ISSN: 0974-5823 Vol. 7 No. 4 April, 2022

International Journal of Mechanical Engineering

ADAPTIVE FIRE DETECTION USING CNN AND IMAGE PROCESSING

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Abstract

Background/Objectives: The fire caused great damage to industry and environmental pollution. Conventional sensors sometimes give false alarm while investigating, assessing, and monitoring.

Methods/Statistical analysis: This research is designed to develop a comprehensive process to ensure a safe and effective warning system. Establish safety procedures and study maps to understand the process and variation of electrical measurements.

Findings: The framework detected 98% of fire image and 95% accuracy in detecting the smoke images. In either case the error rate was reported between 0-0.5 percent.

Novelty/Applications: When monitoring the use of convulsive neural systems to provide continuous fire detection to minimize false alarms, similar strategies are incorporated into the perspective based on fire detection perspective.

Keywords: machine learning technique, Fire hazards, industries and environmental pollution, image processing

1. Introduction

Fire is one of the most unusual phenomena in the industry. Reducing fire and hazards is important in the environment [1]. Failure to anticipate a fire can lead to further damage and environmental pollution. Check fires and shutters on the power plant. According to a 2015 NFPA report, there were a total of 1345,500 fires in the United States. About 78% of home fires are caused by fire. A typical fire occurs every 33.5 minutes. One death occurs every 160 minutes [2]. Monitoring is not required to receive the alarm in a timely manner or if the alarm fails due to routine ratings used for monitoring and evaluation. So it is difficult for pregnant women and patients to escape.

First, the flames were detected using paint and flicker. He was too fast, too bad. Then, bubble-face feature extraction was applied. It works better than large pixels. But you can still read the best pictures. So it is difficult to do special training. Patch level detection can solve the problem in two ways. Emergencies involving hazardous materials, terrorism, nuclear power plants, floods, earthquakes, and wildfires. Regardless of the nature of the disaster, effective management requires certain characteristics. These activities include prevention, early warning, early detection, advance information to the public and relevant authorities, responsible collection, damage management, medical care, and assistance to affected citizens.

In the past, scientists have conducted experiments comparing images, shapes, colors, and properties of different flames. It does not separate fire from objects such as fire. Marbach et al UVV color scheme + sound features = fire and non-fire pixels. Doreen and others underwent physical and environmental testing. Along with YCbCr, Celik and Demirel, special chromium and incandescent lamps are far from perfect. Borges and Escurido use color, curve and pro classifications to combat fire. The waves, energy and graphics for lowering the alarm clock were provided by Rafi et al. M. M.L. et al. learn to move and move flames and objects. Fosia and others created many places to explore the real flames. Numerous studies have been completed using motion detection, flame color properties, and the SVM classifier for small flame detection.

The process of applying technology in fire stations is a multi-disciplinary course. The main problems with such devices are the rigorous design of the building features, their low efficiency, and the fire alarm. Upgrading the system works with computer vision and intelligence. Computer Vision based energy measurement algorithm provides direct fire measurement. It constantly captures video feed from the camera. Then, use the pre-determined process used on the map to identify the fire. Ambient temperature, smoke pixels and fire pixels are constantly monitored. The alarm will be turned off in the event of a dispute. From previous work, fire detection can be compared to countless. Direct current is converted by integrating existing imaging processes, CNN and existing processes. These procedures prove to be effective and safe for live fire detection, which helps to reduce the risk.

2. Overview of the Proposed System

The structure handling corrosive, toxic and explosive chemicals should properly be designed to withstand severe environmental condition. However, structural leakage can cause fire accidents. Industries uses multiple sensor based systems to detect the fire, cracks and leakages. The major advantage of the proposed system [Figure 1] is, it reuses the existing devices, sensors and infrastructure. To get the improved results, sensors are combined with adaptive fire detection (AFD) methodology. High resolution cameras and CCTVs are used in monitoring systems and are used to detect the presence of fire. Many methods of detecting fire fail when the lights and color change, but people do not.

Sensor, Camera units sends their data to an IoT Gateway. IoT Gateway collects the sensor data, video feeds and segregates as structure, semi-structured and un-structured data [4]. Metrics from sensor, historical data from the database will be semi or fully structured. But video, images, document processing will be un-structured. The footage was captured by a CCTV camera. Adaptive fire detection techniques are used to separate fire pixels from background images. The stored video is periodically monitored by a data analysis module based on live streaming and in-deep learning technology.

