Retraction

Retraction: Real Time Fire detection and Localization in Video sequences using Deep Learning framework for Smart Building (J. Phys.: Conf. Ser. 1916 012027)

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This article (and all articles in the proceedings volume relating to the same conference) has been retracted by IOP Publishing following an extensive investigation in line with the COPE guidelines. This investigation has uncovered evidence of systematic manipulation of the publication process and considerable citation manipulation.

IOP Publishing respectfully requests that readers consider all work within this volume potentially unreliable, as the volume has not been through a credible peer review process.

IOP Publishing regrets that our usual quality checks did not identify these issues before publication, and have since put additional measures in place to try to prevent these issues from reoccurring. IOP Publishing wishes to credit anonymous whistleblowers and the Problematic Paper Screener [1] for bringing some of the above issues to our attention, prompting us to investigate further.

[1] Cabanac G, Labbé C and Magazinov A 2021 arXiv:2107.06751v1
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Real Time Fire detection and Localization in Video sequences using Deep Learning framework for Smart Building

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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.

Keywords: fire detection, Building environment, Computer vision, Deep learning framework, surveillance video

1. Introduction

Computer vision based event detection system has been addressed for many vision oriented detection applications like fire accident, smoke, electrical burst, human, and object detection. Of these detection applications, fire accident detection has attracted the researcher’s attention because fire accident causes economical loss, human deaths, environmental damage. The root causes of fire accident are human made fault or fire detection system failure. The US National Fire Protection Association reports that 5 human died per 10000 fire accident with smoke sensor 118 died per 10000 fire accident without smoke sensor. This sensor type fire detection approach has few limitations:

- The sensor may provide unreliable data.
- The sensor should be very close to fire.

2. Related works

[1] probed fire pixel characteristics and examined the chromatic features of the flames pixel in RGB and HSI color space and temporal disorder characteristics of the fire. The color pixel study created the rules which find the fire pixel in a frame or image. The dynamic analysis approach detects the fire pixel by frame dis-order threshold of two consecutive frames. Furthermore, Dynamic analysis method fails non relevant subsequent frames in video due to irrelevant pixel correlation between the frames.
[2] proposed image processing based fire detection system. This work is based on the HSI color space of 70 training images is used for taking the fire feature vector. This predictor is used for creating the rules. This complete work provides high detection accuracy and removes spurious flame regions. Even this approach gives provides good detection accuracy compare to the other works false rate is so high in numbers. The experimental works has shown 35% of false negative and 81% false positive.

[3] proposed generic rule based approach for the real time fire pixel detection system. This work examines the flame pixel by using the YCbCr color space, due to failure of the RGB color space in various light conditions. This approach provides 99% detection accuracy and minimal computation complexity for hardware implementation. Thus, this proposed work implements real time fire detection. However, this method produce 31.5% false alarm rate. [4] proposed an early fire detection approach using image processing approach and support vector machine (SVM). These approach consists of set of methods correspondingly to Gaussian distribution, modified background subtraction and temporal luminance variance histogram. In RGB color space, with the support of Gaussian distribution, the fire pixel region is detected by the probability based threshold method. After, this hybrid background subtraction method removes non-fire pixel if which are not remove in Gaussian method. Luminance filter enhance the fire region by luminance mapping then temporal luminance variance is calculated and identified the fire pixel by using variance threshold. Finally, the wavelet transform coefficients are used for analyzing the moving region in the frame. It can discriminate the fire region from moving region by its higher magnitude. SVM with radial basis function (RBF) kernel is applied to these coefficients for this binary classification. In this proposed work, computational complexity and execution time is more for third method. Due to this reason detection frame rate should be 15/sec. This approach could not detect fire region perfectly. Though still this work could not scale down the false alarm rate.

[5] proposed vision based for fire detection system. This approach consists of two methods. (i) Color model based (ii) motion based. This work handle L*a*b* color space in input frame then create the four rules for identifying the fire pixel. It can be reduce the false negative rate. This work was tested on ten different fire videos. The experimental result show that detection accuracy is 99.88%, false positive is 1.1%, false negative rate is 11.5%. [6] proposed automated flame detection system using computer vision based approach. This work detects the fire region by using change of low level feature vector on frame to frame such as color, skewness, boundary roughness size of the fire region, surface coarseness in the fire region. This work feature vector skewness is the powerful descriptor to detect the fire region because red channel saturation is occurred frequently. Thus, this approach could not be reduced the false positive rate with this low level feature vectors.

