Single Image Dehazing Method Based on Semi-Training Color Stripping

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Abstract. In this paper, a semi training color stripping dehaze-net (STCSDN) is proposed which is a new method of dehazing with strong adaptability. It mainly depends on two important properties of convolution neural network in the process of dehazing. One is that the learning speed of convolutional neural network for contour and shadow information is faster than that for color information. The other is that network is not sensitive to haze concentration. Based on property one, STCSDN extracts the haze free gray image from the hazy color image by using the semi trained generator as the sketch extraction module through the CycleGAN. The gray image only contains the image contour and shadow information, and discards the original color information interfered by haze information. This method has strong adaptability, visibility and authenticity, and can be applied to any scene. Based on property two, STCSDN can process hazy images with different concentrations and get better results. Through the simulation experiments on different types of dehazing data sets, it is proved that the STCSDN proposed in this paper can remove the influence of haze, restore the image details and enhance the visual effect.

Keywords: Semi-training, DehazeNet, stretch-model.

1. Introduction

In the field of computer vision, image quality has a great impact on the completion of target detection, image recognition and other tasks. However, the images obtained in the real application environment are often affected by the suspended solids in the air (haze, haze, dust, etc.). These effects will make the image blurred, and eventually which lead to the difficulty in extracting the effective features of the image. Therefore, how to achieve efficient image dehazing has become an important content in the field of computer vision.

In order to eliminate the influence of suspended solids in the air on the image, the traditional dehazing methods can be divided into three categories. The first method is mainly based on the principle of signal processing, such as histogram equalization method [1], homomorphic filtering method, contrast enhancement [2, 3], multi-scale Retinex [4], etc. This kind of dehazing algorithm mainly relies on the general image enhancement technology to enhance the content of people's interest and suppress other content to improve the visibility of the image. However, this kind of method does not analyze the characteristics of haze, at the same time, it will cause the loss of image content, so the effect of dehazing is not good enough; the second kind of method is mainly based on the physical model algorithm of
atmospheric scattering model. According to different methods of estimating depth of field parameters, it is further divided into 3D modeling method based on scene depth information [5, 6], image dehazing method based on prior theory [7-13] and machine learning method [14-19, 23-27]. Due to the physical model used for image degradation and restoration, the dehazing method based on atmospheric scattering model has higher authenticity and better effect than the method of image enhancement. However, because of the limitations of the scene, and it cannot ideal for the edge processing at the abrupt change of scene depth, the effect of the method based on a priori theory is not completely satisfactory. At present, the method based on 3D model and deep learning can achieve the best effect, but it needs to rely on large standard data set, which is extremely difficult to obtain in real environment, so it is limited to the laboratory environment and has poor adaptability. The method based on image conversion [20, 21] relies on CycleGAN [22] framework, it solves the problem of data set dependence of deep learning, and has good adaptability. However, these methods are enhance the basic performance of CycleGAN to enhance the effect of dehazing. There is no research on the characteristics of haze, resulting in the model for the analysis of the image is not enough, and cannot completely separate the haze from the image. The effect of dehazing is not very ideal as the image conversion was interference by residual haze information.

In this paper, we propose a new dehazing method-semi training color stripping single image dehazing method. We found that when using CycleGAN for image dehazing experiment, the generator after 1000 times of training will be in a state. In this state, the generator can extract the line, light, shadow and other primary information of hazy image, but it has not learned the advanced information such as color and content. This semi training generator can convert hazy image into gray image. In this gray image, because the color information is discarded, the haze information is also discarded, so the existence of haze is almost not felt. Using this phenomenon, we use the trained semi training generator to remove the haze image and get the gray image without haze.

Because the semi training generator does not learn the content knowledge of the image, it is not limited to the training set, but can be applied to any scene. It has very good adaptability. But like other methods, our approach has limitations. When the concentration of haze in the scene changes suddenly, clear edges will be produced. In our method, the dense haze with clear edges will be processed into cloud and retained in the gray image.

Our main contribution:

In this paper, a new idea of image dehazing is proposed. We use the feature of neural network that the learning speed of the primary information such as contour and shadow is faster than that of the advanced information such as content and color in the training. We can input the hazy image into the semi trained neural network and get the gray image without haze.

We propose a training strategy, which can effectively train the semi training neural network for image dehazing [34, 35].

By studying the properties of semi training neural network, it is found that this kind of semi training neural network has two properties: one is not sensitive to the content of the image, and can not be limited to the data set used for training; the other is not sensitive to the concentration of haze, and can effectively dehaze images with different concentrations.

