Vision Based Fire Flame Detection System Using Optical flow Features and Artificial Neural Network

Anila R. Kurup

M. Tech, Department of CSE, Sree Narayana Gurukulam College of Engineering, Kerala

Abstract: ***Detecting the break-out of a fire rapidly is vital for prevention of material damage and human casualties. VFD technology is becoming the focal point of research with its advantages of high intuitive, speed and anti-jamming capability. But most of current methods for video fire detection have high rates of false alarms.Here a novel video fire flame detection method based on 3 flame colour model, optical flow features and neural network is presented.. The method is proposed as followed, first, candidate fire regions are determined by 3 flame colour model they are RGB, HSV and YCbCr instead of single colour space RGB. Even though RGB colour space can be used for pixel classification, it has disadvantages of illumination dependence. Then, a pyramidal implementation of Lucas Kanade feature tracker is used to analyzing dynamic optical flow features such as average and variation of optical flow velocity and optical flow orientation in the candidate region. Then a back-propagation neural network is used to learn and classify the statistic of the flames from nuisances based on the optical flow features. This method can distinguish flame videos from disturbances which having the same colour distribution as flame, such as car lights, and have a remarkable accuracy..Also, In this method by calculating ratio of the area of the fire pixels in the video, and whole pixel area it give alert message "danger" when this value increase from a threshold during testing the video, also by using this value we can understand the rate growth of fire.***

Keywords: VFD (video based fire detection), optical flow features, Lucas Kanade feature tracker, Flame colour model, Back-propagation neural network

1. Introduction

Video-based fire detection (VFD) is a newly developed technique which bases on machine vision and pattern recognition technique. VFD has many advantages over traditional methods, such as fast response, non-contact, no limit of space and so on. Because the application of VFD has a broad market prospect, more universities and research group, as well as companies, conduct research in this area. Automatic fire detection in images and videos is crucial for early fire detection which can solve the aforementioned problems. Video-based systems can detect uncontrolled fires at an early stage before they turn into disasters. With the video image, we can solve the prominent defects such as high error rate, strong dependence on the environment, and sometimes it cannot be processed in real time. The advantages of fire detection technology based on the video image can be summarized as the following points: first, detection techniques are very intuitive. Second, due to the speed of light transmission and induction is far higher than the smoke and temperature, such fire detection with high real-time has no delay caused by induction time. Third, the remote surveillance cameras can be adjusted freely and not to be confined to the indoor and outdoor space. So its detection range is larger other methods. Fourth, the image can save more scene information through color and texture, which promotes the diversification of the fire detection method greatly. Fifth, it is convenient for people to verify record or query the fire with the saved video monitor screen, so this technology has a higher reliability and real-time performance. Up to now, most of methods make use of the visual features of fire including colour, textures, geometry, flickering and motion.

But most of current methods for video fire detection have high rates of false alarms in the case of fire like situation such as car light and they were influenced by the wind, the distance, the flame size changing, the flame shape changing, white smoke, black smoke Here in through this thesis a vision based fire flame detection system has been proposed here candidate fire regions are determined by 3 flame color model they are RGB, HSV and YCbCr instead of single colour space RGB. Even though RGB colour space can be used for pixel classification, it has disadvantages of illumination dependence.The pixels that pass the color model are set as candidate regions and are further checked by calculating the dynamic features through the optical flow computation, Optical flow is an important technique in motion analyzing of machine vision. A pyramidal implementation of Lucas Kanade feature tracker is used to analyzing dynamic feature in the candidate region. Then a back-propagation neural network is used to learn and classify the statistic of the flames from nuisances based on the optical flow features such as average and variation of optical flow velocity and optical flow orientation. This method can distinguish flame videos from disturbances which having the same color distribution as flame, such as car lights, and have a remarkable accuracy. This method not influenced of wind, the distance, the flame size changing, the flame shape changing, white smoke. This method overcome black smoke problem up to a limit.. Also, , In this method by calculating ratio of the area of the fire pixel in the video, and whole pixel area it give alert message "danger" when this value increase from a threshold during testing the video, also by using this value we can understand the rate growth of fire

2. Related Works

In many ways, flame detection is used to provide fast response to growing fires and activation of suppression and safety shut-down systems. Video image flame detectors represent a relatively new technology that has been gaining popularity and using in many applications. There are several methods in the literatures developed for fire flame detection from video images. Almost all of the current methods use motion and color information to detect the flame.

H. Yamagishi, J. Yamaguchi[11] Present a Fire flame detection algorithm using a color camera, In this method, the contour of the flame area, which is normalized in size, is extracted. The extracted contour data is calculated by a polar coordinate transformation. The results of the polar coordinate transformation of every input image are placed in time series. Then we get a fluctuation data, as a space-time data on the contour. Further, a pattern of the frequency component distribution is obtained by Fourier transform of the fluctuation data. Entering the pattern into a neural network, the fire flame is detected. Method could not be influenced by the wind, the distance, the flame size changing, the flame shape changing, the white smoke and so on. Accordingly, it is considered that our method is useful for fire detection in the ordinary scene. But If a faraway person has the flashlight and the flashlight is swinging, it may misjudge, In this case, the contour shape and the pattern of the frequency component distribution are similar to fire flame. In this way, there are some cases that the artificial light may be misjudged. The method may influenced by black smoke. which causes flame splitting, flame appear and disappear