A dictionary of rules is generated for better fire detection. Every image is parsed with a list of probable combinations of outcomes. Multiple rule based filter model and adaptive model is used to derive improved results [4]. When system detects the disaster, it alerts the stakeholders. Optimized transmission method is used to send the image files.

The field of AI, Deep Learning, Natural Language Processing, and voice recognition are recent emerging trends [5]. It helps to recognize the objects and fire spots. Modern hardware and abundance of data enables to build powerful networks. DNN and CNN architectures are preferred for fire object detection and parsing complex data model. A simple CNN pipeline is shown in the [Figure 2]. CNN is capable for learning and understanding complex video and images with minimal training effort. This is inspired by Human Visual System. The movement of the fire through the air or other external factors shown in [Figure 3] makes it difficult to detect. In the event of an explosion, coverage and movement will change dramatically.

Convolution or transformation layer is the core building block. Multiple transformation layers extracts information from the input. Sub sampling is done by applying [Figure 4] the 2*2 max-pooling techniques. After the path curve and the maximum stacked layer, the fully integrated layer achieves the highest level of consideration. Creates fully integrated layer classifications by combining all the exact properties of the previous layers.

3. Methodology

3.1. Data Preparation

Fire and non-fire images are mixed in one package. The computer again learns to distinguish between fire and non-fire images. The main job is to separate objects such as fire and flames.

3.2. Preliminary Fire Detection Module

Video is acquired from the CCTV camera. Standard metadata of the video such as duration, height, width, resolution are detected. Frames are extracted from the video. Metadata of the frames such as number of Red pixels, Green Pixels, Blue Pixels are extracted. Boundary of the frame is detected. This frame is sent to multiple detection algorithms.

3.2.1 Module 1: Detection of fire using OPENCV and NUMPY

This module is simple and straight forward. OpenCV and NUMPY are used in this module [6]. It uses GaussianBlurring Algorithm and HSV transformation for detecting the fire from the background Image.Initial range of BGR, Gaussian parameter, and standard deviation is set. AGaussianBlurring Algorithm is applied on an image to detect background and foreground images and an HSV transformation is applied on the blurred image. This result behaves like an MASK. Perform a bitwise AND operation on the input video and HSV transformed Video and the MASK. This process is repeated for all the frames.

3.2.2 Module 2: Apply Standard Deviation and CNN

To get better accuracy, image is resized to different resolutions. Pre-trained model is applied on the resized image. Similarly, input frame is sliced to get the fire spot's contour. To get exact fire spot a bitwise AND operation is performed between Input Image and the fire spot's contour.

3.2.3 Module 3: Detecting edge of the fire.

Grayscale detection technique and RGB threshold technique are used for detecting the area and edge of the fire [7]. Grayscale detection is primarily used for smoke detection and HSV technique is used for detecting fire. From the image, threshold of RGB (GrayScale Threshold) is calculated. In general, Grayscale threshold is 1/3 of (R+G+B). Pixels are iterated, if current pixel value is greater than Grayscale threshold value then FIRE pixel is detected else it is a non-fire pixel. This "calculated fire pixel count and spots" are saved in memory. Its deviation is compared with the subsequent frames. Area of the fire can be obtained by calculating the absolute difference between the subsequent images. Totally 470 frames were extracted from the 26-second video for capture. Random examples of 5 images are shown in [Figure 5]. The next important step is to locate and remove the tip of the flame.

3.3. Adaptive fire predictive technique

3.3.1 Basic concepts

For human beings change in luminance and chrominance will not be a factor for detecting fire. But many of the algorithms fail. It is important to build an Adaptive Fire Detecting (AFD) module. Factors like mean, standard deviation, and illumination constant plays a vital role. A video is captured number of frames are extracted. In every frames K number of pixels are detected. Every pixel is segregated based on the color value.

At a given point {X,Y},

- A pixel is represented as PXPT.
- Its value will be represented as I(PXPT) and value at a selected color channel would be Ii(PXPT)

● Red, Green and Blue pixels are represented as R(PXPT) , G(PXPT) and B(PXPT) respectively.

MEAN and STANDARD DEVIATION helps to determine the movement of the fire pixels. Simple steps are used to determine the initial value of MEAN and STANDARD DEVIATION (SD).

1) Estimation of MEAN is simple. MEANi(PXPT) is the mean value of Ii(PXPT).

2) Absolute difference between consecutive frames gives SDi(PXPT).

The initial MEAN and SD value might have errors and it could be inaccurate. The system recalculates the value based on multiple parameters. The red, green and blue models distributed are DMRED, DMGREEN and DMBLUE respectively.

