A method for filtering smoke in images

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Abstract. *The treatment of images captured in situations where there the we have bad visibility like smoke or foggy weather conditions is a great challenge. In this sense, we have developed a technique of filtering smoke and foggy in images that have the potential to benefit many applications of understanding and computational vision. Our algorithm is based on a series of mathematical methods to capture the noise by means of its density, in the end our results demonstrate that the method is quite effective to solve the problem of the test images.*

1. Introduction

The treatment of images captured in situations where there is smoke is a great challenge. The images corrupted by natural effects tend to lose contrast and color quality due to the light being dispersed and being absorbed by the cloudy medium formed by particles present in the atmospheric environment, so the image is with low visibility of details [Narasimhan 2004]. In addition, systems that rely on image quality for performing specific analyzes or other tasks tend not to end up with satisfactory results because of the level of degradation in the image.

In this sense a noise removal technique in digital images will benefit many applications of understanding and computational vision of images, for example, classification of images [Shao et al. 2014], aerial images [Woodell et al. 2006], image recovery [Han et al. 2013], video analysis and recognition [Liu and Shao 2013].

In the literature it is demonstrated results of the use of noise removal techniques similar to those solved in the work proposed here, these techniques are divided in 4 classes: algorithms based on physics [Narasimhan and Nayar 2003], algorithms based on retinex [Xie et al. 2010], algorithms of contrast stretching [Stark 2000] and multi-scale fusion algorithms [Ancuti and Ancuti 2013].

Contrast stretching-based algorithms are known to enhance the visual effect of the image without the need to reduce the image, however, the physics-based techniques are generally able to achieve better performance compared to others. The effectiveness of physics-based methods is due to consider a mechanism of degradation and are used prior knowledge for filtering the image, on the other hand, these algorithms has its own limitation.

In this paper we present an efficient method for suppressing smoke and foggy in outdoor images. The method is formed by the combination of a boundary constraint inherent in scene transmission along with a weighted regularization between neighboring pixels, thus resulting in images with good quality characteristics.

2. State of art

In literature several approaches have been proposed to fuzzy images, such as the method based on Dark Channel Prior described in [He et al. 2011], by He proposed in 2011, it presented the most efficient results to date. Although quite effective, it is necessary to take into account color distortion and overestimated transmission around white objects.

Also in 2011, a tolerance-based method to recalculate the transmission map of the bright areas was proposed in [Jiang et al. 2011]. However, in their tolerance calculation authors need to adjust the parameters for different images, thus, if the tolerance is too small, the distortion can not be totally eliminated; if it is too large, this leads to restoration errors in non-bright areas and also reduces the filtering ability of the method.

In [Fattal 2008] the algorithm demonstrated exploits the fact that the scene albedo and the transmission are not locally correlated with the image. It is physically sound approach and can produce impressive results. However, it is deeply based on color and, which makes it difficult to use a gray level image.

In the technique proposed by [Kratz and Nishino 2009] an image is modeled as a Random Markov factorial field, where the albedo and the depth of the scene are two latent statistically independent layers. The method can retrieve an image with fine-edge details, but the results often tend to be overcome.

There is also the linear method demonstrated by [Zhu et al. 2015]. In this work the authors used the color attenuation and derived the estimation of the depth of the scene. However, the Zhu method is likely to be unstable, since the fixed dispersion coefficient is not applicable for several images.

Based on the research of the methods described above and other solutions available in the literature [Wang et al. 2016] [Cai et al. 2016] [Meng et al. 2013] [Berman et al. 2016], the proposed method to filter the images with smoke was implemented.

3. Methodology

The interpolation model shown below is widely used as a representation of the formation of an image corrupted by the similar problem, the fog.

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

where $I(x)$ is the observed image, $J(x)$ is the radiation of the scene, A is the atmospheric light and $t(x)$ is the transmission of the scene. The transmission function $t(x)(0 \leq t(x) \leq 1)$ correlates with the depth of the scene. Taking into account that the smoke is normally homogeneous, we can express $t(x)$ by means of:

$$t\left(x\right)=e^{-\beta d(x)}, \tag{2}$$

where β is the mean extinction coefficient, and $d(x)$ is the depth of the scene. Then it is necessary to recover the radiation of the scene $J(x)$ of $I(x)$ based on equation 1. This requires estimation of the transmission function $t(x)$ and the global atmospheric light A. Since we estimate $t(x)$ and A, the brightness of the scene can be retrieved by the following equation:

$$J(x) = \frac{I(x) - A}{[max(t(x), \epsilon)]^{\delta}} + A, \tag{3}$$

where ϵ is a constant to avoid division by zero, and exponent δ, which has the function of mean extinction coefficient β in equation 2, is used for destructive effects adjustments. However, the destruction of a single image is highly insufficient, since the number of unknowns is much larger than the number of available equations. in this sense we first explore more constraints on the unknowns.

