Journal of Computational Information Systems 8: 17 (2012) 7355–7365
Available at http://www.Jofcis.com

Method Design of Small-scale Fire Detection

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Abstract

In this paper, we propose a small-scale fire detection method. This fire detection method consists of two steps. The first step of the proposed method exploits the color and the intensity variation information of the pixels to determine the candidate to the fire region. The second step refines the results of the first step to obtain the ultimate fire region. The first and second steps have the following merits and effects: the first step is able to detect almost all of the true fire regions but it also takes some non-fire regions as the fire, which are referred to as 'false' fire regions. On the other hand, the second step can greatly eliminate the 'false' fire regions generated from the first step. The second step achieves this by using a learning method that first captures a number of training samples of the moment features of the true and false fire regions generated from the first step and then exploits the training samples and an improved K nearest neighbor (KNN) classifier to produce the ultimate detection result. The experimental results show that the proposed method performs very well in detecting small-scale fire.

Keywords: Fire Safety; Fire Detection; Pattern Recognition

1 Introduction

Fire detection is very significant and in many fields a fire detection system is necessary [1,2,3]. Fire detection is usually performed using a pattern matching approach, which has been widely used in the field of pattern recognition [4]. In the past, many video-based fire detection methods have been proposed [5-18]. It is clear that the video-based fire detection technology is usually much cheaper than the sensor-based detection methods such as the fire detectors [19,20,21]. Moreover, video-based fire detection is less affected by the distance, whereas the conventional sensor-based detection is usually effective only within a small distance.

In reviewing literatures, we see that some researchers exploit the information of the fire color [8-13] to detect the fire. It is assumed that the color components of the fire region have some distinctive characteristics in comparison with the other regions. Researchers also use the temporal variation of fire intensity [14,15,16] to detect the fire. In other words, the intensity variation information of the pixels is exploited to distinguish the fire from other regions. Some methods

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September 1, 2012

also simultaneously use the temporal and spatial information of the image to detect the fire [17,18]. Recently Turgay Celik et al. [22] developed a statistical model on the color for detecting the fire. Most of the state of the art color-based approaches in video fire detection use RGB color space, sometimes in combination with HSI/HSV saturation [23, 24,25]. One of the main reason for using RGB is the equality in RGB values of smoke pixels and the easily distinguishable red-yellow range of flames [23]. Rule-based techniques have been widely used to detect the firecolored pixels. Typical examples of these techniques include Gaussian-smoothed color histograms [26], statistically generated color models [27], and blending functions [28]. The fact that literatures [24-28] have been frequently referenced also evidences that the above techniques are the state of the art video fire detection techniques [23].

We also note that how to reduce the false fire alarm rate is a challenge problem. False alarms might be caused by slow moving clouds, flashing lights on vehicles and building lights in residential areas, etc. [29,30]. Though the literatures [29,30] have proposed some methods to reduce false fire alarms, these methods are not very applicable to our applications. In our applications, the goal is to detect small-scale fires in the self-service bank and the majority of false fire regions are caused by moving people whose clothes have similar color to the fire, the solar flare and flicking objects color of which is similar to that of the fire. As a result, we must devise new methods.

With this paper, we use a two-step fire detection method to intelligently monitor the possible fire in the self-service bank. The first step of the proposed method tries its best to determine all the candidates to the fire regions using the color and the intensity variation information of the pixels. As the obtained 'fire regions' include false fire regions, the second step further exploits a learning-based method to eliminate the false fire regions and to ultimately identify the genuine fire regions. A dedicatedly designed improvement to the conventional KNN classifier is the key of the second step.

The remainder of the paper is organized as follows: in Sections 2 we describe the first and second steps of the proposed method. In section 3 we present the experimental results of fire detection on a number of videos. In section 4 we offer our conclusion.

2 The Proposed Fire Detection Method

We show the main flow chart of the proposed fire detection method in Figure 1. The first and second steps of the fire detection method are carried out in sequence. If within 30 video frames the second step of the fire detection method obtains one positive result, then our method triggers a fire alarm. In Figure 1, 'positive result' means that the first or second step of our method detects the 'fire', whereas 'negative result' means that the first or second step of our method does not detect the 'fire'.

