COLOR CHANNEL-BASED SMOKE REMOVAL ALGORITHM USING MACHINE LEARNING FOR STATIC IMAGES

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ABSTRACT

Images acquired from digital cameras are usually interfered by smoke, which may degrade the performance of object detection. There are few algorithms focused on smoke removal for still images so far and we usually use haze removal algorithms to remove smoke instead. However, there exist some differences between haze and smoke (e.g. particle properties and localization). Thus, a dehaze algorithm usually has limited performance for smoke removal. In this paper, we propose a novel smoke removal algorithm based on machine learning and smoke detection techniques. Moreover, we observed that the intensity distributions are not the same for different color channels in smoky images. Therefore, the proposed algorithm trains the models corresponding to each color channel and remove smoke from RGB channels separately. Simulations show that the proposed algorithm can significantly remove smoke. Moreover, as far as we know, the proposed algorithm is the first smoke removal algorithm for static images.

Index Terms— Smoke Removal, Machine Learning, Color Channel, Image Restoration, Static Image

1. INTRODUCTION

Smoke may scatter and absorb reflected light of the scene. It degrades our visibility when we want to save lives, perform disaster analysis, and pattern recognition. Therefore, the smoke removal algorithm is very important in disaster relief systems and surveillance systems. However, there are few researches about smoke removal. In [1], they proposed a video smoke removal algorithm. In [2]-[5] they developed smoke detection methods. However, none of these works are about smoke removal in still images.

By contrast, there exist many works about haze removal. He *et al*. [6] proposed the dark channel prior (DCP) to remove the haze and the algorithm was further improved in [7]-[9]. Fattal *et al*. [10, 11] proposed some methods based on the assumption that transmission do not have correlations locally and surface shading. Tang *et al*. [12] proposed a novel transmission map estimation algorithm which is based on the random forest [13] method.

There are some similarities between hazy and smoky images. Both of them can be modeled as follows [14]:

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

where $J(x)$ is the original image and $I(x)$ is the hazy or smoky image we observe. The atmospheric light A is the luminance of the light source from infinite distance away. The transmission map $t(x)$ can be expressed as $t(x) = e^{-\beta d(x)}$ where $d(x)$ is the pathlength and β is a constant. Moreover, the real scene can be recovered by (2) if we know A and t.

$$J(x) = \frac{I(x) - A}{t(x)} + A. \tag{2}$$

However, smoke and haze are virtually different. First, particles are always non-homogeneous for smoke while they are homogeneous in the haze case. It may cause the error in transmission map estimation because the thickness of smoke may be different. The second difference is that smoke is usually concentrated in some local region while haze is distributed uniformly. In addition, we also found two phenomena: (i) The intensity of the blue channel in a smoky region may be stronger than that in a hazy region. Thus, the smoky region may be bluish when we apply haze removal algorithm on it. (ii) Thick smoke cannot be removed clearly by a haze removal algorithm. These are why we need to develop an algorithm focusing on smoke removal.

In this paper, we develop a novel algorithm to remove smoke for static images effectively. Our proposed model is based on machine learning and color-channel based smoke removal. We also develop a hybrid smoky region detection method which can help us to find the smoky regions and use this information to remove smoke in these regions. Moreover, we also proposed a new smoky training data synthesis method. In section 2, we review some haze removal and smoke detection algorithms. In section 3, we illustrate the proposed algorithm in detail. We show our experimental results in section 4 and a conclusion and a systematic comparison are given in section 5.

2. RELATED WORKS

From the scattering model in (1), the critical factors in smoke and haze removal are the transmission map $t(x)$ and the atmospheric light A. The original image can be well-recovered if $t(x)$ and A can be determined accurately.

