FIRE DETECTION USING IMAGE PROCESSING

Thanigaivel M[1], Maurya Vijayaramachandran[2], Shabarish haren. V[3]

[1]*(Department of ECE, Sri Venkateswara College of Engineering, Sriperumbudur, India)*
[2]*(Department of ECE, Sri Venkateswara College of Engineering, Sriperumbudur, India)*
[3]*(Department of ECE, Sri Venkateswara College of Engineering, Sriperumbudur, India)*

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Abstract - *Forest fires represent a real threat to human lives, ecological systems, and infrastructure. Many commercial fire detection sensor systems exist, but all of them are difficult to apply at large open spaces like forests because of their response delay, necessary maintenance needed, high cost, and other problems. In this paper, we will discuss the generalized and more accurate form of Convolutional Neural Network [YOLO V3] to detect fire and impending hazards associated with it.*

Key Words: Fire detection, CNN, YOLO, FireNET.

1. INTRODUCTION

Fire accidents are the most commonly occurring disasters nowadays. Fire, especially in buildings, can spread quickly and cause great loss of life and property. Due to the rapid increase in the number of fire accidents, the fire alarm systems form an integral part of the necessary accessories in any sort of construction. Therefore, early fire detection and warning is imperative. In order to mitigate the number of fire accidents, a large number of methods have been proposed for early fire detection to reduce the damage caused by such accidents. Apart from the problem of early fire detection, present fire alarm systems also prove to be inefficient in terms of the false triggering of the alarm systems. In this paper we would explore how the detection of fire is made using the image processing technique.

1.1 ANALYSIS:

Fires start when a flammable material combines with sufficient quantity of oxygen gas. Flames consist primarily of carbon dioxide, water vapour, oxygen, and nitrogen. Fire is a chemical reaction known as combustion, involving rapid oxidation or burning of a fuel. There are three elements to consider are:

FUEL: Fuel can be any combustible material. Solid, liquid or gas.

OXYGEN: Fire only needs an atmosphere with at least 16 percent oxygen to burn as we breathe is about 21 percent oxygen.

HEAT: Heat is the energy necessary to increase the temperature of the fuel to a point where sufficient vapours are given off for ignition to occur.

Fire extinguisher is mandatory in every building according to the norms of government. Generally, people don't have the knowledge how to use the fire extinguisher and even at times of critical situation people will become panic, and doesn't react to the situation. Trained professionals are required here. So, we have come up with a system which would detect the fire automatically and directly turn on the extinguisher on its own. We would be placing camera at various location in the building. Using camera, we would be detecting the fire using image processing.

For higher accuracy we are using smoke and temperature sensors. For doing this first we need to train the system to identify fire. Using advance colour recognition algorithm, we would be training the system to identify fire. Once the system has learnt to identify fire it can easily detect the fire on its own and turn on the extinguisher on its own. Convolutional neuron work is used for early fire detection varying indoor and outdoor environments. Convolutional neural network for detection of fire using the videos and images taken from the cameras installed for the surveillance. The convolutional neural network used for image classification and recognition because of its high accuracy. It is an efficient recognition algorithm which is widely used in pattern recognition and image processing.

2. LITERATURE SURVEY:

In Paulo Vinicius Koerich Borges, and Ebroul Izquierdo, proposed a new identification metric based on colour for fire detection in videos. Also identified important visual features of fire, like boundary roughness and skewness of the fire pixel distribution. The skewness is a very useful descriptor as the frequent occurrence of saturation in the red channel of fire regions is identified. For newscast videos, model the probability of occurrence of fire as a function of the position, yielding an efficient performance.

While comparing with other methods which extract complicated features, the features discussed here allow very fast processing, making the system applicable not only for real time fire detection, but also for video retrieval in news contents, which require faster than real-time analysis. In Osman Gunay, Behçet Ugur Toreyin, Kivanc Kose, and A. Enis Cetin, an EADF is proposed for image analysis. In this work assumed that several sub algorithms are combined to get the main algorithm for a specific application. Each of the sub algorithm yields its own decision to representing its confidence level. Decision values are combined with weights, updated online by using nonorthogonal e-projections onto convex sets describing sub algorithms. This framework is applied to a real time problem of wildfire detection. The proposed adaptive decision fusion method uses the feedback from guards of forest which is a limitation for the system.

In Martin Mueller, Peter Karasev, Ivan Kolesov, and Allen Tannenbaum proposed two novel optical flow estimators, optimal mass transport (OMT) and Non-Smooth Data (NSD). The dynamics of fire have motivated the use of motion estimators to differentiate fire from other non-fire object. The obtained moving region provides useful space on which to define motion features. These features reliably detect fire and reject non-fire motion, on a large dataset of videos. There is a chance for false detections in the presence of significant noise, partial occlusions, and rapid angle change. In Kosmas Dimitropoulos, Panagiotis B armpoutis and Nikos Grammalidis, proposes a fire-flame detection to be used by an early fire detection and warning system. The first step is to identify candidate fire regions using background subtraction and colour analysis. Then the fire features are modelled by using various spatio-temporal features such as colour, flickering, spatial and spatio-temporal energy. Dynamic texture analysis is used in each candidate region. The robustness of algorithm can be increased by estimation spatio-temporal consistency energy of each candidate fire region by comparing current and previous frames. The last step is to classify candidate region using SVM classifier In Pasquale Foggia, Alessia Saggese, and Mario Vento, proposes a method that is able to detect fires by analysing videos. It introduce complementary information, based on colour, shape variation, and motion analysis, and combined using a multiexpert system known as MES. A descriptor based on a bag-of-words approach has been proposed to represent motion of objects. The method identifies moving objects based on background subtraction which is an effective method as compared to others. Then based on colour, shape and movement the multiexpert system works for identifying fire region.

