Accurate Fire Detection through Fully Convolutional Network

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Abstract

The devastating effects of wildland fires is an unsolved worldwide problem, resulting in human losses and the destruction of natural and economical resources. Assisting firefighters in controlling this kind of natural disasters is an important task. Nowadays, technology advances can help to fulfil this complex task. We propose a new convolutional neural network architecture able to detect fires in images, with high accuracy and high performance which enable the operation of the system in real-time. Preliminary results show that the proposed approach, called SFEwAN-SD, outperforms state-of-the-art approaches both in accuracy and processing time. This performance will be useful in the development of our UAV fire monitoring system that can detect and track fires in real-time.

1 Introduction

Forest and wildland fires represent a major risk in many countries in the world. Every year, more than 350 million hectares are affected by fires worldwide [29]. Forest fires cause environmental damage through deforestation, desertification and air pollution (CO2 emissions representing 20% of total emissions, recirculation of heavy metals and radionuclides). They also cause financial losses (wood loss, destruction of houses, buildings, public equipment, and firefighting equipment), and human losses.

For coping with this major risk, several fire detection systems can now be found aiming to efficiently manage, prevent, and fight forest and wildland fires. For this purpose, it is fundamental to acquire the knowledge of the phenomena involved in the start and propagation of fires, and to improve the understanding of the fire propagation models [19, 14, 17, 13, 20]. These models require the acquisition of the geometric characteristics of fire fronts, such as: height, position, inclination and rate of spread. These characteristics are also important for the estimation of the safety distance for firefighters [14] or to analyse the efficiency of different retardants on fire spread [26].

Despite the wide variety of existing work on fire detection, there is little work dealing with the measurement in the context of forest fires. In order to get useful measurements in the context of wildland fire, the analysis must be focused on fire research conducted outdoor. In this context, computer vision techniques are well suited for this purpose, as video cameras can cover a wide range of vision, and the gathered data can be properly processed to obtain the required fire characteristics. The first fundamental step in this context, is the automatic detection of fire present in images.

Several video-based fire detection algorithms can be found in the literature. Most of these algorithms focuses on colour and shape features, combined with the temporal behaviour of fire and smoke [27, 23, 3, 1, 16, 7, 4, 6]. Normally, these approaches follow two strategies: to build a rule-based algorithm, or to obtain a multi-dimensional feature vector that can be utilised for a machine learning algorithm: SVM, Neural Networks, etc.

We propose a new fire detection algorithm based on Convolutional Neural Networks (CNN), able to detect fires near real-time with high accuracy, but also avoiding the detection of false positives. The proposed detector will be part of a new Unmanned Autonomous Vehicle (UAV) detection system for monitoring wildfire, and estimating their location and spread.

This article is organised as follows. Section 2 is a brief review of the state-of-the-art on fire detection. Then, Section 3 describes the proposed convolutional neural network architecture. Next, Section 4 presents comparative results of our approach with recent solutions based on CNN. Finally, Section 5 presents our conclusions and future work.

2 Previous Work - Fire Detection in Images

In this section, fire detection techniques using video sequences are discussed. We focus the discussion in aspects related to the applicability of these techniques in the context of UAV automatic detection of fire, aiming at providing basic information for obtaining the geometrical features of the fire front.

The literature in fire detection using images and video sequences is becoming extensive [4, 7], including the utilisation of different ranges of the electromagnetic spectrum. In [27], the authors propose a multi-sensor approach fusing visible light spectrum with thermal images, and considering the movement of objects in the scene. Processing in the infrared spectrum is easier than in visible images, as the intensity of fire pixels is considerably higher in infrared [13]. However, hot gases can produce similar infrared responses, inducing detection errors [24].

The utilisation of movement information and colour features is a common element in most of the approaches, taking advantage of the distinctive colours of fire [1, 3, 11, 23, 28, 21] and its dynamic behaviour [18, 15, 5, 23]. In terms of exploiting the dynamic behaviour of fire, optical flow approaches are used to represent the movement of objects in the scene as a set of motion vectors [18, 15]. Optical flow can characterise the direction of the fire and other moving objects, and difference the fire from other moving objects because of its particular motion patterns. Nevertheless, the movement of an UAV during capture could disturb the detection of the fire. In [23] similar problems can be found for UAV as the authors consider an initial three-frame difference operation to determine regions of motion. Wavelet transform methods focus on the temporal behaviour of the fire and smoke, being able to characterise the chaotic behaviour of fire in a wide band frequency [5, 23]. Consequently, the stabilisation of the camera is essential for utilising methods considering motion information.

