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Evaluation of histogram image defogging methods based on histogram equalization, dark channel prior, and convolutional neural network

Maojia Chen[1, †], Xiaoqing Li[2, †] and Yifan Liu[3, 4, †]

[1]School of Economics and Management, Chongqing University of Posts and Telecommunications, Chongqing, 400065, China
[2]School of Artificial Intelligence, Beijing Normal university, Beijing, 100010, China.
[3]School of Computer Information Engineering, Changzhou Institute of Technology, Changzhou, Jiangsu, 213032, China

[4]21030614@czust.edu.cn
[†]These authors contributed equally.

Abstract. Air pollution condition is getting worse with the advancement of society development, environmental pollution has gradually intensified, and smog frequently occurs in more and more cities. On foggy day, the saturation and contrast of an image could be low, and colors tend to drift and distortion. As a result, seeking a simple and effective image de-fogging technique is important for the subsequent research. In this study, three existing classical de-fogging algorithms are reproduced: histogram equalization, dark channel prior method, and convolutional neural network. The three de-fogging algorithms were compared respectively under the conditions of thin fog, thick fog, high brightness, and low brightness, so as to analyze their advantages and disadvantages. It is concluded that there is no obvious difference among the three algorithms in the de-fogging effect under the conditions of thick fog and high brightness, but relatively speaking, the de-fogging image generated by the dark channel prior is more real. When the fog is thin, the dark channel prior and convolutional neural network work better. Under the condition of low brightness, the histogram equalization has a better de-fogging effect.

Keywords: defogging, machine learning, histogram equalization, convolutional neural network.

1. Introduction

Air pollution is getting intense with the advancement of industry, and many cities are experiencing frequent haze. Foggy images collected tend to suffer from low contrast, and color shift. As a result, seeking efficient image defogging technique is important for subsequent research [1,2]. Existing image capturing equipment is very sensitive to the environmental change. In haze environments, outdoor images obtained often degrade severely, which hinders the feature captureing of images by computer vision systems [3,4]. It could affect following analysis, greatly reducing the application performance of vision system and hence could limit the usability of images. Therefore, the significance of image defogging lies in removing interference from weather factors from degraded images, enhancing the

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clarity of images, and maximizing the recovery of useful image features, making the restored image better applied in many computer vision systems [5]. The main purpose of the defogging algorithm is to reconstruct original clear images from images captured in haze environments.

2. Method

The three algorithms used in this study are histogram equalization, dark channel prior method, and convolutional neural network. The main advantages of global histogram equalization are simple algorithms and fast speed. But the disadvantage is that it is sensitive to noise and easy to loses details, resulting in enhanced problems in some result areas [6]. The advantage of local histogram equalization is local adaptive, which can enhance image details to the maximum extent. But the disadvantage is that it is difficult to control the image quality, which will introduce noise. Using the dark channel de-fogging algorithm can avoid serious distortion of the picture, and the overall de-fogging effect of the picture is more delicate. But the disadvantage is that the de-fogging capacity is insufficient the sky area. Under the condition of dense fog, the images obtained by the dark channel de-fogging algorithm are fuzzy and rough. In addition, the images obtained by the dark channel de-fogging algorithm tend to be darker. The convolutional neural network inputs data with normalized data, which is difficult to learn from various data size. The convolutional neural network has no memory function.

2.1. Histogram equalisation

The histogram equalisation includes global histogram equalisation and local histogram equalisation [7,8]. The purpose of this algorithm is to widen the spacing of the greyscale of the image or uniformly distribute the greyscale, so as to increase the contrast, clarify image details, and realise image space enhancement.

2.1.1. Global histogram equalisation. Global histogram processing equalises histograms through R, G and B channels of RGB images. This algorithm first counts the number of image elements, and then calculates the probabilities of pixel values, then conduct the correspondence of probability normalisation, multiply the probability of normalisation by the gray value, and correspond to the original and normalized pixel value. Finally, the model seeks original corresponding pixel value, change it to the current normalised pixel value, and get the balanced image. Although this algorithm is simple and fast, it may cause excessive enhancement in some areas.

