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# Fire Detection Using Video Processing based On Computer Vision

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**Abstract**: *A unique real-time fire detection system based on HMMs is provided in this work. First, we describe a fire characteristics analysis that supports the usage of HMMs to detect fire; second, we suggest a method for discovering candidate fire pixels that includes moving pixel detection, fire-color inspection, and pixel clustering. This paper's main contribution is the creation and use of a hidden Markov fire model that combines state transitions. To eliminate data redundancy between fire and non-fire with fire motion information the final choice is yours. The training provides parameters for the application, which is based on this model, which includes training and application. This is an HMM application. The results of the experiments reveal that the approach has a high detection rate and a low false alarm rate and a low false alarm rate. Furthermore, real-time detection has been effectively realized via the learned parameters of the HMM, since the most time-consuming components such as HMM training are performed off-line.*

**Keywords**: Hidden Markov Model (HMM), Hue Saturation Value (HSV), etc.

## I. INTRODUCTION

One of the most important components of video surveillance and monitoring is a fire detection system that allows for precise and timely fire detection. Systems, because fire might result in death and major property damage. Property damage has occurred. In general, traditional approaches are used. Detectors with a narrow range, such as chemical or gas detectors, should be used. Traditional sensors, on the other hand, are suboptimal. First and foremost, a fire detection system's accuracy. Its precision and dependability are extremely important. Sensors, sensing space size, and sensor distribution sensing devices If a more precise fire detection system is required, If required, the sensors must be distributed widely.

In the area of detection Second, false detection is very easy to make. Occur as a result of various sources of smoke or fire, such as even a smoldering cigarette. Third, there are temporal delays that are lethal. Sensors to detect fire or smoke that could lead to the since the alarm is not sounded until there is a fire. The sensors are activated when gas or chemical particles reach them. Finally, the cost of sensors can have an impact on the price. The price of the system video processing techniques on the other hand, provide numerous benefits. Surveillance cameras and Due to the rapid development of monitoring systems, they are now being used in many structures and human situations.

Advancements in digital cameras and video processing process that are cheaper. As a result, there's no need to think about it. Additional costs, and all that is required is the inclusion of software to process the surveillance and monitoring output in real-time system Furthermore, a video-based technique has the potential to early detection of flames leads to better results. Many researchers have researched video processing algorithms for fire detection in recent decades [1-7]. Only color hints from the fire were employed in the beginning [2]. [3] produced fire pixel classification in color video sequences, in which fire was recognized using three fire-color conditions established in an RGB color scheme and a flame dynamics analysis. Recently, the mobility and geometry of fire areas, in combination with fire-color circumstances, have been used.

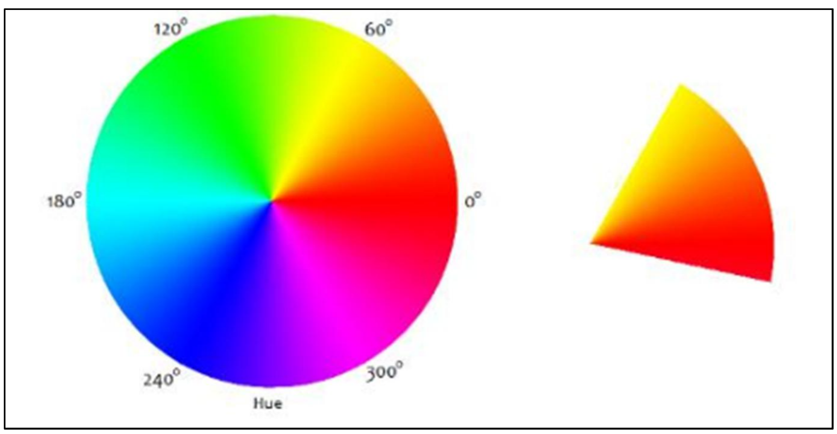
For example, to examine high-frequency information about fire, a wavelet analysis was applied [4]. Although the method produced good results for a variety of test data, it required far too many heuristic criteria, making it unsuitable in real-world applications.

## II. FIRE CHARACTERISTICS

Prior to dealing with formal fire detection, it's vital to examine the features of fire in order to justify our technique's application in fire detection We collect data created by the red component values of fire and non-fire pixels in relation to frames in order to establish two databases: one for fire and one for non-fire pixels. As well as a non-fire database the fire database is made possible by the red color component of pixels that are being monitored. In most frames, the pixels are previously recognized as fire pixels, while the background observation is used to create the non-fire database.

Pixels or pixels with a red color component that are similar non-fire pixels are known to have movements with fire. In order to explain the differences between fire pixels and other types of pixels typical red pixels, frequency-domain characteristics Figure 1 depicts fire and non-fire data. In Fig. 1, the non-fire data is a pixel with an ordinary red color. The red component of the pixel in RGB space represents the vertical axis of the graphs in the original database. Frequency graphs are created by applying a Fast Fourier Transform (FFT) on the original data; because the graph is symmetrical, only non-negative numbers are shown. The magnitude and frequency are represented by the vertical and horizontal axes of frequency-domain graphs, respectively.

