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Analysis and Synthesis of Image Dehazing Using Deep Learning Algorithm

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Abstract: Artificial intelligence technology is revolutionizing the automation, dependability, and robustness of industrial sectors while also improving overall quality and production. Visual sensor networks are used by most industrial and surveillance industries to monitor their surroundings by capturing numerous pictures of it. Polluted suspended atmospheric particles, on the other hand, degrade the entire monitoring system and the image quality during severe weather. This paper provides a lightweight convolutional neural network that is computationally effective and is utilized for picture reconstruction to address these problems. The proposed module adjusted the atmospheric effects models to jointly evaluate the "transmission map" and the "atmospheric light", unlike current learning-based systems that assess the "transmission map" and the atmospheric light separately. An extension to the Atrous Spatial Pyramid Pooling (ASPP) approach is used to construct a context vector in a bottleneck that is made up of multi-scale context information to reduce colour distortion in the dehaze image. The quantitative and qualitative examination of many photographs from the NH-Haze dataset supports the suggestion's superiority over existing image dehazing methods.
General Terms: Atmospheric light, Deep Learning, "transmission map", Algorithms, Haze Image.

Keywords: *Convolution Neural Network, Image-Dehazing, Dark Channel Prior, Guided Filter, Atrous Spatial Pyramid Pooling*

1. Introduction

Frequent, naturally occurring weather phenomena that instantly affect contrast and image quality are haze, air particles and fog. The random dispersion of light within the medium at irregular angles causes haze, which hinders all the image's pixels from being properly rebuilt as the image acquisition point. Consequently, reduced visibility outdoor images in hazy leads to poor performance of computer vision algorithms for "*object detection, tracking, and image segmentation*".

Numerous single-image haze reduction studies have been conducted in an effort to address this issue. The majority of "single-image dehazing" techniques are based on the "Dark Channel Prior" (DCP). The DCP presupposes that in outdoor images without haze, numerous small areas contain a small number of pixels with intensities that are nearly zero in at least one-color channel. Haze artefacts are a concern with DCP-based single-picture dehazing systems, despite their simplicity and effectiveness. In order to resolve this issue, He et al. propose "soft matting as a post-refinement process, which significantly increases computational complexity". To further minimize computing complexity, a guided filter is used in place of soft matting. After the guided filtering procedure, the halo artifacts remain [1].

In image taken outside, without haze, the DCP assumes that most local patches include a few pixels with intensities that are almost zero in at least in one colour channel. The drawback of DCP-based single-picture dehazing techniques is the presence of haze artefacts, despite their simplicity and effectiveness. He et al. suggest soft matting as a post-refinement technique to address this issue, significantly raising the computing complexity in the process. As an alternative to a guided filter, when its cloudy outside, images taken with an optical device have a propensity to be hazy because the breakdown and absorption of air particles can make things less clear and visible. It also increases the difficulty of applications using vision and data analysis. Although both algorithms have more exacting requirements for image processing, they both give trustworthy results. As a result, a popular topic of research for dehazing techniques involves deleting duplicate pictures from a single image. Although this process produces respectable results, colour and radius distortions are easily introduced. Many clear outdoor photographs and natural images were deleted before incorporating the guided filter method into the data to increase the efficiency of the dark channel. Background data is provided using a hybrid DCP with a guided filter to assist the technique [2]. In computer vision and image processing, enhancing hazy images—both indoor and outdoor—is

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essential to achieving haze-free photos without sacrificing the integrity of the original image. Scene pictures and satellite photographs appear differently when there is haze. The suggested method for enhancing low visibility images using DCP before utilizing the haze imaging model can be constructed by directly determining the haze's thickness and obtaining an outstanding haze-free image.

2. Connected Research Work

This section provides a quick overview of image dehazing techniques, including advantages and disadvantages. The scientific community has devised several approaches for image dehazing. To keep things simple, there are two categories into which the literature on single-Image dehazing can be divided:

1 Technique for Prior-Based Image Dehazing
2 A deep learning technique.

Hong-Kyu Shin et al. [02], A weighted dark "channel-based single image dehazing" method was created in order to prevent the halo effects. The weighted dark channel is then started by averaging the minimal color components of a subset of pixels with high enough related probability. Weighted DCP is used to compute the "dehazed image" and the "transmission map". The author experienced problems since it was difficult to eliminate the haze and stop halo artifacts from forming.

