat{t}(z))] / \hat{t}(z) \quad (1.3)$$

(5)

So far many improvements are being made using different ways, there are still many factors which obstruct the performance of these methods and the results are not close to optimal solution. This is due to:

1. Deviation in the accuracy level in estimating the transmission-map which converts to de-hazed result having low quality.

2. Previously described methods are not efficient to capture the relation between the transmission-map, the light in atmosphere and de-hazed image. Due to this, the disintegrated optimization may hamper the total performance for de-hazing.

So, to understand the de-hazing better, we will look into the next chapters in detail.

(6)

CHAPTER 2: LITERATURE SURVEY OF IMAGE DE-HAZING

2.1 IMAGE DE-HAZING USING BASIC OPERATIONS

During the past times, the fast approach was used to eliminate the haziness if any fast semi-inverse image approach[1] had wherein by applying one operation per pixel on real and original image, it can generate a 'semi-inverse' for its same real-image. It becomes easy to identify misty/shady areas based on per-pixel estimation and also depends on hue difference between original and semi-inverse images. It also proves useful in simple and clear evaluation of air light constant along with the transmission-map for an image. Due to this, the parallelization becomes suitable and the sharp details near the edges are also retained. Nowadays, the contrast enhancement methods are highly used in image processing field. The most commonly used automatic procedures is 'histogram equalization'. When the contrast characteristics for an image differs even in a limited proportion, this procedure is not effective. Adaptive Histogram Equalization proves useful by generating the suitable translation for each and every pixel of an image generated from output-histogram present in the nearby window.

Adaptive Histogram Equalization does not permit the image's degree of contrast enhancement to be varied or monitored. In many applications, the extent to which the character or text of the image is changed is not desirable. So, by using contrast enhancement system of an image using spatially adaptive histogram equalization along with temporal filtering [2], it allows us to propose a contrast enhancement system for images which can be collected in a definite order and help in improvising local-contrast for the image. The histogram-equalization allows us to attain a uniform and stable histogram for the output image. The technique called 'histogram modification' can be stated as - image improvement technique which adjusts the highly variable range of pixel-values resulting in vision-based information which can be communicated to all the viewers and the method called non-overlapped block adjustable technique depending on values and features of pixel-intensities in the surroundings is also used.

The main disadvantage for this histogram-equalization method is loss of randomly distributed pixel-intensity values because of the global pre-evaluation on given image. Also, the histogram remodeling technique do not prove easy to perform in the real-time scenarios because of high amount of requirements for computation and storage. However, in the parallel manner, the way in which non-overlapping block adjusting technique is to resulting in restricting the fact at the risk of savings in computation and memory capacity. Thus, it becomes the requirement to restrict it in real time applications. Adaptive image contrast enhancement of an image using generalizations of histogram equalization [3] allows us to propose a precise and accurate mathematical description of Adaptive Histogram Equalization which allows to display that - the output framework could be widely used to obtain a large variation of contrast improvement effects for an image using the Histogram Equalization.

(7)

This can be achieved by mentioning the alternative forms of a given function called as the cumulative function. This cumulative function can be defined in terms of two parameters, both of them having a simple interpretation. But the above steps which involve the preprocessing techniques is applicable and help in producing the de-hazing results for single images only. De-hazing of images using the technique called Polarization[4] allows us to remove the hazy effects from images easily. It also depends on the light air dispersed by particles in the atmosphere which gets partially altered. To remove the haze effects, polarization filtering alone cannot help. The mentioned method is useful for a range of varying atmospheric conditions. When we consider the effects on atmospheric-scattering due to polarization, we can analyze these image formation process. This process can be inverted where in the haze can be removed from the images. Thus, this method is applied to few images eg: two images captured through polarizer at specific angles. In this way, this can instantly work without depending on alterations in climatic conditions. Considering the by-products, this method obtains a range-map for the scene and related information including the characteristics of particles in atmosphere. It is dependent on peculiar sources of radiation and hardware which include detection feature.

This paper focuses on the approach which do not need changes in the climatic conditions to be made and can be applied instantly. The scattering properties vary with wavelength and depends on inspecting images captured using a polarizer. The filtering using polarization is widely used for photography including hazy-effect. However, optical filtering is adequate on days without haze using weak-light scattering commonly due to molecules of air, when sun is aligned with an inclination of 90 degrees to the direction of viewing. These situations also help the photographers to set an orientation for the polarization filter which can improve the image contrast in best manner. Here, we have focused on the image formation process considering the effects of polarization of hazy atmospheric scattering. This process can also be used to retrieve all the de-hazed scenes which helps in obtaining details about scene structure and different properties of atmosphere.

This approach do not require altering of the randomly scattered particles' size or related precise mechanisms. It focuses on the very basic principle where the image has two components to be estimated – radiance of the scene in haze absence and air light ie., the ambient light propagating towards observer. To find these components, the need is for two individual images. These two images can be obtained easily because air light is moderately polarized. This method requires the air light to produce some identifiable incomplete polarization. Also, the level for the removal of hazy-effects in a real-scene situation which can be demonstrated when high level of optical filtering ie., without using our algorithm is ineffective. In general, the analysis of polarization filtered images was useful for computer vision. However, the filtering in polarization solely was ineffective in removing the haze-effect of images. The efficiency of polarization acting as an aid to eradicate the effects of weather is restricted to mist and fog as the scattered light particles are majorly depolarized. The major drawback of this method is that it can't be used for dynamic/moving scenes to which alterations have been made than the filter-rotation to find the extreme levels of polarization.

(8)

Using Contrast-Restoration of Weather Degraded Images[5], it uses such a method where the contrast of a particular scene can be restored from those images captured into similar unfavorable atmospheric conditions. This also helps to present a single-color scattering model in atmosphere which elaborates in which ways the intensities of an image scene get changed by homogeneous air conditions. It can be used for clear, close to-IR spectra and for broad scope of air conditions like fog, haze, aerosols and mist. The advantage of this process is that it do not depend on requirement of the atmosphere's scattering properties which need to be fixed wrt light's wavelength for a wide spectrum scope. It can also be assumed that climatic conditions tend not to change in the field of view based on space, when we consider short range of distances. We also focus on how a scene's contrast can get degraded varying with distance using the monochrome weather model.

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The conclusion can be derived here is that at a fixed distance from the sensor, the conventional contrast improvement manner could manage a region within one scene only. It also includes an easy and quick contrast reinstatement technique which works much alike contrast expanding used for those scenes where in depth partitioning is called "priori". To view the strong physical constraints related to the scene structure, the variations in intensities of particular scene can be reviewed under the changing climatic conditions. To detect the depth obstructions in a scene on its own and to retrieve back the entire scene-structure captured from those two images which have been clicked under separate conditions of weather during day-time, these constraints are used. With the help of computed structure, the contrast could be recaptured back from single weather-distorted image of one scene. Here, there is no requirement for the accurate prediction of the weather information. The algorithms can be extended to handle video and can be used to picturize a simple formula to recover the counter-image of mobile objects present in same scene with undefined depth parameters. Also, these ways could be applicable individually to many images having multiple spectral-bands also.

These modes could also be applicable to the images captured using cameras which have gray-scale, greater-ranged RGB, multi-spectral with narrow-ranged IR. Here, entire analyzation has been performed for single-color and single narrow-spectral ranged images only. But with Deep Photo using Model-Based Photograph Enhancement[6], a tool for manipulating, browsing and enhancing the casual outside photographs, it already exists by highlighting the georeferenced digital ground and recent models. It also includes an easy communicative registration method which includes a way to align the photograph that gets fits into that model. Also, once registration for the photograph and/or its model is done, the information having many parameters like GIS data, texture and depth is then instantly made available for the system. These specifications then help in enabling multiple functions ranging from de-hazing and highlighting photographs to review the mixture and overlapping with geographic details. This approach also includes the available 3D models helping in adding the depth to photographs. As a result, a new model-based image execution method is obtained which allows to broaden the field-view and perform the higher-quality of synthesis view.

