Real-time Fire Detection Method Combining AdaBoost, LBP and Convolutional Neural Network in Video Sequence

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Abstract: **This paper presents a novel algorithm for detection certain types of emergencies relating to fire, smoke and explosions by processing the data recorded from the camera monitoring, based on cascaded approach. First, the combination of Adaboost and Local binary pattern (LBP) are using for getting Region of Interest (ROI) and reducing time complexity. Next, to alleviate common problems of vulnerable such as false positive, we propose to use Convolutional Neural Network (CNN). The final experimental results showed that the accuracy rate of this method for emergencies detection could reach 95.2%.**

Keywords: **computer vision, fire detection, smoke detection, Adaboost, local binary pattern, convolutional neural network.**

I. Introduction

Fires that are most distributable kind of anthropogenic emergencies, may lead to a considerable material damage and serious injury or even death.

In order to avoid such losses, widely practiced use flame and smoke detectors. However, realization such functions in video surveillance system is more reasonable, because it allows monitoring large areas and open space that traditional systems of fire or smoke control cannot do.

In additional, methods, which allow identify the presence of smoke or fire in video sequences has the following advantages: can be used on large open areas; there is a possibility for operator to visually confirm presence, intensity and the size of the hazards; lower cost for installation and further exploitation, because cameras are already available almost at each large enterprise for surveillance purposes.

After analyzing the existing system of binary classification of the presence or absence emergency situations on the images [1], we can hardly say that today there is no universal system that would meet two key requirements applied to the life safety systems: high classification rate and speed of data processing allowing it to work in real time. Accordingly, it is necessary to develop a system of detection of emergencies that would meet the above requirements.

II. Related Work

The problem of hazards detection in video sequences devoted a lot of research articles. The vast majority of them foresees the use of different color models such as RGB [3], YCbCr [4], CIE L*a*b [5], HSV [6] etc. For this, interactive segmentation performed in the image area surveillance and, according to the statistical distribution of pixels forming the boundary conditions within which is determined pixel belongs to the desired area [2].

Regarding the segmentation using different color model, we can study the results listed in [7]. According to these, the use a single color segmentation is not enough for developing an effective smoke and fire detection system. In addition, there are a couple methods, which can identify movement in the video sequence (frames difference, background subtraction, etc.) [8]. But the main disadvantage of these methods, in the context of fire detection, is that flame take on different colors and speed.

However, video-based emergency detection usually is limited by surrounding situations and depends on data preprocessing techniques to a certain extent [9, 10]. In contrast to the available techniques for detecting an emergency in video sequences, we propose to use the Adaboost [11] and LBP combination for generating ROI.

For verify area generated at the previous stage, we propose to use CNN, which allows raising performance by studying global and local features on all levels. To reduce the number of false positive and negative samples, the cascaded CNN was proposed.

III. Methodology

The proposed framework for emergency detection consists two main parts as illustrated in Fig. 1. At the first stage, to generate possible regions where flame or smoke can be present, AdaBoost and LBP algorithms are combined. This combination is fast, but the method has a high false positive rate. Therefore, the CNN architecture has been proposed to tackle this problem. This makes the algorithm performance better and reliable. At the last stage, two SVM classifiers give a conclusion about the presence of desired objects in video sequences.

