Outdoor image restoration based on belief propagation algorithm and formalized MTF

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Abstract. Single image dehazing technology can be applied to many fields. In order to solve this problem, an improved framework is proposed here, which can be used to estimate the light transmittance $t$ in a given single input image and then the belief propagation (PB) algorithm is applied to image dehazing. At first, a coarse transmission map is calculated through Dark Channel Prior (DCP) knowledge. Next, the belief propagation methodology is introduced to correct the transmission map when the object in degraded image is similar to the airlight over a large local region. As a result, the transmission map can be estimated better and the important drawback of artifacts phenomenon can be avoid to some extent. At last, through this effective estimation to transmittance, the formalized MTF can be predicted to restore degraded images, then the haze-free scene contrasts can be better recovered. The experimental analysis results show that compared with defogged images acquired through DCP algorithms, our proposed algorithm can provide good results. Our method is more effective and robust.

1. Introduction

Outdoor images are usually degraded by aerosols, molecules and other particles in the atmosphere. The effect of bad weather (e.g. fog, haze and smoke) are mainly caused by atmospheric absorption and scattering, which degrades the image quality. The brightness captured by the image plane of camera from the scene point is attenuated along the line of sight. The scattering effects of aerosols, molecules and other particles in the atmosphere play an important role of resulting in image degradation and low image contrast. In order to solve this challenging but imperative issue, many researchers have made much efforts in this field, and a large number of findings on the restoration of foggy images[1-14] is published.

The removal of fog and haze from the captured foggy images are required to estimate the atmospheric transmittance. Image defogging methods can be roughly divided into two categories i.e. image enhancement and image restoration through atmospheric optics model[14]. The methodology of first category deals with degraded image based on the image feature information which comes from the low image brightness and contrast caused by different image degradation processes [1-6]. In addition, the algorithm of second category recovers image based on the image degradation model in turbid atmosphere [7-14].
The atmospheric optics model is firstly proposed by McCartney, then the theoretical description for this model is set up by Narasimhan. Only the effect of atmospheric scattering and attenuation is considered in this model. Many researchers adapt this simple model in different image processing applications. The common approaches derived from optics model are Fattal method[7], Tan method[8], Markov Random Field(MRF) with Bayesian algorithm and He method[10], images fusion method, PDE algorithm and so on.

Image degradation process described by Koschmieder’s law can be expressed as follow,

\[
I(x) = J(x)e^{-\beta d(x)} + A(x)(1 - e^{-\beta d(x)})
\]

where \(I(x)\) denotes the degraded image, \(A(x)\) represents the airlight or atmospheric light, \(d(x)\) represents the scene depth, and \(J(x)\) represents the original image (or haze-free image). The term \(A(x)e^{-\beta d(x)}\) is called the scene transmission. The first term on the right-hand side of second line of Eq.(1) is called direct attenuation, which exponentially degrades the scene radiance in proportional to \(d(x)\); the second term is called atmospheric light, which is a white atmospheric veil reducing the image contrast.

He[10] method is based upon DCP knowledge which is widely used for single-image dehazing. The DCP knowledge is primary derived from the statistics of the outdoor fog free image, which is based on the assumption that some pixels are having very low intensity in any one of the colour channel in the case of regions which do not cover the sky, which is called dark pixels. For foggy images, the intensity of the dark pixels is mainly contributed by the airlight. The atmospheric transmittance is estimated based on these dark pixels. Then, a coarse transmission map is acquired and a guide filter[15] is used to refine the transmission map.

The dark channel is expressed as follows:

\[
J_{\text{dark}}(x) = \min_{r,g,b} \{ \min_{y \in \Omega(x)} (J^c(y)) \}
\]

where \(J^c\) is a RGB channel of degraded images and \(\Omega(x)\) is a local patch, which is centered on \(x\).

The transmission map is estimated by the following equation:

\[
t(x) = 1 - \frac{I_{\text{dark}}(x)}{A(x)}
\]

The transmission map \(t(x)\) is important for single-image defogging. The method is simple, but can get an impressive result.

However, it is quite possible that some areas of the image can not satisfy the conditions of DCP knowledge. For instance, the colour of the dehazing images is likely to be changed, when the scene object in degraded image is inherently similar to the atmospheric light over a large local region and the degraded image is addressed by DCP method, especially when no shadow is cast on the object. As a result, the transmission map estimated from natural image contains “white” object will have missing values.

First, in this paper, belief propagation algorithm is used to restore the corrupted transmission map. Then a new method is proposed to restore outdoor image with transmission map and formalized MTF.