(9)

In this approach, there has also been described how to implement many of such applications as well as elaborate its feasible extensions. The outcomes definitely explain the additional photographs possessing available 3D-models in the world help in implementing a variety of many recent ways to deal with day-to-day snap-shots. The main point to be noted here is that the procedures which we deploy are quite detailed, but still there are less chances of achieving a high level of preciseness and the accuracy of detailing that is required to make use of these processes to generate photographic and effective images directly. Hence, the main challenge here in is to make one understand how to grasp 3D details provided at its best level by using these procedures, while retaining photographic quality levels of source image at the same time. Visibility in Bad Weather from a Single Image using Markov Random Field [7], it becomes an easy removal of haze as well as improve clarity for a single image in bad weather conditions. The process includes multiple steps which need to be followed.

When we are provided input/source image, the first step is to estimate amount of atmospheric-light with the help of which the light chromaticity could be calculated. Using the chromaticity of light, the lightest color of input image is removed. In next step, we calculate two costs: data and smoothness costs for each pixel. Firstly, data cost can be calculated by measuring contrast using an image with a cropped small patch, while smoothness cost can be measured by calculating the difference/distance between neighboring pixels' labels. Also, ensuring that labels match to their corresponding air-light measures. These two costs: data and smoothness sum total to fulfill the MRFs that could be later increased using the already-in-use conclusive methods which also help in estimation of values of the air-light. Later, depending on the estimated values of air-light, the direct attenuation is finally computed which represents the scene with improved visibility. The main focus is on increasing the input image's contrast resulting in improved level of image visibility.

The basic two observations from this method are:

1) image having increased clarity, also could be termed as - clear-day images always possess a high contras value than the image which is affected by foul weather

2) light-air values whose changing behavior varies with the distance between objects and observer which requires to be clear and smooth.

Depending on these above mentioned observations, a cost-bases function in the entire proposal of Markov random fields (MRFs) is developed which in turn proves its efficiency in implementing different processes and techniques like as belief propagation or graph-cuts. This mode is used for both – gray and colored images. In this paper, the intention is not to completely retrieve scene's natural and original colors/albedo. Instead, the MRF model could be used in future to improvise outputs. This way could greatly help us to obtain the particulars and forms from images which have haze-effect.

(10)

It is observed that the final images supposed to possess greater bearing levels because this mode aims on modification and clarity solely and do not focus on recovering the scene radiance physically. Also the result might consist of halo-effects in deep distortions nearby.

2.2 IMAGE DEHAZING USING LOCAL PATCH BASED PRIORITY

Single Image Haze Removal Using Dark Channel Prior [8] is way to present the stats of images with no haze captured in outside environments.. It mainly depends on a single and important observation — many small patches in output images not having haze consist of few pixels which have low power for at the max single color's channel. By implanting this method with imaging-model, haze's thickness could be calculated straightly and image free from haze could be easily recaptured. There are multiple results for varying effects on hazy- images which highlights importance for this priori. Also, it is observed that during the process of haze removal, depth map having a fair quality of values could be also generated as side-product as explained in the figure 3.

Since above mentioned feature is proposed to eradicate the space-based steady haze when there is fluctuation in the value of depth of the image. This method proves useful only when there is requirement to clear thin hazy-film referencing to nearby articles. The improvement in the quality of the image should be based on space varying when parameter of depth is not constant. These models prove less worthy when they are not able to estimate the extent to which the contrast could be improvised, such that the far-away materialistic objects could not recover in their initial state. Also, concerned for their foundation, it do not depend on haze-dependent imaging modes, they could not provide possible way to estimate depth-based map. The unilluminated channel priori method is not completely attracted by the famous "dark-object subtraction technique" which is most commonly deployed in multi-spectral remote sensors. The space-dependent uniform-haze can be cleared by eliminating fixed amount mapped to most dark object in image-scene.

The less illuminated channels usually have low intensities mainly because of the below mentioned factors:

1) shadow e.g., shadows of inside of windows in city-scape images, buildings, cars or shadow of rocks, trees and leaves in images having some landscape regions.

b) colored objects/surfaces e.g., an object having less disinclination towards any specific color-channel eg., grass/plants (green), flowers/leaves (red or yellow) and water (blue) could lead to lower measured values in less-illuminated channels.

(11)

c) unilluminated objects/surfaces e.g., tree-trunks or stones (dark-colored). Also, as natural outspace images are full of colors and shadows, less-lighted channels of corresponding images tend to be also less-lighted simultaneously.

The less-illuminated channel priori method depends on fact based on out-spaced images free from haze. In few light patched images, there is minimum one colored channel which possess few pixels whose color-depth is very less and approaches to 0. On other hand, the low-level intensity in similar patched image approaches to 0. As mentioned method depends on haze imaging model, this method can sometimes prove itself wrong or failed when it itself proves wrong. So, different techniques are applied on the hazy images to improvise the efficiency of less-lighted channel priori-based method. In a finding of de-hazing effects for image makes the de-hazing effects for image and video recording for surveillance systems effective.

Here, aim is – achieving fair and good quality de-hazed images & videos on receiver's end and maintaining low-valued bit rates using compression in transmission pipes. At initial stage, this method offers an informal method for one-image de-hazing that could be helping hand for investigation. It functions at higher speed compared to current ways and could help in avoiding halo-effects incorporating the median-operation.

(a) (b) (c)

Fig 3: (a) Input-hazy image (b) Image-after-haze removal (c) Recovered depth-map

(12)

Later, we can examine effects of de-hazing in contraction just like in An Investigation of Dehazing Effects on Image [9] de-hazing ways during the course of contraction. The point where the focus lags is on quantification of performance for a space-based adaptive process when compression is applied before or after the enhancement. Thus, investigation will be done in next chapters detailing about the previously highlighted issues. It can be also over-blown by transformation-domain alterations particularly discrete cosine transform-dependent contractions. We can conclude here that better de-hazing activity with limited count of theories and effective efficiency for coding can be executed when we apply de-hazing effect before contractions.

Also a novel type of explicit image filter - guided filter [10] was previously used to reduce the time consumption. The guided-filter produces outputs for filtering by keeping in mind details of reference images which could act as input images themselves or some other different images derived from local linear model. The well-designed filters can act as marginalized operations for smoothening effect just like famous bilateral-filters , but possess more thorough behavior around the margins. It also links up with Laplacian-matrix , resulting in more generalized concepts rather than smoothening operators and could help in utilizing matrices in the assisting images. Moreover, the guided–filters have quick & non-approximative linear-time based algorithms whose evaluation-based complications are not dependent on kernel size filtering.

2.3 IMAGE DEHAZING USING NON-LOCAL PATCH BASED PRIORITY

Now using non local patch based prior algorithm for image de-hazing[11] , it depends on presumption that colors applied in haze-free images could be approximated effectively by limited specific colored particles that create packed clusters suspended in RGB spatial region. The main inspection is the pixels in provided group are mostly ordinary i.e., it is widely distributed all over the plane of image and placed at changing displacements to camera. In haze's presence, these changing displacements get translated into the altering transmissive - coefficients. Haze do not depend on the scene's brightness while has dual effects on captured image. It diminishes each light-signal of scenes seen by the humans and it brings into focus an extra part for image knows as "ambient light"/air-light (scene's colors captured at infinite points). Reduction in characteristics of image is originated by haze which gets increased when there gap from camera increments. The scene's radiance decrements and magnitude of the air-light rises up, so hazy-images could be showcased as single-pixel converging combination of haze-free images and air-light. As a result, every color's cluster present in clean image output results in forming straight lines in RGB space-based regions which is denoted as "haze-line".

(13)

Using above hazy-lines, this main algorithm can recover dual requirements: distance map & haze-free images. The process behaves in a straight manner wherein image's size is determined without any training. The target is - to retrieve back RGB parameters and its values of haze-free images & transmission ie,. coefficient of the converging mixture for each & every pixel. Here, the observations are used which states that colors emitted from haze-free images could be effectively roughly measured with using some distinct color shades. It also means that pixels present in any full-haze image could be represented by RGB-lines in space which passes through air-light vertices. These RGB-lines are termed as "haze-lines" to lay emphasis on this feature (Fig. 4, 5). Pixels aligned with haze-lines originate from the objects which tend to have similar radiant- colors placed in entire plane of images. Those objects get fixed at varying locations from camera. Since acquired colors could be changed by a converging combination for radiant colors & air-light's color, those objects will sketch straight lines in RGB-based space. We bring into life those lines in order to give an idea about each-per-pixel transmission value depending on pixel's inclination along line it matches to.

