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Fire smoke detection in video images Using Kalman filter and Gaussian Mixture Color model

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Abstract—**Fire smoke detections are crucial for forest resource protections and public security in surveillance systems. A novel approach for smoke detections with combined Kalman filter and a Gaussian color model is proposed in the paper in open areas. Moving objects are firstly generated by image subtractions from adaptive background of a scene through Kalman filter and MHI(Moving History Image) analysis. Then a Gaussian color model, trained from samples offline by an EM algorithm, is performed to detect candidate fire smoke regions. Final validation is carried out by temporal analysis of dynamic features of suspected smoke areas where higher frequency energies in wavelet domains and color blending coefficients are utilized as smoke features. Experimental results show the proposed method is capable of detecting fire smoke reliably.**

I. Introduction

Detections of smokes, when a fire occurs, are crucial to minimizing damages and saving lives. In recent decade, research in detecting smoke using surveillance cameras has become very active as smoke detection in videos takes advantages over traditional sensors on (1) video cameras do not require a close proximity to the smoke; (2) compared to conventional methods, video smoke detections can provide information about fire location, size, burning degree etc. However, there still are many technical challenges to achieve high performances in monitoring systems of smoke detections. Smoke is a compound of hydrogen, carbon, and oxygen. In image processing and analysis field, objects of smokes with special characteristics difficult to be identified: (1) smoke color, a key visual clue, varies with temperatures of burning materials from light gray to dark; (2)fire smokes are non-rigid moving objects with changeable shapes and flicks on their contours; (3)smoke appears semitransparent with blurring effects to weaken edge information. In addition variations of illuminations exist in open areas.

In recent years, there are many researches on smoke detections mainly taking a procedure of motion detection, color matching and verification from temporal features. Frame differences, background subtraction and optical flow are generally used for motion detections. Frame differencing approach is computational effective but with holes at internal regions of moving objects. In [6] an accumulated frame difference is utilized to produce a denser region. A joint frame difference with background subtraction is proposed to extract moving objects [1]. Motion segmentation from the background subtraction performs better in case of both adaptive Gaussian Mixture models [3] and Kalman filtering [4]. Although both of which enable background update with scene variations, Kalman filtering presents efficient and effective background estimation on its nonlinear property. Another visual indicator of fire smoke is described by color histogram to measure similarity color features with respect to reference histograms of sampled smoke templates [2]. Dynamic features of fire smoke are collected for verification of candidate smoke regions where shape irregularity [1, 2, 5], texture information [6] and blurring effects (higher frequency energy in wavelet domain)[7,8] are evaluated on temporal analysis.

To achieve efficient smoke detection, a novel approach for online fire smoke identification is proposed with several points:(1) combined Kalman filtering and MHI to extract continuous motion regions from images;(2) instead of color histograms, offline trained Gaussian mixture model in RGB color space is performed online to delete some moving objects dissimilar to the smoke color model. (3) a color blending coefficients , describing color variations from light gray to dark, and higher frequency energy of candidate regions in wavelets are analyzed in time series for dynamic feature verification.

II. Spatial features of fire smokes

A. Motion detection

1) Motion model from Kalman filtering

Kalman filter is a widely-used recursive technique to track linear dynamical systems under Gaussian noise. It can be viewed as a background model where the mean and variance of the background are updated to accommodate changes in illuminations in a scene. By using characteristics of Kalman recursive low-pass filtering, approximated background is achieved from accumulating weighted average of a fixed length video image to segment foreground with movements. Kalman filter as a background model has several advantages: (1) quality of the extracted initial background is independent to starting time; (2) adaptive to illumination changes from lightering.

A slow movement in an image could be segmented as a series of images passes through the Kalman filter. Here the

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updated background model is given below:

$$B(i,j,k+1)=B(i,j,k)+g(k)(I(i,j,k)-B(i,j,k)) \quad (1)$$

$$g(k)=\beta(1-M(i,j,k))+\alpha M(i,j,k) \quad (2)$$

$$M(i,j,k)=\begin{cases}1 & if\ |I(i,j,k)-B(i,j,k)|>T \\ 0 & otherwise\end{cases} \quad (3)$$

Where $B(i,j,k)$ and $B(i,j,k+1)$ are the intensity value of pixel (i,j) in background image at time k and $k+1$ respectively. $I(i,j,k)$ refers to the intensity value of pixel (i,j) in a current image at time k . $g(k)$ is a updating factor related to motion detection in the image where $M(i,j,k)$ has a binary value 1 or 0 corresponding to moving (if intensity difference between current image and background larger than a preset threshold T) or static (otherwise).

In Eq.(2) α and β (both $\in [0,1]$) refer to motion factor and background factor respectively and have much influence on model performance. If the β too small, background adaptation would be weakened, otherwise more fast changes would be transferred to the background as it approach one; moving factor α reflects influence of foreground movements on background with much smaller value than β to secure extract moving objects from the background.

