Smoke and Fire Detection in Videos

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Abstract— This paper presents a computer vision-based approach for automatically detecting the presence of fire and smoke in video sequences. Since the fire causes serious disasters, fire detection has been an important study to protect human life. In this paper, the system proposed the fire- smoke detection algorithm in video sequence. The system focuses on optimizing the flame detection by identifying gray cycle pixels nearby the flame, which is generated because of smoke and of spreading of fire pixel and the area spread of flame. The model uses different color model for both fire and smoke and also the model use fuzzy logic or fuzzy inference system (FIS) to detect fire pixels. These techniques can be used to reduce false alarm by giving the accurate result of fire occurrence along with fire detection methods. The color models are extracted using statistical analysis of samples extracted from different type of video sequence and images. The extracted models can be used in complete fire/smoke detection system which combines color information with motion analysis. The strength of using video in flame detection is the ability to monitor large and open spaces. The system also give the opportunity to adjust the system by applying different combination of fire detecting techniques which will help in implementation of system according to different sensitive area requirement**.**

Keywords—Fire detection, Smoke detection video precessing, Fuzzy Inference System (FIS), Mamdani Model, RGB, YCbCr

I. INTRODUCTON

Fire is considered as one of the important and indispensable resources. In view of the conventional fire –smoke detection, it is necessary to bring in a new method for effective fire detection with high false alarm rates. Fire detection system sensors are used to detect occurrence of fire and smoke, to make decision based on it. However, most of the available sensors used such as smoke detector, flame detector, heat detector etc., take time to respond. It has to be carefully placed in various locations. Also, these sensors are not suitable for open spaces because it has high false alarm rate and it cannot properly discriminates between fire and fire like colored-objects. Due to rapid developments in digital camera technology and video processing techniques, conventional fire detection methods are going to be replaced by computer vision based systems. The existing fire detection is not very much accurate.

Fire, if not detected early can cause huge amount of loss, in terms of life and property. With the increase in fire intensity, smoke and flame will be visible. So in order to detect the occurrence of fire, both fire and smoke need to be analyzed. Computer Vision based systems generally make use of three characteristic features of fire: color, motion and geometry. There are lots of fire detection systems in which the color information is used as a pre-processing step.

YCbCr color space is used rather than other color spaces because of its ability to distinguish luminance from chrominance information. In this paper, the system has further improved the model to detect fire pixels using fuzzy logic and proposed a model for smoke pixel detection. The implicit

fuzziness or uncertainties in the rules obtained from repeated experiments and the impreciseness of the output decision is encoded in a fuzzy representation that is expressed in linguistic terms. The single output decision quantity is used to give a better likelihood that a pixel is a fire pixel. The fuzzy model achieves better discrimination between fire and fire like colored objects. Since the color based pre-processing is essential part for all image processing based fire and smoke detection systems, an efficient color model is needed.

II. LITERATURE REVIEW

Existing hardware sensor based smoke and heat detection systems have a high false alarm rate. Current image processing based systems also have considerably high false alarm rates and also lack accuracy [1], [3]. A fire in an image can be described by using its color properties. This color pixel can be extracted into the individual elements as R, G and B, which can be used for color detection. Using R and G elements, a correlation between G/R ratio and temperature distribution can be found, where, as temperature increases, the G/R ration also increases. So, due to this, color of flame can provide useful information to guess on the temperature of a fire and also fire phase [2]. The algorithm uses both RGB and YCbCr color space for the detection of fire pixel intensity. The advantage of using YCbCr color space is that it can separate the luminance from the chrominance more effectively than RGB color space [3].This method has both higher detection rate and lower false alarm rate. In terms of RGB values, color intensity detection depends on the following inter-relation between R, G and B color channels: R > G and G > B. The combined condition for the fire region in the captured image is R > G > B. But using RGB channel increases the margin for error as this color model considers and pixel having high R-

channel value as a fire pixel. .   The color red shows dominance in a fire image and so it should be more stressed than the other components, because R becomes the significant color channel in an RGB image of flames. This imposes another condition for R as to be over some pre-determined threshold, RT [2]. So, input image is converted to the YCbCr model before detection is carried out. The input image is pre-processed for extraction of its RGB channels. These separated components are then converted to Y, Cb and Cr channel image fragments Also, lighting conditions in the background may adversely affect the saturation values of flames resulting in similar R, G and B values which may cause non flame pixels to be considered as flame colored. Area dispersion detection is an important concept for fire detection. It refers to detecting the spreading of the high intensity color region in the input video. When an object catches fire, the flame spreads on the object's surface over time. This detection of area dispersion is done by sequential comparison of video frames. The fire detection algorithm then processes these individual components by comparing them with each other before applying fuzzy logic to check for presence of fire in the input image. Using fuzzy interference system, the margin of error can be reduced as it allows for better distinction between fire-like regions and actual fire in the given image.