The algorithm is categorized into four necessary points:

1) Requirement of pixels to be together clustered into haze-lines

2) Initial transmission–map to be suggested and quantified

3) Standardization

4) De-hazing

This method is common, useful and do not segregate image into patches. However, the patch-dependent procedures require much care to ignore theories and facts either by working with multiple sized patches[19] or highlighting on the patch - overlapping & standardization effect by bringing into working the connection-networks between far away particles . Here in, pixels which create hazy-lines are distributed randomly all over complete images & hence captures a broad-level phenomenon just not only restricted to small-patched images. Thus this priori method is highly efficient & time-effective significantly. Through this method, an efficient algorithm is proposed which is linear along with the image's size. It detects the hazy-lines & later uses to de-haze the images on its own.

(14)

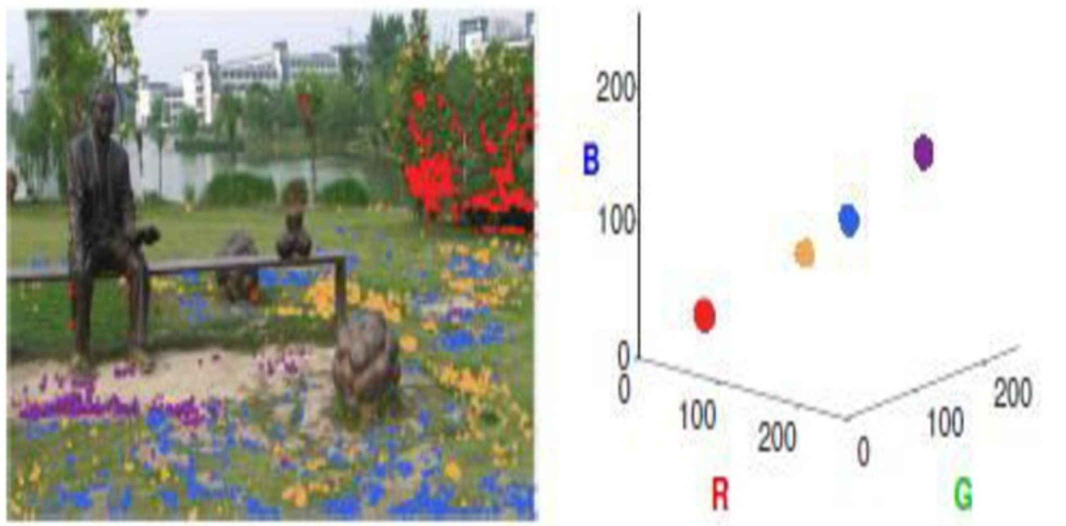

Fig 4: (a) Haze-free image (b) Corresponding clusters

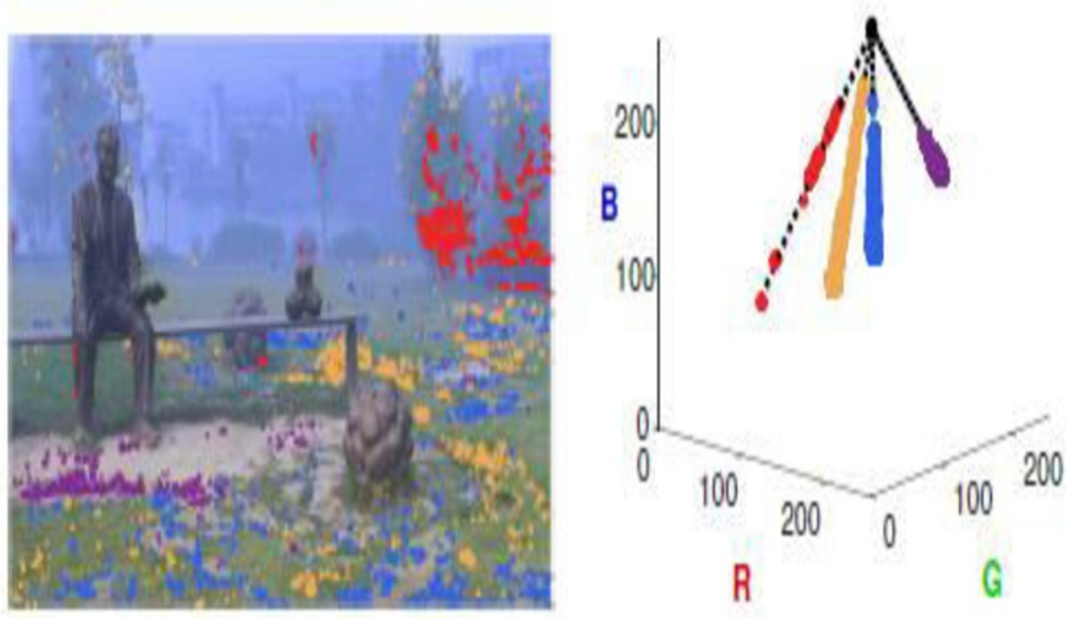

Fig 5: (a) Synthetic hazy image (b) Corresponding haze-lines

(15)

2.4 IMAGE DEHAZING USING LEARNING BASED METHODS

Nowadays, the neural–structure dependent deep-learning methodologies are very widely and frequently used in various applications. Basically, a neural network takes in the required number of inputs which are then processed in the hidden layers using the weights that are adjusted during the training process and depending on the type of learning whether supervised or unsupervised followed by the model that gives out a prediction. The weights are then adjusted to determine the patterns in order to make better and accurate predictions. Here, using the deep learning framework, there is no requirement for the user to mention or explain what different patterns to look for— the neural network determines and learns on its own. The various kinds of different neural network architectures like Artificial Neural Networks (ANN), Convolutional Neural Network (CNN), etc are used for different applications in computer background, language evaluations etc. For image de-hazing, the neural-networks called Convolutional Neural Network (CNN) are used which comprises of one input & output layer, also having many unrevealed layers.

The concealed films of CNN consists of convolutional -layers, RELU layers i.e., fully-connected, normalization, activating-functions & pooling layers. Researchers have been motivated by the achievements of Convolutional Neural Network into various computer-based visions. It had also helped them to discover their capacity to grasp non-linear translation directly between input-hazed images and its supporting transmissive-maps. Throughout, the CNN-network was proposed called De-hazeNet[12] for providing an estimate to generate transmission-maps when input-based hazy-images are given. De-hazeNet captures hazy-image as source input & generates a transmissive-maps as its output which is afterwards called in to retrieve haze-free images by applying atmosphere-based scattering models. De-hazeNet applies the Convolutional Neural Networks (CNN) dependent deep-architectures for whose layered based architecture is especially designated to include the settled presumptions/priori in image's de-hazing.

Particularly, layers for Max-out sections are deployed for feature's output from which all hazy-related features could be generated. The approach as well as proposes an ideal non-linear activating function into De-haze Net, termed Bilateral Rectified Linear Unit (BReLU) helping to improvise quality for the retraced-back hazy-free images. It also establishes the connectivity within several parts of suggested De-hazeNet.

The chief benefactions have been notified below:

a) De-hazeNet is throughout system. It retains and calculates mapping translations between hazy-patched images & its medium transmission-values. This could be executed by sepcific designing of deeply-explained architectures to include the well-entrenched images de-hazing guidelines.

(16)

b) This method also proposes a novel non-linear activating - functions in De-hazeNet, termed Bilateral Rectified Linear Unit (BReLU). BReLU extensify the Rectified Linear Unit (ReLU) & describes its worthiness in producing the correct image's restoration back. Properly, BReLU makes into use bilateral restraints to decrement search - space and improves concoursement.

c) It also includes the feature to set-up connectivity between the parts of De-hazeNet & those presumptions/priori already used de-hazing mechanisms and elaborates that De-hazeNet can help in improving on mentioned mechanisms by auto-driving it to learn these sections throughout.