H. Yamagishi, J. Yamaguchi[10] present a method called, A Contour Fluctuation Data Processing Method For Fire Flame.Some flame colors areas are extracted using color information. The processing order of the area is decided by the variance of HS (Hue-Saturation) data and the continuous flame colors degree in sequential input images. The contour of the area is detected by an edge operator and is calculated by the polar coordinate transformation. The results of the polar coordinate transformation of every input image are placed in time series. Then a space-time fluctuation data on a contour of the flame colors area is obtained. By two-dimensional Fourier transform, a pattern of frequency component distribution is obtained. Entering the pattern data into the neural network, the fire flame is detected.. This method were not influenced by the wind, the distance, the flame size changing, the flame shape changing, white smoke, black smoke. This method overcome black smoke problem up to a limit with low detection accuracy. But it have limitation in the detection of 3D position of fire

M. Shah, N. Da Vitoria LoboW. Phillips III, [15] present a method.' Flame recognition in video' In this technique, first, a color predicate is built Based upon both the color properties, and the temporal variation of a small subset of images, a label is assigned to each pixel location indicating the inference that each pixel is a fire pixel. Based upon some conditions determine if this test will be reliable.. If the test to find fire has been successful, an erode operation is performed to remove spurious fire pixels. A region- growing algorithm designed to find fire regions not initially found. This method has been effective for a large variety of conditions. False alarms, such as video of the sun moving are not detected by this method because in all realistic sequences, the rate of global motion is almost always much less than the expected speed of the fire. Lighting conditions also have no effect upon the system; it has been able to detect fire in a large variety of fire images. Certain types of fires, such as candles, blow torches, and lighters, are completely controlled, and always bum exactly the same way without flickering. Unfortunately, the algorithm fails for these cases because of the lack of temporal variation.These methods have the following two drawbacks. First, a region composed of fire-colored pixels is too simple a model of fire since fire also has spatial structure, namely the core is brighter than the periphery.Second, temporal variation in image pixel color does not capture the temporal property of fire which is more complex and benefits from a region level representation. For example, pixels of the core of the fire exhibit less temporal variation than the other pixels.

P. Wu and T. Chen, Y. Chiou, [16] propose an early fire-detection algorithm.Firstly, moving regions are segmented from the captured image sequences and thus used as candidates for checking if they are fire or smokes. By chromatic features fire-pixels and smoke-pixels are extracted from these moving regions. To distinguish from fire-aliases and smoke-aliases, dynamic features including growth and disorder are utilized for validating these fire-pixels and smoke-pixels extracted. It should be pointed out that if these fire-pixels and smoke-pixels satisfy the dynamic features, there is a real fire surely. But if only fire-pixels satisfy the dynamic features, there may be a real fire due to the fact that the burning of some special fuels will generate nearly transparent smokes, which can't be captured by the video camera. Finally, fire-alarm raising conditions inspected simultaneously to check if the fire is going to spread out, not only for the general burning but also fur the explosion-like burning. As soon as anyone raising condition is satisfied, the fire-alarm is given. But reliability of this method is less

Ahuja Nand Liu Chebin. [1] have proposed a vision based fire detection algorithm based on spectral, spatial and temporal properties of regions. First, extract potential fire regions from an image using fire spectral and spatial models. Second, represent boundaries of these regions using Fourier coefficients. Third, estimate parameters of an AR model of each region with its correspondence in previous images in the image sequence. Last, Fourier coefficients and AR model parameters are used as features of each region for a classifier that recognizes fire regions. This algorithm detects fire with high accuracy, both in single images as well as in image sequences. This method approximate scale invariance for FD by dense sampling of region boundary. However, spatial quantization errors for small regions are likely to introduce considerable noise in the FD. To avoid this problem, place a threshold to eliminate regions of small size (number of pixels). And also exclude large but thin regions. Consequently this algorithm does not detect very small or far away fire

Horng, Wen-Bing, Peng, Jian-Wen [8] proposed a fast and practical real time image-based fire flame detection method based on color analysis. They first build a fire flame color feature model based on the HSI color space by analyzing 70 training flame images. Then, based on the above fire flame color features model, regions with fire-like colors are roughly separated from each frame of the test videos. Besides segmenting fire flame regions, background objects with similar fire colors or caused by color shift resulted from the reflection of fire flames are also extracted from the image during the above color separation process. To remove these spurious firelike regions, the image difference method and the invented color masking technique are applied. Finally, the fire flame burning degree is estimated so that users could be informed with a proper fire warning alarm. The reaction time of the system is very fast. The color information is really an important static feature of the flame. But only with the color feature to detect fires may decrease the recognition rate of the system.

Jin, Hong, Rongbiao, Zhang [9] combined fire flicker and color clues to reach a final fire decision. First the image difference method and color analysis technique based on the HSI color model are applied to extract the fire-like moving region between two consecutive frames. Then the spectrum of the fire-like region flickering could be got by the Discrete Fourier Transform of the fire-like moving region sequence. Finally, a simple method is devised to estimate the fire alarm grade so that users could be informed with a proper alarm.

.