In order to remove haze from remote sensing photos, Hou Jiang and Ning Lu (2018) [03] showed how to use a multi-scale residual convolutional neural network containing both spatial and spectral input (MRCNN). The network sends haze and receives input from foggy regions. The clear image blocks used to create the training datasets mimic the haze degrading process. To reduce the "mean squared error" between the projected values and true actual transmissions (MSGD) and an early-stopping strategy, MRCNN is trained using minibatch stochastic gradient descent. After training, the network can predict the "transmission map" of nearby fuzzy pictures. In order to fix the latent residual in "dehazed images", post-processing is required.

The network receives input from foggy areas and sends haze. The clear image blocks used to create the training datasets mimic the haze degradation process. By using "mini-batch stochastic gradient descent" (MSGD) and early-stopping techniques to train the MRCNN, the "mean squared error" between the predicted values and actual hazy transmissions is decreased. The network can forecast when fuzzy images will be transmitted nearby once training is complete. Post-processing is necessary to correct the latent residuals in dehazed pictures. It has a particular type of visual artefact, though, like a halo effect and less effective edge, texture, and colour preservation.

While minimizing minute changes in the "transmission map", the DCP approach proposed by Nitit WangNo et al. (2020) [04] is more effective than the bilateral filter at retaining edges. Images with air-light and contrast distortion that come as an output of the A-guided filter will enhance the DCP process. In this study, a guided filter is used to increase stability, although it produces a halo effect.

For only-picture dehazing, H. Ullah, K. Muhammad, M. Irfan, and Victor Hugo C. De (2021) [05] introduced the CNN-based LD-Net system, which is computationally effective. The three steps of LD Net deployment include training, retrieving "dehazed image" and improving the visual quality of dehazed photos. The author proposed a CVR module that uses color intensity aggregation to improve contrast and color qualities while correcting any color distortions in the dehaze image. The CVR module compensates for the color loss resulting from the LD-Net design, which eliminates haze from the image, by equating the per-channel histogram of the "dehazed image". The study did not look into how color is preserved semantically.

Many image-dehazing techniques are proposed to address this problem. The remaining algorithms compute "transmission map"s and ambient light from foggy photos by utilizing scene depth, polarization filters, and image texture.

An image dehazing model was developed by Y. Li and colleagues in 2015 [6] for the purpose of processing photographs taken in the evening mist. In the beginning, they reduced the glow so that they could quantify the geographic variability and direct transmission of the light from the atmosphere. In comparison to the procedures used by SOTA, their performance was outstanding. However, as their models are based on artificial images, the performance is still constrained when handling hazy real-world images.

An image dehazing technique for hazy satellite image data was created by W. Ni, X. Gao, and Y. Wang (2016) [7] as part of the ongoing research that is being conducted in this sector. For the purpose of enhancing the visibility of the satellite approach, they performed local property assessment and linear intensity changes. details provided. It is possible to achieve good results with this strategy when experimenting with a thin layer against a whole white fog background. In the event that the procedure is confronted with a thick coating, such as the one depicted in the images, it is utterly unsuccessful.

It has been determined by Yuan et al. (2017) [08] that a strategy known as "region-wise medium transmission-oriented" has been devised. Following the division of the fuzzy image into numerous components, such as the sky, trees, and buildings, the authors compute the region-wise transmission by making use of the colour properties of each region. On the other hand, the contrasting colours and sharpness of the photos that have been cleansed can become less noticeable over time when using their procedure. They presented a method for estimating region-wise medium transmission, which takes a hazy image and breaks it up into several parts (such the sky, trees, and buildings), then uses the specific color characteristics of each region to estimate transmission. However, with time, their method deteriorates the dehazed photographs' sharpness and contrast.

