Transmission: A New Feature for Computer Vision Based Smoke Detection

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Abstract. A novel and effective approach is proposed in this paper to detect smoke using transmission from image or video frame. Inspired by the airlight-albedo ambiguity model, we introduce the concept of transmission as a new essential feature of smoke, which is employed to detect the smoke and also determine its corresponding thickness distribution. First, we define an optical model for smoke based on the airlight-albedo ambiguity model. Second, we estimate the preliminary smoke transmission using dark channel prior and then refine the result through soft matting algorithm. Finally, we use transmission to detect smoke region by thresholding and obtain detailed information about the distribution of smoke thickness through mapping transmissions of the smoke region into a gray image. Our method has been tested on real images with smoke. Compared with the existing methods, experimental results have proved the better efficiency of transmission in smoke detection.

Keywords: smoke detection, dark channel prior, soft matting; transmission.

1 Introduction

Traditional smoke and fire detections which have been widely applied in the buildings are based on sensors. Such detection approaches require a very close proximity to fire or smoke and are often disturbed by a variety of noises, so they may be not reliable and cannot be spread into open spaces and larger areas. Vision based fire detection approaches make it possible to serve large and open spaces, such as auditoriums, tunnels and forest, and they also provide abundant visual information about fire or smoke. Within the computer vision based fire detection, smoke location and analysis are very important, especially in the cases that flame is covered by smoke during burning or there is obvious smoke but little flame during the initial procedure of fire disaster.

Color, shape and texture are three usually used important features in detecting smoke from one single image or the video sequence. Color is widely used in either single image or multiple frames, while shape and texture are mostly utilized in continuous video frames. Color feature provides a clue as the precondition to locate the possible smoke regions. Chen et al. [1] and Yuan [2] proposed chrominance

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detection approaches which specify the color ranges of smoke in RGB color space and the intensity ranges of smoke in HSI color space. Shape feature is used as a good indication of the presence of smoke in the view field of camera, and its variation is analyzed by geometry differences of successive frames, which can be implemented by background subtraction or neighbor frames subtraction. Fujiwara [3] assumed that smoke shapes have the property of self-similarity, and thus proposed the technique for extracting smoke regions from an image using fractal encoding concepts. Chen et al. [4] used a shape disorder decision rule involving the quantity of smoke pixels to verify a real smoke extracted by the color feature from the captured image sequences. Xu et al. [5] extracted features of the moving target including growth, disorder, and self-similarity as important components of a joint shape feature vector to recognize fire smoke. Toreyin et al. [6] detected the boundary of smoke region and then used the high frequency nature of boundaries represented in wavelet domain as a clue to model the smoke flicker, which helps detect smoke in video. Texture is another feature which can express the difference between smoke and non-smoke, and is usually extracted and analyzed by two popular approaches including Gray Level Co-occurrence Matrices (GLCM) [7] and wavelet-based analysis [8]. Cui et al. [9] investigated the smoke texture and the non-smoke texture with wavelet packet and GLCM, and then a neural network is used to help judge whether a fire occurs. Fazekas et al. [10] proposed a method for detecting regions with dynamic texture in video sequences, and segmented the frame into static regions and dynamic regions using a level set scheme. Yu et al. [11] proposed a method of texture analysis for real-time fire smoke detection, using neural network to classify smoke and non-smoke regions based on the texture features. Ferari [12] adopted the discrete wavelet transformation on suspicious regions, describe the intensity of texture features with wavelet coefficients and then determine whether smoke exists according to whether the details of texture features reduce.

However, the existing methods using the aforementioned smoke features cannot achieve satisfying results: (1) they can locate heavy smoke regions but have difficulty to detect the light smoke regions; (2) they cannot directly provide the thickness distribution of smoke region which is important for fire estimation. Therefore, it is necessary to investigate new and more essential features for smoke to solve these two problems in smoke detection.

