SVM Based Forest Fire Detection Using Static and Dynamic Features

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Abstract. A novel approach is proposed in this paper for automatic forest fire detection from video. Based on 3D point cloud of the collected sample fire pixels, Gaussian mixture model is built and helps segment some possible flame regions in single image. Then the new specific flame pattern is defined for forest, and three types of fire colors are labeled accordingly. With 11 static features including color distributions, texture parameters and shape roundness, the static SVM classifier is trained and filters the segmented results. Using defined overlapping degree and varying degree, the remained candidate regions are matched among consecutive frames. Subsequently the variations of color, texture, roundness, area, contour are computed, then the average and the mean square deviation of them are obtained. Together with the flickering frequency from temporal wavelet based Fourier descriptors analysis of flame contour, 27 dynamic features are used to train the dynamic SVM classifier, which is applied for final decision. Our approach has been tested with dozens of video clips, and it can detect forest fire while recognize the fire like objects, such as red house, bright light and flying flag. Except for the acceptable accuracy, our detection algorithm performs in real time, which proves its value for computer vision based forest fire surveillance.

Keywords: Forest flame, Color segmentation, Static feature, Shape matching, Dynamic feature, SVM.

1. Introduction

Currently many institutions are trying to develop reliable and efficient methods to forecast the fire disasters, which may induce heavy casualty and property loss as well as serious social impact. The traditional method to detect fire is employing some people as inspectors, but human resource is expensive and such approach has very low efficiency. Fire sensors have already been used as another method to detect the particles generated by smoke or fire, temperature, relative humidity, etc. But they must be placed in the proximity of fire or their detecting range is usually exceeded, and the approach fails to supply the additional information about the process of burning, such as fire

location, size, growing rate, and so on. Fortunately, computer vision based fire detection brings us a new kind of method which can overcome the key deficiencies of the aforementioned methods. However, this new approach still remains immature, and many tough problems exist in its 3 main stages: image segmentation, target tracking and object classification. What's more, one certain detection algorithm cannot work well for all kinds of fire disasters, e.g. tunnel fire, building fire or forest fire.

Moving objects' estimation is often used to segment the possible fire region from video sequence, and two main traditional algorithms include consecutive frames subtraction and background subtraction [1-6]. In the algorithm of consecutive frames subtraction, transient change of image can be detected, but the overlapping region of two consecutive frames can be mistakenly taken as background. In the algorithm of background subtraction, intact target region can be extracted because of the static state of the background image, but the extracted target may be vague and inaccurate if the background image cannot be updated in time. For forest environment, the whole scene does not keep still due to waving trees, changing weather, varying light, moving shadow, shaking camera, and so on.

Therefore, compared with moving estimation, color based segmentation is more suitable for forest fire extraction. Celik et al. [7] described the color features of fire in RGB color space, and decided whether one pixel belongs to the fire region using rules represented by two groups of inequations. Chen et al. [8] tried to segment the fire region from one image in RGB color space based on three deduced decision rules, within which the saturation value of each extracted possible fire pixel needs to be more than one threshold value in order to exclude the other fire-like regions. Celik and Demirel [9] proposed a generic color model for flame pixels' classification in YCbCr color space with several rules, and they used three polynomials to model the region containing 16309070 fire pixels from 1000 sample images in CbCr chrominance plane. Phillips et al. [10] used test data where the fire has been isolated manually to create a color lookup table by creating a Gaussian smoothed color histogram to detect the fire colored pixels, thus their approach based upon training is scene specific with increased accuracy if training sequences are available for specific kinds of fires. Toreyin et al. [11] obtained the fire color distribution from sample images, and represented the 3D point cloud in RGB color space using a mixture of Gaussians, then the pixel with color value inside one of the distributed Gaussian spheres is assumed to be a fire colored pixel. Krstinic et al. [12] compared the lookup table method and the probabilistic model method, and their experiments proved that lookup table classifier achieves the lower performance. Further validations [13,14] have been performed based on fire color based segmentation to improve the extraction accuracy.

Besides color information, dynamic features of fire are significant clues used to distinguish fire from other fire-like objects [15-21]. To identify a fire's growth, size variation of fire area is calculated from some consecutive video frames [17]. If the number of extracted fire pixels is increasing with time and greater than the explicitly defined threshold, a fire alarm will be given. Flickering frequency is an important clue for fire since flames flicker with a

characteristic frequency of around 10 Hz independent of burning material and burner, and there are several approaches to compute fire flickering frequency [18-20]. Zhang et al. [18] thought the height of flame is changeable due to flame flicker and the changing pattern differs from the jamming sources, so the change of flame height is taken as a dynamic feature. Yuan et al. [19] directly utilized the temporal variation of flame contour as clues for detecting whether a pixel is fire or not in video images. The stochastic characteristics of fire motion are estimated by an autoregressive model of changes in Fourier coefficients of the region boundary [20], and temporal changes of the coefficients are used as the signatures of fire. Toreyin et al. [11] kept on tracking the history of red channel for each pixel which is part of fire contour in a relative short time, and took them as the input of wavelet method. Apart from the changing of fire region's area and flicker, Hu et al. [21] employed the changing of fire region's roundness which describes complexity of the shape, to help filter the regions with regular shape.

