Improved image defogging method based on adaptive neighborhood window size of PMS network

Ai XianHong*, Tian Shan, Chen chao, Zhong Jiandan
College of Communication Engineering, Chengdu University of Information Technology, Chengdu, China
*a3180402019@stu.cuit.edu.cn

Abstract—Aiming at the failure of prior theory of dark channel in bright area, an improved algorithm based on PMS-Net is proposed. First, the selection of atmospheric light in dark channel images under different neighborhood windows is optimized, and the atmospheric light value is accurately estimated. Then an improved transmittance estimation method is used to make the transmission map estimation of the bright area more accurate. The improved PMS-Net defogging algorithm is compared with the existing excellent algorithms, and the experimental results show that the algorithm can overcome the color distortion of existing algorithm in processing bright areas. The effectiveness of the algorithm is verified by objective evaluation indicators.

1. INTRODUCTION
Image defogging has always been a pathological problem. It is very difficult to obtain clear images from limited known parameters. However, the prior theory of dark channel proposed by He et al.[1] provides a more effective solution for image defogging, they start from the imaging mechanism of the fog map, and obtains the dark channel prior theory through a large number of statistical observations. Although the dark channel prior theory is in the image defogging is very powerful, it is limited by the sky area and large white areas.

Bao et al. [2] Re-estimated the atmospheric light value and transmission map by distinguishing the sky area, trying to solve the problem of the failure of the priori theory of the dark channel in the sky area. But the effect is not very obvious. In recent years, with the rise of deep learning. The random forest model was proposed by Tang et al. [3] to learn the features of a large number of foggy images to obtain the best transmission image. Cai et al.[4] proposed Dehaze-Net, they used Convolutional Neural Network (CNN) to build an end-to-end learning model and directly restore the fog image. Ren et al. [5] proposed a multi-scale convolutional neural network(MSCNN). Kim et al.[6] proposed a quadtree CNN network to eliminate fog. The densely connected pyramid defogging network(DCPDN) proposed by Zhang et al. [7].

This paper proposes a new defogging scheme based on PMS net. The difference from reference [8] is that we use compensation mechanism to make the estimated transmission map of sky area closer to the real value, thus avoiding the color distortion of the region, then we optimized the atmospheric light estimation method to make the atmospheric light estimation more reliable. The algorithm has good performance in global defogging, defogging in high-brightness areas, edge color retention and structure retention.
2. RELATED WORK

2.1 PMS neural network

According to the previous dark channel defogging algorithms, the selection of neighborhood window size is usually based on experience, and this size is usually globally fixed. It means that some fog images may have good defogging effect, but different degrees of color distortion [2] will be reflected in the sky area and highlight area.

In order to solve the above problems, Chen et al. [8] proposed PMS-Net to learn the mapping relationship between fog image and patch map [8] to find the optimal neighborhood window patch size of each pixel by this method. In the training process of the network, the restoration image with different sizes of neighborhood windows is first determined, then find out the error between the restoration image and the real value under different window sizes. The error function is defined as:

$$E_i(X) = |J_{est}(x) - J_i(x)|, i = 1, ..., n$$  \hspace{1cm} (1)

Finally, the neighborhood window size with the smallest error function for each pixel is found, and this value is assigned to the patch map. The network structure of PMS-Net is shown in the figure1.

![PMS-Net network structure diagram](image)

Figure 1. PMS-Net network structure diagram

The establishment of the entire network is divided into the following steps. The first step use 16 3 * 3 convolution kernel to convolve the input fog map to obtain high-dimensional data. The second step uses a three-layer pyramid model, In the first layer of pyramid model, 5 * 5, 3 * 3, 1 * 1 convolution...
kernels are used for high-level feature extraction to retain more special feature information of different proportions. The last step is to build the deconvolution module of the pyramid model. The first layer uses 3 * 3 deconvolution kernels, and the second layer uses 5 * 5, 3 * 3 deconvolution kernels. After deconvolution, the global convolution module GCN [12] and the boundary refinement module BR [12] are used.

