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Lab Color Space Model with Optical Flow Estimation for Fire Detection in Videos

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ABSTRACT : *Detecting the breakout of fire rapidly is vital for the prevention of material damage and human casualties. The vision-based flame detection has drawn significant attention in the past decade with camera surveillance systems becoming quite common. Conventional fire detectors use physical sensors to detect fire. However, this may lead to false alarms. In order to prevent false alarms, a computer vision-based fire detection algorithm is developed. In this paper, a new method for identifying fire is proposed .Firstly the RGB image is converted to Lab color space and Optical flow estimation computes correspondence between pixels in the current and the previous frame of an image sequence to detect the moving pixels. Secondly Chan-Vese model is applied for segmentation. Segmentation means partitioning a digital image into multiple segments; Chan-Vese model for active contours is a powerful and flexible method to segment images and here the fire region is segmented. And then a novel fire color model is developed in CIE Lab color space to identify fire pixels. Experimental results show the proposed approach can classify flame and non flame objects, and also has a high time effectiveness.*

Keywords – *Chan-Vese model, CIE Lab Color Space, Flame Detection, Optical Flow, Segmentation.*

1. INTRODUCTION

As soon as a fire breaks out, detecting at the right moment to prevent material damage and human casualties is a particularly serious problem in situations of congested automobile traffic, naval vessels, and heavy industry. It is preferable that the detection system has the capacity to report the earliest stages of fire. Most of the fire detection systems use built in sensors to detect heat or smoke. It is also a must that these sensors should be distributed densely for higher accuracy of the system. The fire detection in outside areas using the sensors is impractical because there is necessity of a large distribution of sensors in close proximity.

The fast developments in digital camera technology, video and image processing techniques have lead to a major trend to replace the sensor based fire detection methods with computer vision based systems. The computer vision-based fire detection systems employ mainly three stages: Classification of fire pixels, segmentation of moving objects, and candidate region analysis. Mainly this analysis is based on two figures: the region shape and the temporal changes of the region. The fire detection performance critically depends on the effectiveness of the pixel classifier, which classifies the region on which rest of the system have to exercise. So the fire pixel classifier has to be very accurate. There are a few algorithms which directly deal with the fire pixel classification in the literature.

In both grayscale and color video sequences the fire pixel classification can be considered. Raw *R*, *G*, and *B* color information was used by Chen and others [1] and a set of rules were developed to classify the fire pixels. Toreyin and others [2] used a mixture of Gaussian models in RGB space which is obtained from a training set of fire pixels instead of using the rule-based color model as in Chen and others. The authors of a recent paper, employed Chen's fire pixel classification method along with motion analysis and Markov field modeling of the fire flicker process [3].

Celik and others [4] used normalized RGB (rgb) values for a generic color model for fire. In order to overcome the effects of changing illumination the normalized RGB was proposed. Using the statistical analysis carried out in r-g, r-b, and g-b color planes the generic model was obtained. Three lines are used to specify a triangular region representing the region of interest for the fire pixels, due to the distribution of the sample fire pixels in each plane. Therefore, to classify a pixel triangular regions in respective r-g, r-b, and g-b planes are used. A pixel if falls into three of the triangular regions in r-g, r-b, and g-b planes is declared to be a fire pixel. Low-cost CCD cameras were used by Krull and others [5] to detect fires in the cargo bay of long range passenger aircraft. Statistical features based on grayscale video frames was used in this method, which include mean pixel intensity, standard deviation, and second-order moments as well as non-image features, such as humidity and temperature to detect fire in the cargo compartment. In order to reduce the number of false alarms caused by the smoke detectors, these systems is commercially used in parallel with standard smoke detectors and it also helps the aircraft crew confirm the presence or absence of fire providing visual inspection capability. However, in the standalone fire detection system the statistical image features are not considered to be used as part of it.

A set of motion features was proposed by Martin Muller and others [6] based on motion estimators. Exploiting the difference between the fast, turbulent, fire motion, and the structured, rigid motion of other objects is the key idea. For the fire detection task, two optical flow methods are specifically designed: fire with dynamic texture is modeled by optimal mass transport, while saturated flames was modeled by a data-driven optical flow scheme. Then, to discriminate between fire and non-fire motion, characteristic features related to the flow magnitudes and directions are computed from the flow fields. However it may fail, based on lighting conditions.

In computer vision-based fire detection systems a good color model for fire modeling and robust moving pixel segmentation are essential because of their critical role in it. In this paper, an algorithm is proposed that models the fire pixels using the CIE $L^*a^*b^*$ color space. The main reason for using CIE $L^*a^*b^*$ color space is because it is perceptually uniform color space, therefore making it possible to represent color information of fire better than other color spaces. By optical flow estimation the moving pixels are detected. And for segmentation Chan-Vese model is applied.

