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SINGLE IMAGE DEHAZING USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract:
Images captured in weather conditions like fog, haze, smog, or atmospheric particles might lack clarity and visibility due to details being obscured. This necessitates dehazing to enhance the quality of images. Removing haze can enhance color vibrancy, contrast, and overall image quality, making them more visually pleasing. In this paper, single image dehazing using Convolutional Neural Networks (CNN) is proposed. An end-to-end encoder-decoder training model is used to produce dehazed images. The proposed method is experimented on several hazy images and results are evaluated using Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM) parameters.

Introduction

Images captured may lose their quality due to presence of fog, haze, smog, or atmospheric particles in air. Image enhancement methods [1] can only alleviate this problem slightly. It is helpful to develop effective dehazing methods to recover the clear image from an input hazy or foggy image. Under this formation different approaches have been proposed in the literature [2]. To dehaze a single image, approaches often assume that the atmospheric light is constant for every pixel in one input image and can be estimated in pre-processing step simplifying the problem latera s a transmission estimation problem. Transition estimated can be done using Dark Channel Prior approach [3], regression model can be used to estimate transmission, [4] or local color-lines prior in clear images can be utilized to estimate the transmission. [5]. Since there are also images that does not meet the assumption that atmospheric light is constant, these method fails to capture intrinsic features of the hazy image.
Over the last several years neural networks-based techniques have played an increasingly important role in image classification/annotation [6] [7], object detection [8][9], semantic segmentation [10], and image denoising [11]. In the literature we also find few methods employing Neural Networks. Ren et al. [12] directly estimate the whole transmission map from an input image under the multi-scale FCN (fully convolutional networks) framework [13]. Cai et al. [14] use a regression network to estimate the transmission of each pixel from its local surrounding patch. Yafei Song et. Al. [15] presented a novel Ranking Convolutional Neural Network (Ranking-CNN) to obtain effective features for single image dehazing]. Inspired by the usefulness of CNN, in this paper we employ CNN architecture to automatically learn the haze relevant features from hazy images.

Literature Review

In this section, we briefly review existing dehazing methods.
Ngo [16] proposed a comprehensive approach involving the utilization of a depth map to recover depth information, the implementation of an adaptive linear model with color attenuation prior characteristics, the precise removal of haze from images, and the introduction of a straightforward method for reconstructing scene radiance using a tropospheric dispersion model. The foundational image can be efficiently restored through the derived depth map. Despite efforts to address fog-induced issues such as image brightness and saturation to establish scene depth, challenges persist. This is due to the constant nature of the scattering coefficient under consistent atmospheric conditions, preventing

effective recalibration. The study emphasizes the necessity for a versatile model, as current single-image dehazing techniques heavily rely on ongoing assumptions for their outcomes.

Feng Yu et.al [17] introduced a novel strategy termed "View based Cluster Segmentation" tailored for image and video dehazing. Their approach aims to enhance the visibility of sky and white objects while circumventing distortions in sky regions through a view-based cluster segmentation technique. In this approach, adjustments are made to the estimation of the sky region based on distance to mitigate distortion, while the initial clustering of depth employs a Gaussian Mixture Model (GMM). This method proposes the utilization of individual components such as GMM clustering, color attenuation prior, transmission estimation, and atmospheric light estimation for both the hazy image and depth map. To mitigate color distortion and enhance overall contrast, the approach is refined by incorporating view based cluster segmentation. Furthermore, the technique offers a means for video dehazing employing an online GMM cluster.

Yongmin Park et.al [18] presented a rapid implementation methodology for dehazing outdoor videos using dark-channel priors. It achieves the swift implementation of the dark-channel priors approach aimed at the dehazing of outdoor footage. While maintaining the original method's dehazing quality, up to 49% less execution time is utilized generally. The signal processing method known as "dehazing" is used to remove haze. Every pixel in the picture has a different level of haze density. Therefore, finding the black pixel in a picture clears out any haze. Camera records the blurry image and locates the air light. A cost function made up of a term for the standard deviation and a term for the histogram uniformity is developed to assess the contrast. In the end the test results reveal that the proposed approach effectively enhances the clarity of the scenery by eliminating haze.

