An Early Smoke Detection System based on Motion Estimation

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Abstract— **Smoke detection becomes more and more attractive for the social security and commercial applications. In this paper, we present an early smoke detection system based on motion estimation, which investigates stable characteristics of smoke. For trade-off of the accuracy and computational efficiency, our system utilizes an approximate median method to extract moving blocks, and color of smoke is analyzed in order to select candidate blocks. Finally, the direction of motion vector for candidate blocks is estimated to decide whether smoke occurs. Experimental results show that our proposed warning system provides lower false detection rate of smoke before the fire burns up.**

Keywords- Video smoke detection; motion estimation; computer vision

I. INTRODUCTION

There are several traditional methods to detect smoke [1]. However, these methods are based on particle sampling, temperature sampling and relative humidity sampling. Therefore, most of them require a close proximity to the source of smoke and will false in open or large spaces. In addition, these methods cannot detect quickly and are not reliable at all.

Now a day, there are a lot of novel techniques have been proposed to improve the performance and computation of smoke detection. One of them is vision based smoke detection. This method is not only the ability to serve large in open spaces, but also the ability to provide to more reliable information about smoke. Thus, many smoke detection algorithms based on vision have been proposed. A real-time image processing technique for detecting smoke in steaming video was presented in [2]. In this method, a statistical hidden Markov tree (HMT) model derived from coefficients of the dual-tree complex wavelet transform (DT-CWT) in small local regions of the image sequences was used to characterize the steam texture pattern, and a support vector machine (SVM) classifier was used to detect smoke. In [3], they presented a wavelet based method to detect semi-transparent smoke. They made rules that scene becomes grayish and it has periodic behavior in smoke boundaries. They also improved their work by incorporating with contour characteristic of smoke [4].

In addition, there are some methods detecting smoke by analyzing the static features and dynamic feature of smoke. A smoke detection method for early fire alarming system based on video processing was proposed in [5]. In this method, they used two decision rules: a chromaticity-based static decision rule and a diffusion-based dynamic characteristic decision rule. The chromatic decision rule is deduced by grayish color of smoke and dynamic decision rule is dependent on the spreading attributes of smoke. Some more universal features are suggested, such as the changing unevenness of density distribution and the changing irregularities of the contour of smoke. Support vector machine is used to detect smoke [6]. However, these methods require tremendous computational time and high false detection rate of smoke. To reduce false detection rate and computational time, we propose a method to detect smoke early based on motion estimation.

This paper is organized as follows. Section 2 analyzes features of smoke. Section 3 describes our proposed method for an early smoke detection. Section 4 presents our experimental results, and Section 5 concludes this paper.

II. FEATURES OF SMOKE

By analyzing several smoke video clips, we acquire important features of smoke. Important features of smoke consist of the followings. The color of smoke ranges from white-bluish to white when the temperature of smoke is low. In addition, it ranges from black-grayish to black when the temperature rises until it catches fire. When smoke appears, it usually spreads out and drifts upward out basically in way of diffusion process. From this feature, we can find out the direction of motion vector, which usually goes up. This implies us that we should estimate the direction of motion vector for candidate blocks and compare with the threshold to decide whether the smoke occurs.

III. VEDEO SMOKE DETECTION ALGORITHM

Our algorithm is composed of the following steps:

1. The moving blocks in the current frame are segmented,
2. Candidate blocks are by analyzing the color of smoke,
3. Direction of motion vector for candidate blocks is estimated.

A. Moving Blocks Detection

Moving blocks detection is a fundamental and key step in video smoke detection. It is related the first stage of our algorithm. Now a day, there are several methods for moving

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blocks detection: optical flow method, temporal deference method and back ground subtraction method. Optical flow method [7] aims at computing an approximation of the 2D motion fields by means of spatio-temporal changes of image intensity. It can be used in the presence of camera motion, but most optical flow methods are computationally complex, and it cannot be applied to full-frame video streams in real-time without specialized hardware. In contrast, temporal difference method [8] takes into account differences two consecutive frames. This approach is very adaptive to dynamic environment, but it strictly depends on the velocity of moving block in the scene and it is subject to the foreground aperture problem. Compared with the above two methods, background subtraction method is more practical and effective. It uses the image sequence itself to maintain a background image, and considers differences between current image and the reference background image. Suitable background modeling is very crucial for background subtraction method. As the name suggests, background subtraction is the process of separating out foreground objects from the background in a sequence of video frames. Many difference methods have been proposed in which each has different strengths and weaknesses in terms of performance and computational requirements [9]. For trade-off of the performance and computation efficiency, the approximate median method is used for moving block detection in our algorithm.

