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Smoke Region Detection from a Single Color Image

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Abstract
Proposed here is a smoke region detection method from captured color image. In this method, the difference between the gray image and average image of original color image is computed. The difference image is then squared and normalized from which a binary image is generated based on a chosen threshold. Using this binary image, the pixels of the gray scale image corresponding to the white region of the binary image are extracted and binarized with appropriate threshold to get another binary image. The two binary images are then XORed to generate another binary image with the smoke regions common to both. Then, the binary image is smoothened by applying an average filter to reduce the unwanted noises in the non-smoke regions. The remaining unconnected noises are removed using connected component analysis. The image is then dilated to restore the smoke regions which were removed during the process of removing noises. The smoke region in the original image is extracted by mapping with dilated binary image. The method has been applied to the image frames of the video captured when smoke is raising up. It has been found that the smoke regions in each frames are appropriately detected and extracted. The proposed method is fast and simple and can be used for real time monitoring of fire detection system.

Keywords: *Fire Detection, Flame Detection, RGB Color Variance, Color models, real-time fire detection.*

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I. INTRODUCTION

Smoke is the first sign of occurrence of fire. Prevention of fire breakout would be easier and effective if we could detect smoke and prevent the fire at the initial smoke state. This would save significant amount of time, effort and unwanted damage to lives and properties. Visually, smoke can be easily detected. However, detecting smoke by a computer using image processing method is quite challenging. Because smoke does not have a definite shape or pattern, it disperses in the air and its intensity varies with density. Moreover, its color depends on the material being brunt and does not have distinctive chrominance components. Several approaches of smoke detection have been proposed by different researchers. In [3] a smoke detection is proposed based on RGB and HSV color models. As smoke does not contain prominent chrominance components, it is assumed that absolute difference of any two RGB channels is in the range of 15 to 25 and accordingly deduced that the image region whose saturation values less than or equal to 0.1 corresponds to smoke. In [1], background region is separated based on motion detection and finds the probable block of occurrence of smoke. It computes the HoG (Histogram of Oriented Gradients) and HOF (Histogram of oriented Optical Flow) to get spatio-temporal features from which smoke region is detected using K-means and SVM classifier. In [5] describes and evaluates several histogram-based smoke detection algorithms. In [6], smoke features are extracted from candidate regions by analyzing the spatial and temporal characteristics of video sequences such as edge blurring, gradual energy changes, and gradual chromatic configuration changes. These three features were combined using a support vector machine (SVM) technique and a temporal-based alarm decision unit (ADU) was also introduced to make the smoke detection result more reliable.

Simone Caldera [2] used motion segmentation and wavelet coefficient energy and image color to detect smoke regions. In [12], wavelet analysis and weber cluster analysis is for smoke and flame region detection from a captured video image. It used motion detection for identification probable smoke and fire flame regions which are then separated using adaptive background subtraction. The probable candidates are then classified as moving blobs or not based on color segmentation, spatial and temporal wavelet analysis, Weber contrast analysis. In [7], wavelet energy and optical flow measures are used for smoke detection. It first removes the background using dual background modelling and then wavelet and optical flow transforms are applied to detect the smoke region. In [14] a real-time video fire flame and smoke detection method based on foreground image accumulation and optical flow technique. Accumulation images extracted using frame differential method from which the flame regions are detected by a statistical model and smoke regions are detected by optical flow. In [4] changes in scene is detected by background subtraction. It then unifies the parts of corresponding flame and smoke regions using morphological operations. The smoke and flame regions by distinguished based on the color probability, boundary roughness, edge density and area variability.

A different smoke detection method based on atmospheric scattering models is proposed in [11]. It separates an image frame into quasi-smoke and quasi-background components which is formulated as convex optimization that solves a sparse representation problem using dual dictionaries for the smoke and background components. A novel feature is constructed as a concatenation of the respective sparse coefficients for detection. It uses a method based on image matting to separate the true smoke and background regions. It claims that the proposed method can differentiate smoke from fog/haze, cloud, etc. with similar visual appearance in a gray-scale frame. In [8, 13, 15], deep learning and convolutional neural network have been used for smoke detection. These methods are more complex and less suitable for real-time smoke and fire detection applications.

