Characteristic Measurement and Smoke Detection using Image Processing

Aliya Bi Can

Master of Engineering Student
Information Technology & Engineering
Goa College of Engineering, Ponda-Goa, India

Abstract *:* Image processing is used for detecting smoke in outdoor videos. The technique of background subtraction using Gaussian Mixture Model(GMM) is used to obtain the moving regions in video images. Foreground detection is done using GMM. Improved Fuzzy C-Means (FCM) clustering algorithm along with Color-Based Decision Rule is used for detecting the smoke regions. The basic idea is finding the foreground using mask. Improved FCM works on each frame so that every pixel in the frame is checked if it is a smoke pixel based on Color-Based Decision Rule. During each iteration of improved FCM, pixels assignment of each frame is carried out for forming clusters. According to Color-Based Decision Rule, the pixels in cluster will be checked for smoke and non-smoke pixels. Finally the smoke region will be shown with pink area for highlighting the region of interest.

***Index Terms* - Background Subtraction Method, Color-Based Decision Rule, Fuzzy C-Means, Optical Flow, Video Frame.**

I. INTRODUCTION

History has proven that early fire detection and the signaling of alarm remain important factors in preventing large losses due to fire. Properly installed alarm systems provide the user with indication of fire well in advance and can help to increase the survivability while decreasing loss of property. There are methods which are proposed to build fire safety systems. Existing methods are based on light sampling, temperature sampling, relative humidity sampling, air transparency testing and analysis of color of fire[1]. Smoke is the first indication for the presence of fire. Hence detection of smoke in early fire signaling systems is important for safety.

II. BACKGROUND SUBTRACTION METHODS

The aim is to detect foreground in the current input frame against the background frame and to locate areas of interest. The areas of change can be obtained through background subtraction technique. Different methods of foreground detection are as follows.

1. Frame Differencing: It is a commonly used method in image processing. Here background frame is formed by averaging frames at different time in the starting period. It detects the foreground by subtracting frame pixel by pixel from a background frame.

2. Median Filtering: In this technique buffer of video frames is formed, of which their median is calculated that provides the background. Later pixel of current frame is checked with the background frame, if pixel of current frame is found to be greater than background pixel, then the pixel of background is increased by one and vice versa. Thus a state is reached where half of pixels are less and half of pixels are greater than background frame.

3. Gaussian Mixture Model: In this method each pixel act as a data point , so it is natural to say that each of the pixel from the frame is modeled into Gaussian Distribution. At the very beginning all the pixels are divided by their intensity in Red, Green and Blue color space. Later the probability of each pixel is calculated. This makes the decision simpler for including the pixel in foreground or background.

III. LITERATURE REVIEW

A. Background

Fire continues to occur in modern architecture, causing huge loses to the people’s lives and property. In order to decrease the extension of fire at any location automatic fire signaling device is placed into the premises. Already existing solution to fire detection is the fire signaling system.

B. Analysis of Papers

In paper[1], the authors have proposed a method to detect smoke as the area of interest in video frames . The technique of foreground detection is used to obtain new regions in video frame containing fire. The Fuzzy C-Means (FCM) method, which is the well known clustering technique is used to cluster only smoke regions as the target object in the frame from these new regions. Any method for smoke detection shall have good accuracy for detecting true presence of smoke in the frame. The algorithm used in this paper provides a better accuracy rate than the conventional algorithm for smoke detection.

Paper[2], have introduced a method for smoke detection in outdoor frames of the test video. They made an assumption that the camera is placed on a tilt equipment. The method comprises of three steps. The initial step is to keep the camera moving and not static so that it can cover full surveillance. With the camera in moving state, the second step is to detect the areas of change in the current frame of input video against the background frame and to locate areas of interest by connected component analysis. The approach is block-based which applies on first and second step. Using the k-temporal information of color and shape of area of interest the decision of the region being smoke or non-smoke is made in the final step.

Paper[3], presents an approach based on machine learning technique of Deep Belief Network which focuses on forest fires. Stacked layers of Restricted Boltzman Machine makes up Deep Belief Network and is used in this paper for smoke detection. Here the smoke and non-smoke areas are simultaneously detected by the network. The higher is the detection rate the better is the smoke method and the lowest is the time of pre-training and fine-tuning the speeder is the method for smoke detection[3].