2) Motion segmentation combined with MHI

Although motion detection is well performed using Kalman filter, detected smoke pixels in a region are not connected as threshold T is preset value and smoke pixels changes frame by frame. To achieve accumulative effects for smoke motion, MHI (Motion history Image) is used after Kalman filtering. The technique is first proposed by Aaron F. Bobick[9] to present how the motion of human is moving and it is later used for smoke moving detection in[2]because of its accumulative effects. In MHI, pixel intensity is a function of the motion history at that point:

$$MHI_{\lambda}(i,j,t)=\begin{cases}\lambda & if\ M(i,j,t)=1 \\ \max(0, MHI_{\lambda}(i,j,t-1)-1) & otherwise\end{cases} \quad (4)$$

Where λ is a preset maximum value for a pixel of current motion, M is the generated motion image from Kalman filter. In MHI images, brighter values refer to more recent movement and darker values to history of motions. In this way, collective fire smoke pixels are formed by thresholding the MHI image.

B. Building smoke color model

In open areas, the background of the scene contains many non-static objects such as tree branches and bushes whose movement depends on the wind in the scene; while the problem is that smoke motion would has similar pixel intensity variations as the non-static objects. To further extract smoke from candidate pixels of movements, Color feature, a significant cue for smoke detection in human visual system, should be utilized. In this paper Gaussian mixture model is considered in RGB color space where objects in an image are described by their color components.

Any pixel intensity of an image, in a separated color channel $b \in \{R,G,B\}$, is modeled as a Gaussian Mixture model with K components. The possibility of intensity value x_t at any time t is given below:

$$p_b(x_t)=\sum_{i=1}^{K} w_{it}\eta(x_t,\mu_{i,t},\textstyle\sum_{i,t}) \quad (5)$$

Where K is the number of Gaussian components (K is a small number from 3 to 5). $w_{i,t}$ is a weighted value of the ith Gaussian distribution at time t. $\mu_{i,t}$ and $\sum_{i,t}$ correspond to mean and variance of the ith Gaussian distribution at time t respectively. η , possibility density of a Gaussian distribution:

$$\eta(x_t,\mu,\textstyle\sum)=\dfrac{1}{(2\pi)^{1/2}|\sum|^{1/2}}\ e^{-1/2(x_t-\mu)} \quad (6)$$

A standard method for maximizing the likelihood of the observed data is expectation maximization(EM for short). Unfortunately, each pixel intensity in each channel varies over time as the illumination changes and online EM algorithm is computational expensive. So there are some methods taken for smoke extraction: (1)RGB model are normalize using Eq.(7) to restrain illumination variations[10]. (2) Sample images with smoke patterns are trained offline using EM algorithm to extract smoke color model from resulting Gaussian Mixture model.

$$I_b^{'}=I_b/\sqrt{I_G^2+I_B^2+I_R^2}\ , \quad b\in\{R,G,B\} \quad (7)$$

Candidate pixels of Fire Smokes identified by color Gaussian mixture model in the following:

step1. Get smoke color model using EM algorithm by offlinesample images containing smoke regions.

step2. Separate video into RGB frames and do normalizationusing Eq.(7) in RGB space Where $I_b^{'}$,normalized color value in channel b.

step3. For each pixel of current frame, check that if $| I_b^{'} - \mu_s | < 2.5\sigma_s$. If it is true, then the pixel is considered as a candidate smoke pixel where μ_s and σ_s .are mean and variance of smoke objects.

III. Temporal analysis of fire smokes

To reduce false alarm of moving object with similar colors to smokes, verification process is carried out by temporal analysis of a neural network. Based on candidate regions generated in the previous phases, two features correspond to blurring effects and color blending factors when smokes are spreading are estimated in frame sequences.

A. Energy variation in wavelet domain

When fire smoke covers on a region of backgrounds, details of backgrounds are disappear and higher frequency contents are degraded with time. By using wavelet analysis, it is easy to observe behavior of higher frequency energies with respect to the background.

$$\rho = \frac{\sum w_I(n)}{\sum w_b(n)} \tag{8}$$

Where w_I and w_b are higher frequency energy of an observed frame and that of corresponding background at any sub-channel of a preset scale respectively. Value ρ would gradually drop with time if the region is covered by smokes.

B. Color blending coefficients

A smoke has a property of semitransparent and the color distribution in a smoke region could be considered as mixture of the background and fully denser smokes. The color blending coefficient $B_b(i, j)$ at any point measures how likely a pixel's color belongs to the background.

$$B_b(i,j) = {I_b^{'}(i,j) - I_{bg}(i,j)} \Big/ {s - I_{bg}(i,j)} \tag{9}$$

Where $I_{bg}(i, j)$ and s are intensity value of background at (i, j) and that of reference smokes respectively. An averaged value is calculated for a given region as a temporal color feature.