2. Related work

Through the efforts of many scholars, many haze removal algorithms based on atmospheric scattering model have been proposed and achieved good results. He Kaiming (hereinafter referred to as he) put forward a very effective and far-reaching prior theory of dark channel prior knowledge [10] which based on the obtained from observation, statistics and analysis of all kinds of clear images under clear weather, namely dark primary prior theory. For the vast majority of outdoor clear images in non-sky area, there is at least one-color channel in local area, which has very low pixel value or even tends to zero. Using this prior knowledge, the atmospheric scattering model can be optimized to obtain the relatively rough transmission of haze map. In order to eliminate the halo problem due to the abrupt change of the depth of field due to the rough transmittance, he et al, first used the soft matting algorithm to optimize the
existing rough transmittance, and then proposed the guided filter [23] algorithm to improve the optimization efficiency. Meng [11] extended the work of dark channel priori by regularizing the transfer function of edge to alleviate the lack of analytical power. The dehazing algorithm based on the color attenuation theory proposed by Zhu [13] is another prior theoretical dehazing algorithm. Berman [14] also takes advantage of the influence of haze on the distribution of color channels.

Some scholars introduce the deep learning method into the field of image dehazing, extract and analyze the input image features through CNN network, estimate the transmittance for each pixel, and then use the atmospheric scattering model to remove the image haze, which can get good results. DehazeNet of Cai [15] obtains the transmission matrix by inputting the hazy image into the network, and then brings it into the atmospheric scattering model to obtain the haze free image. Ren [16] proposed a multi-scale neural network dehazing method, which estimates the depth of field of the scene through the coarse scale, and refines the mesh with the fine-scale network. Based on Cai and Ren, Zhao estimates the transmission matrix through the deep full convolutional regression network (DFCRN), and achieves better results for larger networks. AOD-Net [26] of Li transformed the atmospheric scattering model into a new parameter to represent the transmittance and the atmospheric composition, and transformed the hazy image into the non-haze image directly by using the simplified U-NET network. The gate fusion network (GFN) proposed by Ren [27] is based on the threshold fusion network. It extracts the features of different colors or contrasts through various transformations of hazy images. Then, the transformed images are input into the network, and then fused through the training weight matrix to get the final dehazing image, which has good effect. The gate context aggregation network (GCAN) proposed by Chen [28] solves the shortcomings of other methods of mesh artifact by smoothing hole convolution, and obtains good results. Qin [27] (feature fusion attention network, FFA net) focuses on the channel and pixel separately, and gets the final image by weighted fusion.

In order to overcome the problem of data set dependence of dehazing algorithm based on machine learning, researchers have proposed some dehazing algorithms based on CycleGAN network framework, which can complete training without pairing data. Cycle-dehaze [22] proposed by Engin increases the cycle perception loss on the basis of CycleGAN, and enlarges the image by Laplace transform after outputting the image to obtain high-definition dehazing image.

The dehazing method based on CycleGAN network framework can complete the training without relying on the standard dataset, which greatly increases the practicability of the algorithm. It can use the real natural image for training. However, its unsupervised training method leads to the insufficient analysis of the model for the image, which cannot completely separate the haze from the image, and is affected by the residual haze information in the image conversion. The effect of disturbing and dehazing is not very ideal.

We found a new idea of image dehazing by studying the phenomenon of CycleGAN in image dehazing training. At the same time, the problem of separating haze information from image color information is avoided.

3. Method
In the process of image dehazing research using traditional CycleGAN, we found a phenomenon. By outputting the intermediate effect image in the training process and comparing it with the corresponding no haze image, we found that there will be a maximum value point in 1000 iterations, SSIM can reach more than 4, and then it will drop rapidly and the generation is close to the limit climb slowly until 70000 times. As shown in Figure 1.
Through the observation of these intermediate images, it is found that in only a few hundred iterations, the neural network has completed the contour extraction. This gray image contains very little color information, only contains the contour information and shadow information of the original image. When we observe this gray image, we find that there is almost no haze in this image. The picture is very clean, and the details of the scene covered by haze are very clear. As shown in the third column of Figure 2.
Fig. 2 Example gray image output by sketch module

Because this gray image has very clear detail texture, but does not contain color information, there will be a small peak when calculating SSIM. However, as the training continues, the output image will begin to be colored. The color information at the beginning is very inaccurate, so the SSIM value is quickly lowered. With the deepening of training, the color information is gradually full and accurate, and the dehazing effect reaches the limit of the model. This phenomenon occurs because of the convolutional neural networks (CNN) has representation learning. The task of convolution kernel is to extract line information such as edge. The line and light-dark relationship information belong to shallow information. The learning speed of the model is very fast. After hundreds of iterations, the learning can be completed. But at this time, the deep knowledge such as color information and haze information has not been mastered by the model, so the generated image appears the phenomenon that profile information of image is very clear and color information has been striped off.

