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Wildland Forest Fire Smoke Detection Based on Faster R-CNN using Synthetic Smoke Images

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Abstract

In this paper, Faster R-CNN was used to detect wildland forest fire smoke to avoid the complex manually feature extraction process in traditional video smoke detection methods. Synthetic smoke images are produced by inserting real smoke or simulative smoke into forest background to solve the lack of training data. The models trained by the two kinds of synthetic images respectively are tested in dataset consisting of real fire smoke images. The results show that simulative smoke is the better choice and the model is insensitive to thin smoke. It may be possible to further boost the performance by improving the synthetic process of forest fire smoke images or extending this solution to video sequences.

Keywords: video smoke detection; wildland forest fire smoke; faster R-CNN; deep learning; synthetic smoke image

1. Introduction

Wildland forest fires pose a serious threat to natural environment and public safety. The early detection of a forest fire is very important for an effective fighting, as once a forest fire reaches a certain size it can be hardly controlled. Compared with satellite monitoring, video fire detection systems build on ground can detect a forest fire more quickly.

According to detecting objects, video based fire detection methods can be classified into two categories: flame detection and smoke detection. Since the smoke produced by wildfires is visible before the flames, video smoke detection get more attention for early fire alarm in forest fire protection engineering. The traditional video smoke detection methods mainly focus on the combination of static and dynamic characteristics for smoke recognition. The typical characteristics of smoke contain color, texture, motion orientation, etc. Genovese et al. [1] studied smoke color characteristics in YUV space. Yuan [2] proposed a method using the LBP and the variance of the LBP (LBPV) to extract the texture feature of smoke. Toreyin [3] used spatial wavelet transform to monitor the translucency of smoke. Yu [4] used optical flow computation to calculate the motion features of smoke. Jia [5] proposed a saliency based method for early smoke detection in video sequences. The different approaches are able to get good performances in specific images dataset. However, due to the poor robustness of the algorithms, the performances tend to be worse in different images dataset and those approaches can hardly eliminate complex interference in actual engineering applications.

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In the past few years, artificial intelligence technology and computer vision technology have been expanding rapidly. Deep learning methods, especially Convolutional neural networks (CNNs) have achieved a state-of-the-art performance on the computer vision tasks, including image classification, object detection, pose estimation and sematic segmentation, etc. In contrast to traditional computer vision approaches, deep learning algorithms avoid hand-crafted design features and can learn complex representations from large amounts of images dataset. Therefore, it is reasonable to believe that CNNs can also promote the development of video smoke detection. Recently, researchers have tried to use CNNs for forest fire detection. Frizzi [6] proposed a convolutional neural network with nine layers for identifying fire or smoke in videos. Hohberg [7] trained a convolutional neural network for recognizing wildfire smoke. Zhang [8] proposed a model consisting of a full image CNN and local patch NN classifier for forest fire detection, both classifiers share the same deep neural networks. However, the frameworks proposed above focus on image classification and need sliding windows or region proposals to generate candidate blocks first. Faster R-CNN is a highly successful framework for generic object detection. We can use it to recognize and localize smoke in video sequences concurrently.

Meanwhile, the datasets previously used are still relatively small and monotonous. Available smoke images for training are obtained generally from Internet and experiments, which are limited in scale and diversity for training deep CNN model. Due to the lack of data, Labati et al. in [9] proposed to create smoke image sequences by generating smoke plume that is inserted into an image sequence without smoke. Our group provided the first attempt to apply the deep domain adaptation method using synthetic smoke images for video smoke detection [10]. Moreover, we made the codes and images dataset publicly available at http://smoke.ustc.edu.cn.

In this short paper, aim to verify the effectiveness of using the synthetic smoke images to train CNNs, we used two methods to synthesize a large number of forest smoke images. The first method is to extract real smoke from green background and insert it into the forest background. The second method is to generate synthetic smoke using rendering software and insert into the forest background as before.

2. Smoke Images

2.1. Real smoke + forest background

With the purpose of inserting smoke into forest background images, both the entire area and texture of smoke should be extracted from smoke images. The smoke areas extracted based on movement characteristic or brightness threshold are incomplete and biased. It is very difficult to determine these thresholds due to the change of smoke velocity and illumination of the environment. In order to extract the smoke accurately, we took smoke videos indoor with a green background, as shown in Fig. 1.

Fig. 1. Smoke frame with green background

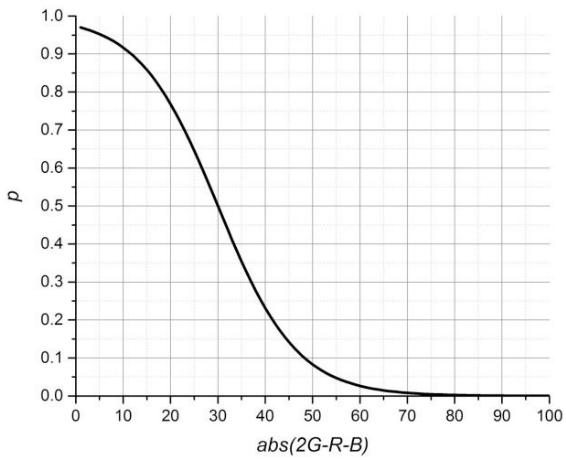


Fig. 2. Smoke frame with green background

The smoke produced by shrub burning is almost close to gray. It means that the R, G, B components of forest smoke are very close in RGB color space. With the use of green background, smoke area can be extract effectively. In the area without smoke, the G component is higher than the R and B components with about 30 ~ 40. In the area with smoke, the G component is gradually approaching the R and B components with the smoke concentration increasing.

