Dynamic Analysis for Video Based Smoke Detection

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Abstract

In recent years, video based fire detection technologies received much attentions from both industrial and academic world. Since smoke is usually generated before flames and can be observed from a great distance, it is an important feature for many early fire alarm system. In this paper, a video based smoke detection system is developed for the surveillance of early fire. Besides traditional color and texture features of the video smoke, the authors proposed a combination of block based Inter-Frame Difference (BIFD) and LBP-TOP to analyze the dynamic characteristics of the smoke. In order to reduce the false alarms, the Smoke Histogram Image (SHI) is constructed to register the recent classification results of candidate smoke blocks. SVM is employed to evaluate the performance of the propose features in the classification of candidate smoke blocks. Experimental results show that the proposed method can achieve better accuracy and less false alarm compared with the state-of-the-art technologies.

Keywords: *smoke detection, dynamic texture, BIFD, LBP-TOP, SHI.*

1 Introduction

Fire is one of the major disasters of the modern society, it has serious impact on the lives and properties of human beings. In order to eliminate the fire hazards at very early stage, during the past decades, significant efforts have been made by researchers to develop accurate and highly effective early fire detection technologies. Various fire alarm systems are developed for the requirements of fire detection in different applications.

Since smoke is usually generated before flames and can be observed from a great distance, it is an important feature for many early fire alarm system. Conventional smoke detection systems depend on point smoke detectors, which measure the presence of certain particles generated by smoke using ionization or photometry. However, such point detectors inherently suffer from the transport delay of the smoke from the fire to the sensor. They cannot work effectively if the fire is far away.

With the increasingly wide usage of video surveillance systems, in recent years, video based fire detection technologies received more and more attentions from researchers. Since the video camera can accomplish real-time monitoring in a large range, the smoke of uncontrolled fire can be easily observed by it. Therefore, video based technologies are much more competent in fire detection especially for large and open areas.

Many methods are proposed for fire detection in the field of view of the camera. Color models of fire and smoke pixels was introduced by Chen et al. [1] [2], the estimated candidate fire and smoke regions were verified by dynamical measuring of their growth and disorder. False alarms are inevitable if the scene has fire-colored moving objects due to no usage of texture information. Toreyin et al. [3] proposed a wavelet based real-time smoke detection algorithm, in which both temporal and spatial wavelet transformations were employed. The temporal wavelet transformation was used to analysis the flicker of smoke like objects, while the spatial wavelet transformation was implemented to calculate the decrease in high frequency content corresponding to edges caused by the blurring effect of smoke. The boundary roughness [4] was introduced to improve the performance of [3], three-state Markov models were trained to discriminate between smoke and non-smoke pixels. Liu and Ahuja [5] proposed spectral, spatial and temporal models for fire detection. Fourier Descriptors (FD) were used to represent fire shapes but FD is sensitive to noise. Celik et al. Yuan [6] presented a real-time video smoke detection method using an accumulative motion model, but it can not detect smoke drifting in any direction. In [7] Zhang et al. presented a real-time forest fire detection system using dynamic characteristics of fire regions. Maruta et al. [8] considered that the image information of smoke is a self-affine fractal, local Hurst exponent was extracted to analyze the self-similarity of suspect smoke region. In [9], Yuan proposed an effective feature vector by concatenating the histogram sequences of Local Binary Pattern (LBP) and Local Binary Pattern Variance (LBPV) pyramids, and a BP neural network was used for smoke detection. Ko et al. [10] detected candidate fire regions by motion and color, and created a luminance map to remove non-

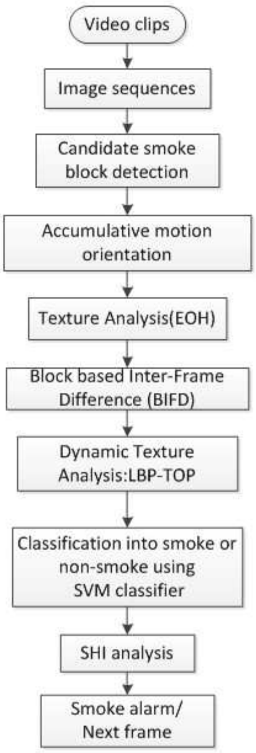


Figure 1: The flowchart of the proposed video smoke detection algorithm.

fire pixels. SVM classifier was used for final decision. In [11], a double mapping framework is proposed by Yuan to extract partition based features of smoke, AdaBoost was employed to enhance the performance of classification.