III.   METHODOLOGY

A. Color models for fire and smoke

The color model approach has been followed due to its simplicity and effectiveness. For that, color space RGB, YCbCr and HSV is chosen. A digital colored image has three planes: Red, Green and Blue (R, G, and B). The combination of RGB color planes gives ability to devices to represent a color in digital environment. Each color plane is quantized into discrete levels. Generally 256 (8 bits per color plane) quantization levels are used for each plane, for instance white is represented by (R, G, B) = (255, 255, 255) and black is represented by (R, G, B) = (0, 0, 0). A color image consists of pixels, where each pixel is represented by spatial location in rectangular grid (x, y), and a color vector (R(x, y), G(x, y), B(x, y)) corresponding to spatial location (x, y).

In order to create model for fire and smoke, the proposed system have analyzed the images which consist of fire or smoke samples. YCbCr color space is chosen intentionally because of its ability to separate illumination information from chrominance more effectively than the other color spaces. The rules defined for RGB color space in order to detect possible fire or smoke-pixel candidates can be transformed into YCbCr color space and analysis can be performed. However the rules fall short in coming up with a single quantitative measure which can indicate how likely a given pixel is a fire pixel. The implicit fuzziness or uncertainties in the rules obtained from repeated experiments and the impreciseness of the decision variable can be encoded in a fuzzy representation. This provides a way to express the output decision in linguistic terms. The single output decision quantity expressed as a number between zero and one will then give the likelihood that a pixel is a fire-pixel or smoke- pixel.

1) Fire detection

The flame detection module will give us output whether flame is present in the flame. The module works by considering two consecutive frames in the video and all processing are done for each of the frame set. The processing start by converting the input RGB frames into frames in YCbCr color space.

a) A. Selection and comparison of Consecutive Frames

The processing starts by taking consecutive frames in the video. For a frame *i*, (*i-1*) [th] frame is considered as the consecutive frame. Two frames are being selected. The frames should be resized to 255*255 resolutions.

Fig.1-Selection and comparison of Consecutive Frames

b) RGB to YCbCr transformation

The resized frames are converted into frames in YCbCr color space. For the built- in function rgb2ycbcr is being used. Y, Cb, Cr are Luminance, Chrome: Blue, Chrome: Red or Green (Y), Blue (Cb), Red (Cr) (digital video color space) which represents color brightness and two color difference signals. Here, Y is brightness (luma), Cb is blue minus luma (B-Y) and Cr is red minus luma (R-Y).

c) Color Based Transformation

The detection of fire is carried out using the YCbCr samples. The proposed system has observed that the fire samples show some deterministic characteristics in their color channels of Y, Cb, and Cr. In Fig.2, an image with fire and its color channels are shown. As can be observed from Fig.2, for a fire pixel it is more likely that, $Y(x, y)$ is greater than $Cb(x, y)$ where (x, y) refers to pixel's spatial location. This is because the luminance information which is related to the intensity is naturally expected to be dominant for a fire pixel. Repeated experiments with fire images have shown that the greater the difference between $Y(x, y)$ and $Cb(x, y)$ components of a pixel, the higher the likelihood that it is a fire pixel. Fig.2 also hints that $Cb(x, y)$ should be smaller than $Cr(x, y)$. Similarly, a higher