In Figure 2, the first and second columns are clean images and corresponding hazy images. The third column images are gray images processed by the semi training generator extracted from 2000 iterations in the process of training CycleGAN network. It can be found that the semi training generator has a very good description of image details, highlighting the line information, shadow information and light and shade covered by haze. The influence of haze is greatly removed. Only when the concentration of haze changes suddenly and forms cloud like haze, the haze residue can be seen.

Although there is no color information, it can still let people recognize the complete basic information of the scene. In some application scenarios, it is fully qualified for use. With the continuous training and color filling, the original clear scene information is interfered by the color information affected by haze noise. In this paper, the color stripping and dehazing network proposed in this paper uses this rule to extract the profile information from the image through a semi trained generator and strip off the color information to obtain a dehaze gray image with only contour and shadow information. The image dehazing is completed.

3.1. Overall framework of STCSDN

The overall framework of STCSDN is based on the CycleGAN, as shown in Figure 3. The network carries out image dehazing through sketch module which is acquired by insufficient training through a CycleGAN. The grayscale only describes the content of the original image by contour information, which is similar to the sketch in painting, so we call the generator sketch module.
3.2. Training methods of STCSDN

For STCSDN training, we cannot define the target image, and there is no accurate loss function to guide the model too. According to the observation rules, we can find that the generator which can generate haze free gray image exists in a certain training stage of CycleGAN network in the process of dehazing task. In order to find the optimal model in this stage, we adopt the method of random training, intensively save the training intermediate process of CycleGAN and output the effect diagram. We train about 10 groups of CycleGAN networks, and each group trains 2000 times to terminate the iteration. Output one generated image every 50 iterations and save the node. At the end of the training, the dehazing direction generator of the corresponding node which the image with best effect will be selected as the sketch module. We also call this model which is not fully trained as the semi training model. Through the experiment, it is found that the training set selects I-HAZE, which is a data set with few samples and clear and simple scenery, can obtains a high success rate of sketch module. Through observation, it is found that this semi training model has just completed the feature extraction of the object contour, and has not yet analyzed the color information of the image. It only interested in simple gray information such as lines and shadows. Through data analysis, it is found that although the 3-channel image with gray-scale image features has RGB channels, the values of the three channels are very close, so the color of image looks like grey.

As shown in Figure 4, for the CycleGAN training of this figure, in the first 250 iterations, the network has basically learned the shadow and light and dark information, but the line information is still not very clear. When it reaches 300-550 times, the line information becomes more fresh and the image is sharper. However, after careful observation, it is found that the details are still blurred. When the number of iterations is 600-850, the network still has a fuzzy situation. We can see that the color information has started to learn, but the influence of color information is not very big at this time, and it is still acceptable. Within this iteration range, the network has reached an ideal state for learning the shadow and light and dark information, especially the images of the 700 th, 750 th and 850 th are very clear. Therefore, we can try to use the corresponding nodes of these images. The best nodes are selected as the final parameters of the sketch module.
4. Experiment and Result Analysis

4.1. Experimental environment
The system environment used in this experiment relies on tensorflow framework 1.8.0.

4.2. STCSDN verification experiment
The principle of STCSDN is based on convolution neural network. The learning speed of shallow knowledge such as line, shadow and light-dark relationship is faster than that of deep information such as color and content. Therefore, when we train STCSDN well, the model has not learned other knowledge except line, shadow and light-dark relationship, that is, the knowledge learned has nothing to do with content, datasets and haze concentration. Through network training on I-HAZE dataset, we select a best model to test in different datasets. We input hazy images of different datasets into the model and output gray image.

4.2.1. Verification of STCSDN on O-HAZE dataset. We use the model trained on the I-HAZE dataset to transform the hazy images on the O-HAZE dataset. The resolution of the input image is the original size, and the resolution of the output image is 2000 × 2000.

![Fig. 5 Comparison of applying Sketch module to O-HAZE dataset](image)

It can be seen in the figure 5 that STCSDN is very thorough in extracting the outline, shadow and light-dark relationship information of outdoor real image, which greatly highlights the details covered...
by haze. Even the details that are difficult to distinguish by human eyes are strengthened and become visible to the eye. At the junction of the sky and the scenery, the STCSDN processing is very good. STCSDN filter out the influence of halo and the edge is very clear. In the processing of branches, leaves and other scenes, the edge’s processing is very clear, the shadow relationship is also very clear. Also, when the local concentration of haze is too high, the sudden change of concentration result obvious edge information, so that the part of thick haze can be preserved as the cloud.

4.2.2. STCSDN verification on I-HAZE dataset. We transform the hazy image of I-HAZE dataset, and the output content is shown in Figure 6. It can be seen that STCSDN has a very good effect on haze removal, which highlights all the details of the scene. Only in the area affected by the halo, the image is not clear enough because of the large brightness, but the edge information after the halo is also enhanced.

