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Two-Step Cascading Algorithm for Camera-based Night Fire Detection

MinJi Park, Donghyun Son, ByoungChul Ko*
Department of Computer Engineering, 1095, Dalgubeol-daero, Dalseo-gu, Daegu, Republic of Korea
minjiP9607@gmail.com, tbc01204@gmail.com, niceko@kmu.ac.kr (Corresponding author)

Abstract

In this paper, we propose a new fire monitoring system that automatically detect fire flames in night-time using a CCD camera. The proposed system consists of two cascading steps to reliably detect fire regions. First, ELASTIC-YOLOv3 is proposed to better detect a small fires. The main role of ELASTIC-YOLOv3 is to find fire candidate regions in images as the first step. The candidate fire regions are passed to the second verification step to detect more reliable fire region results. The second step takes into account the dynamic characteristic of the fire. To do this, we construct fire-tubes by connecting the fire candidate regions detected in several frames, and extract the histogram of optical flow (HOF) from the fire-tube. However, because the extracted HOF feature vector has a considerably large size, the feature vector is reduced by applying a predefined bag of feature (BOF) and then applied to the fast random forest classifier to verify the final fire regions instead of heavy recurrent neural network (RNN). The proposed method has been experimentally shown a faster processing time and higher fire detection accuracy with lower missing and false alarm.

Introduction

As the building has become bigger and complex, the scale of damage increases when a fire breaks out. According to NAPA(National Fire Protection Association), damage from fires in the United States in 2017 was $23 billion, with 3,400 people losing their lives[1]. To reduce the damage caused by the fire, it is very importance to detect the fire at an early stage. Especially in the case of a shopping complex, if early stage fails in a fire breaks out, the extent of the damage is uncontrollable. For this, it is necessary to develop a system that can detect fire without human interference in the early stage.

Traditional fire detectors are mainly based on sensors that are based on temperature, gas, carbon monoxide and smoke. However, these sensor-based systems are not suitable for early fire detection because they generates a fire-warning alarm when a temperature, gas or smoke over a certain degree. In addition, sensor-based systems cannot confirm the detail information related to fire such as size, location, and spread direction.

To compensate for the aforementioned short point, we propose a fire detector using videos so that a person can immediately check the extent of the fire. When using a camera, it is easy to determine the scale of the fire from the camera video when a fire alarm occurs. However, fire detection in nighttime is more difficult than daytime because night fire has similar brightness and movement with street light or car headlight as shown in Figure 1. In this paper, we propose a two-step cascading algorithm for night fire detection based on deep neural network and random forest classifier considering spatio-temporal characteristics of fire.

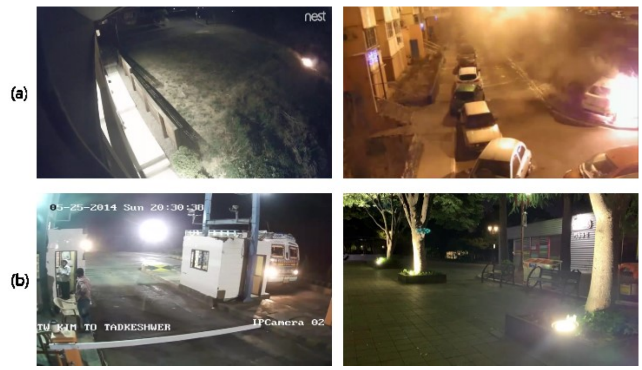

Figure 1. Examples of night fire flame and flame-like light, (a) fire with flame reflection fire flame on the floor, (b) flame-like street light and car headlight

Related Work

The early research of the fire detector based on CCD camera focused on traditional machine-learning. Chen et al.[2] proposed the early fire detection method using the strength and saturation of a red component in the RGB model in a continuous frame. Wang et al.[3] proposed a fire detection model based on the dispersion of the components of the fire HIS color model. However, color-based fire detection methods are generally susceptible to external interference factors such as light, background, and shadows.