discrimination between Cb(x, y) and Cr(x, y) means that corresponding pixel is more likely a fire pixel. So we can summarize overall relation between Y(x, y), Cb(x, y), and Cr(x, y) as follows: [1]
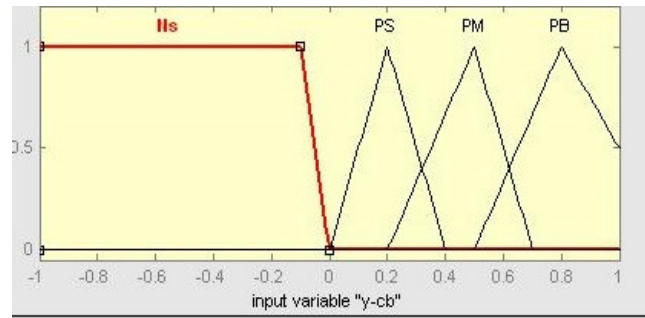
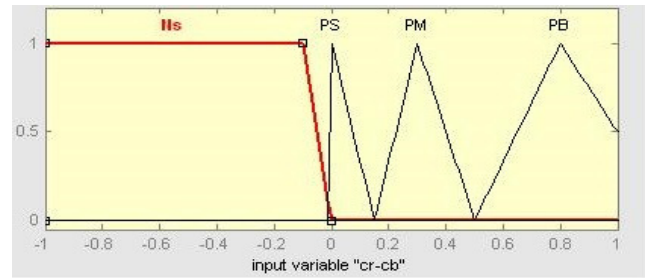$$Y(x, y) \geq Cb(x,y) \geq Cr(x,y) \qquad (1)$$

Fig. 2 - RGB input image and it's Y, Cb and Cr channels, Original RGB image, Y channel, Cb channel, Cr channel.

Let $P_f(x, y)$ be defined as a measure that shows how likely a pixel located at spatial location (x, y) belongs to fire pixel. Its range is in the range of [0, 1], and it is a mapping of the observation defined in equation (1) to a quantity which describes the likelihood that a given pixel is a fire pixel. In order to evaluate, combination of triangular and trapezoidal membership functions are used both for the differences between Cr(x, y) and Cb(x, y), (i.e., Cr(x, y) - Cb(x, y)), and the difference between Y(x, y) and Cb(x, y), (i.e., Y(x, y) - Cb(x, y)). [1]
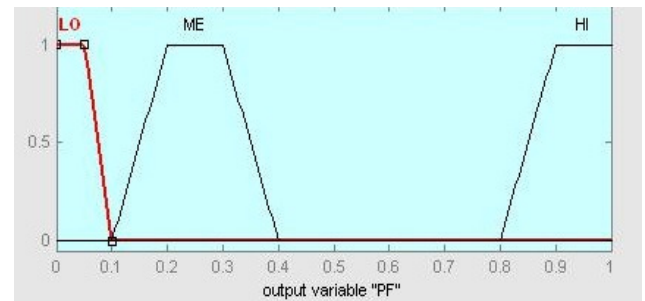
Fig. 3a, 3b and 3c show respectively membership functions for Y(x, y) - Cb(x, y), Cr(x, y) - Cb(x, y) and $P_f(x, y)$. It should be noted that, Mamdani type fuzzy inference system (FIS) is used with the rules defined in Table 1. The distribution of membership functions and rules defined in Table 1 is found using experimental analysis. Table 1 show the rules used in our FIS. The rules are defined in such a way to reflect our expectation for a fire pixel. A total of 16 rules are constructed to account for all possible combinations of input variables. [1]

(a)

(b)

(c)

Fig. 3 - Membership functions for (a) Y(x, y) - Cb(x, y), (b) Cr(x, y) - Cb(x, y), and (c) $P_f(x, y)$.

In the shown original image, each channel is normalized with respect to following formula:

$$y = y \div Imax$$

$$Cb = Cb \div Imax \qquad (2)$$

$$Cr = Cr \div Imax$$

Where *Imax* is the maximum intensity value in set defined by the combination of Y, Cb, and Cr channels. The equation in (2) normalizes all the samples to the interval of [0 1]. So that their difference are in the range of [-1 1] which is used in membership function definitions as shown in Fig.3. Given a set of inputs from Y(x, y) - Cb(x, y) and Cr(x, y) - Cb(x, y), the crisp output of the fuzzy system is computed as follows: first, the inputs are fuzzified based on the membership functions shown in Fig.3a and Fig.2b. Then, the min implication operator is applied on the fuzzy rules. Centre of area defuzzification is applied on the union of all rule outputs in order to find a quantitative measure for $P_f(x, y)$. Y(x, y) -