Yunyang Yan, ZhiboGuo, Hongyan Wang [19] propose a new color model used to detect flame in an image is found in literature. The model is based on the features that were linear transformed from RGB of the image color. Flames in video sequences are detected by using the features of color and its distribution

AungKyaw, Soe, Zhang, Xianku..[2] used the static image characteristics of the light blue flame to detect fires. The image is grabbed in the memory and fire-suspected regions are defined by using the region of interest (ROI) technique. The blue flame character pixels which are commonly found in gas fire are then checked in each ROI by using color intensity composition detection algorithm. If at least one ROI has the threshold amount of blue flame character pixels, this ROI is assumed to have a fire breakout. Furthermore, the average light intensity of the whole image is also calculated in order to use different threshold values of the blue flame for different background lights. This method can detect the gas fire flame with a less number of false alarms. But with only one feature to test fire also has some limitations. Since the conventional smoke-based fire detectors tend to exhibit high false alarm behavior.

Liu Peixun. [13] put forward the algorithm that extracts the suspected flame region through the conditions of three visible lights. And the algorithm based on the four kinds of color space: RGB, YCbCr, HSI, and HSV and the system used the flame detection algorithm based on the YCbCr color space to extract the suspected region of the flame in the visible light conditions. It is not only able to extract the flame region accurately, but also can exclude the interference of the objects whose color is similar to the flame. For infrared video, using a simple algorithm to extract the suspected region of the flame, at the same time add some restrictions to exclude the interference of reflective objects in the algorithm.

3. Proposed System

In order to overcome the demerits of existing video based fire detection method, a passive method based on 3 colour model an optical flow features and neural network has been developed. The proposed method has four major stages. They are Detecting Fire-Coloured Pixels (fire colour classification), area calculation, Optical Flow Computation, Fire Flame Feature Classification Using Back-Propagation Neural Network. First, candidate fire regions are determined by 3 flame color model they are RGB, HSV and YCbCr. In 2nd stage the pixels that pass the color model are set as candidate regions and are further checked by calculating the dynamic features through the optical flow computation, Optical flow is an important technique in motion analyzing of machine vision. A pyramidal implementation of Lucas Kanade feature tracker is used to analyzing dynamic feature in the candidate region. Then a back-propagation neural network is used to learn and classify the statistic of the flames from nuisances based on the optical flow dynamic features such as average and variation of optical flow velocity and optical flow orientation

a) Detecting Fire-Coloured Pixels (Fire Colour Classification)

Conventional optical flow techniques used to calculate the whole images pixels which led to very large calculation. In order to reduce the computational complexity of optical flow, feature points are selected before the optical flow calculations. Candidate regions are selected through colour classification. There are a number of different ways of detecting fire colored pixels. In this method 3 kinds of color space: RGB, YCbCr, and HSV are used to classify pixels as being fire colored or not instead of single colour space. The colour of the flame is not a reflection of the natural light, but it is generated as a result of the burning materials. In some cases, the colour can be white, blue, gold or even green depending on the chemical properties of the burnt material and its burning temperature.

