Single Image Dehazing Based on Weighted Variational Regularized Model

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SUMMARY Image dehazing is of great significance in computer vision and other fields. The performance of dehazing mainly relies on the precise computation of transmission map. However, the computation of the existing transmission map still does not work well in the sky area and is easily influenced by noise. Hence, the dark channel prior (DCP) and luminance model are used to estimate the coarse transmission in this work, which can deal with the problem of transmission estimation in the sky area. Then a novel weighted variational regularization model is proposed to refine the transmission. Specifically, the proposed model can simultaneously refine the transmittance and restore clear images, yielding a haze-free image. More importantly, the proposed model can preserve the important image details and suppress image noise in the dehazing process. In addition, a new Gaussian Adaptive Weighted function is defined to smooth the contextual areas while preserving the depth discontinuity edges. Experiments on real-world and synthetic images illustrate that our method has a rival advantage with the state-of-art algorithms in different hazy environments.

key words: image dehazing, total variation, alternating direction algorithm, dark channel prior

1. Introduction

Nowadays, haze weather has become a common natural phenomenon. Owing to the scattering by haze particles, the visibility of outdoor images often has been degraded. Outdoor images captured in haze environment show low contrast and saturation. Poor visibility images impact consumer photography and computer vision applications [1], [2]. Research on how to obtain clear images in haze environment is very important for computer vision. However, due to ill-posedness, image dehazing has always been a difficult problem in the field of computer vision.

Earlier methods mainly based on multiple input images [3], [4] or additional information [5], [6]. However, these methods have poor real-time performance.

Therefore, single image dehazing has attracted more attention. However, due to ill-posedness, some priors or assumptions [7]–[10] are used for image dehazing work. Moreover, methods based on physical models achieved good performance. These techniques based on Atmospheric Scattering Model (ASM) [11]. Among them, He et al. [12] found that a haze-free image for at least one color channel should include a very low intensity and very close to zero within a local patch, which is called DCP. With this famous prior, the estimation of coarse transmission can be obtained accurately. Many methods were proposed to refine the initial transmission based on DCP [13]–[21]. In addition, other prior-based methods such as non-local prior [22], and variational model [23], [24] are also used for image dehazing. However, these methods do not consider the noise effect.

More recently, the convolutional neural network (CNN) has made brilliant achievements in image dehazing. Some prevalent networks, such as Multi-Scale (MSCNN) [25], Dehaze-Net [26], AOD-Net [27] have been proposed. Up to now, more and more learning-based defogging methods have been proposed [28]–[30]. Nevertheless, these learning-based dehazing methods rely heavily on data sets.

This work aims to study a new variational model to solve the key parameters in the dehazing of a single image, so that the restored image has a good visual and quantitative evaluation effect, and considers the noise factor ignored by the traditional Atmospheric Scattering Model.

In this study, a novel effective dehazing method is proposed. Initial transmission is acquired by DCP and lumi-

![Fig. 1](image-url) Our dehazing framework. (a) Input image, (b) dark channel of (a), (c) weighted fusion-based rough estimate for initial transmission map, (d) refined transmission map with the proposed method, (e) noise we estimated, which shifted by +0.5 for better visualization, (f) final restored haze-free image for (d).
nance model. A weighted variational regularized model is then proposed to refine the transmission. The haze-free images can be restored through the improved ASM. Our dehazing framework can be shown in Fig. 1.

We summarize in two points our contributions:

- A novel weighted variational regularization model considering the inevitable noise for single image dehazing is proposed. Unlike most previous dehazing algorithms, our method can simultaneously estimate transmission map, remove noise, then restore a clear image at last.
- We define a new Gaussian Adaptive Weighted function to smooth the contextual areas while preserving the depth discontinuity edges.

2. Related Work

Although the dehazing algorithm based on DCP [12] restoration has a strong representative effect and scope of application, experimental analysis shows that it tends to have obvious color cast and blocky effects when dealing with large areas of the sky. Inspired by the characteristics of haze and the method of dehazing, neural networks have made significant progress in some fields, especially computer vision research in recent years. In terms of image dehazing, researchers have carried out in-depth related work based on neural networks.