In this approach, atmospheric - light could not be judged as a comprehensive constant we can learn along with support - transmission in collective structure. Also, it is understood that the atmospheric - scattering models could be understood with the help of neural - networks where though out translations for haze & hazy-free images could be finished without dependency on the medium's transmission directly. Using Multi-Scale Convolutional Neural Networks (MSCNN)[13], we can use a proposed way where the multiple-scaling deep-neural networks helps us learning the plotting for hazy images & their matching transmissive - maps. Experiment was conducted wherein the researchers initially deployed fine-scalar networks to roughly guess a integrated transmission-map, in next stage, the refinement of a fine-scale network is used in generating maps with more detailing. Recently, CNN models are being widely deployed for understanding hazy-related priori but basically works as net-level image-filters.

To overcome these challenges, Semantic Single-Image De-hazing[14] is used which emphasized on issue of color's warpness in previous CNN-based presentations by arranging a multiple-staged CNN. In 1st stage, its network mixes the color's information available in hazy-images & obtains the multiple-channel in depth-maps whilst 2nd stage helps to give an estimation about the scene's transmission- map using a multiple-channel's multiple scaled CNN. Here this paper proposes a symbolic approach directing towards haze-effect removal from single image. Comparing to existing theories, it prefers the color-priori & its basis lying on gathered semantic characteristics. The point of argument here is that the rhetoric context could be over-used to provide helpful clues for (1) quantifying an ambient lighting, (2) absorbing color priori on clear and detailed image. This outline also permitted this structure to retrieve back the cleared images with large errors and mismatch, e.g., the saturated lighting color & sky-shaded regions in images. Here, also have introduced a semantic approach towards single image de-hazing. We are the first to explicitly exploit the semantic features for learning semantic priors which are used to provide informative priors for producing and generating underlying clean scene.

(17)

Here, we focus at how we can achieve the commendable performance for synthetic hazy-effect images & our model proves in accurately recovering all the clean scenes under strong estimation ambiguity, e.g. strong haze and semi-saturated ambient illumination with learned semantic priors. Our dataset contains only indoor scenes and outdoor road scenes which point that a lag for semantics of general real world objects as well as their corresponding real colors is because of the difficulty this method faces in acquiring real world training data. Hence, it becomes challenging to learn and identify the semantic-color priori for natural world outdoor structures that do not have visibility during the tutoring which means the model can generalize well to natural outdoor scenes unless the relevant datasets are made available. Mentioned methodologies consider transmission-maps only in CNN frame-references and have limited access to its capabilities to execute throughout de-hazing. This issue is addressed by using All-in-One De-hazing Network[15] . The design is based on a calculative scattering- model in surroundings. Since the most previous models provided the estimating the transmissive-matrix & atmospheric-light individually, but AOD-Net has the capability to directly produce the fresh image using cipher-CNN.

Its pioneering design enables it to be deployed with AOD-Net used for rest of the deep-models, for e.g., Faster R-CNN for helping to improvise the elevated level tasks on hazed-images. Later, when appending AOD-Net after Faster R-CNN, there is a great changes and improvement in object detection presentations for hazed - images. The proposed AOD-Net has two components: K-estimating module which includes 5 convolutional films to quantify K(x), followed by new image generating module which has element-based multiplication layers and few element-based addition layers to obtain recovery images via measurements. AOD-Net is built keeping in mind that physical and surfaced models could be described in "more end-to-end" manner having all variables & parameters calculated for single model. In AOD-Net, it generates de-hazed output-image directly as output not with in between steps to quantify the variables. This throughout grasping performance takes time from haze-affected images to transmission-matrix. Also, complete throughput measurement of AOD-Net fixes main gap & bridges the hazy and non-hazy image. To retrieve haze-free image from hazy-input directly, Gated Fusion Network for Single Image De-hazing[16] algorithm is used.

The preferred rules attaches to throughout upskilled neural-networks which has dual pair: encoder & decoder. Encoder can be used to capsulize input images' context while decoder provides the contribution of each & every input for its end-product ie., de-hazed outcome by implementing retained notations linked with encoder. Network so constructed adapts a rhetoric mixture-based plotting through which the 3 inputs captured from original hazy-image are derived by pertaining to few algorithms like: Gamma Correction (GC), Contrast Enhancing (CE) and White Balance (WB). The detailed pixel-based confidence - maps basis appearance's variations for several inputs can be computed in mixing information related to inputs & save areas with good clarity and vision. Final de-hazed images are obtained by providing the highlighted properties of input's image. To make network or structure aware about the requisites, multiple-scaled procedure is introduced, hence the halo-facts could be ignored.

(18)

Here, in such a way, we have considered only one image de-hazing issue by using a multiple scaled gated fused network (GFN), a combined encoder & decoder structure by incorporating confidence-maps for produced inputs. On comparing the progress of this method with other methods, the other methods force the limitations on individual scene's transmission and light in the atmosphere. However, the offered GFN needs to be quite effective in implementation. Also the described method do not depend on predictions and calculations including transmission of atmospheric light signals. Firstly, the white balancing method can be helpful in retrieving color of the scene which generates double contrast improved images leading to higher clarity. Then the GFN is done to quantify and generate confidence-maps for every single input. In last phase, the confidence- maps are used which help in deriving the input sources to obtain end-point de-hazed output. However, many existing methods work with a pre-conceived notion that constant atmospheric light model follows a two-step process which involves priori-dependent ways for calculating the transmission-map along with the estimating the de-hazed image output by using closed-form solution. To overcome ongoing problem, the Joint Transmission-Map Estimation & De-hazing using Deep-Networks[17] has been referenced in this paper. The method using the constant atmospheric light assumption is not preferred. However, a consolidated single-image de-hazing model takes over where in it produces transmission - map and implements de-hazing. In different terms, this new recommended proposition is effective in providing a throughout learning methodology where-in ingrained transmission-maps and de-hazed outcomes are estimated in conjunction with help of loss-function.

The proposed network comprises of below mentioned modules:

1. Transmission - map estimations

2. Images having haze-effect and its feature - extraction

3. Transference managed image de-hazing

Here primary module tells us how we can calculate and generate estimated transference-maps from its consistent hazy intake images. The secondary module teaches us how to extract the related features with hazy-effect from input blurry image. While, next module tries to execute de-hazing of the image with clubbing feature-specific details captured from image full of haze with estimated transmission-map. Through this paper, there is a trial performed to share a new multiple-task throughout the entire CNN-based structure that tends to grasp and retain the transmission-maps and accomplish image's de-hazing together. But, on contrary to old ways that assume and include the transference effect and de-hazing effect for the individual images as both are differently processed and executed, this paper provides a common solution and mend the distance between it by implementing learning for multiple-task. It can be accomplished by relieving non-varying assumptions for atmospheric - light in conventional image abasement project. In other terms, this structure is guided to calculate transmission-map, then used it later for de-hazing. Thus, it follows the standard image degradation model for image de-hazing.

(19)

In this article, I have also proposed a latest and complete de-hazing method for one image, known as Densely Connected Pyramid De-hazing Network[18] , which could learn transmission-map, atmospheric-light and de-hazing as well. By considering a network using scattering model for atmosphere, the complete learning can be achieved directly. It also ensures that the process driven scattering model for de-hazing is strictly followed for the same. There are multiple networks in the system which can manifold increase the flow of data incorporating the different specifications at varying levels. This method also proposes a latest edge-preserving tightly-packed encoder-decoder model having multiple-level pyramid stature combined to provide an easy solution to calculate the transmission map.

This network has been developed introducing a newly launched edge-preserving loss-function. Furthermore, the proposal for collective-discriminator basis generative adversarial network has been issued where in the common structural specifications between estimated transmission-map and de-hazed image has been incorporated resulting in to decide whether the corresponding de-hazed images and transmission-maps confirm to real or fake estimations. As a result, the informal completely configurable de-hazing network has been also proposed. This approach permits the network to estimate multiple parameters like the transmission-maps, atmospheric-light and de-hazed images together. Using a stage-wise learning method, the entire model rests its basis on. Also, for better approximation of transmission-maps, single edge-protecting pyramid with highly joined network has been offered. In addition, this is developed by a recently proposed edge-protecting loss-function. Since we know that there is a high level of correlation linking the estimated transmission-map and de-hazed images, a connecting differentiator within the GAN framework comes into play when there is a requirement to find if paired samples like transmission-map and de-hazed image belong to same distribution of data or not.