Wang and others [9] utilised a single-picture haze elimination technique that utilised a linear relationship between the estimated "transmission map" and the image that was hazy in order to recover a haze-free image. This technique was used in order to remove haze from just one photo. High-resolution photos are difficult to dehaze with this method; the restored image exhibits greater dehazing and a black appearance, requiring the employment of further image processing methods.

A reconstruction approach that recovers “fog-relevant features” from a foggy image to predict the fog's density was proposed by Z. Ling et al. (2017) [10]. Second, they used the local relationship between the fog density and an approximation of the optimum “transmission map” using the real and imaginary parts of the “transmission map”.

T. M. Bui et al. (2017) [11], on the other hand, built a colour ellipsoid, increased the image's contrast, and avoided oversaturated pixels to approach the “transmission map”. Both methods introduce the hallow effect, which interferes with the restored image's inherent contrast.

Aside from their own advantages and disadvantages, the above techniques typically fall short when trying to recover photos impacted by the intense haze. Furthermore, these outdated techniques employed statistical models that have poor performance for dehazing outdoor, naturally foggy images with a general haze density. The results are still either dark or undersaturated, even when computationally demanding processing techniques are used. To get over these issues, a variety of deep learning-aided techniques are combined with learnable end-to-end networks to rebuild high-quality dehaze images.

To lessen picture haze, Zhang et al.'s [12] proposed employing a deep network architecture that incorporates a perceptual pyramid design. The technique employed in this process involves leveraging the inherent connection between a blurred image and its associated depth image to recover the image with reduced haze. Their methodology concentrates on the regions affected by haze and systematically reduces the optical differentiation of the image.

S. Ki, H., and others (2018) [13], focusing on the architecture of encoders and decoders, found similar results for the picture dehazing problem and recommended a conditional GAN. However, their approach is unable to reconstruct a dense fog image because of the substantially reduced image quality. Additionally, their network only performs effectively on fake images created from inside and outdoor surveillance since it learns the mapping function from fuzzy artificial images.

Based on two CNN models, Dudhane and Murala (2019) [14] presented a unique image dehazing method. In their approach, they first extract haze-related information from the observed hazy image using the RNet and YNet architectures. In the second stage, a fusion network was used to combine the retrieved characteristics and rebuild a clear image.

Chongyi et al. (2019) [15] had suggested the PDR-Net CNN architecture, which makes use of two subnetworks to take the dehazed picture's visual quality into account. The first subnetwork eliminates all haze from the image, while the second subnetwork enhances the “dehazed image” color and contrast. Both approaches need a lot of computing because they require two CNN architectures to extract more fog-related information.

Chia-Hung et al. developed a “multi-scale residual learning network-based image reducing hazing” method in 2019 [16]. To obtain relevant data for computer vision techniques including object detection, tracking, and image segmentation, they employ a “multi-scale residual learning” (MSRL) network. To reduce the impacts caused by environmental contamination, these elements are then added to photos that were captured in foggy conditions.

All things considered, these learning-based techniques outperformed traditional prior-based systems in picture dehazing tasks and effectively overcome their shortcomings. While all these strategies have benefits and downsides, some of them were created using artificially hazy data, which presents issues when used with hazy photographs that actually exist in the real world. However, the highly complicated topologies of many CNN-based dehazing methods increase the total computational cost and complexity of the hazy picture reconstruction process. However, there are two ways in which our suggested method differs from the current deep learning-based methods. First, it reduces the overall processing cost and complexity by approximating the “transmission map” and natural light at the same time. To recover important data, it also has a CVR module that improves the contrast and color characteristics of the cleaned-up and restored image.

3. The Framework of the Proposed System

The proposed system can broadly be categorized into four subsections:

1) DCP using Guided filter.
2) Generator CNN Encoder-Decoder
3) Atrous Spatial Pyramid Pooling (ASPP)
4) Discriminator

Light-absorbing and light-scattering air particles cause the haze phenomenon. Image enhancement of hazy images (indoor and outdoor) has developed into a highly essential work in computer vision and image processing [21][22][25]. This is because it allows to produce haze-free shots without losing the information of the original image. Haze has an impact on how scene shots and satellite images seem. At conclusion, due to this limited visibility, foggy outdoor images perform worse when computer vision techniques like object detection, tracking, and image segmentation are applied.

