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A Comparative Analysis on Different Image Processing Techniques for Forest Fire Detection

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Abstract - Image processing techniques are widely used now a day to detect fire from still images and videos. The basic technique to label a pixel as fire pixel is by analyzing its color information. One of the main setbacks of color models is that they can wrongly detect fire-colored ordinary objects as fire regions. It is very important to distinguish between fire and fire-colored ordinary objects, because generating a lot of false alarms reduces the efficiency of the fire detection system to a great extent. Various characteristics of the fire flame other than its color clues are utilized to make the fire pixel classification more precise. The fire flame has a distinctive texture characteristic than other ordinary objects, so combining the texture analysis along with the color information reduces the false alarms considerably. Another unique characteristic of the fire flame is its flickering motion. Proper classification of smoke pixels also helps to detect the fire at its initial stage. This paper is a study of different techniques that can drastically reduce the false positive rate.

Keywords – *Rule Based Color Model, Classification of Fire Pixels, Texture Analysis, Flicker Motion Analysis, Fuzzy Inference System.*

1. Introduction

Forest fires are natural phenomena that occur regularly on earth, a large quantity of forest area and wildlife are destroyed annually due to the forest fires. It causes drastic loss of lives and valuable natural resources and individual properties. The forest fire has significant effects on the global climate. The problem has become more severe than previous years. The human encroachment over forest areas is a major cause of forest fire. It is very essential to detect and avoid the fire at its initial state itself. Traditional fire protection methods use mechanical devices or humans to monitor the surroundings. The most frequently used fire smoke detection techniques are usually based on air transparency testing, particle sampling, and temperature sampling. An alarm is not raised unless the particles reach the sensors and activate them. The huge leap in image processing technology and the reduced cost of digital cameras make fire detection based on image processing more feasible than any other traditional methods like fire watch towers, sensors, satellites etc. In the case of fire watch towers, humans are made to observe the location throughout. The main limitation of this approach is the lack of accuracy due to operator fatigue, time of day, geographic location etc. The sensors are devices capable of sensing their environment and computing data. The sensors sense physical parameters like pressure, temperature and humidity, and chemical parameters such as carbon monoxide, carbon dioxide, and nitrogen dioxide. In a wireless sensor-based fire detection system, coverage of large areas in forest is impractical because of the requirement of regular distribution of sensors in close proximity and the battery charge is also a big challenge. Satellites based system can monitor a wide area, but the resolution of satellite images is low. A fire is detected when it has grown quite a lot, so real time detection cannot be provided. Moreover, these systems are very expensive. Weather condition (e.g. clouds) will seriously reduce the accuracy of satellite-based forest fire detection.

Compared to the traditional methods, the fire detection techniques that are based on image processing can monitor the forest for 24 hour real-time. It is capable of generating alarms at the very early stages of the fire. Moreover the image processing techniques costs less since the algorithms used are cheap in computation. In the case of forest fire detection, it is possible to detect the fire by distinguishing between the color of the forest (green) and the fire (red), or by using the difference between sequential images to detect the rapid formation of smoke. The issue with smoke analysis is that it cannot provide additional details such as fire location, size of fire, and growing rate of fire. Hence it is more reliable to look for fire pixels in an image than smoke particles. Figure 1 shows a forest watch camera for detecting fire. The main two problems faced by image processing based fire detection systems are,

- Complicated lighting conditions resulting from day and night, artificial lights, light reflection, and shadows.
- Complex scenes with objects and/or people moving in velocities and sizes similar to that of a fire.

Most of the existing methods use two steps to detect fire. The first step creates a mathematical/rule-based model, defining a sub-space on the color space that represents all the fire-colored pixels in the image. But all the fire colored pixels might not be fire. Bright sunlight and fire like colored ordinary objects are also chosen here. The problem with this step is the false positives raised by high illumination value or reddish-yellowish objects. The second step tries to eliminate this false positive by using temporal data. In this paper different methods for classifying fire pixels are evaluated. At first a generic rule based color model is discussed. As shown in Figure 2 the use of color information alone creates a considerable amount of false alarms. Hence various other methods that use additional information to reduce the false positive rate are further discussed.