2.1. Haze Removal Algorithm

For haze removal, He *et al*. [6] proposed the dark channel prior which assumes that, for a natural image, one of color channels is near to zero or has a low value:

$$J_{Dark} = \min_{k\in\{r,g,b\}}\left(\min_{y\in\Omega(x)} J^k\right) \cong 0 . \quad (3)$$

where $\Omega(x)$ is a patch centered at x. Then, (1) can be rewritten as:

$$\min_{y\in\Omega(x)}\left(\frac{I^k(y)}{A^k}\right) = \min_{y\in\Omega(x)}\left(\frac{J^k(y)}{A^k}\right)t(x)+1-t(x) \;\; k\in\{r,g,b\} . \quad (4)$$

From (3), the transmission map $t(x)$ can be estimated from:

$$t(x) = 1 - \min_{k\in\{r,g,b\}}\left(\min_{y\in\Omega(x)} \frac{I^k(y)}{A^k}\right). \quad (5)$$

Tang *et al.* [12] proposed a novel transmission map estimation method based on the random forest [13]. They found the most important feature in transmission estimation is the dark channel. In the training process, the haze-relevant features in multiple patch sizes are extracted and the true transmission maps are treated as ground truths. Zhu *et al.* [15] proposed the color attenuation prior to estimate the depth map by a linear model.

Fattal *et al.* proposed the contrast optimization [10] and the color line methods [11]. The former one maximizes the contrast and has good performance in the thin haze case. The second method maps the RGB component into a line to estimate the transmission value of the patch by its bias and slope. Ancuti *et al*. [16] presented a haze detection and removal technique based on the semi-inverse image method.

2.2. Smoke Removal and Smoke Detection Algorithm

From our survey, there is only one existing work for smoke removal. Yamaguchi *et al*. [1] proposed an optical imaging model and to remove the smoke by DCP from the video. In order to reconstruct the video clearly, they apply space-time weightings to compensate the recovered frame.

For smoke detection algorithms, Maruta *et al*. [2] extracted features from the video and use the support vector machine to identify smoke. Piccinini *et al*. [3] proposed a smoke region detection method using the wavelet transform and color analysis. Chen *et al*. [4] developed an early fire-alarming system in video that detects smoke by the diffusion-based dynamic characteristic and chromaticity. Çelik *et al*. [5] used statistical analysis techniques to detect both fire and smoke in the video.

However, until now, none of the existing algorithm is used to detect the smoke in the still image.

3. PROPOSED METHOD

In sections 3.1 to 3.4, we will illustrate each part of our smoke removal algorithm in detail. The system framework is in section 3.5 and the flowchart is shown in Fig. 3.

TABLE I. AVERAGE RGB CHANNEL INTENSITY INVESTIGATION

Regions	Intensity		
	Red Channel	***Blue Channel***	***Green Channel***
Hazy Regions	147	144	146
Smoky Regions	159	182	169
Non-Smoky Regions	102	92	98

a. We investgate 80 hazy and smoky images.

3.1. Channel-Based Smoke Removal

When we use the traditional dehazed algorithms for smoke removal, the recovered images may be bluish since the residuary smoke in each channel is different. In Table I, we choose a large set of smoky and hazy images and calculate their mean intensities in RGB color channels for the hazy part, the smoky part, and the ordinary part, respectively. From Table I, we can see the intensity in each channel may be higher in smoky and hazy regions. It is reasonable because haze and smoke may whiten the images. However, we note that, in smoky regions the blue channel intensity may be stronger than the other two channels comparing to hazy regions. Moreover, in [17], they found that the hue of smoke locates in the blue region. Based on these results, we can conclude that smoky regions contain a little more blue component. Thus, when we use the dehazed algorithm to remove smoke, the result will be bluish and the residuary smoke in B channel is more than other channels.

In Figs. 5(b)(c) and in the 2nd column and the 3rd coulmn of Fig. 6, we can see that the dehaze algorithms cannot remove thick smoke clearly and the desmokimg result may become bluish.

The reasons causing this phenomenon is that, in current haze removal algorithms, the transmission maps for all color channels are assumed to be the same. However, this assumption may lead to error estimation on smoky scenarios.