Due to the arbitrary shapes of smoke, illumination and intra-class variations, occlusions and etc., video base smoke detection is still a challenging task. Being enlightened on the fact that human can easily recognize the existence of smoke only according to dynamic characteristics observed, in this paper, we concentrate on study the dynamic characteristics feature extraction methods for video based smoke detection. The remainder of this paper is organized as follows. Section 2 presents the details of the algorithms. Section 3 illustrates the performance of the proposed method is evaluated and compared with some state-of-the-art technologies. In section 4, a brief conclusion is presented.

2 Algorithms

A flowchart of the proposed video smoke detection algorithm is depicted in Fig. 1. In the following parts of this section, each step of the proposed algorithm is presented in details.

2.1 Candidate smoke block detection

In order to get candidate smoke regions for further estimation, moving detection and characteristics of smoke color are used. Each video frame is divided into non-overlapped blocks. Supposed that image width, image height, block width and block height are W_I, H_I, W_B and H_B, respectively. The row number N_r and column number N_c of blocks in each frame are calculated by:

$$N_r = \lfloor \frac{H_I}{H_B} \rfloor \tag{1}$$

$$N_c = \lfloor \frac{W_I}{W_B} \rfloor \tag{2}$$

where $\lfloor \ \rfloor$ is an operator of truncating a floating point number to get an integer number.

Block B_{ij} of t-th frame is regard as a moving block if

$$\sum_{(x,j)\in B_{ij}} [f(x,y,t) - f(x,y,t-1)] > T_B \tag{3}$$

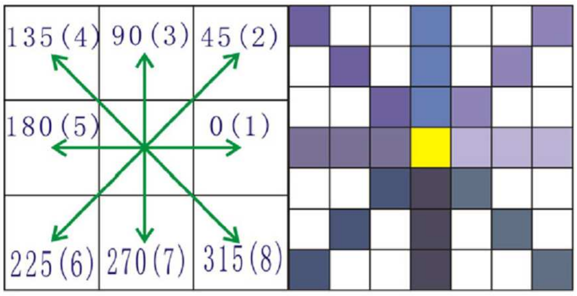
where T_B is a predetermined threshold, and block B_{ij} is on the i-th row and j-th column in the video.

Then, the estimated moving blocks are verified by several rules of smoke color in RGB color space [6].

2.2 Accumulative Motion Orientation

Since the smoke of fire commonly move upward due to high temperature, motion orientation information is helpful for fire detection. In this paper, the block based Accumulative Motion Orientation (AMO) proposed in [6] is adopted to analysis motion of the candidate smoke regions. The orientation of motion is discretized into 8-directions: 0, 45, 90, 135, 180, 225, 270 and 315 degrees. These discrete directions are coded as 1, 2, 3, 4, 5, 6, 7 and 8, respectively. The 3-pixel searching displacement as described in Fig.2 is applied at each direction to find the sift orientation of the candidate smoke regions. The estimated temporal motion orientation histogram $\mathcal{H}(i,j,t)$ were accumulated in a sliding time window W_t to enhance the accuracy. The ratio of the sum of frequencies at upward motion directions to the sum at all directions are calculated by Eq. (4), where $\mathcal{H}_B$ is the histogram of accumulative motion orientation of block B. The block with $UMR < T_U$ is regard as non-smoke. Where T_U is a predefined threshold. In our implementation, $T_U = 0.55$ is used.

$$UMR = \frac{\sum_{\theta=2}^{4} \mathcal{H}_B(\theta)}{\sum_{\theta=1}^{8} \mathcal{H}_B(\theta)} \tag{4}$$



(a) Discrete directions (b) Searching scheme

Figure 2: Discrete direction and searching scheme of AOM

2.3 Edge Orientation Histogram

Local edge orientation histogram (EOH) was introduced by Levi and Weiss [12] for face detection at first. During the past decade, it has been widely used in vision tasks such as object detection, image classification, human action recognition and etc. The steps of extract EOH feature are briefly illustrated in Fig. 3. To compute the EOH features, the pixel gradient magnitude m and gradient orientation θ of each pixel at location (x, y)in block are calculated as follows:

$$m(x,y) = \sqrt{f_x^2 + f_y^2} \tag{5}$$

$$\theta(x,y) = \tan^{-1}(\frac{f_x}{f_y}) \tag{6}$$

where f_x and f_y are the respective gradients in the horizontal and vertical directions obtained by convolving the image with an edge operator. In our implementation, the Sobel operator is applied to generate the image gradients (f_x and f_y). The gradient orientation θ is evenly divided into k_θ bins in the range $[0°, 180°]$. The sign of the orientation is ignored; that means the orientation θ between $180°$ to $360°$ are deemed the same as $(\theta - 180)°$. Then, the gradient orientation histograms in k-th orientation bin of i-th block $E_{i,k}$ is obtained by summing all the gradient magnitudes who belong to the k-th orientation in block B_i.

