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Fire detection in Surveillance Videos using a combination with PCA and CNN

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***ABSTRACT**. This paper proposes a novel approach to early fire detection system from closed-circuit television (CCTV) using combination Principal Component Analysis (PCA) and Convolutional Neural Networks (CNN). It takes full advantage of the existing traditional methods like color or motional characteristics information of fire. However, CNN based fire detection system needs more computational requirements, high memory and time, in this paper, we propose energy-friendly CNN architecture for fire detection deep neural networks, inspired by MobileNet. The main role of PCA is to perform feature extraction of row data and then send it to CNN architecture. The experimental results on benchmark fire datasets reveal that the proposed method can achieve better classification performance and indicates that using CNN to detect fire in video captures is an effective way.*

***KEYWORDS:** Convolutional neural networks (CNN), deep learning, Principal component analysis (PCA), fire detection, surveillance networks, image classification.*

1. Introduction

Fire is one of the disasters affecting everyday life in our society, and to avoid severe damage scale caused by fire, an efficient fire detection system should be designed. Nowadays, more and more fire detection systems can be seen in airports, hospitals, shopping malls, educational institutions, etc. However, most of these present systems are based on traditional sensors. Traditional sensor-based systems have been used extensively because there is no other alternative, in addition they have disadvantages in practice. Furthermore, traditional sensors have useless in the outside environment and cannot detect fire locations. Over 95% of all fire alarm signals generated from automatic fire alarm systems are false or unwanted [1].

Fire detection systems based on video processing can be an effective method to prevent fires in large space and areas where traditional fire detectors cannot be used. These techniques, based on video capture, are viable alternatives or complements to the existing fire detection methods and have been shown more quickly and accurately to solve several problems in traditional sensors [2].

These days, many cameras are installed in numerous places. Our approach specifically addresses to CCTV system due to the enormous quantity of them. However, identifying and distilling the relevant information is the greatest challenge currently facing video security and monitoring system operators. There is a real need for intelligent video content analysis to support the operators for undesired behavior and unusual activity detection before they occur.

Intelligent video processing techniques for the detection and analysis of fire are relatively new. To avoid large scale fire and smoke damage, timely and accurate fire detection is crucial. Video-based fire detection techniques are well suited to detect fire in early stages. The sooner the fire is detected, the better chances are for survival. Furthermore, it is also crucial to have a clear understanding of fire development and the location. Initial fire location, size of the fire, the direction of smoke propagation, the growth rate of the fire are important parameters which play a significant role in analysis, and essential in assessing the risk of escalation [2]. Furthermore, computer-assisted video surveillance data analysis is of the major commercial and law enforcement interests [3]. Video-based fire detection techniques are well suited to detect fire in the early stages. Considering that our aim is getting benefit from the existing surveillance system. CNN automatically learns a set of visual features from the training data.

2. Related work

Most of the fire alarm systems are developed based on vision sensors [4], [5] but considering its affordable cost and installation, the majority of the research is conducted for fire detection using cameras.

Recently, Foggia *et al.* [6] proposed a real-time fire detection algorithm based on color, shape, and motion features.

Celik *et al.* [7] propose using the YCbCr color space to construct a generic chrominance model for pixel classification flames. They also proposed novel rules for separating the chrominance and luminance components. However, their proposed way is unable to detect fire from a large distance and small scales of fire.

Rafiee *et al.* [8]presented a method for fire and smoke detection through image processing. Their algorithm detection the deferent objects in an image and discerning smoke and fire objects among the detected objects, and then apply two-dimensional wavelet transformation to an image. Their method reduced the rate of false alarms by considering variation in energy as well as shape, however, false alarms can be higher in this approach for the case of rigid body movements within the frame.

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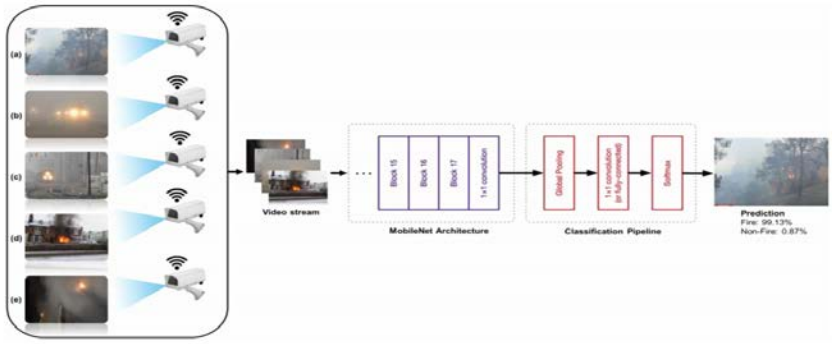

Fig.1. Fire detection system.

Muhammad *et al.* [9] proposed a MobileNet (V2) based architecture for fire detection with a cost-efficient CNN. Isha Garg *et al.* [10] explored design model structure by compression technique with explainable design heuristics for optimizing network architecture.

In our method, we present a perfect combination with PCA and CNN. PCA helps extract image features and then selects the most important feature components to reduce data dimensions before sending then to CNN architecture. The experiment results show that a combination provides excellent results.

3. Proposed Approach

This section explores our proposed method, describing the concept of detection a fire at an early stage. Our proposed framework, based on deep learning models, possible detect fire at early stages during surveillance. Fig. 1. shows our method, we try to use a computationally cheap and effective way to detect small-sized fire in a large distance and use light-weight deep neural networks with no dense fully connected layers.

