An Efficient Method for Vision-Based Fire Detection Using SVM Classification

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***Abstract*—In this paper, we present a new vision-based algorithm for fire detection problem. The algorithm consists of three main tasks: pixel-based processing to identify potential fire blobs, blob-based statistical feature extraction, and a support vector machine classifier. In pixel-based processing phase, five feature vectors based on RGB color space are used to classify a pixel by using a Bayes classifier to build a potential fire mask (PFM) of image. Next step, a potential fire blob mask (PFBM) is computed by using the difference between two consecutive PFM and a recover technique. In blob-based phase, for each potential blob in a potential fire blobs image (PFBI) an 7-feature vector are evaluated; this vector includes three statistical features of colour, four texture parameters and one shape roundness parameter. Finally, a SVM classifier is designed and trained for distinguish a potential fire blob are fire or fire-like object. Experimental results demonstrate the effectiveness and robustness of the proposed method.**

***Keywords*-Vision-based fire detection; support vector machine classifier; pixel-based processing; blob-based processing;**

I. Introduction

Fire is one of the leading hazards affecting everyday life around the world, so that if we can alarm fire as soon as possible, we will minimize loss of human lives and property. Traditional fire detection systems usually use heat sensors, optical sensors, ion sensors, or thermocouples as fire detectors [1]. Although these sensors often work well and efficiently in some particular condition and situation, they also have some disadvantages. These sensors suffer from the transport delay of the fire (heat or smoke particles) to the sensor, and thus increase detection latency. As point detectors, the range of detection is also limited. Other methods such as beam or aspirated smoke detectors try to reduce the detection latency, but do not really solve the problem. In addition, all these methods usually lack effective human-in-the-loop validation capabilities [2].

Vision-based Fire Detection (VFD) is a relative new technology that detects fire through intelligent analysis of video and image using advanced analytical algorithms. There are several advantages of VFD over traditional methods. First, video camera is a volume sensor. It potentially monitors a larger area and has much higher probability of successful early detection of smoke or flame. VFD is suitable for cases where traditional point sensors are difficult to deploy such as large open facilities and outdoor locations. Second, a video camera has the capability of remote verification. In case of alarms, human operators are kept in the loop for further verification to minimize false alarms. Third, with the growth of surveillance and security industries, more and more surveillance cameras have been installed for various security and safety applications. VFD can be easily embedded into existing systems to enable more intelligent functionality [2]. Finally, VFD even has the potential to be placed on mobile platforms such as planes and robots to detect and fight fire.

Over the last years, VFD has been received wide attention from industrial and academic researchers. Most of the vision-based fire detection systems apply some type of hybrid model combining color, motion, flickering, edge blurring, and textures. Some papers in field of VFD have been attractive are [1] - [11]; in these, color is considered one of the most important clues for fire detection. Beside, some other clues such as temporal changes, spatial difference, flickering are also involved.

In [3], Chao-Ching Ho at el. analyzed the spectral, spatial and temporal characteristics of the flame and smoke regions in the image sequences. Then, the continuously adaptive mean shift vision tracking algorithm was employed to provide feedback of the flame and smoke real-time position at a high frame rate. P. V. K. Borges and E. Izquierdo in [4] analyzed the frame-to-frame changes of specific low-level features such as color, area size, surface coarseness, boundary roughness, and skewness within estimated fire regions to describe potential fire regions and used Bayes classifier to indicate a frame contains fire or not. In [5], Celik T. et al. developed two models, one for fire detection and the other for smoke detection. For fire detection, the concepts from fuzzy logic were used to make the classification fire and fire-like colored objects. For smoke detection, a statistical analysis was carried out using the idea that the smoke shows grayish color with different illumination. In [6] , the authors also used a probabilistic metric to threshold potential fire pixels. This was achieved by multiplying the probabilities of each individual color channel being fire. Habiboglu et al. proposed a video-based fire detection method, in [7], which used color, spatial and temporal information by dividing the video into spatio-temporal blocks and used covariance-based features extracted from these blocks to detect fire. In [8], the authors proposed a method based on the changes of the statistical features in the fire regions between different frames and then classified by Bayes classifier, and the final result is defined as fire-alarm rate for each frame. Decision function of fire-pixel in [9] was mainly deduced by the intensity and saturation of red component, the color are also main clues in [10] and [11].