In recent years, some research works are carried out on haze removing based on the airlight-albedo ambiguity model. Inspired by the model, we introduce the concept of transmission into smoke detection and test its validity through experiments. In haze removal algorithms [13-14], transmission is only used to recover the scene radiance of the image. Comparatively, we use transmission as a new feature of smoke to detect smoke region and its thickness distribution. Based on our knowledge, there is no such attempt previously.

The paper is organized as follows. Section Ⅱ presents the optical model for smoke. In Section Ⅲ, smoke transmission is preliminarily estimated using dark channel prior, then refined through soft matting algorithm, and then smoke regions can be detected and their thickness distributions can be described based on the calculated transmissions. Section Ⅳ provides the experimental results on real images. Section Ⅴ concludes this paper with brief discussion.

2 Optical Model for Smoke

Based on References [13-17], the final image observed intensity consists of two parts: scene radiance and global atmospheric light, while the relationship between these two parts can be represented with the airlight-albedo ambiguity model described as:

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

For one pixel $x(i, j)$ of the image with three RGB color channels, $I(x)$ stands for the observed intensity, A is the global atmospheric light, $J(x)$ is the surface radiance vector at the intersection point of the scene and the real-world ray corresponding to pixel x, and $\tau(x)$ describes the portion of the light that is not scattered and reaches the camera.

Considering that in our work we focus on smoke detection and take transmission as the essential feature of smoke, we specially define an optical model based on Equation (1) for smoke as:

$$I(x) = (1 - t(x))J(x) + t(x)S \tag{2}$$

In our defined model, S is the global smoke color vector which is constant and available to reference, and $t(x)$ is the smoke transmission of pixel x describing the portion of S that contributes to the ultimate observed intensity.

Therefore, the defined model of Equation (2) can be applied for the image in the presence of smoke. By calculating the smoke transmission $t(x)$ we can judge whether the pixel x belongs to the smoke region or not. If pixel x is decided to be within the smoke region, transmission $t(x)$ can imply the information about smoke thickness at the pixel.

3 Estimate the Smoke Transmission

3.1 Preliminary Estimation Using Dark Channel Prior

The dark channel prior is described as: at least one channel among R, G and B color channels has very low intensity at some pixels in a block. According to Reference [14], the color channel whose value is the lowest is called dark channel. In most cases of the real world, color of smoke may be prone to white color and the dark channels in the areas where smoke exists have high values. Therefore, the intensity of the dark channel can be taken as a rough approximation to describe the thickness of smoke, and we use the intensity property to estimate the smoke transmission preliminarily.

Based on the descriptions above, we express the dark channel for an image J as:

$$J_{dark}(x) = \min_{c \in \{r,g,b\}} \left(\min_{y \in \Omega(x)} \left(J_c(y) \right) \right) \tag{3}$$

where $\Omega(x)$ is the local block or window with pixel x as the center point, and the block size can be adjusted with parameter.

We denote $\tilde{t}(x)$ as smoke transmission of block $\Omega(x)$, which is assumed as the minimum value of transmission values of all the pixels in region $\Omega(x)$. We take $\tilde{t}(x)$ as the preliminary transmission of any pixel in $\Omega(x)$, i.e. all pixels in block $\Omega(x)$ have the same preliminary transmission. Then the min operation is performed for $\Omega(x)$, and Equation (2) can be rewritten as:

$$\min_{y\in\Omega(x)}\left(I_c(y)\right)=\left(1-\tilde{t}(x)\right)\min_{y\in\Omega(x)}\left(J_c(y)\right)+\tilde{t}(x)S_c \tag{4}$$

Considering that S_c is the constant global smoke color vector and is always positive, after both sides are divided by S_c, Equation (4) is equivalent to:

$$\min_{y\in\Omega(x)}\left(\frac{I_c(y)}{S_c}\right)=\left(1-\tilde{t}(x)\right)\min_{y\in\Omega(x)}\left(\frac{J_c(y)}{S_c}\right)+\tilde{t}(x) \tag{5}$$