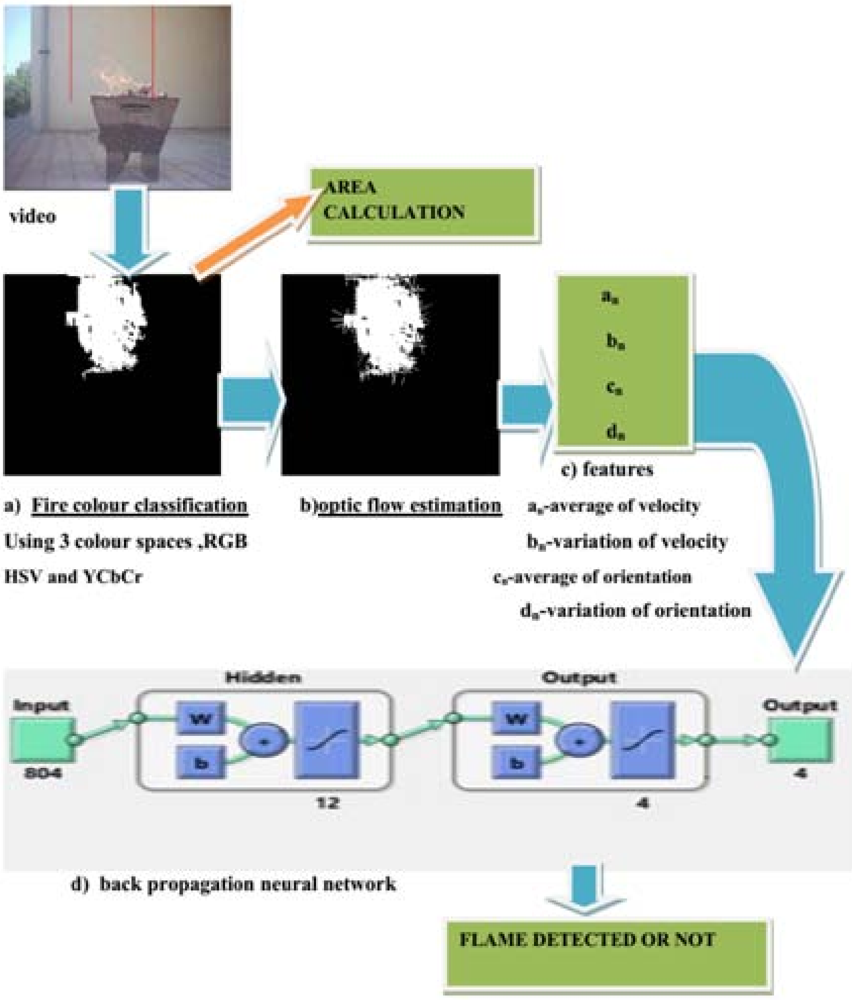

Figure 1: Proposed fire detection system

However, in the cases of organic materials such as trees and bushes, the fire has a characteristic red-yellow. In this way the colour of the fire varies according to the material burned and also Even though RGB colour space can be used for pixel classification, it has disadvantages of illumination dependence. It means that if the illumination of image changes, the fire pixel classification rules cannot perform well. Furthermore, it is not possible to separate a pixel's value into intensity and chrominance. The chrominance can be used in modeling colour of fire rather than modeling its intensity. This gives more robust representation for fire pixels. YCbCr and HSV colour space which further alleviate the harmful effects of changing illumination and improves detection performance. So the combination of 3 colour space make the fire coloured pixel detection efficient and this way that improve the performance of the system. In this project to detect the fire coloured pixel, here use both the condition of RGB colour modal and conditions of YCbCr and HSV colour model. To detect fire colored pixel, the conditions are formed as follows:

$$F(i\,j)= \begin{cases} 1 & \begin{aligned} &\text{If}(\ (R(i,j)>=G(i,j)\text{and} \\ &G(i,j)>B(i,j)\ \text{and} \\ &R(i,j)>R_T\ \text{and} \\ &S>((255-R(i,j))*(S_T/R_T)))\ \text{or} \\ &((0.02<H(i,j)<0.3)\ \text{and} \\ &(0.2<S(i,j)<1)\text{and} \\ &(0.98<V(i,j)<1)\ \text{and} \\ &(\ Y(i,j)<=Y\text{mean}\ )\text{and} \\ &(\ Cb(i,j)>=Cb\text{mean})\ \text{and} \\ &(\ Cr(i,j)<=Cr\text{mean}))) \end{aligned} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

b) Area calculation

After the candidate fire region is identified using colour modals, we can calculate area of fire pixels. By using this value the proposed system give additional information about dangerous situation by calculating ratio of area of fire pixel and whole pixel also using this ratio we can understand the rate of growth of fire by plotting graph. Area= area of candidate region and W= whole area, then ratio of (Area/W) greater than a threshold value, it implies the dangerous situation. Here we use threshold value as.05

c) Optical Flow Computation

In this paper, fire flame dynamic feature analyzing using optical flow computation. Optical flow is an important technique in motion analyzing of machine vision. Optical flow is the distribution of the apparent velocities of objects in an image. By estimating optical flow between video frames, we can measure the velocities of objects in the video. In general, moving objects that are closer to the camera will display more apparent motion than distant objects that are moving at the same speed. Optical flow estimation is used in computer vision to characterize and quantify the motion of objects in a video stream, often for motion-based object detection and tracking systems. Optical flow is a method used for estimating motion of objects across a series of frames. The method is based on an assumption which states that points on the same object location (therefore the corresponding pixel values) have constant brightness over time. Optical flow can be said to have two components, normal flow and parallel flow. Normal flow can be computed directly without any further constraints. However, Parallel Flow cannot be computed this way. Here Lucas-Kanade method is used for compute Parallel Flow; The Optical Flow block estimates the direction and speed of object motion from one image to another or from one video frame to another using the Lucas-Kanade method. Here a pyramidal Lucas Kanade feature tracker is used to calculate the velocity vectors of the feature points of the fire candidate regions.

1) Image Pyramid Representation

In this section the Pyramidal implementation of the Lucas Kanade feature Tracker will be briefly summarized. First, pyramid representations of I and J should be built recursively according to equation (4)

$$I^L(x,y)=\frac{1}{4}I^{L-1}(2x,2y)+$$
$$\frac{1}{8}(I^{L-1}(2x-1,2y)+I^{L-1}(2x+1,2y)+I^{L-1}(2x,2y-1)+I^{L-1}(2x,2y+1))+$$
$$\frac{1}{16}(I^{L-1}(2x-1,2y-1)+I^{L-1}(2x+1,2y+1)+I^{L-1}(2x-1,2y+1)+I^{L-1}(2x+1,2y+1)) \qquad (2)$$

The value L_m is the height of the pyramid. I and J are two 2D gray scaled images. The two quantities I(x) = I(x; y) and J(x) = J(x; y) are the gray scale value of the two images at the location x = $[x\ y]^T$ The image I will be referenced as the previous frame image, and the image J as the current frame image. After the pyramidal building, we have images I and J:

$$\{I^L\}_{L=0,\cdots,L_m} \text{ and } \{J^L\}_{L=0,\cdots,L_m}.$$

Consider an image point $[u_X u_Y]^T$ the first image I. The vector d= $[d_X d_y]^T$ is the image velocity at x. w_x and w_y are two integers determine the half size of the so called integration window above x. We define the image velocity d as being the vector that minimizes the function &defined as follows

$$\varepsilon^L(d^L)=\varepsilon^L(d_x^L,d_y^L)=\sum_{x=u_x^L-\omega_x}^{u_x^L+\omega_x}\sum_{y=u_y^L-\omega_y}^{u_y^L+\omega_y}(I^L(x,y)-J^L(x+g_x^L+d_x^L,y+g_y^L+d_y^L))^2 \qquad (3)$$

