Novel Approach for Early Fire Detection in Forest Monitoring

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Abstract:-**The proposed project had the objective of designing a truly modern and efficient forest fire monitoring system with alarm indication of large scale forests fires. A computer vision based system for automatically detecting the presence of fire in stable video sequences is the current need. Forest fires represent a constant threat to ecological systems, infrastructure and human lives. The only effective way to minimize damage caused by forest fires is their early detection and fast reaction, apart from preventive measures. To detect flames in infrared IR video, the sections restraining the flames are to be differentiated from the unaffected segments. Boundaries of flames can be represented in spatial domain and the high frequency nature of the boundaries of fire regions may be used as a clue to model the flame flicker.**

The extracted models can be used in complete fire/smoke detection system which combines color information with motion analysis. The models use different color models for both fire and smoke. The color models are extracted using a statistical analysis of samples extracted from different type of video sequences and images. Contour of fire is found firstly, and then is presented by descriptors with 4 or 8 connectivity in a pre defined direction. Chroma components are analyzed for the boundary tracing with a dynamic threshold.

Extensive experimental assessment on publicly available spatial data illustrated that the proposed approach efficiently detects forest fires

Index terms: Infrared fire detection, wavelet transform, objects contour analysis, edge detection, segmentation.

I. INTRODUCTION

Due to the rapid developments in digital camera technology and developments in content based video processing, more and more vision based fire detection systems are introduced. Vision based systems generally make use of three characteristic features of fire: color, motion and geometry. The color information is used as a pre-processing step in the detection of possible fire or smoke. There are lots of fire detection systems in which the color information is used as a pre-processing step. Annually several hundred million hectares (ha) of forest and other vegetation are deteriorated by the forest fires [13]. The strength of using ordinary video in fire detection is the ability to serve large and open spaces.

Current fire detection algorithms are based on the use of color and motion information in video to detect the flames [1], [2]. If the content is fire, one new kind of fire recognition approach has been adopted, i.e. video based flame detection method. Phillips et al. used color and temporal variation as clues. Whether a pixel belongs to fire area depends on its color and significant temporal variation.

Chen et al. used chromatic and dynamic features to extract real fire and smoke in video sequences [3] Giuseppe Marbach et al. [4] used temporal variation of fire intensity to capture candidate regions and extract characteristic color features to detect fire. Töreyin et al. proposed a real-time algorithm for fire detection in video sequences [14]. They combined motion and color clues with fire flicker analysis on wavelet domain to detect fire

Fires have remarkable influence over the ecological and economic utilities of the forest being a principal constituent in a huge number of forest ecosystems [5]. Due to the rapid developments in digital camera technology and developments in content based video processing, more and more vision based fire detection systems are introduced. Vision based systems generally make use of three characteristic features of fire: color, motion and geometry. The color information is used as a pre-processing step in the detection of possible fire or smoke.

Recently, Celik et al. proposed a generic model for fire color [6,7]. The authors combined their model with simple moving object detection. The objects are identified by the background subtraction technique [8]. Later on they have proposed a fuzzy logic enhanced approach which uses predominantly luminance information to replace the existing heuristic rules which are used in detection of fire-pixels [9]. Other recent methods for video based fire detection are [10],[11],[12]. These methods are developed to detect the presence of smoke in the video. The proposed fire detection algorithm consists of four main sub-algorithms:

(i) **Conversion of the image into a suitable color space transformation**
(ii) **Segmenting the fire region with k means clustering**
(iii) **The bonding of the segmented regions with edge and connectivity operators**
(iv) **Detection of fire pixels with threshold and measuring the degree of fire**

II. COLOR TRANSFORMATION

The strength of using image/video in fire detection is the ability to monitor large and open spaces. Current fire and flame detection algorithms are based on the use of color and motion information in video. The images are segmented in order to facilitate the detection of regions prone to fire. Computer may express a color with the aid of the amounts of red, green and blue phosphor emission necessary to match a color. Conventionally color is denoted by three coordinates or parameters.