Different with the other kinds of fire surveillances, forest fire monitoring has its own properties. The cameras are usually installed on the top of mountains, and they are not very stable because of wind blow. View range of the cameras is relatively wide, can be 3-5 km generally or even about 8 km. Focal length of the cameras is changeable, and the size of objects in recorded images is not constant. Most of the published papers worked on detection and analysis of sole fire region, but in forest fire, there may be more than one flame regions in the monitored area. All of them have caused a great deal of trouble for vision based fire detection, therefore it is necessary to specially study the case of forest fire recognition.

Our proposed forest fire detection algorithm considers static and dynamic features subsequently. The rest of our paper is organized as: color based segmentation including 3D color model with GMM and colors labeling with new flame pattern definition are provided in section 2, computation of static features and SVM based classification are described in section 3, shape based matching of multiple regions among continuous video images is given in section 4, dynamic features computation and based final determination with SVM are provided in section 5, experimental results on images and videos are described in section 6, and the conclusion is given in section 7.

2. Color Based Fire Segmentation

2.1. 3D Color Model

For segmentation of possible flame regions, color values of each pixel in an image are checked with a pre-determined color distribution, which represents the range of possible fire colors in a color model such as RGB space. As shown in Fig. 1, there are 530,000 flame pixels segmented manually from the

fire regions of 23 sample images. Of course, the threshold values along R, G and B axis can be used to define a rough space for fire color. To build a more precise color model, 3D shape of the point cloud is represented by Gaussian mixture model (GMM), and the pixel whose color within the range of the GMM distribution model can be taken as a candidate fire pixel.
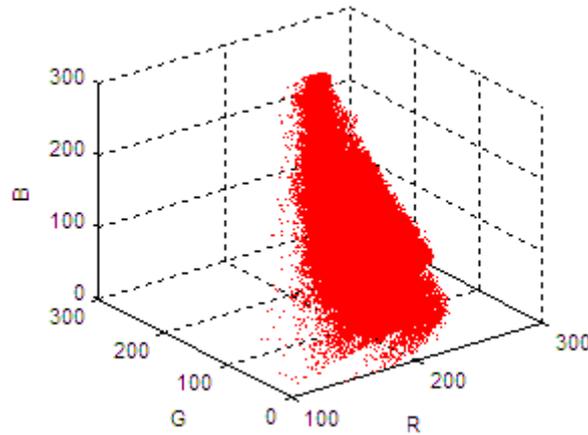

Fig. 1. 3D point cloud of sample fire pixels

First, we use expectation maximization (EM) algorithm to train the GMM parameters: the weight values, the center, and the covariance matrix. Then, whether one pixel belongs to flame region of the image under processing can be decided by calculation of its probability with the following formula:

$$g(x; \mu, \Sigma) = \frac{1}{\sqrt{(2\pi)^d |\Sigma|}} \exp\left[-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)\right] \quad (1)$$

$$p(x) = \sum_i \alpha_i * g(x; \mu_i, \Sigma_i) \quad (2)$$

The weighting value, center and covariance matrix of each Gaussian model are α, μ and $\sum$ respectively. The probability p(x) illustrates how close of point x to the fire region. The number of Gaussian models in GMM can be manually assigned or automatically computed. We tried automatic approach in experiments and the calculated best number of Gaussian models is 8. Based on the trained 3D color distribution model, pixels of one image are checked one by one, and then the possible flame regions within the image can be segmented automatically.

2.2. New Definition for Forest Flame Pattern

Ref. [20] studied color, geometry and motion of fire for recognition, and modeled the fire region in a single image as: (1) it stands in high contrast to its surroundings; (2) it exhibits a structure of nested rings of colors, changing from white at the core to yellow, orange and red in the periphery. This description gives a standard to detect fire. However, with respect to the case of forest flame, many fire regions do not have the structure of obvious nested rings, as shown in Fig. 2, and mostly because that they fail to burn fully.

Fig. 2. Fire regions with non-significant nested structure

Therefore, for forest fire, we present a new definition to describe the flame pattern more properly: (1) the periphery of fire region is in orange or red color; (2) only if the fire burns fully, there are one or more white-yellow color cores.

2.3. Labeling Three Types of Colors

Based on our new definition for forest fire pattern, there may be three types of colors in the segmented fire region: white-yellow, orange, red. Thus the pixels in fire can be labeled with three corresponding marks. As pixels with white-yellow color belong to the high bright flame regions, V value of the HSV color space is employed to help label such pixels. Since flames are often covered with smokes in forest, its bright value will be decreased with different degrees. In this case, we can not use a fixed V value as the threshold. Therefore, an algorithm is proposed to self-adaptively calculate the threshold value of V for fire images, and the algorithm is described as follows.