[7] proposed Convolution neural network based promising fire detection system. The conventional method provides high detection accuracy even though, they have high false positive rate, not to detect tiny fire or large distance detection and manually or algorithm methods detects the feature vectors. This method produce the detection accuracy of this method is 98% for test data. This method proposed the simple design architecture. The detection accuracy and processing time of this method are independent for the original image size. [8] proposed early and accurate automated fire detection system based on computer-vision approach. This work has addressed the early fire detection system by using image processing technique. The method detects the fire color range only red and yellow. This work fails as high similarity between fire and fire-like color region.

[9] proposed machine learning algorithm based real-time fire flame detection system. This work is also the combination of two methods. (i) Color space component ratio based detection and background subtraction method based detection. (ii) Fire flame pixel is detected by probability using logistic regression. This approach provides high detection accuracy and average detection time is suite for real
time detection. This work is compared with color model based approach the detection accuracy is less. [10] proposed early fire detection system using Convolutional Neural Network (CNN). This method can detect the fire in both indoor and outdoor environments. Compare this approach with the other methods such as color model based method, machine learning methods and few deep learning models which detects the fire quickly and good accuracy. This method has faced many challenges such as noisy image, fire like objects and light, flipped images, small size of object fire, different rotation and fire color, time response. These all the challenges, this CNN approach is used for detecting the fire successfully. Even though this work faces many challenges, this architecture is not performed localization of the fire detection works.

3. Challenges

This review paper has been discussed various fire detection approaches and localized the fire region. We examine this review; color model and rule based detection approach could not detect large distance object or small size region. Even this color model based approach gives high detection accuracy; it could not scale down the false alarm rate. The deep learning based approach provides a set of weight vector in each stage which acts as a sensor to highlight or discriminate the fire region from background region. Finally the classifier in the specific a specific architecture gives the class probability and localization vectors of the input frame for finding fire exist or not.

4. The proposed Deep learning framework

The real time fire detection system is a part of the Disaster management system which can be used at surveillance area such as residential building, commercial building, forests, laboratory, and vehicle fire for saving human lives, control the economical loss and environmental pollution. Though early fire detection system is a challenging task by cause of different illumination level, fire colored objects, noise occur during acquisition, nested ring of fire colors such as (red, orange, yellow, white)rotation of the frame and different resolution of the frame. Thus, we need a framework which can give better result with low false alarm rate for this kind of challenges. To satisfy this objective, we probed deep neural network for real time fire detection as CCTV monitoring. YOLO v2 provides state-of-the-art performance in objects detection, classification, and localization and computer vision tasks[11]-[16]. Their purpose in fire detection and localization system considerably increases the fire detection accuracy and downturn the false positive rate. YOLO v2 architecture consists of different type and size of layer which includes convolution layer, pooling layer and fully connected layer is shown in Table 1. These processing layers are aligned in such a manner that the output of the feature map of one layer gives the input of the consecutive layer. Each Convolution layers has more number of filters which generates feature maps. These most meaningful features are taken by using pooling layers. The entire convolution layer filters weights are learnt and updated as the training phase. This weight vector model can perform the target fire detection and localization. The proposed model architecture can be shown in Figure 1.
5. Experimental Output

5.1 Dataset description

Fire detection Frame work using Deep learning architecture is performed using a dataset of approximately 21748 images is collected from different fire datasets of videos. The frame/Image has different resolution. We tested our proposed work on different datasets: 1. Building environment data set 2. Standard data set. Building data set consists of both outdoor and indoor environments. The building dataset has Office, Car parking area. The simulation output is shown in Table 2.

