ISSN:0975-9646

Flame Detection in Videos Based on SVM

Madhuri R. Choutmahal, Prof. Pravin M. Kamde

Department of Computer Engineering, Pune University
Sinhgad College of Engineering, Vadgaon(Bk),Pune, India.

***Abstract*— As we know, as compared to a single image, the video sequences present more details about how the objects and the scenario in that video change over time. While dealing with the videos, we have to consider the continuous image sequences one by one. Automated flame or fire detection has become an active research topic in computer vision and image processing these days. In this paper, a set of the motion features based on motion estimation is considered. The basic idea is to exploit the difference in between the turbulent, fast, fire motion, and the well-structured, rigid motion of other objects. In this paper, two optical flow methods are particularly discussed for the fire detection task: Optical Mass Transport (OMT) which is used to model fire with dynamic texture, on the other hand a data-driven optical scheme is used to model saturated flames. Then, the characteristic features related to the flow magnitudes and directions are extracted from the flow fields to differentiate in between fire and non-fire motion.**

***Keywords*— Fire detection, optical flow, optimal mass transport, video analytics, SVM.**

I. INTRODUCTION

Now-a-days, because of the progress in computer vision technology and video processing, there are extra affordable digital video acquisition devices available in the market. It means that more applications designed for digital video. Unlike the still images, the video sequences provide additional information about how the objects and scenarios change over time, although they need increased space for the storage as well as the wider bandwidth for transmission.

Detecting the break-out of a fire quickly is crucial for prevention of the material damage along with human casualties. The traditional point-sensors can detect heat or smoke particles and have relatively become successful for indoor fire detection. However, they cannot be applied in large wide open spaces, such as ships, or in forests. This paper presents a video-detection approach geared toward these circumstances where point-sensors may possibly be unsuccessful.

Existing methods of visual flame or fire detection depends on spectral analysis. These approaches are still vulnerable to false alarms caused because of the objects which have the same colour as fire, like sun. Toreyin et al. [4] used fire-colored pixels in the moving regions and a temporal/spatial wavelet analysis. Even though they showed good results for quite a few experiment data, they used a lot of heuristic thresholds, which is impractical for real-life applications. Phillips et al. [10] used a color lookup table for detecting the candidate fire regions and temporal variation in these candidate regions to confirm ultimate fire regions. However, since they also used a lot of heuristic features, the similar results cannot be guaranteed if the input data is altered.

For more precise fire detection, we first detect candidate fire regions by modifying the ideas from preceding studies, such as detecting moving regions in addition to fire-colored pixels. After that, two supplementary methods, a luminance map along with support vector machine (SVM), are applied to the candidate fire pixels. As fire regions usually have a higher luminance contrast than the neighboring regions in image sequence, a luminance map is prepared and it is used to eliminate the non-fire pixels. In addition to this, a temporal fire model by means of wavelet coefficients is formed and then applied to a two-class SVM classifier with a radial basis function (RBF) kernel. The SVM classifier is then used for the final fire-pixel detection. It will give us the probability of flame being fire. Fig. 3 shows overall flame-detection procedure.

Vision-based fire or flame detection is composed of the following three steps. Preprocessing (1) is required, e.g., camera hardware along with illumination. Feature extraction (2) is considered for the detection of a specific object or target; Classification algorithms (3) use the calculated features as input and make conclusion outputs concerning the target's existence. Supervised machine-learning-based classification algorithms SVM are analytically trained on a data set of features as well as ground truth.

The remainder of this paper is organized as follows. Section II gives a brief summary of the literature survey and the related work. Section III consists of the proposed methodology in detail. Section IV gives details about the experimental condition and lastly Section V includes the conclusion.