Two threshold values, V_{low} and V_{high}, are defined for V based segmentation. The lower threshold V_{low} is a constant value from our experimental experience, while the higher threshold V_{high} is a value computed automatically. Related with V_{low} and V_{high}, there are two subset of one image: L, set of the pixels whose V value is no less than V_{low}; H, set of the pixels whose V value is no less than V_{high}.

$$L = \{ p_i \mid p_i \in [V_{low}, 255] \}$$
$$H = \{ p_i \mid p_i \in [V_{high}, 255] \}$$

(3)

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Obviously, H is a subset of L. If L is taken as the possible fire region, H can be used for further determination of fire cores. For the number of pixels, the percentage of H in L can be controlled by a parameter α

$$\frac{Num(H)}{Num(L)} < \alpha \qquad (4)$$

The smaller the value of α, the less the number of pixels in H, together with the higher threshold value of V_{high}. The procedure to compute V_{high} is:

Step 1: Define the distribution function F(x) for subset L as

$$F(v(p_i)) = P(t \leq v(p_i)) = \sum_{t=V_{low}}^{v(p_i)} f(t), p_i \in L \qquad (5)$$

Step 2: Find the subset H based on F(x) as

$$H = \{p_i \mid F(v(p_i)) > 1 - \alpha\} \qquad (6)$$

Step 3: Calculate the higher threshold value V_{high} as

$$V_{high} = \min(v(p_i) \mid p_i \in H) \qquad (7)$$

Once we get the higher threshold value V_{high}, we label the pixels as white-yellow if their V value exceeds V_{high}. For the left pixels of the candidate fire region, we use the experiential value of H and S ranges to decide whether they belong to orange or red.

3. Static Features and SVM Classifier

After color based segmentation, the possible flame regions are obtained in one single image. In our method, they are not directly used as fire areas, but are further checked to filter out the false candidates based on some static features with trained support vector machine (SVM). The static features include color distribution, texture parameter and shape roundness.

3.1. Static Features from Single Frame

(1) Color distribution (5 features)

During color segmentation with our new flame pattern, regions with white-yellow, orange and red color are labeled. We calculate the ratio of the pixels' number in each labeled color to the pixels' number in the entire candidate fire region. The ratio of white-yellow pixels (Eq. 8), the ratio of red pixels (Eq. 9) and the ratio of orange pixels (Eq. 10) are all static features of forest fire.

$$\text{Ratio}_{WY} = \frac{num(white - yellow)}{num(entire - region)} \tag{8}$$

$$\text{Ratio}_R = \frac{num(red)}{num(entire - region)} \tag{9}$$

$$\text{Ratio}_O = \frac{num(orange)}{num(entire - region)} \tag{10}$$

With respect to each candidate fire region, their color histograms in different color channels are computed respectively. Suppose I is one gray value in one color channel, Ng is the number of gray levels, P(I) is the ratio of the number of pixels with I value to the number of pixels in the candidate region, the expectation of Eq. (11) and the variance of Eq. (12) are computed as static features, e.g. two features for H color channel.

$$e = E[I] = \sum_{I=0}^{Ng-1} I * P(I) \tag{11}$$

$$\text{var} = E[(I - E[I])^2] = \sum_{I=0}^{Ng-1} (I - e)^2 P(I) \tag{12}$$

(2) Texture parameter (5 features)

Forest fire also has texture features [22-24], thus we can extract the texture parameters from each candidate region and then consider them in decision. Since H value represents the color information in HSV color space, the co-occurrence matrix of the region's H channel is employed to describe the texture feature. From experiments, it can be found that only the co-occurrence matrixes with zero degree have evident differences between fire and non-fire regions, thus parameters of zero degree co-occurrence matrix is used. Among parameters of the N*N co-occurrence matrix, the angular second moment of Eq. (13), the entropy of Eq. (14), the mean of Eq. (15), the contrast of Eq. (16) and the inverse difference moment of Eq. (17) are chosen as static features.

$$\text{Angular Second Moment} \quad \text{ASM} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j)^2 \tag{13}$$

$$\text{Entropy} \quad \text{E} = -\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j) * \log_2 p(i,j) \tag{14}$$

$$\text{Mean} \quad \text{M} = \sum_{i=0}^{N-1} i * p(i) \tag{15}$$

$$\text{Contrast} \quad \text{C} = \sum_{n=0}^{N-1} n^2 \left\{ \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j), |i - j| = n \right\} \tag{16}$$

$$\text{Inverse Difference Moment } \mathrm{IDM} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} p(i,j)/[1+(i-j)^2] \qquad (17)$$

(3) Shape roundness (1 feature)

