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Vision Based Intelligent Fire Detection System

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ABSTRACT: *Computer vision-based fire detection algorithms are usually applied in closed-circuit television surveillance scenarios. Most vision-based Fire detection techniques proposed yet target surveillance applications with static cameras and consequently reasonably controlled or static background. Otherwise, they propose the use of filter banks, frequency transforms, and motion tracking, requiring more computational processing time, making them unsuitable for real time processing. The proposed method analyzes the frame-to- frame changes of specific low-level features describing potential fire regions. These features are color, randomness of fire area size, fire boundary roughness and surface coarseness. Because of flickering and random characteristics of fire, these features are powerful discriminants. The features mentioned above allow very fast processing, making the system applicable for real time fire detection. In comparison to some earlier works, the goal of this method is not to identify fire pixels in a given image or video frame, but to determine if fire occurs in the frame.*

I. INTRODUCTION

Fire detection systems are one of the most important components in surveillance systems used to monitor buildings and environment as part of an early warning mechanism that reports preferably the start of fire. Currently, almost all fire detection systems use built-in sensors that primarily depend on the reliability and the positional distribution of the sensors. The sensors should be distributed densely for a high precision fire detector system. In a sensor-based fire detection system, coverage of large areas in outdoor applications is impractical due to the requirement of regular distribution of sensors in close proximity.

Due to the inherent nature of their design, many of today"s modern, large structures are not adequately protected against smoke and fire. Features like large atriums, vast open areas and high ceilings, can make the use of traditional smoke and fire detection methods impractical, ineffective and difficult to maintain and operate. High airflow and smoke stratification can prevent smoke from reaching spot-type smoke detectors, adding to the ineffectiveness of traditional fire detection in open area facilities.

Due to the rapid developments in digital camera technology and video processing techniques, there is a big trend to replace conventional fire detection techniques with computer vision based systems. Video based fire detection systems can be useful to detect fire in large auditoriums, tunnels, atriums, etc. The strength of using video in fire detection makes it possible to serve large and open spaces. In addition, closed circuit television (CCTV) surveillance systems are currently installed in various public places monitoring indoors and outdoors. Such systems may gain an early fire detection capability with the use of fire detection software which processes the outputs of CCTV cameras in real time.

So nowadays, fire detection systems are one of the most important components in surveillance systems used to monitor buildings and environment as part of an early warning mechanism that reports preferably the start of fire. My paper titled "*Vision Based Intelligent Fire Detection System*" proposes a novel method to detect fire and/or flames in real- time by processing the video data generated by an ordinary camera monitoring a scene. The proposed method analyzes the frame-to-frame changes of specific low-level features describing potential fire regions. These features are color, area size, surface coarseness, and boundary roughness within estimated fire regions. Because of flickering and random characteristics of fire, features are powerful discriminates. The behavioral change of each one of these features is evaluated, and the results are then combined according to the Fuzzy Logic for robust fire recognition.

II. ADVANTAGES OVER RELATED METHODS

Despite a growing interest in the topic, there are still not a large number of papers about fire detection in the computer vision literature. Many fire detection systems are based on satellite images or thermal analysis of satellite sensors. Inside the vision-based scope, the first works used purely a color-based model [2], which is the initial step for many other algorithms, including the one proposed in this paper.

In another approach [3], the authors use pixel colors and their temporal variations. They use an approach that is based upon creating a Gaussian-smoothed color histogram to determine the fire colored pixels, and then using the temporal variation of pixels to determine which of these pixels is actually fire. However, this algorithm is also essentially color based, and does not exploit other statistical characteristics of potential fire regions. In addition, 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. Also, pixels in the core of the fire exhibit less temporal variation than the other pixels.

An alternative approach in color-based detection is to analyze the YC_bC_r color space instead of the RGB space [4]. In this approach, the authors propose the use of a fuzzy logic approach which uses luminance and chrominance information to replace the existing heuristic rules used to generate the PFM. The implicit uncertainties in the rules obtained from repeated experiments can be encoded in a fuzzy representation that is expressed in linguistic terms. The authors argue that the single output decision quantity will then give a better likelihood that a pixel is a fire pixel. Although a very good detection rate is achieved, the method is focused on images and random changes of fire from frame to frame are not exploited.