This paper is organized as follows. The proposed fire detection algorithm is presented in Section II. The analysis and test results are provided in Section III. The conclusion of the paper in section IV.

2. FIRE DETECTION

The details of the fire detection algorithm are covered in this section. Figure 1 shows block diagram of the proposed algorithm for fire detection in a video. It is assumed that the output is produced in RGB format by the image acquisition device. There are three main stages in the algorithm: Optical flow estimation, Chan-Vese algorithm and CIE $L^*a^*b^*$ space color model. The detailed description of each part is given below**.**

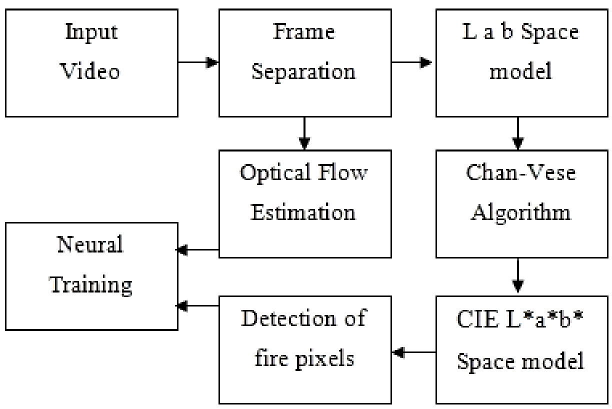

Fig. 1. Block Diagram of the proposed fire detection algorithm.

2.1 Optical Flow Estimation

The pattern of distinct motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer and the scene is defined as Optical flow.

In optical flow estimation, the difference between pixels in the current and the previous frame of an image sequence is found. Central to most approaches in establishing this difference is the assumption of intensity constancy: intensity values are preserved by moving objects from frame to frame. The calculation of some function is the idea of optical flow, velocity vector v = (u,v), for each pixel in an image. How quickly each particular pixel is moving across the image stream along with the direction in which the pixel is moving is described by the function v(u,v). Consider an image stream described in terms of intensity as I(x,y,t). The intensity's position change over time is:

$$I(x+dx,\ y+dy,\ t+dt) = I\ (x,y,t)+ \Delta \tag{1}$$

Δ represents change in position. If there is no change in position over time

$$I\ (x+dx,\ y+dy,\ t+dt) = I\ (x,y,t) \tag{2}$$

To simplify things we define:

$$u = dx/dt \text{ and } v = dy/dt \tag{3}$$

In this respect, u and v are the speeds the intensity is changing. As dt approaches zero:

$$dI/dt = -\ (dI/dx)\ u - (\ dI/dy)\ v \tag{4}$$

Equation 4 above relates the change of a pixel's intensity with time to the spatial rates of change of intensity within an image .Now at a given pixel is just how fast the intensity is changing with time, while and are the spatial rate of change of intensity. From this the moving pixels are detected and are given along with the fire pixels to the neural network for detection.

2.2 Chan-Vese Segmentation

The process of partitioning a digital image into multiple segments (sets of pixels) is known as segmentation. Segmenting written text or segmenting tumours from healthy brain tissue in an MRI image, etc are common segmentation tasks. To segment the fire region is the task here.

Chan-Vese model for active contours is a powerful and flexible method which is able to segment different types of images, including those which are quite difficult to segment in means of "classical" segmentation – i.e., using thresholding or gradient based methods.

Chan-Vese active contour algorithm is derived from segmentation problem formulated by Mumford and Shah.Given an observed image u_o, find a decomposition $\mathbf{\Omega}_i$ of $\mathbf{\Omega}$ and an optimal piecewise smooth approximation of u of u_o,such that u varies smoothly within each $\mathbf{\Omega}_i$ and rapidly or discontinuously across the boundaries of $\mathbf{\Omega}_i$.

To slove the problem, Mumford and Shah proposed the following minimization problem:

$$\inf \left\{ F^{MS}(u,C) = \int (u-u_o)^2 dxdy + \mu \int |\nabla u|^2 dxdy + v|C| \right\} \tag{5}$$

By restricting the segmented image u to piecewise constant function a reduced case of the model is obtained, i.e. u = constant c_i inside each connected component $\mathbf{\Omega}_i$. Then this problem is called "smallest partition problem" and its functional is:

$$E^{MS}\ (u,C) = \sum \int (u-c_i)^2 dxdy + v|C| \tag{6}$$

It is easy to see that, for a fixed C, energy from above equation is minimized in the variable c_i by setting

$$c_i = \text{mean}\ (u_o) \text{ in } \mathbf{\Omega}_i. \tag{7}$$

By curve $C = \partial\omega$,and the function for "smallest partition problem", with $\omega \in \mathbf{\Omega}$ an unwrap subset and two unknown constants c_1 and c_2 denoting $\mathbf{\Omega}_1 = \omega$, $\mathbf{\Omega}_2 = \Omega - \omega$. With c_1,c_2 and C we have to minimize the energy :

$$F(c_1,c_2,C) = \int (u_0(x,y) - c_1)^2 dxdy + \int (u_0(x,y) - c_2)^2 dxdy + v|C| \tag{8}$$

So the content of the image is segmented by Chan-Vese algorithm and here it segments the brightest fire region. From this the fire pixels are found out for detection.