Video and digital photography systems extensively utilize the 'YCbCr', color space. Y' represents the luminance component and Cb and Cr represent blue-difference and red-difference chrominance components respectively. In order to distinguish the luma, which means that light intensity is nonlinearly encoded using gamma, the prime Y is used. Chroma *Cb* and chroma *Cr* correspond to the *U* color component and the *V* component of a general *YUV* color space. The equations to convert RGB into YCbCr color space are as follow

$$Y = 0.2989R + 0.5866G + 0.1145B$$

$$C_b = -0.1688\mathrm{R} - 0.3312\ \mathrm{G} + 0.5000\mathrm{B}$$

$$C_r = 0.5000\ \mathrm{R} - 0.4184\mathrm{G} - 0.081\mathrm{B}.$$

Figure1a.Original Image -I

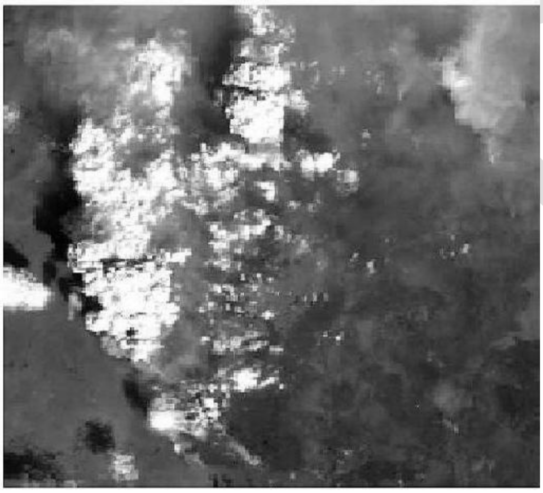


Figure1b.Y Component of I

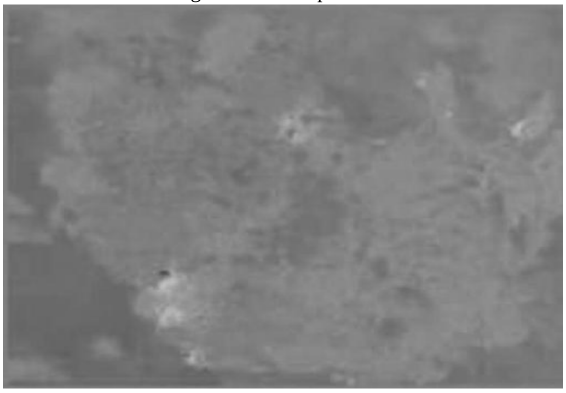


Figure1c.Cb Component of I

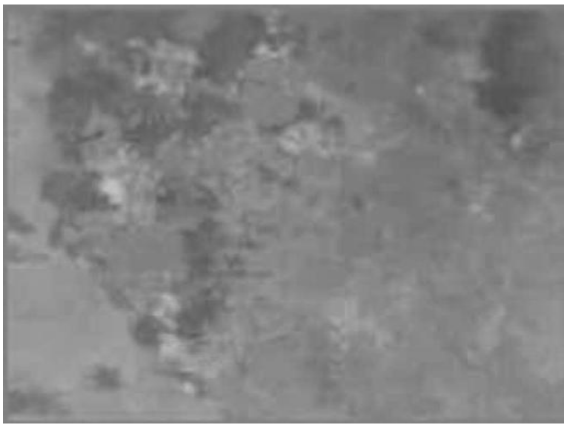


Figure1d.Cr Component of I

III. CLUSTERING WITH K MEANS ALGORITHM

Image segmentation is a low-level image processing task for dividing an image into identical regions. The segmentation results can possibly be employed to identify the regions of interest and objects in the scene that is very advantageous to the subsequent image analysis. Color image segmentation is more tedious when compared to the grey image segmentation owing to the reason that the inherent multi-features not only contain non linear relation individually but also comprise inter-feature dependency between R, G, and B (or YCbCr)

The Segmentation is done on the *YCbCr* color space transformed image. The detection of fire is carried out using the *YCbCr* samples We have observed that the fire samples show some deterministic characteristics in their colour channels of *Y*, *Cb*, and *Cr*. In Figure 1, an image with fire and its color channels are shown. As can be observed from Figure 1, 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. Figure1 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:

$$Y\ x, y \geq Cr\ x, y \geq Cb\ x, y)$$

Taking gray value as the input of Otsu method, fire and smoke regions are segmented from the background. Since the shape of forest smoke is normally continuous in one image, the smaller and isolated regions are deleted as noises. Then taking Y value in the *YCbCr* color space as input of Otsu method, the fire region is segmented from the left large and continuous regions.

Clustering is a way to separate groups of objects. K-means clustering treats each object as having a location in space. It finds partitions such that objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. K-means clustering requires the number of clusters to be partitioned and a distance metric to quantify how close two objects are to each other.