Then a standard Lucas Kanade algorithm is used to calculate the residual flow vector
d=$[d_x\ d_y]^T$

2) Interactive Lucas Kanade Optical Flow method

In computer vision, the Lucas–Kanade method is a widely used differential method for optical flow estimation developed by Bruce D. Lucas and Takeo Kanade. It assumes that the flow is essentially constant in a local neighborhood of the pixel under consideration, and solves the basic optical flow equations for all the pixels in that neighborhood, by the least squares criterion. By combining information from several nearby pixels, the Lucas–Kanade method can often resolve the inherent ambiguity of the optical flow equation. It is also less sensitive to image noise than point-wise methods. On the other hand, since it is a purely local method, it cannot provide flow information in the interior of uniform regions of the image. Optical flow can be said to have two components, normal flow and parallel flow. Normal flow can be computed directly without any further constraints. However, Parallel Flow cannot be computed this way. Here Lucas-Kanade method is used for compute Parallel Flow; The Optical Flow block estimates the direction and speed of object motion from one image to another or from one video frame to another using the Lucas-Kanade method. Interactive Lucas Kanade Optical Flow Algorithm is as follows;

If the vector d^L minimizes the matching function, then we have

$$\left.\frac{\partial\varepsilon^L(d^L)}{\partial d^L}\right|_{d^L=d_{opt}}=[0,0] \qquad (4)$$

After expansion of the derivative, we obtain:

$$\frac{\partial\varepsilon^L(d^L)}{\partial d^L}=-2\sum_{x=u_x^L-\omega_x}^{u_x^L+\omega_x}\sum_{y=u_y^L-\omega_y}^{u_y^L+\omega_y}(I^L(x,y)-J^L(x+g_x^L+d_x^L,y+g_y^L+d_y^L))\cdot\begin{bmatrix}\frac{\partial J^L}{\partial x} & \frac{\partial J^L}{\partial y}\end{bmatrix} \qquad (5)$$

If we substitute,

$$J(x+d_x,y+d_y)$$

by its first order Taylor expansion about the point $[0\ 0]^T$, we obtain

$$\frac{\partial\varepsilon^L(d^L)}{\partial d^L}\approx 2\sum_{x=u_x^L-\omega_x}^{u_x^L+\omega_x}\sum_{y=u_y^L-\omega_y}^{u_y^L+\omega_y}(\nabla I^T d^L-\delta I)\nabla I^T \qquad (6)$$

∇I is merely the image gradient vector:

$$\nabla I=\begin{bmatrix}I_x\\ I_y\end{bmatrix}=\begin{bmatrix}\frac{\partial J^L}{\partial x} & \frac{\partial J^L}{\partial y}\end{bmatrix}^T \qquad (7)$$

Equation (6) can be written in another form:

$$\frac{1}{2}\left[\frac{\partial\varepsilon^L(d^L)}{\partial d^L}\right]^T\approx\sum_{x=u_x^L-\omega_x}^{u_x^L+\omega_x}\sum_{y=u_y^L-\omega_y}^{u_y^L+\omega_y}\left(\begin{bmatrix}I_x^2 & I_xI_y\\ I_xI_y & I_y^2\end{bmatrix}d^L-\begin{bmatrix}\delta I\cdot I_x\\ \delta I\cdot I_y\end{bmatrix}\right) \qquad (8)$$

Denote

$$G = \sum_{x=u_x^L-\omega_x}^{u_x^L+\omega_x} \sum_{y=u_y^L-\omega_y}^{u_y^L+\omega_y} \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

$$\bar{b} = \sum_{x=u_x^L-\omega_x}^{u_x^L+\omega_x} \sum_{y=u_y^L-\omega_y}^{u_y^L+\omega_y} \begin{bmatrix} \delta I \cdot I_x \\ \delta I \cdot I_y \end{bmatrix} \quad (9)$$

Then, equation (8) may be written:

$$\frac{1}{2}\left[\frac{\partial \varepsilon^L(d^L)}{\partial d^L}\right]^T \approx G d^L - \bar{b} \quad (10)$$

Therefore, the optical flow vector is

$$d_{opt} = G^{-1}\bar{b} \quad (11)$$

This expression is valid only if the matrix G is invertible. The computation process of determining the Lucas-Kanade optical flow is the recursive calculations. Then for the pyramid representation process, the result of this computation is propagated to the next level L-1 by passing the new initial guess, this procedure goes on until the finest image resolution is reached

d)Fire Flame Feature Classification Using Back-Propagation Neural Network

In this section, we focus on the feature classification, in which we use a Back-Propagation Neural Network to realize real time flame detection. Here flame and none flame videos are considered, the four statistical values of which are used as input to train the Neural Network to distinguish flame features from disturbances Four statistical characteristics input to neural network are: the average and variation of the optical flow velocity, and also of optical flow orientation..The key to distinguishing between flame and flame-colored objects is the nature of their motion. If we consider the flame is made up of lots of spots, as a result of the flicker movement, the spots' velocity vector will be different from each other and change quickly and periodicity with time. So the variations of optical flow velocity and orientation are selected as they can reflect the special motion of flame feature points. The computation results of the optical flow of the feature points are

$$\{\, d_i \mid d_i = [d_{xi}, d_{yi}]^T, i = 0, 1, \ldots n \,\}, \quad (12)$$

which are a set of pixel displacement vectors. The statistical analyze of the results of optical flow calculation is performed as follows. Average of velocity:

$$a_n = \frac{1}{n}\sum_{i=1}^{n}\sqrt{d_{xi}^2 + d_{yi}^2} \quad (13)$$

Variation of velocity:

$$b_n = \frac{1}{n-1}\sum_{i=1}^{n}\left(\sqrt{d_{xi}^2 + d_{yi}^2} - a_n\right)^2 \quad (14)$$