2.1.2. Local histogram equalisation. Local histogram equalisation includes sub-block non-overlapping, sub-block overlap and sub-block partial overlap. Different parts of the image will use different algorithms. The sub-block non-overlapping method is conducted first. It aims at separating an image into multiple n*n-sized local blocks according to the input segment size of n, and equalises the histogram of each block separately. The method leverages histogram information to equalise pixels in the centre of a local block and processes all the pixels of the local blocks one by one.

The sub-block partial overlap algorithm takes the moving step length to about a few parts of the sub-block size. The greyscale value is leveraged to transfer the greyscale value of all pixels, and to record the number of pixels that have been balanced many times. This algorithm retains the local original features of the image to the greatest extent, but the algorithm is less controllable and less efficient.

2.2. Dark channel prior method

Dark channel prior model is a classical de-fogging algorithm. It is effective in removing fog from most images, but it does not work well in the sky area of the image. In addition, the images processed by this method are generally dark, so the effect of processing dark images is not good [9].

In atmospheric scattering model is defined as:

$$I(x) = J(x)t(x) + A(1 - t(x)) \tag{1}$$

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I(x) is the images with fog, J(x) is the images without fog, t(x) is the transmittance, and A is the global background light. After the atmospheric scattering model is deformed, a formula can be obtained to express the image without fog from the background, transmittance and the images with fog. Therefore, when the global light and transmittance can be estimated, the images without fog can be obtained.

As for the dark channel principle, in most areas outside the sky, some pixels could have low values, because if all three values are very high, the pixel will be close to white. The dark channel can be obtained by calculating the smallest value of each RGB channel and forming a grayscale map, and then conducting minimum filtering on this grayscale map.

As for optimize transmittance, in order to obtain a finer transmittance map, soft matting was used at the beginning. However, it was slow to get a finer result. In order to solve the defects of soft matting, a method called guided filtering was developed later. Compared with the soft matting, it can make the defogging images more delicate and smoother. In addition, the guided filtering method can solve the problem of slow running speed. Although the guided filtering method cannot process images with thick fog very well, it is still better than the soft matting method. Therefore, in the subsequent comparative analysis of algorithms, Dark channel prior method uses the method of guided filtering.

2.3. DehazeNet

DehazeNet is a specially designed deep convolutional network that utilizes deep learning to intelligently learn haze features [10]. The algorithm idea is as follows: Firstly, obtain multiple fog free images and use an atmospheric scattering method for synthesizing defogged images of different concentrations for each image; Secondly, a pre constructed convolutional neural network is trained using multiple non foggy images and foggy images of different concentrations to obtain a defogging neural network model; Finally, input the image to be defogged into the defogging neural network model to obtain the defogging image. However, during the processing, some difficulties are encountered, such as the need to normalize the dataset for convolutional neural networks, the difficulty of training when different sizes are mixed, and the lack of memory function in convolutional neural networks.

3. Result

3.1. Result of histogram equalisation

In the histogram equalisation algorithm, when the fog concentration is low, as shown in Figure 1, the colour sensitivity of pictures processed by global histogram equalisation is not as good as local histogram equalisation. However, because of relatively uniform distribution of pixel values, therefore, the difference between the effects of these two algorithms is not obvious.

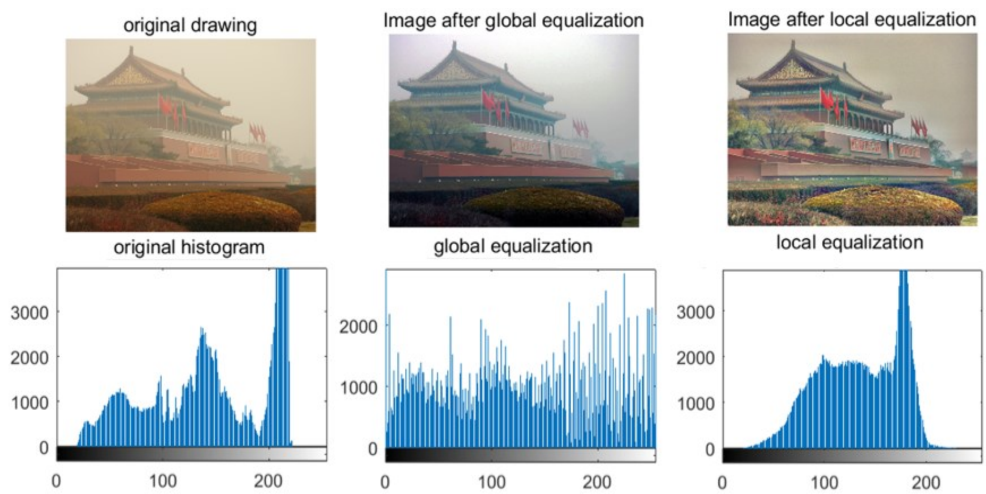

Figure 1. Histogram equalization with sparse fog.