$$E_{i,k} = \sum_{\substack{(x,y)\in B_i \\ \theta(x,y)\in Bin_k}} m(x,y) \tag{7}$$

After extracted the EOH feature of the candidate smoke blocks (analyzed by motion and candidate smoke), we adopted SVM [13] for the classification.

2.4 Inter-Frame variation analysis

In this section, we propose an algorithm to analyze the inter-frame variations of the candidate smoke blocks. A brief description is illustrated in Fig. 4. Let $Block_{p,k}$ be the k-th block estimated as smoke candidate in p-th frame $Frame_p$. The differences of the corresponding blocks between adjacent frames from $Frame_{p-q+1}$ to $Frame_p$ are calculated as

$$\begin{aligned} BDA_{p,q,k} = \{&DIF_{p-q+1,p-q+2,k}, \\ &DIF_{p-q+2,p-q+3,k}, ..., DIF_{p-1,p,k}\} \end{aligned} \tag{8}$$

$$DIF_{i,j,k} = |Block_{i,k} - Block_{j,k}| \tag{9}$$

where $DIF_{i,j,k}$ is the difference between the corresponding blocks of the $Frame_i$ and $Frame_j$.

Then, the mean, variance and skewness of each element of BDA are calculated to analyze the Block based Inter-Frame Difference (BIFD) by the equations below:

$$\mu_i = \frac{1}{W_B \times H_B} \sum_{m=1}^{H_B} \sum_{n=1}^{W_B} BDA^i_{m,n} \tag{10}$$

$$\sigma_i = (\frac{1}{W_B \times H_B} \sum_{m=1}^{H_B} \sum_{n=1}^{W_B} (BDA^i_{m,n} - \mu_i)^2)^{\frac{1}{2}} \tag{11}$$

$$s_i = (\frac{1}{W_B \times H_B} \sum_{m=1}^{H_B} \sum_{n=1}^{W_B} (BDA^i_{m,n} - \mu_i)^3)^{\frac{1}{3}} \tag{12}$$

$$BIFD = \{\mu_1, \sigma_1, s_1, \mu_2, \sigma_2, s_2, \cdots, \mu_{q-1}, \sigma_{q-1}, s_{q-1}\} \tag{13}$$

where BDA^i denotes the i-th element of BDA; W_B and H_B are the width and hight of the block; μ_i, σ_i and s_i are the mean, variance and skewness respectively.

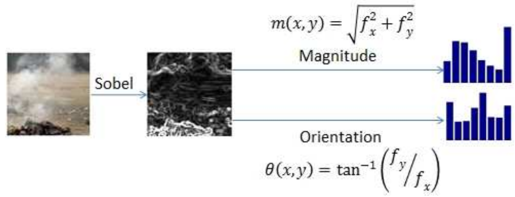


Figure 3: The procedure of EOH's extraction.

Table 1: Videos of training data

Video	Total videos	Total Frames Smoke	Total trained features
Smoke	9	320	4697
Non-smoke	8	480	11788

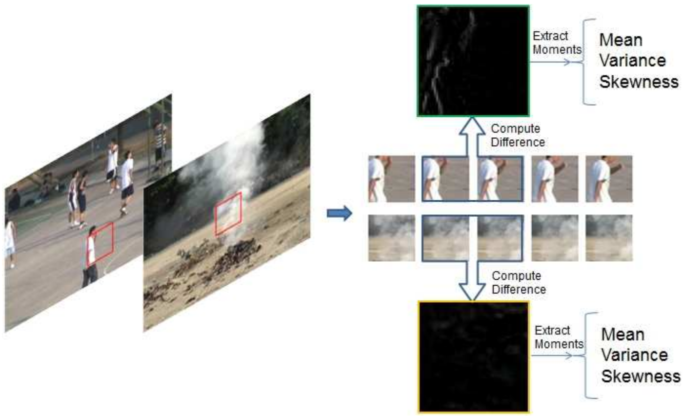


Figure 4: The process of BIFD feature extraction.

