Deep Convolutional Generative Adversarial Networks
Based Flame Detection in Video

Süleyman Aslan, Uğur Güdükbay
Department of Computer Engineering, Bilkent University
Ankara, Turkey
suleyman.aslan@bilkent.edu.tr, gudukbay@cs.bilkent.edu.tr

B. Uğur Töreyin *
Informatics Institute, Istanbul Technical University
Istanbul, Turkey
toreyin@itu.edu.tr

A. Enis Çetin †
Dept. of Electrical and Computer Eng., University of Illinois at Chicago
Chicago, IL, USA
aecyy@uic.edu

Abstract

Real-time flame detection is crucial in video based surveillance systems. We propose a vision-based method to detect flames using Deep Convolutional Generative Adversarial Neural Networks (DCGANs). Many existing supervised learning approaches using convolutional neural networks do not take temporal information into account and require substantial amount of labeled data. In order to have a robust representation of sequences with and without flame, we propose a two-stage training of a DCGAN exploiting spatio-temporal flame evolution. Our training framework includes the regular training of a DCGAN with real spatio-temporal images, namely, temporal slice images, and noise vectors, and training the discriminator separately using the temporal flame images without the generator. Experimental results show that the proposed method effectively detects flame in video with negligible false positive rates in real-time.

1. Introduction

Fires pose great danger in open and large spaces. Flames may spread fast and cause substantial damages to properties and human life. Hence, immediate and accurate flame detection plays instrumental role in fighting fires.

Among different approaches, the use of visible-range video captured by surveillance cameras are particularly convenient for fire detection, as they can be deployed and operated in a cost-effective manner [2]. One of the main challenges is to provide a robust vision based detection system with negligible false positive rates, while securing rapid response. If the flames are visible, this may be achieved by analyzing the motion and color clues of a video in wavelet domain [4], [19]. Similarly, wavelet based contour analysis [18] can be used for detection of possible smoke regions. Modeling various spatio-temporal features such as color and flickering, and dynamic texture analysis [5] have been shown to be able to detect fire, as well. In the literature, there are several computer vision algorithms for smoke and flame detection using wavelets, support vector machines, Markov models, region covariance, and co-difference matrices [3]. An important number of fire detection algorithms in the literature not only employ spatial information, but also use the temporal information [3], [10], [17].

Deep convolutional neural networks (DCNN) achieve superb recognition results on a wide range of computer vision problems [7], [14]. Deep neural network based fire detection algorithms using regular cameras have been developed by many researchers in recent years [9], [20], [8]. As opposed to earlier computer vision based fire detection algorithms, in all of the existing DCNN based methods, temp-
Temporal nature of flames are not utilized. Instead, flames are recognized from image frames. In this paper, we utilize the temporal behavior of flames to recognize uncontrolled fires. Uncontrolled flames flicker randomly. The bandwidth of spectrum of flame flicker can be as high as 10Hz [6]. To detect such behavior, we group the video frames and obtain temporal slice images. We process the temporal slices using deep convolutional networks.

Radford et al. [15] demonstrate that a class of convolutional neural networks, namely, Deep Convolutional Generative Adversarial Networks (DCGANs), can learn general image representations on various image datasets.

We propose a two-stage training approach for a DCGAN in such a way that the discriminator is utilized to distinguish ordinary image sequences without flame from those with flame. Our contribution is the development of a discriminator network classifying regular images from images with flame. We employ the discriminator network of the DCGAN as a classifier.

The remainder of the paper is organized as follows. In section 2, the proposed flame detection method is described. Experimental results are presented in Section 3. The paper is concluded in the last section.

2. Method

The proposed flame detection method is presented in this section. The method is based on grouping the video frames to obtain temporal slice images and processing the temporal slices using a DCGAN structure accepting input with size $64 \times 128 \times 384$ px. We use a densely-connected layer followed by five transposed convolutional layers for the generator, and five convolutional layers with a densely-connected layer for the discriminator. The architecture of DCGAN and the training framework are given in Figure 1.

We first train the DCGAN using images that contain flame and noise distribution $z$. The discriminator part of the DCGAN learns a representation for the temporal nature of flames and distinguishes non-flame videos, because those are not in the training set. Then, we refine and retrain the discriminator without generator network, where actual non-flame video images obtained from the cameras constitute the “generated” training data and regular flame images correspond to “real” data as usual. Compared to a generic CNN structure, training the DCGAN using the flame data, noise vector $z$, and the actual non-flame data makes the recognition system more robust.