Early smoke appears as light gray considered a blending color model from background color and a referenced smoke color models. Color blending ratio measures how much percentage of a current pixel belongs to a referenced smoke pixel.

IV. Experiments and conclusion

Experiments are implemented using the proposed approach. A sequence of video images was taken in an open area with resolution 720X480. results of motion detection is given in Fig.1 where (a)and (b)are original image of the 42th frame and estimated background image generated by Kalman filter using Eq.(1). Motion detection by Kalman filter by Eq.(3) is shown in Fig.1 (c) where moving pixels consist of leaves of trees and smokes but smoke pixels at middle, bottom and upper right of the image are not compact. Taking MHI operation to memorize recent history of motions, denser areas of the smokes are given in Fig.1(d). To further analysis color features of smokes, a trained color Gaussian mixture model is generated by offline EM algorithm by a sample image of a frame. Candidate smoke pixels are determined in Fig.2(a) by the statistical model of smokes in RGB channels. An integrated consideration of both motion and color feature of smokes is taken and further morphological operations are performed to suppress noises shown in Fig.2 (b).

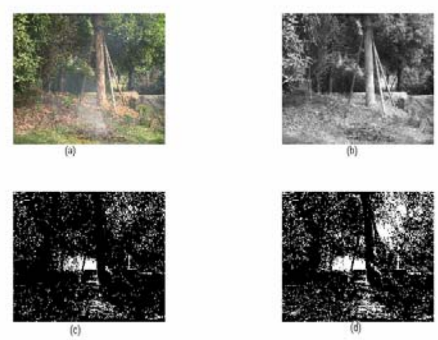

Fig.1 motion detection using Kalman filter and MHI

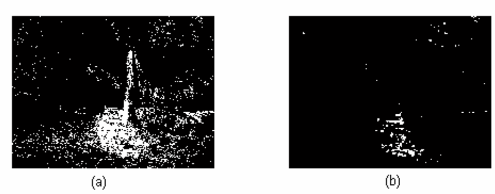

Fig.2 Results of candidate smokes using a Gaussian mixture model

Post-operations include labeling and tracing windows are executed to track dynamic features of blurring effects of smokes in period of 25 frames of time sequences. Fig.3 gives a comparative results of energy ratio ρ in Eq.(8) where large drops in energy ratio in Fig.3(a) indicate a smoke region and energy ratio of a region for tree leaves shows a small variation.Fig.4presents profiles of color blending coefficients in red channel for both a smoke region (Fig.4(a)) and a tree leave region (Fig.4(b). It can be seen that the trend of color blending coefficients in the smoke region increases approaching to one but that of tree leaves varies randomly.

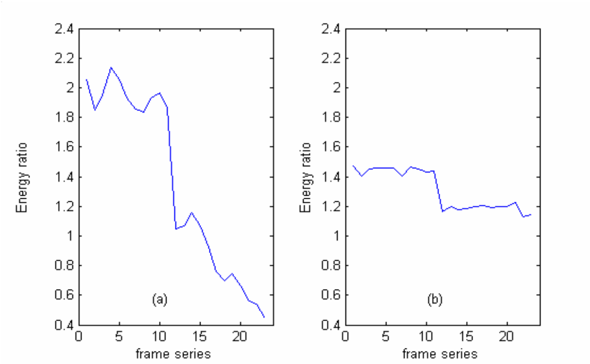

Fig.3 energy ration comparison

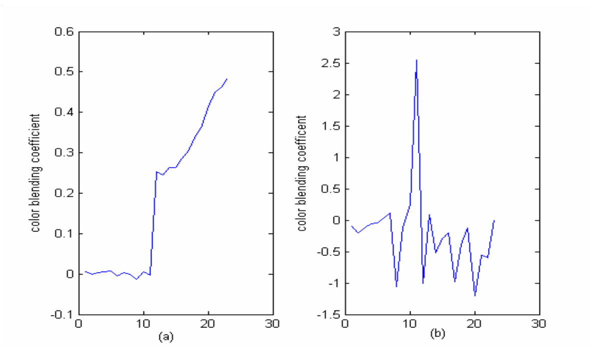

Fig.4 color blending coefficients

In this paper, an approach to detect the fire smoke is presented in an open area. Fire smokes are characterized in spatial and temporal analysis where Kalman filter with MHI for motion evaluation and color Gaussian mixture model, trained by EM offline, for smoke-color like detection are performed. Furthermore, dynamic features of smokes, energy ratio of higher frequency for a candidate region in wavelet and color blending coefficients, are evaluated to reflect blurring effects during smoke expansion. The experimental results show that fire smoke can be successfully detected on the method proposed in the paper.

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