Computer Vision based Early Electrical Fire-detection in Video Surveillance oriented for Building environment

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Abstract. This work presents autonomous electrical fire-detection and localization using computer vision based techniques. The proposed work uses YOLO v2 to extract the electrical fire features more effectively than other conventional and machine learning approaches. This working model is tested on commercial and residential building as well as indoor and outdoor environments. This framework has achieved high detection accuracy and low false alarm rate. Besides, the proposed framework can be used for early real-time electrical fire detection in surveillance videos and we present experimental results for electrical fire localization in CCTV footage using the deep learning architecture proposed in this work.

1 Introduction

In surveillance system, Electrical fire detection plays a crucial role in disaster management. The abnormal events such as electrical-fire hazard in video surveillance are very important for immediate action. Disaster management is primarily focused on Electrical fire detection in residential building, lamp pole and power house. The causes of electrical fire accident are human fault, failure of detection system or faulty electrical outlet, outdated home appliances, material defects and degraded insulation. National Crime Records Bureau (NCRB) reported that 2255 died due to Electrical fire accident in 2015. Further reported that 13 average deaths are occurring per day due to electrical fire issues. In building attribute 40% fire accidents happened due to electrical issues. Association India (ICA-India) reported that 11,444 electrical fire accident deaths happened during the year of 2016-17 in India. So, early electrical fire detection is needed for reducing the human deaths and economical loss. In next section, the researcher explored various fire detection approaches which include conventional method and vision sensor based approaches. [1]

2 Related works

Electrical fire detection is a one of the most important research topic for disaster management. Electrical fire detection is similar to the fire detection approach for computer vision based techniques. In this section researchers have probed various approaches for fire detection which includes conventional method and computer vision based approaches. [2] proposed fire detection approaches belonging to first section which is based on multi-sensors, requiring close proximity to the fire detection or electrical issues, creating environmental pollution and might not be reliable. Furthermore, traditional approaches could not give size and exact location and
human verification should be there such as going to electrical fire issue place and to verify and confirm electrical fire in the case of any electrical fire alarm. [3] proposed computer vision based fire detection approach. This approach uses feature vector such as color of fire, motion. Motion and Flicker process of Markov model discriminate the motion of the fire and fire like objects. Even though this work experimental results shows high false alarm rate. [4] proposed the image processing technique for preventing the large scale fire occurring in tunnel. This work used the CCTV camera for detecting the fire, smoke by using two image processing algorithm. This work handles the color, motion and edge predictors for detecting the fire and smoke. However this work could not provide the good comparison result for dynamic fire condition.

[5] proposed the dimensional characterization of the gaseous flame for monitoring the flame. Three vision sensors are placed for capturing the flames in three different dimensions. This dedicated algorithm reconstructs the three 3D models of flames to contour of 2D region of the flames. Hence, these works apply only for steady state simple flames. [6] proposed frequency domain based fire detection system. The combination of wavelet and Fast Fourier transform detects the fire pixel and contour of the flame region correspondingly. This work shows good results compared with wavelet base flame detection. Since this approach has high false alarms. Color space-rule based approach [7-9] proposed generic rules are formed by observation of fire region pixels are extracted from the image/frame. These rules are a kind of filter which isolates the fire region from the background. This kind of fire detection approach provides high detection accuracy. Thus, it gives more false alarm rate. The frequently used fire color models are RGB, YCbCr, HSI and L*a*b*. [10] presented a special type of optical flow approach for flame detection. These works handle motion as a feature vector and flow directions and magnitudes of the motion vector are computed from optical flow fields for discriminating the fire and fire-like object motion. The experimental of this method has been tested against the different parameters such as various illumination, frame rate, resolution and noise. This work has few limitations such as size, location cannot determine, providing false alarm when frame/image has random noise, dynamically change the location of the camera missing rate is high. [11] proposed deep learning based fire detection method. This approach uses simple deep learning architecture model for detecting the fire and smoke. The class probability informs that the environment has normal, smoke or fire. This simple frame work can be used for real time flame detection. But minimal number filters could not discriminate the fire and fire like objects in various environmental illumination conditions. This work cannot identify the size and location of the fire.

3 Challenges
The aforementioned works investigated that detects the fire pixel by color based rule creation or background subtraction algorithm for identifying motion characteristics of fire pixel or probabilistic parameter based identification or frequency domain analysis or any combination of these methods.