Through this paper, it has provided a great understanding of the pros and cons and the limitations of different architectures for image de-hazing. Now, the hazy images are tested on Self Attention based Progressive Generative Adversarial Network which has a residual encoder-decoder (RED) network and a Self-attention based progressive Generative network (SP-GAN) in a stacked manner to perform the removal of noise and haze from the hazy image. This method has also used self-focus based progressive network to direct and handle the long range dependencies and with time has improved the resolution and helped in removing the haze from the colored image where the no hazy image can be generated with efficiently faster, stable and variation rich features. We also highlighted the stabilization and efficient technique for the above mentioned generative model.

(20)

For general reference, these modules are trained individually and then cascaded to perform Image De-hazing. The SPGAN framework is based on following aspects:

(i) Self Attention

(ii) Spectral Normalization

(iii) Progressive growing on input channel

(iv) Two Time Update Rule which are discussed.

The proposed framework is able to generate a visually aesthetic de-hazed images from its hazy source image. Many experiments have been organized for two different synthetic data-sets and single real-world image data-set simultaneously. Further, many collations have been presented for multiple recent approaches. In addition, a research is being organized to highlight the enhancements produced by variety of modules in the proposed network.

(21)

CHAPTER 3: PROPOSED FRAMEWORK FOR IMAGE DE-HAZING

3.1 DE-NOISING MODULE - REDNeT

The proposed architecture initially have a module called de-noising module which is mainly called as "REDNet"—a very extreme layer Residual Encoder-Decoder Networks mainly comprising of large number of convolutional layers as well as symmetric number of deconvolutional layers, as shown in Figure 6. The shown framework is fully convolutional as well as deconvolutional. After every convolutional and deconvolutional layers, the rectification layers are also added as well. The two layers used in the architecture that is the convolutional layer perform the task and acts as a feature extractor, who takes care of the main components of the objects in the given image and also it helps us to eliminate the noise or corruptions. The other layer that is the deconvolutional layer are therefore then combined with initial layers to recover back the precise details of the image contents. Finally, after passing through each of these layers, the obtained output from the deconvolutional layers is the image which is somehow noise free for the given input noisy hazy image. Moreover, in this module, the connections called skip connections are also used in the network which allows us to take an activation from the one layer and feed them to the another different layer with even much deeper in neural network and enables us to train very very deep neural networks. These connections are added from a convolutional layer in the network to its analogous mirrored deconvolutional layer. After that, the features maps generated from the convolutional layers are summed to the feature maps of the deconvolutional layers element-wise, and then they are finally passed to the next subsequent layer after rectification.

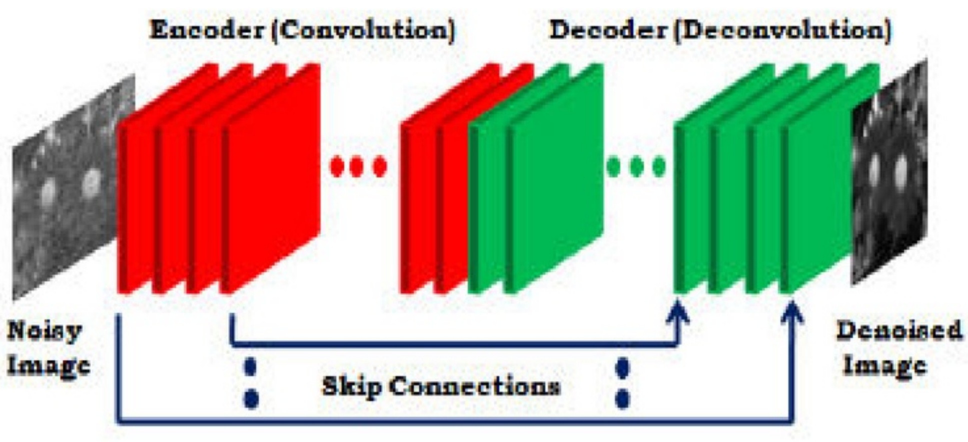

Fig 6: De-noising Module Network Architecture

The proposed architecture consisting of encoder and the decoder used for de-noising purposes. In this module, the deconvolutional decoder has the task of combining the layers of both convolution and deconvolution. With reference to the convolutional layers, these layers have a filter window consisting of multiple input activations are fused to result an output with a single activation, whereas for the case of the deconvolutional layers comprising of multiple outputs and these outputs are associated with a single input activation . In order to have very deep layered fully convolutional neural networks, one can just very simply exchange the deconvolution with convolution. But, they are many existing and the essential differences for distinguishing between our proposed de-noising module and the fully convolution model. For the first case that is the fully convolution case, the step by step removal of noise takes place, i.e., after passing through all layers the network has, level of noise is reduced. During this complete process, precise details of the image's content have the possibility that it may be lost. But, in our network, the convolution helps us to preserves the foremost primary content for an image. Followed by that, then the deconvolution used in the network helps us to compensate the minute details.

For the case of fully convolutional networks, in order to make both the input size as well as the output size equal we use technique of padding as well as up-sampling for the input image. The architecture used in our proposed scheme, here the network mainly has the first 5 layers as convolutional and subsequently the next second 5 layers used are deconvolutional. During the training process, all the various other parameters used are same, i.e., they are actually trained with optimization algorithm called Stochastic Gradient Descent algorithm, in which we consider the noise level has the value for sigma equal to 20. The various different metrics used like Peak signal to noise ratio, the deconvolution often works better and gives the improved performance as compared to the fully convolutional network counterpart. During the process, we noticed that, the initial layers of the fully convolutional network however reduces noise or corruption after passing through the subsequent layers. Both the layers used in the network ie., the convolution helps to preserve the primary image contents and the deconvolution aims to recover the some details for an image.

As in the figure 7, it can be seen that the skip connections are added between the two analogous convolutional as well as deconvolutional layers in which the dotted line marks denotes deconvolution and the solid rectangle indicates convolution. The + sign indicates the element-wise sum of the corresponding feature maps. Primarily, these types of connections are generally used due to its two reasons. The very first reason is that, when the network having large number of layers ie., when it goes deeper, as it is mentioned above, the details of an image have the probability that it can be lost, thereby the task of deconvolution becomes difficult to recover them back. But, there is a chance that the deconvolution could help us to recover a good quality of clean image because the associated feature maps carry the details for given image since they are passed by the connections called skip connections. The very next reason is for easier training of deeper neural networks, these skip connections also have an advantage for achieving the benefits while back-propagating the gradient to the next subsequent bottom layer.

These skip layer connections used in our network architecture are very different and unique, as they are only concerned on the optimization side and we need to pass all the information of the feature maps for the convolutional layers to its next corresponding deconvolutional layers.

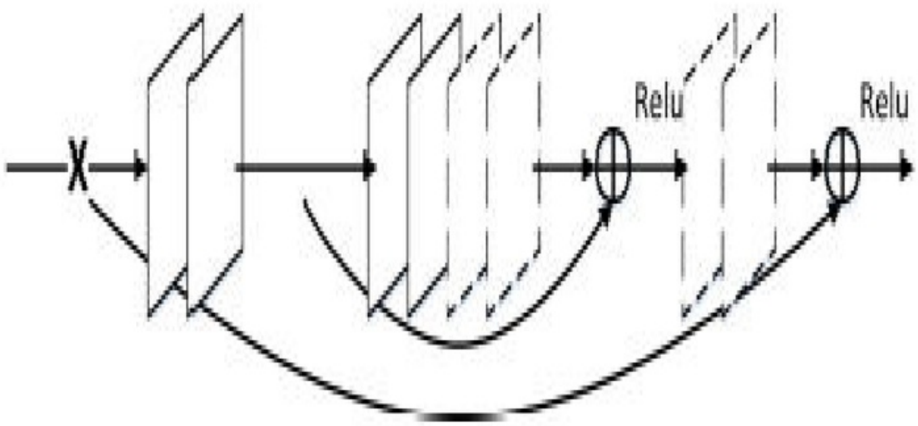

Fig 7: The building blocks - Use of skip connections

The de-noised image that is the output obtained from the network is as:

$$Z^{\wedge}k = E.(Yk) \tag{3.1}$$

The REDNet module helps to remove and eliminate the various different corruptions/artifacts arose by minimizing the loss function:

$$loss_{LR} = \frac{1}{K}\sum_{k=1}^{K}\frac{1}{2} \parallel Z_k - \hat{Z}_k \parallel_2^2 \tag{3.2}$$

Here, E - REDNet model, Yk - noisy hazy image and $Z^{\wedge}k$ - de-noised image.