Because of the large variations of these features vision-based fire detection algorithms become great challenges. The major problem of current vision-based fire detection systems is robustness to handle false alarm sources, for example, waving red tree leaves in the fall, reflections of sun on water, strobe lighting, moving people with red shirts, etc. In general, fire detection systems first use some key features as a precondition to generate seed areas for candidate fire regions, and then use the other features to determine the existence of fire in candidate fire regions. In most existing approaches, the color information and their derived descriptors like area size, surface coarseness, boundary roughness and skewness were mainly used for classification features. However, using the color channels is not reliable enough to perform classification. Similarly, the classifying tasks based on the features derived from the color information can not perform properly.

In this paper, we present a new vision-based fire detection algorithm. The algorithm consists of three modules: pixel-based processing to identify potential fire blobs, blob-based statistical feature extraction, and a support vector machine classifier. In pixel-based processing phase, the color and the difference between two frames are computed to construct potential fire blobs. In blob-based phase, statistical features consist of eight elements of a blob are evaluated. Finally, a SVM classifier is designed and trained for distinguish a potential fire blob is fire or fire-like object. The rest of this paper is organized as follows. In Section II, we present an overview of SVM for classification. In Section III we propose our algorithm of fire detection, including a phase of pixel-based processing, a method of feature extraction based on potential fire blobs and a support vector machine classifier. Section IV presents the experimental results and some discussion. Finally, Section V concludes the paper.

II. SVM FOR CLASSIFICATION

Support vector machines (SVM) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. As presented in [12], SVM were originally first developed for binary classification problems, is the use of hyper-planes to define decision boundaries separating between data points of different classes. SVM are able to handle both simple, linear, classification tasks, as well as more complex, i.e. nonlinear, classification problems. Both separable and non-separable problems are handled by SVM in the linear and nonlinear case. The idea behind SVM is to map the original data points from the input space to a high-dimensional, or even infinite-dimensional, feature space such that the classification problem becomes simpler in the feature space. The mapping is done by a suitable choice of a kernel function.

In this work we use C-Support Vector Classification (C-SVC) in LIBSVM at [13] for tranning and classifying. Therefore, in this section we represent a brief of C-SVC that was given in [13], reference [12],[14] for more detail about SVM.

Given training vectors $x_i \in R^n, i = 1, ..., l$, in two classes, and an indicator vector $y \in R^n$ such that $y_i \in \{1, -1\}$ solves the following primal optimization problem.

$$\min_{w,b,\xi}(\frac{1}{2}w^T w + C\sum_{i=1}^{l}\xi_i) \tag{1}$$

subject to

$$y_i(w^T\phi(x_i) + b) \geq 1 - \xi_i, \tag{2}$$

where $\xi_i \geq 0, i = 1, ..., l$, $\phi(x_i)$ maps x_i into a higher-dimensional space and C ¿ 0 is the regularization parameter. Due to the possible high dimensionality of the vector variable w, usually we solve the following dual problem.

$$\min_{\alpha}(\frac{1}{2}\alpha^T Q\alpha - e^T\alpha) \tag{3}$$

such that

$$y^T\alpha = 0 \tag{4}$$

in which, $0 \leq \alpha_i \leq C, i = 1, ..., l,$, $e = [1, ..., 1]^T$ is the vector of all ones, Q is an $l \times l$ positive semidefinite matrix, $Q_{ij} \equiv y_i y_i K(x_i, x_j)$, and $K(x_i, x_j) \equiv \phi(x_i)^T\phi(x_j)$ is the kernel function.

After problem (1) is solved, using the primal-dual relationship, the optimal w satisfies

$$w = \sum_{i=1}^{l} y_i\alpha_i\phi(x_i) \tag{5}$$

and the decision function is

$$sgn(w^T\phi(x) + b) = sgn(\sum_{i=1}^{l} y_i\alpha_i K(x_i, x) + b) \tag{6}$$

The values of $y_i\alpha_i \forall i$, b, label names, support vectors, and other information such as kernel parameters in the model will be store for prediction.

III. Vision-based fire detection using SVM

In contrast to some works, we propose a new approach to solve the problem of fire detection by determining potential fire blobs based on the color and temporal change of pixel, and then this region is used to establish a features vector. Finally, support vector machine classifier is applied to indicate the potential region is fire or fire-like object. The diagram of our proposed method is shown in Figure 1.