Other methods for fire detection use diverse techniques to represent the spatial variation of the fire, differentiating fire pixels from ordinary objects with similar colour [22, 9, 2, 8]. Among these techniques, works can be found using wavelets [22], local binary patterns [9], histogram analysis [2], and correlation descriptors [8], among others.

Finally, there is a wide range of approaches for pixel fire detection algorithms using machine learning [11, 6, 24]. In [11], the authors apply support vector machines (SVM) to pre-filtered regions of interest classified as fire. They use the SVM classifier for verification of the fire pixels. In [6], the authors train a Convolutional Neural Network from a segmented fire image, obtaining a neural classifier of fire pixels.

3 Fully Convolutional Network for Fire Detection

The proposed fire detection architecture is based on the AlexNet[12] Fully Convolutional Network (FCN). We name the proposed architecture as Simple Feature Extraction with FCN AlexNet, Single Deconvolution (SFEwAN-SD). The model is presented in Figure 1.

In the proposed architecture, two convolutional neural network models are integrated. The first model is an adaptation of AlexNet, aiming at characterising fire in terms of shape and texture. The second model is a sequence of convolutions, not reducing the dimensions of the input image, with the objective of extracting colour and texture features, applying convolution blocks of size 3×3. The benefit of integrating both models is that the adapted AlexNet branch has a strong capability for finding fire regions, but loses resolution, while the model of the second branch is adequate to detect fire, but tends to generate a significant number of false positives.

Each convolution layer is followed by a ReLU (Rectified-Linear Unit) layer, except the last convolution performed by the AlexNet branch (Conv 1.8), where the union of resulting channels from each branch is performed, in order to obtain a score map (grayscale image).

Considering as input an image of size 640×480, after the deconvolution phase, an image of size 671×511 is obtained. In order to ensure the right association between the resulting map and the input image, a Crop Layer is applied to the image obtained from the deconvolution, based on the input image size.

Finally, the partial results from each model branch (the adapted AlexNet and the colour/texture feature model) are joined by applying a simple sum operation, element to element. Note that both elements in the join operation are considered with the same weight.

It is also important to mention that the training process of this model has been performed considering a pre-trained AlexNet model(convolutionalised ILSVRC2012-trained Alexnet model).

4 Experiments and Results

In order to validate the SFEwAN-SD architecture, we have performed tests considering 50 images from benchmark database proposed in [25] for fire detection. We have also incorporated 10 negative images representing aerial views of elements that could be misclassified as fire. We have tested our approach against the model proposed by Frizzi *et al.* [6]. Both models were trained using the Caffe framework [10], considering 450 positive and 50 negative images. A computer with the following characteristics has been used: Ubuntu 16.04 x64 bits with Intel i5-6400 @ 2.7GHz x4 -DDR4 16GB - GTX 970 4GB MSI. The obtained results are summarised in Table 1. For the evaluation of results, two metrics were considered:

$$F1 - Score = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} \quad (1)$$

$$Accuracy = \frac{TP + TN}{2 \cdot TP + TN + FP + FN} \quad (2)$$

Figure 2 presents the ROC curve comparing the proposed SFEwAN-SD model and Frizzi *et al.* [6] approach. Figures 3 and 4 show the results per image, for the Accuracy and F1-score metrics.