In this paper, a simpler but effective way for smoke detection from a single RGB color image is proposed. Two different gray images are generated from the color image – one gray is from the usual RGB image to gray image conversion method and the other image is the average of RGB color planes. Both these images have more or less the same gray shade in the smoke region but significantly different gray shades in the non-smoke regions. Morphological operations are used to separate the common smoke regions from rest of the background regions. It has been found that the proposed smoke detection can effectively detect smoke region from a given color image. It is fast and hence it could be suitably used in real-time smoke detection.

II. COLOR ANALYSIS OF SMOKE REGIONS

Fire has well distinctive color components. This makes the separation of fire regions from other non-fire regions in an image possible by using a suitable color model. YCbCr is one of the most commonly used color model in fire detection. It can separate luminance and chrominance components and the fire regions can be detected from the chrominance components [9]. The fire regions in an image can also be detected effectively from the variance of RGB color [10]. In the case of smoke images, there is no clear distinctive color component. As a result, separation of smoke regions becomes difficult in most of the color models. Figure-1 shows original smoke image and its luminance (Y) component. Figure-2 shows the chrominance components of the original smoke image in Figure-1(a). It can be seen that smoke region appears more prominent in the luminance component than in any of the chrominance components. In other words, when a smoke image is converted into luminance and chrominance such as YCbCr or HSV, the smoke region is lost from the chrominance components which shows that smoke regions cannot be detected from the chrominance components. This clearly shows that processing in the luminance i.e., intensity component will be more effective for detection of smoke region in an image. However, separating smoke region from the intensity or gray level image is difficult as there are many non-smoke regions in the image whose intensity range is similar to the intensity range in the smoke region. So, we must find a way to enhance the gray level image to distinguish the smoke regions from its surrounding. This can be done by subtracting the average image from the gray level image. Figure-3(a) shows the normal gray level image of the smoke image and the average gray image is shown in Figure-3(b). The difference of the average image from the gray image is shown in Figure-4. It can be seen clearly that the smoke region is much more distinct in the difference image i.e., Figure-4 than in any of the gray images of Figure-3(a), Figure-3(b) or Figure-1(b). In other words, separating smoke region from the surrounding would be easier and more effective in difference image than in gray level image.

Figure-1(a): Original Smoke Image

Figure-1(b): Y-Component

Figure-2(a): Cb Component

Figure-2(b): Cr Component

Figure-3(a): Normal gray image

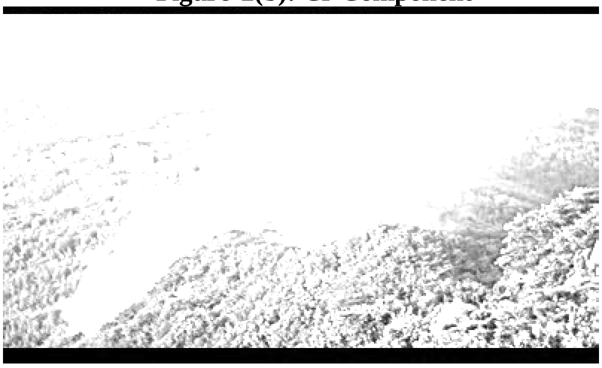

Figure-3(b): Average gray image

Figure-3(c): Difference gray image

III. DETECTION OF SMOKE REGIONS

It is observed that smoke region does not have any prominent chrominance component. So, it is difficult to find a suitable color model for detection or identification of smoke region in an image. Smoke region stands out clearly in the luminance or intensity image. Processing intensity image would be more effective for detection of smoke region in a captured image or an image frame extracted from a video. To detect the smoke regions, we consider two gray images of the same RGB image. The first one is the gray image Gr, using the following relation.

$$Gr= 0.2989 * R + 0.5870 * G + 0.1140 * B$$

The second is the gray image A, obtained by averaging the R, G and B components. That is,

$$A=(R+G+B)/3$$

The difference of Gr from A suppresses most of the non-smoke region and makes smoke region more distinct. This makes the separation of smoke regions from the rest of the image easier. Note here that both Gr and A are unsigned integers since R, G, and B components are 8-bit unsigned integers. Let D be the difference image having more prominent smoke region.