Therefore, we perform the smoke removal by using different models for different color channels. We can modify (2) into (6) [17]:

$$J^k(x) = \frac{I^k(x)-A^k}{t^k(x)} + A^k , \;\; k\in\{r,g,b\} . \quad (6)$$

The smoky images may be well-recovered by (6) and A^k and $t^k(x)$ which can be estimated in section 3.5.2.

3.2. Hybrid Smoky Region Detection

Detecting the smoky region accurately is important for smoke removal. We develop a smoky region detection technique based on the methods in [16] and [17]. In [17], they found that the hue of smoke is between 180 degree and 270 degree. Thus, we can set

$$SR_1(x) = 1 \quad \forall x, \; s.t \;\; 180° < H(x) < 270° . \qquad (7)$$

Ancuti *et al*. [16] applied the semi-inverse image I_{si}^{k} and the hue disparity $HD(x)$ as follows to detect haze:

$$I_{si}^{k} = \max_{k\in\{r,g,b\}} \left[I^{k}(x), 1 - I^{k}(x) \right], \; HD(x) = \left| I_{si}^{hue} - I^{hue} \right| . \quad (8)$$

The hue disparity of the smoky pixels may be close to zero because $I_{si}{}^{k}$ is usually equal to I^k. Therefore, we can set

$$SR_2(x) = 1 \qquad \forall x, \; s.t \;\; HD(x) = 0 . \qquad (9)$$

We then combine (7) and (9) by the AND operator.

$$SR(x) = SR_1(x) \,\&\, SR_2(x) . \qquad (10)$$

If $SR(x)$ = 1, then x is identified as a pixel in the smoky region, as the example in Fig. 1.

(a) (b) (c) (d)

Fig. 1. Smoky region detection. (a) Orignal image, (b) $SR_1(x)$ defined in (7), (c) $SR_2(x)$ defined in (9), (d) $SR(x)$ defined in (10).

3.3. Training Data Synthesis

In the learning process, we develop a novel smoke synthesized technique method which first applies the statistic result in Table I and (11) to synthesize a smoke patch:

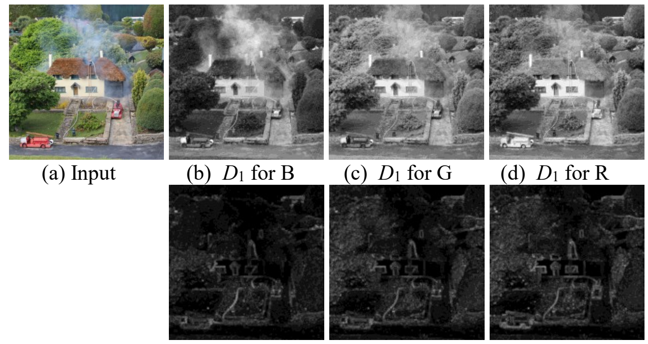
$$p_I^k = t^k p_J^k + \left(1 - t^k\right) A^k \quad k \in \{r, g, b\} \qquad (11)$$

where p_I and p_J are smoky and non-smoke patches, respectively. From the analysis in section 3.1, we can see that smoky pixels are usually more bluish and the smoke density in the B channel is higher. Thus, different from the work in [12], instead of setting the same transmission map for all color channels, the proposed method synthesizes different transmission maps to different channels. Moreover, since the smoky image is closer to original scene when t is higher. Thus, we can set $t_b \in [0, 1]$, $t_g = t_b + \alpha$, and $t_r = t_g + \beta$ where α, $\beta \in [0, 0.1]$. Moreover, we set A = [1, 1, 1] in order to prevent uncertainty in learning process. By setting the B channel with a lower value in the transmission map, the bluish problem can be avoided.