The works presented by Toreyin in [5] and [6] also yield good results, where boundary of flame s are represented in wavelet domain and high frequency nature of the boundaries of fire regions is also used as a clue to model the flame flicker spatially. However, the approach used presents two drawbacks: first, the algorithm assumes that the camera is stationary; and second, it presents a high computational complexity despite working in real-time. Considering that the videos have at least 25 frames/s, the analysis would be very time consuming.

In another approach, the authors also use a probability metric to threshold potential fire pixels. This is achieved by multiplying the probabilities of each individual color channel being fire. However, this metric can be very sensitive: if the value of one of the channels is not very close to the expected stochastic mean for that channel, the result of the metric is significantly decreased, increasing the number of false-negatives. The probabilistic metric for thresholding potential fire pixels in the proposed method minimizes this effect.

In contrast to the earlier works, the goal of the proposed method is not to identify fire pixels in a given image or video frame, but to determine if fire occurs in the frame. The contributions presented of the proposed method can be listed as follows.

1. A probabilistic model for color-based fire detection is proposed, which outputs a degree of confidence for each pixel as representing fire or not. We illustrate that an efficient PFM can be generated from this model. This approach can be directly employed to different fire detection methods that used color to indicate candidate fire regions.
2. Unlike many works in the literature which use shape descriptors to analyze the amount of flame motion, we use the boundary roughness of the potential fire regions. This brings the same amount of discernibility with a more efficient processing speed.
3. This method also proposes the use of the variance as a feature, due to the randomness or coarseness observed in fire surfaces.
4. For real fire regions, the amount of fire varies from frame to frame due to flame flickering. Therefore, the change in fire area is also used as a feature with classification power.
5. The features are combined according to the fuzzy logic concept to achieve an practical low detection error rate.

The proposed method uses a new detection metric based on color for fire detection in videos. In addition, this has exploited important visual features of fire, like boundary roughness and variance of the fire pixel distribution. In contrast to other methods which extract complicated features, the features discussed here allow very fast processing, making the system best suitable for real time fire detection.

III. STATISTICAL CHARACTERISTICS OF FIRE

It is well known that fire has unique visual signatures. Color, geometry, and motion of fire region are all essential features for efficient classification. In general, in addition to color, a region that corresponds to fire can be captured in terms of the spatial structure defined by the boundary variation within the region. The shape of a fire region often keeps changing and exhibits a stochastic motion, which depends on surrounding environmental factors such as the type of burning elements and wind. The physical characteristics of fire is explained below that validate their applicability.

Color The fire has very distinct color characteristics, and although empirical, it is the most powerful single feature for finding fire in video sequences. Based on tests with several images in different resolutions and scenarios, it is reasonable to assume that generally the color of flames belongs to the red-yellow range.

Laboratory experiments show that this is indeed the case for hydrocarbon flames, which are the most common type of flames seen in nature. Other types of flames, such as blue liquefied petroleum gas flames, are not considered since they do not represent the typical flame seen in a surveillance or catastrophe scene. It is noticed that for a given fire pixel, the value of red channel is greater than the green channel, and the value of the green channel is greater than the value of blue channel. Several additional characteristics also hold, such that for a given fire pixel $f(m, n)$ in an image f *we* have

$$f_R(m,n) > \overline{f_R} \quad (1)$$

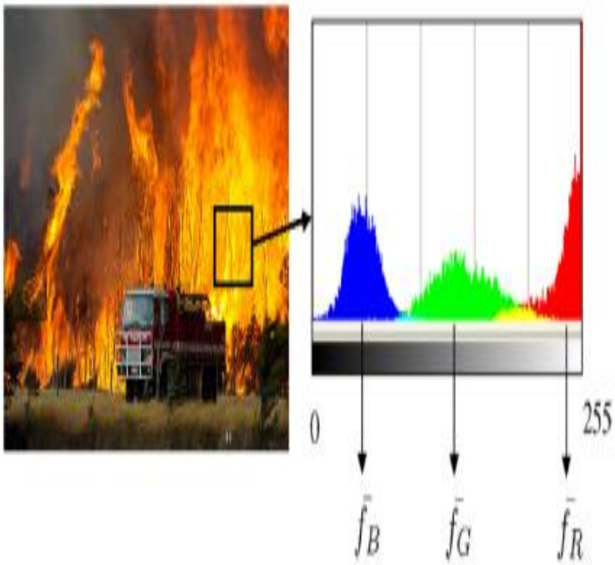

Figure 1 Histogram of a fire region.