2.2 Optimized atmospheric light estimation

Firstly, the patch map generated by PMS-Net is used as the candidate neighborhood window value, and then the repeated values in the patch map are removed to ensure that the maximum value is limited to 120. Although the large neighborhood window size will make the non bright area of dark channel map close to zero, it will also lead to halo and more computation, which is the reason for removing duplicate values. After the dark channel map of each size obtained by guided filtering [9], the first 1% value of the maximum intensity value under the size is selected to calculate the corresponding average value of each point in the original fog image as $A^k$. The transmittance at the current neighborhood window size can be obtained by the following methods:

$$I(x) = J(x)t(x) + A(1 - t(x))$$  \( (2) \)

$$t(x) = \frac{1 - \min_{y \in \Omega(x)} \left( \frac{I^k(y)}{A^k} \right)}{1 - \min_{y \in \Omega(x)} \left( \frac{J^k(y)}{A^k} \right)}$$  \( (3) \)

Formula 2 is a general mathematical model to describe the formation of fog images, $I(x)$ is the fog image, $t(x)$ is the atmospheric light transmittance, and $A$ is the global atmospheric light value. Since the atmospheric illumination value calculated under the large window is closest to the actual value, we use $A^k$ under the maximum window size as the global atmospheric light $A$.

2.3 Transmittance correction

According to the a priori theory of the dark channel, the transmittance of the non-sky area can be accurately obtained, but the real fog image usually contains large sky areas, white areas and other scenes that do not conform to the a priori theory of the dark channel, so we need to correct this problem. Therefore, based on the literature [11] and combined with the adaptive neighborhood size of Patch Map, we specify the following optimization scheme.

According to different neighborhood window sizes, we define the coordinate $(u, v)$ of the highlight in the dark channel image as $I^\max$:

$$I^\max = \min_k (I^k(u,v)) = \max_k (\min_{y \in \Omega(x)} (J^k(y)))$$  \( (4) \)

The coordinates $(b, d)$ is defined as the darkest point $I^\min$ in the dark channel:

$$I^\min = \min_k (I^k(b,d)) = \min_k (\min_{y \in \Omega(x)} (J^k(y)))$$  \( (5) \)

$\Omega(x)$ is the adaptive neighborhood selected according to Patch Map. We can estimate $\min_{y \in \Omega(x)} \left( \frac{J^k(y)}{A^k} \right)$ in the following way:

$$\min_{y \in \Omega(x)} \left( \frac{J^k(y)}{A^k} \right) = \frac{\min_{y \in \Omega(x)} (I^k(y)) - I^\min}{I^\max - I^\min} \cdot \min_{y \in \Omega(x)} \left( \frac{I^k(y)}{A^k} \right)$$  \( (6) \)
The \( \min_{y \in \Omega(x) \cap (r,g,b)} (I^k(y)) \) in the above formula is the dark channel map under the current neighborhood window and satisfies \( I^{\min} \leq \min_{y \in \Omega(x) \cap (r,g,b)} (I^k(y)) \leq I^{\max} \).

Since the pixels in the dark channel image corresponding to the sky area or higher brightness have very large values, so \( \min_{y \in \Omega(x) \cap (r,g,b)} (I^k(y)) \) is close to \( I^{\max} \). On the contrary, the values of non-sky areas or low bright spots are very small, so \( \min_{y \in \Omega(x) \cap (r,g,b)} (I^k(y)) \) approaches \( I^{\min} \), it means that the pixel is in a non-sky area. For pixels in sky or high brightness areas, \( \min_{y \in \Omega(x) \cap (r,g,b)} (I^k(y)) \) is close to \( I^{\max} \) and slightly smaller than \( I^{\max} \). So we introduce \( \psi \) as an adjustable weight to estimate:

\[
\min_{y \in \Omega(x) \cap (r,g,b)} \left( \frac{I^k(y)}{A^2} \right) \approx \frac{\min_{y \in \Omega(x) \cap (r,g,b)} (I^k(y))}{A^2}
\]

For image areas that meet the dark channel prior, \( \omega \) is usually used to make the recovery results effect more realistic.