2.1 The first step of the proposed fire detection method

Before we use the color and the intensity change information of the pixel to obtain candidates to the fire region, we have explored the color-based fire detection method presented in [13]. The color-based method regards that if the pixel satisfies the following conditions, then it is a fire pixel:

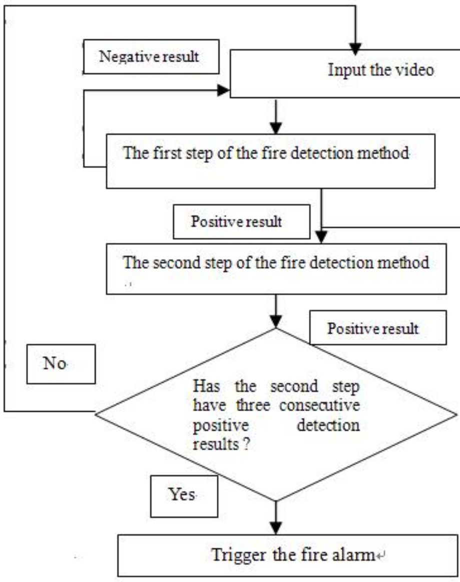


Fig. 1: The main flow chart of the fire detection method

$$R > G > B \tag{1}$$

$$R > R_t \tag{2}$$

$$S \geq (255 - R) * S_t / R_t \tag{3}$$

where the thresholds R_t and S_t should be in the range of $55 \leq S_t \leq 65$ and $115 \leq R_t \leq 135$, respectively. In the experimental section we set R_t and S_t to $R_t = 65$ and $S_t = 135$. R, G, B denote the red, green and blue components of the RGB color, respectively. We exploit the following formula to convert the RGB color into S:

$\max = \max(R, G, B)$, $\min = \min(R, G, B)$

$$S = \begin{cases} 0 & if \quad \max = 0 \\ \frac{\max - \min}{\max} & otherwise \end{cases} \qquad S = \begin{cases} 0 & if \quad \max(R, G, B) = 0 \\ 1 - 3 \times \frac{B}{R+G+B} & others \end{cases}$$

We apply (1), (2) and (3) to the video frame to generate a binary fire color image. Let I_m^0 denote the original video frame. The binary fire color image F_m generated from I_m^0 has the same size as I_m^0. F_m and I_m^0 have the following relationship: for each pixel of I_m^0, if it satisfies (1), (2) and (3), then the corresponding pixel in F_m is set to 1; otherwise it is set to zero.

When we exploit the color criterions (1), (2) and (3) and assume that if the connected region of 'fire' pixels are more than the threshold then the connected region of 'fire' pixels are in the fire region, we can detect almost all of genuine fire regions. However, we also obtain a large number of false fire regions. Some genuine and false fire regions are shown in Figure 2. We found that these false fire regions might be caused by the indoor lamp light (Figure 2-(b)), the light of the headlight set in a moving car (Figure 2-(c)), or the people whose clothing contains a region that has the color of fire (Figure 2-(d)).

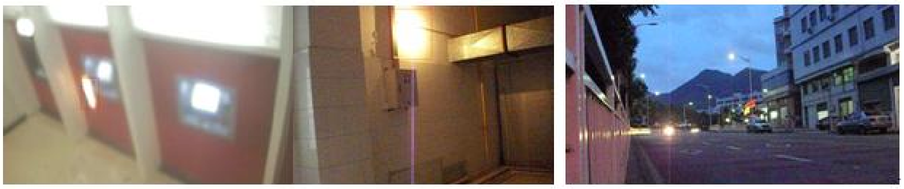


Fig. 2: Some genuine and false fire regions obtained using the criterions (1), (2) and (3)

We note that the fire flame has the following distinct dynamic characteristic: the fire flame is indeed a moving object and the fire flame flicker has a frequency of about 10HZ [7]. On the other hand, the false fire regions such as those shown in Figure 2 usually have no this characteristic. Thus, if we take into account the dynamic characteristic of the fire when determining the fire region, we will be able to eliminate the false fire regions obtained using the color criterions (1), (2) and (3). Moreover, though the fire flame is dynamic but the whole fire region is always located in a fixed location, whereas other moving objects have varying locations. Thus, in order to reduce false fire detections and accurately detect the fire, the first step of our fire detection method simultaneously uses the color and intensity variation information of the pixels to determine candidates to the fire region.

