영상감시시스템에서 은닉마코프모델을 이용한 불검출 방법

TengZhu*, 김정현*, 강동중*, 김민성**, 이주섭***
*부산대학교 기계공학부, **동명대 정보통신공학과, ***㈜NedTech
e-mail : {tengzhu, mare, djkang}@pusan.ac.kr, minsung@tu.ac.kr, jslee@nedztech.co.kr

Fire detection in video surveillance and monitoring system using Hidden Markov Models

TengZhu*, Jeong-Hyun Kim*, Dong-Joong Kang*, Min-Sung Kim**, Ju-Seoup Lee***
*School of Mechanical Eng., Pusan National University,
**Dept. of Telecom. Eng., Tongmyong Univ., ***NedTech Co., Ltd.

Abstract

The paper presents an effective method to detect fire in video surveillance and monitoring system. The main contribution of this work is that we successfully use the Hidden Markov Models in the process of detecting the fire with a few preprocessing steps. First, the moving pixels detected from image difference, the color values obtained from the fire flames, and their pixels clustering are applied to obtain the image regions labeled as fire candidates; secondly, utilizing massive training data, including fire videos and non-fire videos, creates the Hidden Markov Models of fire and non-fire, which are used to make the final decision that whether the frame of the real-time video has fire or not in both temporal and spatial analysis. Experimental results demonstrate that it is not only robust but also has a very low false alarm rate, furthermore, on the ground that the HMM training which takes up the most time of our whole procedure is off-line calculated, the real-time detection and alarm can be well implemented when compared with the other existing methods.

1. Introduction

People's life and properties will be severely damaged if there are fires breaking out in their living places. Therefore, it is doubtless very significant to explore early, accurate and prompt fire-detection techniques. The traditional techniques are generally based on sensors which have some important weaknesses that the precision of them almost depends on the precise of sensors, the size of the sensing space and the distribution of the sensors, and it can easily be confused by some sources of fires in other ways, even a cigarette, in addition, it needs much time for sensors to detect fires or smokes which result in fire spread. On the contrary, the video processing technique has many advantages, such as discovering fire in an earlier time, better reliability and unnecessary additional cost for sensors.

The video processing technique has been studied by many researchers such as M. R. Naphade, Omar Javed and Mubarak Shah [1,2]. In some works, fire color classification and motion information are used [3,4], moreover wavelet analysis is added to analyze high-frequency information of fire [5]. A rule-based generic color model for flame pixel classification is proposed [6], although testing on two sets of images which contain fire and fire-like regions, they only make use of color information which is insufficient. Both wavelet and HMM are utilized [10], but the method of HMM training is a little simple that it just counts the number of the state transitions for each state and then calculates the covering of the total state transitions as the transition probabilities which doesn't take full advantages of using HMM. We developed a novel method utilized the Hidden Markov Model which is a mature model and successfully applied in many areas such as speech recognition and segmentation, motion video analysis and tracking. The paper is organized as followings. All the algorithms are described in Section 2 which contains moving objects detection in 2.1, fire color pixel detection in 2.2, pixels clustering in 2.3 and algorithms related to HMM in 2.4. The whole procedure which illustrates how to integrate all the algorithms mentioned in the paper is given in Section 2.5 to give a distinct knowledge of our method. The experimental results and performance analysis are provided in Section 3 and we come to a conclusion in Section 4.

2. Fire detection algorithm

We detect fire first by using moving objects detection, whose results will be the input of the fire-color pixel detection and then the candidate fire pixels are clustering, finally we check every cluster formed in the previous step whether it is fire or not by using the established HMM.

2.1 Moving objects detection

As we all know, what the fire keeps moving as time goes by is a significant attribute of fire. Hence, the first step is to detect moving pixels and regions in order to filter most of the unwanted information.