The variance of the red color component of pixels is the seen random model in our situation, and the hidden stochastic process is the change of states between fire and non-fire. HMMs learn patterns that change over time to discriminate between fire and non-fire. We calculate the mean value and standard deviation of fire and non-fire scenarios, respectively, for further study. One mean value and one standard deviation can be generated from forty consecutive data elements. In a fire condition, the mean and standard deviation of 1000 sequences are 206.56 and 34.58, respectively, while in a non-fire situation, the mean and standard deviation are 184.06 and 21.45. This suggests that there is a distinction between fire and non-fire conditions. As a result, HMMs are appropriate for use in fire detection.




## III. FIRE PIXELS DETECTION

Because the system's incoming data is streamed video, it's required to convert it into a series of fixed-rate frames in order to make further processing steps easier. Detecting pixels in motion regions, evaluating fire-color pixels, and clustering pixels based on a sequence of frames yield candidate pixels for fire judgement.

### 3.1. Detection of Moving Pixels:

In the first phase, we use one of the most important aspects of fire, which is that it continues to move as time passes, to detect pixels in motion regions. This feature is used to filter out the majority of the undesirable data. Moving pixels are often obtained by subtracting the intensity values of two nearby frames, ht+1 and ht, as illustrated in equation (1). In our study, we use the function (,) t h XY to express the mean value of three nearby frames for each pixel, as illustrated in (2). This small change can lead to great progress. In comparison to the two-frame method, no useful information is omitted, but superfluous and unnecessary data is not passed on to the next stage.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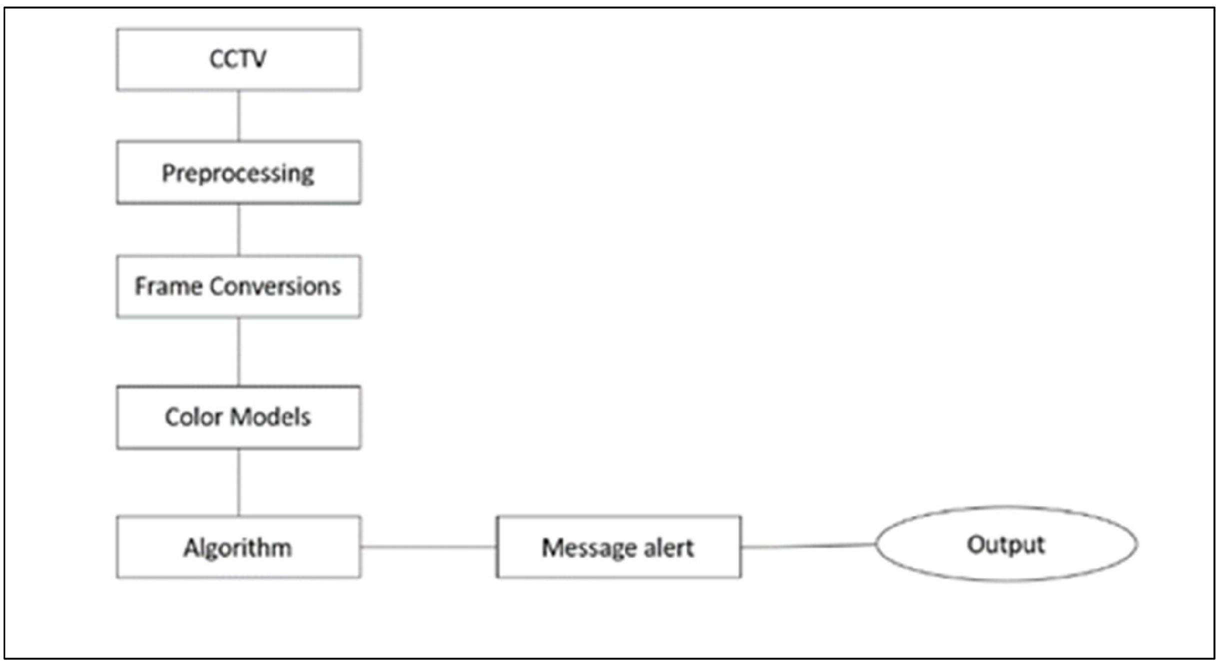
### 3.2. Detection of Fire-color Pixels:

Another essential aspect of fire is color. Only moving pixels are tested to see if they satisfy the fire-color requirements in this step, which deals with pixels generated during motion detection. Many scholars have investigated the characteristics of fire color and have come to the conclusion that fire's color range is red-to-yellow. This is the first of three fire-color conditions [3,7], represented by R G, G B >. Furthermore, because the red channel is the most important component in an RGB image of fire flames, and the red channel value of fire is higher than that of common objects, we must define what constitutes a strong R value in the acquired fire image. As a result, the value of R that exceeds a threshold RT is specified as the second criteria of fire color. The impacts of backdrop illumination should be evaluated as the final feature to consider. The saturation value of the extracted fire flame must surpass a certain threshold in order to remove any fire-like color that could lead to false fire detection [3].