Average of orientation:

$$c_n = \frac{1}{n}\sum_{i=1}^{n} e_i \quad (15)$$

Variation of orientation:

$$d_n = \frac{1}{n-1}\sum_{i=1}^{n}\left(e_i - \frac{1}{n}\sum_{j=1}^{n} e_j\right)^2 \quad (16)$$

While

$$e_i = \begin{cases} \arctan(\frac{d_{yi}}{d_{xi}}), & (d_{xi} > 0, d_{yi} > 0) \\ \pi - \arctan(\frac{d_{yi}}{d_{xi}}), & (d_{xi} < 0, d_{yi} > 0) \\ \pi + \arctan(\frac{d_{yi}}{d_{xi}}), & (d_{xi} < 0, d_{yi} < 0) \\ 2\pi - \arctan(\frac{d_{yi}}{d_{xi}}), & (d_{xi} > 0, d_{yi} < 0) \end{cases} \quad (17)$$

For simplicity, we can use a threshold to segment the output value to determine whether it is a fire or not. The BP neural network consists of the input layer, output layer and one or more hidden layers. Each layer of BP includes one or more neurons that are directionally linked with the neurons from the previous and the next layer. The output layer uses a log-sigmoid transfer function, so the output of network is constrained between 0 and 1. The sigmoid function is defined by the expression; The constant c is 1 arbitrarily

$$f(x) = \frac{1}{1 + e^{-cx}} \quad (18)$$

4. Results

For testing and training of the system many videos were used which contains the videos with fire and without fire. After detecting the fire pixels from videos using 3 colour models, dynamic features of candidate fire region are analyzed using Lucas Kanade Optical Flow method. Then the back propagation neural network is trained with dynamic features. So after training the neural network, when videos were given for testing, it correctly give result that flame is detected when videos contain fire otherwise it give result that flame not detected. In this method by calculating ratio of the area of the fire pixel in the video, and whole pixel area it give alert message "danger" when this value increase from a threshold during testing the video Also this method can distinguish flame videos from disturbances which having the same color distribution as flame, such as car lights, in such case it give the result that no flame detected and have a remarkable accuracy.

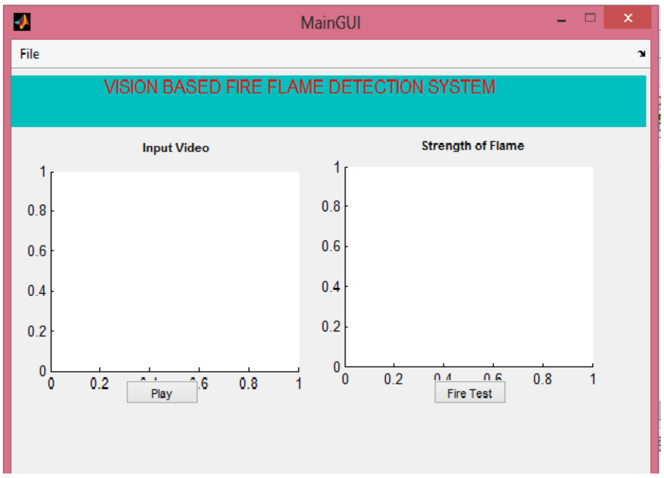

Figure 2: Here, in the home page have options such as selecting the video, after that simply play the video, there is an another option for testing the video for fire flame

