Deep Learning model for wildfire detection through the fusion of visible and infrared information

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Abstract

Early wildfire detection is of vital importance to prevent the damage caused by wildfires to both the environment and human beings. We propose a Deep Learning (DL) model that leverages the information fusion of visible and infrared images for accurate wildfire detection in controlled datasets; we expect the said model to display a lower rate of false-positives in comparison with current techniques. To this end, it is necessary to first investigate, analyze, and test existing early wildfire detection and image fusion methods. Additionally, we will create a dataset comprised of fused visible-infrared images. In the present paper, we introduce the proposed approach and preliminary results regarding the evaluation of two state-of-the-art image fusion techniques on the Corsican Fire Database, as well as advances towards the fused image dataset generation.

1 Introduction

1.1 Motivation

Wildfires can occur naturally or due to human activities and have the potential to get out of control and have a significant impact on the environment, properties, and lives. Recently, there have been several wildfires of significant proportions worldwide, such as the Australian wildfires of 2019 and 2020. CNN reported that the said fires took the lives of at least 28 people [1]. Another more recent example is the ongoing wildfire season in California in the US. According to the BBC, as of September 17, 2020, 6.7 million acres have burned and more than 30 people have died [2]. Early wildfire detection is one of the most relevant aspects to be considered to avoid as much damage as possible.

1.2 Research problem

Currently, there are three main categories of forest fire remote detection techniques: ground-based systems, aerial vehicle-based systems, and satellite-based systems. Unfortunately, these techniques present several disadvantages; in contrast, UAVs with computer vision-based sensing systems provide a flexible, low-cost alternative [3]. Nevertheless, current UAV and computer vision methods display several problems for fire detection, with the false-positive rate being one of the most significant.

The particular problem that the present project aims to solve is forest fire detection in controlled datasets through a DL model through the usage of visible and infrared information. The said model is expected to yield a lower false-positive rate than existing techniques. One essential step towards the achievement of the proposed system is the generation of fused fire images. To this end, we explore state-of-the-art image fusion techniques for the particular task of fire image fusion. In the present paper, we present the proposed pipeline for the said DL-based fire detection system and preliminary results of the evaluation of two image fusion techniques.

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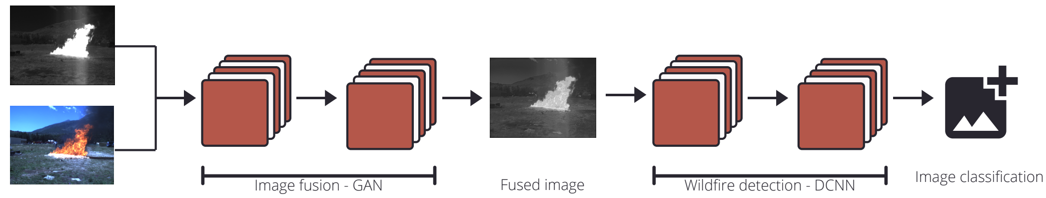

Figure 1: Pipeline for the proposed system, from the image fusion phase to the wildfire detection state. The sample fused image was generated with the method by Ma et al. [4].

Table 1: Results for the two evaluated methods.

Metric	VGG19	FusionGAN
EN	6.341551	6.007289
CC infrared - fused	0.797674	0.965768
CC visible - fused	0.763721	0.410448
PSNR infrared - fused	19.201477	22.509020
PSNR visible - fused	19.225560	15.390010
SSIM infrared - fused	0.833715	0.838937
SSIM visible - fused	0.900734	0.778314

2 Technical contribution

2.1 System architecture

Figure 1 displays the pipeline for the proposed system, from the fused image generation from a visible-infrared image pair, potentially through a Generative Adversarial Network (GAN), to the final detection of a fire with a Deep Convolutional Neural Network (DCNN).

2.2 Preliminary results

Currently, we are in the process of selecting and adapting an image fusion technique for the particular application of fire image fusion. We have implemented the method proposed by Li et al. in [5], the work presented by Ma et al. in [4], and are in the process of implementing the model proposed by Zhao et al. in [6]. The works by Li et al. and Ma et al. are available as Github repositories [7, 8]. We evaluated them by generating fused images from the 640 visible-infrared image pairs present in the Corsican Fire Database by Toulouse et al. [9] and measure their performance through the following metrics: image entropy (EN), correlation coefficient (CC), peak signal-to-noise ratio (PSNR), and structural similarity index measure (SSIM). In Table 1, we present the average results from applying the methods by Li et al. [5] in the $VGG19$ column and Ma et al. [4] in the $FusionGAN$ column.

3 Discussion and future work

Both methods perform reasonably well across all metrics except for the PSNR metric. It is relevant to note that, in the case of the method by Ma et al. [4], the model was pre-trained in the TNO and directly tested on the fire images. We will train the model by Zhao et al. [6] in the RGB-NIR dataset, and then also evaluate it directly with the fire images. The latter will be a relevant analysis of how well these models can generalize to different domains. Finally, the best performing of the three will be selected and subjected to a transfer learning phase to further optimize it for fire images, generating the final fused image . In the next steps, we will employ the said to train the to-be-implemented DL model for fire detection. The most relevant previous work in this regard, given the scope and objectives of the project, is the one proposed by Zhao et al. in [10]. We will take its architecture as a launching pad to further optimize and adapt it to incorporate the generated fused information.

Broader Impact

The goal of this project is to develop a DL model that can perform accurate and consistent wildfire detection, displaying better performance than the current state-of-the-art. It is relevant to note that the proposed model will be further constructed for its future implementation in operative scenarios.

The said implementation presents a risk: if the system fails to detect an existing fire, it could lead to the fire extending and potentially causing damage. On the other hand, if the system outputs a false positive detection, it could lead to a misplaced deployment of resources such as additional surveillance systems or even firefighters.

However, if successful, the benefits stemming from this project could be three-fold: for the computer vision community through the evaluation, optimization, and adaption of both image fusion techniques and the open-source release of the system for wildfire detection, the fire research community through the analysis of the relevance of image fusion for fire identification, and to the firefighting forces, through its implementation in operative scenarios and successful detection of wildfires.

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