2.3 RGB to CIE $L^*a^*b^*$ Color Space Conversion

The output is provided in RGB color space by most of the existing CCTV video cameras, but there are also other color spaces used for data output representation. The conversion from any color space representation to CIE $L^*a^*b^*$ color space is straightforward. Given RGB data, the conversion to CIE $L^*a^*b^*$ color space is formulated as follows:

$$\begin{aligned} X &= R \times 0.412451 + G \times 0.357580 + B \times 0.180423 \\ Y &= R \times 0.212671 + G \times 0.715160 + B \times 0.072169 \\ Z &= R \times 0.019334 + G \times 0.119193 + B \times 0.950227 \end{aligned} \tag{9}$$

$$L^* = \begin{cases} 116 \times (Y/Y_n)^{1/3} - 16, & \text{if } (Y/Y_n) > 0.008856 \\ -903.4 \times (Y/Y_n), & \text{otherwise} \end{cases}$$

$$a^* = 500 \times (f(X/X_n) - f(Y/Y_n))$$

$$b^* = 200 \times (f(Y/Y_n) - f(Z/Z_n))$$

$$f(t) = \begin{cases} t^{1/3}, & \text{if } t > 0.008856 \\ 7.787 \times t + 16/116, & \text{otherwise} \end{cases} \tag{10}$$

where X_n, Y_n, and Z_n are the tri-stimulus values of the reference color which is white. Data ranges of RGB color channel is between 0 and 255 for 8-bit data representation. Meanwhile, the data ranges of L^*, a^*, and b^* components are [0, 100], [–110, 110], and [–110, 110], respectively.

2.4 Color modelling for fire detection

By using its visual properties a fire in an image can be described. Using simple mathematical formulations these visual properties can be expressed. Figure 2 depicts a sample images which contain fire and their CIE $L^*a^*b^*$ color channels (L^*, a^*, b^*). Some clues about the way CIE $L^*a^*b^*$ color channel values characterize fire pixels are given by Figure 2. We develop rules to detect fire using CIE $L^*a^*b^*$ color space using such visual properties.

An interval of color values between red and yellow defines the range of fire color. To define measures to detect the existence of fire in an image we can use the property that color of fire is generally close to red and has high illumination. For a given image in CIE $L^*a^*b^*$ color space, the following statistical measures for each color channel are defined as :

$$L^*_M = \frac{1}{N} \sum \sum L^*(x, y)$$

$$a^*_M = \frac{1}{N} \sum \sum a^*(x, y)$$

$$b^*_M = \frac{1}{N} \sum \sum b^*(x, y) \tag{11}$$

where L^*_m , a_m^* , and b_m^* are a collection of average values of the L^*, a^*, and b^* color channels, respectively; the total number of pixels in the image is N; and spatial pixel location in an imaging grid is (x, y). The numeric color responses L^*, a^*, and b^* are normalized to [0, 1]. It is assumed that the fire in an image has the brightest image region and is near to red color. Thus, to define a fire pixel, following rules can be used :

$$R1(x,y) = \begin{cases} 1 & \text{if } L^*(x, y) \geq L^*_m \\ 0, & \text{otherwise,} \end{cases}$$

$$R2(x,y) = \begin{cases} 1, & \text{if } a^*(x, y) \geq a^*_m \\ 0, & \text{otherwise,} \end{cases}$$

$$R3(x,y) = \begin{cases} 1, & \text{if } b^*(x, y) \geq b^*_m \\ 0, & \text{otherwise,} \end{cases}$$

$$R4(x,y) = \begin{cases} 1, & \text{if } b^*(x, y) \geq a^*(x,y) \\ 0, & \text{otherwise,} \end{cases} \quad (12)$$

where R1, R2, R3, and R4 are binary images which represent the existence of fire in a spatial pixel location (*x*, *y*) by 1 and the non-existence of fire by 0. R1(x, y), R2(x, y), and R3(x, y) are calculated from global properties of the input image. R4(x, y) represent the color information of fire; for example, fire has a reddish color.Using equation 12 a final fire pixel detection equation can be defined as :

$$F(x,y) = \begin{cases} 1 & \text{if } \sum R_i(x, y) = 4, \\ 0, & \text{otherwise,} \end{cases} \quad (13)$$

where F(x, y) is the final decision on whether a pixel located at spatial location (x, y) results from fire or not. So from this we get the fire color pixels which are then applied to the neural network.

