Single Image Dehazing Through Feed Forward Artificial Neural Network

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Abstract. Due to light scattering by air particles, images taken under bad lighting conditions (such as haze, fog, mist, or smog) have a reduced level of visibility. One blurry image can be made visible again using single image dehazing techniques. Due to the ill-posedness of the Single image dehazing problem, it is difficult to solve. Even though, the Dark channel prior (DCP) has been the most prevalent method for image dehazing algorithms, but it suffers from huge computational time and picture quality. The accurate transmission map estimation is one of the best preferred ways to achieve the least computational time and high picture quality in DCP. Hence, this work is focused on constructing transmission map of a hazy image based on feed forward artificial neural network. The recommended method uses a feed forward ANN to conduct the transmission map straight from the minimum channel and a normalizing procedure to increase the re-covered image information. With a training set of eighty images, the network is trained by means of mean square error (MSE). The proposed method utilizing peak signal to noise ratio (PSNR) and structural similarity (SSIM) index measures are used to assess the restoration quality. The investigational conclusions have demonstrated that, the suggested method outperforms the dehazing of an input image without degrading visible quality (PSNR = 69.16, SSIM index = 0.8913). In addition, the proposed method is suited for real-time applications given the average computing time it achieves is 1.03 s.

Keywords: Dark channel prior · Dehazing · Transmission map · Multilayer perceptron · Restoration

1 Introduction

Haze is a normal environmental oddity that is caused by minute particles like dirt, fume, and airborne fog, which reduces the clarity of the picture. Dehazing calculations were traditionally used for a narrow range of purposes since experts considered it as a photo handling technique to recover image details. But the requirements of significant level computer vision assignments, the rapid advancement of independent frameworks, and artificial insight have all led to a renewed interest in more advanced picture dehazing

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techniques [1]. Dehazing estimation improvement has thus become possibly the most important topic of artificial intelligence, and one of its most fundamental applications is the use of dehazing computations to advance the display of autonomous structures and stages for adverse barometer conditions.

Most often, a computer vision framework's optics are designed under the assumption that there will be beautiful weather patterns, in which case each pixel color intensity will only be related to the brightness of the initial scene. As a result, learners in the early stages of computer vision tasks specifically missed the state of bad weather [2]. However, experts rapidly realized the value of photo reclamation techniques. Outside images are unavoidably adversely impacted by the environment, and refraction, scattering, and maintenance do occur even on reasonably sunny mornings resulting in the loss of specific information and low differentiation. Unfavorable consequences on independent frameworks are undoubtedly caused by these degraded images [3]. Figure 1, depicts the basic atmospheric scattering model in which the haze is formed on the images.

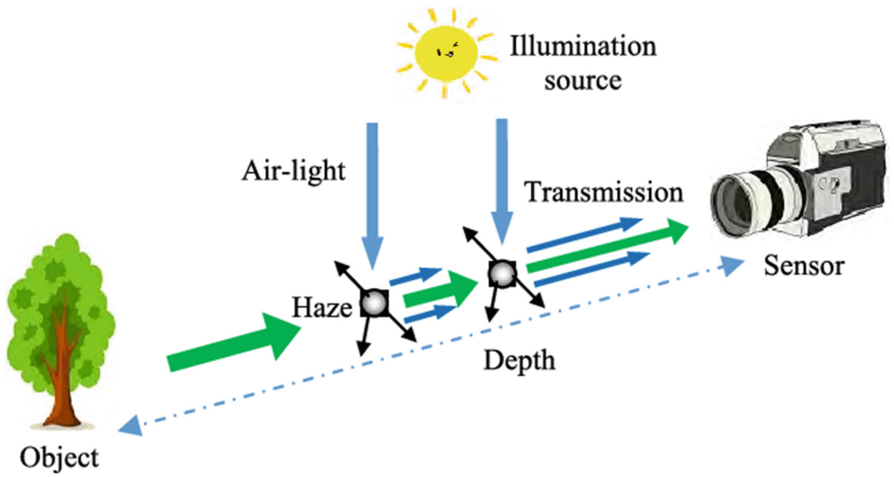

Fig. 1. Haze creation model.

