A Video Smoke Detection Algorithm Based on Wavelet Energy and Optical Flow Eigen-values

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***Abstract*—In this paper, a novel smoke detection method based on wavelet energy and optical flow is proposed. Firstly, smoke motion is extracted by dual background modeling. Then, candidate smoke regions are determined. Thirdly, two basically smoke eigen-values are calculated by using wavelet transformation tools and Lucas-Kanade optical flow method. The motion directions are estimated in every small region. These two eigen-values can effectively express image texture and move orientation feature, respectively. Lastly, these two eigen-values are given different weights. The experimental results have proved that the proposed algorithm have a robust and better appearance.**

***Index Terms*—Smoke detection; Optical Flow; Wavelet Transformation; Smoke Eigen-values; Dual Background Modeling;**

I. Introduction

Fire is a disaster caused by the burning which is a loss of control [1]. Generally, the fire accident frequently causes economical and ecological damage as well as endangering people’s lives. Therefore, timely and accurate fire detection is essential. The majority of fire detection systems used today is based on particle sampling, temperature sampling, and air transparency testing. Unfortunately, these systems are generally limited to indoors, require a close proximity to the fire and cannot provide additional information about fire circumstances such as size, location, and propagation. A further drawback of those conventional detectors is the transport and threshold delay, i.e., the time for particles to reach and to activate a detector. Thus, the traditional detectors are limited in the actual application.

Video-based fire detection is a newly developed technique in the last few years, and it can greatly serve the fire detection requirement in large rooms and high buildings, and even outdoor environment. In order to overcome the shortcomings of conventional detectors and provide more reliable information about fires, researchers all over the world have done a lot of work on the fire detection based on video images [2], [3], [4]. They determine whether there is fire by analyzing color, motion, textures, geometry and so on. But as we know, most fires start at the smoldering phase in which smoke usually appears before flame. Due to the high diffusion, smoke is easier access to monitoring range. In these cases, smoke detection gives an earlier fire alarm. But compared to flame, the visual characteristics of smoke such as color and grads are less trenchancy, so that smoke is harder to be differentiated from its disturbances. So the extraction of smoke’s visual features becomes more complicated. Researchers began to use many kinds of features for the study of video smoke detection in recent years. Yu et al. [5] used background estimation and color-based decision rule to determine candidate smoke regions. Toreyin et al. [6] used partially transparent feature of smoke, and implemented by extracted the edge blurring value of the background object in wavelet domain. Vicente and Guillemant [7] extracted local motions from cluster analysis of points in a multidimensional temporal embedding space in order to track local dynamic envelopes of pixels, and then used features of the velocity distribution histogram to discriminate between smoke and various natural phenomena such as clouds and wind-tossed trees that may cause such envelopes. Yuan [8] have reported a block by block approach based on chrominance and motion orientation. They propose a new fast algorithm for motion orientation estimation and test them on four videos. However, the chrominance based methods they use have a disadvantage in their dependence on the color of smoke. Also, the motion estimation algorithm is very time consuming in the context of smoke detection. Thou-

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Ho et al.[9] propose a rule based system to detect smoke which is based on pixel intensity. They perform intensity based characterization of smoke. Dongil Han and Byoungmoo Lee [10] combined Motion History Image and invariant moment to implement smoke detection for early real-time detection of a tunnel fire. Jayavardhana Gubbi [11] proposed a novel method for smoke characterization using wavelets and support vector machines. Cui [12] combined tree-structured wavelet transform and gray level co-occurrence matrices to analyze the texture feature of fire smoke. In Xiong's [13] study, they thought that smoke and flames were both turbulent phenomena, the shape complexity of turbulent phenomena might be characterized by a dimensionless edge/area or surface/volume measure. Those proposed algorithms above are mostly pixel-based and detect smoke based on all candidate smoke regions. They all can achieve real-time. However, when there are many moving objects coexist with smoke, the result is unsatisfactory.