3.1 Principal Component Analysis

Principal Component Analysis is a useful and common statistical technique that has been found in many application fields, such as finding patterns in data of high dimension. The aim of PCA is to explain the independence of a large number of variables by the smaller number of fundamental variables [11]. Considering a set of training data (A) size *M x N* matrix, the mean (μ) of variable A is defined by

$$\mu=\frac{\sum_{i=1}^{M} A_i}{M} \tag{1}$$

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where $1 \leq i \leq M$, A_1 is one row of A. Distance vector is as follows,

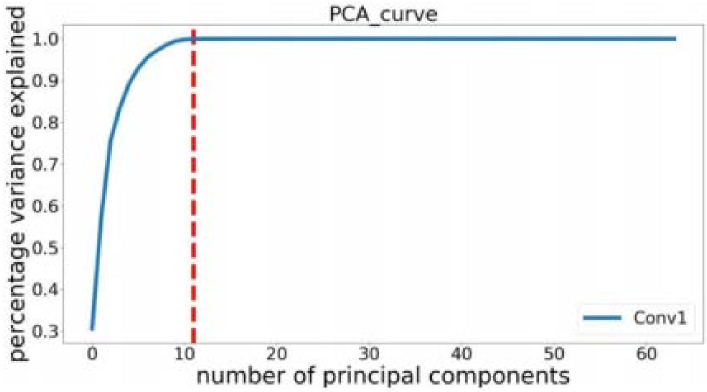

Fig. 2. An example of PCA.

$$x_i = A_i - \mu \tag{2}$$

The covariance C_X is defined by

$$C_X = XX^T \tag{3}$$

Where matrix X = [$x_1, x_2 \ldots, x_M$]. The covariance matrix is solved by calculating the eigenvalues (Λ) and eigenvector (λ) as follows

$$C_X \text{ U} = \text{U } \Lambda \tag{4}$$

$$\Lambda = diag[\lambda_1, \Lambda_2, \ldots, \Lambda_M] \tag{5}$$

Where Λ is a diagonal matrix defined by the eigenvalues of matrix C_X and U is the associated eigenvectors of λ. The eigenvectors represent the directions of the PCA space, and the corresponding eigenvalues represent the scaling factor, length, magnitude, or the robustness of the eigenvectors. In Fig. 2. a sample out of PCA.

Most filters in CNN layer are highly correlated and potentially detect the same function, therefore it makes a small contribution to accuracy. We consider that in case of redundancy, it can be recreated by a linear combination of the remaining filters, while the retrained network will not lose accuracy. Therefore, optimal architecture as an internal property of a space defined by the entire set of features, rather than by the objects themselves. Redundancy can be removed by the optimal model design is framed as a dimensionality reduction problem with the intention identification of the number of uncorrelated 'eigen-filters'. By utilizing PCA, the notion of the significance of a filter was removed. We believe that the dimension determines the optimal space of the corresponding transformations, and the network can learn the necessary filters in this space after training.

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3.2 Convolutional Neural Network Architecture

The Convolutional Neural Networks was first introduced in 1980 by Fukushima [12]. CNN shows good performers in computer vision applications, like object detection [13], image classification [14], and image segmentation [15]. A typical CNN is composed of a convolutional feature extraction block followed by a fully connected block. The convolutional feature extraction block consists of a series of convolutional layers and pooling layers. Many different architectures for the feature extraction block have been proposed [16], [17], [18]. After extracting the feature maps from the convolutional feature extraction block, they are flattened into a feature vector that is used by the fully connected block to perform the task [19]. CNN widely used due to its hierarchical structure, which automatically learns very strong features from raw data.

Table 1 Comparison of the proposed approach with various fire detection methods in terms of False Positives, False Negatives and Accuracy

Method	False Positives	False Negative	Accuracy
Proposed method	8.87 %	2.12 %	94.50 %
Celik *et al.*	29.41 %	0 %	83.87 %
Rafiee *et al.*	17.65 %	7.14 %	87.10 %
Foggia *et al.*	11.67 %	0 %	93.55 %

In our method, we optimize a pre-trained network with low effort in terms of retraining iterations. First of all, we begin with a pre-trained network and analyze the activations of all layers simultaneously using PCA. After that, determine the optimized networks layer-wise width from the number of principal components required to explain in 99% of the cumulative explained variance. The next stage is calling these new significant dimensions of each layer and optimize the depth based on when these significant dimensions start contracting.

4. Experimental Results

In this section experiment on real-world datasets are performed. Up to now, there are no standard dataset benchmarks available, therefore our datasets were obtained from many sources, including Foggia *et al.*[6], Chino *et al.*[20] and other internet resources. Our databases were gotten from various resources for the experiments. The detailed information comparison results were present in Tab. 2.

All our video contained datasets from experiments available in these websites are shown below[i]. The algorithms in using an intel processor core i5 CPU and 64GB RAM.

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5. Conclusion

The paper has proposed a fire detection system using CCTV surveillance systems. With CNN`s great potentials, we propose a combination PCA with light-weight CNN based on MobileNet architecture for fire detection in CCTV surveillance networks. Our approach has been tested in a big database, and experimentation confirmed the effectiveness of our method, which allows to achieve better performance. Moreover, our proposed system balanced the accuracy detection and size of the fire. With recent achievements of CNN for solving problems, our future studies will be devoted to the convolutional neural networks-based methods via edge intelligence with reasonable accuracy and running time.

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