Recently, convolutional neural network (CNN)-based fire detection research has been actively conducted. Zhang et al. [4] used full image CNN and local patch NN classifier and these classifiers share the same deep neural network (DNN) to detect forest fire. Muhammad et al. [5] proposed a fire detector based on CNN inspired by the SqueezeNet architecture. Hu et al. [6] proposed a fire detector based on long short term memory (LSTM). This method extracts the optical flow features based on the RGB color model to generate dynamic features. The LSTM network temporarily accumulates this feature vector to determine the fire. Although recurrent neural network (RNN) or LSTM are generally used to the fire detector in image sequence, it is not suitable for real-time system because they require a significant amount of memory resource and computational time. In addition, most of the fire detection studies proposed so far are aimed at the daytime environment. In daytime environments, fire flames have prominent colors, shapes, and movements, which can provide reliable results. However, in the night environment, the movement of the flame is relatively small, and it is difficult to distinguish from surrounding lights that have similar characteristics such as car headlights, street lights and neon signs. In particular, night fires can cause more life and property damage than day fires. Therefore we propose an algorithm that can

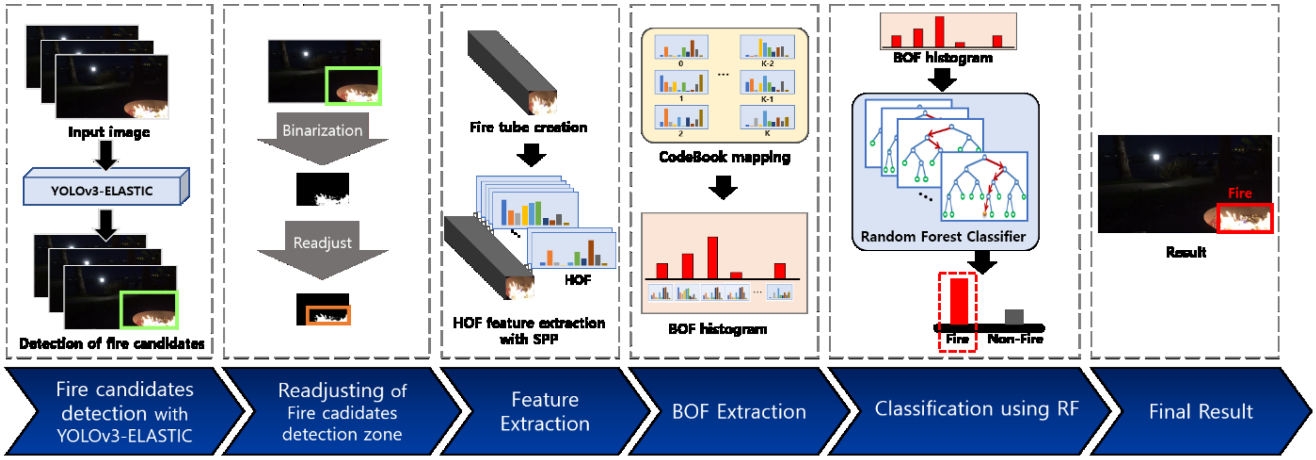

Figure 2. Overall procedure of the proposed fire detection method.

detect various fires occurring in the night environment by using two cascading steps consist of ELASTIC-YOLOv3 and random forest (RF) based on spatio-temporal features.

Proposed

The purpose of this paper is to design automatic fire detection system in the night environment using CCD camera. The fire spreads to the periphery in a short time in one place, and the outer edge of the fire has a continuous irregular movement. Therefore, we propose two-step cascading algorithm required to analyze the spatio-temporal features of fire and to construct a reliable fire detector. First, we detect the fire candidate regions using the CNN on the input image, and secondly, extract the features considering the dynamic change characteristics of the fire. Then the feature vectors are apply to the RF classifier to verify whether the candidate-region is fire. The proposed method has the advantages that the processing speed is very fast compared to the RNN and LSTM methods considering the dynamic characteristics of the fire, and it is possible to capture the fire dynamic movement for a long time.

Step 1 : Detection of fire candidate regions.

First, we use the YOLOv3 network [6] to quickly detect fire candidate regions. The existing YOLO [7] has a lower region accuracy than SSD[8] or Faster R-CNN[9] because there is no region proposal network, but has some advantage that it is very fast and can be operated on CPU. The most important factor in fire detection is the early-stage detection and the fire in early-stage are very small size. However, the detection performance of a small object in the case of YOLO is low. Recently, YOLOv3 has been proposed to improve this problem, but there is still a limit that has a relatively lower accuracy rate for smaller objects compared to larger ones. To improve the performance of the existing CNN based detection models, deeper and wider layers have been used, which increase the amount of computation and parameters required. Recently, the ELASTIC Block [10] was introduced to improve the detection performance of objects of various sizes by using down-sampling and up-sampling in the convolution layer while keeping the number of parameters similar to the computations that the existing CNN model has. Therefore, we propose the ELASTIC-YOLOv3 network by combining ELASTIC block with the existing YOLOV3 network to construct a network with high detection accuracy in fire region with small scales. We use ELASTIC-YOLOv3 to detect primary fire candidate areas for input images.