$$D=Gr-A$$

Since Gr and A are unsigned integers, the minimum value of D is 0 and the maximum value is some positive integer less than or equal to 255. To ensure that D has a range between 0 and 255, it is multiplied by a factor N as

D=N*D
where N= 255/max(D)

Once the normalized difference image is obtained, it is binarized to separate the smoke regions from the non-smoke regions in the image at an appropriate threshold. The threshold value can be determined using iterative method or Otshu method as these methods give more or less similar threshold values when applied to binarize the normalized difference image.

Algorithm for smoke detection:

1. Step-1: Convert the RGB image into gray using following relation
   Gr= 0.2989 * R + 0.5870 * G + 0.1140 * B
2. Step-2: Find the average of the RGB image
   A=(R+G+B)/3
3. Step-3: Find the binary image df from the square of difference between Gr and A based on some threshold T1
   df=(Gr-A)^2>T1
4. Step-4: Create a binary mask image bf from the Gr and df as
   bf= Gr*df>T2
5. Step-5: Mark the common smoke region in df and bf by xoring them
   bw= $df \otimes bf$
6. Step-6: Remove the noisy white regions which are not part of smoke region
7. Step-7: Smoothen the black regions by a filter
8. Step-8: Remove the background noises from the non-smoke regions
9. Step-9: Dilate the denoised binary image by about 5 pixels around
10. Step-10: Extract the smoke regions from the original color image

After getting the difference of the two gray images Gr and A, we generate two binary images df and bf as shown in Figures 5(a) and 5(b). From these two binary images, we find the common smoke region by XORing them and the removed the smaller noise components outside the smoke region to get the binary image shown in Figure-5(c), which is then dilated by about 3 pixels around to get the smoke region mask in Figure-5(d). The smoke region in Figure-5(e) is extracted using the mask in Figure-5(d) to get the detected or extracted smoke region in Figure-5(f).

