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Procedia Computer Science 147 (2019) 124-130



www.elsevier.com/locate/procedia

2018 International Conference on Identification, Information and Knowledge in the Internet of Things, IIKI 2018

Single Image Dehazing using CNN

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Abstract

Haze is a natural phenomenon in which the dust, smoke and other particles alter the vision of the sky to reduce the visibility. Hazy images cause various visibility problems for traffic user, tourists everywhere, especially in hilly areas where haze and fog are very common. In this paper, a method for single image dehazing using convolutional neural network is proposed. Outdoor images have been used on which particular filters are applied to find the haze in image. Hazy images contain small value in only one-color alpha channel from Red, Blue, green RGB channel. The intensity of these pixels is mainly bestowed by air light depth map. Estimating these low value points of haze transmission map are useful to obtain a high quality dehazed image. An end-to-end encoder-decoder training model is utilized to achieve a high quality dehazed image. The approach is validated on datasets which consists of around 1500 outdoor images. The method also gives transmission map of the hazy image which can further be used to enhance visibility of the scene.

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Peer-review under responsibility of the scientific committee of the 2018 International Conference on Identification, Information and Knowledge in the Internet of Things.

Keywords: Image Dehazing, Guided filter, Transmission map, Depth map, Atmospheric light, Encoder-Decoder

1. Introduction

Outdoor images lose their quality due to the reflection off sunlight i.e. air pollution (haze) or water droplets in the air (fog) or combination of both smoke and fog (smog). Haze is the natural process in which the dust and smoke particles reflect the sunlight casing the vision loss [1]. The visibility from the camera is faded due to the interference

with the environmental light source reflected by the dust particles. The blurred images gain noise and loses the colour attenuation, as described in Figure 1.

Haze removal is highly desirable in different fields like computer vision algorithms, image processing and photography [2,3]. First, removal of haze from the image increases the visibility of hazy image caused by the atmospheric particles. In most computer image processing techniques, from bigger scale image processing to advanced scale shape detection considers that the corresponding image is the scene Luminant. The evaluation of these techniques depends on the scenes. If the image or scene is dull, then vision algorithms face many issues and do not show efficient performance. So, removing haze is needed for better results and efficiency. The bad images can be put to better use. The amount of dispersion depends upon the length of scene from the camera and this degradation is spatial-variant. Removal of haze from the image increases the visibility of hazy image caused by the atmospheric particles. Haze-free images are more delightful than hazy images, as shown in Figure 1.



Figure 1: (a) Hazy and (b) Haze Free Image.

Tan hypothesized that the initial input image must have capable brightness than the input hazy image and removed haze from the image by boasting the neighbour pattern of the reclaimed image [5]. The results were corrected by vision that can't be validated mathematically. Fattal computed the albedo of the environment and then infers the transmission map by considering that transmission map and the shady part of the image are logically unrelated [4]. It can be validated because it gives the remarkable conclusions. However, in this research they did not consider the indoor images which may cause inaccurate results if the hypothesis goes wrong [4].

To overcome the aforementioned problems, a new method for single image dehazing using convolution neural network is proposed. An end-to-end encoder and decoder are used to obtain the dehazed image, for the training purpose outdoor images are considered. The method is based on the low value of pixel in the hazy image in at least one colour from RGB channel. In hazy image, the value of these pixels give us the hazy part of the image. By this, these particular pixels provide clear computed image of haze transmission. After that, we are using convolution neural network on it and recover high quality image which is dehazed image.

The paper is organized as follows. Section II provides relevant literature on image dehazing. Section III illustrates the methodology adopted to overcome the issues. Experimental results are presented in Section IV. The last section concludes the research work

2. Literature Review

In the computer vision, image enhancement and haze removal is a very challenging task. The classical image dehazing model [4,5,6] can be explained as:

$$Q(a) = W(a)i(a) + P(L - i(a))$$
(1)

Where Q is the highest value that is hypothesized, W is the deflection of light, P is the average sunlight present in the environment and i is the glow that doesn't scattered and plan to the target. This equation is used to recover W (reflected light), P (light source) and i (transmission medium) from the intensity (Q).

The first variable in Eq (1) describes the light reflected from the surface and its decay in that medium (direct

attenuation) and the second variable describes the light source which result from the previous scattered light source which lead to the change of scene color [7]. When the environment is same, the conveyance I can be defined as;

$$R(b) = z - \exists o(b) \tag{2}$$

Here, \exists indicates that surface light is exponentially link with depth scene o. Geometrically, Eq-1 defines that they are in one color channel, vectors P, W(a), and O (b) are the end which lies in the same plane.

In 2008 R. Tan's Model focuses on the improvement on visibility of an image [5]. It was used for the visibility of bad weather images. Tan model approach is based on two basic observations. First, the dehazed image has more contrast than hazy images and second the air light intensity change depend on the distance from object to camera. Based on these two observations, the author developed a function in the framework of MRF (Markov Random filed) in order to enhances the output image by obtaining the detail and structure from the image. This method focusses on the enhancement of visibility, it does not aim for the recovery of reflected areas.