Lee, S., Yun, S et.al [19] outlined a technique for addressing single image blurriness through a fractional order dark channel prior. This study offers a method for deblurring photos that uses a fractional order dark channel prior (FODCP) and a fractional order operator to improve hazy images. Additionally, the half-quadratic splitting approach is used to solve the non-convex problem, and many measures are put in place to gauge the effectiveness of the deblurred photos. The findings of quantitative and qualitative trials support the idea that when used on artificially and naturally blurred photos, the suggested approach produces cutting-edge results.

Liu, Juping et.al [29] presented a paper titled "Enhancing Visibility in Day and Night Images through Combined Dark and Bright Channel Priors for Haze Removal." By combining the dark-channel prior with the multi-scale-retinex theory, they created an improved haze removal method for this investigation. They were able to accomplish dynamic optimisation of the transmission map, leading to better visibility, by combining the combined dark channel prior (DCP) and bright channel prior (BCP) with the multi-scale retinex (MSR) method. The suggested approach efficiently decreases picture noise while utilising retinex theory's basic ideas. The testing results show that the suggested strategy considerably improves image quality in situations when fog predominates at night as well as throughout the day. The outcomes demonstrate that the new method significantly improves picture quality, as seen by significant gains in measures like PSNR and SSIM.

Zhu, Pengcheng et.al [20] presented Single-Image Dehazing Based on Improved Bright Channel Prior and Dark Channel Prior The authors present a novel approach for single-image dehazing, leveraging an enhanced Bright-Channel prior (BCP) [26] and Dark-Channel prior (DCP) to yield more precise estimations of transmission maps and atmospheric light, ultimately leading to the restoration of clearer, haze-free images. The initial proposition addresses a shortcoming of the DCP method in handling sky regions. To overcome this, the authors introduce an Otsu segmentation using Particle-Swarm Optimization (PSO) to organize hazy images into sky and Non-sky regions. Subsequently, parameter estimation is performed utilizing the improved BCP and DCP methods. To further enhance parameter fusion between BCP and DCP, weighted fusion functions are proposed. These functions contribute to more accurate transmission map and atmospheric light estimations, respectively.

Shanshan Huang et.al [21] have presented a novel approach titled "Enhancing Automated Driving Image Clarity through Enhanced Dark Channel Prior-Based Defogging." The authors of this paper suggest a novel method to enhance the defogging process of dark channel images. This approach includes automatic colour equalisation, quick bilateral filtering for transmittance optimisation, and adaptive Domain Dark Channel computing. Experimental outcomes validate the effectiveness of this method. The suggested technique has outstanding features in terms of picture clarity and general brightness. Moreover, enhancements are observed in mitigating undesirable halo effects and block artifacts. The method also succeeds in maintaining favourable image contrast, color saturation, and realism. As a consequence, this method offers a robust solution that holds promise for improving image detection and processing within automated driving systems.

Zhiqin Zhu et.al [22] presented Dehazing Algorithm Based on Atmospheric Light Estimation for Remote Sensing Images with an objective to improve the haze-affected remote sensing photos' visual quality. The first step in producing scene depth maps for remote sensing photos is to optimise the parameters of a linear scene depth model using a differentiable function. The subsequent scene depth map is used to approximation the atmospheric light present in each foggy remote sensing picture. The researchers then use an atmospheric scattering model to successfully remove the haze from the remote sensing photos using the estimated atmospheric light and a transmission map. The researchers put up a dataset of 100 remote sensing photos taken under cloudy conditions to test their methodology. The effectiveness of the suggested dehazing method is supported by thorough comparison studies as well as theoretical research.