In Figure 5, some important results can be observed. The images show that SFEwAN-SD performs a more complete detection of the fire region, while not generating false alarms in the case of pixels similar to fire in colour (e.g. sunset). The results show that the proposed approach outperforms Frizzi *et al.* [6] approach in every image, showing a great capability of detecting fire pixels, with low false alarm ratio. Also, the proposed model shows a significant improvement in computational

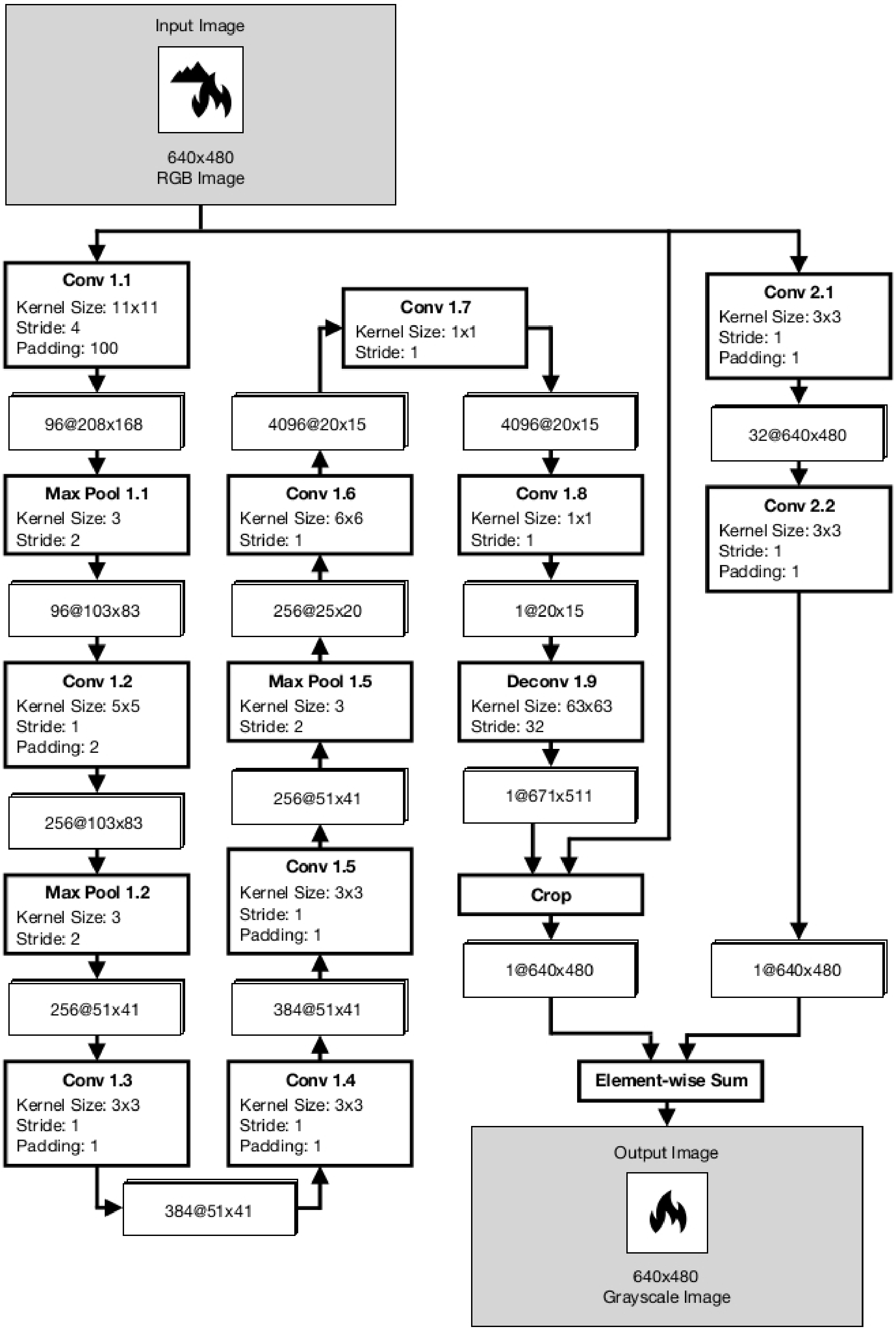

Figure 1. The proposed Convolutional Neural Network model.

Model	Accuracy	F1-score	Training		Inference	
			CPU	GPGPU	CPU	GPGPU
SFEwAN-SD	**94.76%**	**90.31%**	1d 9h	**30m 46s**	**2s 996ms**	**39ms**
Frizzi *et al.* [6]	86.96%	74.56%	**14h 4m**	1h	12m 59s	1m 7s

Table 1. Summary of results. Accuracy takes into account the mean value considering both positive and negative samples. F1-score considers the 50 positive samples. Also, the mean computational time in seconds for CPU and GPGPU versions is presented.