It is because that those non-smoke regions do not meet some characteristics of smoke image, such as smoke changes. In order to improve the detection rate of the current smoke detection algorithms, in the previous our work, we proposed a smoke detection approach based on connected domain[18]. In these algorithms, each connected domain is consisted by many motion blocks. We detect the characteristics of smoke based on connected domain rather than all candidate smoke regions to determine whether there is smoke. In this way, we can effectively eliminate the non-smoke moving objects, and can quickly and accurately detect the appearance of smoke. But there are still some drawbacks exist, for example it is easy to be affected in the light change condition.

Aiming at this case, we improved the approach proposed in literature 18. In this paper, there are two main highlights of improvements. Firstly, we adopt dual background modeling method to get moving object, it can obtain more accurate results. Secondly, after moving detection, we adopt optical flow as the movement features, it can avoid too sensitive to light changing. Some works in this paper are on the basis of previous work, and some statements are translated straightforward about the introduction of some research work and wavelet transform and experimental implemented environment, respectively.

This paper is organized as follows: in section2, improved moving detection and optical flow calculation process are introduced. In Section 3, calculating the high/low frequency energy through discrete wavelet transformation and the movement maintenance according to the result of the optical flow are described. In Section4, the several experiments are described and the results are discussed. In the last section, this paper is concluded.

II. Moving Region Extraction and Calculating Optical Flow

A. Moving Detection by Dual Background Modeling

The prospect of extraction technologies can get a moving area from complicated video frame picture, and this procedure could decrease the burden of algorithm analysis and enhance the result of further work. There are a lot of algorithms of detecting moving objects. Background subtraction is commonly used in fixed-camera surveillance system and is often used in smoke detection [14], but this method usually is not applied to the situation because the scene is changeable. The main reason is people could not update the background timely in such condition. Optical flow is time consuming and sensitive to noise [15], the frame difference method is fast but not stable [16,17]. So in this issue, there are still some problems need to be solved.

In this study, we focus on improving Background subtraction to extract the prospect object. An improved dual background modeling is used. In order to avoid light sensitive default of traditional methods, we build a fixed background.

Traditional moving average algorithm own lower time time-complexity, but it usually be easy to be affected when illumination changing. Therefore, in building fixed background, we add a judgment procedure of H space and V space in HSV color space. This judgment could eliminate negative impacts bring from illumination changing.

Moving Average algorithm can be operated as follow:

Firstly, it updates pixels according to the rules like expression (1):

$$\mu_n(i,j) = \mu_{n-1}(i,j) + \alpha(I_n(i,j) - \mu_{n-1}(i,j)) \quad (1)$$

here, $\mu_n(i,j)$ are the pixels in background after the n-th frame image is updated, and $I_n(i,j)$ denotes the value of a pixel, α is a parameter controlling update speed.

In expression (1), illumination changing facts is not to be considered, so Koller's idea[12] is be adopted, and we defined α again as expression (2):

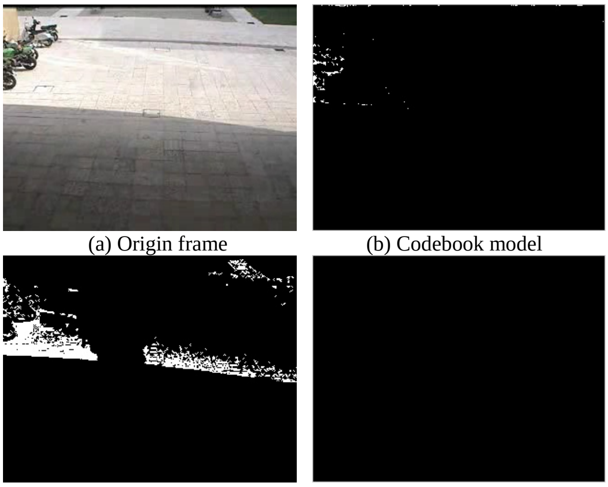
$$\alpha = \alpha_1 M_n + \alpha_2(1 - M_n) \quad (2)$$

here, $M_n(i,j)$ is defined as expression (3):

$$M_n(i,j) = \begin{cases} 0, & |I_n(i,j) - I_{n-1}(i,j)| < T \\ 1, & |I_n(i,j) - I_{n-1}(i,j)| \geq T \end{cases} \quad (3)$$

here, parameters $(\alpha_1, \alpha_2) \in (0,1)$ and the value of the parameters will affect the adaptive effects in background separation process.