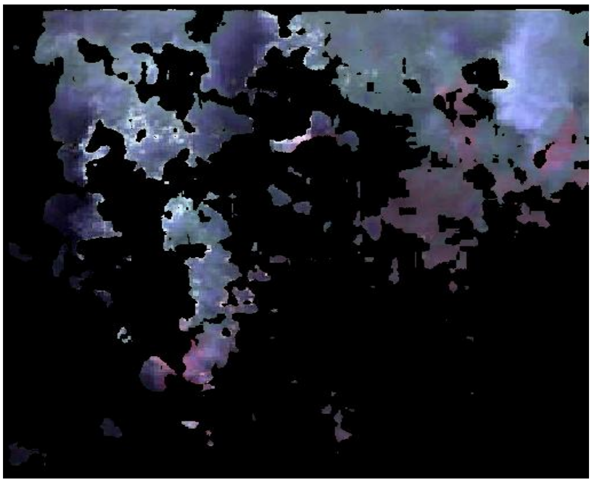


Figure2a.Object clustered as 1

The proposed algorithm combines the objects into three clusters using the Euclidean distance metric. For every object in your input, kmeans returns an index corresponding to a cluster.

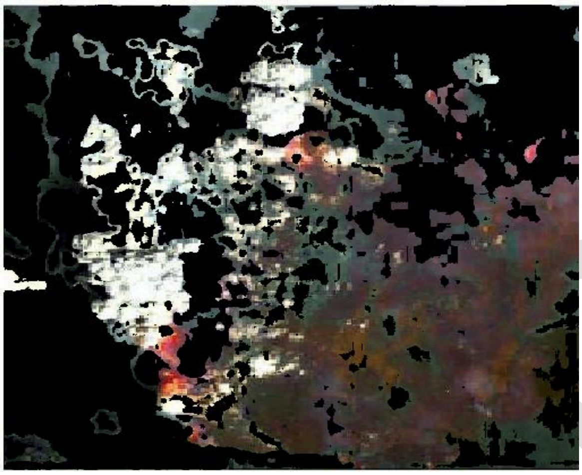


Figure2b.Object clustered as 2

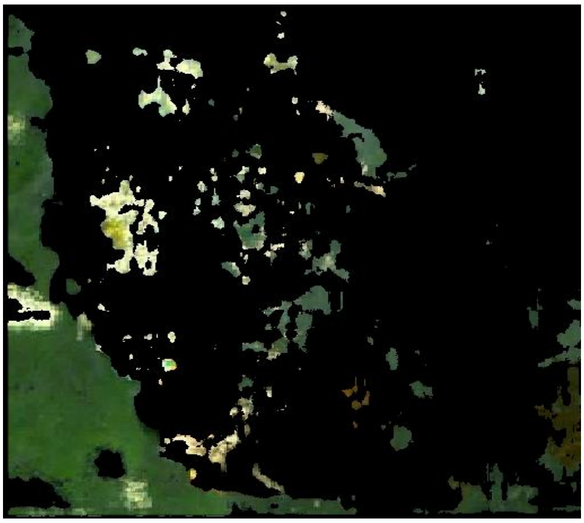


Figure2c.Object clustered as 3

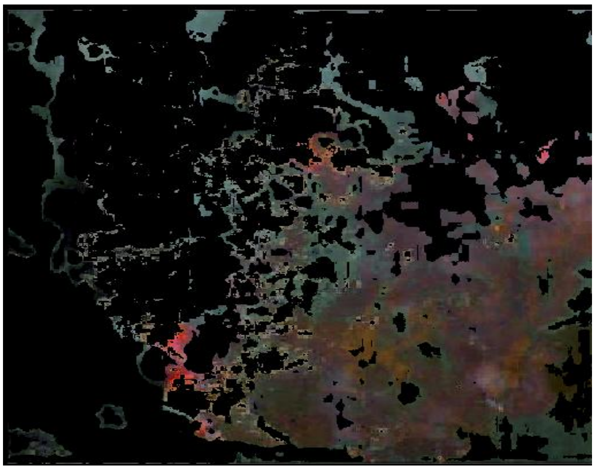


Figure2d.Object clustered as Fire nuclei

IV. EDGE DETECTION AND BOUNDARY DESCRIPTORS

Edge detection algorithm takes an intensity image I as its input, and returns a binary image BW of the same size as I, with 1's where the function finds edges in I and 0's elsewhere. Few algorithms detect the edges by thresholding the gradient.

For the Laplacian/Gaussian method, EDGE thresholds the slope of the zero crossings after filtering the image with a spatial domain filter. Canny method, thresholds the gradient using the derivative of a Gaussian filter. By default, the edge function automatically computes the threshold to use.