3.4. Smoke-Relevant Feature Extraction

In the machine learning process, the features we adopt are the dark channel [6], contrast [18], hue disparity [16], and saturation [12]. For the features of the dark channel, contrast, and saturation, we use multiple patch sizes which are 1, 4, 7, and 10 to increase the variety of input features. We denote these features as [D_1, D_4, D_7, D_{10}], [C_1, C_4, C_7, C_{10}], and [S_1, S_4, S_7, S_{10}] respectively.

Different from the work in of Tang *et al*. [12], instead of just extracting features from the color image, for the the dark channel and contrast, we also extract features from each of the color channels (B, G, R). From Fig. 2, we can see that the dark channel features and the contrast features for each color channel are also helpful for identifying the smoky region. For the smoky part, the dark channel is larger and the contrast value is smaller, especially in the B channel.



(a) Input (b) D_1 for B (c) D_1 for G (d) D_1 for R

(e) C_4 for B (f) C_4 for G (g) C_4 for R

Fig. 2. Dark channel D_1 and contrast C_4 in B, G, and R color channels.

3.5. Smoke Removal Algorithm

We illustrate the flowchart of the proposed system in Fig. 3, which consists of the training and the recovery processes.

3.5.1. Training Process

First, we sample 25000 clear 32×32 patches uniformly from 600 images as the training data. These clear patches are synthesized to smoky patches by using the technique proposed in section 3.3. We then extract features from these patches by the method in section 3.4. In the learning process, we use the random forest as our regression model. For our regression model, we set 400 trees and one third features may be used in each tress. The input is the features extracted from smoky patches and the output is their corresponding transmission maps t_r, t_g, t_b in the synthesis process. To prevent the correlation between image information and smoke-relevant features, we randomize the values of each feature type in each scale instead of using sort method in [12] before the learning process. It can make our training features and transmission not content-specific.

3.5.2. Recovery Process

We first detect the smoky region by the method in section 3.1. We then divide the smoky region into 32 × 32 overlapping patches, extract smoke-relevant features described in section 3.4, and use the regression model to predict their transmission maps in each color channel. Furthermore, we apply the guided filter [19] to refine our transmission map. For atmospheric light estimation, we search the 0.1% brightest pixel in the dark channel for each color channel. Finally, we recover the original image by (2).

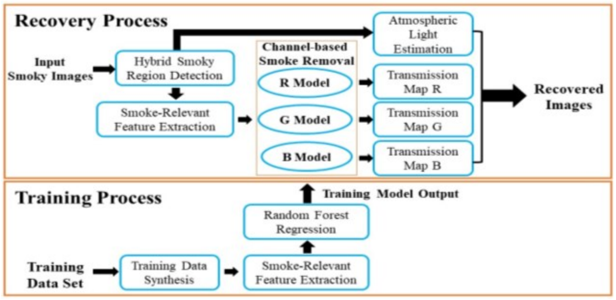
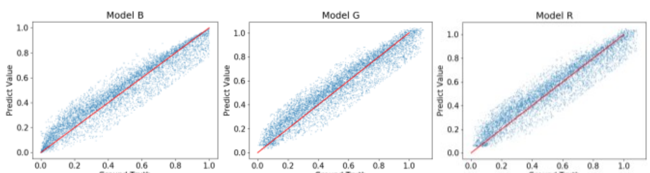


Fig. 3. Framework of the proposed algorithm.

TABLE II. COMPARISON BETWEEN THE PROPOSED ALGORITHM AND EXISTING METHODS

Algorithm	Comparison
[6],[7],[8],[9],[10],[11],[12],[15],[16],[18]	They have good performance in hazy or fog scenes. However, they may cause the bluish problem in thick smoke scenarios.
[2],[3],[4],[5]	Only detect the smoke region in the video.
[1]	It can detect and remove the smoke in the video.
Proposed algorithm	It can detect the smoke region and remove the smoke significantly in static images.