Fattal introduced another image dehazing model [4]. It assumes that the scattered light is removed in order to increase the vision and recover haze from the image. In this approach, the author redefined image model that account for surface shading in addition to transmission function. Based on this image model, the image is divided into small parts of constant albedo. The light source ambiguity is removed by adding a function which require surface shading and medium transmission function to be locally statistically unrelated. Fattal used a physics-based approach to produce haze-free image and require statistical based assumption in the local patches which make it non-convenient. Color attenuation prior model is used to remove haze from images [8]. A linear model with supervised learning is used for the scene depth of the hazy image. In this way, a link between the image and its depth map is established. By estimating the depth map of an image, the haze can be easily recovered. This approach has high efficiency and better dehazed effect however did not performs well in all cases.

Codruta Orniana [9] proposed a technique to obtain the dehazed image using the original degraded information, accurately. The aim is the enhancement of visibility similar to Tans model.

Segmenting the super pixels technique is proposed to remove the haze from image [10]. The earlier methods for removing haze might not work under some conditions due to the noise distribution. So, to overcome the affect, an improved method by combining the segmented pixel with light intensity of a haze image was proposed to compute the sunlight instead of dark channel prior. They also proposed to estimates the transmission map. Color space conversion in done by converting RGB into HIS. In RGB channel, pick the brightest pixel and record the location of that particular pixel.

The worst weather conditions were considered by [11, 12] in which the images were taken in rainy weather which has noise and shady effect due to water droplets on the camera lens. Images which are taken in hazy environment conditions give the poor visibility, which will have a great effect on the outdoor computer vision systems, such as video surveillance, traffic surveillance camera, and security purpose systems. The authors used polarization and dark channel prior method to solve the mentioned problems.

3. Methodology

Haze removal methods fails under certain conditions. Which includes polarization techniques where the haze is removed by applying haze removal filter such as mean guided filter. In some other studies, they also computed the transmission map to further clear the visibility of the hazy image [13-16].

The proposed training model first extracts the dehazed feature from the image using the convolution operation and fed-up the feature map to 1st hidden layer. These features will not be enough in order to remove haze from the given datasets. So, there is need to extract some high-level features. For this purpose, the size of feature map is reduced which extract the significant part in the 2nd hidden layer. The output layer can check whether the input image is hazy or not. Figure 2 shows the architecture of methodology.

This dehazing method is applicable only to outdoor images. The main technique is to find the low intensity pixel from the hazy image by applying a filter [17-18]. These intensity pixels further compute the transmission map which further improve visibility. By this, these particular pixels can give us the accurate computed haze model. After that, apply some methods on it and recover high quality dehazed image. The proposed method is applicable to handle the distant objects even in the very high turbid medium.

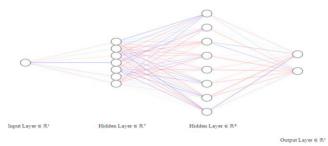


Figure 2: Architecture of proposed methodology

The encoding and decoding phase is shown in Figure 3, filters of all the previous approaches forming an opaque convolutional neural network is applied to extract feature map from the hazy image. This CNN model contains 7 neurons in the 2nd hidden layer and 8 neurons in the 3rd hidden layer forwarding the information in a feed-forward manner as shown in Figure 3. The type of model presented in the paper ensures the efficient method to pass the parameters in both forward and backward propagation pass.

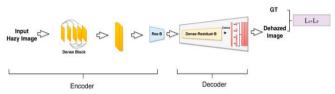


Figure 3: CNN model for haze from removal

The decoder function is similar to the encode phase except that it uses residual function which ensures that each hidden neuron is fully connected to all other neuron connected in the second layer as shown in Figure 3. The advantage of this function is that it improves the learning rate and converge our training data set model.

A non-linear relation is established between a hazy image and estimated ground truth. This relationship recovers a high quality dehazed image from a hazy image in an efficient manner. The proposed model involves an encoder-decoder structure using a deep neural network. The involvement of gradient descent increases the reliability of convergence of training dataset model. The mean squared error and residual loss function play a vital role in training of the dataset model. This approach is based on the mentioned hypothesized of the hazy images: in most of the non-environmental. Some of the color from the RGB channel has very low value in some parts of the images [18]. In general, the lowest value in such scenarios should be;

$$Wmax(z) = low(low(Wc(x))) {}_{c}\{r, g, b\} x \Omega(a)$$
(3)

Here Wc is the original hazy image W and Ω (a) is a neighbourhood part of the image which point at the centre. Our hypothesized scenario says that except for the environmental part, the value of WMax is small and move towards 0, if W is a clear image. We say, WMax the high value of W, and therefore assign the above image method to be image dehazing [19]. The low values in the color channel are due to dimness light, brighter images and dark object [20].