In the illumination changing case, the brightness of whole image change dramatically. Using the character, we judge the change condition of H space and V space in HSV space. If the judgment condition meets, the fixed background will be updated. In fig 1, it can be seen that this method can get better prospects.



(a) Origin frame (b) Codebook model

(c) Gaussian mixture model (d) Our method

Fig1. Foreground extraction effect comparison

In fig.1, (a) is origin frame image, and (b) is extracted by codebook model, and (c) is extracted by Gaussian mixture model, and (d) is extracted by our method. It can be seen our method can get better effect.

B. Moving Direction Estimation by Optimal Flow Method

After exacting a stable moving results, an accurate moving direction need to be estimated. This procedure can decrease flase detection rate effectively. And a more accurate moving character of smoke moving also be wanted.

According to the characteristics of smoke diffusion, it usually drifts upwards continually by hot airflows. At the same time, smoke has several characters like a bottom-up movement, diffusion, swing. So how to extract the mainly moving feature is the most important. In our earlier work [18], a moving estimation based on conected region is be proposed. In this method, we define eight directions, and calculate the difference between the two ajacent pixels, the eight direction is shown in fig 2. Then , we can get eight difference-values denote pixels changing degree in eight directions and then find the biggest value form them. In this way , a main moving direction can be testimated in small area.

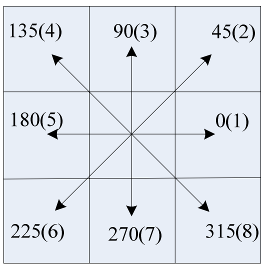


Fig.2 Discrete direction of motion

But, there are still shortcomings in this method, and the main problem is high unstable, and highly dependent on foreground extraction results. At the same time, it is too sensitive to noise, so it will seriously impact the estimation results of directions.

In this paper, we choose optical flow to make statistics of smoke moving characters. Optical flow tools are good at analyzing the motion characteristics because of considering a whole light changing situation. And optical flow can better present moving directions and moving speed simultaneously. From the above, an optical flow tool can get moving changing characters from light changing situation as well as suppresses the disturbance from light changing factor.

Calculation of optical flow is generally based on the following two assumptions. The first one is assume that an observed object point will be unchanged in a short period of time. The second one is that pixels around object move at a same direction. In a image *I*, we assume that $f(x, y, t)$ denotes the value of a pixel in location (*x*,*y*) in time *t*. Then we can represent a dynamic changing image as a function according to each allocation on the timeline. It can be extended into Taylor series as following expression:

$$\begin{aligned} & f(x+dx, y+dy, t+dt) = \\ & f(x, y, t) + f_x dx + f_y dy + f_t dt + O(\partial^2) \end{aligned} \tag{4}$$

If we have *dx, dy* and *dt*, then we can get the expression as:

$$\begin{aligned} & f(x+dx, y+dy, t+dt) - f_t = \\ & f(x, y, t) + f_x \frac{dx}{dt} + f_y \frac{dy}{dt} \end{aligned} \tag{5}$$

here, f_x, f_y, f_t can be obtained approximately, and the speed can be expression as:

$$Speed = \left(\frac{dx}{dt}, \frac{dy}{dt}\right) = (u, v) \tag{6}$$

But this calculation method is based on a global idea. In our work, we only get extracted results. Deal with intensity is not constant in a global image is flabby idea, enables the light to flow to the spread of global local binding. Therefore, Lucas-Kanade optical flow method is chosen [19].

Lucas-Kanade optical flow method is based on partial least squares method. In Lucas-Kanade optical flow, it must meet the constraint conditions as follow:

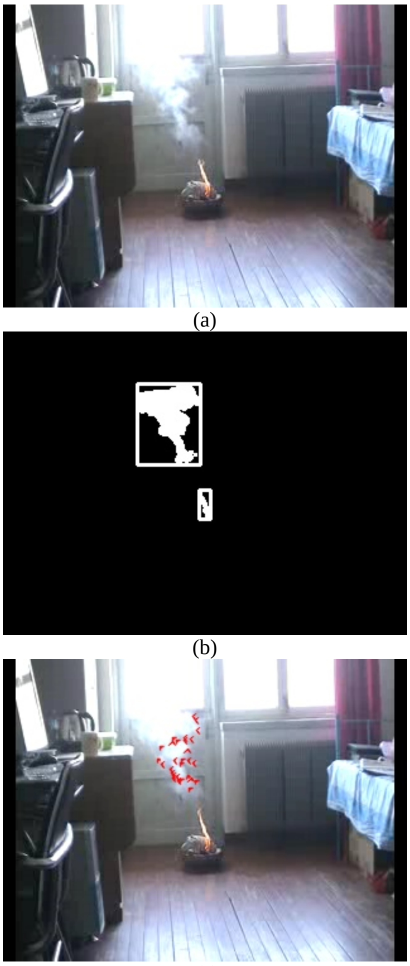
$$I_x u + I_y v + I_t = 0 \tag{7}$$

These pixels around object pixel changing in the same level, then they are given different rights. So, calculation of optical flow can be express as follow:

$$\sum_{x \in \Omega} W^2(x) \left[\nabla I(x,t) \mathbf{v} + I_t(x,t)\right]^2 \tag{8}$$

here, Ω denotes the small area of pixels around the object pixel. *W(x)* is a window function which give rights of pixels.

Lucas-Kanade optical flow method uses the Gaussian pyramid to calculate optical flow level by level. Along with the increase of the level, the resolution is lower and lower. Fig 3 shows smoke's optical flow extraction by this method.



(a) (b) (c)
Fig.3 calculate optical flow from prospects

In fig.3, (a) denotes origin frame image, (b) denotes extraction using moving detection results and (c) denotes optical flow results. It can be seen that optical flow only appears in prospects area.

III. SMOKE DETECTION IN CANDIDATE SMOKE REGION

In this section, we will discuss how to statistic wavelet energy, and then how to estimate moving direction by optical flow.

A.Energy Analysis using the Discrete Wavelet Transform

The smoke images own different texture and edges characters from other images. And wavelet tools usually are good at expressing image texture and edge characters, so smoke area usually is reflect by high wavelet energy. At the same time, background image of the scene usually are smooth and lack of object and these area usually own lower wavelet energy. Based on this fact, the background of the scene is estimated and decrease of high frequency energy of the scene is monitored using the wavelet transforms of the current and the background images in [6]. However, it is difficult to distinguish accurately background and prospect because of complicated environmental factor in practice.

When smoke does not completely cover background, the average of high frequency energies in non-candidate smoke regions is largely different from candidate smoke regions. For this reason, we compare the changes of the average energy between smoke regions and non-candidate smoke regions to achieve smoke detection. If the background is smooth, the change of energy is not obvious. In order to increase the rate of change, we need to exclude the smooth area in the non-candidate smoke regions. Therefore, we use the two-dimensional discrete wavelet to decompose the image. Wavelet image contains four wavelet sub-band images as HH, HL, LH, and LL, and LH, HL and HH contains horizontal, vertical and diagonal edges of the original image respectively. And we also define wavelet low-frequency and high-frequency energies same with the literature [18]. The energies of each pixel are computed as:

$$Lw_n(x,y) = \left| LL_n(x,y) \right|^2 \tag{10}$$

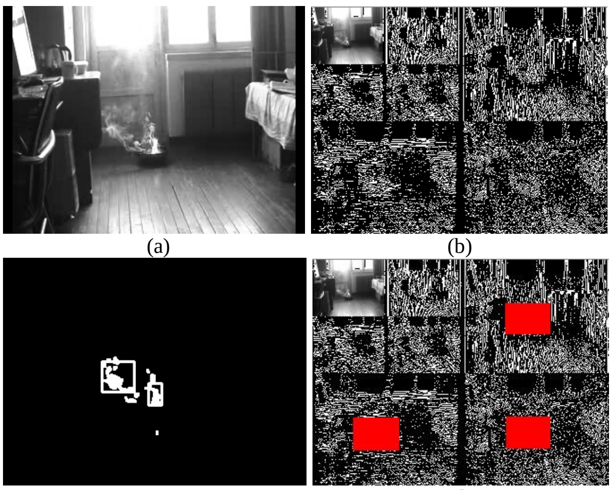
$$Hw_n(x,y) = \left| LH_n(x,y) \right|^2 + \left| HL_n(x,y) \right|^2 + \left| HH_n(x,y) \right|^2 \tag{11}$$