Probability Density Approximation of I(PXPT) is represented PI(PXPT).

*PI(PXPT) = DMRED(R(PXPT)) * DMGREEN(G(PXPT)) * DMBLUE(B(PXPT))*

Distributions are independent. So,

*Pi(Ii(*PXPT*)) = [1/((square root of (2Pi)) * (SDi(*PXPT*)))] * exp [((Ii(*PXPT*)- MEANi(*PXPT*))^2)/(2 * ((SDi(*PXPT*)^2)))]*

Hence the system can predict the presence of fire "statistically".

3.3.2 Statistical detection

Density of Red, Green and Blue channel is calculated. In Fire Bubble Material, the following condition we need to follows: Red Channel > Green Channel > Blue Channel Density. This is called the channel density policy (CDP). Fire data is closely observed between Red and Green channel. Based on CDP, it is observed that fire pixels have high saturation within Red channel. If observed, in a fire object, some portion of the pixels will not be changed it will be constant. This value will be considered as Red MEAN/RMEAN. If selected pixel value is greater than RMEAN, then the fire is said to be 'STATISTICALLY' detected.

The movement of Flame is observed in [Figure 5], pixel level deviation plays an important role. The flame moves from left to right. However, some RED pixels remain unchanged and can be called RMEAN. The value of RMEAN is not affected by wind or other external factors. Average / Average R (PXPT) value is given as RMEAN.

In an ideal environment, sudden blast or fire hazards can surge the presence of fire pixel. The ideal curve for fire presence is represented in [Figure 5]. Initially the count of fire pixels will be zero. Outbreak of fire rapidly changes the presence of fire pixels in the video. Once it is extinguished, the count of fire pixels will be zero. Hence there is a need to track the pixel level changes between pixels between two time period/frame.

3.3.3 Adaptive pixel change detection

Imagine the frames as a collection of 2 dimensional array. Let 0 represent no-fire element and 1 represent fire element. Hence the list of arrays would look like

A0[3,3]={0,0,0,0,0,0,0,0,0} A1[3,3]={0,0,0,0,1,1,0,0,0}

A2[3,3]={0,0,0,1,1,1,0,0,0} A3[3,3]={0,1,0,1,1,1,0,1,0}

A4[3,3]={0,1,1,1,1,1,1,1,0} A5[3,3]={0,0,1,1,1,1,0,0,0}

A6[3,3]={0,0,0,0,1,0,0,0,0} A7[3,3]={0,0,0,0,0,0,0,0,0}

Consider the first two pixel array A0 and A1. 2 pixel points has fire component. And its density varies between A0 to A7. Therefore, it is important to find a consistent change in pixels. You need to check if the pixel has been added, modified or removed in the extension frames. Each pixel must be tracked and counted. To determine whether a pixel is forward or backward, the global value is initially defined. Global values begin to change as the environment changes. Global value is used for fast moving pixels and slow power for high pixels. It determines whether the pixel is forward or reverse.

3.3.4 Estimation of Mean and Standard deviation of frames for a given period of time

Value of a pixel changes with respect to time and frame. For ex: Place a video camera on an open place for a week. The probability of occurrence of an event twice will be negligible.

1. Select a pixel from the 'i' th channel of each selected for t and t + 1.

2. Store the pixels Ii(n)(PXPT)[t] and Ii(n+1)(PXPT)[t+1].

3. MEANi(PXPT) and SDi(PXPT) used to compute optimal channel were i in {R,G,B} and new P(I(PXPT)) is calculated.

*MEANi(t) = (1/N) * (sum range from t=1toN(Ii(x) on a given time T))*

SDi(t) = arg max absolute difference of Ii(t+1) and Ii(t) where t ranges between t=1 to N.

Illumination, natural effects, density of the color channel changes the behavior of the Mean and Standard deviation.

3.3.5 Adaptive illumination constant and color constant

1) In the video, light and natural influences change the situation over time. This modification provides ALPHA (i) .BETAi (PXPT) color change. This predicts a change of color channel.

a) When the difference between \ BETAi (PXPT) is 1 ([[MEANi (PXPT)) to Ii (PXPT) (ALPHAi * SDi (PXPT)]]) or 0 is greater than the other

b) The smaller BETAi (PXPT) will carry more load for the current time and the older models.

2) Alpha and beta optimal values are adjustable and changeable by color. So think,

a) $ALPHA_R = ALPHA_G = ALPHA_B = ALPHA$ and

b) $BETA_R = BETA_G = BETA_B = BETA$.