Step 2 : Verification of fire regions

In this step, the detected fire candidate regions are extracted with considering the dynamic motion change characteristics of the fire and then it combined with the RF classifier to verify the final fire region. First, because the scale of the fire candidate previously detected may be larger than the actual fire region, the fire candidate regions are readjusted by eliminating unnecessary regions through the binarization processing. Then we measure the amount of change in the fire's motion that occurs in 100 consecutive frames. To implement this, we generate the fire-tube by connecting fire candidate regions detected in N (100) frames, and extract the histogram of optical flow (HoF) from the fire-tubes between each frame. At this time, the scale of the candidate fire regions varies widely, so the spatial pyramid pooling (SPP) is applied to represent information about objects of various scales. We divide the region of a fire candidate tube into 1x1, 2x2 blocks, and then extracted the HoF feature vectors in each block. Because the extracted HOF vector exists for a total of N frames, the dimension of the feature vector becomes significantly large, and it is required a large processing cost and time. Therefore, we applied the extracted HOF feature vectors to the bag of feature (BoF)[11] to reduce the dimensions. The BoF feature vector is applied the RF classifier to verify the final fire region.

In the training process, we extract the HoF feature vectors from the fire-tube in the entire training image sequences. It performs grouping into K clusters through K-Means clustering and defines a code book using K visual features representing each cluster. The HoF feature vector extracted from the fire-tube is generated a fire and non-fire histogram with the K visual code defined above, and the BoF is constructed using it. Finally the RF classifier is trained using the collected with the BoF feature vectors.

In the test process, we extract the fire candidate regions from each continuously captured images using ELASTIC-YOLOv3 and then create fire-tubes for the fire candidate region of the successive N frames.