In 2016, CAI et al. [26] first proposed a dehazing network called Dehaze-Net to estimate the transmission of hazy images. Dehaze-Net [26] joins the Maxout network [31] in the feature extraction layer network, so that it can be connected with the existing dehazing theory (such as the DCP [12]), and automatically improve these theories through neural networks. Dehaze-Net is based on the characteristics of the physics model of hazy images and goes beyond the traditional methods. It uses artificial intelligence methods in the field of defogging, providing a new idea for image dehazing. However, Dehaze-Net regards the global atmospheric light as a constant without learning, which is inconsistent with the characteristics of the actual haze image.

LI et al. [27] proposed a model (AOD-Net) that uses CNN directly to generate haze-free images. AOD-Net unifies the two transmission parameters and the global atmospheric light component in the mathematical expression of the ASM into one formula, and finds the mapping relationship and the parameters in the formula through CNN, and realizes the image dehazing work.

To simplify the estimation of transmission and atmospheric light, several effective depth neural networks [29], [32], [33] restore the haze-free image via an end-to-end architecture. In addition, to make the trainable neural networks more densely, processing based on physical models has also been added to CNN [34]–[36]. These deep CNN-based methods are largely superior to contrast enhancement methods. However, these neural networks are based on some traditional architectures, and there is no major improvement, and the effect of the image dehazing problem is not greatly improved.

Furthermore, in order not to rely entirely on synthetic data sets, unsupervised dehazing neural networks are also being studied [37]–[39]. These neural networks make the restored image closer to the real image from the perspective of image conversion or domain conversion, or just rely on the features of the hazy image itself. However, due to the complex nonlinear relationship between hazy and haze-free images, and the neural networks are restricted by speed and space, the learning-based dehazing effect is limited to a certain extent.

3. Improved Atmosphere Scattering Model (IASM)

In foggy conditions, the traditional ASM have been widely described in the foggy image processing process [3], [4], [7], [8], which can be indicated as:

\[
I(x) = J(x)t(x) + A(1 - t(x)),
\]

where \(x\) denotes the pixel coordinate, \(I(x)\) is the observed image in haze weather. \(J(x)\) denotes the scene radiance, i.e., the clear image which needs to be restored. \(A\) is the atmospheric light. \(t(x) \in [0, 1]\) is the transmission map, which represents the part of light reaching the camera.

However, images are inevitably contaminated by noise in the imaging process, so image denoising is extremely important. The traditional ASM does not consider the noise in optical imaging, which can easily cause the phenomenon of noise amplification. So, the noise term is considered in the IASM. The IASM is given by:

\[
I(x) = J(x)t(x) + A(1 - t(x)) + N(x),
\]

where \(N(x)\) represents image noise at pixel \(x\).

4. Proposed Method

4.1 Weighted Variational Regulation Model

Generally, the regularization model based on total variation (TV) has been broadly used in computer vision [23], [24], which has the effect of maintaining sharp edges. Thus, TV-based regularization is very fit for constraining \(t(x)\) and \(J(x)\). Therefore, a novel weighted variational regularized model is proposed that can calculate transmission map, scene radiance, and noise. The initial transmission map is estimated using [12], [40]–[42] based on DCP and the luminance model. The objective function can be expressed as:

\[
\arg \min_{J, t, N} \| J \cdot t + A(1 - t) + N - I \|^2_2 + \alpha \| W \circ \nabla t \|^1_1 + \beta \| \nabla J \|^1_1 + \delta \| N \|^2_2,
\]

where \(J, t, N, A,\) and \(I\) are the scene radiance, the transmission map, the noise, the atmospheric light, and the hazy image, respectively. \(\alpha, \beta \) and \(\delta \) are positive regulation parameters. \(\| \cdot \|^1_1\) and \(\| \cdot \|^2_2\) represent \(L_1 - norm\) and \(L_2 - norm\), respectively.
respectively. \( \nabla \) is first-order differential operator, and \( \circ \) denotes the dot product operator. \( \| J \cdot t + A(1 - t) + N \|_2^2 \) is data-fidelity term, which measures the distance between \( J \cdot t + A(1 - t) + N \) and the hazy input image \( I \). \( \| \nabla J \|_1 \) is a total variation (TV) regulation term that can stably estimate the process. \( \| \nabla f \|_2^2 \) limits the overall intensity of noise. \( \| W \circ \nabla t \|_1 \) is a weighted L1-norm regulation term, which is used to constrain the gradient of coarse transmission map. \( W \) is an adaptive weight function. When the gradient of coarse transmission map at one pixel is small, \( W \) should be large, and vice versa. A new Gaussian Adaptive Weighted function \( W \) is defined and can be expressed as:

\[
W = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{c^2}{2\sigma^2}},
\]

where \( \sigma \) and \( c \) are control parameters. Experiments show that the proposed weighted function can achieve the effect of edge preservation and smoothing.

The proposed model (3) can preserve the edges while suppressing the unwanted artifacts.

4.2 Optimization Scheme

The solution of Eq. (3) is a non-convex optimization problem, so an alternating direction scheme is exploited to solve this problem. For better numerical calculation, \( I^* = A - I \) and \( J^* = A - J \) are redefined in Eq. (5), and two variables \( X = \nabla t, Y = \nabla J^* \) are introduced in Eq. (5). So, Eq. (3) can be rewritten as:

\[
\begin{align*}
\arg \min_{J^*, N, t} & \| I^* - t \cdot J^* + N \|_2^2 + \alpha \| W \circ \nabla t \|_1 + \\
& \beta \| \nabla J \|_1 + \delta \| N \|_2^2,
\end{align*}
\]

s.t. \( X = \nabla t, Y = \nabla J^* \)

its augmented Lagrangian function is expressed as:

\[
\zeta_A = \| I^* - t \cdot J^* + N \|_2^2 + \alpha \| W \circ \nabla t \|_1 + \\
\beta \| \nabla J \|_1 + \delta \| N \|_2^2 + \\
\lambda_1 \| X - \nabla t - \frac{\varepsilon}{\lambda_1} \|_2^2 + \lambda_2 \| Y - \nabla J^* - \frac{\eta}{\lambda_2} \|_2^2,
\]

where \( \varepsilon \) and \( \eta \) represent the Lagrangian multipliers, \( \lambda_1 \) and \( \lambda_2 \) are positive parameters. The alternating direction method of multipliers (ADMM) [43], [44] is adopted to disintegrate \( \zeta_A \) into three subproblems. These subproblems can be solved until the solution converges.

1. \( (X, Y) \)-subproblems: Assume that \( J^* \) and \( t \) are fixed in Eq. (6), \( (X, Y) \)-subproblems can be solved by:

\[
\begin{align*}
X & \leftarrow \min_X \{ \alpha \| W \circ X \|_1 + \lambda_1 \| X - \nabla t - \frac{\varepsilon}{\lambda_1} \|_2^2 \}, \\
Y & \leftarrow \min_Y \{ \beta \| Y \|_1 + \lambda_2 \| Y - \nabla J^* - \frac{\eta}{\lambda_2} \|_2^2 \}.
\end{align*}
\]

Equations (7) and (8) can be solved by the shrinkage operator [45], i.e.,

\[
X \leftarrow \text{shrinkage}(\nabla t + \frac{\varepsilon}{\lambda_1} \cdot W, \frac{\lambda_1}{2\lambda_1}),
\]

\[
Y \leftarrow \text{shrinkage}(\nabla J^* + \frac{\eta}{\lambda_2}, \frac{\lambda_2}{2\lambda_2}).
\]

2. \( (J^*, t) \)-subproblems: Assume that \( X \) and \( Y \) are fixed in Eq. (6), and the values of \( X \) and \( Y \) are acquired from the previous calculation, so \( (J^*, t) \)-subproblems can be solved as:

\[
\begin{align*}
J^* & \leftarrow \min_J \{ \| J^* - I^* + N \|_2^2 + \lambda_1 \| \nabla J^* - Y + \frac{\eta}{\lambda_2} \|_2^2 \}, \\
t & \leftarrow \min_t \{ \| t + I^* + N \|_2^2 + \lambda_1 \| \nabla t + X - \frac{\varepsilon}{\lambda_1} \|_2^2 \}.
\end{align*}
\]