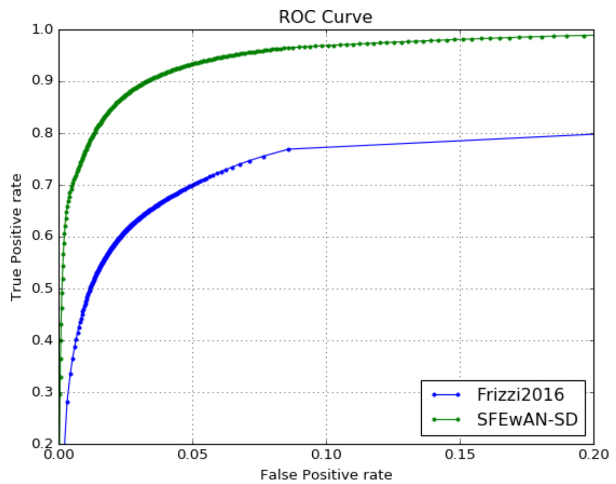

Figure 2. ROC curve comparing our approach with Frizzi *et al.* [6] approach.

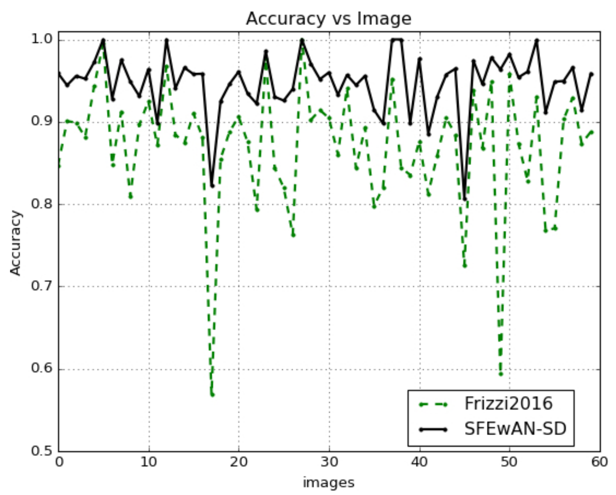

Figure 3. Accuracy for the 60 images considered in the experiment.

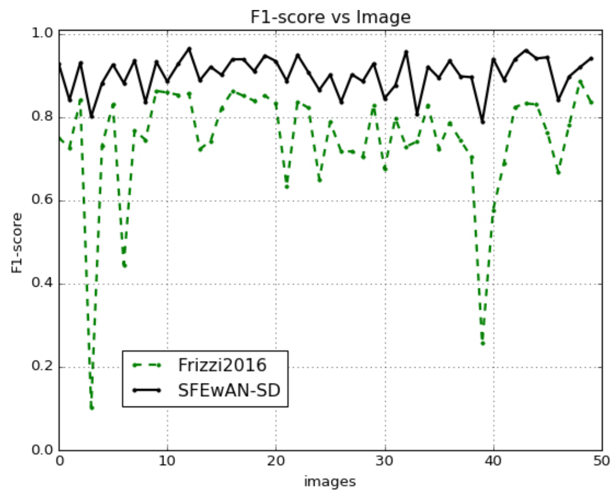

Figure 4. F1-score for the 50 positive samples considered in the experiment.

time, reaching detection speed that, even if not at frame rate, can be useful for real-time UAV performance.

5 Conclusion

We have presented a new FCN architecture, called SFEwAN-SD, able to accurately detect fire in images, with a computational time performance which makes our approach operational for detection using UAV.

Preliminary results outperform a previously proposed CNN model. Nevertheless, further validation is required, comparing the performance of the proposed approach with other techniques.

Future work includes tests with a larger image database, considering images from real UAV views. Also, the approach will be tested for detection of smoke, using similar techniques. The obtained results will lead to the generation of valuable ground-truth data that can be used to set a baseline for objective comparison of fire and smoke detection techniques. The fire detection results can be used to feed other algorithms considering temporal features. Finally, the integration of this information with multisensory data will permit to future UAV fire monitoring systems to properly calculate relevant characteristics of the fire front.