Cb(x, y), and Cr(x, y) - Cb(x, y) is normalized to [-1, 1] before entering into FIS. The surface for 16 rules is shown in Fig.4. The fig. 4 shows the likelihood $P_f(x, y)$, as a function of inputs $Y(x, y) - Cb(x, y)$ and $Cr(x, y) - Cb(x, y)$. The visual appearance of Fig.4 is as expected and interpreted as follows; when $Y(x, y)-Cb(x, y)$ is less than zero, corresponding $P_f(x, y)$ approaches to 0, and if both $Y(x, y)-Cb(x, y)$ and $Cr(x, y)-Cb(x, y)$ gets closer to value of 1.0, the approaches to 1. The plateau below the peak is used to give low likelihood to objects which show similar behavior to fire color but it is not the fire, i.e. the smoke pixels around fire regions which are colored like fire because of reflectance property of smoke pixels. It is clear from the surface that, the P_f gets high values at the values where $Y(x, y)-Cb(x, y)$ and $Cr(x, y)-Cb(x, y)$ behaves like fire. [1]

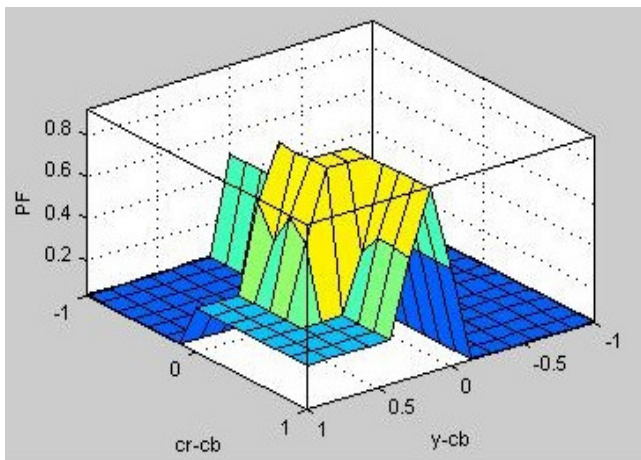Table 1 – Rule table for fuzzy inference system.

Fig.4- View of surface of rules given in Table 1 and used in FIS.

Fig.5 shows some images and its corresponding. It is clear that P_f gets higher values over fire regions and lower values over non-fire regions. Note that, P_f has values in the range of [0 1]. [1]
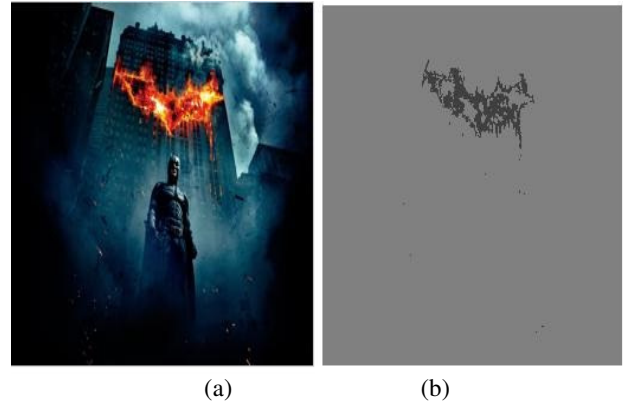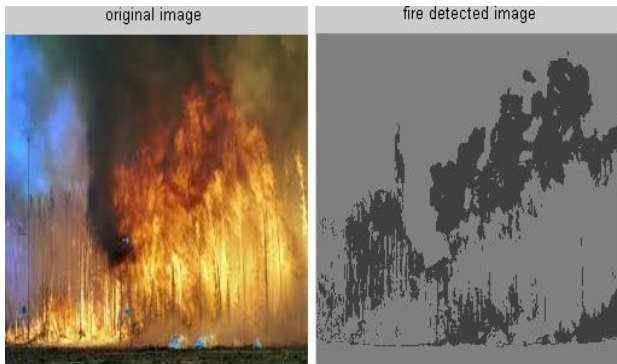

(a)   (b)

Fig. 5 - RGB input image and it's Pf, Column (a) RGB input image, Column (b) P_f for corresponding input image.

$P_f(x, y)$		Cr(x, y) - Cb(x, y)			
		NS	**PS**	**PM**	**PB**
Y(x, y) – Cb(x, y)	**NS**	LO	LO	LO	LO
	PS	LO	LO	HI	HI
	PM	LO	HI	HI	ME
	PB	LO	ME	ME	ME

2) Smoke Detection

Similar to the fire detection, the smoke detection module will give as output, the probability of presence of smoke in the frame. The module works by considering two consecutive frames in the video and all processing are done for each of the frame set. The processing starts by converting input RGB frames into HSV color space. Then a smoke color model is created.