II. RELATED WORK

The perception of Computer vision concepts are usually inspired by human vision. In [6], the proposed method analyses the frame-to-frame changes of particular low-level features like colour, area size, surface coarseness, boundary roughness, and skewness describing possible fire regions. Also, the flickering, a typical characteristic of the fire, presents a popular feature has also been analysed in the wavelet domain [2], [4]. In [7], they developed a method which is suitable for both smooth (laminar) and turbulent flames, and also it can be used to animate the burning of either solid or gas fuels. The authors of [2] have considered the temporal variation intensity of pixel for the fixed pixel positions. Classical optical flow algorithms have been analysed in [8] for the recognition of various dynamic textures.

None of above authors has established the concept of optical flow as [1] and [2]. In [1], Horn–Schunck has developed a method for finding the optical flow pattern which assumes that the apparent velocity of the brightness pattern in the image varies smoothly almost everywhere in image sequence. In [3], Lucas/Kanade has introduced the method which is used broadly for optical flow estimation, assumes that the flow is essentially constant in a local neighbourhood of the pixel in image under consideration, and it also solves the basic optical flow equations for all the pixels in that particular neighbourhood.

It can be seen in [6] that for a particular fire or flame pixel, the value of the red channel is greater than the green channel, and the value of the green channel is greater than the value of the blue channel, as shown in Fig. 1.

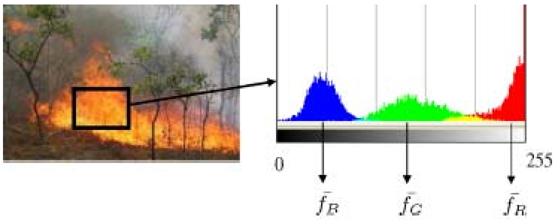

Fig. 1. Histogram of a fire region inside the black square, for the red, green, and blue channels. [6]

In [5], a RGB frame in the video sequence is given in fig. 2 (a) and its respective scalar-valued image is shown in fig. 2 (b). Colour is taken as the generalized mass.

(a) (b)

Fig.2. Example for the generalized mass transformation.(a): Original image. (b): Respective generalized mass (black - 0, white - 1). [5]

III. Proposed Work

As discussed in section I, flame or fire detection in videos consists of three steps. Pre-processing (1), feature extraction (2) and finally classification (3). Let's see one by one.

A. *Pre-processing*

In the pre-processing, first we have to divide the given video into RGB image frames. Then these RGB frames must be converted to scalar-valued frames, weighting high fire-like colour pixels.

B. *Optical Flow Estimation*

The video is consists of single or multiple 'moving' objects. It means some of the objects, or all the objects in the continuous image frames are in the motion. Optical flow is nothing but the pattern of apparent motion of these moving objects, surfaces, and edges in the continuous image frames in a visual scene caused by the relative motion between an observer or camera and the video scene. So, to know precisely about the relative motion of the moving objects in the video, first we have to deal with the optical flow.

Optical flow computation results in the motion direction analysis and motion velocity determination at image points. Horn/Schunck [1] and Lucas/Kanade [2] from 1981 first introduced the concept of optical flow estimation.

1) *Classical Optical Flow:*

Optical flow estimation is generally based on the following two assumptions:

1. The observed brightness or intensity of particular object point is constant over time.
2. Close points in the image plane move in a similar way (Called as the velocity smoothness constraint).

Optical flow estimation gives correspondence in between the pixels in the current and the previous frame of an image sequence of that particular video.

$$\frac{dI}{dt} = I_x u + I_y v + It = 0 \qquad (1)$$

Where $I(x, y, t)$ is a sequence of continuous image frames with the spatial co-ordinates $(x, y) \in \Omega$ along with the variable of time $t \in [0, T]$. The flow vector $(u, v) = (x_t,, y_t)$ points into the direction where the pixel (x, y) is moving in that particular image sequence.

2) *Optimal Mass Transport (OMT) Optical Flow:*

As the classical optical flow methods are based on some assumptions as discussed in III-*A*, like intensity or brightness constancy and flow smoothness, which are not met by the fire motion.

