

000 Fire and Smoke Detection using CNNs trained with Fully Supervised methods and Search by 001 Quad-Tree

003 Gonçalo Perrolas
004 goncalo.perrolas@tecnico.ulisboa.pt
005 Alexandre Bernardino
006 alex@isr.tecnico.ulisboa.pt
007 Ricardo Ribeiro
008 ribeiro@isr.tecnico.ulisboa.pt

Instituto de Sistemas e Robótica
Instituto Superior Técnico
Lisboa, Portugal

010 Abstract

012 Wildfires prevail as one of the most destructive and uncontrollable natural
013 disasters for man-kind. The fire-fighting combat team can greatly benefit
014 from reliable information about the current position of active burning
015 areas. It is also important to detect as early as possible the fire ignition
016 sources through the smoke columns produced.

017 In this work we use aerial images taken from drones of the wildfires
018 to detect fire and smoke using deep neural networks. A set of tests is
019 presented to evaluate the performance of the network used in the fire and
020 smoke detection. To solve the multi-scale detection problem we use a
021 Quad-Tree method in the search task.

022 The proposed system shows an adequate performance in real drone
023 aerial images.

024 1 Introduction

026 This article presents initial results of the Firefront Project (www.firefront.pt). Its main objective is to create a support system to the fire combat
027 teams. The system will transmit valuable information about the wildfire
028 in real-time to the ground teams using aerial vehicles to capture images of
029 the scene. Next, the images taken, are used to detect fire and smoke using
030 a convolution neural network able to segment the respective areas.

031 It comes as a challenge the detection of variable size portions of both
032 fire and smoke, and due to the small input size image that can be feed to
033 the common CNNs an extra algorithm was used for doing detection on
034 smaller image sections dynamically using a Quad-Tree search method.

036 1.1 State-of-the-Art

037 The problem of fire and smoke detection using RGB images has been
038 highly studied on the last few years, using different approaches and tech-
039 niques. Existing methods can be divided into two big groups: classic
040 methods and methods that use deep learning.

041 The classic methods tend to use the RGB components of images via
042 histogram analysis, to evaluate what colours are more related to fire ar-
043 eas. One example is the method used by Cruz *et al.* [1] that relies on in-
044 dexes based on RGB components to boost fire detection and then applies a
045 threshold to binarize the image into the classes. This process is very time
046 and computing power efficient but results in poor detection performances
047 and this method is very constrained to the environment conditions of the
048 images taken and the camera characteristics. The active system CICLOPE
049 that is operating in Portugal, developed by Batista *et al.* [2] uses a back-
050 ground subtraction method using fixed cameras to do smoke detection.
051 This technique makes use of the advantages of comparing consecutive
052 frames with the same background, showing a good performance but, as
053 we intend to use aerial vehicles to gather the images, a different method
054 must be used.

055 At the other side of the spectre, deep neural networks can be used in
056 this detection problem, as this area of investigation is evolving increas-
057 ingly year after year. The most common type of neural network used in
058 these types of problems is convolutional neural networks. These are able
059 to extract image information on an abstract level allowing to choose the
060 characteristics that better represent fire or smoke portions of the image.
061 Frizzi *et al.* [3] used a type of CNN using weak supervision training to
062 do fire and smoke segmentation. Training is a crucial stage while work-
ing with CNNs and requires a large set of images paired with the corre-
sponding labels for fire and smoke. The results shown proved that the
trained network was over-fitted to the data because of the small dataset

used, which is an important challenge due to the lack of fire and smoke
datasets available. There are a lot of CNN extensions, one of them being
the R-CNN. Barmoutis *et al.* [4] made use of this type of CNN and got
good results, it showed an efficiency way of detecting one instance of fire
with a bounding box. On that work it was used an interesting and com-
plete fire dataset called Corsican Fire Dataset [5] which was pretty useful
for the training of our networks.

025 2 Methodology

Firstly the system requires an aerial vehicle to capture the images from a
wildfire or the beginning of one. Then, two independent systems are used,
one in charge of fire segmentation and other for smoke segmentation. As
input to these systems we are going to feed small portions of the images
(patches) to be able to detect small or big areas of fire/smoke on those
images. The process of slicing the image into smaller patches it is going
to be done using a Quad-Tree methodology. An overall diagram of the
complete system and the corresponding results are shown in Figure 1.

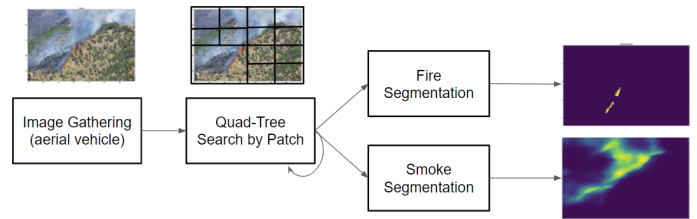


Figure 1: Global Diagram of the system.

2.1 Search by Quad-Tree

Quad-Tree methods are often used to partition a two-dimensional space
by recursively subdividing it into four quadrants or regions. This is useful
for doing a dynamic search for fire or smoke occurrences on the images,
starting first with larger scale patches and, if nothing is detected, then
moving on to smaller patches by slicing the previous ones in four seg-
ments. By using this method we solve the issues related to the multi-scale
nature of fire/smoke, areas, in large patches are difficult to be detected
by the neural networks (small input size) and patches that are almost
filled completely with fire or smoke can have dubious detection results
due to the lack of more external features that define the phenomenon.

2.2 Patch Processing (Classification + Segmentation)

The detection system is composed of two different neural networks, one
for classification and other for segmentation. The classification network
chosen was a SqueezeNet model [6] due to its level of accuracy compared
to state-of-art models like Alex-Net while having a lot fewer parameters
making the model more suitable for smaller datasets. For segmentation
we used U-net [7], one of the most used state-of-the-art models for se-
mantic segmentation.

By using a classification stage before doing segmentation the over-
all performance is increased due to the fact that it is easier to create a
more complete dataset with image level labels than with pixel level. This
reduced the number of false detection on the segmentation.

The overall logic of the system can be explained as following: each
patch of the image produced by the Quad-Tree stage is given as input to