Notice that the min operation is performed on three color channels independently, we still need to choose the minimum value among these three values on Equation (5). Thus we have:

$$\min_c\left(\min_{y\in\Omega(x)}\left(\frac{I_c(y)}{S_c}\right)\right)=\left(1-\tilde{t}(x)\right)\min_c\left(\min_{y\in\Omega(x)}\left(\frac{J_c(y)}{S_c}\right)\right)+\tilde{t}(x) \tag{6}$$

According to the conclusion from the dark channel prior, the dark channel J_{dark} of the smoke-free radiance J should be prone to zero:

$$J_{dark}(x)=\min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(J_c(y)\right)\right)=0 \tag{7}$$

Obviously,

$$\min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}\left(\frac{J_c(y)}{S_c}\right)\right)=0 \tag{8}$$

By substituting Equation (8) into Equation (6), the block's smoke transmission (or the preliminary transmission of any pixel in the region) $\tilde{t}(x)$ can be derived as following:

$$\tilde{t}(x)=\min_c\left(\min_{y\in\Omega(x)}\left(\frac{I_c(y)}{S_c}\right)\right) \tag{9}$$

3.2 Refine Preliminary Estimation through Soft Matting

Although the smoke transmission $t(x)$ of one pixel can be estimated simply and approximately with $\tilde{t}(x)$ depending on foregoing assumptions, the equations (2)-(8) above are based on blocks rather than specific pixel. To obtain the more precise transmission for each pixel, the soft matting algorithm [18] is used to refine the preliminary transmission $\tilde{t}(x)$. Based on Reference [18], the optimal transmission can be acquired through solving the following large sparse linear equation:

$$(L+\lambda U)t=\lambda\tilde{t} \tag{10}$$

In Equation (10), t and $\tilde{t}$ are denoted as the vector form of $t(x)$ and $\tilde{t}(x)$ respectively, L is the Matting Laplacian matrix put forward by Levin [18], λ is a regularization parameter and we set the value as 10^{-4} in our experiment, U is an identity matrix of the same size as L. Any element in matrix L can be described as:

$$L(i,j)=\sum_{k|(i,j)\in w_k}\left(\delta_{ij}-\frac{1}{|w_k|}\left(1+(I_i-\mu_k)^T\left(\Sigma_k+\frac{\varepsilon}{|w_k|}U_3\right)^{-1}(I_j-\mu_k)\right)\right) \tag{11}$$

In Equation (11), I_i and I_j are the color vectors of the ith pixel and the jth pixel of the input Image I, δ_{ij} is the Kronecker delta, μ_k and Σ_k are the mean and covariance matrix of the color vectors in window w_k, U_3 is a 3×3 identity matrix, ε is a regularizing parameter, and $|w_k|$ is the number of pixels in the window w_k.

To solve the large sparse linear Equation (10), we choose the Preconditioned Conjugate Gradient (PCG) algorithm as solver. By solving this equation, the outcome of transmission t for each pixel can be used to detect the smoke regions and imply the corresponding distribution of smoke thickness.

3.3 Smoke Detection Based on Transmission

For images used in experiment, we set the value of S_c as the color vector of the pixel whose dark channel value is the largest in the related image. As for the rule of smoke detection based on transmission, we consider a pixel as a smoke pixel belonging to smoke region if its value of smoke transmission is larger than the threshold value, otherwise it is taken as a non-smoke pixel. We denote the threshold value and the maximum value of smoke transmission as t_0 and $t_{\max}$ respectively. To represent the thickness distribution of smoke region, we simply map the smoke transmission range $[t_0,t_{\max}]$ to the gray color range $[t_0\times255,255]$ by:

$$G(x)=\begin{cases}\frac{(t(x)-t_0)}{(t_{\max}-t_0)}\times(255-t_0\times 255) & \text{if } t(x)>t_0\\ 0 & \text{else}\end{cases} \tag{12}$$

From Equation (12), we can find that the grayish value is larger where the smoke transmission is larger, therefore the gray image can visually imply the smoke thickness distribution in the detected smoke region.