A. Pixel-based processing

A fire region is generally brighter than neighborhood in indoor and outdoor scene. In addition, the shape of fire can be constantly changed by airflow caused by wind or burning material. From these characteristics, we first detect candidate fire regions using fire color information and frame difference. In general, the researchers usually detect moving regions first and then they use fire-color model to determine potential fire regions. However, in the early state of fire the flame flickers slowly. For this reason, in the proposal we determine potential fire regions as following sequence: use fire-color model to detect possible fire region, and then using the difference between two frames to find potential region, finally we use region growing technique to improvement quality of potential fire regions.

1) Fire-color pixel detection: The fire-color is one of the most important clues. All fire-color model proposed in [1]-[9] work well in some particular situations and also do not work well in some others. To overcome this difficulty, in this paper the authors using the model of fire-color proposed in [15]. Using color space RGB, this segmentation method separates a pixel into two class, fire or non-fire. Different from other approach, this proposal uses several combinations from three elements R, G, B to establish 5-feature vectors for a pixel as following:

- $X^{I} \in$ 3-dimention space of [R, G, B]
- $X^{II} \in$ 2-dimention space of [R, G]
- $X^{III} \in$ 2-dimention spcae of [R, B]
- $X^{IV} \in$ 2-dimention space of [G, B]
- $X^{V} \in$ 3-dimention space of [R-G, G-B, R+G+B]

So that, for pixel p at location (x, y) the classifier will investigate on all features vector $x^{I} = [r, g, b]^T$, $x^{II} = [r, g]^T$, $x^{III} = [r, b]^T$, $x^{IV} = [g, b]^T$ and $x^{V} = [r - g, g - b, r + g + b]^T$, where r, g, b are three element R, G, B of p, to indicate p is fire or non-fire pixel. In this research, the Bayes classifier as proposed in [15] is used to construct a two-class classification. In this phase, for the input image I, using the trained decision function to establish *Potential Fire Mark* (PFM) as

$$PFM(x, y) = \begin{cases} 1 & \text{if } f_p(a(x, y)) > 0, \\ 0 & \text{Otherwise,} \end{cases} \tag{7}$$

where $PFM(x, y)$ is potential fire mark at (x, y), $a(x, y)$ is the all features vector of pixel at (x, y) in I and $f_p(a(x, y))$ is the Bayes decision function as proposed in [15].

2) Potential fire blob mask detection: In order to detect potential blob of fire, we use the difference between two consecutive potential fire marks, PFM, and PFMp (potential fire mark of previous image), and then recover each connected component to get whole information about them. Although there are some techniques to estimate the changes, but most of them are complex and time consuming, it is not suitable for real-time application. In this paper we directly get the changes such as the difference between two consecutive potential fire marks by subtracting as:

$$PFBM(x, y) = \begin{cases} 1 & \text{if} |PFM(x, y) - PFM_p(x, y)| > \beta, \\ 0 & \text{Otherwise,} \end{cases} \tag{8}$$

where $PFBM(x, y)$ is the Potential Fire Blob Mask (PFBM) at (x, y) and β is positive threshold. Follow (8), all pixels of fire-like object are removed. However it will be removed all pixels in fire blob if it is not changed. In order to solve this problem, we propose a method to recover these pixels as below. In the early state of fire, although the flame flickers slowly, the pixels in the core of fire rare move, but in the peripheral region it is not true. Rely on this characteristic; we present a technique to recover the pixels in the core of fire as:

- Determine all connected components in PFBM, and also remove all small components;
- For each connected component, S, if $PFBM(x, y) = 0$ and the location (x, y) is inside S then let $PFBM(x, y) = 1$;

when each connected component is used to get a potential fire blob in next section.

B. Blob-based processing

According to the result of pixel-based processing, Potential Fire Blobs Image (PFBI) is defined as:

$$PFBI(x, y) = \begin{cases} I(x, y) & \text{if } PFBM(x, y) = 1, \\ 0 & \text{Otherwise,} \end{cases} \tag{9}$$

in which, $I(x, y)$ is the color of pixel at (x, y) in I. A potential fire blob is defined as a connected component on $PFBI$. For each potential fire blob we compute an 7-feature vector which includes 3 statistical features of color, and 4 texture parameters.