Boundary Descriptors trace region boundaries in a binary image. Algorithm connects the exterior boundary of objects, as well as boundaries of holes inside these objects. It also descends into the outermost objects (parents) and traces their children (objects completely enclosed by the parents). In a binary image of boundary detection nonzero pixels belong to an object and 0-pixels constitute the background.

After the fire region is obtained, the classical Laplacian operator detects its boundary, and then the eight-connected boundary chain code can be easily retrieved to represent the fire contour. The 4 point or the 8 point neighborhood specifies the connectivity to use when tracing parent and child boundaries. The directions of connectivity also play a vital role in image analysis and classification.

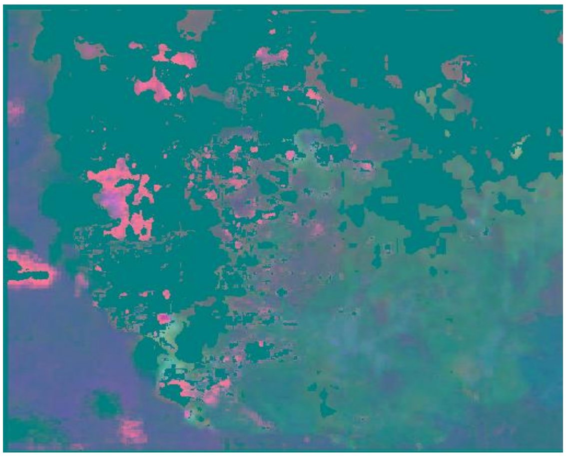


Figure 3a .Segmented Fire nuclei image

V. DETECTION OF FIRE PIXELS WITH THRESHOLD AND MEASURING THE DEGREE OF FIRE

Fire colored regions are calculated per frame and are then are combined to create a cumulative fire color matrix which is akin to the cumulative time derivative matrix. The pixels associated with strong intensity and saturation is considered more likely candidates to be fire colored. The final step of color detection is to eliminate all pixels that are less than the average so as to suppress those pixels which are not as strongly fire colored..The highly likely fire areas as of this point are defined as fire mask boundaries.

Merged image is composed of several areas that are considered to have a high likelihood of being fire. However, to further eliminate false positives a method of growth and erosion is used. The image is then dilated to combine the areas with a high likelihood of being fire. Then the areas that remain one or two pixels before dilation are then eliminated as they are often non-fire outliers and ultimately eroded back to its original size before dilation.