4 Experimental Results

The proposed novel approach for smoke detection is implemented on PC with 2.79 GHz Intel(R) Core(TM) 2 Duo CPU and 2.0 GB RAM using OpenCV library. To validate the performance of our approach, the existing method based on color feature from Reference [2] is used for comparison.

Experimental results on real images with heavy smoke are shown in Figure 1. It can be found that our approach detects the smoke regions accurately, and also provides more detailed information about thickness distribution, i.e. smoke is thicker where the mapped gray value from transmission is larger.

Fig. 1. Detection results of heavy smoke, Top: original images; Middle: results from Reference [2]; Bottom: our results

Experimental results on real images with light smoke are shown in Figure 2. The semi-transparent light smoke often exists with fire, and it can appear with non-grayish color caused by the covered objects, e.g. soil, trees, or flame. Thus the existing methods using color, shape or texture features have difficulties to detect the light smoke. Different with them, we adopt transmission as one essential smoke feature, and can greatly reduce the effects from covered objects.

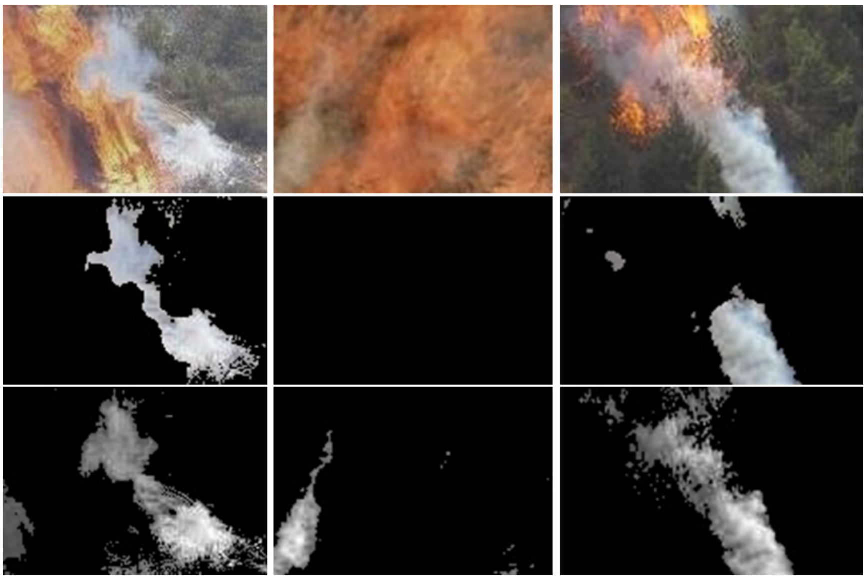

Fig. 2. Detection results of light smoke, Top: original images; Middle: results from Reference [2]; Bottom: our results

5 Conclusion

In this paper, a novel approach to detect smoke using transmission is proposed. We estimate the preliminary smoke transmission using dark channel prior and then refine the result through soft matting algorithm. According to the calculated transmission value, smoke pixels can be detected accurately and the detailed information about thickness distribution of smoke region can also be provided directly. Our method has been tested on real images with heavy or light smoke, and the experimental results have proved its efficiency.

Of course, the estimation method of smoke transmission is preliminarily based on dark channel prior, so our approach is currently limited in detecting gray-white smoke. Although most smoke in natural fire disasters is prone to gray-white, in a few cases there really exist smoke of other colors and gray-white objects like motionless marbles, which will affect the accuracy of our method. In the future, we will add color range to recognize smoke with other colors and take motion feature to eliminate the effect from gray-white non-smoke objects.

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