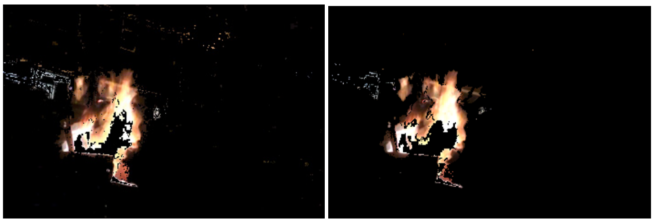
Generally, the moving pixels are extracted by subtracting the intensity value of image frame x_n and x_{n-1}. Based on this algorithm, we have some improvements which make the performance better. In our work the moving pixels is extracted by calculating the mean of adjacent three frames as shown in the equation 1.

$$Diff_t(\mathrm{X,Y}) = \left| \frac{f_t(X,Y)+f_{t-1}(X,Y)+f_{t-2}(X,Y)}{3} - \frac{f_{t-1}(X,Y)+f_{t-2}(X,Y)+f_{t-3}(X,Y)}{3} \right| \quad (1)$$

$\mathrm{f_t(X,Y)}$ denotes the value of the red channel of pixel position $\mathrm{(X,Y)}$ at frame t, when the difference between frames are larger than a threshold, the pixel will be reckoned as a moving pixel. The threshold is set to 5 in our work.

Compared with the conventional method, our algorithm has a better performance without providing excessive and unnecessary information to the next step as shown in Fig.1, Fig.2 (a) and (b).

Fig.1 Original image



(a) (b)

Fig.2 (a) Conventional method to detect the motion pixels by image difference;
(b) Our method to detect pixels in motion

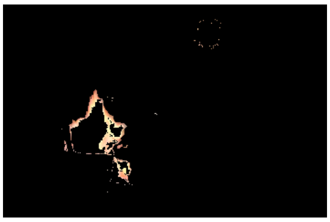
2.2 Fire-color pixel detection

In this step, the moving pixels are treated as the input of the fire-color detection. That is to say, only the moving pixels are checked whether they satisfy the fire-color conditions, which greatly reduces the calculation complexity and contributes to the realization of the real-time detection.

To define a fire-color pixel, three conditions based on the RGB color system should be satisfied [3]. The corresponding RGB value will be mapped to the conditions: R>G and G>B, i.e., the color range of red to yellow. Thus, the condition of fire's colors to be detected is defined as R>G, G>B for the fire region in the captured image. Furthermore, there should be a stronger R in the captured fire image due to the fact that R becomes the major component in an RGB image of fire flames. This is because that fire is also a light source and the video camera needs sufficient brightness during the night to capture the useful image sequences. Hence, the value of R component should be over a threshold, $\mathrm{R_T}$. However, the background illumination may affect the saturation of fire flames or generate a fire-similar clutter, and then result in a false fire-detection. To avoid being affected by the background illumination, the saturation value of fire-flame extracted needs to be over some threshold in order to exclude other fire-similar clutters. This will deduce three decision rules for extracting fire pixels from an image, as described in the following:

Rule 1: $\mathrm{R} > \mathrm{R_T}$
Rule 2: $\mathrm{R} > G, G > B$
Rule 3: $\mathrm{S} \geq (255 - \mathrm{R}) \times \mathrm{S_T}/\mathrm{R_T}$

Setting $\mathrm{S_T}$ and $\mathrm{R_T}$ to 60 and 170 respectively according to our experiments and applying the above three conditions to our algorithm, the results are achieved as Fig.3.



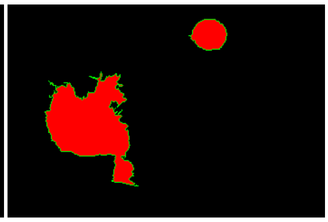


Fig.3 Fire-color pixels detected (left)
Fig.4 Clustering of the fire (right)

2.3 Pixels clustering

Through the above algorithm we can judge one pixel is fire-pixel or not, however it's arbitrary if we give the decision just by one pixel, moreover, fire is a changing process, hence we make clusters of fire pixels of 30 frames just like the forming of an object before going to the final conclusion, which gives more information of pixels to the final decision (Fig.4). Then in the next step we will arrive at the decision by every cluster.

2.4 Fire decision using Hide Markov Models (HMM)

It has been observed that the flames flicker frequency of about 10 Hz is not greatly affected by either the fuel type or the burner size tested [8]. That is to say, flames flicker especially boundaries will emerge many times in a second casually no matter what reasons cause the fire. The fact that how the flicker and oscillate of the next frame will change is up to the state of current frame is exactly coincided with the Hidden Markov Chain's precondition -for the sequence of random variables to be a Markov Chain the conditional probabilities must only be a function of the last random variable in the condition [9]. Therefore, fire detection can be well appropriate for applying HMM.