In our model, for the training of the networks, we use batch normalization [12] and dropout [16] layers after each layer in the generator network, except the last layer. Similarly, for the discriminator network, apart from the last layer, we add Gaussian noise to the inputs and apply dropout after each layer. Convolution layers in the discriminator are initialized according to the “MSRA” initialization [11]. Finally, we use the Adam optimizer for stochastic optimization [13]. The representations of algorithms are supported by TensorFlow system [1].

2.1. Temporal Slice Images

Exploiting the evolution of flames in time, we obtain slice images from video frames. We first split the videos into blocks containing 64 consecutive frames with size $128 \times 128$ px. Then, for each column, we extract the pixels along the time dimension, resulting in 128 different
128×64 px images (see Figure 2).

In order to feed the slice image data to the DCGAN model, we stack all 128 slices on top of each other. Thus, we obtain an RGB image cube of shape $64 \times 128 \times 384$, because slice images have 3 channels each. Figure 3 shows an example of an image cube.

![Example of an image cube](image-cube.png)

Figure 3. Example of an image cube obtained from the input video.

### 2.2. Proposed GAN-type Discriminator Network

Flames, by their nature, has no particular shape or specific feature as human faces, cars, and so on. Therefore, it is more suitable to focus on the temporal behavior of flame instead of the spatial information.

The DCGAN structure is utilized to distinguish regular camera views from flame videos. The discriminator part of the GAN produces probability values above 0.5 for real temporal flame slices and below 0.5 for slices that do not contain flame, because non-flame slices are not in the initial training set. In the second stage of training, we refine and retrain the GAN using the gradient given in (2).

In standard GAN training, the discriminator $D$ which outputs a probability value is updated using the stochastic gradient

$$SG_1 = \nabla_{\theta_d} \frac{1}{M} \sum_{i=1}^{M} (\log D(x_i) + \log(1 - D(G(z_i)))),$$

where $x_i$ and $z_i$ are the $i$-th temporal slice and noise vector, respectively, and $G$ represents the generator which generates a "fake slice" according to the input noise vector $z_i$; the vector $\theta_d$ contains the parameters of the discriminator. After this stage, the generator network $G$ is “adversarially” trained, as in [7]. During the first round of training we do not include any flame-less video. This GAN is able to distinguish flame, because regular camera views are not in the training set. To increase the recognition accuracy, we perform a second round of training by fine-tuning the discriminator using the stochastic gradient

$$SG_2 = \nabla_{\theta_d} \frac{1}{L} \sum_{i=1}^{L} (\log D(x_i) + \log(1 - D(y_i))),$$

where $y_i$ represents the $i$-th image containing regular camera views. The number of non-flame slice samples, $L$, is smaller than the size of the initial training set, $M$, containing flame videos. In the refinement stage characterized by (2), we do not update the parameters of the generator network of GAN, because we do not need to generate any artificial images at this stage of training.
3. Experimental Results

In our experiments, we use 112 video clips containing flame frames, and 72 video clips without any flame frames. Flame videos contain various events, such as burning buildings, fire explosions, fireplaces, campfires, forest fires, and burning vehicles.

Throughout the experiments, we first obtain the temporal slice images for both flame and non-flame videos. For that purpose, at every second, we sample 10 previous frames at equal intervals, to be included in a block. Since blocks contain 64 frames, they capture the motion for almost six and a half seconds. Video clips are partitioned into non-overlapping temporal slices. Each video clip has a duration of one minute. Consequently, the dataset is composed of over 210 thousand slices from over 1600 blocks in total.

After this procedure, we split the data into training, validation, and test sets with a ratio of 3:1:1. We pick the parameters and stop training the network based on its performance on the validation set, then report the final results obtained on the test set.

We evaluate the proposed method, namely, DCGAN with Temporal Slices, in terms of frame-based results. Since all the other deep learning methods are essentially based on CNNs, we compare the CNN with Temporal Slices, DCGAN with Video Frames (no temporal information) and DCGAN without refinement stage based approaches to our CNN implementation. It should be also noted that, researchers use different fire datasets, therefore the recognition results are not comparable.

Our approach targets at reducing the false positive rate, while keeping the hit-rate, as high as possible. Results indicate that, our method achieves the best results on the test set (cf. Table 1), where a false-positive rate of 3.91% is obtained corresponding to a hit-rate of 92.19%. We show that the adversarial training in DCGAN structure yields more robust results when compared to a CNN (same architecture as the discriminator). As for the utilization of temporal slices to exploit flame evolution, it can be seen that, utilizing the temporal information of the flames results in much lower false positive rates.