After obtain the wavelet transform image, we need re-statistics the energy of smoke area, and this area has been confirmed in procedure of extracting candidate smoke area. The energy in candidate area is defined as:

$$EL_{smoke} = \sum_{(x,y)\in C_{i,j}} Lw_n(x,y) \tag{12}$$

$$EH_{smoke} = \sum_{(x,y)\in C_{i,j}} Hw_n(x,y) \tag{13}$$

We choose the two-dimensional discrete wavelet, and fig.4 shows how the wavelet tool decomposes a smoke image. Wavelet tool's transform scale is chosen 2. It can be seen that only rely on wavelet energy is not very good at distinguishing between smoke and the background. In fig.4, (a) denotes origin frame, (b) denotes origin frame transformed by wavelet, (c) denotes candidate smoke area, and (d) denotes wavelet energy of candidate smoke area.



(a) (b) (c) (d)
Fig.4 wavelet energy diagram

So far, we can statistics the wavelet high/low frequency energy of candidate smoke area and non-smoke area wavelet high/low frequency energy respectively. And we can rely on the ratio of candidate/non-candidate energy. When smoke appear in image, it own high wavelet energy, so the ration becomes bigger. After a great deal of experiments, the threshold is generally chosen by 0.3. If the ration bigger than the threshold, it can be identified as smoke area, otherwise it is not considered a smoke area.

B. Movement Directional Calculation

Smoke usually drifts upwards continually by hot airflows. For this reason, moving direction of smoke is a good judgment. According to this movement characteristic, we can better distinguish smoke movement and other disturbs movement.

In part II, we introduce how to calculate light flow results, and we statistics optical flow energy as express (14):

$$E_{OF} = \sum_{i=1}^{W}\sum_{j=1}^{H} w_{i,j}(n)\, v_{i,j}^{2}(n) \qquad (14)$$

here, E_{OF} denotes energy of optical flow, v denotes speed and w denotes weight.

We define $\Delta X_{i,j}$ as the offset on x axis in unit time, and $\Delta Y_{i,j}$ as the offset on y axis. We can get movement direction by calculating angle. The angel variable can be defined as:

$$Angle_{i,j} = \arctan\frac{\Delta Y_{i,j}}{\Delta X_{i,j}} \qquad (15)$$

In candidate smoke area, we need estimate a main movement direction. Each pixel is given a weight according to value of optical flow energy. When a pixel owns a larger optical flow, has a larger weight.

$$Weight_{i,j} = E_{OF} / Sum(E_{OF}) \qquad (16)$$

So, we can get the main movement direction as express (17):

$$\theta_{Main} = \sum(Angle \times Weight) \qquad (17)$$

here, θ_{Main} denotes main movement direction of smoke area, each area is set 30*30 pixels.

Fig.5 main movement direction

It can be seen from fig.5 that the schematic main movement direction.

C. Effective Smoke Detection Strategy

In part A of this section, we used wavelet energy to distinguish smoke image, and gave a wavelet energy threshold. This method can roughly judge candidate smoke area. But there are still some movement characters can be used. In part B of this section, we used Lucas-Kanade optical flow to make statistic of move directions as movement features. And these movement features can help proving the accuracy of judgment of smoke. Therefore, in part c we propose a smoke detection strategy which combines both of them effectively.

In this smoke detection strategy, we determine the suspected smoke area firstly, in this procedure, we use moving detection by dual background modeling. Then, we use wavelet energy threshold to further judge. Thirdly, on the basis of first two steps, we further judge rely on movement directions. In general, smoke usually drifts upwards, so the range of angles is set in 30 to 150 degrees. So, we make a statistics of main movement directions from many tiny optical flow directions. If main movement direction conforms to restriction, we will judge it as smoke area, otherwise this area is obstruct area. The main process is expressed in fig.6.