Where, f_R is the red channel representation of f *and* $\overline{f_R}$ is the average pixel value of f_R. In addition,

$$f_R(m,n) > f_G(m,n) > f_B(m,n) \quad (2)$$

For the type of flames considered (hydrocarbon flames), it is noticed that for a given fire pixel, the value of red channel is greater than the green channel, and the value of the green channel is greater than the value of blue channel, as illustrated in Fig 1.

Several additional characteristics also hold, which are discussed in the following, where color detection metric is proposed. This detection metric is used to generate the PFM, which will then be further analyzed with the other non-colour fire features.

Proposed Color Based Detection Metric:

Let a fire pixel at position (m, n) in an image be represented as $f(m,n)$,

$$f(m,n) = \begin{bmatrix} f_R(m,n) \\ f_G(m,n) \\ f_B(m,n) \end{bmatrix} \quad (3)$$

Where f_R, f_G and f_B are the red, green, and blue channels representation of f, respectively. Let $\overline{f_R}$, $\overline{f_G}$ and $\overline{f_B}$ represent the sample average of the pixels in a fire image region, for the red, green and blue channels, as shown in Fig 5.1.

Interpreting $\overline{f_R}$, $\overline{f_G}$ and $\overline{f_B}$ as random variables, we employ a Gaussian model for these variables, such that $\bar{f}_R \sim \mathcal{N}(\mu_{\bar{f}_R}, \sigma^2_{\bar{f}_R})$, $\bar{f}_G \sim \mathcal{N}(\mu_{\bar{f}_G}, \sigma^2_{\bar{f}_G})$ and.

$\bar{f}_B \sim \mathcal{N}(\mu_{\bar{f}_B}, \sigma^2_{\bar{f}_B})$.

Notice that a distinction should be made between the distribution of the pixels in f_R and the distribution of $\overline{f_R}$, i.e., the distribution of the sample average of the pixels in f_R. The same is valid for $\overline{f_G}$ and $\overline{f_B}$.

With these assumptions, let us define

$$D_{C_R} = p_{\overline{f_R}}(\overline{f}_{R_{obs}}) \big/ p_{\overline{f_R}}(\mu_{\overline{f_R}}) \tag{4}$$

$$D_{C_G} = p_{\overline{f_G}}(\overline{f}_{G_{obs}}) \big/ p_{\overline{f_G}}(\mu_{\overline{f_G}}) \tag{5}$$

$$D_{C_B} = p_{\overline{f_B}}(\overline{f}_{B_{obs}}) \big/ p_{\overline{f_B}}(\mu_{\overline{f_B}}) \tag{6}$$

Where $p_x(x_0)$ represents the evaluation of the probability density function (PDF) of a random variable x at value x_0.

In this case $\overline{f}_{R_{obs}}$ represents the average value in the red channel of an observed set of pixels. Fig 2 illustrates that the maximum value for D_{C_R} is obtained when $\overline{f}_{R_{obs}} = \mu_{\overline{f_R}}$.

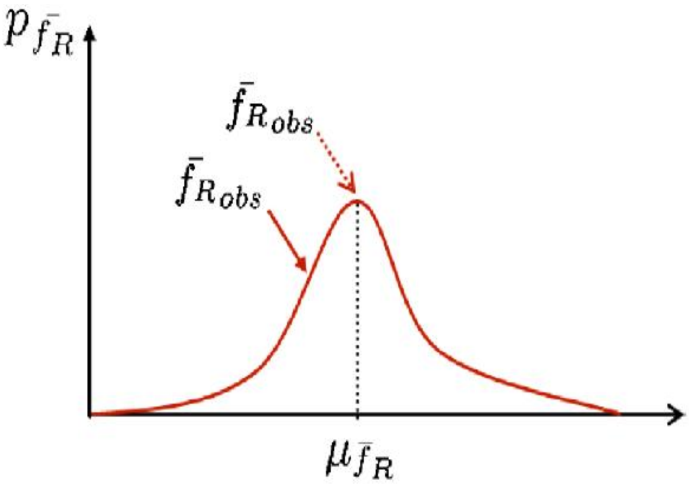

Figure 2 Graphical representation of the D_{C_R} parameter.