Given a segmented candidate fire region, we retrieve its boundary using the classical Laplacian operator of $\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$, then it is convenient to compute the 8-connected boundary chain code [25,26] for the region, as illustrated in Fig. 3. From the chain code, it is easy to calculate area S of the region and perimeter L of the boundary. Accordingly, we compute the shape roundness as L^2/S, which can describe the complexity of shape, i.e. more complex shape has larger soundness value. Shape roundness helps to get rid of the candidate regions less complex than fire, e.g. regular red car in image.
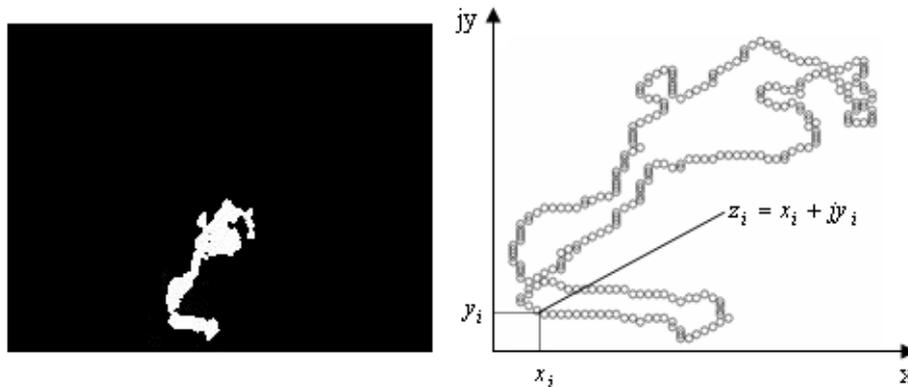

Fig. 3. Candidate region with its boundary chain code

3.2. SVM Classifier with Static Features

Support vector machine (SVM) is a set of related supervised learning methods that analyze data and recognize patterns, thus it is employed in our method for features based classification. The open source package (LIBSVM) is used to construct a two-class SVM classifier. To train the SVM, the above 11 static features are computed and collected from sample images with real fire or fire like objects. With the help of these features and radial basis function kernel, we can obtain the main parameters C=299.25 and γ =0.2295 for SVM. Therefore, the segmented candidate fire regions are further checked by the trained SVM classifier, and the false regions can be deleted. Of course, static features can help filter the candidate regions segmented from one

single image, but are not enough to describe the forest fire changing in video sequences.

4. Shape Based Flames Matching

Before computing dynamic characteristics of varying fire, the corresponding candidate fire regions should be found among consecutive video frames, which is a problem of pattern matching. Although the camera may mildly wobble and the candidate flame regions may randomly flicker, locations and shapes of the corresponding candidate regions among consecutive video frames do not change seriously. Therefore, two parameters of overlapping degree and varying degree are defined to evaluate the matching of two regions in our approach. Suppose R1 and R1' (or R2 and R2') are the corresponding regions (there may be multiple matching pairs) in two neighbor frames, as illustrated in Fig. 4.
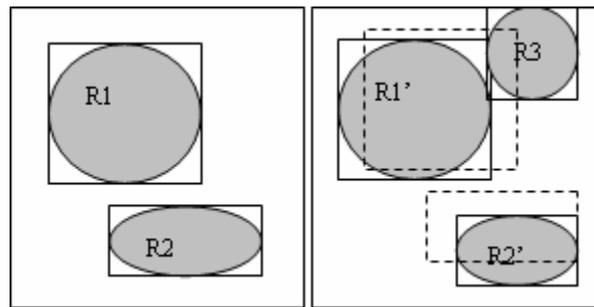

Fig. 4. Region matching of consecutive frames

The overlapping degree of two regions is

$$\frac{S(R_1 \cap R_1')}{\max(S(R_1), S(R_1'))} > \alpha, \;\; 0 \le \alpha \le 1 \tag{18}$$

where $S(R_1 \cap R_1')$ represents the overlapping area of region R_1 and region R_1', $\max(S(R_1), S(R_1'))$ represents the larger area of R_1 and R_1', and α is an experiential value, i.e. the two corresponding regions are more like the same flame with the larger value of overlapping degree.

The varying degree of two regions is

$$\frac{|S(R_1) - S(R_1')|}{\min(S(R_1), S(R_1'))} < \beta, \;\; 0 \le \beta \le 1 \tag{19}$$

where $S(R_1)$ represents the area of region R1, $S(R_1')$ represents the area of region R_1', $\min(S(R_1), S(R_1'))$ represents the smaller area of R_1 and R_1', and β is an experiential value, i.e. the two corresponding regions are more like the same flame with the less value of varying degree.

Fig. 5. Matching results of five fires from continuous frames

The proposed definitions for flames matching are tested by some collected video clips. As shown in Fig. 5, the first row displays the source images, the second row refers to results from color segmentation, the third row illustrates the matching results. In the matched results, fire regions with the same color mean that they are the corresponding regions of the same flame.
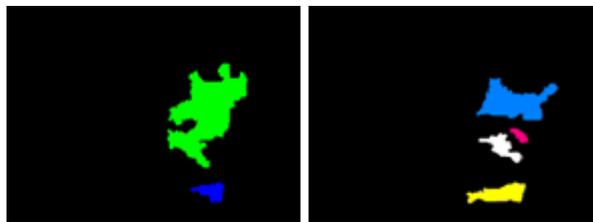

Fig. 6. Detection of the breaking behavior

Behaviors of forest fire are very complex with time, e.g. one fire region can slowly break into several small parts, or the small fires can burn into one region. Our matching algorithm has the ability to detect such changes. As illustrated in Fig. 6, one flame divides into several small regions, and the small parts cannot match with the whole fire. In this case, the number of candidate fire regions increases and the matching operation is performed on the new set of regions.