The suggested system's architecture is depicted in Figure 3, where an image with haze is input into the model, and a guided filter algorithm and DCP are used to produce an image without haze. The features of the transmitted and fuzzy images can be extracted using the CNN Encoder model. The CNN decoder, which can also be used to create synthesized images from inputs, can be used to unlock the features in this image of extracted features.

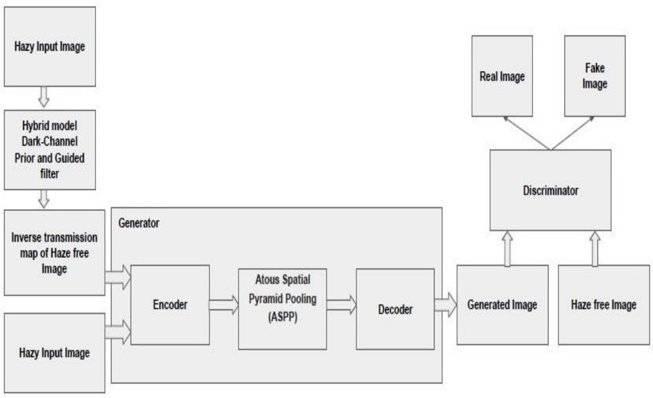

Fig 3 Proposed System Architecture

Additionally, an extension called Atrous Spatial Pyramid Pooling (ASPP) is used to build context vectors in bottlenecks out of multi-scale context data. CNN-Discriminator function can be used to generate Real or Fake Images by generator and haze-free images. With the NH-Haze dataset, the proposed technique for haze removal is effectively implemented.

3.1 Dark Channel Prior

The Dark Channel Earlier is the method that has been used traditionally for removing from individual photographs. In photographs that were taken outside without any haze, the majority of the local patches have a few pixels that have very low intensities in at least one colour channel in the highlights of the digital camera picture. Through the integration of this information with the haze imaging model, we are able to directly compute the thickness of the haze and recover an image that is devoid of any haze.

Four main steps make up the DCP dehazing process:

1. "Estimating atmospheric light"
2. "Estimation of transmission map"
3. "Refinement of transmission map"
4. "Reconstruction of Images"

3.2 Hazy Image Formation

A hazy image is mathematically modeled as follows:

$$H(^{X}) = F(^{X})\,\mathrm{e} - \beta d(\varkappa) \; + \; AT\,(1 - \mathrm{e} - \beta d(\varkappa)\,) \qquad (1)$$

H denotes the observed image with haze, F = "clear image", AT= "total atmospheric light", d= "depth of the scene", AT stands for the "atmospheric scattering coefficient", and x for the pixel. Details and the map of transmission are provided by:

$$Htr(^{X}) = \; (\mathrm{e} - \beta d(\varkappa)) \qquad (2)$$

When the sky is clear, we have $\beta \approx 0$, and as a result $H \approx F$. However, for fuzzy photos, β becomes non-negligible. As the scene depth rises, F(x) tr(x), the first term of Eq. (1), gets smaller. In contrast, when the depth of the scene grows, AT (1 − tr(x)) (the airlight), the second term of Eq. (1), rises. After AT and tr have been determined from H, the objective of picture dehazing is to recover F from H. F can be calculated mathematically as:

$$J = \frac{H(x) - AT}{tr(x)} + AT \qquad (3)$$

However, it is not simple to estimate A and t. Because 'tr' spatially varies based on scene depth, the number of unknowns is equal to the no. of picture pixels. As a result, it would be impossible to directly estimate 'tr' from 'H' without making any assumptions or prior knowledge. To recover F, AT, and tr from H is the purpose of haze removal.

3.3 Atrous Spatial Pyramid Pooling (ASPP)

Additionally, Atrous Spatial Pyramid Pooling (ASPP) is used as an extension to generate context vectors in the bottleneck which is composed of multi-scale context information.