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When the fog concentration is large, as shown in Figure 2, the local histogram equalisation effect is better, and the residual fog is smaller.

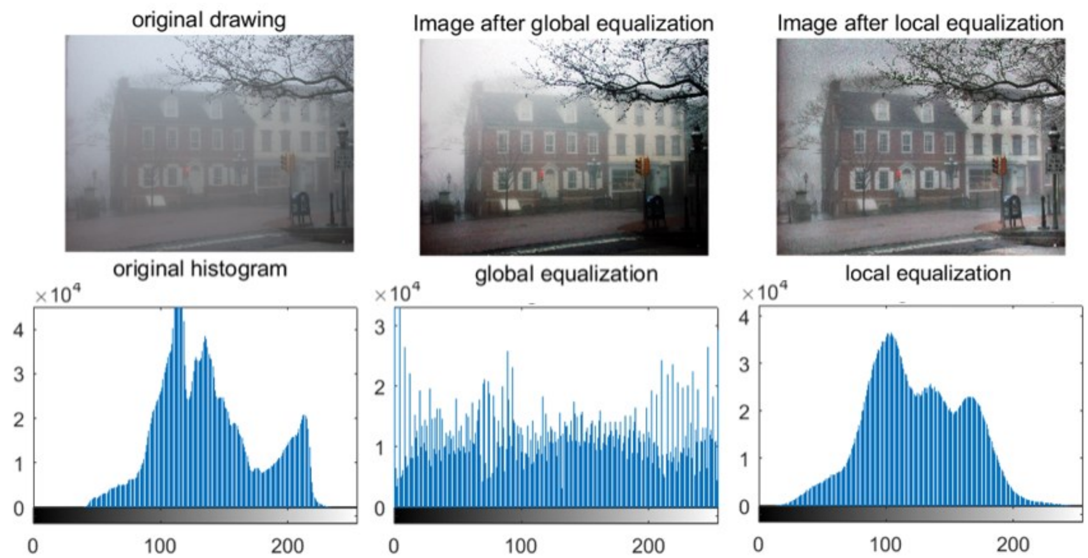

Figure 2. Histogram equalization with dense fog.

In the case of brightness -150 and +150, respectively demonstrated in Figure 3 and Figure 4, the fog removal effect of the global histogram equalisation algorithm for some too dark or too bright parts of the picture cannot be effectively enhanced. However, the local histogram equalisation process can maintain the local characteristics of the original image at a certain level and improve the effect of defogging.