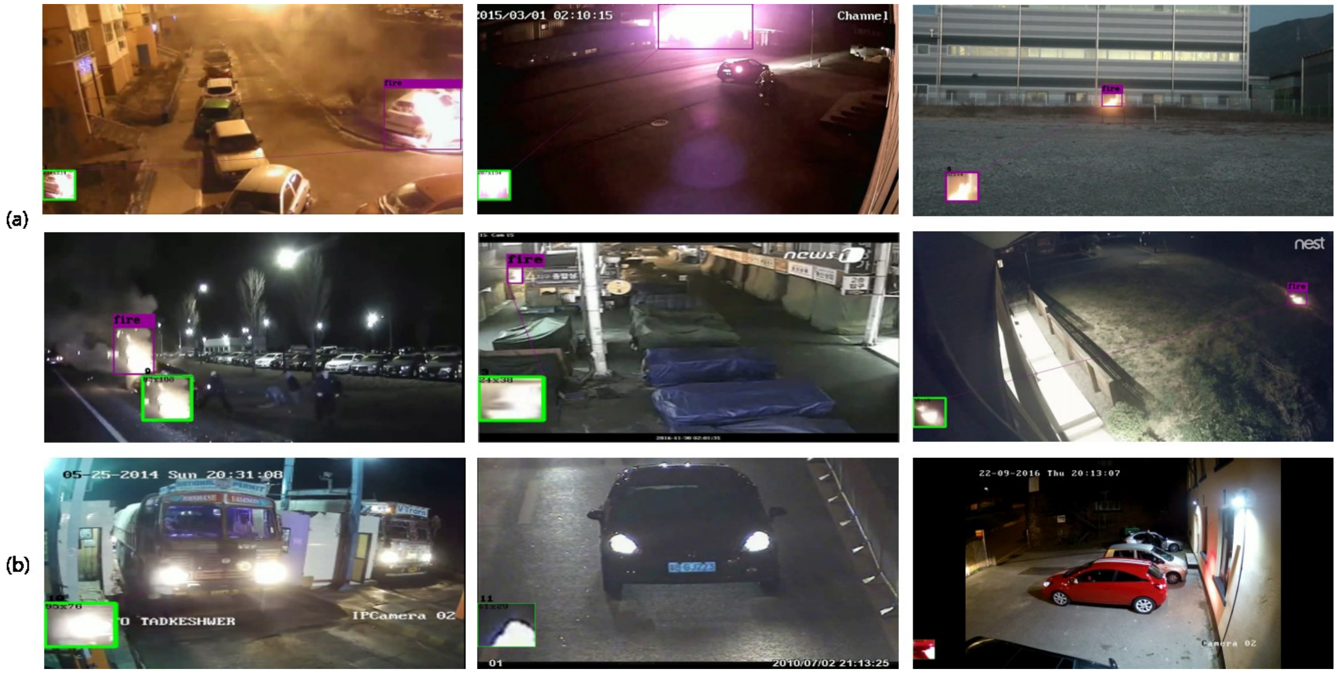

Figure 3. A fire detection results. (a) the fire images and (b) the non-fire images. The green boxes at the bottom of the image are the candidate fire region of the ELASTIC-YOLOv3, and the red boxes in image are verified final fires of the proposed method based on the Fire-Tube.

We configure the HoF feature in extracted fire tubes and then make the BoF feature vector using it. This feature vector is applied the RF classifier to verify the final fire region.

Experiments

To demonstrate the detection performance of proposed method in the night environment, night fire datasets were collected from installed surveillance camera and used in the experiment.

The first dataset consisting of still images including night fire scene. This dataset was collected from YouTube and consists of 4000 still images including fires from real night environments. Collected fire images include several types of fires from a variety of environments, including large factory warehouses, squares, and roads.

The second dataset consisting of continuous image sequences includes 20 real-time night fire videos and 14 non-fire videos collected from YouTube. The training data is composed of 10-night fire videos and 4 non-fire videos to train the RF classifier using fire-tube feature. The testing data comprises the 10-night fire videos and 10 non-fire videos to measure the performance for the proposed method with comparison methods. It includes a variety of fires in various environments, including roads, large factory warehouses, shopping malls, parks and gas stations in night environments. The non-fire video also includes vehicle headlights, street lights, and neon signs that resemble night fires.

In the experiments, we performed a comparative experiment with the proposed the Elastic-YOLOv3 with SSD[7] and Faster R-CNN[[8], which are used for object detection. At the same time, we evaluated the performance of using only Elastic-YOLOv3 and using Elastic-YOLOv3+RF-Firetube to prove the effectiveness of the proposed mehtod. As shown in Table 1, the proposed ELASTIC-YOLOv3 showed the best F1-score among the object detection methods such as SSDs, Fast R-CNN, and YOLOv3 with 97.42%. Specially, The ELASTIC-YOLOv3 showed better performance compared to the existing YOLOv3 while maintaining almost the same processing time. In addition, we confirmed that ELASTIC-YOLOv3 + RF-Firetube considering the spatio-temporal characteristics of night fire flame can distinguish fire-like background lights from real-fire flame efficiently with highest performance in terms of three measures.

Table 1. performance comparison for fire detection

	Precision (%)	Recall (%)	F1-score	ms/frame
SSD [8]	99.0	67.73	80.43	15ms
Faster R-CNN [9]	81.72	93.48	87.21	30ms
YOLOv3 [6]	97.96	77.11	86.29	7ms
ELASTIC-YOLOv3	97.29	97.54	97.42	10ms
Proposed method	98.7	96.35	97.5	14ms

Figure 3 shows the fire detection results in the fire and non-fire images, when the proposed method was used. In this figure, the green boxes at the bottom of the image are the detection results of candidate fire regions using the ELASTIC-YOLOv3 and the red boxes are final results of the proposed ELASTIC-YOLOv3+RF-Firetube method. As shown in the Figure 3 (b), the ELASTIC-YOLOv3 detected the headlights of the car as a fire, but this region was excluded from the fire region through the RF-Firetube.

Conclusion

In this paper, we proposed a two-stage cascading algorithm for camera-based night fire detection. In the first stage, we used the

ELASTIC-YOLOv3 that detects smaller fire regions better than YOLOv3. In the second stage, the fire regions connected to make the fire-tube. The Fire-tube considers spatio-temporal features and consists BOF histogram. Then Random forest classifier determines the Fire-tube whether it is fire.
The proposed method has been experimentally shown a faster processing time and higher fire detection accuracy with lower missing and false alarm because of considering spatiotemporal features although there is no significant difference in speed.

Acknowledgement

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