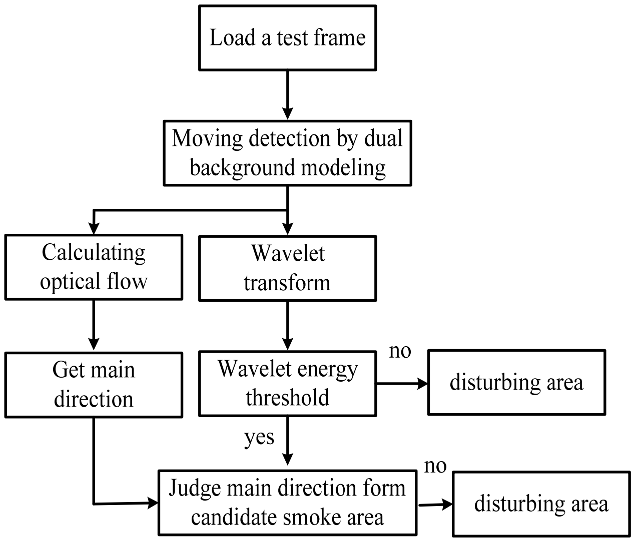


Fig.6 Main process of our smoke detection strategy

IV. EXPERIMENT

The proposed method is implemented on a PC platform with an Intel Core(TM)2 Duo E7200+2.53GHz processor and 1Gb memory, and tested for a large variety of conditions including real-time and off-line movies containing only smoke, and movies with no smoke. All tested movies are downloaded from the machine vision laboratory of Bilkent university (http://signal.ee.bilkent.edu.tr/VisiFire/) and video surveillance online repository (http://imagelab.ing.unimore.it/visor/videocategories.asp).

In order to verify the effectiveness of the algorithm, we tested same 12 videos which have been tested in literature [18]. The comparison methods are Toreyin's method [6], Yuan's method[8] and our proposed method in literature [18].Testing indicators are processing speed, detection rate, and Error detection rate. Here, movie1 to movie6 are smoke movies, and movie7 to movie 12 are the videos used for interference test. Movie7, Movie8 and Movie9 are car lights, passerby and moving car respectively, Movie10, Movie11 and Movie12 are jumpy lamplight, swing fans and waving curtains respectively.

In our experiment, the size of block is 8*8 in calculating of optical flow. And each 30*30 scope, we will calculate a main movement direction. Number of Layers in the pyramid is 5. Due to adopting optical flow features in analysis of movement, our method own stronger anti-interference than our previous work. In Table 1, we make a statistics of the efficiency of the algorithms. At the same time, we also make the statistics of the precision rate, error detection rate, and we have defined them in detail in literature [18], so in this paper we not state over and over again. Here, we define r+ as the precision rate of smoke detection and r- as error detection rate.

From the Table 1, we can see that our method cans almost real-time processing though it may take more time than the method in literature [18] because of calculating optical flow. In effect of smoke detection, firstly because Toreyin's method is pixels based, so it own worst effect. Yuan's method in paper considers only the upward movement of smoke, so if smoke moves to the left and right, it wills products wrong results. Our method in literature [18] adopt motion block and fusion of multi-characteristic, so can get better results, but it can't small smoke or lighter smoke, since the quantity of motion block are few, there are often false negatives. The method we proposed in this paper avoids this problem partly. Though our method increase 12ms per frame, it own better performance.

TABLE 1

ALGORITHM COMPARISON

Smoke Video	r+(%)			
	Toreyin's method	Yuan's method	Method in literature[18]	Our method
Movie1	88.2	79.4	85.3	85.3
Movie2	79.2	95.8	91.7	93.3
Movie3	78.4	90.2	96.1	96.1
Movie4	82.6	78.3	84.8	86.6
Movie5	87.8	96.0	94.6	94.6
Movie6	87.5	93.8	93.8	93.8
No-smoke Video	r_-(%)			
	Toreyin's method	Yuan's method	Proposed Method in literature[18]	Our method
Movie7	12.5	0	0	0
Movie8	5.30	0	0	0
Movie9	0	0	0	0
Movie10	6.25	6.25	0	0.13
Movie11	0	2.5	0.59	0
Video12	0	0	0	0

V. CONCLUSIONS

In this paper, we improved a smoke detection approach based on block movement by analyzing the characteristics of early smoke. We first use dual background modeling method to get moving object, it can obtain more accurate results. Secondly, after moving detection, we adopt optical flow as the movement features, it can avoid too sensitive to light changing. These two improvements are good at avoiding detection error in light changing condition. The experiment indicates that our method can decrease error detection rate in light changing condition and improve effect of the algorithm.