2.5 Classification via Neural Networks

The simplest way of classifying is to threshold each of the features based on heuristically determined cut off values and makes a decision by majority voting. Here the pixels determined by optical flow and the Section II-D are given as the input to the neural network. Probabilistic neural networks can be used for classification problems. When input is presented, the function of the first layer is to compute distance from the input vector to the training input vectors and produces a vector whose elements indicate how close the input is to a training input. The function of the second layer is to sum these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a transfer function on the output of the second layer picks the highest of these probabilities, and produce 1 for that class and 0 for the other classes.

3. ANALYSIS AND TEST RESULTS

The performance of the proposed fire color model is tested first. The testing of color model is done on different video sequences for a variety of environmental conditions, for example, daytime, night time, indoor, and outdoor. To each frame of each video, Equation (13) is applied. When the number of connected fire pixels detected is greater than four the fire alarm is raised.

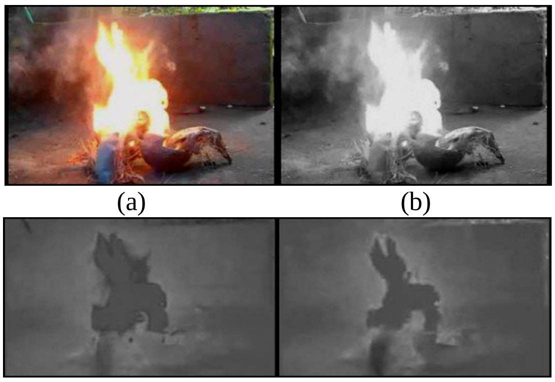

Fig. 2.Sample RGB image containing fire and their CIE *L***a***b** color channels: (a) RGB image, (b) *L** color (c) *a** color and (d) *b**color channels.

The number of frames of a video sequence is F_t, and F_f is the number of frames containing fire in a video sequence. The number of frames (including fire and non-fire frames) that correctly classify fire pixels by the proposed algorithm is F_c. When the system recognizes fire in an image frame when there is no fire then it means false positive. Similarly, false negative means that the system does not detect fire in an image frame when there is indeed fire. The detection rate, R_d, of a video is defined as:

$$R_d = F_c / F_t \quad (14)$$

The average detection rate that can be achieved is more than 99.88% tested on different sample videos. The false negative detection rates are mainly due to very small fire regions on the initial combustion in some of the video sequences or due to fire like moving objects in the video.

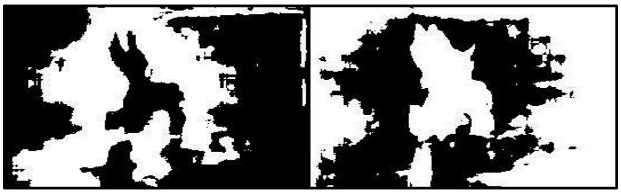

Fig. 3. Chan-Vese segmented images

Figure 3 shows the output of Chan-Vese algorithm for the a^* color and b^*color channels of the image in figure 2.Chan-vese algorithm is used to segment the image. Here the fire region is segmented. The number of iterations defines the accuracy of the segmented image. The fire pixels are detected from this segmented image and are given to the input of neural network.

Finally the input to the neural network consist of the moving pixels determined from optical flow estimation and the fire pixels determined from the segmented image by the color space model defined in Section II-D. And classification is done based on trained set of values.

4. CONCLUSION

Based on computer vision techniques a new video-based real-time fire detection method was proposed which is. There are three main stages in the proposed method: moving pixel detection using optical flow estimation, Chan-Vese segmentation for segmenting the fire regions and finally fire pixel detection using color space model. This method will clearly detect fire and will reject non fire motions which include small flames like candle flame. A detection rate of 99.88% is achieved by the proposed fire color model on some of the tested video sequences with diverse imaging conditions. Furthermore, the experiments on benchmark fire video databases show that the proposed method achieves comparable performance with respect to the state-of-the-art fire detection method.

To characterize fire regions the motion information of fire is also considered. The proposed system assumes that the fire will grow gradually in a spatial domain. This might not be the case in some situations. For instance, the system might not be able to detect a fire caused by a sudden explosion. In order to alleviate such cases, the proposed system will be further improved to include different scenarios. Furthermore, to improve the system's fire detection performance the texture and shape information of fire regions will also be investigated.

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