1) Statistical features of color: For each blob, we compute the average value of red - R_a; green - G_a; and blue - B_a. In case of the color of flames belongs to the red-yellow, which are the most common type of flames seen in the nature, R_a is greater than G_a and G_a is greater than B_a. These values compute as:

$$R_a = \frac{1}{N} \sum_{(x,y) \in PFB(i)} R(x, y) \tag{10}$$

$$G_a = \frac{1}{N} \sum_{(x,y) \in PFB(i)} G(x, y) \tag{11}$$

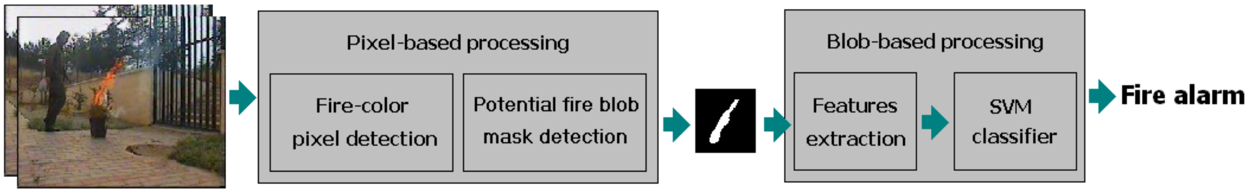

Figure 1. The diagram of proposed method

$$B_a = \frac{1}{N}\sum_{(x,y)\in PFB(i)} B(x,y) \tag{12}$$

in which, $PFB(i)$ is i-th blob in $PFBI$, N is number pixels of $PFB(i)$; $R(x,y)$, $G(x,y)$ and $B(x,y)$ are three elements of red, green and blue at (x,y) respectively.

2) Texture parameters: As analyzing in [4] and [8], fire blob has some texture characteristics. In this work we use: mean - Mn, standard variance - Sv, entropy - En, second moment - Sm, invert difference moment Dm as texture parameters. Denote p(v) as normalized intensity histogram of a blob, v is intensity, then these texture parameters are defined as:

$$M_n = \frac{1}{N}\sum_{v=0}^{L-1} p(v) * v \tag{13}$$

$$S_v = \frac{1}{N}\sum_{v=0}^{L-1} p(v) * (v - M_n) \tag{14}$$

$$E_n = -\sum_{v=0}^{L-1} p(v) * log_2(p(v)) \tag{15}$$

$$S_m = \frac{1}{N}\sum_{v=0}^{L-1} p(v) * (v - M_n)^2 \tag{16}$$

where L is number of intensity is used in image.

C. The algorithm

The features vector of blob is 8-feature as:

$$b_V = \begin{bmatrix} R_a \\ G_a \\ B_a \\ M_n \\ S_v \\ E_n \\ S_m \end{bmatrix} \tag{17}$$

To determine whether a potential fire blob is fire or non-fire object, we also use a SVM classifier as:

$$f_A(i) = \begin{cases} 1 & \text{if } f_b(b(i)) > 0, \\ 0 & \text{Otherwise,} \end{cases} \tag{18}$$

in which $f_b(bV)$ is the SVM decision function for blob classification, and $b(i)$ is the features vector of $PFB(i)$. The final fire alarm factor, $AFactor$, is the sum of $f_A(i), i = 1,..,K$, where K is the number of blobs in $PFBI$. By combination all of mentioned above, the vision-based fire detection algorithm using SVM can be described below.

The algorithm

Input: Image I;

Output: The information about fire, $AFactor$;

1) *Detect PFM using decision function $f_p()$;*
2) *Detect PFBM using the difference between two consecutive PFM, PFMp and a proposed recover method;*
3) *Construct PFBI, determine the number of blobs, K, in PFBI ; initialize i = 1, AFactor=0;*
4) *While $i \leq K$*
   a) *Evaluate the features vector of i-th blob, $b(i)$;*
   b) *Calculate $f_A(i)$ using decision function $f_b()$;*
   c) *AFactor = AFactor+$f_A(i)$;*
   d) *i = i+1;*
5) *Return AFactor;*

IV. Experimental results

To evaluate this proposal, we collected 10 videos which consists of 7 fire videos and 3 non-fire videos, and the video resolution is 320×240. In this section, we present two experiments, the first for fire-color pixel segmentation and the second for final algorithm performance.