Haze ejection is particularly appealing in a variety of industries, including computer vision analyses, image processing, and visual art [4, 5]. To begin with, the visibility of a dim image brought on by air particles is improved when the haze is removed from the image. The scene is the related image. Luminant is used in the majority of computerized image processing techniques, including sophisticated scale shape identification. The scenes are what are used to evaluate these techniques. When the image or picture is tedious, visual computations struggle and struggle to perform well. In this way, removing the fog is necessary for improved results and productivity. The likelihood of using the horrible images increases [6].

The term spatial variation refers to the corruption that results from scattering that is dependent on the distance of the camera from the scene. The capacity to perceive the dim picture caused by the air particles is increased by the removal of murkiness from the image [7]. Therefore, the focus of this work is on creating an algorithm for image dehazing that has high accuracy and requires minimal calculation time while maintaining acceptable picture quality [8]. This can be achieved by employing the perfect transmission map estimation in DCP algorithm, which can be accomplished through feed forward ANN. Here, the transmission map has been approximated through a minimum channel without lowering the image quality and the network has been trained using a data set of 80 images with MSE.

2 Related Work

Most single-image dehazing computations use learning-based highlights or previously computed picture handling highlights to predict transmission, whereas exact techniques are used to measure the barometric light (the exemption being start to finish learning-based calculations). However, recently the single image dehazing based on convolutional neural network (CNN), artificial neural networks (ANN), and deep neural network (DNN) has attained enormous significance among the research community as they have offered less computational time and high accuracy when compared to conventional dehazing algorithms (DCP, Fast DCP).

Using clear photos as positive instances and hazy images as negative instances, a unique contrastive regularization (CR) based on contrastive learning has been proposed [9] which is used to take advantage of both the information contained in each type of image. CNN grounded Deep architecture has been presented [10], and its layers are specifically created to encapsulate the established presumptions/priors in picture dehazing. The authors in [11] also developed a CNN based dehazing algorithm. To unswervingly rebuild the dehaze image, the authors of [12] presented an endwise feature fusion attention network (FFA-Net).

Image haze removal techniques traditionally rely on estimating a transmission map. The lack of depth information makes this a poorly presented challenge when dealing with single photos. The authors in [13] proposed an end-to-end learning-based method for directly removing haze from an image by employing a modified conditional generative adversarial network. A GAN for a single image that is cycle-consistent dehazing method called CD-Net has been suggested; it is trained on a dataset of real-world hazy images in an unpaired fashion [14].

For single-image dehazing, the authors of [15] developed a particular generative adversarial network (GAN). The authors in [16] were driven to consider the Laplacians of Gaussian (LoG) of the images, which astonishingly preserves this information, in order to address the problem of single image haze removal due to the challenges in single picture dehazing. According to the authors of [17], ignoring a continual atmospheric light guess, a unique dehazing network that concurrently estimates the transmission map has been proposed.

A unique method to eliminate haze degradations in RGB photos has been developed by the authors in [18] utilizing a layered conditional Generative Adversarial Network (GAN). To remove the haze on each color channel separately, it uses a triplet of GAN. Numerous authors have developed single image dehazing algorithms based on CNN, DNN and GAN, which highlights the effective estimation of the transmission map of dark channel image. Numerous new investigations based on Arduino integrated with

IOT [19–23] perceive the requirement for ongoing handling and the advancement of methods to lessen the capacity, intricacy, handling time and other related angles without compromising the presentation. Hence, in this work a feed forward artificial neural network has been proposed for effectively estimating the transmission map of hazy image without degrading image quality by a means of trained data set of eighty images.

3 Methodology

Usually, the DCP consists of four major steps for image dehazing such as; atmospheric light estimation; transmission map estimation; transmission map refinement; reconstruction. The major disadvantage of DCP methodology is its computational time. Introducing ANN in transmission map refinement stage has reduce the computational time.