Consequently, they are inadequate to model the existence of the fire in the images or video for two causes. First, fire does not satisfy the intensity or brightness constancy assumption Eq. (1), since rapid change of intensity or brightness takes place in the burning process due to the fast pressure in addition to heat dynamics of the fire. Second, the smoothness regularization could be counter-productive to the detection of fire motion, which is likely to have a turbulent, i.e., non-smooth, motion field. That's why, an optical flow estimation modelling fire as a dynamic texture, the optimal mass transport (OMT) optical flow, was introduced in [8].

OMT models fire with dynamic texture.

3) *Non-Smooth Data (NSD) Optical Flow:*

NSD optical flow is computationally cheap. It is used to categorize between fire and non-fire motion. The NSD flow directions have entirely driven by the data term under the drawback that flow magnitudes are not too large. While this method is not likely to perform well for standard optical flow applications where the flow smoothness plays a major role, it proves helpful for detecting saturated fire in the videos.

IV. PROGRAMMER'S DESIGN

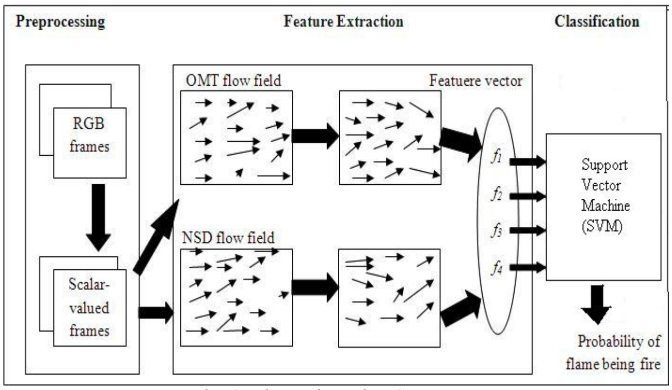

Fig. 3. Flame detection System

A. *Implementation*

1. Preprocessing:
   - Fire image database: it contains number of fire images.
   - Color Transformation: Convert RGB-frames to scalar image weighting high fire-like colors.
2. Feature extraction module: To extract features of the images.

Optical Flow Estimation:
   - Optimal Mass Transport, OMT
   - Non-Smooth Data, NSD

Essential Pixels: Rejection of little motion pixels
   - Features:
   - f_1 = OMT transport energy
   - f_2 = NSD magnitude
   - f_3 = OMT source match
   - f_4 = NSD directional variance

3. Classification: SVM can be used for classification purpose.
   - Supervised Classification: Support Vector Machine.

B. *Mathematical Model*

Let 'S' be the flame detection in videos system defined as,

$S = \sum (I, O, D, F, f(x))$

I: Input Flame video.

O: Get Probability of flame being fire using NN.

D: It is the flame Video/image database

F = 4D feature vector.

f(x): It provides a set of functions that performs on the input flame image, defined as,

f(x) = {split_video(), rgb2scalar(), OMT(), NSD(), ess_pix(), get_features(),classify(), get_proba()}

Step 1: split_video()

First we have to divide the input video into the RGB frames of spatial dimension of 240 by 360 pixels.

To reduce the complexity, we can reduce the dimension.

Then $I=\{I_0, I_1, I_2, I_3, \ldots\ldots, I_n\}$

Step 2: rgb2scalar()

Then we will convert the RGB frames into scalar-valued frames.

Where $I_0(x,y)= I(x,y,0)$ and $I_1(x,y)= I(x,y,1)$ are gray-scale images.

Step 3: Optical Flow estimation

We have to compute the optical flow to detect the flame.

There are two methods for that:

- Optimal Mass Transport(OMT) and
- Non-Smooth Data(NSD).

Using OMT() and NSD(), we can estimate the optical flow.

OMT() : models fire with dynamic texture

NSD() : to discriminate between fire and non-fire motion.

Step 4: ess_pix()

Sub region of Essential pixels is considered.