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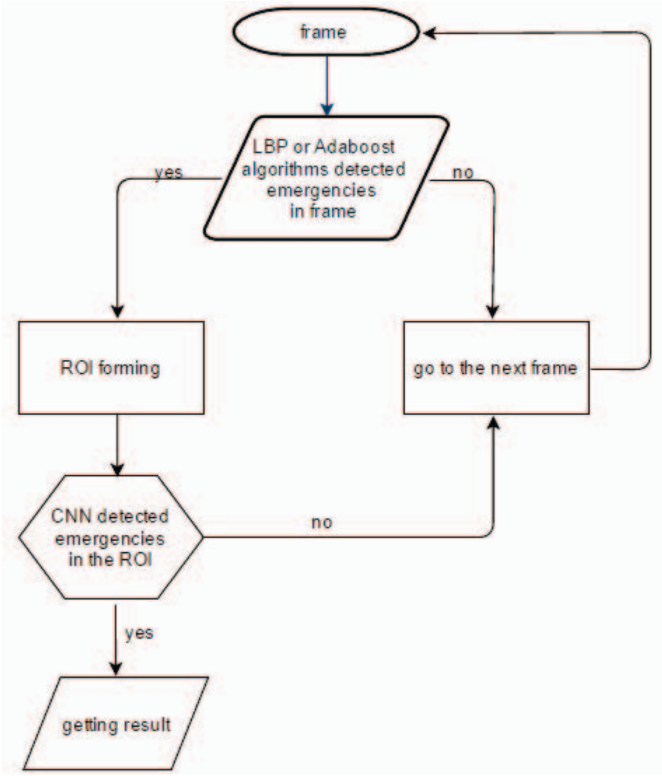

Fig. 1. A sketch of the proposed framework of object detection

Considering the fact that speed of CNN is extremely slow to calculate the entire frame, from previously step we getting ROI, in the area of which can accommodate an emergency. Since the flame and smoke particles constantly moving and changing direction, ROI should be updated at each frame taking into account their movement characteristic. The detailed step of this algorithm is described in Algorithm 1.

The input receives information about objects that visually can resemble flame or smoke. This information is generated by the detector Adaboost and LBP and includes:

Hi - the height of the found object;

Wi, - the weight of the found object;

Pi(x,y) – central coordinates of the found object;

ROI described as a rectangle with four coordinates (R1(x,y), R2(x,y), R3(x,y), R4(x,y)). They need not go beyond the image, that is why we used functions HandleTop, HandleLeft and HandleRight.

Unlike from the traditional structure of the CNN, which consists of two convolutional layers and two subsampling layers [12], our structure includes three convolutional and three subsampling layers with different size core. In particular, information about the smoke and flames presence in the image are based on information received from the second and third subsampling layer, which then fed to two SVMs for classification. This approach has allowed allocating not only local but also global features, which can describe flame or smoke.

Algorithm 1: ROI calculate

Input: H_{i-1}, W_{i-1}, $P_{i-1}(x,y)$
Output: $R_1(x,y)$, $R_2(x,y)$, $R_3(x,y)$, $R_4(x,y)$

$P_{ROI}(x, y) \leftarrow P_{i-1}(x, y)$
$W_{ROI} \leftarrow W_{i-1} \times 1.5$
$H_{ROI} \leftarrow H_{i-1} \times 1.5$

function Border($P_{ROI}(x, y)$, W_{ROI}, H_{ROI})
  $R_1(x, y) \leftarrow P_{ROI}(x - (W_{ROI} \div 2), y - (H_{i-1} \div 2))$
  $R_2(x, y) \leftarrow P_{ROI}(x + (W_{ROI} \div 2), y + (H_{ROI} \div 2))$
  $R_3(x, y) \leftarrow P_{ROI}(x - (W_{ROI} \div 2), y + (H_{ROI} \div 2))$
  $R_4(x, y) \leftarrow P_{ROI}(x + (W_{ROI} \div 2), y - (H_{i-1} \div 2))$
  return $R_1(x, y)$, $R_2(x, y)$, $R_3(x, y)$, $R_4(x, y)$
end function

function HandleTop($P_{ROI}(y)$, H_{ROI}, $F_{max}(x)$)
  if $P_{ROI}(y + (H_{ROI} \div 2)) > F_{max}(y)$ **then**
    $R_2(x, y) \leftarrow P_{ROI}(x + (W_{ROI} \div 2), F_{max}(y))$
    $R_3(x, y) \leftarrow P_{ROI}(x - (W_{ROI} \div 2), F_{max}(y))$
  end if
  return $R_2(x, y)$, $R_3(x, y)$
end function

function HandleLeft($P_{ROI}(x)$, W_{ROI}, $F_{min}(x)$)
  if $P_{ROI}(x - (W_{ROI} \div 2)) < F_{min}(x)$ **then**
    $R_{1,2,3,4}(x) \leftarrow P_{ROI}(0)$
  end if
  return $R_{1,2,3,4}(x)$
end function

function HandleRight($P_{ROI}(x)$, W_{ROI}, $F_{max}(x)$)
  if $P_{ROI}(x + (W_{ROI} \div 2)) > F_{max}(x)$ **then**
    $R_{1,2,3,4}(x) \leftarrow P_{ROI}(F_{max}(x))$
  end if
  return $R_{1,2,3,4}(x)$
end function