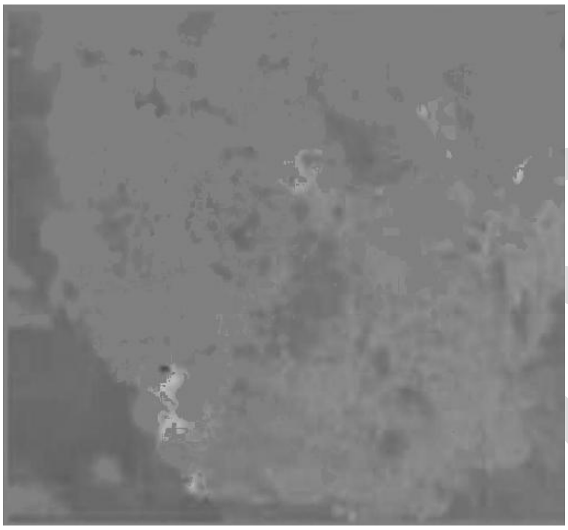


Figure 3a . Fire nuclei image-Cb component

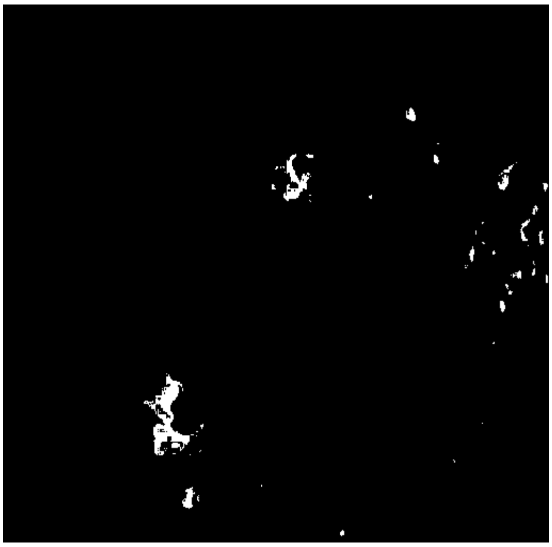


Figure 3b .Fire pixels Detected image

EXPERIMENTAL RESULTS

The proposed method has been effective for a large variety of conditions. Two experiments were described in detail. The first case corresponds to a forest fire. Figure 1,2,3 shows the infrared (a) and visual (b) images corresponding to this case. The second case is a fire originated in a open space. The original image and the fire processed images of this scene are illustrated in Figure (5). First, the target region is segmented using the k means clustering. The oscillation function is applied and the results of the oscillations analysis in the case illustrated in corresponds to one with high possibility to be generated by a forest fire (74.3%).In the second case (Fig. 5), the target does not oscillate in the sequence of IR images, and it is quantified with a low fire possibility value (5.2%).Lighting conditions also have little effect upon the system; it has been able to detect fire in a large variety of fire images.

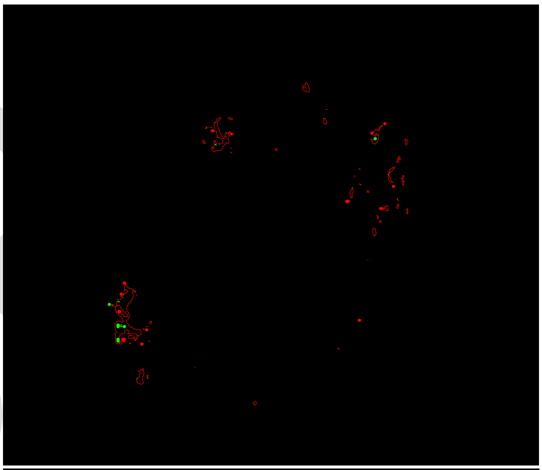
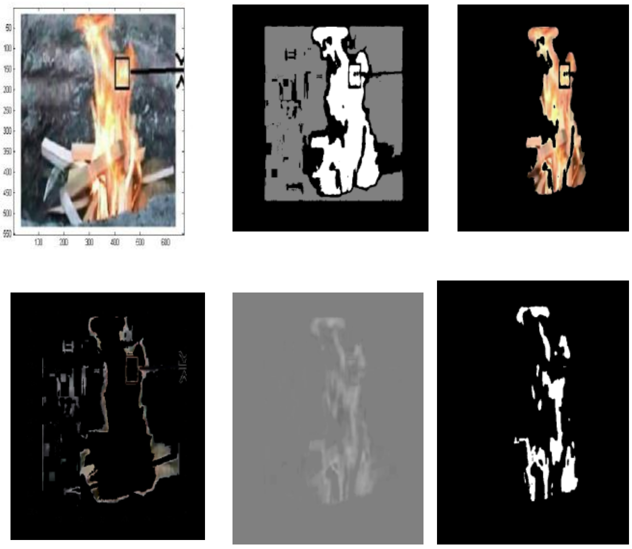


Figure 3c .Boundary traced fire region

As it can be observed, *YCbCr* color space outperforms other color spaces both in correct detection rate and false alarm rate. This is due to the ability of *YCbCr* colour space to separate luminance from chrominance. For other models the rules fall short in describing a single quantitative measure which can indicate how likely a given pixel is a fire pixel. As a result, it becomes difficult to discriminate between fire regions and fire-like regions. The implicit fuzziness or uncertainties in the rules is encoded in a fuzzy representation. This provides a way to express the output decision in linguistic terms. As a result, the most needed discrimination between fire and fire-like regions is enhanced

Certain types of fires, such as candles, blowtorches, and lighters, are completely controlled, and always burn exactly the same way without flickering Unfortunately, the algorithm. In this proposed algorithm, the dynamic infrared threshold value is kept as 144 using images with 256 intensity levels. The region is segmented and tracked in several consecutive infrared images.



Figure(5):Second Image

CONCLUSIONS

This paper has presented a robust system for detecting fire in color image and video sequences. This algorithm employs information gained through both color and spatial domain variation to detect fire. Images clipped in a variety of conditions are exposed to this algorithm in which fire can be detected, and a way to determine when it cannot. Through these tests, this method has shown promise for detecting fire in real world situations, and in movies. It is also useful in forensic and fire capture for computer graphics. The quantitative analysis is tabulated below.

Threshold	**Detection rate**	**False Alarm rate**
128	77.5	68.25
135	84.2	52.5
144	94.3	23.21
154	83.25	64,32
175	72.76	47.43

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