3.1 Atmospheric Light Estimation

The haze image is a combination of image coordinates, observed image, haze free image, atmospheric light, scattering coefficient and scene depth [3], which is represented using (1). The dark channel from the input hazy image is estimated by the majority of traditional DCP-based dehazing techniques and it is represented using (2).

$$I_{haze}(x) = J_{haze-free}(x)e^{-\beta d(x)} + A\left(1 - e^{-\beta d(x)}\right) \quad (1)$$

$$J^{dark}(x) = \underset{y \in \Omega(x)}{min}\left(\underset{c \in \{r, g, b\}}{min} J^{c}(y)\right) \quad (2)$$

3.2 Transmission Map Estimation

From Eq. (1), β is the atmospheric scattering coefficient and d is the scene depth. The transmission map has been estimated [3] with β, and d values and it is represented using eq. (3).

$$t(x) = e^{-\beta d(x)} \quad (3)$$

3.3 Transmission Map Refinement

False textures and blocking artefacts might result from improper estimate of the transmission map. Hence, transmission map refinement based on feed forward artificial neural network has been considered for accurate refinement. The multilayer perceptron approach, which was developed from neurons, is utilized in transmission map refining. The basic building blocks of the brain and nervous system are biological neurons, often known as nerve cells or just neurons. These are the cells that receive sensory input from the outside world via dendrites, analyses it, and then transmit it to other cells via axons. The feed forward neural network is supplemented by the multi-layer perceptron (MLP).

A data set of 80 images having mean square values have been trained in perceptron which are having the dimensions of 512 × 512 and having different picture quality. The transmission map has been evaluated flowed by preprocessed dark channel construction. As depicted in Fig. 2, it has three different sorts of layers: input layer, output layer, and hidden layer [24].

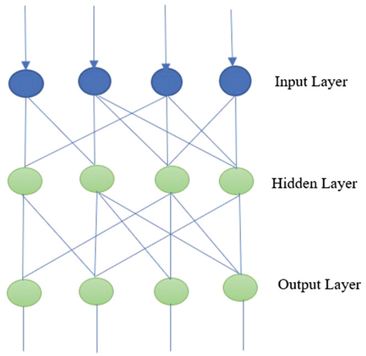

Fig. 2. Representation of Feed Forward ANN with Single Hidden Layer [24].

The signal is received at the input layer, where it will be processed. The output layer completes the necessary tasks, such as classification and prediction. The true computational engine of the MLP is composed of an arbitrary number of hidden layers sandwiching the input and output layers. Similar to a feed forward network, data moves forward from an MLP's input layer to its output layer. The back propagation learning approach is used to train the MLP's neurons [24]. A perceptron receives n input features ($x = x_1, x_2, \ldots, x_n$), and each one is given a weight (see Fig. 3). It is vital to have features for numerical input. As a result, in order to use a perceptron, nonnumeric input properties must be transformed into numeric ones.

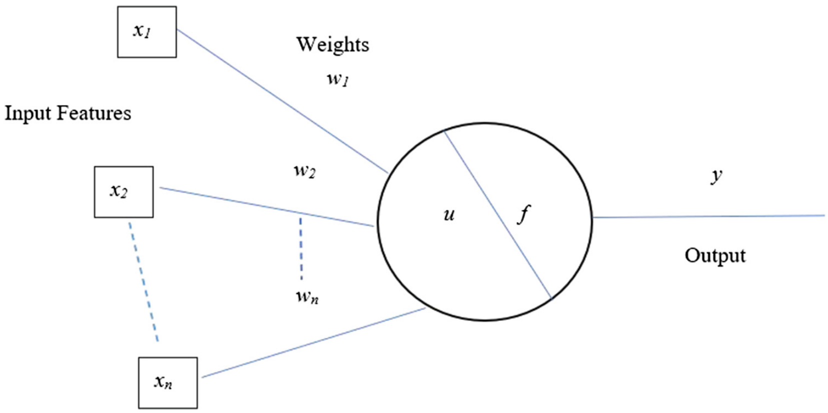

Fig. 3. Representation of Perceptron with n input features [24].