4.2.3. STCSDN verification on RESIDE dataset. We can also use the STCSDN on RESIDE dataset. As the Figure 7 shows, scene in the city can be extracted well. The details of water drops, cloud and branch are very clear. Due to the small image size of the RESIDE dataset and insufficient pixel details in the black part, the currently trained STCSDN will produce dark red patches in the extremely dark areas, but it will not affect the overall effect.
Fig. 7 Comparison of applying Sketch module to RESIDE dataset

Due to the combination of haze images with different parameters for the same scene in the RESIDE dataset, haze images with different concentrations are presented. We input the haze images with different parameters of the same scene into the STCSDN. As shown in Figure 8, we can see that the gray-scale images converted from haze images synthesized by different transmittance and atmospheric composition are almost the same. Even under the condition of $T = 1$ and $a = 0$, which is no haze condition, the obtained sketch image is the same as the hazy image. It shows that our STCSDN is not sensitive to the haze concentration change when the haze is relatively uniform and there is no obvious edge caused by concentration mutation, and the same gray image without haze can be generated. It is proved that our STCSDN is not sensitive to color information, but sensitive to contour, shadow and shading information.
4.2.4. Verification of STCSDN on D-HAZY dataset. We use STCSDN on the D-HAZY dataset, and the effect is shown in Figure 9. The indoor visible details can be proposed by STCSDN. However, due to the large proportion of atmospheric light components set by D-HAZY in the haze map synthesis, which corresponds to the situation of high haze concentration, the visibility of the scene drops sharply with the change of depth in the scene with small change of depth. Due to this feature of D-HAZY, STCSDN will be preserved as white entity for dense haze. Therefore, in the output sketch image, the brightness of dense haze will be too high. However, the STCSDN still extracts the contour information which is almost invisible to the naked eye in the area with excessive brightness.
4.2.5. Verification of STCSDN on Dense haze dataset. We use STCSDN on the Dense haze dataset, and the effect is shown in Figure 10. In the real thick haze scene, the STCSDN can still highlight the contour information of the scene from the almost invisible Dense haze, and obtain the gray image with use value. In the indoor scene with uniform haze, the effect is almost the same as that of I-HAZE with ordinary haze. In outdoor scenes, although the haze almost completely covers the scene, STCSDN separates the scene from the haze by enhancing the contrast between the edge and the background. By comparing the gray images generated in dense haze and haze scenes, it is found that in O-HAZE dataset, local dense haze will be retained, while in Dense haze, dense haze will not be retained. The main reason is that local dense haze will produce edge information, while global dense haze has no edge information. STCSDN is more sensitive to edge information than to color information such as haze. However, due to the excessive haze concentration, the performance of STCSDN is still affected, and the color block phenomenon is more serious than other data sets.

4.2.6. Verification of STCSDN on natural images. We use STCSDN to process some popular natural images and compare them with other methods. The processing effect is shown in Figure 11. In terms of vision, although our sketch image has no color information, the content of the image is restored very accurately and the details are very clear. It has great practicability and good visual effect.
Fig. 11 Comparison of Sketch model and other methods on popular natural environment images

4.2.7. Conclusion. According to the results of the experiment, it can be seen that the gray image obtained by STCSDN has achieved good dehazing effect, which can meet the needs of most dehazing tasks. STCSDN trained by I-HAZE dataset can extract contour, shadow and light and dark information without any difference in processing images of other datasets. Even in dense haze dataset, STCSDN can still play a good role. This shows that STCSDN does not learn the specific deep content of a specific image, only learns the shallow information such as contour information. The images of any scene have good adaptability. Some local hazy phenomena in the image are also caused by the excessive concentration of local haze. The sketch image retains the information of brightness, but still highlights the contour information of the scene blocked by haze. However, it is also noticed that the red color spots appear in the extreme dark, which is caused by insufficient training of STCSDN, which requires a smaller step size to keep the nodes close to the optimal model when training the STCSDN. To sum up, the above verification experiments fully verify the correctness of the proposed sketch module dehazing theory, and prove that the semi training generator has the ability to extract image contour information, shadow information and light-dark relationship, and is not affected by the image content. When the haze concentration is uniform, the background information is not completely blocked, and there is no sharp edge formed by the concentration mutation, it can deal with the haze map of each concentration and complete the task of dehazing well.

5. Summary
We first analyzes the challenges of CycleGAN based image dehazing algorithm. Aiming at these challenges, combined with the phenomenon that the semi training generator can extract the image contour, shadow and light and shade information, while discarding the color information of the image, a semi training color striping network is proposed, the theoretical basis and implementation method of this method are introduced in detail, and full verification experiments are done. This method is a new method of dehazing, and has strong adaptability and practicability.
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