Therefore, the transmittance can be accurately estimated as:

\[
t(x) = \begin{cases} 
1 - \frac{\min_{y \in \Omega(x) \cap (r,g,b)} (I^k(y))}{A^2}, & \text{highlight area} \\
1 - \omega \frac{I^{\max}}{A^2}, & \text{other} \\
1 - \omega \min_{y \in \Omega(x) \cap (r,g,b)} (I^k(y)) / A^2, & \text{other}
\end{cases}
\]  

According to our experiments, it is found that the best recovery effect is when the value \( \omega \) is 0.95 and \( \psi \) is 0.90.
3. COMPARISON OF EXPERIMENTAL RESULTS

3.1 Subjective evaluation

We compared some excellent defogging algorithms, such as DCP, AOD-Net, MSCNN, PMS-Net and found that the algorithm in this article has relatively good results.

As shown in Figure 2, The algorithm presented in this paper performs well in defogging effect, color fidelity and high brightness area processing. The DCP algorithm performs better in processing images with uniform brightness, uniform fog and no sky area, but it will cause serious color distortion when there are sky areas and bright areas. However, AOD-Net and MSCNN have excellent color fidelity in processing high-brightness areas, but it does cause excessive color enhancement for the slightly darker fog. PMS-Net still has a little color distortion in the processing of bright sky areas. The algorithm proposed in this paper has good processing effect in high brightness sky area or low brightness area, and the processing result is the most similar to the original image.

In addition, we analyzed the difference between PMS-Net and our proposed algorithm in the recovery graph, as shown in Figure 3.

Please pay attention to the part marked in the red box. For PMS-Net, high-brightness areas and dark areas have different degrees of color distortion, the darker parts of the original image are over enhanced. However, our proposed algorithm avoids the above problems and has a good defogging effect.

3.2 Objective evaluation

Since subjective evaluation is easily affected by subjective factors, we used the general PSNR and SSIM indexes of quantitative analysis. The higher the value of PSNR and the closer the value of SSIM to 1, the better the recovery effect. The mathematical definition of PSNR is as follows:
\[ \text{PSNR} = 10 \log \left( \frac{\text{MAX}^2}{\text{MSE}} \right) \]  

\[ \text{MSE} = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} |U(i,j) - K(i,j)|^2 \]  

Where \( \text{MAX} \) is the maximum value of image color and \( \text{MSE} \) is the mean square error. The mathematical definition of \( \text{SSIM} \) is as follows:

\[ \text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \]  

\( \mu_x, \mu_y, \sigma_x^2, \sigma_y^2, \sigma_{xy} \) are the mean of \( x \), the mean of \( y \), the variance of \( x \), the variance of \( y \), the covariance of \( x \) and \( y \) respectively. \( c_1 \) and \( c_2 \) take default values. \( \text{SSIM} \) is based on the measurement of brightness, contrast and structure between samples \( x \) and \( y \).

In order to make our quantitative index true and effective, we strictly stipulate the size of the image and the parameters of the above two formulas. According to the experiment, the data shown in Table 1:

| FIG | DCP | AOD-Net | MSCNN | PMS-Net | Ours |
|-----|-----|---------|-------|---------|------|
| row 1 | 0.8761 | 19.7972 | 0.8584 | 14.9284 | 0.9300 |
| row 2 | 0.8055 | 14.7798 | 0.8299 | 15.7560 | 0.9131 |
| row 3 | 0.8202 | 19.3029 | 0.7820 | 14.4919 | 0.9250 |
| row 4 | 0.8691 | 22.0044 | 0.7523 | 13.9895 | 0.9308 |
| row 5 | 0.8362 | 19.9655 | 0.8599 | 14.1033 | 0.7805 |
| row 6 | 0.8103 | 15.7842 | 0.8589 | 15.2037 | 0.8454 |
| row 7 | 0.8246 | 19.9418 | 0.8116 | 15.2921 | 0.9286 |

Through the analysis of the above data, the algorithm in this paper is relatively excellent overall. The results show that the performance of PMS-Net also has advantages compared with other algorithms, but our algorithm performs better. Compared with the results of PMS-Net defogging algorithm, the structure similarity is improved by 8%, and the peak signal-to-noise ratio is increased by 20%.

4. CONCLUSION

It is effective to use the PMS network to generate an adaptive dark channel neighborhood window, but the transmission map obtained only through the adaptive window size is flawed. On this basis, an optimization scheme for the selection of atmospheric light value and the correction of the transmission map is proposed. Through the comparison of objective experimental results, it is found that our method has an improved effect on the PMS-net defogging method, and this method can also complement other existing defogging algorithms.

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