HMM is a doubly stochastic process, which includes stochastic chain process and output process. In our method, first two Hidden Markov Models including fire model and non-fire model are trained through large numbers of fire and non-fire videos. Then when given an observation sequence under test, similarities between the test sequence and the two models are calculated respectively by using Viterbi algorithm and at last the larger similarity of the two will lead us to the conclusion that the observation sequence is fire or not. How to train HMM is showed in subsection 2.4.1 where algorithm called Baum-Welch re-estimation is explained. In subsection 2.4.2 how to apply the HMM we have trained is illustrated where Viterbi algorithm is utilized.

2.4.1 HMM training

In HMM training, we use 30 frames of the temporal history of the red channel of a pixel to form a sequence. Although the results of moving pixels detection which comes out as "color values" are known, the input of the HMM is a sequence of states. Therefore, we need an algorithm to change "color values" to states which is described in Fig.5.

We define three states in HMM, consisting of F1, F2 and NF. F1 and F2 represent the two states of fire as the color varies within a flame and the NF stands for non-fire state. The "color values" is defined as: If the pixel under test is not a moving pixel, the color value will be set to 0, otherwise the color value will be equal to the red channel value of the pixel in RGB color representation.

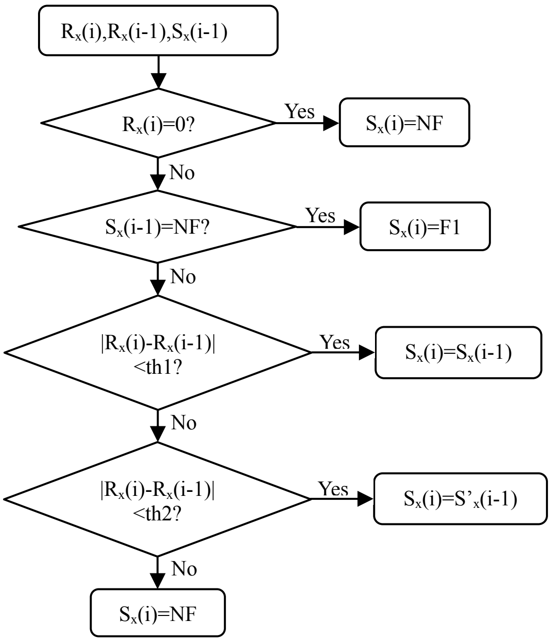


Fig.5 Flow chart of changing "color values" to states

In this figure, $R_x(i)$ indicates the "color value" of the pixel x in the frame i; $R_x(i-1)$ denotes the "color value" of the pixel x in the frame i-1; $S_x(i-1)$ stands for the state of the pixel x in the frame i-1; $S'_x(i-1)$ means if $S_x(i-1)$ is F2, then $S'_x(i-1)$=F1 and if $S_x(i-1)$ is F1, $S'_x(i-1)$ will be F2.

With $\lambda^{(t)}=<\{a_{ij}\},\{b_{ij}\},\pi_i>$, estimate expectation of following quantities:
1). Expected number of state i visiting;
2). Expected number of transitions from i to j.

$\Updownarrow$

With following quantities:
1). Expected number of state i visiting;
2). Expected number of transitions from i to j.
Obtain the Maximum Likelihood of
$\lambda^{(t+1)}=<\{a'_{ij}\},\{b'_{ij}\},\pi'_i>$

Fig.6 Baum-Welch re-estimation algorithm

Two kinds of data including fire and non-fire are collected to establish two models. The data are processed by the above converting algorithm and results in two kinds of sequences of states with which we use Baum-Welch re-estimation algorithm to estimate the parameters of HMM (Fig.6).

We first give an initial value of λ, secondly, carry out iterative procedures that locally maximize $P(O|\lambda)$, here, O is the training data, then select the parameters that maximize the probability function of the observed sample using Maximum Likelihood Estimation, finally re-estimate the value of λ. Through these steps the two fire and non-fire HMM can be achieved.