According to equation 1, a pixel corrupted by smoke will be "pushed" to the global atmospheric light A, as a result it is possible to reverse this process by a linear extrapolation from A to I, by recapturing the clean pixel $J(x)$. The appropriate amount of extrapolation is given by:

$$\frac{1}{t(x)} = \frac{\|J(x) - A\|}{\|I(x) - A\|}. \tag{4}$$

Restriction of the boundary is more fundamental. In most cases, the overall atmospheric light is a bit darker than the brightest pixels in the image. These brightest pixels usually come from some light sources in the scene, for example, the bright sky or the headlights of cars. In these cases, the dark channel prior [He et al. 2011] will fail for these pixels, while the proposed limit constraint is still valid.

Usually pixels in a local image patch share a similar depth value. With this assumption, we derive a patch-wise transmission of the constraint limit. On the other hand, this contextual assumption often ceases image stains with abrupt depth leading to significant halo artifacts in the results.

To solve this problem it is possible by adding a weighting function $W(x, y)$ on the constraints, that is,

$$W(x, y)(t(y) - t(x)) \approx 0, \tag{5}$$

where x and y are two neighboring pixels. The weighting function plays a "switch" of the constraint function between x and y. When $W(x, y) = 0$, the corresponding context-sensitive restriction $t(x)$ between x and y will be canceled.

Noting the fact that depth jumps usually appear at the edges of the image, and that within the local patches pixels of a similar color generally share a similar depth value, it is possible to calculate the color difference of the local pixels to build the weighting function. Here is an example of a weighting function, which is based on the luminance difference of the adjacent pixels:

$$W(x, y) = \left(|l(x) - l(y)|^{\alpha} + \epsilon\right)^{-1}, \tag{6}$$

where the exponent $\alpha > 0$ controls the sensitivity for difference between pixels, l is the luminance channel of the image $I(x)$ e ϵ is a small constant to avoid division by 0.

As a contribution, our method uses a minimum filter with a window in motion to filter each color channel for an input image, shortly thereafter the maximum value of each channel is used as an estimate of the component of A.

We found an optimal transmission function $t(x)$ minimizing the objective function shown below:

$$\frac{\lambda}{2}\left\|t-\hat{t}\right\|_2^2+\sum_{j\in\omega}\left\|W_j\circ(D_j\otimes t)\right\|_1, \tag{7}$$

where the first part is the data term that measures the fidelity of $t(x)$, the second part models the contextual constraints of $t(x)$ and λ is used as a regularization parameter for the equilibrium of the two terms.

Then, to optimize this algorithm, an efficient method based on the division of variables is used. The main and simplified idea of this method is to use several auxiliary variables to construct a sequence of simple sub-problems, whose solutions finally converge to the ideal solution of the original problem.

In order to optimize equation 7 more specifically we present the following auxiliary variables, denoted by $u_j(j\in\omega)$ and convert equation 7 to a new cost function as shown below:

$$\frac{\lambda}{2}\left\|t-\hat{t}\right\|_2^2+\sum_{j\in\omega}\left\|W_j\circ u_j\right\|_1+\frac{\beta}{2}\left(\sum_{j\in\omega}\left\|u_j-D_j\otimes t\right\|_2^2\right), \tag{8}$$

where β functions as a weight. Thus, as $\beta\to\infty$ the solution of equation 8 will converge to that of equation 7.

The minimization of equation 8 to a fixed β is performed with an optimization with respect to u_j and t, so we initially solve for every u_j by fixing t, then we solve each t by correcting u_j until there is convergence.

4. Results

Figure 1 illustrates the image corrupted by smoke, the results of scene transmission functions recovered and filtering results of our algorithm respectively.

In the examples, as can be seen, our method was able to recover the details quite well, as well as the vivid colors where the smoke region was.

The transmission function reflects the density of the smoke captured in each image, in this sense with the results shown we can see that the amount captured by our algorithm is very consistent with the type of noisy image used.

It is also worth noting that due to the amount of smoke being different between the different captured images, it may be necessary to modify the default values set in the algorithm, for example the regularization parameter λ, by default set to 1.0.

For these tests we used as an experimental hardware platform a notebook with 2.0 GHz Intel Core i3 processor and 4GB of RAM, in addition said that 5 images of size 970x600 pixels were used.

Figure 1. Results of our filtering method: first the input image, just below the recovered transmission function and below it the filtering result

5. Conclusion

In this paper, we propose a method for filtering images with natural phenomena based on the capture of smoke and foggy by means of the detection of noise density with the use of various mathematic techniques.

With the results demonstrated our method proves to be quite effective for recovering details of difficult visibility due to the strong density of noise in some images.

For the future we propose to improve the mathematical method of filtering and to improve the speed of results processing so we can apply it in real time capture systems, such as aerial images captured by drones or images captured by others mobile robots in a fire zone.

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