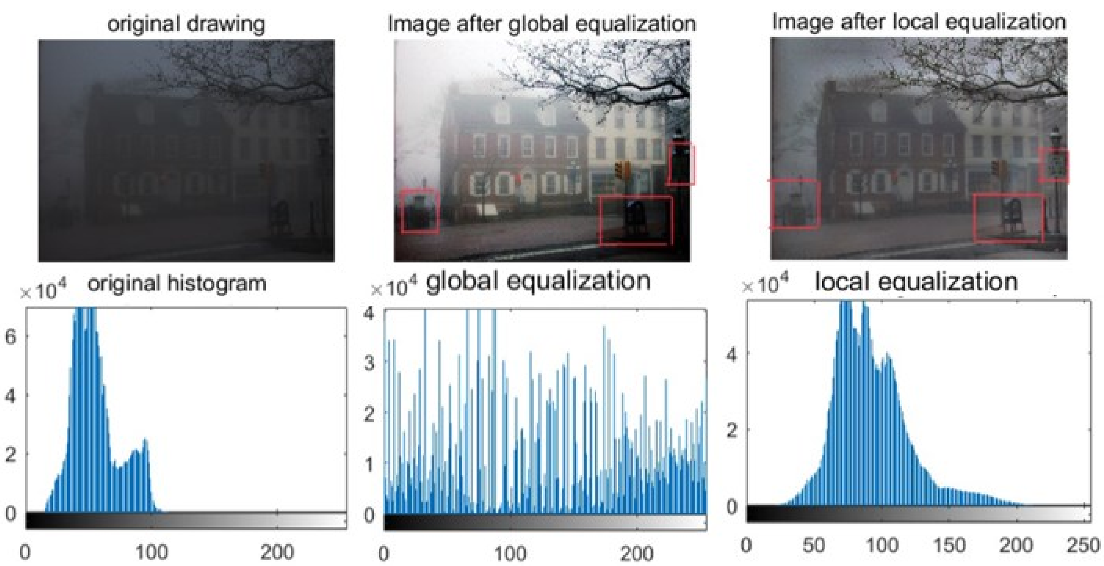

Figure 3. Histogram equalization with -150 brightness.

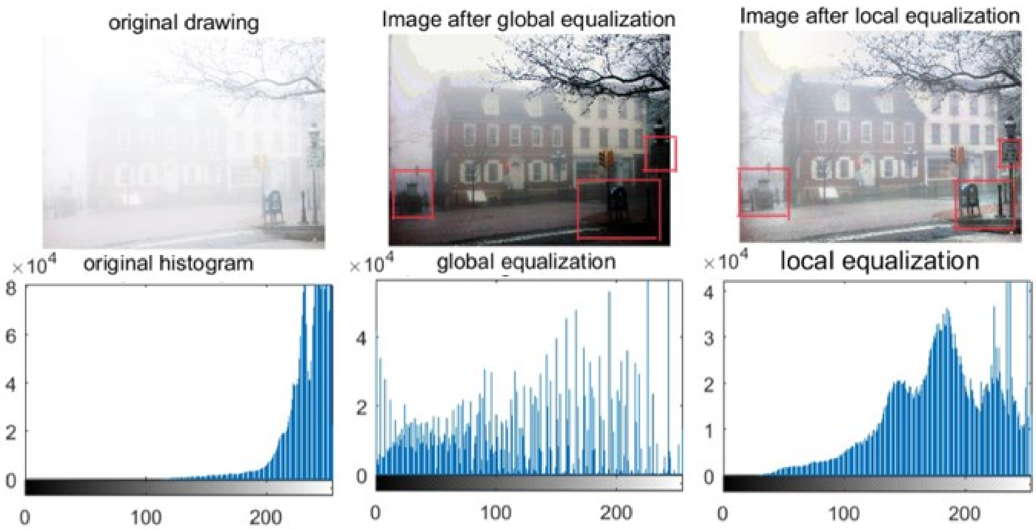

Figure 4. Histogram equalization with +150 brightness.

3.2. Model comparison

When the fog concentration is low, no obvious discrepancies are observed of these three methods, but the dark channel priori algorithm is relatively better. Their performances on image with sparse fog, dense fog, low brightness, and high brightness are demonstrated in Figure 5. The colour sensitivity of histogram equalisation is relatively worse and the image bluntness of convolution neural network processing is more serious. In the case of thick fog, it is similar to the case of mist. Relatively speaking, the dark channel priori method is more applicable. In the case of brightness-150, it is obvious that the processing effect of histogram equalisation is better than the other two. In the case of brightness +150, the dullness of the image processed by the convolution neural network is more serious, which is not as good as the other two methods. Compared with the histogram equalisation algorithm, the colour sensitivity of the dark channel priori method is better, and the colour distortion problem is not easy to occur.