A. Experiment 1

This experiment show some result about fire-color pixel detection. For this objective, we choose 54 images from 10 videos contain fire, and then make a mask for each of these images. The mask for each image is a binary image, the value at (x,y) is 1 if the pixel at (x,y) in corresponding image belong to fire blob, and it is 0 for otherwise. For training of Bayes decision function, $f_p()$, we collect 258765 samples includes 112367 positive and 146398 negative samples from 20 images, the samples are positive or negative if its corresponding mask is 1 or 0. In segmentation phase, we compare our method, using $f_p()$ classifier, with fire-color model proposed in [4], [9], [10] and [11]. The number of pixels that is not belong to fire blob but it was wrong classified, denote $n+$ and the number of pixels in fire blob that was not identified is $n-$; these values are computed from 54 images and its corresponding masks. The results of each method are shown in Table I.

Table I
FALSE-CLASSIFIED FROM TEST DATA

Method	$n+$	$n-$	*Total number of false-classified pixels*
[15]	23888	35832	59720
[4]	36628	77835	114463
[9]	33841	50762	84603
[10]	57779	76590	134369
[11]	76292	28218	104509

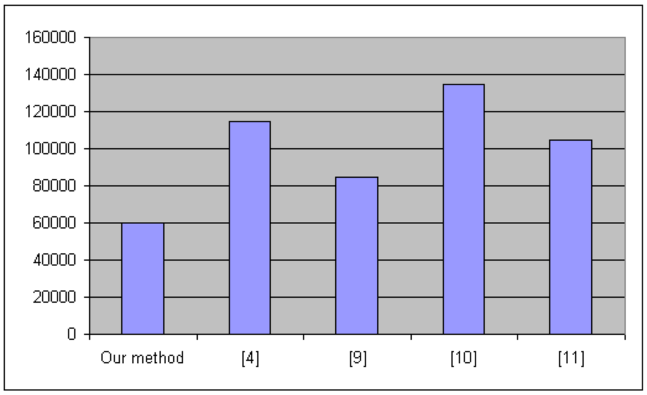

Figure 2. Total number of false-classified pixels

The results in Table I and Figure 2 show that our method gives the best performance. These results are means that other method is not good, it depends on the training and test data.

B. Experiment 2

In this experiment we test the performance of the proposed algorithm with 10 videos which mentioned above. The samples from these videos are shown in 3. The results are shown in Table II.

The third column in Table II is the order of the first frame in video sequences that contains fire, and the fourth column is the order of the first frame in video sequences in which fire was detected. For the video from 1 to 7, this method detect fire immediately after maximum 3 frames. For the case of fire of candle (video 8), the method can not detect fire as soon as possible due to the fire circumstance was in close space with nothing of movement and color of pixel of fire were white.

The last column in Table II are false-negative detected rate and false-positive detected rate for for video contained fire and video without fire respectively. For normal fire in room and out door (video 1 to 5), the false-negative detected rates are not too large. It is high in the case of fire of lighter and fire of candle because the difference of the color and movement. The false-positive detected rate are low for the case of video in the test.

V. CONCLUSION

In this paper, we present a new approach to vision-based fire detection. Based on the characteristics of pixel and blobs of fire, this proposal concentrates into two main techniques: pixel-based processing and blob-based features extraction. The final algorithm is a combination of two main above tasks and SVM classifier. The experiments shown that our fire-color model, as a Bayes classifier, gives better results. The test with some videos indicates that the final algorithm can detect fire as soon as possible. In spite of not comparing about the complexity and time consuming of our algorithm with others, it is easy to recognize this algorithm is an efficient approach for video-based fire detection.

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Figure 3. The samples from tested videos

Table II
THE PERFORMANCE OF THE ALGORITHM

Videos	*Number Frames*	*First frame with fire*	*First frame detected*	*Number of frames with fire*	*Number of frames detected as fire*	*False detected (%)*
Fire in room 1	402	2	3	402	296	26(-)
Fire in room 2	300	2	3	300	207	31(-)
Fire outdoor 1	116	2	3	116	82	29(-)
Fire outdoor 2	633	2	5	633	455	28(-)
Fire outdoor 3	707	2	4	707	456	36(-)
Fire of lighter	100	49	50	52	11	79(-)
Fire of candle	658	2	278	658	9	99(-)
Moving object	150	-	-	0	0	0(+)
Traffic 1	467	-	-	0	2	0(+)
Traffic 2	773	-	395	0	73	9(+)

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