Consider a frame or a subregion of a frame $\Omega \in R^2$. Assume that the optical flow field $\vec{\mathbf{u}} : \Omega \mapsto \mathbf{R}^2$ is computed. Then, the set of essential pixels $\Omega_e \in \Omega$.

Step 5: get_features()

4D feature vector is calculated.

$F = (f_1, f_2, f_3, f_4)$

Where,

- f_1 = OMT transport energy
- f_2 = NSD magnitude
- f_3 = OMT source match
- f_4 = NSD directional variance

Step 6: classify()

- Classify the sub regions according to their features with help of Support Vector Machine (SVM).

Step 7: get_proba()

Get the output from SVM, which is nothing but the probability of flame being fire in a video sequence.

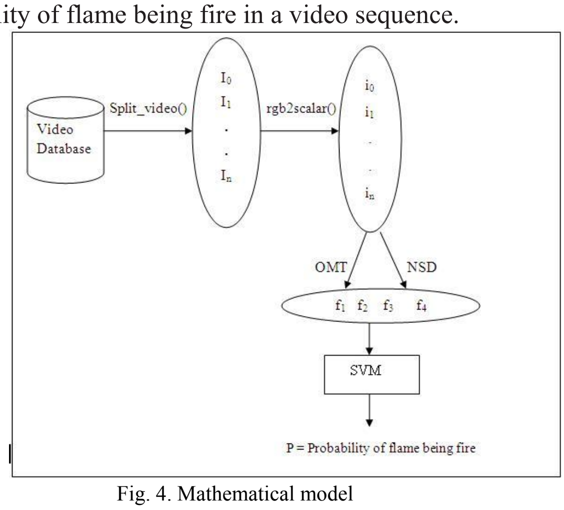

Fig. 4. Mathematical model

V. CONCLUSIONS

The proposed flame detection in videos system has been presented two novel optical flow estimators, Optimal Mass Transport (OMT) and Non-Smooth Data (NSD) that will overcome the drawbacks of classical optical flow models when applied to fire content. The obtained motion fields can be used to define motion features. These features will reliably detect fire and reject non-fire motion and give us the better results.

REFERENCES

1] B. Horn and B. Schunck, "Determining optical flow," Artif. Intell., vol. 17, nos. 1–3, pp. 185–203, 1981.

2] B. Ko, K. Cheong, and J. Nam, "Fire detection based on vision sensor and support vector machines," *Fire Safety J.*, vol. 44, no. 3, pp. 322–329, 2009.

3] B. Lucas and T. Kanade, "An iterative image registration technique with an application to stereo vision," in Proc. Int. Joint Conf. Artif. Intell., vol. 2. 1981, pp. 674–679.

4] B. Toreyin, Y. Dedeoglu, U. Gudukbay, and A. Cetin, "Computer vision based method for real-time fire and flame detection," *Pattern Recognit.Lett.*, vol. 27, no. 1, pp. 49–58, 2006.

5] M. Mueller, P. Karasev, "Optical Flow Estimation for Flame Detection in Videos", IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 22, NO. 7, JULY 2013.

6] P. Borges and E. Izquierdo, "A probabilistic approach for vision-based fire detection in videos," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 20, no. 5, pp. 721–731, May 2010.

7] R. Fedkiw, J. Stam, and H. Jensen, "Visual simulation of smoke," in Proc. Conf. Comput. Graph. Interact. Tech., 2001, pp. 15–22.

8] S. Fazekas and D. Chetverikov, "Analysis and performance evaluation of optical flow features for dynamic texture recognition," Signal Process., Image Commun., vol. 22, nos. 7–8, pp. 680–691, 2007.

9] T. Çelik and H. Demirel, "Fire detection in video sequences using a generic color model," Fire Safety J., vol. 44, no. 2, pp. 147–158, 2009.

10] W. Phillips, III, M. Shah, and N. da Vitoria Lobo, "Flame recognition in video," Pattern Recognit. Lett., vol. 23, nos. 1–3, pp. 319–327, 2002.