Figure.1 Early Electrical fire detection with deep learning model for disaster management
The color model based rule creation approach fails to detect the fire pixel due to dynamic behavior of camera and more color similarity between fire and fire-like objects or colors. The combination of motion and color based approach handle many parameters for flame pixel detection which limits the real time usefulness. Furthermore, these approaches even provide high detection accuracy; it could not detect the small or large distance fire. The above-mentioned literature work, we observed that the relationship between flame detection accuracy is inversely proportional computational time. Based on this observation, we develop the electrical fire detection system with low false alarm rate, high detection accuracy and minimum computation time and small or large distance electrical fire because early stage fire is small.

4. The Proposed Deep Learning Framework

From the last two decade the frequently used framework for fire detection approaches are conventional or color model based or motion based or combination of these works [11]-[13]. The main limitations of such works are human effort and time consuming for feature extraction high false alarm rate. For coping with such problem, we observed and analyzed deep learning framework for early autonomous for electrical fire detection. We explored much deep learning architecture for improving the electrical fire detection accuracy and reduce the false alarm rate. Our deep learning framework for early electrical fire detection in surveillance camera can be shown in Figure 1

4.1 Convolution Layer

Convolutional Neural Network is a framework of deep learning which is influenced by visual sensation of living human being. CNN is mainly used for object classification with achieving high detection accuracy and minimum false alarm. In order to get high experience from automatically extracting feature vector, we use large raw dataset. CNN has generally three operations. 1. Convolution layer has several filters with different sizes which are convolved with raw input data which make the feature maps. These feature maps as the input of next operation which is called pooling which selects the essential are identified from the small window neighborhood. This operation is rotation invariance for particular degree and reduces the feature vector dimension. The last operation of CNN is fully connected layer which is mainly used for classifying the features of classification objects. In these three operations, convolution and fully connected have only the weights which are adjusted for better accuracy as the training process.

For electrical fire detection problem we propose a YOLO v2 architecture framework can be shown in Figure 2. The reasons for selecting YOLO v2 architecture are better accuracy, minimum computation time and minimum false alarm. The intended framework has 23 convolution layers and 5 max pooling layers. The filter size in last stage is modified by 30 filter according for our electrical fire classification problem and fixing the number of classes are electrical burst and non-electrical burst. The structure of the proposed architecture is tabulated in Table 1.
Figure 2 Deep learning framework for early electrical fire detection system

5. Experimental Results and Discussion
This section, experimental result and compare with other approaches are explained. We performed the experiments on dataset which are collected from Smart Space Lab and YouTube Videos. It can be seen in Table 2. The frames of these videos have different resolution such as 640x352, 198x360, and 640x360. All experimental works are done by Intel Core i7 CPU with 32 GB RAM and NVidia QuadroP1000 4GB. The experimental test is mainly performed on Smart Space Lab and YouTube Videos. The total number of frames/images used in training is 26296. The simulation output of the proposed method is shown various environment such as indoor and outdoor in Table 3. Our proposed method is not only detected and localized the electrical burst fire detection region

| S.No | Layer             | Filters | Size/Stride | Input          | Output              |
|------|-------------------|---------|-------------|----------------|---------------------|
| 0    | Convolution Layer1| 32      | 3x3/1       | 416x416x3      | 416x416x32          |
| 1    | Max Polling Layer1| 2x2/2   |             | 416x416x32     | 208x208x32          |
| 2    | Convolution Layer2| 64      | 3x3/1       | 208x208x32     | 208x208x64          |
| 3    | Max Polling Layer2| 2x2/2   |             | 208x208x64     | 104x104x64          |
| 4    | Convolution Layer3| 128     | 3x3/1       | 104x104x64     | 104x104x128         |
| 5    | Convolution Layer4| 64      | 1x1/1       | 104x104x128    | 104x104x64          |
| 6    | Convolution Layer5| 128     | 3x3/1       | 104x104x64     | 104x104x128         |
| 7    | Max Polling Layer3| 2x2/1   |             | 104x104x128    | 52x52x128           |
| 8    | Convolution Layer6| 256     | 3x3/1       | 52x52x128      | 52x52x256           |
| 9    | Convolution Layer7| 128     | 1x1/1       | 52x52x256      | 52x52x128           |
| 10   | Convolution Layer8| 256     | 3x3/1       | 52x52x128      | 52x52x256           |
| 11   | Max Polling Layer4| 2x2/2   |             | 52x52x256      | 26x26x256           |
| 12   | Convolution Layer9| 512     | 3x3/1       | 26x26x256      | 26x26x512           |
13 Convolution Layer 10 256 1x1 /1 26x26x512 26x26x256
14 Convolution Layer 11 512 3x3 /1 26x26x512 26x26x256
15 Convolution Layer 12 256 1x1 /1 26x26x512 26x26x256
16 Convolution Layer 13 512 3x3 /1 26x26x512 26x26x256
17 Max Polling Layer5 2x2 /2 13x13x512 13x13x512
18 Convolution Layer 14 1024 3x3 /1 13x13x512 13x13x1024
19 Convolution Layer 15 512 1x1 /1 13x13x1024 13x13x512
20 Convolution Layer 16 1024 3x3 /1 13x13x512 13x13x1024
21 Convolution Layer 17 512 1x1 /1 13x13x1024 13x13x512
22 Convolution Layer 18 1024 3x3 /1 13x13x512 13x13x1024
23 Convolution Layer 19 1024 3x3 /1 13x13x1024 13x13x1024
24 Convolution Layer 20 1024 3x3 /1 13x13x1024 13x13x1024
25 Route 16
26 Convolution Layer 21 64 1x1 /1 26x26x512 26x26x64
27 Reorg 27 /2 26x26x64 13x13x256
28 Route 24
29 Convolution Layer 22 1024 3x3 /1 13x13x1280 13x13x1024
30 Convolution Layer 23 30 1x1 /1 13x13x1024 13x13x30
31 Detection