Dat Ngo et.al [23] introduced a novel and straightforward approach for eliminating haze in single images, specifically designed for real-time vision-based systems. The authors presented an image enhancement-oriented method that effectively removes haze while producing satisfactory results. Their strategy is based on the finding that haze tends to mask picture details and boost overall brightness. The authors use a single blurry image as the source to create a series of under-exposed, detail-enhanced photographs to demonstrate their method. The fusion procedure is directed by weight maps that were generated using the Dark Channel Prior (DCP) approach, a well-known haze indicator. The authors use adaptive tone remapping as a post-processing step to improve the findings even further. This process aids in increasing the final image's dynamic range, which enhances visual quality. Compared to traditional methods used to remove the haze, recent advances include the use of Neural Network (NN) architectures to learn the feature of haze image and eliminate the haze. Deep neural networks are more powerful algorithms compared to traditional approaches [24][25].

To obtain effective features for single image dehazing, ranking based Convolutional Neural Network is proposed by Yafei Song et. Al. [26]. A ranking layer is proposed to extend the structure of CNN so that the statistical and structural attributes of hazy images can be simultaneously captured. By training, haze-relevant features are automatically learned from massive hazy image patches. Based on these features, haze is removed by using a haze density prediction model trained through the random forest regression. S. Satrasupalli et. Al. [27] have employed computationally efficient encoder-decoder model based convolutional neural network (CNN). Objective analysis depicts that the proposed architecture is relatively better in terms of SSIM & PSNR compared with the recent methods. Jiang et. Al [28] proposed a multi-scale residual convolutional neural network (MRCNN) that can learn the mapping relations between hazy images and their associated haze transmission automatically. MRCNN behaves well in predicting accurate haze transmission by extracting spatial–spectral correlation information and high-level abstract features from hazy image blocks. Experiments on Landsat 8 Operational Land Imager (OLI) data demonstrate the effectiveness of MRCNN for haze removal. From the literature, it is evident that a deep network for haze removal of different kinds of images is crucial and has lot of potential in contributing their improvements in haze removal methods.

Methodology

In this paper, we propose a deep learning approach to enhance the quality of hazy images by removing atmospheric haze and restoring visual clarity. Our aim is to significantly improve image quality, measured by metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM), contributing to image enhancement and computer vision.

Data preparation is vital for training our deep learning-based image dehazing model. This involves resizing and organizing the training dataset into a uniform size of 256 x 256 pixels. The prepared dataset is crucial for training a deep learning model for image dehazing, as demonstrated in subsequent code. The architecture utilized for image dehazing follows an encoder-decoder design, as illustrated in Figure 1.

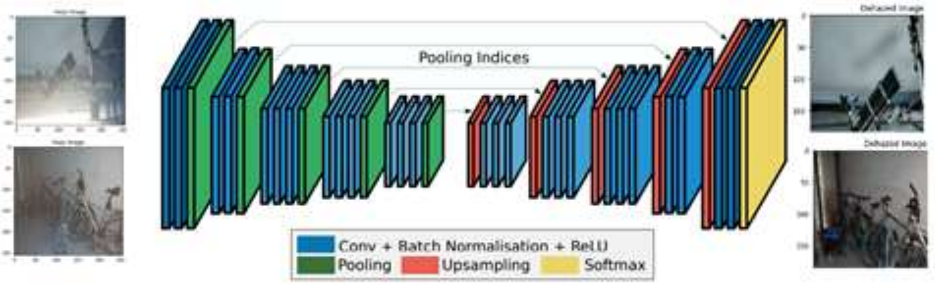

Figure 1. CNN encoder-decoder architecture

The encoder extracts essential features from the input hazy image using convolutional layers with ReLU activation functions and batch normalization. The decoder reconstructs the dehazed image from these features using transposed convolutional layers, also with ReLU activation functions and batch normalization. The final layer produces the dehazed image by reducing the number of channels to 1.
During training, we employ the Mean Squared Error (MSE) loss function to measure the discrepancy between predicted and ground-truth images. The Adam optimizer is used to optimize the model's parameters and minimize the loss.
The training process consists of iterating over a predefined number of epochs (typically 1000), shuffling the training data at the start of each epoch to introduce randomness, and updating model parameters through forward-propagation, loss computation, and backpropagation to minimize the loss. Our methodology ensures effective image dehazing by minimizing the difference between predicted and ground-truth images, facilitated by the Adam optimizer and MSE loss function.