Then \( J^* \) and \( t \) can be computed directly as:

\[
\begin{align*}
J^* & \leftarrow \mathcal{F}^{-1} \left( \frac{\mathcal{F}(I^* + N) + \lambda_2 \mathcal{F}(\nabla) \mathcal{F}(Y - \frac{\eta}{\lambda_2})}{\mathcal{F}(I) + \lambda_1 \mathcal{F}(\nabla) \mathcal{F}(\nabla)} \right),
\end{align*}
\]

\[
\begin{align*}
t & \leftarrow \mathcal{F}^{-1} \left( \frac{\mathcal{F}(I^* + N) + \lambda_1 \mathcal{F}(\nabla) \mathcal{F}(X - \frac{\varepsilon}{\lambda_1})}{\mathcal{F}(I) + \lambda_2 \mathcal{F}(\nabla) \mathcal{F}(\nabla)} \right).
\end{align*}
\]

where \( \mathcal{F} \) represents the Fast Fourier Transformation (FFT) operator, \( \mathcal{F}^{-1}(\cdot) \) is the inverse FFT operator, \( \mathcal{F}(\cdot) \) denotes the complex conjugate operator, and \( I \) is an identity matrix.

3. \( N \)-subproblem: Removing the terms without \( N \), the solution of \( N \) can be expressed as:

\[
N \leftarrow \min_N \{ \| N + I^* - t \cdot J^* \|_2^2 + \delta \| N \|_2^2 \},
\]

The solution of \( N \) is given by:

\[
N \leftarrow \frac{J^* \cdot t - t^*}{1 + \delta},
\]

4. Lagrangian multipliers update: \( \varepsilon \) and \( \eta \) can be updated in each iteration as follows:

\[
\varepsilon \leftarrow \varepsilon - s \cdot \lambda_1 (X - \nabla t), \quad \eta \leftarrow \eta - s \cdot \lambda_2 (Y - \nabla J^*),
\]

\( \text{Fig. 2 Convergence curves for different images. (a) Most of the realistic images, (b) Most of the synthetic images. } \)
where \( s \) is a step-length that controls the magnitude of the update.

Therefore, the single image dehazing method can be used to solve Eq. (5). Especially, \( J^*, t \) and \( N \) can be obtained at the same time. Then the scene radiation \( J \) can be restored, and can be manipulated through gamma transformation to increase the overall brightness. The iterative curves are showed in Fig. 2. These curves show that our optimization algorithm can converge quickly, and most hazy images generally converge after 9 iterations. Algorithm 1 describes the entire process of the proposed method.

**Algorithm 1** Outline of the proposed method.

- **Input** hazy image \( I_o \)
- **Initial transmission** \( t(x) \) by luminance model [41]
- **Estimate** \( A \) via DCP [12]

**Inputs:** \( t(x), A, I_o, \) coefficients \( \tau, \alpha, \beta, \delta, \lambda_1, \lambda_2, s, \sigma \) and \( c \).

**For** \( c = r, g, b \)

**Initialization:** \( \varepsilon = \eta = N = 0 \)

**While** not converged do:
- Update \( X \) via Equation (9)
- Update \( Y \) via Equation (10)
- Update \( J^* \) via Equation (11)
- Update \( t \) via Equation (12)
- Update \( N \) via Equation (16)
- Update \( \varepsilon \) and \( \eta \) via Equation (17)

**End**

**Output:** the restored scene radiation \( J = A - J^* \)

5. **Experimental Results and Analysis**

Our method is implemented using MATLAB 2019b. Comprehensive experiments were performed using both synthetic and real-world images to compare our method with other state-of-the-art dehazing methods, e.g., He [12], Meng [21], Berman [22], Ren [25], Cai [26] and Li [27]. In our experiment, parameters were manually set as: \( \tau = 3.4, \alpha = 0.1, \beta = 10, \) and \( \delta = 2.5 \times 10^{-1}, \lambda_1 = 1 \times 10^4, \lambda_2 = 1 \times 10^3, s = 1.588, t_0 = 1 \times 10^{-1}, \sigma = 1 \) and \( c = 1 \times 10^1. \) The effectiveness of these parameters for our method has been proven through a large number of experiments.