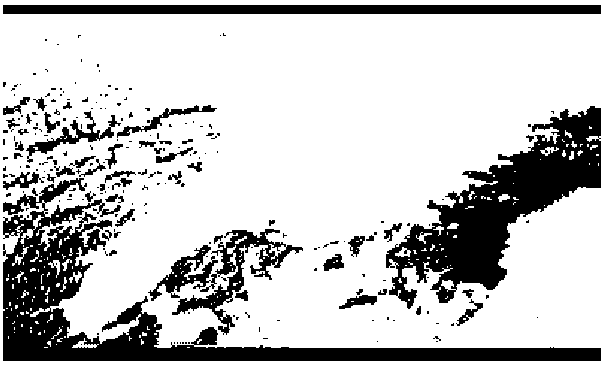

Figure-5(a): df image

Figure-5(b): bf image

Figure-5(c): Image after removing noise

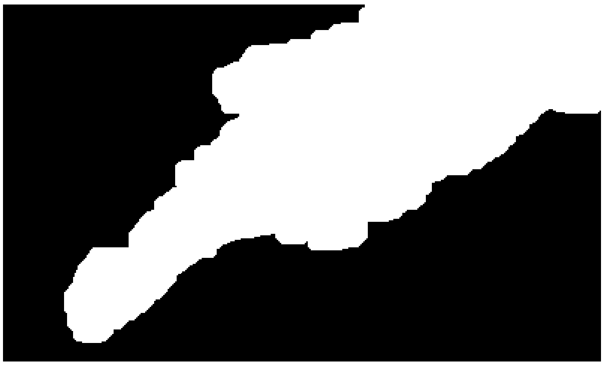

Figure-5(d): Dilated smoke region

Figure 5(e): Original smoke image

Figure-5(f): Extracted smoke region

IV. EXPERIMENTAL RESULTS

To test We apply the proposed smoke detection method to the image frames extracted from the smoke video available at the Kaggle site. The smoke video can be downloaded from the site https://www.kaggle.com/csjcsj7477/fire-detection-model-keras-for-video/data.The image frames of the video are extracted and altogether there are 3596 images are in the video. We apply the smoke detection algorithm in almost all image frames. It is found that the smoke detection algorithm works perfectly in detecting smoke region from the image frames of the video. The smoke region detected is dependent on the values of the thresholds T1 and T2. It has been found that the value of threshold T2 has more influence on the size or the coverage of the detected smoke region. If the value of T2 is more, it covers mainly the thicker and whiter smoke region. If the value of T2 is less, thinner or sparse region are also covered in the detected smoke region. It is found that the threshold value of T1 is in the range 75 to 110 and T2 in the range 115 and 135 works perfectly. Any value within the range can be chosen as threshold value, there will be hardly any difference in the result. For safer side, the values near the mid values of the specified ranges can be chosen as threshold.

As it is not possible to show all the image frames of the video and their corresponding detected smoke regions in the paper, only three images are randomly chosen. The three randomly chosen image frames of the smoke video and their corresponding detected smoke regions are shown in Figure-6. In Figure-6(a), Figure-6(c), Figure-6(e), the smoke images of image frame 653, 1673 and 2867 are shown and their corresponding detected smoke regions are shown respectively in Figure-6(b), Figure-6(d) and Figure-6(f). It could be seen that the smoke regions are detected as expected. However, it misses very thin and transparent smoke regions.

Figure-6(a): Smoke Image of frame-653

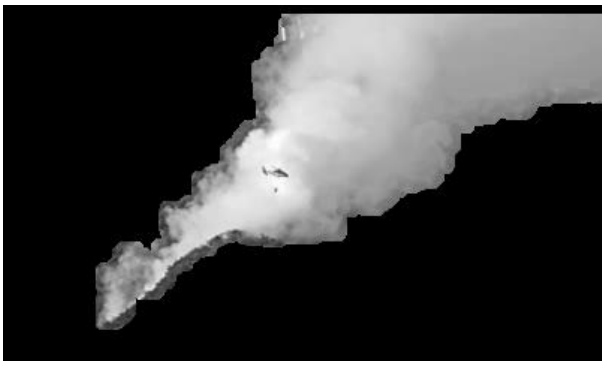

Figure-6(b): Detected smoke region of frame-653

Figure-6(c): Smoke Image of frame-1673

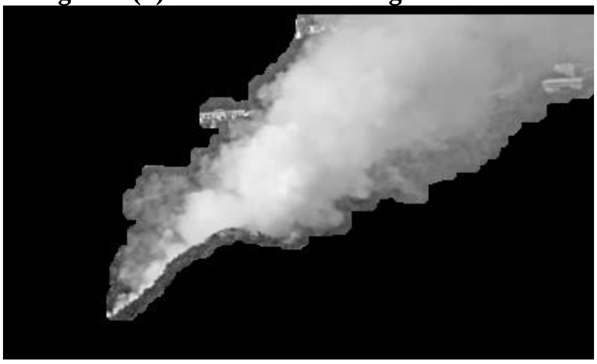

Figure-6(d): Detected smoke region of frame-1673

Figure-6(e): Smoke Image of frame -2867

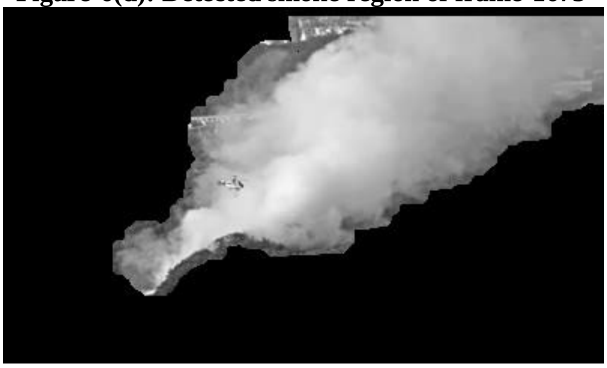

Figure-6(f): Detected smoke region of frame-2867

V. CONCLUSION

A new smoke detection method based on the processing of gray level images has been described. In this method, the gray level image is enhanced by using average image to make the smoke region more distinct than the surrounding non-smoke regions. This makes the separation of smoke regions than the surrounding easier. Also, method for removing background noises from a binary image has been described. It has been tested in all image frames in the smoke video available at Kaggle site. In can successfully detect most of the smoke regions in all images except the very thin and transparent regions. It can be used for detection of smoke regions in other images or image frames of different smoke videos. It is simple, fast and effective and hence can be used in a real-time smoke detection device or system.