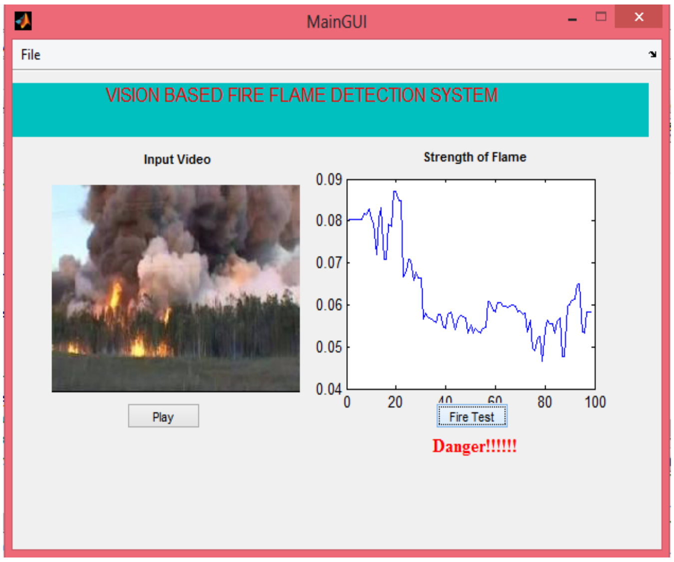

Figure 3: Danger message

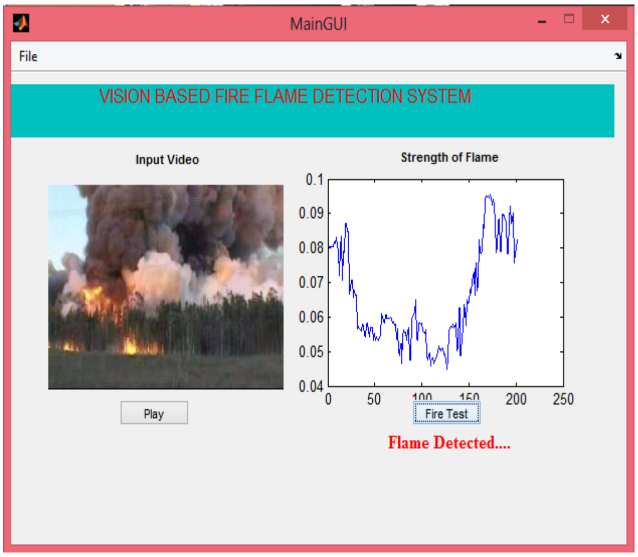

Figure 4: Flame detection

Figure 3 &4 show the detection of fire flame. Figure 3 indicate the dangerous situation during the burning of fire. This is done calculating of candidate fire region area and area of whole video, after that calculating the ratio of area of candidate region and whole area. The graph is plotted as strength of flame. If the ratios exceed the threshold value message is given as “danger” and at last it give the result as “flame detected”

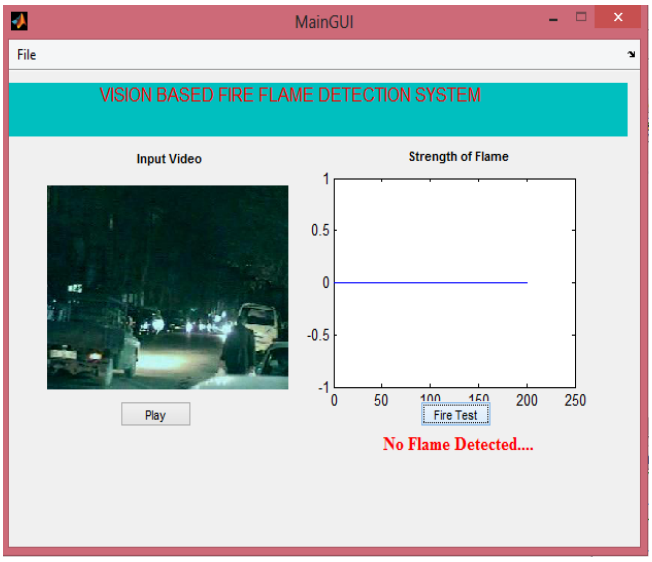

Figure 5: Results show that this method can distinguish flame videos from disturbances which having the same color distribution as flame, such as car lights, and have a remarkable accuracy

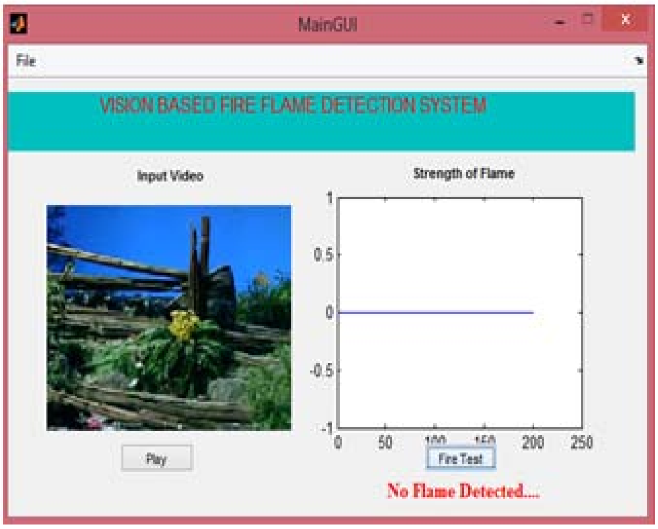

Figure 6: testing video without flame

In the figure 6, When the video selected for fire flame testing first it under go colour classification using 3 colour model, this video not contain any fire colored pixel and there is no candidate region for analyzing dynamic features by optical flow. So the result is given as no flame is detected and strength of fire is given as 0

5. Future Enhancement

The project can give right alarm most of time. The performance can be improved through further analysis of the velocity vectors of fire flame regions, as well as more training of Neural Network

6. Conclusion

In this paper, a video flame detection method combining color and dynamic features is proposed. In this project candidate fire regions are determined by 3 flame color model they are RGB, HSV and YCbCr instead single colour model, RGB, it has disadvantages of illumination dependence. It means that if the illumination of image changes, the fire pixel classification rules cannot perform well. So in this project we use HSV and YCbCr also, it solve the problem due to illumination change. It improves the performance of the system. Then by optical flow technique, Optical flow is important techniques in motion analyzing of machine vision it extract the velocity vectors and orientation vectors of the feature points of the candidate regions which are determined through color based decision rule. Four statistical values (dynamic features) of videos are used as input to train the Neural Network to distinguish flame features from disturbances. Combined use of back propagation neural network and optical flow method further improve the performance of the system Results show that this method can distinguish flame videos from disturbances which having the same color distribution as flame, such as car lights, and have a remarkable accuracy. Also if give an additional information about dangerous situation by calculating ratio of area of fire pixel and whole pixel, through which we can understand the rate of growth of fire.