5. SVM Determination with Dynamic Features

Based on the matched results, dynamic features of the candidate fire regions from continuous video frames can be extracted, and used to further identify forest fire from the other fire like objects. In our method, the dynamic features include the variations of color distribution, texture, roundness, area, contour and the flickering frequency.

5.1. Dynamic Features from Matched Regions

(1) Variation of color distribution (5 features)

It is defined as the variation of color distributions (from Eq. 8 to Eq. 12 in section 3.1) of one candidate region among a sequence of video frames.

(2) Variation of texture (5 features)

It is defined as the variation of texture parameters (from Eq. 13 to Eq. 17 in section 3.1) of one candidate region among a sequence of video frames.

(3) Variation of roundness (1 feature)

It is defined as the variation of shape roundness (in section 3.1) of one candidate region among a sequence of video frames.

(4) Variation of area (1 feature)

It is defined as the variation of area of one candidate region among a sequence of video frames. Area is represented by the number of fire pixels in one region, and the area of forest fire is continuously changing since fire is an instable and developing procedure.

(5) Variation of contour (1 feature)

It is defined as the variation of contour of one candidate region among a sequence of video frames. Since the shape of fire region is changeable owing to air flowing, we can calculate the contour fluctuation to measure the disorder. Assume there are N points on the boundary, and they are expressed in the complex form $\{z_i \mid z_i = x_i + jy_i\}$, where (x_i, y_i) are the coordinates of the ith point on the boundary traversed clockwise, as shown in Fig. 3. Coefficients of the discrete Fourier transform (DFT) [26,27] of z_i are then calculated as

$$F_w = \frac{1}{N}\sum_{i=1}^{N} z_i \exp(-j\frac{2\pi}{N}iw) \qquad (20)$$

where F_0 represents the centre of gravity of the transformed 1D boundary, which does not carry shape information, so we neglect it to achieve the

translation invariance. Experiments show that only a few dozens of the Fourier coefficients are really needed to describe the contour, thus the front 32 ones $D = (\left\| F_1' \right\|_2, \left\| F_2' \right\|_2, ... \left\| F_{32}' \right\|_2)$ are used, and the difference of two consecutive Fourier descriptors corresponding to two neighbor frames is defined as

$$D_i = \sum_{w=1}^{32} \left| \left\| F_w^i \right\|_2 - \left\| F_w^{i-1} \right\|_2 \right| \qquad (21)$$

If D_i is greater than Td and lasts for a time period longer than Tm, where Td and Tm are statistical threshold values from experiments, it means that there is a drastic change in shape and the region is probably a fire.

(6) Flickering frequency (1 feature)

Flickering frequency is another important clue for forest fire since the flames flicker with a characteristic frequency around 10 Hz. We compute the variance of every two consecutive Fourier descriptors in a relatively short time and then analyze the sequence of variances with temporal wavelet. The video capturing rate should be high enough to capture flame flickering, i.e. at least 20 Hz to deal with the 10 Hz fire flickering. In our experiment, the digital camera can capture 30 frames per second, so it works.

As shown in Fig. 7, $x_n[k, l]$ represents the variance of Fourier descriptors between the nth and the (n+1)th frame, and each $x_n[k, l]$ in a relatively short time is assigned to a two-stage filter bank. The two-channel decomposition filter is constituted of high-pass filter (HPF, {-0.25, 0.5, -0.25}) and low-pass filter (LPF, {0.25, 0.5, 0.25}). If there is high frequency variation, high-band sub-signals d_n and e_n should be non-zero value. On the contrary, if the nth frame stay stationary compared with the consecutive frame, these two sub-signals should be equal to zero or very close to zero due to the high-pass filters. Thus the number of zero crossings of the sub-band signals d_n and e_n in one period is used as fire flickering frequency.
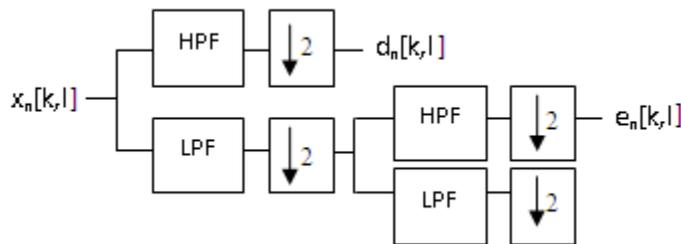

Fig. 7. A two-stage filter with HPF and LPF

5.2. SVM Classifier with Dynamic Features

Since the flickering frequency is a constant value of about 10 Hz, it can be directly used as one dynamic feature of forest fire. For color distribution, texture, roundness, area and contour, variations of them (13 features) from n consecutive images are computed and then taken as dynamic features.