We present the main steps of the first step of our proposed fire detection method below.

Step 1. Calculate the foreground image.

Let I_m $(m = 1, 2, \ldots, M)$ be a series of frames of the foreground image generated from the video. In this paper, I_m is simply set to the difference between two consecutive original video frames. That is, we calculate I_m using $I_m(p, q) = |I'^0_{m+1}(p, q) - I'^0_m(p, q)|(p = 1, \ldots, P, q = 1, \ldots, Q)$, where I'^0_{m+1} and I'^0_m represent the image matrices of the gray images of the $m + 1$th and mth original video frames obtained using the video camera, respectively. We use $Gray = R * 0.299 + G * 0.587 + B * 0.114$ to convert the RGB color to the gray intensity. We use the Otsu method [31] to obtain the binary image I'_m of I_m. In other words, I'_m is the binary image of the so-called motion region of the m frame. We use $I'_m(x, y, t)$ to stand for the value of the pixel located in (x, y) at time t.

Step 2. Dynamically update the MHI. Put the current video frame into the cache.

After we obtained consecutive binary images $I'_1, I'_2, \ldots, I'_m$, we used the following formula to calculate motion history image (MHI) [35]. First, history matrix $H_m(x, y)$ is defined by

$$H_m(x,y) = \begin{cases} m & if \;\; I'_m(x,y) = 1 \\ 0 & if \;\; I'_m(x,y) = 0 \;\; and \;\; H_{m-1}(x,y) \le (m-\delta) \end{cases}$$

. $H_m(x, y)$ stands for an element in the history matrix with coordinate (x, y) at time-point m. m also indicates that the m-th frame is being processed. δ stands for the maximum duration i.e. the number of frames in a motion. In our method δ is set to 5. If $m \ge \delta$, the MHI will be updated using.

$$MHI_m(x,y) = \begin{cases} \frac{H_m(x,y)-(m-\delta)}{\delta} \times 255 & if \;\; H_m(x,y) \ne 0 \\ 0 & others \end{cases}$$

. $MHI_m(x, y)$ stands for the intensity of the pixel with coordinate (x, y) in the m-th frame. As MHI records the history information of the motion region, it allows us to obtain the representation that varies with the time of the motion object.

Step 3. If thirty video frames have been cached, then we use criterions (1), (2) and (3) to determine binary fire color images respectively generated from the first and fiftieth video frames. Let F_1 and F_2 be the binary fire color images respectively corresponding to I_1^0 and I_{30}^0. As shown previously, in F_1 and F_2 the fire pixel is set to 1 and the other pixels are set to zero.

Step 4. Produce the ultimate fire region.

We execute the logical AND operation

$$F_3 = F_1 \quad AND \quad F_2 \tag{4}$$

to get F_3. Our motivation of using Eq.(5) is if in one video frame there is a region that has the color of fire but in the following video frame the color of the same region is not the color of fire, then it is usually a moving object in which some region has the color of fire rather than the genuine fire. We refer to F_3 as accumulative fire region. We further execute the following logical AND operation to refine the fire region:

$$F = F_3 \quad AND \quad I_{MHI} \tag{5}$$

F is referred to as the ultimate fire region. Eq.(6) enables us to take into account the dynamic characteristic of the fire flame when determining the fire region. Suppose that there is a still region that has the color of fire, then the same region of its MHI should usually have zero-values and this region will not be took as the ultimate fire region by our method. In conclusion, the uses of Eqs.(6) and (5) can prevent still and moving targets that have the color of fire from being taken as the fire, respectively. For example, though Figures 2-(b), 2-(c) and 2-(d) are erroneously regarded as 'fire' regions by the color criterions (1), (2) and (3), the first step of our proposed fire detection method does not do so.