The project can give right alarm most of time. The performance can be improved through further analysis of the velocity vectors of fire flame regions, as well as more training of Neural Network

References

[1] AhujaN, Liu Chebin and., Vision based fire detection [A]. In: Proceedings of ICPR 2004. Proceedings of the 17th International Conference on [C]. 2004. 4(4):34~137
[2] AungKyaw, Soe, Zhang, Xianku. ―Fire detection by static image characteristics of the light blue flame using roi-based color intensity composition detection algorithm‖. ICIC Express Letters, December Vol.5, No.12, 2011, pp.4479-4486.
[3] Bouguet, J. Y.: Pyramidal Implementation of the Lucas Kanade Feature Tracker, Intel Corporation, Microprocessor Research Labs, 2000,
[4] Byoung Chul Ko, Sun Jae Ham, , Jae Yeal Nam. ―Fire-flame detection based on fuzzy finite automation‖. Pattern Recognition (ICPR), 2010 20th International Conference.2010, pp. 3919 -3922.
[5] Carlo Tomasiand, Jianbo Shi Good features to track, Proc. IEEE Comput. Soc. Conf. Comput. Vision and Pattern Recogn, p593-600, 1994
[6] Computer Vision Based Fire Detection Nicholas True University of California, San Diego9500 Gilman Drive, La Jolla, CA 92093
[7] Du Xiaoxiao Zhou Junying,.―Image recognition technology in fire detection‖. Fire Science and Technology, Vol.26, No.4, 2007, pp. 417-420
[8] Horng, Wen-Bing, Peng Jian-Wen. ―A fast image-based fire flame detection method using color analysis‖. Tamkang Journal of Science and Engineering, September 2008. Vol. No.3, p p. 273-285.
[9] Jin, Hong, Rongbiao, Zhang. ―A fire and flame detecting method based on video‖. Proceedings of the 2009 International Conference on Machine Learning and Cybernetics, Vol. 4, 2009, pp. 2347-2352
[10] J. Yamaguchi. H. Yamagishi A contour fluctuation data processing method for fire flame detection using a color camera, IEEE 26th Annual Conference on IECON of the Industrial Electronics Society, Volume: 2, 22-28 Oct. 2000: 824-829
[11] J. Yamaguchi.H. Yamagishi Fire flame detection algorithm using a color camera, 1999.MHS '99. Proceedings of 1999 International Symposium on Micromechatronics and Human Science, 23-26 Nov. 1999: 255-260
[12] Learning Optical Flow Deqing Sun1, Stefan Roth, J.P. Lewis, and Michael J. Black Department of Computer Science, Brown University, Providence, RI, USA Department of Computer Science, TU Darmstadt, Darmstadt, Germany
[13] Liu Peixun. ―All-weather fire detection system based on video surveillance‖. Master degree thesis. Jilin University, 2011
[14] Lucas, B. and Kanade, T. (1981) An iterative image registration technique with an application to stereo vision. Proc. DARPA IU Workshop, pp.121-130
[15] M. Shah, N. Da Vitoria LoboW. Phillips III,. Flame recognition in video, Fifth IEEE Workshop on Applications of Computer Vision, 4-6 Dec. 2000: 224-229.
[16] P. Wu and Y. Chiou] T. Chen, ―An Early Fire-Detection Method Based on Image Processing, ‖ in Proc. of IEEE ICIP '04, pp. 1707–1710, 2004.
[17] Real Time based Fire & Smoke Detection without Sensor by Image Processing Prerna B. Pagar& A. N. ShaikhDept. of Electronics & Telecommunication, L.E.C.T.'s Savitribai Phule Women's Engineering College, Aurangabad, Maharashtra, India
[18] UgurToreyin, B., Yigithan, Dedeoglu et al., Computer vision based method for real-time fire and flame detection [J]. Pattern Recognition Lett. 2006, 27 (1), 49-58.
[19] Yunyang Yan, Hongyan Wan,.ZhiboGuo ―Fire detection based on feature of flame color‖. Proceedings of the 2009 Chinese Conference on Pattern Recognition, CCPR 2009, and the 1st CJK Joint Workshop on Pattern Recognition, CJKPR, 2009, pp. 349-353.
[20] Zhang Jinhua, Du Haifeng, ZhuangJian, Li Xiaohu.WangSun'an ―A flame detection algorithm based on video multi-feature fusion‖. Lecture Notes in Computer Science. Vol. 4222, 2006, pp.784-792
[21] ZHANG Xi, MEI Zhibin, YU Chunyu- Machine vision based fire flame detection using multi-features, shenyang fire research institute of MPS, shenyang, liaoning 110034, china

Author Profile

Anila R. Kurup received the B-Tech degree in computer science and engineering from Younus College of Engineering and Technology, University of Kerala, Thiruvananthapuram, Kerala, India in 2012.Now pursuing M-Tech in computer science and engineering from Sree Narayana Gurukulam College of Engineering, Mahatma Gandhi University, Kottayam, Kerala, India.