To make sure that fire detection performs in real time and gives alarms without delay, n should be a relative small number. Based on the fact that the flames flicker around 10 Hz and the recorded videos have 30 frames per second, n is assigned with the value of 20. That is, dynamic features are computed for the forest fire from every 20 consecutive video frames. Therefore, an n*m matrix is constructed for fire features of a video clip, where n=20 while m=13 is the number of aforementioned dynamic features. Suppose $X(i, j)$ is one element of the matrix corresponding to the ith video frame and the jth fire feature, dynamic features based on the matrix are defined as the average

$$E(j) = \frac{1}{n} \sum_{i=1}^{n} X(i, j) \tag{22}$$

and the mean square deviation

$$S(j) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (X(i, j) - E(j))^2} \tag{23}$$

Therefore, for any video clip, there are 2*13=26 varying dynamic features, i.e. the average and the mean square deviation of color distribution, texture, roundness, area and contour. Together with the flickering frequency, the 27 dynamic features are used as input of SVM classifier, and the trained SVM is applied for the final decision.

6. Experimental Results

We developed our algorithm with C++ and Open CV under VC .NET in Windows XP, and tested it on a lot of video clips with real fires or fire like objects. As our algorithm includes color based segmentation and SVM based static and dynamic classifications, not only the final recognition, but also the intermediate results are displayed and analyzed.

6.1. Results of Color Based Segmentation

As shown in Fig. 8, video frames (the 1st, 2nd and 3rd columns) and still images (the 4th column) in the 1st row are collected and used as the experimental data. For comparison, the color based segmentation method of

Ref. [7] is tested first. Results from the first group of inequations in [7] with relative loose limits are shown in the 2nd row, and it can be found that many other regions remain as they have the similar color as fire. Results from the second group of inequations in [7] with relative strict limits are shown in the 3rd row, and it can be found that only a few real fire regions are segmented.

Fig. 8. Segmentation results from [7]

Then another color based segmentation method of Ref. [8] is tested based on its three deduced decision rules. In their method, parameters RT and ST of the decision rules must be set manually and they exert crucial influence on fire segmentation, especially for parameter ST. As shown in Fig. 9, the 1st row displays the segmented results from RT=170 and ST=0.3, while the 2nd row displays the segmented results from RT=170 and ST=0.9.

Fig. 9. Segmentation results from [8]

The same images are used to test our method, as shown in Fig. 10. From the experimental results it can be found that our algorithm has the ability to segment fire regions more precisely from the monocular images, and the regions with white-yellow, orange, red colors are also labeled respectively illustrated with different gray value, i.e. the segmented regions from our approach has more information. Of course, the segemented results are only possible fire regions, and they need further determination.
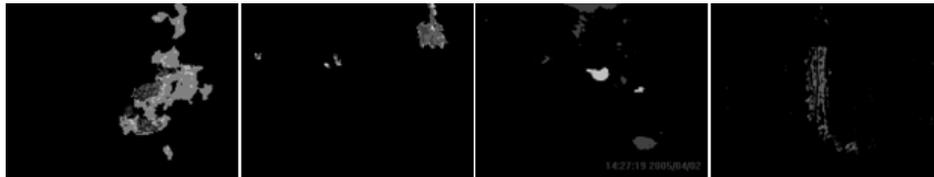

Fig. 10. Segmentation results from our method

Fig. 11. Segmentation results of fire colored objects

Our method is also tested on some images with fire colored non-fire objects such as bright light, flying red flag and moving red car. From Fig. 11, it can be found that the objects with fire like color can be taken as possible fire regions if using only color based segmentation, which also proves the necessity to take the other fire features into consideration except for color.

6.2. Determination with Static and Dynamic Features

The static features defined in our method are used for further determination with the help of SVM classifier. Results of Fig. 12 illustrate that the static features can help remove a lot of fire like regions since there are differences between their color distributions, texture parameters or shape roundness and those of real fire. But for the flying red flag, even its static features are very similar with forest fire, thus the flag still remains after static SVM. Then the dynamic SVM classification is performed on continuous video frames with the dynamic features including variations of color distribution, texture, roundness,

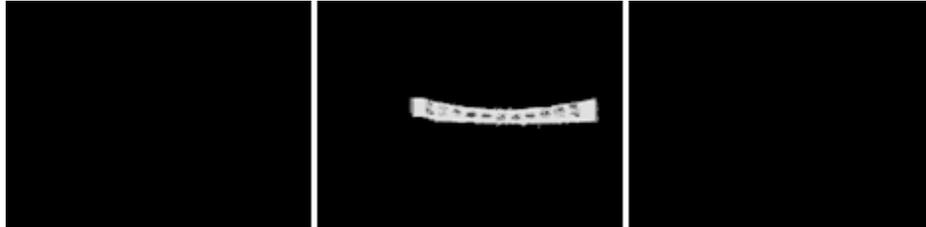area, contour and the flickering frequency. After dynamic SVM, the flying red flag is recognized and filtered.