During pathway, the starting layer has been biased and applied with data stream, and it is continued for all layers until accomplished output has been formed (see Fig. 4). After comparing the network's actual and predicted output values, a fault signal is intended for each output node [25].

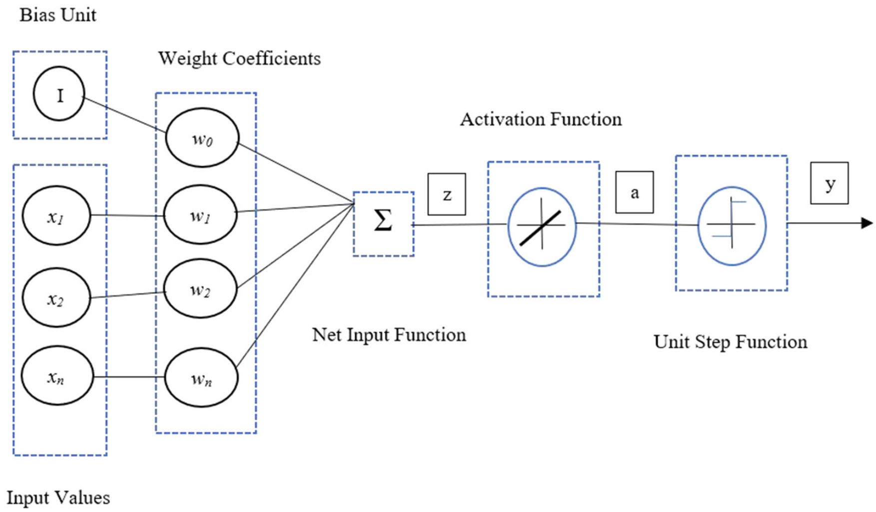

Fig. 4. Feed Forward ANN Architecture with Single Layer [26].

For all hidden layers, until each weight in the system attained a fault signal representing its comparative fault. Then, for each weight the faults are updated until the training patterns are fully encoded.

4 Simulation Results

First, the proposed approach has been applied to the input haze image. It is first applied for dark channel building after being down sampled by four. The dark channel formation was involved in a number of DCP-related processes, and the output was zero-padded. Transmission map has been created following dark channel construction (which is pre-processed). Using a feed forward ANN in the transmission map refining stage has solved the issues with transmission map estimation.

4.1 Subjective Analysis

Subjective analysis is the analysis which uses the observers to make the quality estimation based on their visual opinion of the image. The subjective analysis has been carried out for various hazy images. The simulation results clearly indicates that, the photographic eminence (see Fig. 5) of dehazed images is far better than the input haze image.