D_{C_R} can be interpreted as a normalized metric that indicates the probability that a given region represents fire according to the red channel distribution. For example, if in equation (4) $\overline{f}_{R_{obs}}$ is very close to $\mu_{\overline{f_R}}$, D_{C_R} is very close to 1 and we assume with probability D_{C_R} that the observed region represents a fire region (considering the red channel)

$$D_C = D_{C_R} + D_{C_G} + D_{C_B} - (D_{C_R}D_{C_G} + D_{C_R}D_{C_B} + D_{C_G}D_{C_B}) + D_{C_R}D_{C_B}D_{C_G}. \tag{7}$$

It is interpreted as the degree of confidence (represented by a probability) that a set of pixels represents a fire region.

If $\overline{f}_{R_{obs}}$, $\overline{f}_{G_{obs}}$ and $\overline{f}_{B_{obs}}$ can be assumed independent, D_C can be interpreted as the degree of confidence - represented by a probability - that a set of pixels represents a fire region (based only on colour analysis). If we assume that $\overline{f}_{R_{obs}}$, $\overline{f}_{G_{obs}}$ and $\overline{f}_{B_{obs}}$ are correlated, is an approximation that depends on the correlation level. In practice, however, D_C yields meaningful results.

Based on the metric D_C a binary image PFM is generated for each frame, such that

$$\text{PFM}(m,n) = \begin{cases} 0, & \textit{if } D_C(m,n) < \lambda_C \\ 1, & \textit{otherwise} \end{cases} \tag{8}$$

Where λ_C are confidence threshold level and the values 1 or 0 indicate the presence or absence of fire at the corresponding location in the image f . The threshold λ_C is the same for all pixel locations.

Considering equation (8), we refer to the concatenation of pixels "1" as fire blobs in this project. The PFM is then processed with a connected components algorithm so that the potential fire blobs are concatenated in a contiguous region.

Notice that the threshold λ_C should be very permissive and many non-fire regions may be included in the PFM. For this reason, additional analysis is necessary to further refine the results. To define a real burning fire, in addition to using chromatics, statistical and dynamic features are usually adopted to distinguish other fire aliases. Examples of these fire dynamics include the change in shape, flame movement and flickering. The statistical and dynamic fire features are discussed next.

Randomness of Area Size

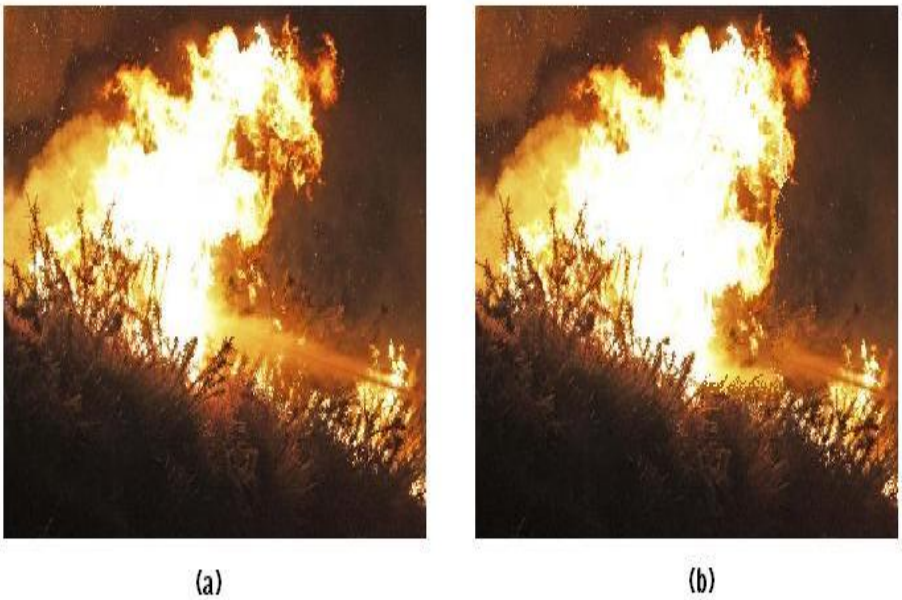

Figure 3 Illustration of the change in fire pixel area
((a) Fire area = 1692 pixels. (b) Fire area = 2473 pixels)

For the estimated fire pixel area, because of the fire flickering, a change in the area size of the PFM occurs from frame to frame, as illustrated in Fig 3. Non-fire areas have a less random change in the area size. The normalized area change ΔA_i for the i^{th} frame is given by $\Delta A_i = \frac{|A_i - A_{i-1}|}{A_i}$ (9)

Where A_i corresponds to the area of the fire blobs representing the potential fire regions in the PFM. In case a hard decision rule is used, fire is assumed if $\Delta A_i > \lambda_A$, where λ_A is a decision threshold. Because of flickering and random characteristics of fire due to the combustion and air flow, this is an efficient classifying feature.