Step 5. Determine the 'true' fire region

We identify all connected regions in F and take the connected region of 'fire' pixels whose area is larger than a predefined threshold th as 'true' fire regions. In the experimental section of this paper, the predefined threshold is determined by using a fire and non-fire videos.

2.2 The second step of our proposed fire detection method

The first step of our proposed fire detection method performs very well in finding the genuine fire regions; however, it still causes some false fire regions. In order to reduce the false fire detections, we propose to modify our proposed fire detection method using a learning method. The proposed learning method is referred to as the modification of the fire detection method, present in Section 2.1. We also refer to it as the second step of our proposed fire detection method.

The second step of our proposed fire detection method first collects a number of training samples from the 'fire regions' obtained using the first step and then exploits the training samples and an improved KNN classifier to greatly eliminate the false fire detections.

2.2.1 Training sample collection

As the fire detection results generated from the first step include genuine fire and 'false' fire, the generated 'fire regions' indeed can be classed into two groups, genuine fires and 'false' fires. We first calculated the Hu's seven-order invariant moment features [32] of 851 genuine fire regions obtained using the first step and refer to the moment features of each genuine fire region as one positive sample. We then calculated the Hu's seven-order invariant moment features of 769 'false' fire regions obtained using the first step and refer to the moment features of each 'false' fire region as one negative sample. The formulae of the Hu's seven-order invariant moment are as follows:

$g_1 = \mu_{20} + \mu_{02}$;

$g_2 = (\mu_{20} - \mu_{02})^2 + 4\mu_{11}^2$;

$g_3 = (\mu_{30} - 3\mu_{12})^2 + (3\mu_{21} - \mu_{03})^2$;

$g_4 = (\mu_{30} + \mu_{12})^2 + (\mu_{21} + \mu_{03})^2$;

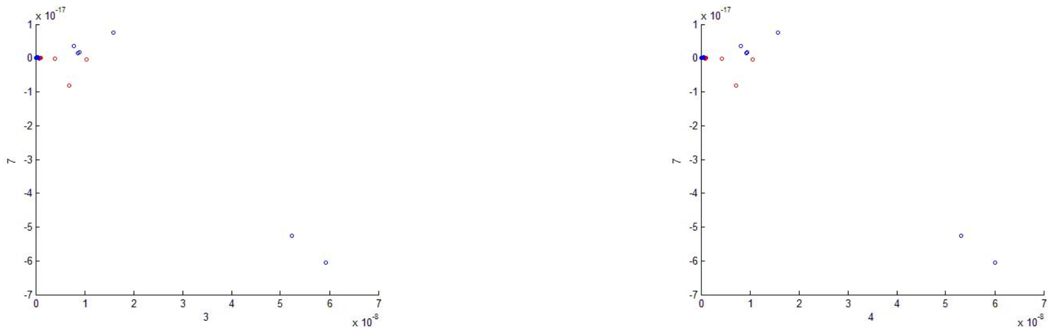
$g_5 = (\mu_{30} - 3\mu_{12})(\mu_{30} + \mu_{21})[(\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2] + (3\mu_{21} - \mu_{03})(\mu_{21} + \mu_{03})[3(\mu_{30} - \mu_{12})^2 - (\mu_{21} + \mu_{03})^2]$;

$g_6 = (\mu_{20} - \mu_{02})[(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2] + 4\mu_{11}(\mu_{30} + \mu_{12})(\mu_{21} + \mu_{03})$;

$g_7 = (3\mu_{21} - \mu_{03})(\mu_{30} + \mu_{12})[(\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2] + (3\mu_{12} - \mu_{30})(\mu_{21} + \mu_{03})[3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2]$;

μ_{pq} is the so-called $p+q$-order central moments and defined as $\mu_{pq} = \frac{1}{m_{00}^{\frac{1}{2}(p+q+2)}} \sum_{(x,y)\in S} (x-\bar{x})^p (y-\bar{y})^q f(x,y)$. $f(x,y)$ denotes the intensity of the pixel located in (x,y). $m_{00} = \sum_{(x,y)\in S} f(x,y)$. $(\bar{x},\bar{y})$ stands for the centroid of the image region.