3. Idea proposed:

Image processing is a method used to perform some operations on an image through an algorithm in order to extract some useful information from it. Image processing is a type of signal processing in which the image is taken as input and the information about the image and features associated with the image is considered as the output. It is among one of the rapidly growing technologies. It establish core research area in engineering. The two types of method employed in image processing are analog image processing and digital image processing. Digital image processing has more advantage than the analog image processing as it allows wide range of algorithm to be given as input data and avoids problem like noise and distortion during processing. A fire is set manually to train a system that recognize fire like colour pixels. The training set like fire images and fire's flame are used to form a look for fire detection system. Colour detection is the main concept involved. Camera is used for the process of image processing. When the system learn to identify fire, it can easily detect the fire on its own and turn on the prevention method on its own. The system would go through the volume intensity of fire break and send the alert to the receiver automatically.

4. Idea subtitle:

Firenet is a web environment with the security of a government site. It enables the NWCG partners to meet their business need for collaboration. It facilitate intergovernmental teamwork by providing a workspace to share, review, schedule, message, develop and store materials among federal, state, tribe local and territorial stakeholders in support of national wildlife fire management.

5. Fire Detection

5.1 . RGB to CIE L*a*b* Color Space Conversion

The first stage in our algorithm is the conversion from RGB to CIE L*a*b* color space. Most of the existing CCTV video cameras provide output in RGB color space, but there are also other color spaces used for data output representation. The conversion from any color space representation to CIE L*a*b* color space is straightforward [10]. Given RGB data, the conversion to CIE L*a*b* color space is formulated as follows

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.412453 & 0.357580 & 0.180423 \\ 0.212671 & 0.715160 & 0.072169 \\ 0.019334 & 0.119193 & 0.950227 \end{bmatrix} \times \begin{bmatrix} R \\ G \\ B \end{bmatrix},$$

$$L^* = \begin{cases} 116 \times (Y/Y_n)^{1/3} - 16, & \text{if } (Y/Y_n) > 0.008856, \\ 903.3 \times (Y/Y_n), & \text{otherwise}, \end{cases}$$

$$a^* = 500 \times \left(f(X/X_n) - f(Y/Y_n) \right),$$

$$b^* = 200 \times \left(f(Y/Y_n) - f(Z/Z_n) \right),$$

$$f(t) = \begin{cases} t^{1/3}, & \text{if } t > 0.008856, \\ 7.787 \times t + 16/116, & \text{otherwise}, \end{cases}$$

5.2. Color Modeling for Fire Detection

A fire in an image can be described by using its visual properties. These visual properties can be expressed using simple mathematical formulations. In Fig. 2, we show sample images which contain fire and their CIE L*a*b* color channels (L*, a*, b*). Figure 2 gives some clues about the way CIE L*a*b* color channel values characterize fire pixels. Using such visual properties, we develop rules to detect fire using CIE L*a*b* color space. The range of fire color can be defined as an interval of color values between red and yellow. Since the color of fire is generally close to red and has high illumination, we can use this property to define measures to detect the existence of fire in an image. For a given image in CIE L*a*b* color space, the following statistical measures for each color channel are defined as

$$L_m^* = \frac{1}{N}\sum_x\sum_y L^*(x,y),$$

$$a_m^* = \frac{1}{N}\sum_x\sum_y a^*(x,y),$$

$$b_m^* = \frac{1}{N}\sum_x\sum_y b^*(x,y),$$

where * Lm , * ma , and * mb are a collection of average values of the L*, a*, and b* color channels, respectively; N is the total number of pixels in the image; and (x, y) is spatial pixel location in an imaging grid.

5.3. Moving Pixel Detection

In moving pixel detection, it is assumed that the video camera is stable, that is, the camera is still, and there is no movement in spatial location of the video camera. There are three main parts in moving pixel detection: frame/background subtraction, background registration, and moving pixel detection. The first step is to compute the binary frame difference map by thresholding the difference between two consecutive input frames. At the same time, the binary background difference map is generated by comparing the current input frame with the background frame stored in the background buffer. The binary background difference map is used as primary information for moving pixel detection. In the second step, according to the frame difference map of past several frames, pixels which are not moving for a long time are considered as reliable background in the background registration. This step maintains an updated background buffer as well as a background registration map indicating whether the background information of a pixel is available or not. In the third step, the binary background difference map and the binary frame difference map are used together to create the binary moving pixel map. If the background registration map indicates that the background information of a pixel is available, the background difference map is used as the initial binary moving pixel map. Otherwise, the value in the binary frame difference map is copied to binary moving pixel map. The intensity channel L* is used in moving pixel detection. The frame difference between the current frame L*(x, y, t) at time t and the previous frame L*(x, y, t−1) at time t−1 is computed and thresholded to create a binary frame difference map, FD, at time t, that is

$$FD(x,y,t) = \begin{cases} 1, & \text{if } \left|L^*(x,y,t) - L^*(x,y,t-1)\right| \geq T_{\mathrm{FD}}, \\ 0, & \text{otherwise}, \end{cases}$$

where TFD is a threshold value. Similar to the FD, the background difference is applied between the current frame and the background image to generate a binary background difference map, BD, that is

$$BD(x,y,t) = \begin{cases} 1, & \text{if } \left|L^*(x,y,t) - BG(x,y,t-1)\right| \geq T_{\mathrm{BD}}, \\ 0, & \text{otherwise}, \end{cases}$$

where BG(x, y, t−1) is background image pixel value at spatial location (x, y) at time t−1, and TBD is a threshold value

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