IV. PROPOSED WORK

This project aims to implement improved FCM algorithm on the video frames that can distinguish the smoke and non-smoke regions based on percentage of pixels that pass the smoke rule. Improved FCM is used, wherein clustering enhancement is based on objective function. Aim is to use video frames with smoke from fire, which will be processed using one of the BS technique and latter improved clustering algorithm will be used that provides result with good accuracy in lesser number of iterations than the custom FCM.

A. Methodology

S.R.Vijayalakshmi et al .[1] discussed the method of background subtraction for segmenting the video images and further applied the FCM technique to obtain the smoke regions. Moreover improved FCM can be used so as to limit the problem of sensitivity and to obtain high accuracy in the experimental results. The distance measurement between cluster 'I' and an object 'o' is referred as the Euclidean distance between x_o and ω_i wherein x_o is the data vector for object o(i =o, . . . , N) and v_i is the vector for cluster i (i =1, . . . , C).

By iteratively optimizing the Fuzzy Membership U and Distance D, deprecation of Objective Function J is achieved. At each step for deprecation, an improvement is guaranteed. The step is discontinued, when J stops to change. The values of U are randomly selected, or chosen based on advance knowledge of structure.

Enhancement is based on the less optimal solution J at each iteration, but in most cases J have many local optimums. The algorithm in many situations leads to local minimum results, when selection for initial centers is over the optimums.

The improved Fuzzy C-Means algorithm steps:

In paper[4], the algorithm presented needs two stages: first stage obtains the introductory initial cluster center's by defining minimum distance rule, second stage carry out the modified algorithm which use a new objective function. Clustering algorithm may be outline by the following steps[4]:

Step 1: Suppose threshold for minimum distance is alpha greater than 0 , calculate distances between any pair point and seek a nearest pair points as first class, and calculate the center of the pair point as cluster center.

Step 2: Calculate all of the sample points based on matrix D, that satisfied the distances larger than alpha to cluster center's in the rest points, and also look for a nearest pair points as another class and calculate the center of the pair point as cluster center.

Step 3: Corresponding to this, seek for all points that the distances from points already found to is larger than alpha in the rest points and also seek a nearest pair points as another class and calculate the center of the pair point as cluster center.

Step 4: Go to step 3, until then find all cluster center $\omega_i(k)$

Step 5: Set k=1 that denote repetitive count.

Step 6: Update the membership values $\mu_{ij}(k)$ based on $\omega_i(k)$ where i =1, ...c, j =1...N

Step 7: Update the cluster centers $\omega_i(k+1)$ based on $\mu_{ij}(k)$.

Step 8: Increment k and go to step 6, until 'e'.

Step 9: If $d_{ij}^2(x_j, \omega_i) < d_{ij}^2(x_j, \omega_k)$, then x_j belong to class i.

B. Detailed Design

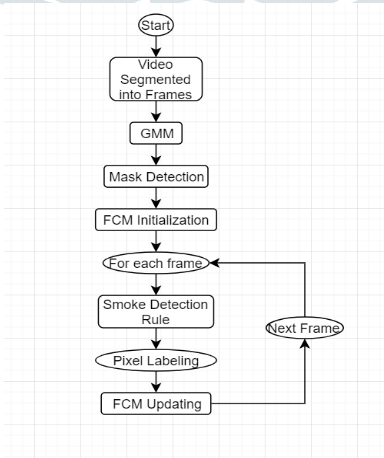

Fig.1. Detailed Design.

The design in Fig.1 depicts the clustering algorithm being used to cluster the regions in the image. It is known that the objective function of FCM clustering algorithm are all based on the fuzzy within-cluster scatter matrix, regardless of the influence of between-cluster[4]. Once clusters are formed, the smoke regions can be the candidate region which can be used in fire detection.

Smoke video frames will be considered as the input for testing and detection of smoke regions in the frame. Gaussian mixture model (GMM), which can be viewed as an extension of the ideas behind k-means, but can also be a powerful tool for estimation beyond simple clustering[6]. Clustering algorithm is run at the background for each frames. When FCM membership is calculated, at the same time smoke rules is applied for checking the pixel membership in smoke region.