Before convolution, a particular feature layer can be resampled at numerous rates using the semantic segmentation module "Atrous Spatial Pyramid Pooling" (ASPP). Utilising this method is analogous to examining the source image at various scales and with unique filters that have effective fields of vision that are complementary to one another in order to capture objects and relevant visual context. Instead of resampling the features, the mapping is accomplished by using a large number of synchronous Atrous layers of convolution with varying sampling rates.

3.4 Activation Function

Mish Activation is employed in the encoder-decoder model Mish is a flat and non-varied activation function which can be defined as:

$$m\,(a) \; = \; a.tanh(softplus(a) \; = \; a.tanh(In(1 = ea)) \qquad (4)$$

The performance of Mish demonstrated better than both Swish and ReLU activation functions.

The network may be trained to transform an input fuzzy image into an into a "dehazed image" by calculating "transmission map" using the CNN-based learning technique, specifically the “Generative Adversarial Network” (GAN) framework.

This enables the network to be trained using losses that are defined in the image and relaxes the constant ambient light assumption. Additionally, we can minimize losses defined in the image space, such as Euclidean loss at the pixel level and perceptual loss. This yield results with enhanced perception and fine details.

3.5. Metrics for Evaluation:

3.5.1. Structural Similarity Index Measure (SSIM)

The “Structural Similarity Index Measure” (SSIM) is used to calculate how similar two provided images are to each other. A quality reconstruction metric for SSIM has been developed that also considers the degree of similarity between the haze-free picture and the haze-free image's edges (high-frequency content). The range of SSIM is 0 to 1.

3.5.2. Peak Signal-to-Noise Ratio (PSNR)

A quality statistic, the “*Peak Signal-to-Noise Ratio*” measures how well a signal is represented when compared to hazy noise, which has an impact on the accuracy of that representation. Typically, PSNR is used to regulate the transmission quality of digital signals.

4. System Implementation

The proposed technique must be optimized using four loss functions.

a) Adverse Loss Lad

b) Feature Factor Fixture Lff

c) Attention Loss Lat

d) Precision Loss Lp

To train the global information and find the original picture format using multiscale feature data, the unfavourable loss and the feature factor fixture are combined to produce the Generative Adversarial Network framework.

The image colour information is preserved by using Attention loss and Precision loss also these two losses strengthen fine features.

$$Total\ Loss\ Loss = L_{ad} + L_{ff} + \lambda\, L_{at} + L_p \qquad (5)$$

4.1 Adverse Loss Lad

The haze-free images in the proposed work are produced using the Generator Framework, and the discriminator divides the images into two categories according to whether they are fake or real. Therefore, a discriminator was used on two scales. $DS1$ and $DS2$.

$$L_{ad} = \min_{Gr} \left[\min_{DS1,DS2} \sum {}_{AT}^{\,l} \begin{matrix} (Gr, DS_i) \\ i = 1,2 \end{matrix} \right] \qquad (6)$$

Where Gr output generated by Generator and lAT(Gr,DSi) is adversarial loss of a single image.

4.2 Feature Factor Fixture Loss Lff

The match between real images and synthesized images generated by generator.

$$Lff = \min_{Gr} \left[\sum {}_{Fd}^{\,l} \begin{matrix} (Gr, DS_i) \\ i = 1,2 \end{matrix} \right] \qquad (7)$$

4.3 Attention Loss Lat

Attention Loss calculates the difference, regarding each α_r activation layer in the CNN architecture, between the attentive features of the hazy image and the resulting haze-free image.

$$Lat = (AY, X) = \frac{1}{h\alpha\, w\alpha\, t\alpha} \;\| \alpha r(AY) - \alpha r(X) \| \qquad (8)$$

Where hα, wα and tα are height, width, and depth of image and AY is final output.

4.4 Precision Loss Lp

Precision loss is defined as the “Euclidean distance between the haze-free image X and the final output AY”.

$$\boldsymbol{Lp = \| X - AY \|2} \qquad (9)$$

5. Experimental Results

Table 1. Comparative performance of Swish and Mish activation functions on training data.