Boundary Roughness

An earlier method represents the shape of fire regions using Fourier Descriptors (FD) based on the coefficients of the Fourier Transform. However, the main drawback of FD is that the evaluation of the FD for every frame is a very time consuming operation. Although the FD are excellent shape descriptors, for fire detection purposes what we are really interested is the randomness or roughness of the shape, and not the shape itself, as fire does not have a specific boundary characteristics. Therefore, we use the boundary roughness of the potential fire region as a feature, given by the ratio between perimeter and convex hull perimeter. The convex hull of a set of pixels *S* is the smallest convex set containing „*S*", as illustrated in Fig 4.

Let C_i be the boundary roughness for the blobs in the FM corresponding to the i^{th} frame in the video. The presence of fire is as

$$\Delta C_i = \frac{|C_i - C_{i-1}|}{C_i} > \lambda_C \quad (10)$$

where λ_C represents a threshold in the rate of change. The inclusion of the term C_i in the denominator normalizes the metric to be independent of the size of the blob. Experiments illustrate that this is an excellent and computationally efficient discriminate for the shape of fire regions, yielding similar results to the use of FD, however with much lower computational complexity. Boundary roughness of the potential fire region can also be described as the ratio between perimeter and convex hull perimeter. The convex hull of a set of pixels *S* is the smallest convex set containing *S* .Boundary roughness of the potential fire region can also be described as the ratio between perimeter and convex hull perimeter. The convex hull of a set of pixels *S* is the smallest convex set containing *S*, The boundary roughness is given by

$$B_R = P_S / P_{CH_S} \qquad (11)$$

Where P_S is the perimeter of S and P_{CH_S} is the perimeter of the convex hull of S. To compute the perimeter, a simple approach is to count the number of pixels connected horizontally and vertically plus $\sqrt{2}$ times the number of pixels connected diagonally. If a hard decision rule is used, fire is assumed if

$B_R > \lambda_{B_R}$, where λ_{B_R} is a decision threshold.

Surface Coarseness

Unlike other false-alarm regions, like a yellow traffic sign, for example (Fig.5), fire regions have a significant amount of variability in the pixel values. Filter banks are frequently used in texture analysis when trying to describe a given pattern. In the case of fire, however, it is very hard to describe its texture with any given model. The randomness observed in fire can vary significantly in frequency response (periodicity is often not present) and gradient angles, for example. The variance is a well-known metric to indicate the amount of coarseness in the pixel values.

Hence, we use the variance of the blobs as a feature to help eliminating non-fire blobs in the PFM. Therefore, fire is assumed if the blob has a variance $\sigma > \lambda_\sigma$, where λ_σ is determined from a set of experimental analyses. Fig 2.5 illustrates how the use of the variance can reduce the false alarm rate of the PFM, for an illustrative threshold $\lambda_\sigma = 50$

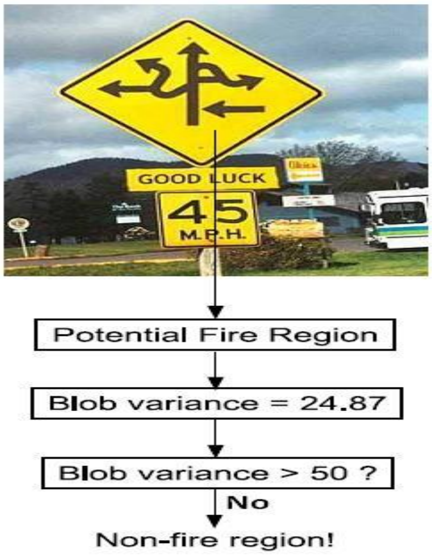

Figure 5 Elimination of potential fire regions

IV. DECISION STRATEGY

Fuzzy Logic based decision fusion strategy is used for recognizing the presence of fire. A fuzzy concept is a concept of which the content, value, or boundaries of application can vary according to context or conditions, instead of being fixed once and for all.By obtaining the values of the discriminants of fire from various training sets, the fuzzy logic is applied to determine whether the fire is present or not. Fuzzy logic is a form of many-valued logic derived from fuzzy set theory to deal with reasoning that is robust and approximate rather than brittle and exact. In contrast with "crisp logic", where binary sets have two-valued logic, fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions.