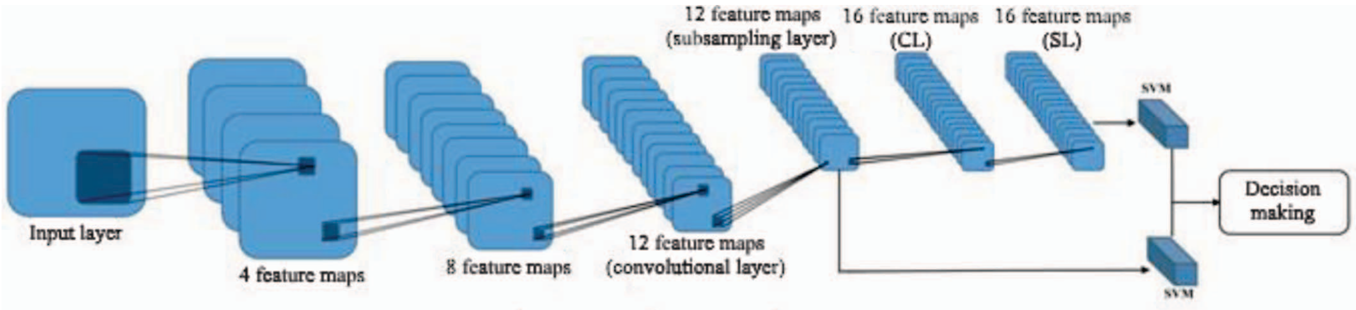

Fig 2. Proposed structure of CNN

IV. Experiments

For test classifications quality we formed the own dataset of images, which is divided into three categories: flame, smoke and without any dangers. A number of copies used for the category "flame" - 150, for “smoke” – 150, for category “other”, which not include any images with smoke or fire – 300. In particular, the last category includes objects, which may look like a flame (bright clothing, lights, garlands, etc.).

To train the classifier we used image dataset that was formed during the previous study [2]. It includes 1876 images with fire and the 4634 images without fire.

The results of the classifier evaluated based on two well-known techniques - precision and recall. High precision relates to a low false positive rate, and high recall relates to a low false negative rate. High scores for both show that the classifier is returning accurate results (high precision), as well as returning a majority of all positive results (high recall) [13].

$$Precision = \frac{TP}{TP + FP} \quad (1)$$

$$Recall = \frac{TP}{TP + FN} \quad (2)$$

where TP - the number of true positives (classifier detect fire or smoke at the image area where were flames or smoke); FP - false-positive operation (classifier detect fire or smoke at the image area without any flames or smoke); FN - false-negative operation (classifier don't detect fire or smoke at the image area where were flames or smoke).

TABLE 1. Results of classification

Category	Precision	Recall
Smoke	85,4 %	94,4 %
Fire	91,9 %	98,2 %
Other	83,6 %	93,1 %
Total	86,96 %	95,2 %

V. Conclusion

We described a method which combining some advantages of the AdaBoost, LBP and Convolutional Neural Network, is used to speed up the processing time while making a better performance in object detection. Execution time was in the millisecond range, thus verifying that the developed system can operate in real time at video rates. In additional, our algorithm makes a better performance using the convolutional neural network. This method is tested on our database with five hundred images, which include such category as “smoke”, “fire”, “others”. The experimental results show that the method could achieve more than 95% correct detection rate. The main direction of future research is improving recognition of categories “smoke” and “fog”, which showed the largest percentage of false positives operation.

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