C. Experiments Conducted

Initially the frames are formed out of the video as shown in Fig.2 and Fig.3. These frames will be later processed to get the foreground mask. The most simpler background subtraction and foreground detection technique is frame differencing, that makes use of frame at time t-1 as the background for the frame of same test video at time t. Because of the use of just single previous frame, frame differencing may not have the ability to detect the interior pixels of a large moving object. Thus a mixture of Gaussians in clustering will be used for truly non-static background.

The background that has faster variations cannot be modeled with just a few Gaussians, this causes problem in sensitive detections. Thus having known that each technique has its own advantage and disadvantage, it is important to perform classification.

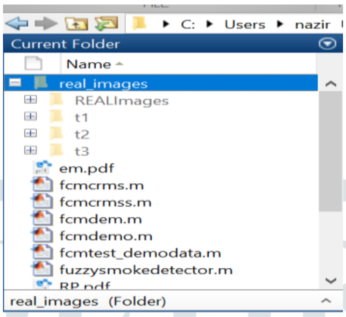

Fig.2. Test Video.

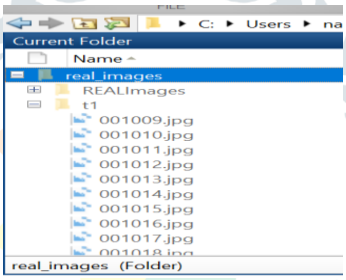

Fig.3. Video Frames.

Classification is the process used in categorizing data into finite set of classes or labels. The process usually involves recognition of the dominant region in the video. The system uses the improved FCM algorithm for classification. Improved FCM works better than normal Fuzzy C-Means in terms of the accuracy rate and iteration count. Frames from video is taken containing smoke regions. The motion of smoke varies in each frame hence optical flow using KLT method was used. On having detected the foreground mask , concept of wavelet processing is applied so as to make analysis easier for object that varies in time. Along with wavelet processing the motion of smoke is detected using the well known KLT method for optical flow. KLT method outputs are shown in Fig.4 with initial frame of test video and with iterations in Fig.5, Fig.6 and Fig.7.

Fig.4. Frame of Video in T1.

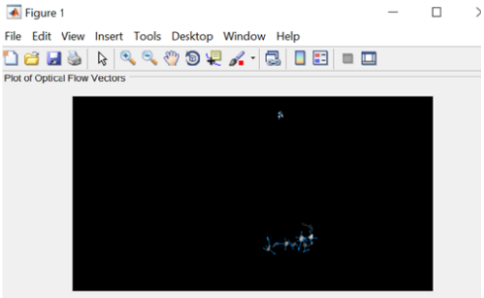

Fig.5. Optical Flow at iteration 1.

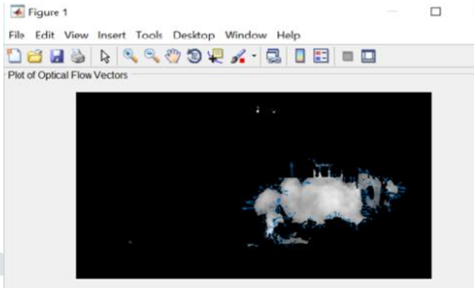

Fig. 6. Optical Flow at iteration 5.

Since smoke as an object has very minimum features, this makes it difficult to detect. Smoke motion is mostly upwards, hence the idea of detecting smoke based on motion was brought into picture. Here KLT is used in finding the motion of the object in test video which will further be used for detecting only smoke as an object apart from any other object in scene.

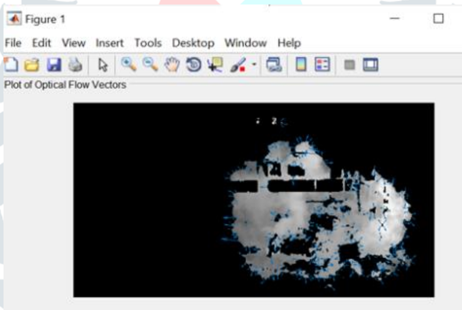

Fig. 7. Optical Flow at iteration 10.