2. Image dehazing with Formalized MTF in turbid atmosphere

However, the multiple scattering light of adjacent pixels blurs the edge of the target pixel, usually called the adjacency effect[16], which is not considered in optical model. When the influence factors mentioned above are considered, the formalized MTF (denoted by \(M'_{TF}\)) is defined to describe the imaging process in the turbid atmosphere, which is shown as follows[18]:

\[
M'_{TF}(\Omega, \lambda) = M_{TF}(\Omega, \lambda) + \frac{I_0(\lambda)}{F_0(\Omega, \lambda)} \times \delta(\Omega)
\]
In Eq. (4), the first term on right is the medium MTF, which can be described by equivalent principle[19], i.e., the term MTF in Eq. (4) can be replaced by Eq. (5):

\[ M_{\Omega}(\theta) = \tan(\theta) \]  

(5)

where \( \Omega \) is the polar angle of received radiance; \( \tau \) is optical depth; \( g \) is asymmetry parameter; \( \omega \) is single scattering albedo. \( \tau \) can be acquired through the transmission map in section 3.

Figure 1 shows the flowchart of method to perform image dehazing. Firstly, our transmission map is derived with the combination of DCP and belief propagation algorithm (section 3). Secondly, formalized MTF in turbid atmosphere is predicted based on several atmospheric parameters (section 4). Finally, formalized MTF is used to perform the dehazing through inverse Fourier transform (section 4).

![Flowchart](image)

**Figure 1** The flowchart to implement our method

### 3. Belief Propagation and Transmission Map Restoration

MRF models, a robust and unified framework for early vision problems such as stereo and image restoration, are widely used in image restoration. A algorithm, which is based on graph cuts and belief propagation, have been found to get better results. [21]

#### 3.1. Problems

The general description for the problems can be defined as follow[20,21]. Let \( B \) and \( L \) are the set of pixels in an image and a finite set of labels, respectively. A label \( f \) assigns a labelling \( f_b \in L \) to each pixel \( b \in B \). It’s assumed that the labels should vary smoothly almost everywhere but may change drastically at some situations such as pixels along object boundaries. The quality of a label is depicted by a cost (energy) function,

\[ E(f) = \sum_{b \in B} D_b(f_b) + \sum_{(b,d) \in ?} W_b(f_b, f_d) \]  

(6)

where \( \kappa \) represents the undirected edges in the four-connected image grid graph. \( D_b(f_b) \) is the cost of assigning label \( f_b \) to pixel \( b \), which can be considered as the data cost. \( W_b(f_b, f_d) \) means the cost of assigning labels \( f_b \) and \( f_d \) to two neighbouring pixels, and is normally treated as the discontinuity cost. Thus, the main issue is to find a labelling that minimizes this cost function, which can be converted to the maximum a posteriori (MAP) estimation problem for an appropriately defined MRF[22-23].

In several computer vision problems, e.g. image denoising, image smoothing and image restoration, the discontinuity cost \( W \) is generally on the dependence of difference between the value of labels, rather than their actual pixel values. For example, when the problem of image restoration is addressed, the labels correspond to the possible disparities or intensity values respectively, and the cost of assigning a pair of labels to neighbouring pixels is determined by the difference between different
labels. Thus, the case where \( W_b(f_b, f_d) = V(f_b - f_d) \) is taken into account in this paper, yielding an energy minimization problem of the form written in Eq. (7),

\[
E(f) = \sum_{b \in B} D_b(f_b) + \sum_{(b,d) \in \mathcal{E}} V(f_b - f_d)
\]  

(7)

The main focus of this article is the maximum product formula for BP algorithm, and the cost (energy) minimization problem in terms of costs, which are proportional to negative log probabilities.

3.2. Loopy Belief Propagation: Max-Product

The maximum product algorithm can be used to approximate the MAP solution to MRF problems. Normally, the knowledge of probability distributions is the basis of this technique. For simplify, an equivalent mathematic expression can be performed with negative log probabilities, where the max-product can be replaced by min-sum. This formulation is less sensitive to numerical artifacts, and more related to the cost (energy) function, which is defined in Eq. (7).

The BP algorithm starts through delivering messages along the four-connected image grid graph. Because of the requirement of iterative calculation, the messages from all nodes are parallel delivered. Each message is a vector of dimension given by the number of possible labels, \( k \). Let \( m_{b \rightarrow d}^t \) be the message that node \( b \) sends to a neighbouring node \( d \) at iteration \( t \). When negative log probabilities is used, all entries in \( m_{b \rightarrow d}^0 \) are initialized to zero, and at each iteration new messages are computed as follow,

\[
m_{b \rightarrow d}^t(f_d) = \min_{f_b} \left( V(f_b - f_d) + D_b(f_b) + \sum_{s \in u(b) \setminus d} m_{s \rightarrow b}^{t-1}(f_b) \right)
\]  

(8)

where \( u(b) \setminus d \) means the neighbours of \( b \) besides \( d \). After \( T \) iterations, a belief vector is computed for each node,

\[
p_b(f_b) = D_b(f_b) + \sum_{s \in u(b) \setminus d} m_{s \rightarrow b}^{T-1}(f_b)
\]  

(9)

At last, the label \( f_b^* \), which minimizes \( p_b(f_b) \) individually at each node, is selected.