3.3.6 Adaptive Mean and Standard Deviation Calculation

The initial values of MEANi (PXPT) and SDi (PXPT) are approx. Initial price will not be charged. The structure is similar. The benefits of MEANi (PXPT) and SDi (PXPT) are temporary. Thus there will be changes in the algorithms and other models

a) MEANi(PXPT)(t) =[BETAi * MEANi(PXPT)(t-1)] +[(1-BETAi)*Ii(PXPT)(t)]

b) SDi(PXPT)(t) =[BETAi * SDi(PXPT)(t-1)] +[(1-BETAi)* | Ii(PXPT)(t) - MEANi(PXPT)(t) |]

c) MEANi (t) and MEANi (t-1) are formats t and t-1, and SDi (t) and SDi (t-1) are different forms of t and t-1.

3.3.7 Changed Pixel Detection

MeanMEANi(PXPT) and Standard deviation SDi(PXPT) helps to find the change of pixel between two frames. If change of pixel continues to stay for 2 or more frames, then there could be a possibility of the fire. For example, consider a two dimensional array representation shown below.

A0[3,3]={0,0,0,0,0,0,0,0,0} A1[3,3]={0,0,0,0,1,1,0,0,0}

A2[3,3]={0,0,0,1,1,1,0,0,0} A3[3,3]={0,1,0,1,1,1,0,1,0}

A4[3,3]={0,1,1,1,1,1,1,1,0} A5[3,3]={0,0,1,1,1,1,0,0,0}

A6[3,3]={0,0,0,0,1,0,0,0,0} A7[3,3]={0,0,0,0,0,0,0,0,0}

Highlighted pixel represents anomaly. This anomaly stays 6 out of 8 frames. Hence this is the most affected zone. This percentage would vary with respect to other pixels. Pixel changes are represented as a Map structure. Therefore, the pixel map is updated through this step.

a) Change the pixel map to CM (PXPT) 1 ((SUMi (BETAi (PXPT)) when I was {R, G, B}) greater than or equal to 2)

b) BCM (PXPT) is a binary exchange chart.

i)when 1 also shows change of address (PXPT)

ii)if 0 for no change.

These algorithms, when combined with the traditional sensor networks it provides an accurate detection.

4. Results and Discussion

A good warning system should have the ability to detect the fire rapidly. Our system detects the fire 99% of the time within half a second.5584 images were taken for the experimentation. Three different types of images were taken and they were mixed together. In the taken sample,25.6% was fire, 31.4% was smoke,and 43 % images were non fire and smoke images.

The test was classified as 4 different classification.

a) Detection of fire and smoke is considered as True Positive.

b) Detection of non-fire/smoke images is considered as True Negative.

c) Failure of detecting fire, bogus alarms is represented as True Positive and False positive.

[Table 1] Shows the result of the experimentation. The framework detected 98.046875% of fire image and 95.6687898089172% accuracy in detecting the smoke images. In either cases the error rate was between 0-0.5 percent

5. Conclusion

In this paper, we have proposed an optimal real-time early fire detection system. The proposed study designed for the study of natural disasters. Computer sensors, computer vision, and in-depth training are used to measure and detect damage. Remove the audio and video after installing the physical game. Future information leaked through computer technology and CNN. To gain intelligence and accuracy, communication about purpose and fire data is unreliable. The actual rate is 98%. Defense is better than science. In the event of a collision, the detection process will continue once the explosion detection process is activated. This creates ultimate protection. Therefore, the future of this project will include wastewater testing and testing.

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Figures

Figure 1. Proposed Framework

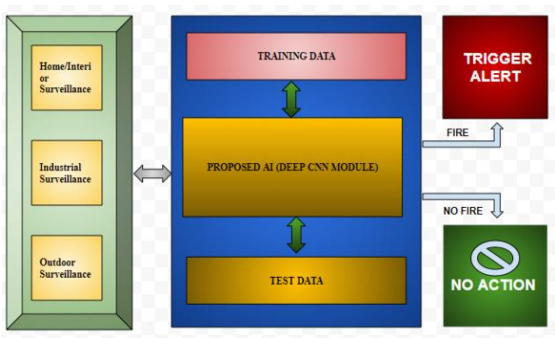


Figure 2: CNN Pipeline

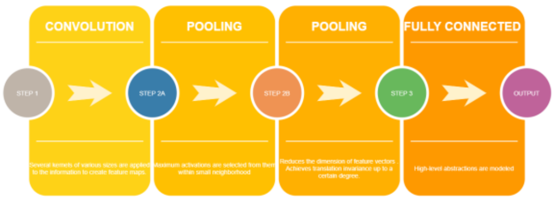


Figure 3. Movement of flame based on the wind.