We use Figure 3 to show the linear separability of the positive and negative samples. We see that when two components of these samples are shown, there exists clear linear separability between the positive and negative samples.



(a) (b)

Fig. 3: Illustrations of the linear separability of the positive and negative samples. Only two components of the Hu's seven-order invariant moment features are depicted. (a) depicts the third and seventh components. (b) depicts the fourth and seventh components. The red and blue dots denote the positive and negative samples, respectively.

2.2.2 An improved KNN classifier

In this subsection, we describe how we design an improved KNN classifier for greatly eliminating the false fire detection results generated from the first step of our method. Actually, before doing so, we have attempted to use the conventional KNN classifier for reducing the false fire detection results. However, we see that the conventional KNN classifier with different Ks cannot produce a satisfactory result. Specifically, a KNN classifier with a certain K cannot simultaneously obtain a low false fire detection rate and low missing detection rate.

We think that the KNN classifier can produce a good result only under the following conditions: first, the K should be a proper value (too large K will make the KNN classifier obtain a worse classification result owing to the interference of the 'far' nearest neighbors and too small K will also not obtain a good result owing to too few available nearest neighbors). Second, the numbers of positive and negative samples should be consistent to the prior probabilities of the fires and non-fires in the real-world cases. In other words, if we know the priors of different classes and we can generate samples in the way where the ratio of two kinds of samples from two classes is the same as the ratio of the prior probabilities of the two classes, the conventional KNN classifier can obtain a good result. However, in real-world applications not only the priors of different classes are usually not clearly known but also we usually cannot obtain an arbitrary number of positive and negative samples. Consequently, the conventional KNN classifier is usually not able to produce a good performance. The following extreme case can illustrate this: suppose that there are two classes and the true prior probabilities (unknown for people) of the first and second classes are 0.1 and 0.9, respectively. If the first class has much more available training samples than the second class (this is possible under a special sample collection condition), then the conventional KNN classifier probably has a large number of classification errors for the testing sample from the second class.

In this paper, before applying the KNN classifier, we have spent much time to generate positive and negative samples. However, we have no knowledge on the true priors of the involved two classes and do not know whether the numbers of the generated positive and negative samples are consistent with the priors of these two classes. As a result, we design an improved KNN classifier that adopts the following criterion: the K and the classification rule of the KNN classifier should be adjustable and the K and the classification rule corresponding to the optimal classification result are the best ones. This improved KNN classifier is referred to as adjustable KNN classifier (AKNNC). We found that AKNNC could obtain the best result, when K was set to 11 and classification rule is "when among the 11 nearest neighbors of a testing sample there are not less than four positive samples, the testing sample is taken as a fire sample and the detection result is referred to as a positive result; otherwise, it is taken as a false fire sample (i.e. negative sample)". Figure 4 shows some examples of the cases where the first step of our method produces 'false' fire regions, whereas the second step of our method eliminates all these 'false' fire regions by exploiting the proposed improved KNN classifier. As presented earlier, if within 30 video frames the second step of the fire detection method obtains one positive result, then our method triggers a fire alarm.

We can formally present AKNNC as a classification procedure that works as follows. It first determines K nearest neighbors of the testing sample from all the training samples. If among the K nearest neighbors n or more than n ones are from the first class, then AKNNC regards that the testing sample is truly from the first class. In order to properly determine K and n in AKNNC, we can attempt to use the following means: first, we generate a validation set that consists of a number of samples of false and true fire regions and in which the class label of each region is known as false and true fire region. Second, we use the training samples to evaluate the classification performance of AKNNCs with different K and n on the validation set. Third, we can select the K and n that produce the best performance for the validation set as the optimal parameters of AKNNC and use them to perform classification for all newly coming testing samples.

Fig. 4: Some examples of the cases where the first step of our method produces 'false' fire regions, whereas the second step of our method eliminates all these 'false' fire regions by exploiting the proposed improved KNN classifier.