Fig. 12. SVM determination of fire like regions

Fig. 13. SVM determination of real fire regions

With the same parameters, SVM classifications using static and dynamic features are consequently performed on the segmented results of Fig. 10 with real forest fire. Since the image of the 4th column in Fig. 10 is a single image and dynamic SVM cannot be applied, only the classification results of the frames from video clips (the 1st, 2nd and 3rd columns) are shown in Fig. 13. It can be found that the main fire regions are detected successfully, but the small fire regions may be filtered. The reason is that there are fire features in the small regions represented by only a few pixels, but the features are relative weak compared with the main regions.

6.3. Flame Detection from Video Clips

Ref. [10] also presented a complete procedure for video based automatic fire detection, so the method is implemented and compared with our approach. The experiments are executed on dozens of video clips, and 8 of them are illustrated in Fig. 14. Data of the first row are videos from F1 to F4 with forest fire, while data of the second row are videos from N1 to N4 with fire similar objects. For video clips with fire, F1 is early fire, F2 is fully burning fire, F3 and F4 are fire covered with thin smoke. For video clips without fire, N1 is a moving red car, N2 is a red house captured with shaking camera, N3 is a bright driving light, and N4 is a red flag flying in the wind. That is, the data can test the detection performance under different situations.

Fig. 14. Fire detection from video clips

Table 1. Performance comparison between Ref. [10] and our method

Videos	Total frames	Fire frames	Alarm frames of Ref. [10]	Alarm frames of our method	Alarm ratio (%) of Ref. [10]	Alarm ratio (%) of our method
F1	154	154	33	85	21.43	55.19
F2	1602	1602	717	1489	44.76	92.95
F3	192	192	115	183	59.90	95.31
F4	450	450	98	187	21.78	41.56
N1	262	0	114	6	43.51	2.29
N2	611	0	367	31	60.07	5.07
N3	192	0	191	1	99.48	0.52
N4	2072	0	1181	67	57.00	3.23

The performance comparisons between Ref. [10] and our approach are shown in Table 1. The 1st column lists the names of video chips in our experiment; the 2nd column and the 3rd column list the total frames and real fire frames respectively; the rest columns list the alarm frames and alarm ratios from two compared methods. For video clips with real fire, our method

gives better detection accuracy with more alarm ratios. For video clips with fire like objects, our method provides higher recognition precision with less alarm ratios. Of course, our approach has lower accuracy for fire with small regions (F1), and the performance is even worse for small fires covered by smoke (F4). Our algorithm runs on a PC with a CPU C1.7G and 512M DDR RAM, and has a speed of 33.02 fps. Therefore, except for the acceptable accuracy, our method can perform in real time.

7. Conclusion

In this paper, a new SVM based approach is proposed for forest fire detection with both static and dynamic features. Compared with the published related works, our novel method has the following advantages:

(1) In color based segmentation, after GMM construction from sample pixels and segmentation of candidate fire regions, we define the specific forest flame pattern and then label three types of colors including white-yellow, orange and red. The labeling introduces a novel feature of forest fire, i.e. color distribution, which is very helpful for further classification.

(2) For the segmented results from single frame, SVM trained on 11 static features is applied to filter out the false regions, and only the remained regions continue with the following steps. In this way, computational expense is saved obviously.

(3) Not only the sole target, but multiple candidate fire regions are tracked by shape based matching among the consecutive frames. With our defined overlapping degree and varying degree, the matching algorithm can also detect complex fire behaviors, e.g. one fire region slowly breaks into several small parts, or the small fires burn into one region.

(4) To compute the fire flickering frequency based on region contour, the temporal wavelet is used to analyze Fourier descriptors representing the variation of flame contour in a short period. Our approach avoids explicitly setting the threshold value in the existing FFT methods, while detects forest fire more accurately than the methods using wavelet transformation only.

(5) A total of 27 dynamic features are considered for SVM based final classification, and the features are computed from every 20 consecutive video frames. Therefore, except for accuracy, the detection algorithm can perform and give alarms in real time.

Our work has been tested with a lot of real video clips and the experimental results have proved its efficiency. However, for fire with small regions or fire regions covered with smoke, there are relative poor static and dynamic fire features, and thus the detection accuracy is still low. In the future, we will try the other ways for such problem, e.g. segmenting smoke first, and considering both fire and smoke together.