3.3. Estimation of Transmission Map

The raw transmission map of degraded image(Figure 2) is acquired through DCP method. The dehazing image using DCP algorithm may suffer colour bias, as illustrated in Figure 3, the DCP knowledge is invalid when the scene object is inherently close to the air-light (e.g. lake in Figure 2). The transmittance of lake in the left side of Figure 3 is not continuous with other scene, e.g. green trees on both sides of the lake.

Belief propagation algorithm does a good job of filling in missing data based on the remaining image, as illustrated in the right side of Figure 3. Note that the method has been applied to measure atmospheric transmittance from a single frame of multi-spectral image for non and weak absorption waveband[24]. Then the transmittance will be used as one input to calculate the formalized MTF in visible band.

![Figure 2. Degraded image](image-url)
4. Image Restoration with formalized MTF

In spatial frequency domain, the process of image degradation can be expressed as follows,

$$ F(\Omega, \lambda) = F'_o(\Omega, \lambda) \times M'_T(\Omega, \lambda) $$  \hspace{1cm} (10)

The formalized MTF is used to describe the effects of attenuation, multiple scattering and atmospheric scattering light. When the case, where imaging through a horizontal homogenous atmosphere, is taken into account here, $M'_T$ can be quantified through four parameters on the dependence of theoretical derivation under some hypothesis[17,18]: medium MTF, light transmittance ($T$), maximum surface albedo ($r_m$) and a parameter ($k$) which only depends on the target itself.

$$ M'_T(\Omega, \lambda) = M'_T(\Omega, \lambda) + \frac{1-T}{kr_m} \delta(\Omega) $$  \hspace{1cm} (11)

Visible images are widely useful to many electro-optic systems which need capture image information under different weather conditions, including surveillance systems, outdoor object recognition system, remote sensing systems, and so on. For visible images, it’s possible that $kr_m$ is 1.0 and single scattering albedo($\omega$) is 1.0, so we arrive at Eq.(12)

$$ M'_T(\Omega, \lambda) = M'_T(\Omega, \lambda) + (1-T) \times \delta(\Omega) $$  \hspace{1cm} (12)

The parameters used by Eq.(5) are selected on the dependence of imaging time, imaging location and weather condition, which is listed in Table 1.

| Degraded Images | Time   | Location             | Weather condition |
|-----------------|--------|----------------------|-------------------|
|                 | 16:30  | Science Island in Hefei (suburbs) | Rain              |

Table 2 displays the $g$ for different weather conditions, so the inputs used by Eq.(5) are as follows:

| g                | Weather conditions |
|------------------|--------------------|
| [0.00,0.20]      | Air                |
| [0.20,0.70]      | Small Aerosol      |
| [0.70,0.80]      | Haze               |
| [0.80,0.85]      | Mist               |
| [0.85,0.95]      | Fog                |
| [0.95,1.00]      | Rain               |

| Input            | Asymmetry factor(g) | Single scattering albedo(\omega) | Atmospheric transmittance(T) (Average transmittance of the lake area) |
|------------------|---------------------|---------------------------------|-------------------------------------------------------------|
|                  | 0.99                | 1.0                             | 0.48                                                        |
Dehazed image is obtained by inverse Fourier transform (Eq.(13), Eq.(14)), as illustrated in Figure 4.

\[ F_T(\Omega, \lambda) = F(\Omega, \lambda) / M'_{\Omega}(\Omega, \lambda) \]  
(13)

\[ I_{\lambda} = \text{Fourier}^{-1}\{F_T(\Omega, \lambda)\} \]  
(14)

Figure 4 shows the degraded image with sky area and lake area(left), as well as dehazed image with DCP method(middle), dehazed image with our method(right). Degraded image in Figure 4 has a relatively low contrast and appears gray. Our method produce a better result in the right side of Figure 4, where the foggy area has clearly been weakened. At the same time, the color of the trees has been restored, the lake is more clearer and the whole picture is brighter, however DCP method can’t restore the degraded image with sky area and lake area well[25].

![Figure 4. Restored Image of different methods: (left) Degraded image; (middle) DCP method; (right) Our method](image)

5. Conclusion
This paper proposes an interesting method to restore degraded image. The transmittance is estimated through belief propagation algorithm and DCP algorithm. This approach can be used to restore foggy images when the problem cannot be solved by optics model alone. The mixing between pixels, or adjacency effect, makes image dehazing more difficult, and ultimately blurs the edge of the target pixel, is considered here. Besides, our method can deal with the problem in the case that colour of the scene object is similar to the sky (or airlight), which can not be addressed well through DCP algorithm. However, there is still an urgent need to solve the problem of image defogging and find a more robust and effective solution.

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