5.1 **Experiments on Realistic Images**

Several realistic hazy images were employed to compare the performance of different dehazing methods. Figure 3 illustrates the qualitative comparison with other methods [12], [21], [22], [25]–[27]. It can be found that He [12] amplifies noise in the sky regions. Figure 3 (c) shows that Meng’s method [21] can get better results for most images, but this method shows low global brightness. Figure 2 (d) shows the method of Berman [22] sometimes suffers from color distortion, and some over-dark areas can be found. Figure 3 (e), Fig. 3 (f) and Fig. 3 (g) show the results of deep learning-based methods. Figure 3 (e) illustrates that Ren [25] fails to effectively remove the haze sometimes. Figure 3 (f) shows the method of Cai [26] cannot eliminate all haze, and it is also prone to color distortion. Figure 3 (g) illustrates that Li [27] can maintain the image structure very well, but also shows low brightness in some local areas.

After comparison, experimental results show that the proposed method can effectively remove haze while retaining fine image details, and it can get a genuine color and improve visibility. Furthermore, our method shows less halo artifacts and noise. The comparison of local areas is also illustrated as shown in Fig. 4. Figure 4 illustrates that our method can operatively improve the brightness of a local area, while eliminating the influence of atmospheric light and noise.

The excellent performance of our method mainly benefits from three aspects. First, the noise term is considered in ASM, and the coarse transmission is estimated through the weighted fusion-based strategy, which has excellent ability to help defogging and color recovery in sky areas. Second, our Gaussian Adaptive Weighted function \( W \) contributes to preserve fine image details while smoothing. Third, the reg-
5.2 Experiments on Synthetic Images

Five images were selected from NYU Depth dataset [46] and the latest HSTS subset of RESIDE dataset [47]. As shown in Fig. 5, the dehazing images through our method are more approximate to the ground truth images in most of cases.

5.3 Quantitative Evaluation

Quantitative evaluation of different methods was conducted on Fig. 5. Both Peak Signal to Noise Ratio (PSNR) [48] and Structural Similarity (SSIM) [49] were used to quantitatively evaluate the above-mentioned methods.

For the original image \( T(x) \) and the processed image \( R(x) \), PSNR can be expressed as:

\[
MS E = \frac{1}{h \times w} \sum_{i=1}^{h} \sum_{j=1}^{w} (T(x) - R(x))^2, \tag{18}
\]

\[
PS NR = 10^\log_{10} \left( \frac{2^n - 1}{MS E} \right), \tag{19}
\]

where \( x \) is the pixel coordinate \((i, j)\) in the original image with height \( h \) and width \( w \), respectively. \( n = 8 \) for the 8-bit image.

SSIM is given by the following formula:

\[
SS IM = c(P, Q) \times l(P, Q) \times s(P, Q), \tag{20}
\]

\[
l(P, Q) = \frac{2 \mu_P \mu_Q + C_1}{\mu_P^2 + \mu_Q^2 + C_1}, \tag{21}
\]

\[
c(P, Q) = \frac{2 \sigma_P \sigma_Q + C_2}{\sigma_P^2 + \sigma_Q^2 + C_2}, \tag{22}
\]

\[
s(P, Q) = \frac{\sigma_{pq} + C_3}{\sigma_P \sigma_Q + C_3}, \tag{23}
\]

where \( P \) represents the original image, and \( Q \) represents the processed image. \( \mu_P \) and \( \mu_Q \) represent the mean value of \( P \) and \( Q \) respectively. \( \sigma_P \) and \( \sigma_Q \) are the variance of \( P \) and \( Q \), respectively. \( \sigma_{pq} \) is covariance of \( P \) and \( Q \). \( C_1 \), \( C_2 \) and \( C_3 \) are constants that makes the denominator not zero.

Table 1 illustrates the quantitative results for the above-mentioned dehazing methods. From Table 1, our method can produce excellent imaging results in most cases. He [12] sometimes brings unwanted artifacts in the restored image, because dark channel prior (DCP) fails in white areas. The methods based on deep learning [23] are vulnerable to the lowest evaluation values, which may on account of that dehazing method based on learning are usually relying heavily on the training data set. Different data sets may be trained to obtain different neural network models, and the dehazing effect is different.