2.5 LBP-TOP

The LBP-TOP [14] was proposed to calculate the Local Binary Pattern (LBP) from Three Orthogonal Planes (TOP), denoted as XY, XT and YT. The operator is expressed as

$$\textbf{LBP–TOP}_{P_{XY},P_{XT},P_{YT},R_X,R_Y,R_T} \quad (14)$$

where the notation $(P_{XY}, P_{XT}, P_{YT}, R_X, R_Y, R_T)$ denotes a neighborhood of P points equally sampled on a circle of radius R on XY, XT and YT planes respectively. Fig. 5 illustrates the procedure of the LBP-TOP descriptor extraction. In such a scheme, LBP encodes appearance and motion in three directions, incorporating spatial information in XY and spatial temporal co-occurrence statistics in XT and YT (see equation 15, 16 and 17). The three statistics are concatenated into a single histogram as Eq. (18). In our implementation, each plane is encoded by uniform LBP (59 dims), therefore the constructed LBP-TOP feature vector is of 3×59 length.

$$LBP_{XY} = LBP_{uniform}(XY) \quad (15)$$

$$LBP_{XT} = LBP_{uniform}(XT) \quad (16)$$

$$LBP_{YT} = LBP_{uniform}(YT) \quad (17)$$

$$\text{LBP–TOP} = \{LBP_{XY}, LBP_{XT}, LBP_{YT}\} \quad (18)$$

To test the performance of LBP-TOP in smoke detection, a data set (see Tabel 1) with 4697 smoke blocks and 11788 non-smoke blocks is employed. The evaluation is repeated for 10 times, in each time, we randomly select half of the data for training, leaving the others for testing. Fig. 6 show the results of classification accuracy. It can be see that, even only LBP-TOP is used, approx 86% of classification accuracy in testing is achieved.

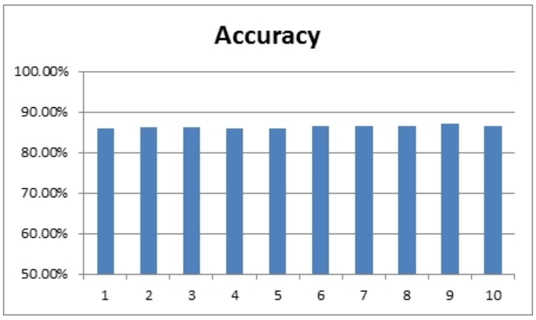


Figure 6: The detection accuracy of LBP-TOP on train data.

2.6 Block-based Smoke History Image

At the final step of our smoke detection method, we proposed an algorithm which computes a confidence value using the current and historical classification results of candidate smoke blocks to reduce the false alarm. Inspired by Motion History Image (MHI) [15, 16], we construct a static image template in which the pixel intensity is a function of the recency classification results, namely Smoke History Image (SHI). The brighter values indicate the corresponding blocks are more recently been classified as smoke candidates. SHI have a max value T, if the i-th block is detected as smoke $Det(i) = 1$, then the SHI value of block is set to T, otherwise the SHI value of block minus one.

$$SHI(i) = \begin{cases} T & Det(i) = 1 \\ SHI(i) - 1 & Otherwise \end{cases} \quad (19)$$

If $Det(i) = 1$ and the $SHI(i) \geq TH$, the i-th block is finally detected as smoke, otherwise non-smoke.

$$Final(i) = \begin{cases} 1 & Det(i) = 1 \&\& SHI(i) \geq TH \\ 0 & Otherwise \end{cases} \quad (20)$$