Fig. 1 Forest watch camera for detecting fire

Fig. 2 Three sample frames resulting in the false positives. The red rectangles indicate misclassified fire regions.

2. Literature Survey

Rule based color models are widely used for marking candidate pixels for fire pixel classification. Most commonly used color spaces are RGB and YCbCr. Out of which the YCbCr color space exhibits better performance due to its ability to distinguish luminance from chrominance. A typical fire is yellowish-red in color. The rule defined for RGB color space is, $R \geq G \geq B$. Figure 3 represents this. This can be translated into YCbCr color space as follows,

$$Y(x,y) > Cb(x,y) \tag{1}$$

$$Cr(x,y) > Cb(x,y) \tag{2}$$

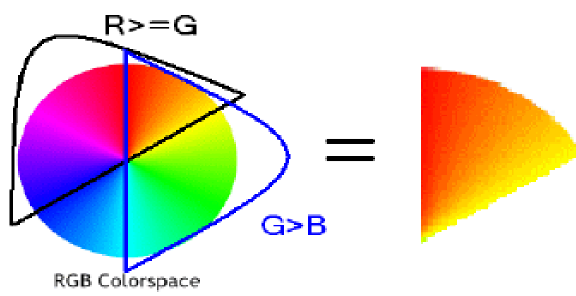


Fig. 3 Fire colors in the range of red to yellow.

The RGB color space can be translated into YCbCr color space using the below equation [1].

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.2568 & 0.5041 & 0.0979 \\ -0.1482 & -0.2910 & 0.4392 \\ 0.4392 & -0.3678 & -0.0714 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} \tag{3}$$

Celik et al. [1] proposes a rule-based generic color model for flame pixel classification. The proposed algorithm uses YCbCr color space to separate the luminance from the chrominance. This method defines a set of five mathematical rules to compare the intensity of the channels in the YCbCr color space. A threshold τ is defined by analyzing a set of 1000 images. The distribution of flame pixels in Cb-Cr plane is modeled using three polynomials *fu*(Cr), *fl*(Cr), and *fd*(Cr). The proposed method has a fire detection rate of up to 99%. The proposed method has a setback of 31.5% false positive rate, and it does not specify how to detect smoke particles.

Celik et al. [2] proposes a color model which uses Fuzzy Inference System (FIS) for identifying fire and smoke. The proposed model uses separate color model for fire and smoke. The model states that higher the difference between Y and Cb components as well as Cr and Cb components of a pixel, higher the probability that it is a fire pixel. This is summarized as,

$$Y(x,y) \geq Cr(x,y) \geq Cb(x,y) \quad (4)$$

The luminance and chrominance channels are normalized and Celik constructs 16 rules to account all combinations of the input variables. The FIS is used with these sixteen rules to produce an output which is a quantitative measure that defines the likelihood that a given pixel is a fire pixel. The paper states that the smoke pixels should have similar intensities in their RGB color channels and the saturation of the smoke color should be as low as possible. This model shows better performance by eliminating fire-like colors which are not actually fire. It has a detection rate of 99.00% and false alarm rate of 4.50% which is a significant achievement. The authors do not carry out the smoke pixel detection tests.

Daniel Y. T. Chino et al. [3] proposes a novel fire detection method: BoWFire (Best of Both Worlds Fire detection), for still images that uses classification based on color features combined with texture classification on superpixel regions. The use of texture is promising; because fire traces present particular textures that permit to distinguish between actual fire and fire-like regions. The BoWFire method consists of three basic steps: Color Classification, Texture Classification, and Region Merge. The two first steps occur in parallel to produce images in which fire-classified pixels are marked. Then, the output from both classifications is merged into a single output image by the Region Merge step. This model uses Naive Bayes and KNN machine learning classification algorithm for performing color classification, and SLIC (Simple Linear Iterative Clustering) method with a modification (instead of Lab color space the YCbCr color space is used) to create superpixels. The texture information is added using the uniform patterns LBP (Local Binary Patterns). A given pixel is added to the final output only if it was detected in both color and texture classifications, otherwise it is discarded. The BoWFire method uses only three parameters. The reduced parameter eases the process of fine tuning the automated detection, and the combination of color and texture information reduces the false positive rate. The proposed algorithm has less than 5% false positive rate. This paper does not provide information for classifying smoke particles.