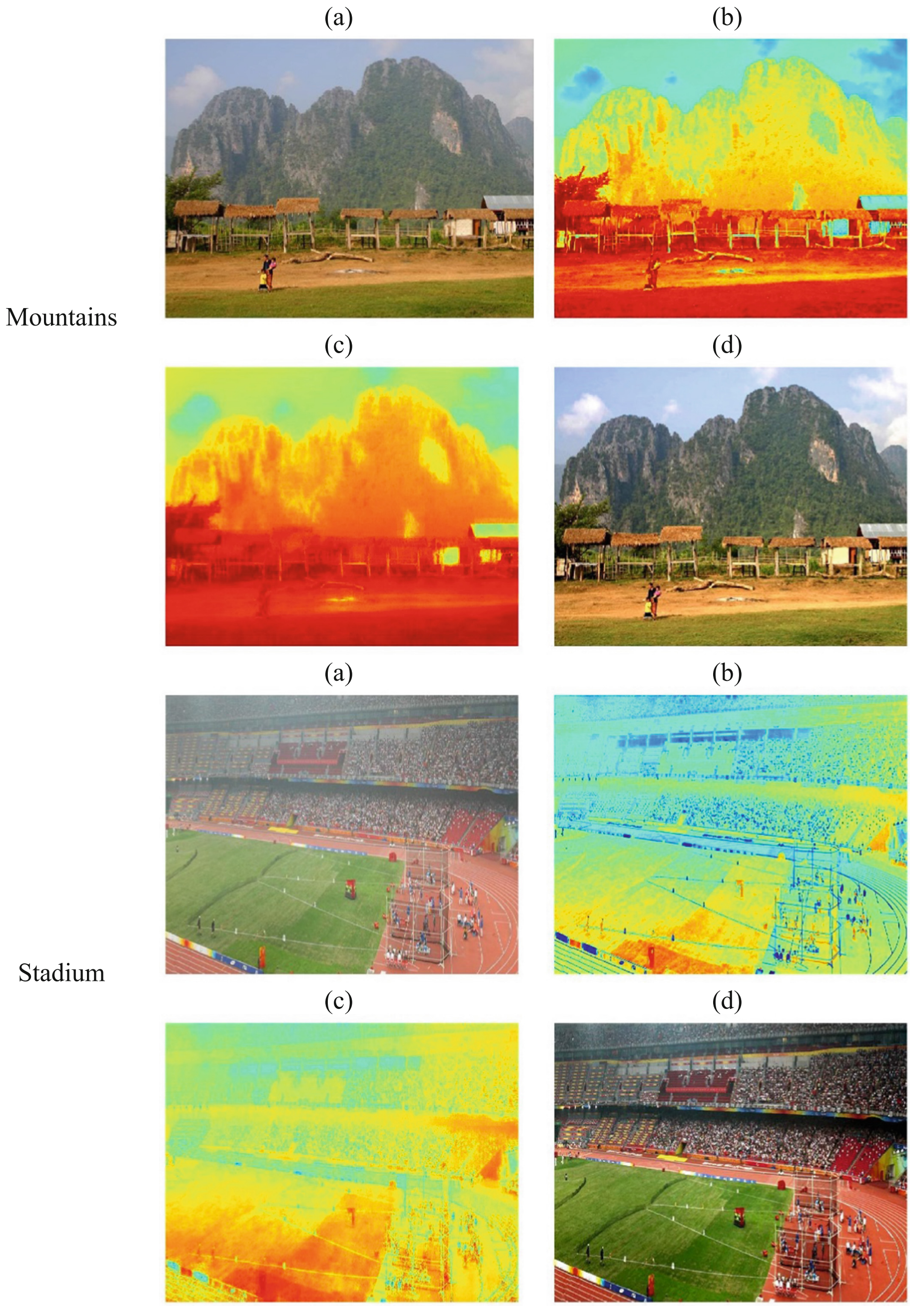

Fig. 5. Simulation Results of Proposed Dehazing Method for different input hazy images (a) Input Hazy Image (b) Initial Transmission Map (c) Feed Forward ANN based Transmission Map (d) Dehazed Image.

4.2 Objective Analysis

The objective analysis has been conducted for the proposed methodology in terms of PSNR, SSIM and computational time. The detailed analysis has been depicted in Table 1. The PSNR and mean square error has been evaluated using (4) and (5) respectively.

$$PSNR = 20\ \log(\frac{Max}{\sqrt{MSE}}) \tag{4}$$

$$MSE = \frac{1}{MM}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \tag{5}$$

Table 1. Performance Measures of Proposed Algorithm for Different Input Images.

Image name	PSNR	SSIM	Computational time (s)
Mountains	68.41	0.9105	1.15
Pumpkins	62.10	0.7469	1.25
Stadium	68.69	0.8695	1.18
Park	61.61	0.7922	1.03
City	62.85	0.6727	1.20
Florence	69.16	0.8913	1.73
Cones	67.66	0.8213	1.08

5 Conclusion

Image dehazing expulsion techniques have become more treasured for many picture handling and computer vision implementations. All the dehazing methods helpful for reconnaissance, for distant detecting and submerged imaging, photography and so forth A large portion of the techniques depend on the assessment of climatic light and transmission map. In, this work the transmission map refinement has been evaluated based on feed forward ANN which is having a train data set of eighty images with normalized mean square error. The proposed methodology achieves acceptable image quality (PSNR-69.16; SSIM-0.9105) and less computational time (1.03 s).

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