D. Results and Discussions

The idea was to use output of KLT for further classifying using one class classifier in neural network. But due to insufficient amount of data KLT cannot be used , as the algorithm doesn't converge. However, with KLT method we can achieve a lot in case of very large data in future with neural network in consideration. As a result method of decision rule for smoke is used for classifying smoke region from among other regions in frame.

Since smoke as an object is not static and it will have movement, so it is obvious to say smoke pixel as a moving pixel. Consider X(a,b) to be moving pixels, which are analyzed using a Color-Based Decision Rule that is based on studies developed by Chen[5]. He assumed that smoke usually displays grayish colors and the condition for R, G, B and I(Intensity) component of HIS color model is between the value of intensity[5].

The rule says that the three components Red, Green and Blue of smoke pixels are equal. The function in smoke decision is that for a moving pixel point (a,b) in consideration is based on the values mentioned below.

From the functions defined by Chunyu et. al.[5].

$$m = max\,(\,R(a,b), G(a,b), B(a,b)\,) \qquad (1)$$

$$n = min\,(\,R(a,b), G(a,b), B(a,b)\,) \qquad (2)$$

$$I_{int} = 1/3\,((\,R(a,b), G(a,b), B(a,b)\,)) \qquad (3)$$

If the pixel X(a, b) satisfies both the condition and at the same time, then the moving pixel X(a, b) is considered as a smoke pixel, otherwise X(a, b) is not a smoke pixel[5]. FCM output on screen will be shown for 600 mili seconds for each frame. We get regions from each cluster of FCM and Color-Based Decision Rule, if 51 percent of pixels are under smoke rules then red color is shown else green.

For each cluster count of smoke pixels is checked, if it is greater than 50 percent then change the cluster color to pink(Smoke indication). Outputs for color change as per smoke rule are depicted in Fig.8 for iteration 1, Fig.9 for iteration 4 and Fig.10 for iteration 17.

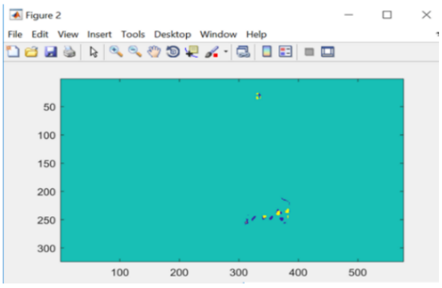

Fig.8. Color-Based Decision Rule output at iteration 1.

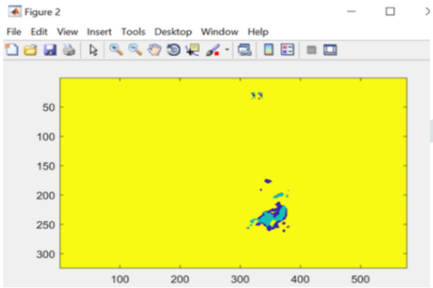

Fig.9. Color-Based Decision Rule output at iteration 4.

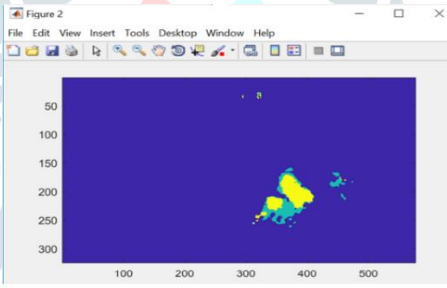

Fig. 10. Color-Based Decision Rule output at iteration 17.

Finally the smoke region is shown in Fig.11 with pink region.

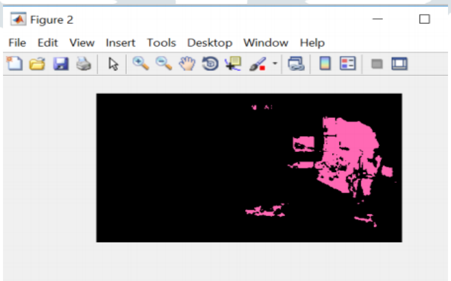

Fig. 11. Smoke region.

V. CONCLUSION

In this work, smoke detection is done taking into account color information. The color based decision rule greatly improve the reliability of smoke detection in video frames. Initially subtraction is done to obtain the foreground mask and this would serve as input to improved FCM. Finally the smoke rules are used to identify the smoke regions in video images, which is meaningful for detection of fire.

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