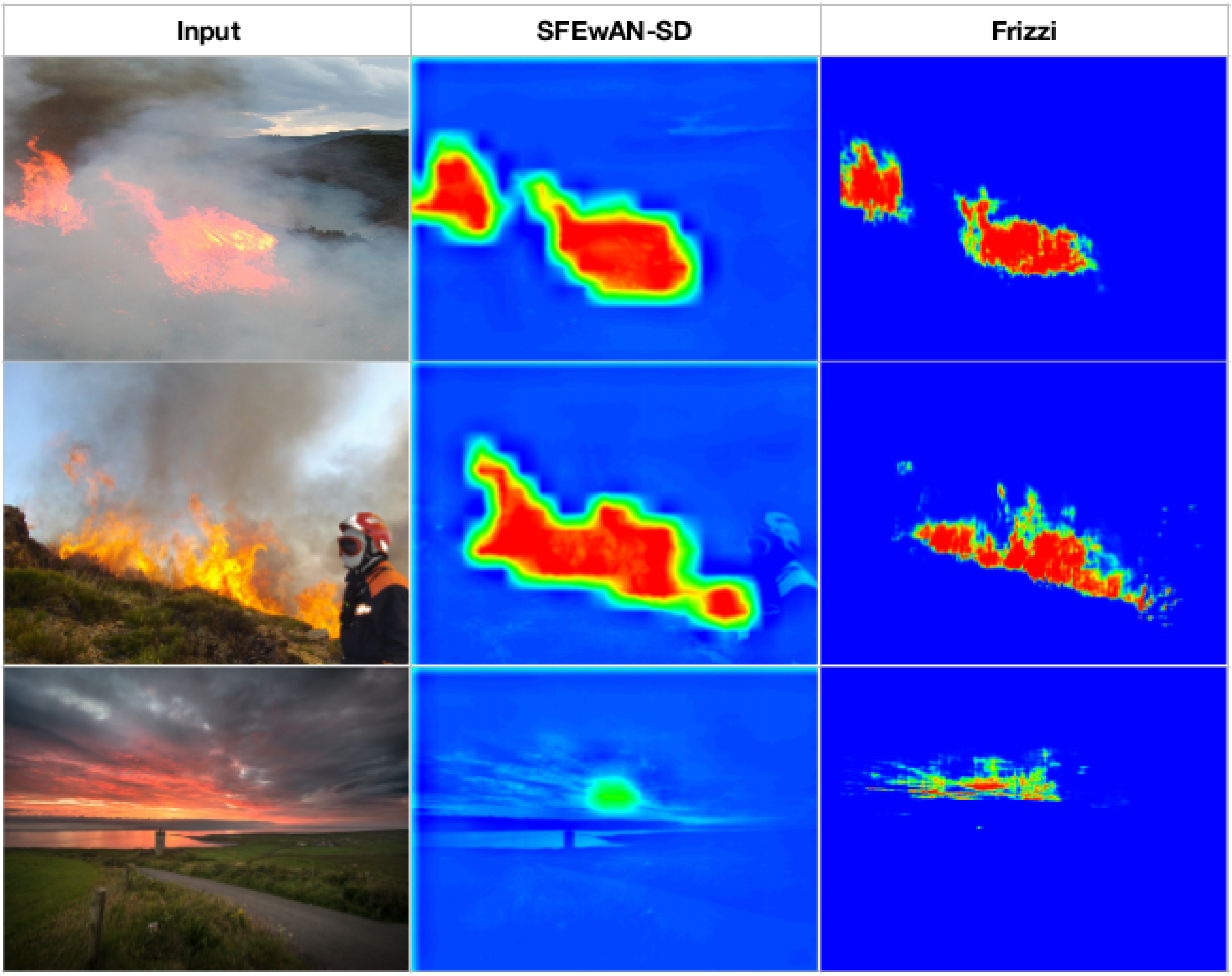

Figure 5. Results obtained for the evaluated approaches. The two first rows correspond to positive samples, while the third row correspond to a negative image.

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