But the smoke pixels do not show chrominance characteristics like fire pixels. At the beginning, when the temperature of the smoke is low, it is expected that the smoke will show color from the range of white-bluish to white. Toward the start of the fire, the smoke's temperature increases and it gets color from the range of black-grayish to black.

a). Selection of Consecutive Frames

The processing starts by taking consecutive frames in the video. For a frame *i*, $(i-1)$ [th] frame is considered as the consecutive frame. Two frames are being selected. The frames should be resized to 255*255 resolutions.

b).RGB to HSV transformation

The resized frames are converted into HSV color space. For that built in function rgb2hsv is being used. H, S and V are hue, Saturation and value which represent the type, purity and brightness of a color.

c).Smoke Model Creation

As can be seen from the Fig.2, most smoke samples have a grayish color. So we can formulate the smoke pixels as follows

$$|R(x,y) - G(x,y)| \leq Th$$
$$|G(x,y) - B(x,y)| \leq Th \qquad (3)$$
$$|R(x,y) - B(x,y)| \leq Th$$

Where '*Th*' is a global threshold ranging from 15 to 25. The equation (3) states that, the smoke pixels should have similar intensities in their RGB color channels. Fig.6 shows the smoke-pixel segmentation using the equation defined in (3). Since the smoke information will be used for early fire detection system, the smoke samples should be detected when the smoke has low temperature. This is the case, where the smoke samples have color ranging from white-bluish to white, which means that the saturation of the color should be as low as possible. Using this idea, the rule defined in (4) is used where HSV color spaces are used, and its application with (3) is shown in Fig. 7. [1]

$$S(x,y) \leq 0.1 \qquad (4)$$

Figure 6 - RGB input image and its H, S and V channels, Original RGB image, H channel, S channel, V channel using equation(3).

As can be seen from the Fig.6, the output is noisy, but the motion property of the smoke can be used to remove such noisy parts. It can be easily observed from the first row of the Fig.6, the sky is detected as smoke, because its property of grayish color. But, if we embed the motion detection part, the sky will be removed because of its constant color over some duration.

Figure 7- RGB input image and smoke segmentation. (a) RGB input image (b) segmented smoke image using equation (3) and (4).

IV.   RESULTS

A. Results

The video clips used in the proposed systems experiments are real-world image sequences taken from a random selection of commercial/training video tapes. These fire video clips can be of different types such as residential fire, warehouse fire or in any environment.

For fire detection, as shown in table-2, for comparison purpose two sets of images are collected which consist of total 50 images. From these two sets of images, one set of 25 images is composed of images which consist of fire and gives successful detection for 24 images with the accuracy of 96%, whereas in the another set of 25 images contain images that does not consist of fire. But fire like colored images such as sun and light bulbs as negative examples, which gives successful detection for 15 fire like colored images with the accuracy of 60%. Two type of comparison is carried out; one for evaluation of the correct fire detection rate and the other is for the false alarm rate.

Now, in table-3, out of 25 fired images, false alarm is detected just for one image and gives accuracy of 4%, while for non-fire images, out of 25, false alarm is detected for 10 images with the accuracy of 40%.

Table 2- Results of Fire Detection.

Image Type	Number of Images	Successful Detection	Accuracy (%)
Fire Image	25	24	96
Non-fire Image	25	15	60

Table3- Results of False Alarm Rate for Fire

Image Type	Number of Images	False Alarm	Accuracy (%)
Fire Image	25	1	04
Non-fire Image	25	10	40

For smoke pixel detection, test results lack the accuracy of fire detection, primarily because of smoke's nature. It doesn't

show robust characteristics like the fire pixels. Because of this reason, the proposed system uses more discriminative features for smoke detection which are combined with the smoke color model i.e. it smoothes edges of the background when the smoke starts.

Table 4- Result of Smoke Detection

Image type	Number of Images	Successful Detection	Accuracy (%)
Smoke	25	20	80
Non- Smoke	25	15	60

Table 5- Result of False alarm Rate for Smoke

Image Type	Number of Images	False Alarm	False Alarm Rate (%)
Smoke	25	5	20
Non- Smoke	25	10	40

V.   CONCLUSION

This paper proposes two models: one for fire detection and another for smoke detection. For fire detection, using the concept of fuzzy logic makes the classification more robust in effectively discriminating fire and fire like colored object. The model achieves up to 96% correct fire detection rate with a 40% false alarm rate. For smoke detection, a statistical analysis is carried out using the idea that the smoke shows grayish color with different illumination. The results of smoke detection indicate that the system has 80% success rate in identifying smoke and around 20% false alarm rate.

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