DATA SET

I-Haze dataset: This dataset is specifically tailored to indoor scenarios simulating hazy or foggy conditions within indoor environments: various sources of pollutants, dust, or other airborne particles that affect image quality. The I-Haze dataset contains 25 indoor hazy images (size 2833×4657 pixels) training. It has 5 hazy images for validation along with their corresponding ground truth images.
O-Haze dataset: This dataset addresses the challenges posed by hazy or foggy conditions in outdoor scenes: factors like air pollution, humidity, and other atmospheric conditions. The O-Haze dataset contains 35 hazy images (size 2833×4657 pixels) for training. It has 5 hazy images for validation along with their corresponding ground truth images.

EXPERIMENTAL RESULTS

In the context of experimental results, the comparison of original images, hazy images, and dehazed images is a visual assessment approach to evaluate the performance of a dehazing algorithm or model. In this research, the I-Haze and O-Haze dataset, containing a diverse collection of hazy images captured under various atmospheric conditions, is chosen [31] [32].
Figure 2. shows a subset of images from the dataset in three columns: the first column displays the original, unaffected images; the second column presents the same images but intentionally degraded by atmospheric haze, referred to as hazy images; and the third column shows the images after applying a dehazing process, resulting in dehazed images.
To evaluate the effectiveness of the proposed approach, a quantitative analysis is performed. Metrics, namely, Peak Signal to Noise Ratio (PSNR) and Structural-Similarity Index (SSIM) are used to assess the quality and perceptual accuracy.

PSNR, commonly employed in image compression, is used as an indicator of the reconstructed image's value. A higher PSNR value indicates superior reconstruction quality. The PSNR is calculated using the equation:

$PSNR=10log10\ (peakval2)/MSE$,

where peakval refers to the image's greatest intensity value and MSE stands for mean square error. Conversely, SSIM aims to capture the perception of variations in structural information, with a specific emphasis on spatially confined or interdependent pixels. This measure is applied to the quantification of picture and video values. SSIM measures the similarity between the original and reconstructed images. It may be computed as follows:

$SSIM(x,y)=[l(x,y)]\alpha.[c(x,y)]\beta.[s(x,y)]\gamma$

where l stands for luminance, c for contrast, and s for structural information. The symbols α, β, and γ were positive constants which are employed in the calculation

Table 1 indicates the mean PSNR and mean SSIM values, showcasing the quality and similarity measures for the evaluated images or image processing results.