Table 1. Yolo V2 parameter details

| S.No | Layer               | Filters | Size/Stride | Input          | Output          |
|------|---------------------|---------|-------------|----------------|-----------------|
| 0.   | Convolution Layer 1 | 32      | 3x3 /1      | 416x416x3     | 416x416x32     |
| 1.   | Max Polling Layer   | 2x2 /2  | 416x416x32  | 208x208x32    | 208x208x32     |
| 2.   | Convolution Layer 2 | 64      | 3x3 /1      | 208x208x32    | 208x208x64     |
| 3.   | Max Polling Layer 2 | 2x2 /2  | 208x208x64  | 104x104x64    |                 |
| 4.   | Convolution Layer 3 | 128     | 3x3 /1      | 104x104x64    | 104x104x128    |
| 5.   | Convolution Layer 4 | 64      | 1x1 /1      | 104x104x128   | 104x104x64     |
| 6.   | Convolution Layer 5 | 128     | 3x3 /1      | 104x104x64    | 104x104x128    |
| 7.   | Max Polling Layer 3 | 2x2 /1  | 104x104x128 | 52x52x128     | 52x52x128      |
|   | Layer Type          | Filters | Kernel Size | Input Shape | Output Shape |
|---|---------------------|---------|-------------|-------------|--------------|
| 8. | Convolution Layer 6 | 256     | 3x3 /1      | 52x52x128   | 52x52x256    |
| 9. | Convolution Layer 7 | 128     | 1x1 /1      | 52x52x256   | 52x52x128    |
| 10.| Convolution Layer 8 | 256     | 3x3 /1      | 52x52x128   | 52x52x256    |
| 11.| Max Polling Layer 4 |         |             |             |              |
| 12.| Convolution Layer 9 | 512     | 3x3 /1      | 26x26x256   | 26x26x512    |
| 13.| Convolution Layer 10| 256     | 1x1 /1      | 26x26x512   | 26x26x256    |
| 14.| Convolution Layer 11| 512     | 3x3 /1      | 26x26x256   | 26x26x512    |
| 15.| Convolution Layer 12| 256     | 1x1 /1      | 26x26x512   | 26x26x256    |
| 16.| Convolution Layer 13| 512     | 3x3 /1      | 26x26x256   | 26x26x512    |
| 17.| Max Polling Layer 5 |         |             |             |              |
| 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          |             |              |
| 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. Fire Localization in various environment

| Output Image                  | Prediction Probability                                           |
|-------------------------------|-----------------------------------------------------------------|
| Building                      | mask_scale: Using default '1.000000'                             |
|                               | Loading weights from yolov2-fire_60000.weights...Done!          |
|                               | frame441.jpg: Predicted in 0.044556 seconds. fire: 53%          |
| Car Parking Area              | mask_scale: Using default '1.000000'                             |
|                               | Loading weights from yolov2-fire_60000.weights...Done!          |
|                               | frame275.jpg: Predicted in 0.040793 seconds. fire: 70%          |
| Cinema                        | mask_scale: Using default '1.000000'                             |
|                               | Loading weights from yolov2-fire_60000.weights...Done!          |
|                               | frame212.jpg: Predicted in 0.045943 seconds. fire: 68%          |
| Home                          | mask_scale: Using default '1.000000'                             |
|                               | Loading weights from yolov2-fire_60000.weights...Done!          |
|                               | frame249.jpg: Predicted in 0.047797 seconds. fire: 59%          |
| Smart Space Lab               | mask_scale: Using default '1.000000'                             |
|                               | Loading weights from yolov2-fire_60000.weights...Done!          |
|                               | frame265.jpg: Predicted in 6.047473 seconds. fire: 63%          |

6. Conclusion
The proposed YOLO architecture yields high detection accuracy and low false alarm rate for various challenging dataset. The proposed architecture detects and localizes the fire region within 0.04 seconds. The early fire detection plays important role in the disaster management. It mitigates human loss, avoiding environmental damage, economical loss and natural resource losses. The proposed work has light weight architecture which provides embedding capability for hardware implementation. The conventional color model methods and time domain analysis provides consider amount of false alarm rate. The simple work gives high false alarm rate and the complex algorithm provides time consuming and incapable hardware implementation. The proposed work has good trade-off between low false alarm and time consuming.
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