References

1. Lai C.L., Yang J.C., Chen Y.H.: A Real Time Video Processing Based Surveillance System for Early Fire and Flood Detection. Instrumentation and Measurement Technology Conference, pp. 1-6. (2007)
2. Toreyin B.U., Cetin A.E.: Online Detection of Fire in Video. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1-5. (2007)
3. Yuan F.N.: A fast accumulative motion orientation model based on integral image for video smoke detection. Pattern Recognition Letters, 29, pp. 925-932. (2008)
4. Han D., Lee B.: Flame and smoke detection method for early real-time detection of a tunnel fire. Fire Safety Journal, 44, pp. 951-961. (2009)
5. Gunay O., Tasdemir K., Toreyin B.U., Cetin A.E.: Video based wildfire detection at night. Fire Safety Journal, 44, pp. 860-868. (2009)
6. Yu C., Fang J., Wang J., Zhang Y.: Video Fire Smoke Detection Using Motion and Color Features. Fire Technology, 46(3), pp. 651-663. (2009)
7. Celik T., Demirel H., Ozkaramanli H., Uyguroglu M.: Fire Detection in Video Sequences using Statistical Color Model. IEEE International Conference on Acoustics, Speech and Signal Processing, pp. II213-216. (2006)
8. Chen T.H., Wu P.H., Chiou Y.C.: An Early Fire-Detection Method Based on Image Processing. IEEE International Conference on Image Processing (ICIP), pp. 1707-1710. (2004)
9. Celik T., Demirel H.: Fire Detection in Video Sequences using a Generic Color Model. Fire Safety Journal, 44(2), pp. 147-158. (2009)
10. Phillips Ⅲ W., Shah M., Lobo N.V.: Flame recognition in video. Pattern Recognition Letters, 23, pp. 319-327. (2002)
11. Toreyin B.U., Dedeoglu Y., Gudukbay U., Cetin A.E.: Computer vision based method for real-time fire and flame detection. Pattern Recognition Letters, 27, pp. 49-58. (2006)
12. Krstinic D., Stipanicev D., Jakovcevic T.: Histogram-based smoke segmentation in forest fire detection system. Information Technology and Control, 38(3), pp. 237-244. (2009)
13. Martinez-de Dios J.R., Arrue B.C., Ollero A., Merino L., Gomez-Rodriguez F.: Computer vision techniques for forest fire perception. Image and Vision Computing, 26, pp. 550-562. (2008)
14. Ko B.C., Cheong K.H., Nam J.Y.: Fire detection based on vision sensor and support vector machines. Fire Safety Journal, 44, pp. 322-329. (2009)
15. Toreyin B.U., Dedeoglu Y., Cetin A.E.: Flame detection in video using hidden Markov models. IEEE International Conference on Image Processing (ICIP), pp. 1230-1233. (2005)
16. Celik T., Demirel H., Ozkaramanli H.: Automatic fire detection in video sequences. European Signal Processing Conference, pp. 1-5. (2006)

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17. Chen T.H., Kao C.L., Chang S.M.: An Intelligent Real-Time Fire-Detection Method Based on Video Processing. IEEE 37th International Carnahan Conference on Security Technology, pp. 104-111. (2003)
18. Zhang J.H., Zhuang J., Du H.F.: A New Flame Detection Method Using Probability Model. International Conference on Computational Intelligence and Security, pp. 1614-1617. (2006)
19. Yuan F.N., Liao G.X., Zhang Y.M., Liu Y.: Feature Extraction for Computer Vision Based Fire Detection. Journal of University of Science and Technology of China, 36(1), pp. 39-43. (2006)
20. Liu C.B., Ahuja N.: Vision based fire detection. 17th International Conference on Pattern Recognition (ICPR), pp. 134-137. (2004)
21. Zhang D.Y., Hu A.K., Rao Y.J., Zhao J.M., Zhao J.H.: Forest Fire and Smoke Detection Based on Video Image Segmentation. SPIE Pattern Recognition and Computer Vision, pp. 67882H-1-67882H-7. (2007)
22. Ferrari R.J., Zhang H., Kube C.R.: Real-time detection of steam in video images. Pattern Recognition, 40, pp. 1148-1159. (2007)
23. Cremers D., Rousson M., Deriche R.: A Review of Statistical Approaches to Level Set Segmentation - Integrating Color, Texture, Motion and Shape. International Journal of Computer Vision, 72(2), pp. 195-215. (2007)
24. Liu X.W., Wang D.L.: Image and Texture Segmentation Using Local Spectral Histograms. IEEE Transactions on Image Processing, 15(10), pp. 3066-3077. (2006)
25. Arrebola F., Bandera A., Camacho P., Sandoval F.: Corner Detection by Local Histograms of Contour Chain Code. Electronics Letters, 33(21), pp. 1769-1771. (1997)
26. Zhang Z., Zhao J.H., Zhang D.Y., Qu C.Z., Ke Y.W., Cai B.: Contour Based Forest Fire Detection Using FFT and Wavelet. International Conference on Computer Science and Software Engineering, pp. 760-763. (2008)
27. Zhang D.Y., Han S.Z., Zhao J.H., Zhang Z., Qu C.Z., Ke Y.W., Chen X.: Image Based Forest Fire Detection Using Dynamic Characteristics With Artificial Neural Networks. International Joint Conference on Artificial Intelligence, pp. 290-293. (2009)

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