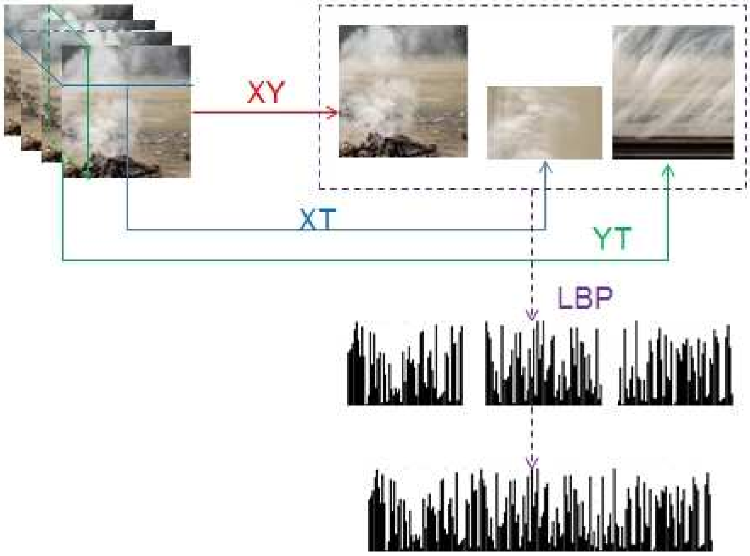
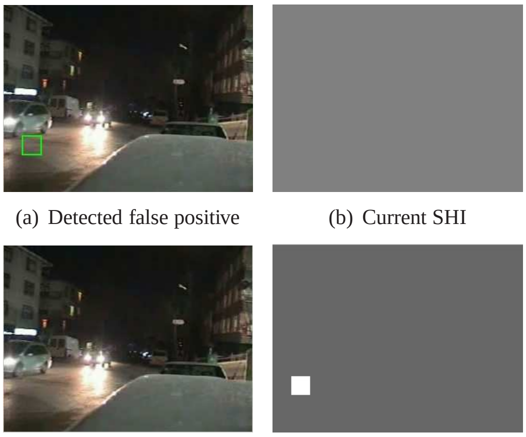


Figure 5: The construction of LBP-TOP.

Fig. 7 (a) and (b) show a detected smoke candidate (indicated by the green rectangle) and the corresponding SHI image. Finally, the smoke candidate is classified as non-smoke since the corresponding value of SHI is less than the predefined threshold. After the final decision of each frame, the SHI is updated (see Fig. 7 (d)). It can be see that the false positive is removed by using SHI.



(a) Detected false positive (b) Current SHI

(c) Final result (d) Updated SHI

Figure 7: An example of removing false positive by using SHI.

3 Result

3.1 Data Set

To evaluate the performance of the proposed smoke detection system, it is implemented by Matlab 2009a (as described in Fig. 1) and tested using a data set with 72 smoke videos and 79 non-smoke videos were used (see Fig. 8 for examples). Some videos of the data set were downloaded from the internet and the others were recorded by the authors. Different kinds of burning matters in various scenarios are considered. For instances, video (a) presents cotton rope smoke captured outdoors; video (b) records the smoke of burning leaves, the video (c) shows a video containing white smoke by burning dry leaves in front of groves of bamboo; video Video (d) contains a white smoke near a wasted basket. Fig. 9 illustrates the examples of the smoke detection results. We can see that suspected smoke areas (indicated by red rectangles) were well detected and located in the real smoke regions and the proposed method seldom produced false alarm.

3.2 Comparison

The proposed smoke detection system is compared with the method (2) presented in [11], which is demonstrated achieving the best performance in regard of state-of-the-arts [3], [6]. We follow the evaluation criterions adopted in [11] including: first alarm at frame number and the number of false alarms. The videos shown in Fig. 8 are used for testing, the reminder of the videos are employed for training. Tabel 2 lists the first alarm comparison results of eight smoke videos.