3 Experiments

We collected a number of videos from the self-service hall of the China bank. We also recorded some fire videos by ourselves. In a very small portion of these videos there is the fire and in the most of the videos there is no fire. The videos captured by us are mainly true fire videos or the ones that contain objects looking like fire. However, the videos collected from the self-service hall of the China bank are mainly non-fire videos and were captured by cameras "SONY SSC-E478P" set in the wall of the hall. The resolution of these cameras is 540TVline. When recording the videos, we used an ordinary camera with the resolution of 352×288. The videos collected from the self-service hall of the China bank were captured by the wide dynamic rang cameras set in the wall of the hall. Most of these cameras have 2.8mm-12mm adjustable lens. The resolution of these cameras is 540TVline. In order to determine a proper threshold th, we used a number of examples of videos to conduct experiments. These examples show that 50 is very suitable for our applications. We used 77 fire videos and 169 non-fire videos to test the proposed fire detection method. We use Figure 5 to show some examples of detected fire. Table 1 shows the experimental results of our method and the method proposed in [33]. False reject rate (FRR) is defined as the ratio of the number of erroneously rejected fire videos to that of all the fire videos. False accept rate (FAR) is defined as the ratio of the number of the non-fire videos that were erroneously accepted as fire videos to the number of all the non-fire videos. AKNNC (i.e. the second step) in our method works as follows: it first determines 17 nearest neighbors for the testing samples. If more than 11 nearest neighbors are positive samples, then our method outputs a positive result to show that the video contains the fire. 17 and 11 are indeed the optimal values of K and n of AKNNC obtained in the experiment.

We also respectively replaced the second step of our method by conventional KNN and SVM and used the above videos to conduct experiments. The experimental results show that low FRRs and very high FARs (44.4% and 49.7%) were obtained. This illustrates that our method is theoretically reasonable and feasible for real-world applications. Especially, our method is suitable for different real-world applications where the numbers of positive and negative samples might vary in a large range.

Fig. 5: Illustrations of correct fire detection results

Table 1: The experimental results of our method and the method proposed in [33] on 77 fire videos and 169 non-fire videos

	Number of erroneously rejected fire videos	Number of the non-fire videos that were erroneously accepted as fire videos	FRR	FAR
Our method	2	30	2.6%	17.8%
The method in[33]	8	13	10.4%	7.7%
Replace the second step by SVM	1	84	1.3%	49.7%
Replace the second step by conventional KNN	1	75	1.3%	44.4%

Table 2: The experimental results of our method and the method proposed in [33] on the 13 fire videos shown in [34]. As all the videos are fire vides, all the methods have the same FAR of zero

	Number of erroneously rejected fire videos	FRR
Our method	3	23%
The method proposed in [33]	5	38%
Replace the second step by SVM	3	23%
Replace the second step by conventional KNN	3	23%

We also collected some fire videos from other scenarios and used them to test our method. The experimental results show that our method is also applicable to fire detection of these scenarios. For example, when we used the 13 fire videos shown in [34] to test our method and the method proposed in [33], the experimental result shows that our method also obtains a much lower FRR. Table 2 also shows that when the second step of our method was replaced by conventional KNN or SVM, the method obtained the same FRR.

4 Conclusions

The proposed two-step fire detection method has the following noticeable merits: first, the proposed two steps enable the color and pixel change information to be fully exploited in detecting the fire. In particular, the consecutive implementation of the first and second steps of the proposed method makes it able to produce a low false detection rate and low missing detection rate. Second, the proposed method integrates the motion segmentation, pattern classification and machine learning technologies in a very good way. It seems that in the first step, the feature-based detection scheme plays an important role in achieving the low missing detection rate on the fire. The learning-based scheme, i.e. the designed improved KNN classifier contributes the most to the low false detection rate. As the improved KNN classifier has adjustable decision rules, it is more suitable and smart for the real-world applications where the priors of different classes are not clearly known. The experimental results support the above claims.

Acknowledgements

This article is partly supported by Program for New Century Excellent Talents in University (Nos. NCET-08-0156 and NCET-08-0155), NSFC under grants No. 61071179, 60803090 , 60902099 and 61001037as well as the Fundamental Research Funds for the Central Universities (HIT.NSRIF. 2009130).

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