3.2 SELF ATTENTION GENERATIVE ADVERSARIAL NETWORK

In Deep learning frameworks different type of architectures are being used in many applications related to image processing, computer vision, etc. With the growing and advancement in technology related to deep learning, the frequent and wide use of Generative Adversarial Network (GAN) came into action. This network mainly consists of 2 different neural networks the network of generators represented by G and the network of discriminators represented by D respectively. Both the networks have their respective functions ie., the aim of the generator network is to give the results that are not distinguishable from the given real data whereas the task of the discriminator network is to categorize whether the sample image had arrived from the distribution of the generator network or any sampling distribution or somewhat from the distribution from the input. The generator network has the possibility of producing consistent images from the realistic world if and only if the network of generators and network of discriminators are trained at the same time. To get a more clear idea that what the network does is, the normal model used is marked against an adversary: a descriptive model which learns to identify whether a sample belongs to the model-distribution or data-distribution. The generator model can be understood as corresponding to group of imitators, which are trying to generate non real or the so called fake/artificial currency and use it without identification, while the discriminator model corresponds to the safety men like police which tries to detect the imitated currency. Within the GAN model architecture, the training of the network is a game in which Nash equilibrium is the surest remedy, but an optimization algorithm called gradient descent algorithm may not be able to converge globally. Since this optimization is a local optimization method, local Nash equilibria is only found when both the generator and the discriminator have the possibility of unilaterally reducing their associated losses if and only if here is a local adjacency near a point in space of parameters. The framework of adversarial modeling is more straight forward and easier when both the network of GAN are multilayer perceptron.

Over the complete data x, the generator's distribution pg is learned. Now, a prior has to be defined on the input variables for noise pz(z), where G(z; Θg) representing a mapping to space of data. A function being differentiable depicted by G represented by a multi-layer perceptron bearing Θg as its parameters. The output of second multi-layer perceptron D(x; Θd) is a single scalar which is also defined. The probability represented by D(x) tells that x does not came from p_g ,rather from data. For maximizing the probability of allocating the true label to the samples coming from G as well as training examples, D is trained. In order to minimize log(1 - D(G(z))), G also trained simultaneously. During the min-max optimization problem, between both the networks of GAN the objective function involving the finding of Nash equilibrium is:

$$\min_{G}.\max_{D} V(D;G) = E_{x\sim pdata(x)}.[\log D(x)] + E_{z\sim pz(z)}.[\log(1 - D(G(z)))] \tag{3.3}$$

Here, the input to GAN is noise less hazy image not the noise. In standard GAN architecture, in the generator network, the noise data vector z is feeded. But, here we follow a different approach by treating the input as zero noise instead of noise vector and noiseless hazy image is treated as a prior. For this approach, the cost function is as follows:

$$L_G = -E_{z \sim p_z;\, y \sim p_{data}} D(G(z); y) \tag{3.4}$$

$$L_D = -E_{(x;y) \sim p_{data}}[\min(0; -1 + D(x; y))] - E_{z \sim p_z;\, y \sim p_{data}}[\min(0; -1 - D(G(z); y)))] \tag{3.5}$$

Now, the aim of the discriminator is to tell that which pair contains the true dehazed image.

In a way to address problem of de-hazing, the generative model of networks based approach helps us to produces images that have realistic view due to advancement in GAN architecture. Due to this, there has been tremendous change and variation in the quality of the image as compared to other deep learning framework based models. But the typical architecture of GAN couldn't provide even the minutest details of the image at large scales and not able to handle long-range-dependencies. When tested on the noisy images, there was a significant decrease in the performance of the network model. So, therefore it lead to the usage of advanced version of GAN network called as Self-Attention Generative Adversarial Network (SAGAN) which overcomes all the issues related to previous architectures of GAN by allowing long-range-dependencies and self-attention block, and is non-critical to convolution operation as shown in figure 8 by improving the art state score of Inception (IS) and Frechet distance for Inception (FID).

In order to ramp up the network, the network is instructed in a progressive manner to have proper and sufficient generalization of features. The first loss that is VGG-16 based content loss and secondly, hinge-adversarial-loss from the critic are the two losses that are used in the generator network. In Convolutional Neural Network based framework, the loss functions plays a very important and vital role during the learning process. Comparing the reality and the predicted images, initial effort on CNN based-image, tasks of regression are revamped over pixel based L2-norm called Euclidean loss/L1 norm Y . The potential to have high contextual or perceptual details are limited due to its complex contours and sharp or pointed edges as they are most likely to give results that are blurred images as mentioned losses run at one-pixel per level. So, for addressing this problem and resolving this issue, it makes use of different loss-functions which are adversarial and perceptual losses in understanding the transmission-map and de-hazed image as well.

1) Adversarial loss: This type of loss proposed in SAGAN architectures is being most commonly used for generation of reality-based images. The both networks of GAN which is the generator-network and the discriminator-network are jointly optimized. The generator's sole purpose is – to synthesize the image which somewhat resembles to the distribution of the images that are used in training dataset, and the goal of discriminator is to check and validate if the images that are fed are just the replica or real. After this when the proposed method becomes successful in generating the reasonable images, it was a great achievement which was helpful in usage of various applications like augmentation of data, pairing and un-pairing of two dimensional or three dimensional to image translation, super resolution of various different images, image de-raining and in-painting. In my task, we suggest to deploy this type of GAN- framework acting as a helping aid ie., loss function which can help in learning of transmission- map. Later, it can be optimized appropriately that will generate the realistic transmission-maps.

2) Perceptual loss: With experience of the researchers, they have demonstrated that this loss function needs to be optimized in order to get better results. The function associated with perceptual loss ie., the perceptual function is generally used for extracting features of high level from a pre-trained convolutional network. The generated restored image and ground-truth images, the sole focus here is in minimizing the perception based difference. Due to this, for dehazed images perceptually better-quality results were obtained. For training the network, in order to perform dehazing, a "VGG-16 architecture" based perceptual loss can be used.

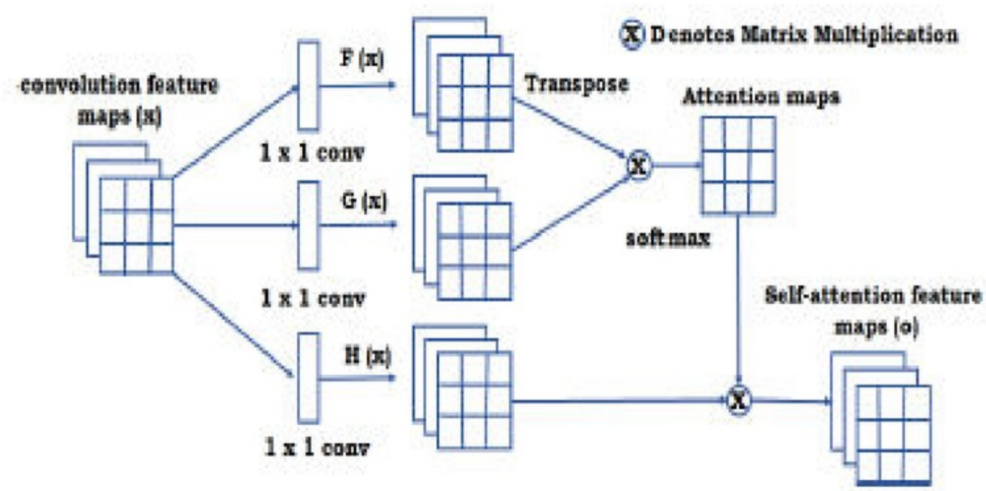

Fig 8: Self Attention Mechanism

In order to overcome the limitations, the use of self attention helps to efficiently model long range spatial regions and also to evaluate attention, the feature spaces are changed and transformed due to feature maps generated from the preceding convolution layers x € R^{CxN}, where: $f(x) = W_f x$ and $g(x) = W_g x$.