From left to right: (a, b) extreme left movement. (c) up-right (d, e) movement to right side

Figure 4. Example of max pooling technique

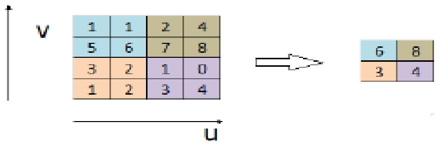
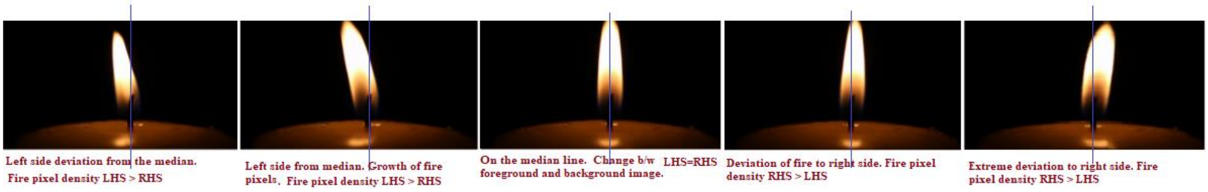
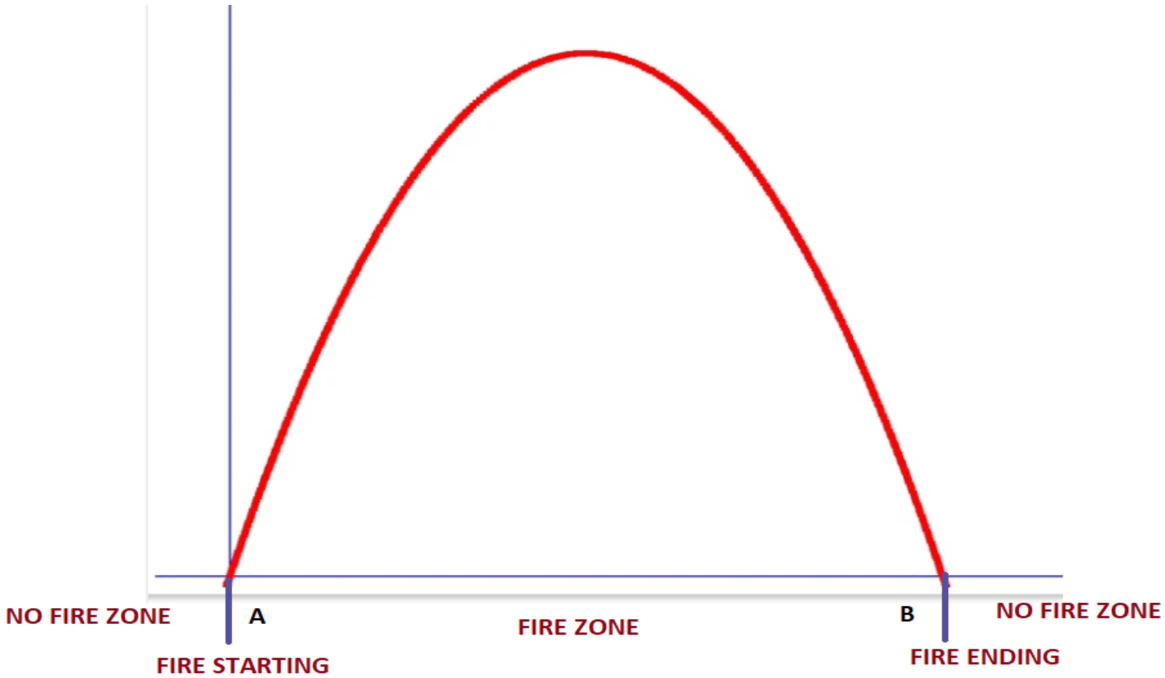


Figure 5. Deviation of flame from the approximated median.



From left to right: (a, b) extreme left movement. (c) up-right (d, e) movement to right side

Figure 6. Existence curve of Fire Pixels.



Tables

Table 1: Results

Hypothesis Class□	**Smoke**	**Fire**
Result (%) ↓		
True Positive	30.04	25.1
False Positive	0.5	0.5
False Negative	0.1	0
True Negative	68.1	74.4