Table 2. Dataset details

| S.No | Dataset Name | Total No of Frames | Resolution | Burst No | Environment | Color | Image Format |
|------|--------------|--------------------|------------|----------|-------------|-------|--------------|
| 1    | TF1          | 5001               | 640x352    | 856      | Indoor      | Red   | .jpg         |
|      |              |                    |            |          |             | Orange|             |
|      |              |                    |            |          |             | White |             |
| 2    | TF2          | 10987              | 640x352    | 834      | Indoor      | Red   | .jpg         |
|      |              |                    |            |          |             | Orange|             |
|      |              |                    |            |          |             | White |             |
| 3    | TF3          | 3785               | 640x352    | 891      | Indoor      | Red   | .jpg         |
|      |              |                    |            |          |             | Orange|             |
|      |              |                    |            |          |             | White |             |
| 4    | EbF1         | 2899               | 198x360    | 2899     | Outdoor     | White | .jpg         |
|      |              |                    |            |          |             | Orange|             |
| 5    | EbF2         | 3624               | 640x360    | 3249     | Outdoor     | White | .jpg         |

Table 2. Dataset details (continued)

| Dataset Name | Total No of Frames | Resolution | Burst No | Environment | Color | Image Format |
|--------------|--------------------|------------|----------|-------------|-------|--------------|
| TF1          | 5001               | 640x352    | 856      | Indoor      | Red   | .jpg         |
|              |                    |            |          |             | Orange|             |
|              |                    |            |          |             | White |             |
| TF2          | 10987              | 640x352    | 834      | Indoor      | Red   | .jpg         |
|              |                    |            |          |             | Orange|             |
|              |                    |            |          |             | White |             |
| TF3          | 3785               | 640x352    | 891      | Indoor      | Red   | .jpg         |
|              |                    |            |          |             | Orange|             |
|              |                    |            |          |             | White |             |
| EbF1         | 2899               | 198x360    | 2899     | Outdoor     | White | .jpg         |
|              |                    |            |          |             | Orange|             |
| EbF2         | 3624               | 640x360    | 3249     | Outdoor     | White | .jpg         |
|              |                    |            |          |             | Orange|             |
6. Conclusion
The dataset is used for training for the proposed architecture. The recent developments in the embedded processors our objective is to develop the affordable cost reliable electrical fire detection system. It helps managing the disaster to protect our environment. Our fine tuned proposed architecture for electrical fire detection on CCTV surveillance system yields high detection accuracy and low false alarm rate. The early fire detection system is very important for disaster management system. The proposed architecture can possible into the embedded processor to make the real time system. In our future work is developing the light weight CNN for early detection.

Table 3. Electrical burst fire detection in indoor environment

|   | TV1 | TV2 | TV3 | EbV1 | EbV2 |
|---|-----|-----|-----|------|------|
|1  |     |     |     |      |      |
|2  |     |     |     |      |      |
|3  |     |     |     |      |      |
|4  |     |     |     |      |      |
|5  |     |     |     |      |      |

TV1.mp4
TV2.mp4
TV3.mp4
EbV1.mp4
EbV2.mp4
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