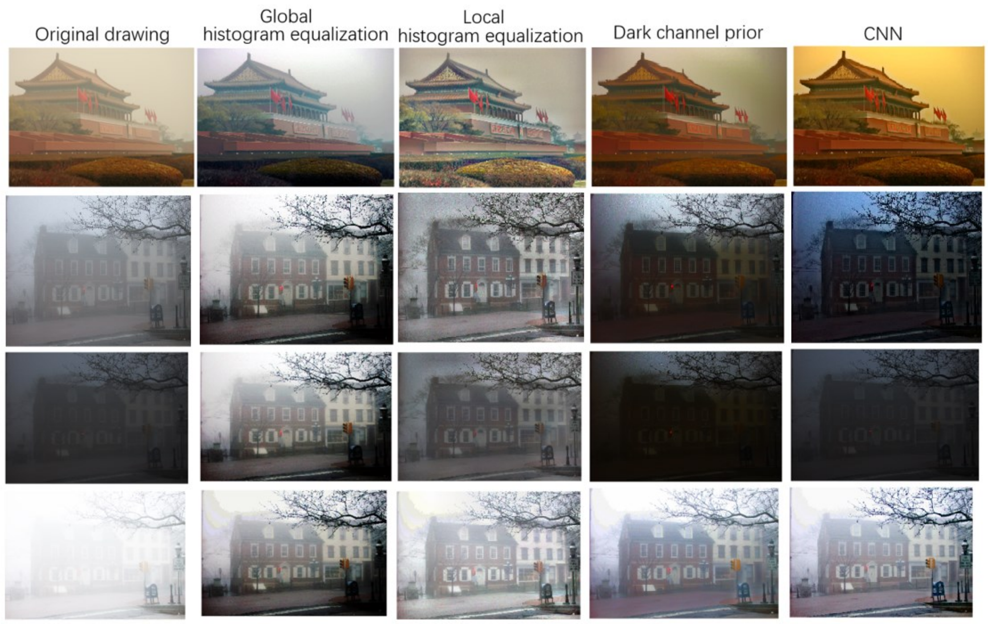

Figure 4. Result comparison.

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4. Discussion

From the comparison of histogram equalisation algorithm, it can be concluded that the local histogram equalisation algorithm is better in terms of fog concentration and light illumination. This is because the global histogram equalisation algorithm shares the standard of the whole image. But the local histogram equalisation is to select a fixed-size sliding window to act on the original image for local processing, and then integrate it into the new image by local histogram equalisation of RGB three channels. Therefore, it can effectively maintain the local features, and the processing effect is better.

In the comparison of the three methods, the dark channel priori is better across different fog concentration and different lighting. Because it improves the histogram equalisation algorithm, based on analysing the halo generation, the algorithm equalises the histogram of the minimum image with fog, which improves the contrast ratio of the minimum image.

The defogging algorithm leveraging convolution neural network is less applicable in this experiment than the other two methods. Because it is easy to form a data disaster when there are many characteristics of objects, and when the amount of data is insufficient, it is likely that the prediction accuracy will decline due to insufficient training. Therefore, CNN is more suitable for feature detection, but the ability to understand features is not good.

Based on the key and difficult points encountered in the field of image defogging research, several prospects for the future are listed. Firstly, a real foggy image dataset is needed: the algorithm using neural networks for defogging performs better than conventional solutions in terms of effectiveness. However, this method is difficult for capturing foggy and non-foggy pairs for training. Therefore, synthesized datasets are collected for training. So, it is important to collect datasets containing foggy and non-foggy samples of real environments. Secondly, a simple defogging model is needed. Currently, good algorithms have extensive time consumption. Finally, there is a need for more applicable defogging algorithms. All the aforementioned models only perform on uniform thin fog condition, but have poor results for dense fog. So, finding a more widely applicable defogging method will be a highly challenging task.

5. Conclusion

In this study, three classical de-fogging algorithms are reproduced, and their de-fogging effects are compared and analyzed under different fog concentrations and image brightness. The research shows that, under the conditions of thick fog and high brightness, the three algorithms have no obvious advantages and disadvantages in the effect of de-fogging, but the images produced by histogram equalization are distorted and the images produced by the convolutional neural network method are rough, so the dark channel prior is more suitable. Besides, the images produced by it are more delicate and real. Under the condition of thin fog, the images produced by the three algorithms can effectively achieve the effect of de-fogging. However, the images without fog produced by histogram equalization have very serious distortion, so the dark channel prior method and convolutional neural network method are better choices when processing images with thin fog. When processing dark images, the images processed by dark channel and convolutional neural network method are too dim, but histogram equalization can solve the problem of low brightness. So, histogram equalization is a better choice when processing darker images. There are still some improvements to be made in this study. The convolutional neural network method used in this study cannot represent all convolutional neural network methods, so a more refined convolutional neural network de-fogging algorithm can be used for comparison in the future. The test samples and scenes used in this study are not rich enough, which may have limitations. In the future, more samples can be used for comparative analysis in more different scenarios.

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