REFERENCES

[1]. Konstantinos Avgerinakis, Alexia Briassouli, and Ioannis Kompatsiaris, "Smoke detection using temporal HOGHOF descriptors and energy color statistics from video". in International Workshop on Multi-Sensor Systems and Networks for Fire Detection and Management, (2012.).

[2]. Simone Calderara, Paolo Piccinini, Rita Cucchiara, "Vision based smoke detection system using image energy andcolor information", Machine Vision and Applications2011,22, 705–719

[3]. Turgay Celik., Huseyin Özkaramanlı, and Hasan Demirel.(2007). "Fire and smoke detection without sensors: image processing based approach". in Signal Processing Conference, 15th European. 2007. IEEE.

[4]. Alexander Filonenko, Danilo Caceres Hernandez, Ajmal. Shahbaz, and Kang-Hyun. Jo, "Unified smoke and flame detection for intelligent surveillance system," in Proc. ISIE 2016 (Santa Clara, 2016).

[5]. Damir Kristinic, Tani Jakovcevic, and Darko Stipanicev, "Histogram- based smoke segmentation in forest fire detection system," Inf. Technol. Control. 38 (3), 237–244 (2009)

[6]. Yu Chen Lee, Chin-Teng Lin, Chao Ting Hong, Miin Tsair Su, " Smoke detection using spatial and temporal analyses". International Journal of Innovative Computing, Information and Control,. 8(7): p. 4749-4770, 2012
[7]. Wen Hui Li, Bo Fu, Lin-chang Xiao, Ying Wang, and Pei-Xun Liu, "A video smoke detection algorithm based on wavelet energy and optical flow Eigen-values," J. Software 8 (1), 63–69 (2013).
[8]. Gaohua Lin, Yongming Zhang, Gao Xu, Qixing Zhang, "Smoke detection on video sequences using 3D convolutional neural networks", Fire Technology2019,55, 1827–1847.
[9]. Y. Kirani Singh and Debasish Deb, "Detection of Fire Regions from a Video Image Frames in YCbCr Color Model", International Journal of Recent Technology and Engineering (IJRTE), Volume 8, No. 8, September, 2019.
[10]. Yumnam Kirani Singh, "Detection of Fire Regions Using RGB Color Variance", International Journal of Research in Engineering and Science (IJRES), Volume -9, Issue-6, PP. 10-14, 2021.
[11]. Hongda Tian, Wanqing Li, Philip O. Ogunbona, Lei Wang, "Detection and separation of smoke from single image frames", IEEE Transactions on Image Processing 2017,27, 1164–1177
[12]. Shipping Ye, Zhican Bai, Huafen Chen, R. Bohush, S. Ablameyko, "An effective algorithm to detect both smoke and flame using color and wavelet analysis", Pattern Recognition and Image Analysis 2017,27, 131–138.
[13]. Zhijian Yin, Boyang Wan, Feiniu Yuan, Xue Xia, Jinting Shi, "A deep normalization and convolutional neural network for image smoke detection" IEEE Access, Vol. 5, pp. 18429–18438, 2017.
[14]. Chunyu Yu, Zhibin Mei, and Xi Zhang, "A real-time video fire flame and smoke detection algorithm," in Proc. 9th Asia-Oceania Symp. on Fire Science and Technology (Hefei, 2013), Vol. 62, pp. 891–898.
[15]. Feiniu Yuan., Lin Zhang, Xue Xia, Boyang Wan, Qinhua Huang, Xuelong Li, "Deep smoke segmentation", Neurocomputing 2019,357,248–260.