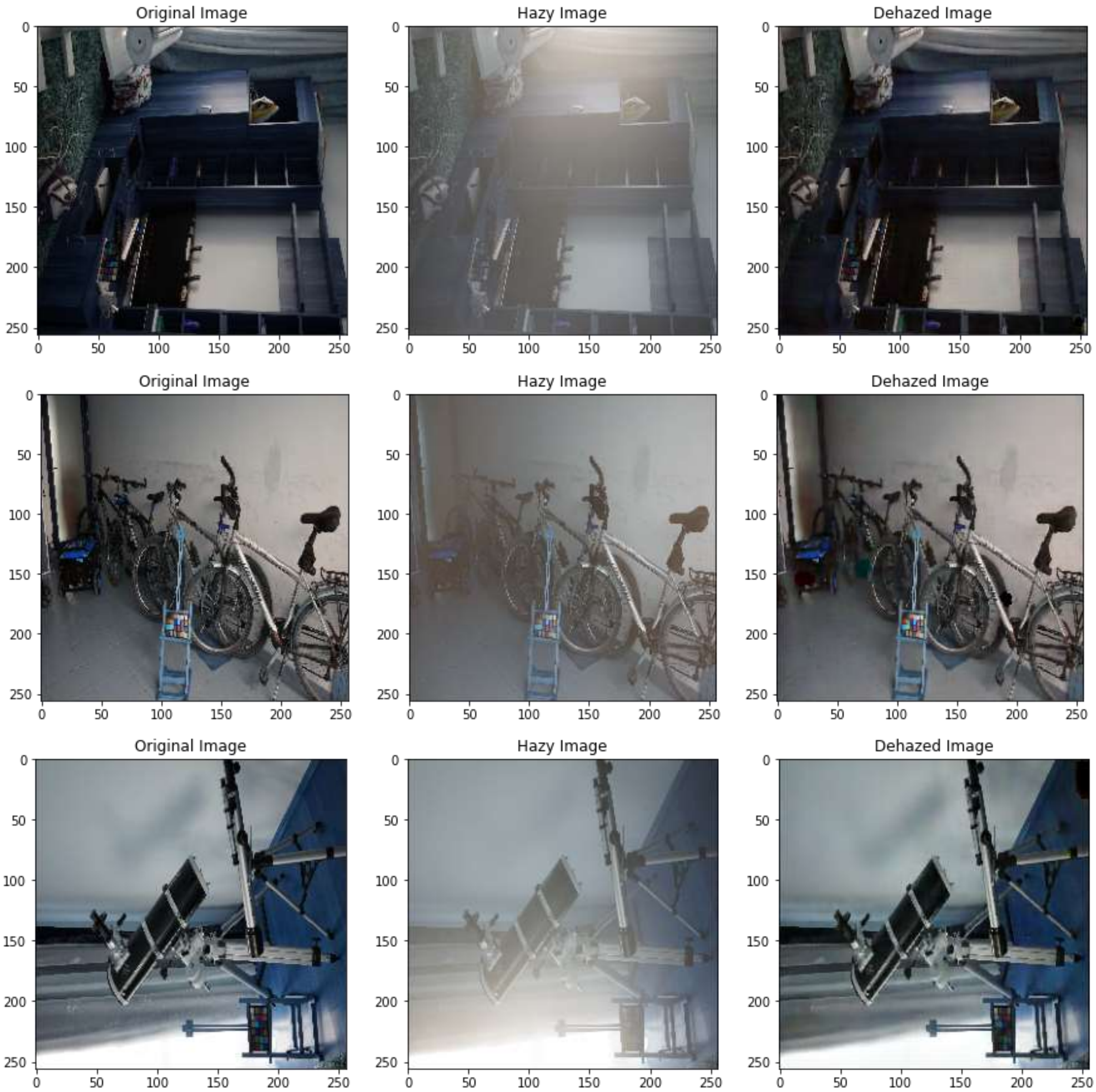

Figure 2. Comparison of different result images

Table 1. Mean PSNR and SSIM for sample set of images

Mean PSNR	Mean SSIM
28.42	0.9237

A mean PSNR of 28.42 dB and a mean SSIM of 0.924 suggest that your model has performed well in enhancing image clarity and reducing haze

5. CONCLUSION

The mean evaluation metrics for the image processing task reveal promising results. The reported mean Peak Signal-to-Noise Ratio (PSNR) of approximately 28.42 decibels indicates a high level of fidelity in the processed images, with a lower presence of noise or distortion compared to the original images. Additionally, the mean Structural Similarity Index (SSIM) of around 0.92 reflects a substantial degree of structural similarity between the processed images and their original counterparts. This suggests that the applied image processing or restoration techniques have effectively preserved important image features, contrast, and overall structure. In combination, the elevated mean PSNR and SSIM values signify successful image processing, where the resulting images exhibit both high fidelity and structural similarity to the original images. These quantitative metrics contribute valuable insights into the quality and similarity aspects of the processed images, complementing any visual assessments that may be conducted.

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