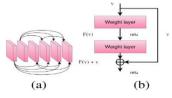


Figure 4 (a) The encode phase (b) Residual function in Decoder

Since, haze usually occurs in outdoor landscape and cityscape scenes. The dehazed landscape and cityscape ones have been picked from the downloaded images which consists of 1500 images. Following is the result of dataset of outdoor hazy image. It can be seen that proposed approach is efficient than the previous approaches and improve the failure cases in all the previous cases. The trained model result of outdoor images is presented in Figure 5.



Figure 5. Left: Dehazed Images in our database Bottom: Ground truth of image .Right: Output Image

Figure 5 shows the dehazed images stored in our database and other images having high intensity pixels. First assume that the atmospheric light A is given. The figure shows different variation of intensities in hazy images. Figure 6 shows the result of proposed training model of indoor images. This model efficiently removes the haze and recover a high quality dehazed image from hazy indoor images. The loss function used in this model recover high transmission value from the input image to further estimate the transmission map from the hazy part of the image. It has been considered that the conveyance in the neighbour pixels $\Omega(z)$ is accurate. The area of conveyance is defined as $t^*(a)$. Taking the minimum operation in the local part on the haze imaging equation. Firstly, consider that the environmental light W is present there. A novelty method for computation of sunlight is shown in Figure 7.



Figure 6. Left: Dehazed Images in our database Bottom: Ground truth of image. Right: Output Image



Figure 7: Haze removal results. Top: input haze Images. Bottom: Dehazed Images. The highlighted part in the Figure shows the novelty for computing the light

We have $low(Wc(z)) = t(x)low + (1 - t(z))Pc. z\Omega(a)z\Omega(a)$ (4)

Keeping in mind that minimum computation is evaluated on RGB channel nonlinearly. *Pc* is always an increasing value. We also have to:

$$low(Wc(z)) = t(x)low(Wc(z)) + (1t(z)) z\Omega(a)y\Omega(a)Ac$$
(5)

According to our approach, the high intensity pixels Wmax of the dehazed radiance W move towards decreasing value:

$$Wmax(x) = low (low(Wc(z))) = 0 c z\Omega(a)$$
(6)

As mentioned earlier that high intensity pixels are not good for mountain and hilly areas region where haze is high. This low value region in not a good approach under certain circumstances. It may fail due to limited vision in the hilly areas. After all the atmosphere is unlimited and the convene move towards 0, the Eq-(6) remarkably shows good result on both the environmental and non-environmental parts [21].

4. Experiment

In experiments, M. Van Herk algorithm is implemented whose time complexity is proportional to the image dimension. The images of 720×480 resolution are considered in experiments. In the proposed methodology, preconditioned conjugate gradient is implemented. The implemented algorithm takes 5 seconds to give the result of 720×480 -pixel image on core i7 processor in MATLAB using filter to test the results. It also uses Pytorch version 3.6 to implement the neural network. It almost took 6 hour to trains the dataset.

Eq-(4) and (5) used to compute the transmission map of the image. The light source in these is estimated in Section IV Figure 9 presents a comparison between our model and Tan's model [5]. The proposed methodology recovers the structure of the image without sacrificing colour information in a better way. Figure 8 presents the comparison of Fattal's result with the proposed approach [4]. This also shows that in case of dark images proposed model gives better result than Fattal's approach.

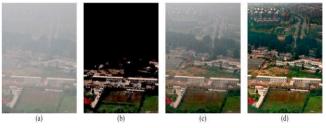


Figure 8: (a) Input Image (b) Before Extrapolation (c) After Extrapolation (Fattal's Result) (d) Our Result If we compare proposed results with the Tan's work, then it also shows significant improvement. Figure 10 shows the comparison of these results.



Figure 9: Left: Hazy Image, Middle: Fattal's Work, Right: Proposed Result

Table 1 shows the comparison of different approaches used with Haze removal and show enhanced results in terms of computational speed, and accuracy and in term of transmission map. Fattal and Tan approach doesn't give transmission map while proposed approach give.

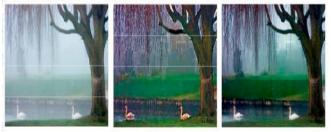


Figure 10: Comparison with Proposed and Tan's Result [5]

Table 1: Comparison of different approaches

Approach/ Parameters	Image Dataset	Transmission Map	Speed Computation	Accuracy
Fattal approach [4]	500	No	High	86%
Tan's Approach [5]	700	No	High	92%
Dark channel Prior [10]	1000	Yes	Low	95%
Proposed Approach	1400	Yes	Low	95%

5. Conclusion

In this paper, we have proposed a very simple and efficient end-to-end encoder and decoder architecture for image dehazing using convolutional neural network. The end-to-end encoder model removes limitations found in the dehazing process. The experiments were carried out on the standard datasets. Proposed approach gives better and efficient results than previous results using high-intensity pixel value. In future, this work may be extended to dehaze those images having no shadow cast and to run on all cases. The real time streaming for dehazing by showing a video that remove haze in real time that will be a great achievement for solving traffic problem in northern areas.

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