A remarkable characteristic of the fire is its flickering property. The spatial variations inside a flame will be more than that of a flame colored region. Figure 4 shows the spatial variations of a flame colored region and an actual flame. Analyzing the flickering motion helps to reduce the false alarms to a great extent. B. Ugur Toreyin et al proposed two methods for analyzing the flicker motion. One uses a Hidden Markov Model and the other uses the wavelet transformation to extract spatial color variations, thereby improving the fire detection rate and reducing the false positive rate.

B. Ugur Toreyin et al. [4] proposes a model which detects flame flicker process in addition to color clues. Hidden Markov Model (HMM) is used to represent flame and flame colored ordinary moving objects and distinguish flame flicker process from motion of flame colored moving objects. This paper states that if the contours of an object exhibit rapid time-varying behavior, then this is a significant sign that the object is a flame. The pixel especially at the edge of a flame appears and disappears several times in one second in a random manner. This characteristic is modeled as a Markov model. This paper describes a flame chrominance model and a three-state Markov model. States of the Markov models are determined based on the color information. The proposed method drastically reduces the number of false alarms and can be used for detecting fire in movies and video databases as well as real-time detection of fire. It is well suited for both indoor and outdoor monitoring.

B. Ugur Toreyin et al. [5] proposes a method for detecting fire from video data by analyzing color clues, ordinary motion, and fire flicker. This paper tries to reduce the false alarms by detecting periodic high frequency behavior in flame colored moving pixels. This is carried out in wavelet domain. The paper explains that turbulent flames flicker with a characteristic flicker frequency of around 10 Hz independent of the burning material and the burner. The proposed method analysis spatial variations inside flame and flame colored regions. The proposed method first determines moving pixels or regions, then the color of the moving pixels are analyzed and if they match to predefined fire colors then high frequency activity is determined using temporal and spatial domains. The RGB color model is used to interpret color information. A two-stage filter bank is used in temporal wavelet analysis which produces two wavelet sub signals whose nonzero values represent high frequency activity. The spatial wavelet analysis is carried out to capture color variations in pixel values. The paper then describes a voting based decision fusion strategy for combining the decisions of the four stages of the algorithm. This proposed method achieves a fire detection rate of 99.9% and has a false positive rate of 0.1%. The proposed method drastically reduces the number of false alarms and can be used for detecting fire in movies and video databases as well as real-time detection of fire.

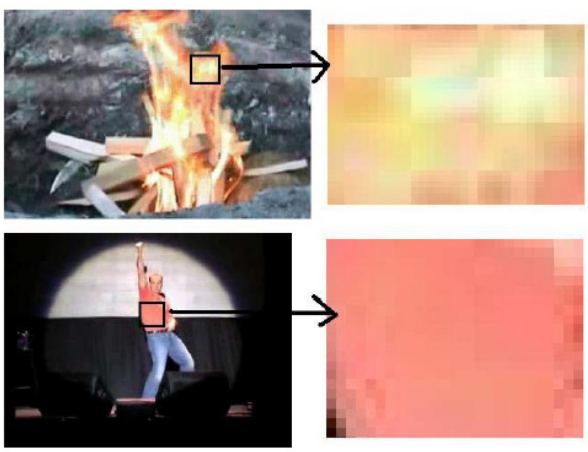


Fig. 4 Spatial variations in fire and a fire colored object.