$$\beta_{j,i} = \frac{\exp(s_{ij})}{\sum_{i=1}^{N} \exp(s_{ij})}, \text{ where } s_{ij} = \boldsymbol{f}(\boldsymbol{x}_i)^T \boldsymbol{g}(\boldsymbol{x}_j) \tag{3.6}$$

and βj,i depicts the degree to which model addresses to ith location and incorporating the jth neighborhood. Therefore, the attention layer has the output which is represented as o= $(0_1, 0_2, \ldots, 0_j, \ldots, 0_N)$ € R^{CxN}, where,

$$\boldsymbol{o}_j = \sum_{i=1}^{N} \beta_{j,i} \boldsymbol{h}(\boldsymbol{x}_i), where \boldsymbol{h}(\boldsymbol{x}_i) = \boldsymbol{W_h x_i} \tag{3.7}$$

Wg € $R^{C^{\cdot}xC}$, Wf € $R^{C^{\cdot}xC}$, Wh € $R^{C^{\cdot}xC}$ are representing the matrices of learned weight, that are used in implementation as 1x1 convolutions and the factor of 'C' has the value of one by eighth the value of C. In order to get the final output, the scale parameter is multiplied with the output of attention layer and the input feature maps are also added. Hence, the final output is justified as,

$$y_i = 0_i + x_i \tag{3.8}$$

3.2.1 SPECTRAL NORMALISATION

GAN architectures are used to produce output model distribution from a given input distribution that we call the target distribution. The networks used in the architecture called the discriminative-network and generative-network has aim to differentiate a target from the model distribution and producing the model distribution. The challenge arrived in stabilization of training of GAN because initially we continuously train the model distribution and discriminator network at every step of the training process helps us to reduce or decrease the difference between the two model distributions. For making the process of overall training stabilize, there were enormous attempts made. The instant at which it completely differentiate the two types of distribution is the time when both the distribution are disjoint which ultimately results in a critic network. In this scenario, the learning of the generator stops as the derivative turns out to be zero, the differentiation is done for by-produced discriminator in respect to the input. In order to overcome the challenge for stabilizing the training of discriminative network, the spectral normalization technique is used.

The advantages of using this technique helps to produce superior quality of images generated in comparison to other various techniques like gradient penalty and helps the training to stabilize. It proves that applying spectral normalization not only stabilizes the training but also allows the network to produce high sheer quality of generated image compared to methods like weight normalization, gradient penalty etc. By having introduced the regularization term, which increases the cost function and the constant of the discriminator network called Lipschitz constant is also controlled.

For controlling the constant in all the layers of discriminator and generator, one needs to replicate the learnable parameters: { W1, W2, W3, ..., Wn } with its spectral normalized weight matrix $Wn \rightarrow Wn / \sigma(Wn)$ having assumed n hidden layers.

$$W \rightarrow W / \sigma(W) \tag{3.9}$$

Since, it's not our interest that in an algorithm, at every iteration the single value decomposition to be used. If it is used at every step, largest singular value of W becomes computationally heavy. To calculate the spectral norm $\sigma(W)$ computational cost is also evaluated. So, there is need of spectral norm and therefore we are estimating it by power iteration trick which reparametrize with less computation time. There could be major motive of using Spectral Normalization ie., in ImageNet like datasets, it has the capability to produce the samples for all labels of the class and enhanced stability though out the training process with small computational time which helps us to calculate the spectral norm of W matrix efficiently. During the recent works, the discriminator with regularization term makes the training of GAN slower. So, to rise above this challenge, it was recommended to uneven the rate of update steps between the generator-network and discriminator-network and in other sense means just updating the discriminator before updating the generator.

3.2.2 TWO TIME UPDATE RULE

A Two time-scale update rule (TTUR) uses stochastic gradient descent algorithm on loss functions of GAN along with used for training GAN. Generally, the learning rate for two modules of GAN architecture is different and separate. The learning rate for discriminator is kept as 5 times as compared to the generator. The discriminator to generator step ratio is 1:1 respectively. For this rule to converge to a stationary local Nash equilibrium, it makes some assumptions and takes the consideration of theory of stochastic approximation. The convergence properties of training the general GAN is a discussion but with some defined assumptions, it can be proved. Using the theory of stochastic approximation, actor-critic learning have been researched. For the training to reach a stationary local Nash equilibrium, it must ensure that the critic is learning as fast as compared to the actor.

The stable limit points of the differential equation coincides with Nash equilibrium, then the convergence was proved via use of a differential equation. Therefore, we track this approach. When the learning rates of both the networks of GAN are different and separate and trained by this update rule that GANs converge to the local Nash equilibrium. This proves and also gives the better results during the various experiments. When the generator network is fixed, the foremost idea is that the discriminator-network merges to a minimum local value. These discriminators will continuously converge to the point and start learning every new pattern till the steps of the generator network are small or it is changing slowly.

This increases the performance of the discriminator as it is able grasp or learn latest patterns. Besides confirming the convergence, its performance could also sometimes improve as discriminator has to first learn the new patterns before it get transferred to generator. Therefore, discriminator is derived by the generator and the discriminator is able to derive new regions without having its earlier captured information. In recent GAN papers, this is the significant improvement in which the discriminator often learns at a faster rate than the generator.

3.2.3 PROGRESSIVE GROWTH OF THE INPUT CHANNEL

Till now, we know that two networks of GAN has its predefined tasks ie., The generator generates the image using a code and the distribution can ideally become impossible to differentiate from the dataset of training. The discriminator is associated with the loss function called adaptive loss function which is of no use if the generator is trained. Between the generated distribution and training distribution by measuring the distance, the challenge could still arise when the gradients are pointing to less or more random directions if the distributions are easily able to tell. The gradient problem is increased when we want to generate high quality of dehazed images as it makes it a very simple task to tell the generated image apart from training image. The training stability could also be compromised when we demand for high resolution dehazed image.

So, our procedure uplifts this by growing both the networks of GAN in a progressive manner. It initially starts with images of low resolution and then by adding new layers, it introduces details of higher resolution when training is in progress. This increases the speed of the training process and improves stability for details of higher resolution. Here, in our method we are not making the architecture of UNet grow but during the training making the size of input image increase as we start training initially of small scale and then make use of pretrained weights.

3.3 PROPOSED METHODOLOGY

The proposed mechanism consists of wide number of steps that helps to get somewhat a de-hazed image as the final desired output by making it passing through various layers of the network in the deep learning framework.

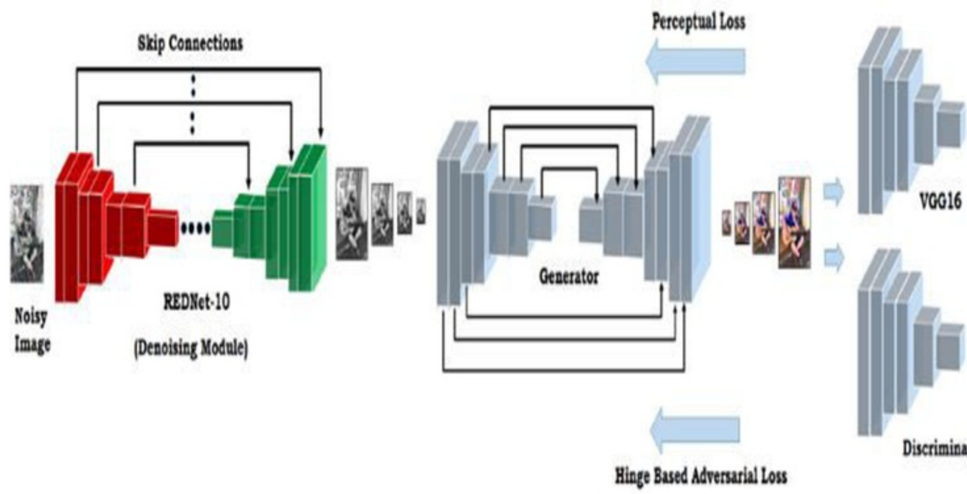

Fig 9: Proposed Attention Based Generative Adversarial Network

The defined framework comprises of two major modules used ie., the de-noising module in which the input to the module is the dehazed noisy image, let it be $X € R^{HxWx3}$ is that shows the image have the height and width represented by h and w respectively and the number 3 indicates that the image comprises of 3 channels ie., RGB channel. Along with this, the image is also degraded with the Gaussian noise having a value of sigma equals to 20 and hence then it is made to pass through to RedNet which is used to process the noisy or degraded image and therefore it results in an output image which is hazy image free from noise. Secondly, the dehazing module in which after passing through the de-noising module, the noise free hazy image ie., having the dimension of HxWx3 and it is made to pass through Self-Attention based Progressive GAN network which comprises of the generator-network and the discriminator-network. Encoder networks are already pretrained residual networks ie., ResNet34 which serves the purpose of extracting the features from the image as well as the architecture for the generator network is encouraged and provoked by the architecture of UNet.

