Semantic Segmentation of Jet Fire Temperature Zones using Deep Learning

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Abstract

Wildfires have been on the rise during the past five years. For this reason, the management of wildfires has become critical for the future. This paper shows the comparison between a Deep Learning model and other image processing methods for segmenting infrared images of fire into three zones delimited by temperature. The goal of the test results presented in this paper, and the subsequent tests that will follow it, is to provide insight into the usage of Deep Learning for this new and specific segmentation task. We will ultimately use the knowledge obtained from the tests while building a wildfire detection system that will provide fire engineers with important information for the management of forest fires.

1 Introduction

1.1 Motivation

During the past five years, there has been an increase in both the occurrence and severity of wildfires. There is a trend for the number of fire incidences to keep on rising on a worldwide scale; during 2019, there were over 4.5 million fires larger than one square kilometer. T he latter represents 400,000 more fires than the ones in 2018 [1]. Given the previously mentioned motivation, we are developing a project to create an Internet of Things and Artificial Intelligence-based system for the detection of wildfires. The said project is to be implemented in a local forest. One task that the system must be able to perform is the segmentation of infrared images of fire into three zones delimited by temperature: the Blue Zone, Middle Zone, and Front Zone illustrated in Figure 1. Efficient and accurate identification of these areas of interest within the fire is relevant since they define the temperature curve within the flames, which can then be employed by experts for the prediction of wildfire propagation.

1.2 Research problem

Image semantic segmentation is a problem that has been addressed in the past using different traditional computer vision and machine learning techniques. However, Deep Learning (DL) architectures, such as Convolutional Neural Networks (CNNs), have been surpassing other approaches recently by

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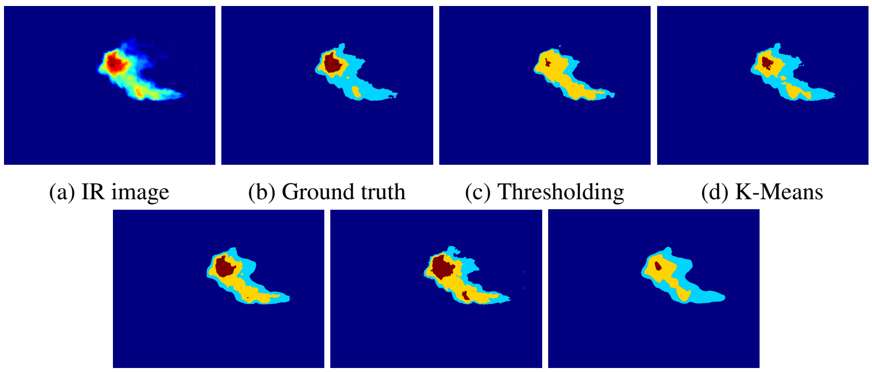
Table 1: Results for the five evaluated methods.

Metric	Hausdorff	Jaccard	Time (s)
Thresholding	1055.1144	0.9227	30.68
K-Means	981.8209	0.9180	3035.148
Chan-Vese	1053.8230	0.9162	18177.50
GMM	1253.0706	0.9218	2723.80
DeepLab	1632.5507	0.8836	568



(a) IR image (b) Ground truth (c) Thresholding (d) K-Means

(e) Chan-Vese (f) GMM (g) DeepLab

Figure 1: Sample resulting images for the different methods. Blue Zone is blue, Middle Zone is yellow and Front Zone is red.

a large margin in terms of accuracy and sometimes efficiency [2]. The use of DL in fire-related applications has been mainly focused on the detection of fire instances [3] [4] [5] and the segmentation of regions with the presence of flames [6] [7] [8].

The extraction of fire's geometric characteristics with DL is an application yet to be explored and, in consequence, presents a lack of information about their performance for these tasks. Given that area of opportunity, this project presents promising results of an initial test that uses a CNNs for the semantic segmentation of temperature zones within fire flames.

2 Technical contribution

2.1 Preliminary results

We carried out a starting test to explore the process of training the DeepLab [9] CNN model. The model used is pre-trained on PASCAL VOC 2012 and has an Xception 65 model as backbone for feature extraction. The training finished in 3000 steps, with a softmax cross-entropy loss function and a batch size of 4. The computer that we used has an Intel Core i7-4710 processor and an Nvidia GeForce GTX 860M graphics card. The data used for the test is from a data set of jet fire images provided by Universitat Politécnica de Catalunya. The data sample has 201 infrared jet fire images, along with their respective temperature zones, manually segmented by experts to serve as ground truth.

To evaluate the resulting segmentation, we used the metrics of Jaccard Index, also known as Intersection Over Union (IoU), where a value closer to 1 is better, and the Hausdorff distance, where a smaller value is better. We implemented four image processing methods and compared their results against the DeepLab model. The four implemented methods are thresholding, K-Means segmentation, the Chan-Vese algorithm, and the Gaussian Mixture Model (GMM). Table 1 shows the average results for the five methods across the whole data sample, as well as the time each method took to generate all 201 segmentation masks. We present a visualization of the results for each method in Figure 1.

3 Discussion and future work

The results show good performance in the Jaccard Index, more than in the Hausdorff distance, with the image processing methods showing better results than the DeepLab model; however, it is relevant to note that the accuracy of Convolutional Neural Networks is highly dependant on the amount of labeled data available. With the small quantity of 201 images, the results given by the DeepLab model show an impressive potential for the segmentation of the desired temperature zones. We will conduct further tests aiming to improve on these results, with a focus on finding the best feature extraction model and loss function for this problem, performing hyperparameter optimization, and enlarging the dataset with data augmentation. Based on these initial results, the following tests are bound to show propitious outcomes that could later surpass the results of the analyzed image processing methods.

Broader Impact

This test is the initial step for a larger comparison between the image processing methods mentioned here and other CNNs besides DeepLab. The comparison aims to find the best model for the semantic segmentation of fire's temperature zones and to give insight into the performance of CNNs for this kind of segmentation task.

The knowledge obtained from this comparison will then be applied while building a wildfire analysis and detection system that aims to give fire engineers the necessary tools for an efficient management of wildfires. With this system in operation, the damages caused by forest fires can be diminished and further help the environment, as well as the resident's health, housing, and resources.

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