Algorithm	SSIM (Train)	PSNR (Train)
Proposed Algorithm Using Swish Activation Function	0.73	22.29
Proposed Algorithm using Mish Activation Function	0.78	24.13

Table 2. Comparison of Performance of Swish and Mish activation functions on test data.

Algorithm	SSIM (Test)	PSNR (Test)
Proposed Algorithm Using Swish Activation Function	0.59	18.01
Proposed Algorithm using Mish Activation Function	0.65	17.79

The above-mentioned experimental findings demonstrate that the “Mish Activation Function” outperforms the “Swish Activation Function” in terms of performance. Also, it is observed that as obvious, the better results on trained datasets as compared to testing data.

Table 3. Comparison of Performance of DCP, DCP with guided filter, Enhanced Pix2pix Dehazing Network (EEPDN) algorithm with the proposed algorithm

Algorithm	SSIM	PSNR
DCP	0.404	10.05
DCP guided Filter	0.491	11.01
Enhanced Pix2pix Dehazing Network (EEPDN)	0.699	16.05
Proposed Algorithm NH-Haze Dataset	0.788	24.13

Employing with the NH-Haze dataset, the proposed methodology for haze removal is effectively implemented. By achieving 24.13 PSNR, the proposed method enhances the SSIM score to 0.788. This is the highest PSNR score ever recorded for object detection in a foggy environment.

a) Input Haze Image b) Output of Proposed System

Fig 2 Test Experimental Output of Proposed Method for Image Dehazing

The proposed method improves the SSIM and PSNR scores up to 0.788 and achieves a PSNR score of 24.13, the best PSNR score ever reported for object detection in a foggy environment. Figures 6 and 7 display the experimental findings in graphic form. As a result, even in cloudy situations, our LD-Net can assist the object detector in functioning.

Experimentation results shows that PSNR and SSIM are the objective parameters are compared of the proposed system and the Enhanced pix2pix Dehazing network using the “NH-Haze” dataset and the results show that the suggested strategy improves the “*Peak Signal to Noise Ratio*” and the “*Structural Similarity Index*”. Same improved performance can be observed in case of subjective parameters.

PSNR and SSIM are the objective parameters are compared of the proposed system and the Enhanced pix2pix Dehazing network using the “NH-Haze” dataset and from the result it is observed that “*Structural Similarity Index*” and “*Peak Signal to Noise Ratio*” are improved for the proposed method. Same improved performance can be observed in subjective parameter.

6. Conclusion

Image enhancement, picture retrieval, and image dehazing are just a few of the computer vision disciplines in which CNN has recently had considerable success. Haze particles impair video content in surveillance systems in a cloudy environment, lowering visual quality and impacting overall performance. Thus far, several “image-dehazing” algorithms have been developed to tackle this problem. Most of these techniques are ineffective for real-time applications because of their high computing costs and general inefficiency. The proposed haze removal system on the “NH-Haze” dataset, is effectively applied. The values of the evaluation measures SSIM and PSNR are much higher than those of the current conventional approach. The suggested technique uses supplementary input produced by the DCP with a directed filter and an inversely transmitted picture of its output that significantly passes to an encoder for better feature extraction. In addition, Atrous Spatial Pyramid Pooling (ASPP) is used as an extension to create a context vector made up of multi-scale context data in bottlenecks. The encoder's significant context features are sent on to the decoder, which then synthesises them to create images out of haze.

The suggested system can perform better than current ones by combining the strengths of CNN Deep Learning methods and Prior based single image dehazing approaches with the addition of guided filters in image preprocessing and optimal function utilization in Deep learning algorithms. As a Part of interpretation for experimental proposed method for image dehazing and statistical data proves optimization in image dehazing using deep learning algorithm by addressing experimental setup.

Avenues for future research

The other deep learning techniques that are now available for image dehazing, such as the Dehazenet Algorithm, AOD-Net Algorithm, Fusion Network (GFN), and End-to-end gated context aggregation network, can be applied for a variety of quantitative and qualitative metrics. Additionally, a novel approach for image dehazing on the NH-Haze dataset can be built by tweaking and improving the best-performing algorithm.

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