### 3.3. Clustering of Pixels:

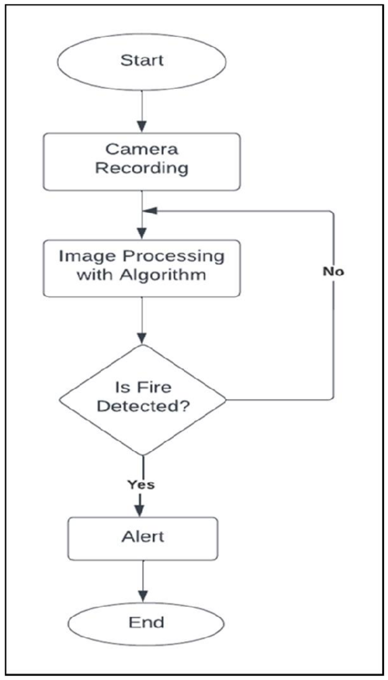
Pixels that meet the color requirements are used in this stage. Section 2 demonstrates that fire is a dynamic entity.
Fire's process and illumination are constantly changing.
Only considers whether or not there is fire in a given situation. A single frame leads to unreliable judgments. Because of the dynamic nature of fire, if one pixel is labelled as a fire-color pixel at frame t, it may be labelled as a non-fire-color pixel in the following frames before being labelled as a fire pixel again. Because it's possible that this pixel is a fire pixel, it can't be ignored.

## IV. SYSTEM ARCHIETECTURE

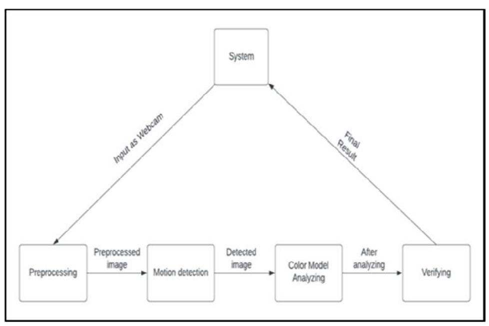



## V. FLOWCHART

Above figure describes the full proposed system, that is the first step of the proposed system is to the re-forced camera footage that is given as input and that video footage is spitted into many frames and the frames are compared one by one with the motion, color and edge detection using HSV algorithm and Hidden Markov Model. After that it will process that and it will tell whether fire is detected or not. If the fire is detected it will alert.




## VI. DATA FLOW DIAGRAM




## VII. RESULT

The suggested fire detection technique was tested on an Intel (R) Core (TM)2 2.13GHz desktop computer with a 360240-picture size. The software has a low computational cost because most of the time-consuming phases, such as HMM training, are done off-line, allowing for real-time operation.

We put our algorithm through its paces with a variety of movies, some of which are shown in Fig. 9, along with a comparison to [6] (the software for [6] was kindly provided by the authors of [6]). [6] also utilized an HMM model to detect fire, but instead of using the EM approach, they just counted the state transitions.

False detection happens when moving fire-colored objects are involved. Meanwhile, there is a little fire in the image in the third row of Figure 9, but the algorithm [6] fails to detect it. Our approach, on the other hand, was able to identify fire in a variety of settings, even when there were several distractions, such as moving fire-color items, running cars with headlights on, burning cigarettes, and so on. We made a total of 30 test video clips, with half of them containing fire. The 15 fire-video clips were effectively recognized using the provided method. All of the scenarios in the test were correctly detected, with a zero false alarm rate. Some of the tests are listed.

## VIII. CONCLUSION

A method for detecting fire was presented in this paper. HMMs are used to make decisions about fire pixels in a video sequence based on moving pixels detection, fire-color detection, and pixel clustering. Experiments encompassing several circumstances with a variety of disruptions were used to assess the reliability, and the findings were positive. HMMs may considerably minimize the percentage of false alarms, and fire can be detected quickly and accurately, according to the experimental results will be extremely valuable in applications relating to social security, business, the military, and other similar fields.

Although the proposed method can accurately detect fire, the number of fire pixels detected is less than the original photos. The approach of [6] has the same issue, in that it only recognizes a tiny area as fire (as shown in the first image of Fig. 9 (c)). We will continue our research in this area in the future, and we will use the proposed approach in conjunction with hardware devices to monitor risky circumstances such as tunnel fire detection.

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