Fuzzy logic and probability are different ways of expressing uncertainty. While both fuzzy logic and probability theory can be used to represent subjective belief, fuzzy set theory uses the concept of fuzzy set membership (i.e., how much a variable is in a set), probability theory uses the concept of subjective probability (i.e., how probable do I think that a variable is in a set). While this distinction is mostly philosophical, the fuzzy-logic-derived possibility measure is inherently different from the probability measure, hence they are not directly equivalent.

V. EXPERIMENTS

The block schematic of the paper implementation is given in Fig 6. The block diagram illustrates the fire detection process for each frame *i*, including the PFM generation, the extraction of features and the classification according to the Fuzzy logic classifier. This fire detection systems use color clues as a precondition to generate seed areas for possible fire regions called a "potential fire mask" (PFM), since color is the most discerning feature. Generally the color of frames belongs to the red-yellow range.

Next step is the blob extraction. A blob (alternately known as a binary large object, basic large object, BLOB, or BLOb) is a collection of binary data stored as a single entity in a database management system. Blobs are typically images, audio or other multimedia objects, though sometimes binary executable code is stored as a blob. In the area o f computer v i s i o n , „blob detection" refers to visual modules that are aimed at detecting points and/or regions in the image that are either brighter or darker than the surrounding. Fire regions have a significant amount of variability in the pixel values. The variance is a well known metric to indicate the amount of coarseness in the pixel values. Hence the variance of the blobs is used as a feature to help eliminating non-fire blobs in the PFM.

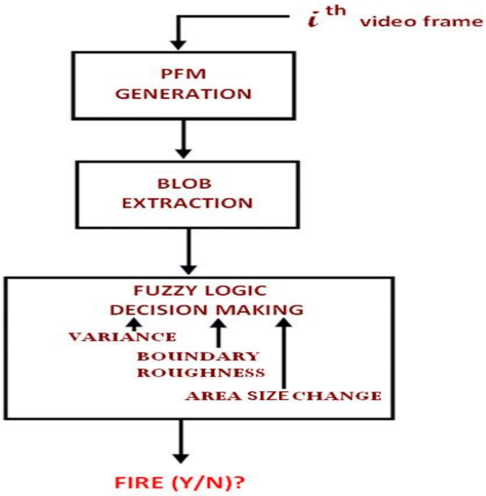

Fig. 6. Fire detection process

Other features such as area size, boundary roughness and variance within estimated fire regions, are used as low- level descriptors for the PFM analysis. Because of flickering and random characteristics of fire due to the combustion and air flow, these are efficient classifying features. The change of each of these features is evaluated, and the results are combined according to the Fuzzy Logic to determine whether or not fire occurs in that frame.

A) Output Screen Shots

Fig. 7. Screen shot showing Bounding Box

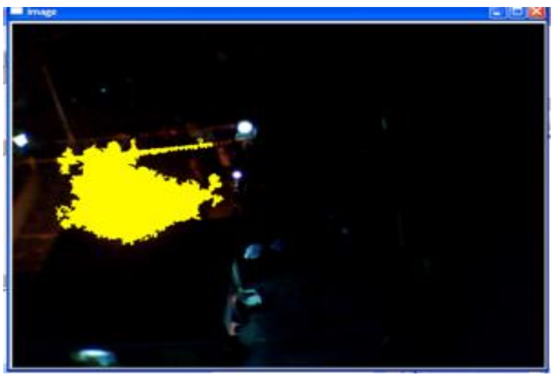

Fig. 8. Screen shot showing Fire Detection

VI. CONCLUSION

This paper proposed a new detection metric based on color for fire detection in videos. In addition, it exploits important visual features of fire, like boundary roughness and surface coarseness of the fire pixel distribution. The coarseness, in particular, is a very useful descriptor because of the frequent occurrence of saturation in the red channel of fire regions. Also, it proposes modifications to motion based features. In contrast to other methods which extract complicated features, the features discussed here allow very fast processing, making the system applicable for real time fire detection.

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