2.4.2 HMM application

Given a Hidden Markov Model and a sequence of states of one pixel, we can get the matching score between them through Viterbi algorithm as the followings [Table1]. Compared the matching score between the given sequence and two Hidden Markov Models, the result that the pixel is fire or not will be given by the larger matching score(Fig.7).

<Table1> Viterbi algorithm

1). Introduction:

$$\delta_1(i)=\pi_i b_i(x_i), \quad 1 \le i \le N$$
$$\psi_1(i) = 0$$

2). Recursion:

$$\delta_{t+1}(j) = \max_{0\le i\le N} \delta_t(i)a_{ij}b_j(x_{t+1})$$
$$1 \le t \le T-1$$
$$\psi_{t+1}(j) = \arg\max_{0\le i\le N} \delta_t(i)a_{ij}$$
$$1 \le j \le N$$

3). Termination:

$$P^* = \max_{0\le i\le N} \delta_T(i)$$
$$q_T^* = \arg\max_{0\le i\le N} \delta_T(i)$$

4). Path backtracking:

$$q_t^* = \psi_{t+1}(q_{t+1}^*)$$
$$t=T-1,\ldots,1$$

In <Table1>, $\delta_{t+1}(j)$ is path probability, and π_i is initial state distribution probability, $\{a_{ij}\}$ is the state transition probability, $\{b_j\}$ is observation probability and $\psi_{t+1}(j)$ is the state sequence.

Fig.7 The output result after using HMM (continued)

2.5 Integration

In this subsection, the algorithms used are arranged again to build a whole procedure of our method as shown in Fig.8 and the method of how to integrate the algorithms represented above will also be given the details.

The decision that one pixel is fire or not can be obtained after processed by HMM, however, what we concern is a cluster is fire or not. The criterion to define a cluster is fire or not is that if the rate of fire pixels of the cluster accounts for the whole number of pixels of the cluster is more than a threshold, the cluster will be labeled as fire.

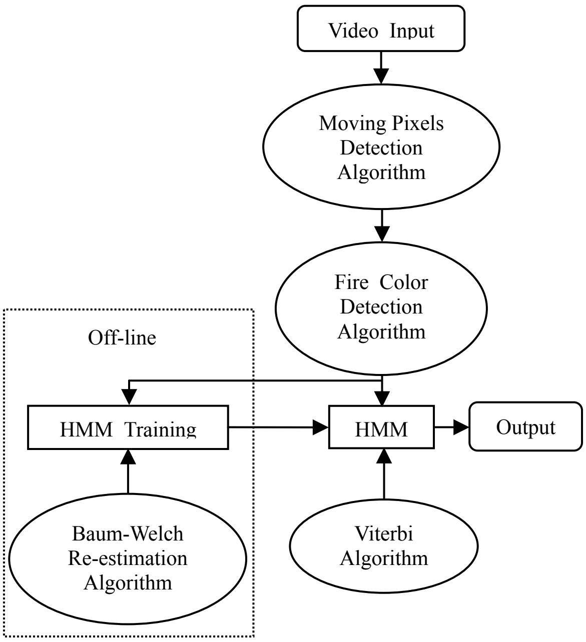


Fig.8 Integration of algorithms

3. Experimental results and performance analysis

We have executed the proposed fire detection on Intel(R) Core(TM)2 CPU 6400 @2.13GHz PC with 360×240 image size. In our work, we choose three groups of compared experiments to validate the performance of our method. The first one is a scene that there is just fire in the night which is the basic test (Fig.9); the second experiment is in the scene of fire in night with disturbed light which is the same color with fire (Fig.10); the last test is under the situation that a person is smoking with a moving and fire-color resembled object on the person (Fig.11). As experimental results reveal, false fire detection has been markedly reduced in our program and the proposed algorithm could be an effective and real-time solution to the fire detection.

Fig.9 Original (left) and result (right) images with only fire

Fig.10 Original (left) and result (right) images with fire and disturbed light

Fig.11 Image with a smoking and moving person on a red bag, the left image is an original image, the middle image is the fire-color processed image and the right one is the result image treated by HMM(without fire)

4. Conclusion

Based on the proposed method and experiments, we provide an approach to detect fire in video surveillance, in the future, we will make use of this program to monitor the dangerous situations such as fire detection of tunnels coordinated with the hardware device.

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