The non-reference fog aware density evaluator (FADE) [50] is also used to assess the dehaze performance objectively. FADE is given by the following formula:

\[
D = \frac{D_f}{D_{ff} + 1}, \tag{24}
\]

where \( D_f \) is the fog density level of the image block, and \( D_{ff} \) is the haze-free level of the image block [41].

A smaller FADE value indicates a lower perceived fog density, which means that the defogging method may be better. The randomly selected pictures in Fig. 3, Fig. 4 and Fig. 5 have calculated the FADE value as shown in Table 2.

From Table 2, our method almost gets the lowest value.
of different images except for the train in Fig. 4, which may be interference caused by the brightness of the train’s lights. The lower FADE value shows that our method is more competitive than other methods.

5.4 Regulation Parameters Sensitivity Experiments

The impact of changes in two important regulation parameters is examined on the dehazing results, i.e., the parameters $\alpha$, $\beta$ in regulation term. In order to survey the influence of each parameter separately. The default values of $\alpha$ and $\beta$ are set as 0.1 and 10 respectively. When one parameter is changed, the other parameter is set as their default value. From Fig. 6, it can be found that the estimated transmission map is gradually dimmed and cannot preserve the overall structures with the increase of $\alpha$. In addition, the restored scene radiance shows severely halo artifacts with the increase of $\alpha$ in Fig. 6 (d) and Fig. 6 (e). This is because $\alpha$ controls the smoothness of the transmission map. In Fig. 7, as $\beta$ increase, the dehazing result is gradually behaving abnormally in Fig. 7(d) and Fig. 7(e). This is due to that $\beta$ controls the effect for the restored scene radiance, and when the increase of $\beta$ is large, the restoration of scene radiance is excessive and abnormal.

After a lot of experiments, $\alpha$ and $\beta$ are set as 0.1 and 10 respectively, which can simultaneously restore the fine haze-free image and maintain the structure-preserving transmission map under most circumstances.

5.5 Weighted Function Sensitivity Experiments

To illustrate the effectiveness of our Gaussian Adaptive Weighted function $W$, the proposed weighted function $W$ is used and do not used to compare the restored results. It can be found that if the proposed weighted function $W$ is not used, the details of the estimated transmission map are obviously blurred (such as the area within the box marked in blue) as shown in Fig. 8 (c). Moreover, the edge of the estimated transmission map and the restored scene radiance (such as the area within the box marked in red) is not well maintained as shown in Fig. 8 (b). Hence, the proposed Gaussian Adaptive Weighted function $W$ has a good edge-preserving and smoothing effect.

6. Discussion and Conclusions

In this study, we focused on the neglected noise term in the atmospheric scattering model and the new variational regularization model for single image dehazing. In order to better achieve the dehazing effect, we first used the classic DCP, and combined with the illumination model to consider the sky area where the dark channel prior failed, and estimated the initial transmission map and atmospheric light. Then a new variational regularization model is proposed to further refine the value of transmission map, and finally the parameters of the model are solved to restore the hazy-free image. The experimental results show that the proposed method can effectively achieve the effect of single image dehazing, and has good performance in both visual and quantitative evaluation.

The rough transmission map is first obtained by the weighted fusion method. Then a novel weighted variational regulation model is proposed to refine the rough transmis-
On the basis of the ASM, and consider the noise, the dehazing issue is conducted as a weighted vari-

ation model which includes a noise term and two variation regulation terms. The optimization problem is solved via ADMM. Unlike the classic two-step defogging frameworks, the proposed method can calculate the transmission map and restore the haze-free image at the same time. Both qualitative and quantitative comparisons with other methods are executed to illustrate that the proposed method executes better on dehazing results. In academic research, the proposed method provides a new single image dehazing model, which has certain significance for image denoising and deblurring.

Nevertheless, the proposed method also has some limitations. On one hand, several parameters in the proposed model cannot be adjusted adaptively. Moreover, sometimes the proposed method makes pixels over-saturated. This because some objects (such as white and grey ones) have a similar color, but different haze densities. Meanwhile, the dehazing speed of our method also should be improved for engineering requirements.

In future work, the proposed method will consider high-order variational models, and will be combined with deep learning methods [51, 52], considering the restoration of more challenging non-uniformly distributed haze images and dense haze images.

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