The motive of using UNet architecture (which is specific architecture for a convolutional-network consisting of one contracting-path and one expansive-path used for down-sampling and up-sampling respectively) to include this technique using spectral normalization. We are using this architecture of UNet but not making it grow ie., by increasing the layers of the network but instead during the progressive training process, the size of the input image is gradually increased. During this process, we down sample the image and gradually training the model. By this flow, the procedure of training becomes fast and generalization gets improved because initially we begin our training on minute scaled images and gradually using these trained weights. The various losses associated with the generator network is firstly the VGG-16 based content loss and secondly, hinge adversarial loss from the critic. The pre - trained VGG-19 recieves the input which is actually generator network's output ie., of size Yg € R^{HxWx3} that is fed as an input to VGG-19 that helps us to compute these two losses.

For getting the better dehazed image, we have used batch normalization, spectral normalization, and the mechanism of self attention. In the decoder network, no activation has been applied. The discriminator network refers to a simple convolutional and neural-network comprising of five deconvolution surfaces. It also includes little bit variation in leaky ReLU, dropout technique, spectral normalization etc. Generally, we are keeping the step ratio of the generator to the discriminator network as 1:5 so that discriminator network's learning rate is 5 times in comparison to the generator network. Along with this, we also makes use of the optimizer known as Adam optimizer with specific values of its first moment and second moment as 0.00 and 0.90 respectively. This results in an output which is a de-hazed image.

CHAPTER 4: RESULTS AND DISCUSSIONS

Several testing trials are being conducted on different datasets for checking and evaluating pixel clarity and corresponding image quality of the de-hazed image and to validate the performance of training and testing real dataset on the proposed architecture. In earlier times, Image De-hazing was not much of major need as there were not many predefined methods and proposed frameworks to remove the haziness from an image. But now with changing times, the need for images which are free from haze having a fair visibility for the scene are highly desirable which is done by eliminating the misty layer from the input hazy image and thereby it becomes visually pleasing. Image de-hazing is the very widely used and has its importance in many applications like computational photography, detection, recognition, etc. Motivated by this application, we tried to fill that gap so that we can better results in day to day life scenarios.

Due to the used architecture for GAN networks, we are able to get superior results ie., the improved version of de-hazed image even in case of noisy images. Also, there could be another reason we have used learned weights of ResNet in the generative network and these weights are trained on ImageNet. Due to maximum possible variation and huge amount of data available in ImageNet, there is possibility we could get many variant of de-hazed images. Depending on the background and the color contrast of the image, the GAN model has tried to remove the haze from the image upto the maximum possible limit. As compared to training associated with Self attention, in Progressive training good quality images has been observed but however the overall improvement has been noticed when both the training methodologies are used. Due to the haze present in the model, it can be formulated shown below:

$$I(z) = J(z).t(z) + A(z).(1\text{-}t(z)) \qquad (4.1)$$

The hazy input test images which are when passed through different modules of the proposed architecture, we get the corresponding de-hazed output test images which is represented below:

$$\hat{J}(z) = [I(z) - \hat{A}(z)(1 - \hat{t}(z))] / \hat{t}(z) \qquad (4.2)$$

The following are the result of set of de-hazed images obtained of the respective hazy image for the proposed architecture of GAN using deep learning framework.

Fig 10: Hazy Input test image_1

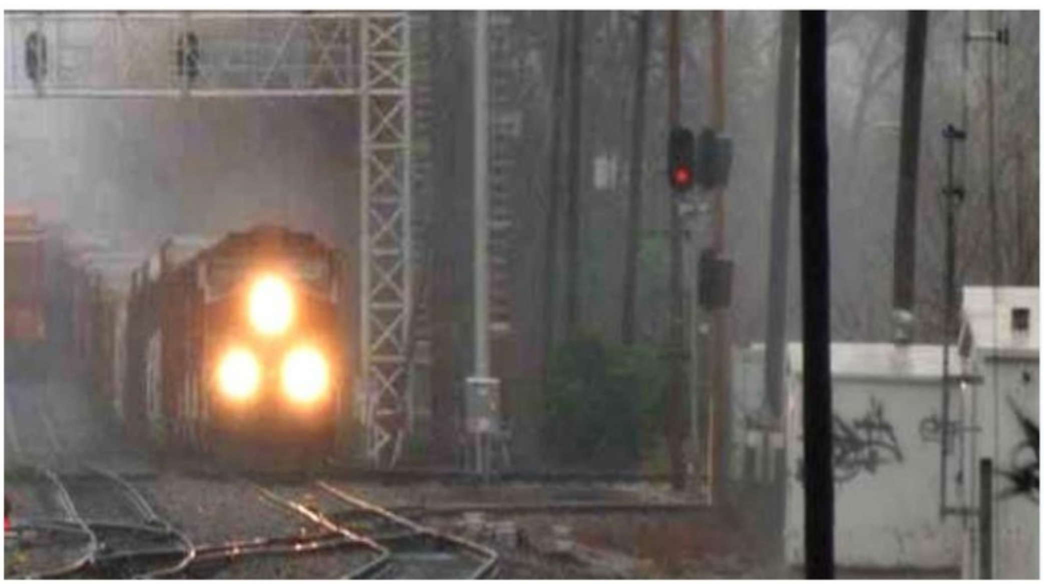

Fig 11: De-hazed output test image_1

Fig 12: Hazy input test image_2

Fig 13: De-hazed output test image_2

Fig 14: Hazy input test image_3

Fig 15: De-hazed output test image_3

Fig 16: Hazy input test image_4

Fig 17: De-hazed output test image_4

Fig 18: Hazy input test image_5

Fig 19: De-hazed output test image_5

Fig 20: Hazy input test image_6

Fig 21: De-hazed output test image_6

Fig 22: Hazy input test image_7

Fig 23: De-hazed output test image_7

Fig 24: Hazy input test image_8

Fig 25: De-hazed output test image_8

Fig 26: Hazy input test image_9

Fig 27: De-hazed output test image_9

Fig 28: Hazy input test image_10

Fig 29: De-hazed output test image_10

CHAPTER 5: CONCLUSIONS

In this thesis, we have studied and proposed Image de-hazing using Self-attention based Progressive Generative Adversarial Network which consists of residual encoder-decoder network and a Self-attention based progressive Generative network in a cascaded form to perform the de-noising and de-hazing of the image. Several images were tested on proposed architecture of GAN which has been used to remove the haziness from the image and get better quality of de-hazed image.

From part1 of the project, initially, the input to the de-noising module is noisy hazy image and the output of this module is noise free hazy image. The function of this module aims for removal of noise from hazy images. Along-with this, the use of skip connections in this module helps us go into the deeper layers as well as provide us to train very deep neural networks.

Later, part of the project includes the self attention GAN framework which consist of a generative model as well as descriptive model. Both the networks have their respective loss functions ie., the aim of the generator network is to give the results that are not distinguishable from the given real data whereas the task of the discriminator network is to categorize whether the sample image had arrived from the distribution of the generator network or any sampling distribution or somewhat from the distribution from the input. The generator network has the possibility of producing consistent images from the realistic world if and only if the network of generators and network of discriminators are trained at the same time.

Further, the generator network is trained progressively to increase the pace of training and proper generalization of features the network is trained using two losses, the VGG-16 based content loss and secondly, hinge adversarial loss from the critic. This type of GAN framework is used to handle long range dependencies. The use of spectral normalization helps us to stabilizes the training procedure along with that image is generated of high quality. The step ratio of discriminative network to generative network is ratio of one is to one along with learning rate of discriminator as 5 times as compared to generator which helps us in faster training of images.

By observing the above results, it is concluded that Self attention GAN network architecture outperforms the previous architectures. Including REDNet network along with using this proposed GAN framework made our results more pleasing and gave us satisfactory results.

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