2800 smoke frames were selected from 10 smoke videos with green background. Then smoke are extracted in two steps. Firstly, the probability of a pixel being smoke is calculated:

(1)

in which a=0.12， c=30, determined empirically. The curve of p is shown in Fig. 2.

Secondly, it will be very rigid if the smoke area in the green frame is pasted to the forest image directly. We used *Thickness* to indicate the smoke concentration of the pixel.

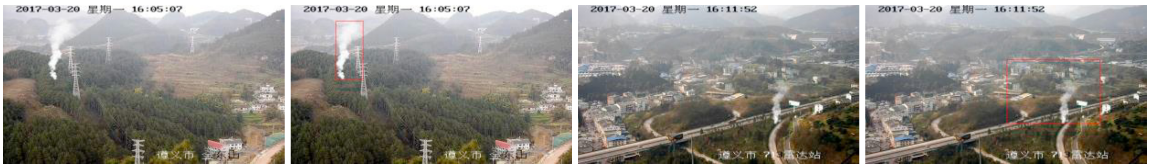
(2)

(a) (b) (c) (d)

Fig. 3. Smoke extraction process (a) original smoke frame, (b) result of p, (c) *Thickness,* and (d) p***Thickness*

Inserting smoke into forest background image is actually increasing the brightness of the pixels. The increase should be related to both the smoke concentration and brightness of the background. For example, smoke is not obvious in the bright sky. The smoke is inserted into forest background images using equation (3). In order to ensure the diversity of smoke images, 2800 smoke frames were used to extract smoke. The smoke was changed in shape freely and inserted into 12620 forest background images at random positions with deformation. Each synthetic forest smoke image contains only one plume of smoke and the location of smoke is given automatically in the inserting process. Fig. 4 shows same examples of forest smoke images produced with real smoke. It can be seen that the smoke is realistic and the red box locates the smoke.

(3)



(a) (b) (c) (d)

Fig. 4. Examples of forest smoke images (a) and (c) training images, (b) and (d) smoke locations

2.2. Simulative smoke + forest background

We build a synthesis pipeline to produce synthetic smoke images with green background as shown in Fig. 5. The smoke simulation software is Blender. Smoke is emitted into a domain from a particle system and smoke movement is controlled by airflow inside the domain. To increase the diversity, the initial flow, airflow, lighting and angle of view are set randomly. 1000 synthetic smoke pictures were obtained by simulation. Using the method in section 2.1, the synthetic smoke was inserted into the same 12620 forest background images. Examples of forest smoke images produced with synthetic smoke are shown in Fig. 5(c) and (d). It can be seen that the synthetic smoke in the forest smoke images is not realistic compared with real smoke as the boundary is clearer and texture is more smooth. And because the background of the synthetic smoke images are cleaner, the positions of the smoke indicated by red boxes are more accurate.

(a) (b) (c) (d)

Fig. 5. Synthetic smoke images (a) Blender window, (b)simulative smoke, (c)training image and (d) smoke location

2.3. Test images

To compare the effectiveness of the two methods, real smoke videos will be used for test. Fig. 6 shows some examples of test images.

(a) (b) (c) (d)

Fig. 6. Examples of test images, (a) video 1, (b) video 2, (c) video 3, (d) video 4

3. Training and Detection Using Faster R-CNN

Deep convolutional neural networks (CNNs) have dominated many tasks of computer vision recently. In object detection, region-based CNN detection methods are now the main paradigm. Faster R-CNN [11] can be simply regarded as the system consisting of regional proposal network and Fast Regions with Convolutional Neural Network Features (Fast R-CNN). Using faster R-CNN to detect smoke in forest have many advantages. There is no need to manually extract features. The original image is used as the whole network input without preprocessing or block segmentation. The processing speed is faster than the previous two generations. Fig. 7 shows the flowchart of forest smoke detection using faster R-CNN. When we use Faster R-CNN to detect smoke in the real scene, real forest smoke images obtained from real forest fire scene can be used to increase the richness of training data. In this work, the difference between synthetic smoke and real smoke used for training is focused. We train Faster R-CNN forest smoke detection models on both of the Real smoke + forest background dataset (RF dataset) and Simulative smoke + forest background dataset (SF dataset). The function model we selected is ZF net [12]. After training, we tested the trained forest smoke detection models on test images referred in section 2.3.