The approximation median method divides the current frame into matrix of square blocks (SB) and then compares with corresponding block in the previous frame. The mean absolute difference (MAD) of two square blocks between two consecutive frames is defined by the following equation:

$$MAD = \frac{1}{n^2}\sum_{i=1}^{n-1}\sum_{j=1}^{n-1}|C_{ij} - R_{ij}|$$

where n is the number of pixels of the square block, and C_{ij} and R_{ij} are the pixels being compared in current square block and reference square block, respectively.

We compare MAD with threshold TH to extract moving blocks. This is deduced by the followings:

If (MAD > TH) then

The blocks are moving

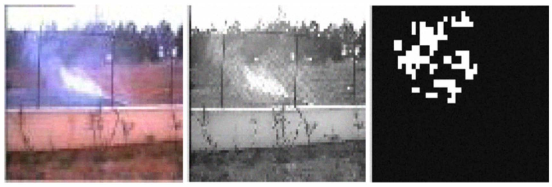
Else

The blocks are not moving.

The approximate median method is different from the frame difference. The background is updated after every frame. This is represented as followings. If a pixel in current frame has a value larger than the corresponding background pixel, the background pixel is incremented by 1. Likewise, if the current pixel is less than the background pixel the background is decremented by 1. In this way, the background eventually converges to an estimate where half of the input pixels are greater than the background, and half are less than the background.

B. Smoke Blocks Detection Based on Color

In this section, we analyze the color of smoke and observe that the color of smoke usually have two cases: (1) the color of smoke is ranged from black-grayish to black and (2) it is ranged from white-bluish to white. We examine the smoke color as followings. When the color of smoke is ranged from black-grayish to black, the intensity (I) of its gray image usually ranges from TH1 to TH2. For its true-color image, three components R, G, B of the pixels have same value. This implies that |max(R,G,B) − min(R,G,B)| < T1. On the other hand, if the color of smoke ranges from white-bluish to white, we observe that B = max(R,G,B), |R-G| < T2, and the intensity (I) of it gray image usually ranges from TH3 to TH4. From these rules, we can select candidate blocks, deciding smoke or none-smoke. Fig.1 (a) and (b) show original smoke videos and results of smoke based on color.



(a)

(b)

Figure 1. Extracting candidate blocks by moving blocks and color of smoke

C. Estimation of Motion Vector Direction

Analyzing feature of smoke showed that. One of the most important features of smoke is spreading and drifting upward. We suppose that all of pixels in the same block have the same motion parameter. For the each candidate block, we determine the direction of its motion vector. Search area is shown in Fig. 2.

Fig. 2 shows candidate block, square block (SB), search area (SA), side of square block (n) and search parameter (p) where n and p is the number of pixels. Therefore, the size of SA is $(2*p+1)^2$, and there are $((2*p+1)^2 -1)$ search points (SP).

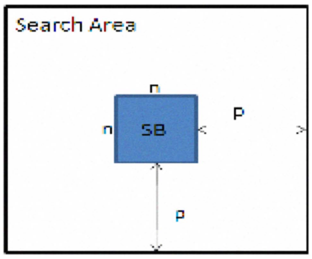


Figure 2. Search area of square block

Fig. 3 shows an example with n = 8, p = 4, size of SA = 81, the number of SP is 80. The coordinate of O, A, B, C and center of SB are (-4, -4), (4, -4), (4, 4), (-4, 4) and (0, 0), respectively. The motion vector of SB points to (3, -4). These points are called matched search points (MSP).

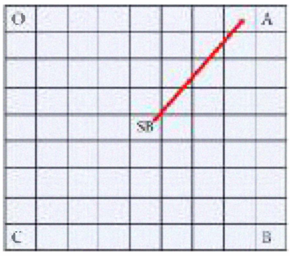


Figure 3. Search points of square block

To improve accuracy of smoke detection, the accumulation of matched search points is used. We create one accumulative matrix (AM) in which its dimension is (2*p+1, 2*p+1). Elements of this matrix are initialized 0 and correspond with SP of SA. For the each search block, we have only one motion vector and MSP. When search block is matched, we receive MSP, and corresponding element of accumulative matrix is incremented by 1. Elements of accumulative matrix accumulate for each search block in one frame and subsequent frames. We divide accumulative matrix into four small parts: above part (AP), under part (UP), left part (LP), and right part (RP) as shown in Fig. 4. AP, UP, LP, RP are numbers of SP of corresponding parts. By analyzing several video clips we acquire remark. For smoke videos, the AP is larger than the UP and the LP approximate the RP.