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REFERENCES

[1] Haase P, Motik B., A Mapping System for the Integration of OWL - DL Ontologies [C]// Proceedings of the first international ACM workshop on Interoperability of Heterogeneous Information Systems (IHIS' 05), Bremen, Germany: [s.n.], 2005: 9-16.

[2] Yamagishi H, Yamaguchi J., Fire flame detection algorithm using a color camera[C]//Proceedings of 1999 International Symposium on Human Science and Micromechatronics (MHS' 99), Nagoya, Japan: IEEE Industrial Electronics Society, 1999: 255-260.

[3] Ugur Toreyin B, Yigithan Dedeoglu, Ugur Gueduekbay, et al., Computer vision based method for real-time fire and flame detection [J], Pattern Recognition Letters, 2006, 27 (1): 49-58.

[4] Turgay Celik, Hasan Demirel, Fire detection in video sequences using a generic color model [J], Fire Safety Journal, 2009, 44 (2): 147-158.

[5] Yu Chunyu, Fang Jun, Wang Jinjun, et al., Video fire smoke detection using motion and color features [J]. Fire Technology, 2010, 46 (3): 651-663.

[6] Ugur Toreyin B, Yigithan Dedeoglu, Cetin A. Enis. Wavelet based real-time smoke detection in video [C]//13th European Signal Processing Conference (EUSIPCO2005).Antalya, Turkey: Curran Associates, 2005.

[7] Jerome Vicente, Philippe Guillemant, An image processing technique for automatically detecting forest fire[J], International Journal of Thermal Sciences, 2002, 41 (12): 1113-1120.

[8] Yuan Feiniu, A fast accumulative motion orientation model based on integral image for video smoke detection [J], Pattern Recognition Letters, 2008, 29 (7): 925 – 932.

[9] Chen,Thou-Ho, Yen-Hui, et al., The smoke detection for early fire-alarming system base on video processing [C]// IEEE 2006 International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIHMSP), California, USA: [s.n.], 2006: 427-430.

[10] Dongil Han, Byoungmoo Lee, Flame and smoke detection method for early real-time detection of a tunnel fire [J]. Fire Safety Journal, 2009, 44 (7): 951 – 961.

[11] Jayavardhana Gubbi, SlavenMarusic Marimuthu, Smoke detection in video using wavelets and support vector machines [J]. Fire Safety Journal, 2009, 44 (8): 1110 – 1115.

[12] Cui Yu, Dong Hua, Zhou Enze. An early fire detection method based on smoke texture analysis and

discrimination[C]//2008 International Conference on image and signal processing (CISP’08). Sanya, China: IEEE Computer Society, 2008: 95-99.
[13] Xiong Z, Caballero R, Wang H, Alan MF, Muhidin AL, Peng P-Y (2007) Video-based smoke detection: possibilities, techniques, and challenges. In: IFPA, fire suppression and detection research and applications—a technical working conference (SUPDET), Orlando, FL.
[14] Collins RT, Lipton AJ, Kanade T., A system for video surveillance and monitoring[C], //Proceedings of 8th International Topical Meeting on Robotics and Remote Systems, Pittsburgh, USA: American nuclear society, 1999.
[15] J.L. Barron, On optical flow[C]//Artificial Intelligence and Information-Control Systems of Robots (AIICSR'94), Bratislava, Slovakia: [s.n.], 1994: 3-14.
[16] Viola, P., Jones, M., Robust, J., 2004. Real-time face detection, Internet J. Compute, Vision 57 (2), 137–154.
[17] Betke Margrit, Haritaoglu Esin, Davis Larry S., Multiple vehicle detection and tracking in hard real time [J], IEEE (9), 351–35, 1996.
[18] Wen-hui Li, Bo Fu, Xiao-lin Chang, Ying Wang, Pei-xun Liu. A Block-based Video Smoke Detection Algorithm. Journal of Jilin University (Science Edition), 2012, Vol. 50, No. 5, 979-986

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