Some examples for false negative and false positive temporal slices are presented in Figure 4.

4. Conclusion

We propose a fire detection method using DCGANs exploiting spatio-temporal evolution of flames. We develop a two-stage DCGAN training approach in order to classify flame and non-flame image sequences. Spatio-temporal dynamics of flames are acquired using temporal slice images obtained from consecutive frames.

Results suggest that the proposed method achieves low false alarm rates while keeping the detection rate high, as opposed to the other deep learning approaches.

References

[1] M. Abadi, P. Barham, J. Chen, Z. Chen, A. Davis, J. Dean, M. Devin, S. Ghemawat, G. Irving, M. Isard, et al. Tensorflow: a system for large-scale machine learning. In Proceedings of the 12th USENIX Conference on Operating Systems Design and Implementation, OSDI’16, pages 265–283, 2016.

[2] A. E. Çetin, K. Dimitropoulos, B. Gouverneur, N. Grammalidis, O. Günyay, Y. H. Habibolu, B. U. Töreyin, and S. Vertstockt. Video fire detection–review. Digital Signal Processing, 23(6):1827–1843, 2013.

[3] A. E. Çetin, B. Merci, O. Günyay, B. U. Töreyin, and S. Vertstockt, editors. Methods and Techniques for Fire Detection. Academic Press, Oxford, 2016.

[4] Y. Dedeoğlu, B. U. Töreyin, U. Güdükbay, and A. E. Çetin. Real-time fire and flame detection in video. In Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing, volume 2 of ICASSP’05, pages ii–669. IEEE, 2005.

[5] K. Dimitropoulos, P. Bampoulis, and N. Grammalidis. Spatio-temporal flame modeling and dynamic texture analysis for automatic video-based fire detection. IEEE Transactions on Circuits and Systems for Video Technology, 25(2):339–351, 2015.

[6] F. Erden, B. U. Töreyin, E. B. Soyer, I. Inac, O. Gunay, K. Kose, and A. E. Çetin. Wavelet based flickering flame detector using differential pir sensors. Fire Safety Journal, 53:13–18, 2012.

[7] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. Generative adversarial nets. In Advances in Neural Information Processing Systems, pages 2672–2680, 2014.

[8] O. Günyay and A. E.Çetin. Real-time dynamic texture recognition using random sampling and dimension reduction. In Image Processing (ICIP), 2015 IEEE International Conference on, pages 3087–3091. IEEE, 2015.

[9] O. Günyay, B. U. Töreyin, K. Kös, and A. E. Çetin. Entropy-functional-based online adaptive decision fusion framework with application to wildfire detection in video. IEEE Transactions on Image Processing, 21(5):2853–2865, May 2012.
[10] Y. H. Habiboğlu, O. Günay, and A. E. Çetin. Covariance matrix-based fire and flame detection method in video. *Machine Vision and Applications*, 23(6):1103–1113, Nov 2012.

[11] K. He, X. Zhang, S. Ren, and J. Sun. Delving deep into rectifiers: Surpassing human-level performance on ImageNet classification. In *Proceedings of the IEEE International Conference on Computer Vision*, ICCV’15, pages 1026–1034, 2015.

[12] S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *CoRR*, abs/1502.03167, 2015.

[13] D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. *CoRR*, abs/1412.6980, 2014.

[14] Y. LeCun, Y. Bengio, and G. Hinton. Deep learning. *Nature*, 521(7553):436–444, May 2015.

[15] A. Radford, L. Metz, and S. Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. *CoRR*, abs/1511.06434, 2015.

[16] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. *The Journal of Machine Learning Research*, 15(1):1929–1958, 2014.

[17] B. U. Toreyin and A. E. Cetin. Online detection of fire in video. In *Computer Vision and Pattern Recognition, 2007. CVPR’07. IEEE Conference on*, pages 1–5. IEEE, 2007.

[18] B. U. Toreyin, Y. Dedeoğlu, and A. E. Cetin. Contour based smoke detection in video using wavelets. In *Proceedings of the European Signal Processing Conference*, EUSIPCO 2006, 2006.

[19] B. U. Töreyin, Y. Dedeoğlu, U. Güdükbay, and A. E. Cetin. Computer vision based method for real-time fire and flame detection. *Pattern Recognition Letters*, 27(1):49–58, 2006.

[20] Y. Zhao, J. Ma, X. Li, and J. Zhang. Saliency detection and deep learning-based wildfire identification in UAV imagery. *Sensors*, 18(3):Article No. 712, 19 pages, 2012.