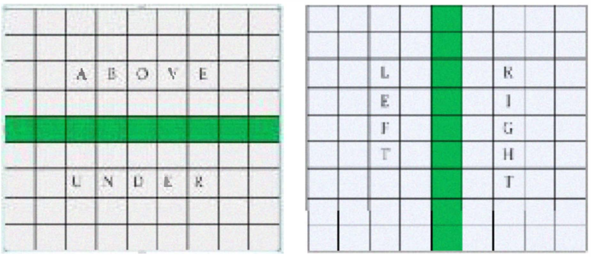


Figure 4. Four parts of accumulative matrix

The numbers of search points in search area are $((2*p+1)^2 - 1)$ which is very large. So, it requires large computational time. To reduce the computational time, this paper utilizes Adaptive Rood Pattern Search (ARPS) [11] which is a fast block matching algorithm. This method consists of two sequential search stages: initial search and refined local search. For each search block, the initial search is performed only once at the beginning in order to find a good starting point for the follow-up refined local search. By doing so, unnecessary intermediate search and the risk of being trapped into local minimum matching error points could be greatly reduced in long search case. For the initial search stage, an adaptive rood pattern (ARP) is proposed, and the size of ARP is dynamically determined for each SB based on the available motion vectors of the neighboring SBs. In the refined local search stage, a unit size of rood pattern is exploited repeatedly, while finding the final motion vector. Fig. 5 shows an example in which the predict motion vector points to (-2, -1).

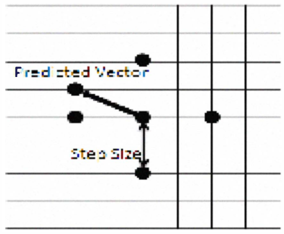


Figure 5. Adaptive rood pattern

IV. EXPERIMENTAL RESULTS

In this study, our proposed algorithm for video smoke detection is implemented using the MATLAB software. By analyzing several video clips, we observe that n = 8 and p = 4 are optimal parameters.

Table I shows the accumulative matrix of MSP in the final frame. From this table we observe that the motion vector direction of smoke usually goes up. The center of matrix is zero because the candidate blocks always move.

TABLE I. ACCUMULATIVE MATRIX OF MOTION VECTOR DIRECTION

256	46	40	77	99	48	51	39	233
34	23	19	10	28	19	13	19	33
35	19	22	9	25	16	19	12	36
31	11	12	21	72	28	12	15	26
52	61	35	51	0	60	44	48	76
33	9	20	47	52	15	8	9	16
33	15	34	25	20	12	15	10	35
41	25	20	16	23	7	11	11	28
147	31	28	51	56	41	34	27	100

Fig. 6 represents the accumulation of motion vector direction of four parts. The red curve, the turquoise curve, the green curve, and the blue curve represent the accumulation of motion vector direction of the above part, the left part, the right part, the under part, respectively. We observe that the red curve is the highest and the blue curve is the slowest. We calculate the ratio of the above part to the under part (RAU), and the ratio of the right part and left part (RRL). We compare RAU and RRL with threshold. If these conditions are satisfied then we decide that smoke occurs.

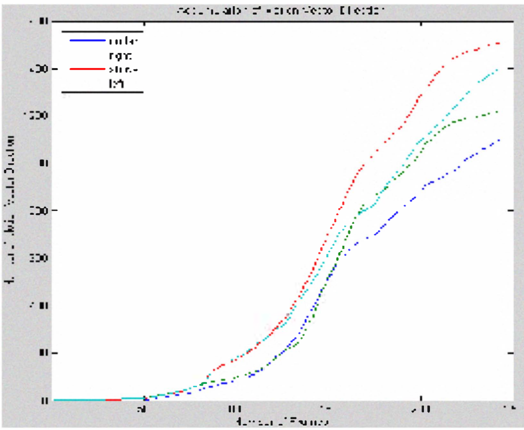


Figure 6. Accumulation of motion vector direction of four parts

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Fig. 7 (a) and (b) represent the results of our algorithm for two video clips. Right images are true-color images, middle images are gray images, and left images are binary images. The results of smoke detection are shown in the right images. Our proposed algorithm is also tested for other video clips with similar results.

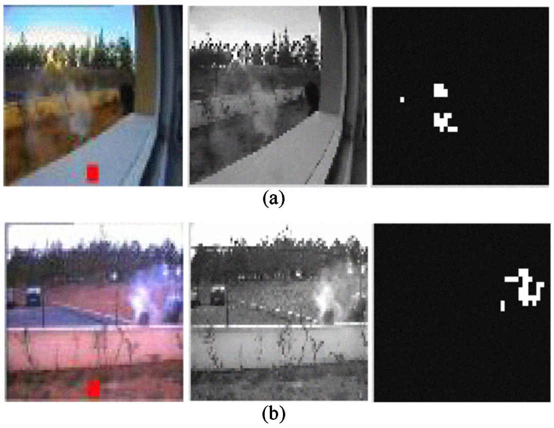

Figure 7. Results of smoke detection

V. CONCLUSION

This paper proposed an early smoke detection system based on motion estimation. The main contribution of this paper is to determine direction of motion vector for candidate blocks while accumulating the number of search point. Experiment results show that our early smoke detection system can detect smoke in open spaces at lower false detection rate before the fire burns up.

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