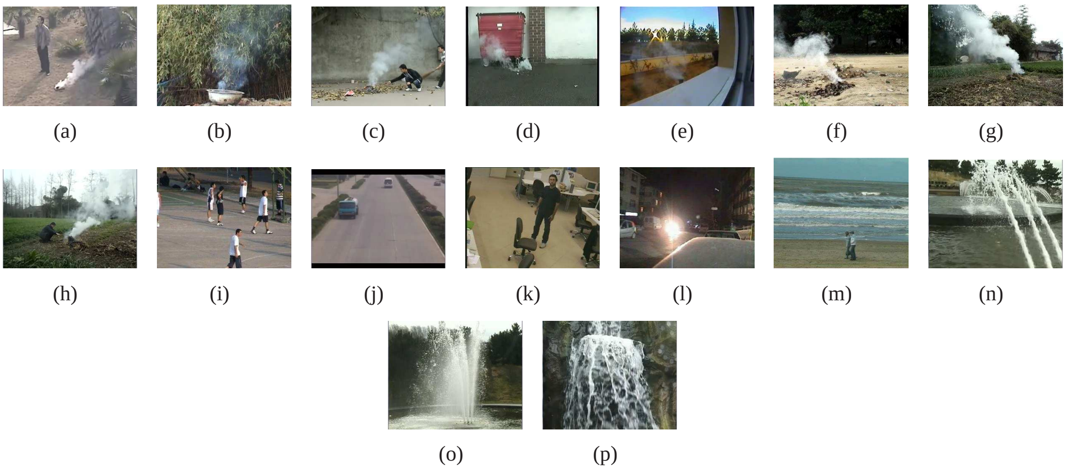


Figure 8: Examples of the video data set, the first two rows are smoke videos, others are non-smoke.

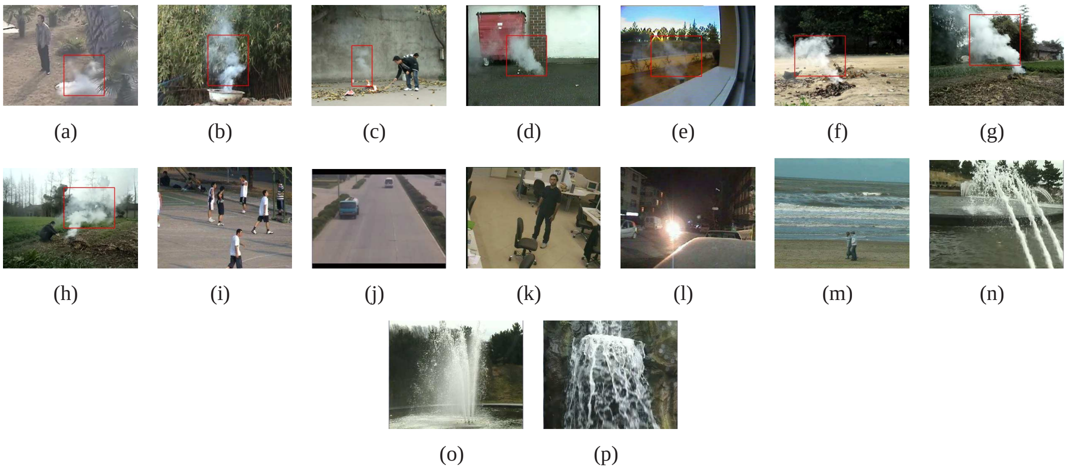


Figure 9: Examples of smoke detection results.

Table 2: Compared with other methods using smoke videos

Alarm at frame number	Video(a)	Video(b)	Video(c)	Video(d)	Video(e)	Video(f)	Video(g)	Video(h)
Paper [11] Method(2)	75	415	509	89	No alram	78	74	73
Proposed	29	328	276	65	134	41	28	20

Table 3: Compared with other methods using non-smoke videos

Number of false alarms	Video(i)	Video(j)	Video(k)	Video(l)	Video(m)	Video(n)	Video(o)	Video(p)
Paper [11] Method(2)	0	0	0	0	0	180	110	73
Proposed	0	0	0	4	0	3	0	0

The smaller number of alarm frame indicates the earlier smoke alarm. For all the videos, the proposed method achieves earlier alarms than method [11]. On the other hand, Tabel 3 gives false alarm comparison results in eight non-smoke videos. Both methods haven't false alarms in Video (i), (j), (k) and (m). Although the proposed method has 4 false alarms in Video (l), it produces much fewer false alarms in Video(n), (o) and (p) in contrast with [11]. Therefore, in summary, the proposed method provides better performance in smoke detection. Additionally, the average process time is 0.685178 seconds for each smoke frame and 0.441138 seconds for each non-smoke frame on a computer with Intel Core2 P8400 2.26GHZ CPU and 2GB RAM. Since a C++ implementation will 15 30 times faster than the Matlab version, the proposed algorithm can be employed for real-time vision tasks.

4 Conclusion

In this paper, we developed a video based smoke detection system for early fire surveillance. A novel spatial-temporal feature combining block based Inter-Frame Difference (BIFD) and LBP-TOP is proposed to analyze the dynamic characteristics of the video smoke. The performance of the proposed features is evaluated utilizing SVM classifier. Additionally, the Smoke Histogram Image (SHI) is constructed to reduce the false alarm. Experimental results show good performances in both detection accuracy and false alarm resistance are achieved compared with the state-of-the-art technologies.

Acknowledgments

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