Celik et al. [6] proposes a method in which background subtraction assisted by foreground objects is used to detect fire. It combines statistical color information with temporal changes in consecutive video frames. A possible fire pixel is defined using color histograms of *r-g*, *r-b* and *g-b*. Simple adaptive background information of the scene is modeled by using three Gaussian distributions, where each of them is used to model the pixel values in each color channel. Each of these distributions is considered to be independent of other distributions. The detected foreground objects are combined with color information and the output is analyzed in consecutive frames to detect fire. The need for a storage area for each pixel values causes additional memory requirement and additional cost. This limitation can be overcome by using maximum absolute difference between consecutive frames to find the standard deviation of each of the pixel values. The proposed system can be applied to real-time applications.

Wen-Bing Horng et al. [7] proposes a method which could detect fire flames and provide burning degree of fire flames. In this paper the authors analyzed 70 flame images based on the HSI color model to create flame features. These features are used to roughly separate fire like regions from the image. The reflection of fire can give fire like colors to other background objects in the image, which are also segmented as fire like regions. These spurious regions are removed by using image difference and color masking techniques. There are not many researches done on determining the burning degree of fire flames. This paper estimates the burning degree of fire flames by analyzing the variation of flame contours. This proposed method is capable of detecting fire within one second of the initial combustion. It achieved a fire detection rate of 96.97% and false positive rate of 2.65%.

Punam Patel et al. [8] propose a method which detects fire in video by combining the color clues, motion detection, and area of dispersion. The paper defines four rules in the YCbCr and RGB color spaces, which it uses to detect fire colored regions in the video frames. Then the frame differencing method is used to identify moving objects, and then analyzes the shape of fire pixels by checking the dispersion of fire pixels. The advantages of this method are moderate computational load and the background model is highly adaptive.

3. Challenges Faced

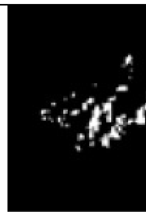
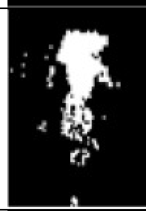
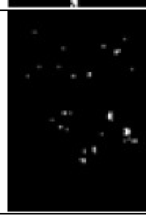
Most of the existing image processing techniques for forest fire detection propose algorithms to classify only fire pixels, only a few approaches takes smoke detection into account. Since smoke is generated during the early phase of the fire, it can be used to generate alarms well before the fire strikes hard. However smoke analysis alone can cause false alarms, because the clouds can also be mistakenly detected as smoke. This drawback can be eliminated by combining smoke detection along with fire detection. Another main issue related to color model based fire pixel classification is the false alarm generated by wrongly classifying bright sun light or bright yellowish-red color as fire pixels. For a fire pixel classification technique to work efficiently, it should reduce the false positive rate as much as possible.

4. Comparison Analysis

Table 1: Comparison of false positive rate

Method	False Positive Rate
Celik et al. [1]	31.5%
Celik et al. [2]	4.50%
Daniel Y. T. Chino et al. [3]	Less than 5%
B. Ugur Toreyin et al. [5]	0.1%
Wen-Bing Horng et al. [7]	2.65%

Table 2: Comparison of outputs of different techniques

Input images	Outputs obtained at different stages		
	Color (alone)	Motion (alone)	Color + Motion + Flame flicker
			
			
			

5. Conclusion

All the methods discussed here have good detection rate. One of the important characteristic that determines the efficiency of a fire detection system is its false positive rate. The table 1 compares the false positive rate of the different methods. Among the various methods discussed here B. Ugur Toreyin et al. [5] has the least false positive rate. Table 2 compares the output produced by three different approaches. It can be clearly seen that using color information alone wrongly labels fire colored ordinary objects as fire pixels, thereby generating a lot of false alarms. Combining color clues, motion analysis and fire flickering techniques eliminated the false positive rate to a great extent. Hence for obtaining better results, it is essential to combine multiple techniques rather than sticking onto color information alone.

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