(a) MSE = 7.51e-3 (b) MSE = 8.2e-3 (c) MSE = 8.16e-3

Fig. 4. Predict value vs. Ground truth of RGB model (The red line is the 45 degree line)

4. EXPERIMENTAL RESULTS

4.1. Performance of Model

We choose 7000 patches as testing patches. We test our RGB models separately. The predict values (recovered transimission map values) vs. ground truths are shown in Fig. 4. The mean square errors (MSEs) are 7.51e-3, 8.2e-3, and 8.16e-3 in the blue, green, and red channels, respectively.

4.2. Smoke Removal Result

Figs. 5 and 6 are the experimental results of smoke removal. We can see that the smoky region may not be bluish by our proposed method in Fig. 5(d) and the 4th column in Fig. 6. Moreover, the proposed algorithm can remove the thick smoke clearly. It is because the proposed algorithm remove smoke in the color channel and our training process is based on the properties of smoke. Furthermore, the color distortion can be prevented by our proposed method because we only remove the smoke locally. (see the road in Figs. 5(b), (c) and 2nd, 3rd column in Figs. 6).

5. CONCLUSION

In this paper, a novel color channel-based smoke removal algorithm based on machine learning technique is proposed. We found that the intensity in the blue channel is always stronger than other channels in the smoky region, which makes the result of haze removal method bluish. Moreover, it is difficult to address the thick smoke by the haze removal algorithm because the differences between smoke and haze.

Therefore, we proposed a color-channel adaptive smoke removal procedure for training and data synthesis. In Table II, we make a comparison with existing haze and smoke removal algorithms. In these methods, the algorithms for smoke removal are few and focus only on video scenarios. However, our proposed algorithm can be used in static images and the experimental results show that it can well remove the smoke and has high performance no matter the smoke density is thick or not.

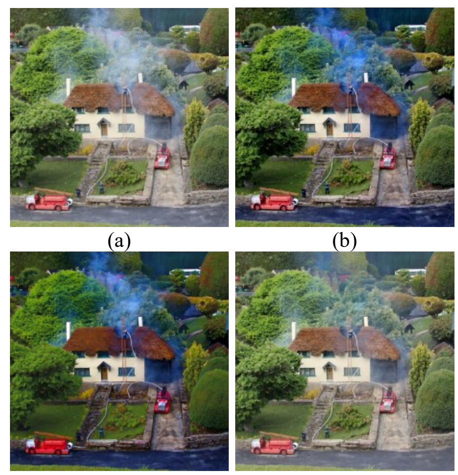

(a) (b) (c) (d)

Fig. 5. Smoke removal results (a) Original image; (b) recovered by the DCP method; (c) by the color attenuation prior; (d) by the proposed method.

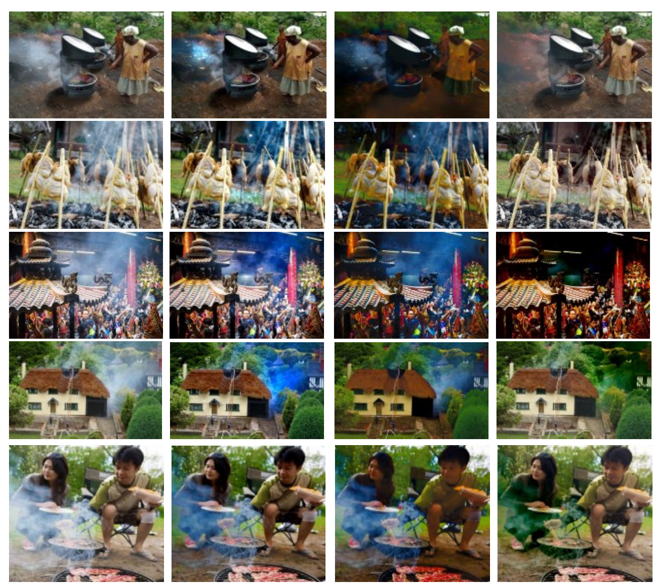


Fig. 6. Smoke removal results (1st column) Original image; (2nd column) recovered by the DCP method; (3rd column) recovered by the color attenuation prior; (4th column) recovered by the proposed method.

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