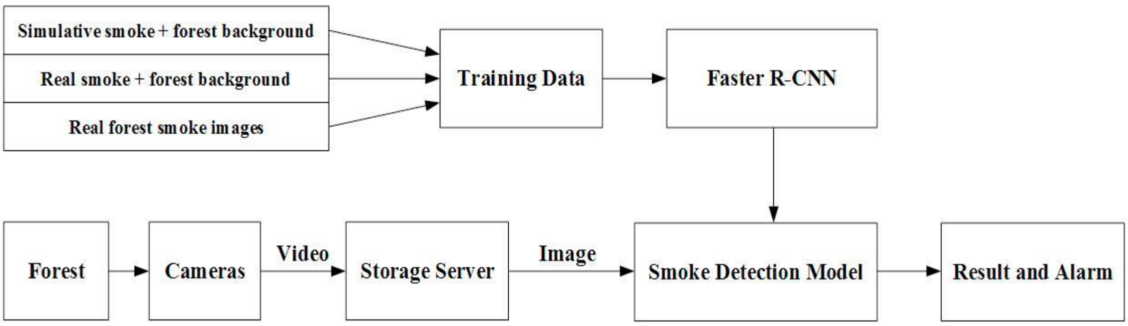


Fig. 7. Flowchart of forest smoke detection using faster R-CNN

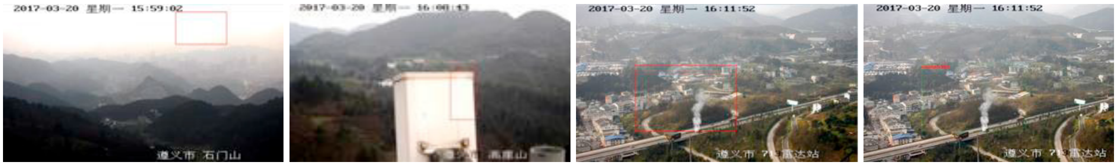
4. Test Results and Analysis

Firstly, the forest smoke detection models trained by RF dataset (Real Model) and trained by SF dataset (Synthetic Model) were cross tested, respectively. The results are shown in Table 1. Both the two models have very high detection rate on their own training dataset. Checking the Non smoke images in Real- Real classification results, we find almost all smoke are hiding in white background as shown in Fig. 8(a) and (b). Actually, both in the RF dataset and SF dataset, we can find about 30 images that have no smoke in appearance as smoke was inserted randomly. Discharge the interference of this factor, we focus on the number of False Non, which are really misclassified.

Table 1. Results of cross test between RF dataset and SF dataset

Model	Test_set	Samples	Smoke	Non	False Non	Detection Rate
Real	Real	12620	12582	38	8	99.94%
Real	Synthetic	12620	11793	827	797	93.67%
Synthetic	Real	12620	12554	66	36	99.71%
Synthetic	Synthetic	12620	12558	62	32	99.75%

Although the images in SF dataset are not visually realistic, the detection performance of Synthetic Model is better than Real Model as Real- Synthetic classification has 797 False Non. Because the background of real smoke image is more complicated, the location of smoke provided in the inserting algorithm is not exact sometimes. As a result, some identification boxes of the Real Model is too big, as shown in Fig. 8 (c) and (d).



(a) (b) (c) (d)

Fig. 8. (a) and (b) smoke hiding in with background, (c) provided box in RF dataset, (d) identification box of Real Model

Test results in real forest smoke images are shown in Table 2 and examples of the testing result are shown in Fig. 9. As each frame in test videos contains smoke, Non images in Table 2 are all misclassified. Results show that the model trained by synthetic forest smoke images is effective in real world. The detection performance of Synthetic Model is better than Real Model again. The detection rate of video 2 is low meaning that the model is insensitive to thin smoke duo to the lack of similar sample in training data. It can be solved by frame statistical algorithm and enrich the training dataset furtherly. Literature [13] proposed a novel smoke type classification concept which divide the visual appearance of smoke in four different categories. The concept of smoke classification is a great inspiration for the establishment of training dataset.

Table 2. Results of test in real forest smoke images

Model	Test set	Samples	Smoke	Non	Detection Rate
Real	video 1(Indoor)	182	180	2	98.90%
Synthetic	video 1(Indoor)	182	182	0	100.00%
Real	video 2	272	141	131	51.84%
Synthetic	video 2	272	154	118	56.62%
Real	video 3	163	120	43	73.62%
Synthetic	video 3	163	159	4	98.77%
Real	video 4	65	65	0	100.00%
Synthetic	video 4	65	65	0	100.00%

(a) (b) (c) (d)

Fig. 9. Examples of detecting result, (a) video 1, (b) video 2, (c)video 3, (d)video 4

5. Conclusion

In this paper, Faster R-CNN was used to detect smoke in forest. As available forest fire smoke images for training deep models are limited in scale and diversity, we produced synthetic forest smoke images by inserting two kinds of smoke, real smoke and simulative smoke, into forest background. The results of test by real forest smoke images prove the feasibility of this solution. It not only solves the problem of data lack, but also eliminates the work of sample labeling. For the two smoke generation methods, although the images produced by second method that inserting simulative smoke into forest background are not visually realistic, the performance is better. The possible reason is that the smoke location provided by second method is more accurate compared with the first method. It may be possible to further boost the performance by improving the synthetic process of forest smoke images or considering to extend this solution to video sequences.

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