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Computer vision for wildfire research: An evolving image dataset for processing and analysis

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ABSTRACT

The last decade has witnessed the use of computer vision for wildfire detection and measurement. The first and most important step for computer vision analysis is the fire pixel detection because it determines the accuracy of the following processing. The evaluation and the comparison of the wildfire detection algorithms of the literature and the development of new ones needs open datasets with a large number of annotated images and their ground truth. We address this issue by presenting a publicly evolving wildfire annotated image database with ground truth data with examples of use. Currently, it contains 500 visible images and, in a more limited number, multimodal images and videos with frame by frame annotations. This is currently the largest dataset released in this research field.

1. Introduction

Wildfires are among the major risks to humans and wildlife around the world [1–4]. Thus, efficient fire detection and behavior anticipation systems play an important role in the reduction of destruction caused by fires. The last decade has witnessed the use of computer vision for efficient fire detection [5–7], early fire suppression [8–10], fire measurement, and fire behavior analysis and prediction [11–13]. The first and most important step for computer vision analysis is the fire pixel detection because it determines the accuracy of the following processing.

Fire emits radiations in a large spectral band ($[0.4; 14]$ μm). The visible domain ($[0.4; 0.7]$ μm) is the reference domain used in wildland fire research because of the operational simplicity of visible cameras, their very affordable price, and the large quantity of published work using this spectrum. Fire pixel detection on color images is a challenging task because the images are highly affected by the environmental and physical conditions. The main difficulties encountered by the detection methods are due to fire color and the presence of smoke. Indeed, the color can be inhomogeneous (varying from yellow to red color), can have different luminance (depending on the background and the luminosity), and the smoke can mask the fire areas. Several fire detection algorithms working with color images are proposed in the literature [14]. A first category of methods uses color rules. The most commonly used color system is RGB [15–20]. Other systems are also exploited. Among these systems are those permitting the extraction of luminance-chrominance components, such as YCbCr [21–23], YUV [24] and $L^*a^*b^*$ [25]. There are also works using so-called cylindrical systems such as TSI [26] and TSV [27]. Finally, some algorithms use combinations of different color spaces [28,29]. A second category of pixel fire detection algorithms uses machine learning [17,19,21,29,30]. These detections need to learn from a dataset containing fire pixels and non fire pixels obtained from a sampling of the test image database. In this case, it is important to have a database including a large number of heterogeneous fire color images. To complete this part, several fire detection algorithms use motion analysis [22] to consider or delete fire pixel candidates selected using color criteria. Three works present the comparison of the performances of fire pixel detection algorithms on datasets of wildfire images [17,23,31]. In Refs. [17,23], the images used to benchmark the methods are mainly from two web databases (ForestryImages.org [32] and WildlandFire.com [33]). As there is no a public ground truth (fire contour area obtained manually) associated with each image in these databases, it is impossible to evaluate independently the metrics and the algorithms used in these works. Moreover, the number of different wildfire images of these databases is insufficient to obtain a wildfire pixel representative learning dataset.

Infrared images are easier to process than visible images because the

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intensity of the fire pixels is much higher than the one of the other pixels [11]. The approach to detect the fire zones in an infrared image is to find the threshold that differentiates the pixels belonging to the fire to those of the background. Several threshold search algorithms that can be applied to the detection of fire pixels are proposed in the literature [5,34–36]. The difficulty to consider infrared images is that areas similar to those of fire corresponding to hot gases can also be present in the images and consequently can produce a difference between the fire areas appearing in the visible domain and those of the infrared domain. Works developed by Rossi et al. [37] show that the near infrared domain ($[0.75; 0.9]$ μm) produces wildfire areas that are very similar to the ones obtained in the visible domain. Tacking into account the fact that it is easier to detect fire pixel in infrared images but that the visible images remains the reference, new fire pixel detection algorithms could be develop by using image fusion [38].

The development of the research on wildland fire pixel detection algorithms needs a publicly available database containing a large number of images of wildfire, showing various dominant fire color, conditions of smoke, environments, background, luminosity characteristics, other similar to fire color elements (cars or firefighters for example), and ground truth data. Thus, it is important to be able to evaluate the robustness of a criterion of pixel detection or of an overall method according to isolated parameters like the dominant color or the texture of the fire, the presence and the type of smoke, the background luminosity or the presence of objects that can produce error detections. Similarly, the comparison of the performances of different algorithms must be done considering common criteria and publicly ground truth. Finally, in order to develop new algorithms based on image fusion and pixels movements, multi-modal images and sequences of wildfire have to be also present in this database. In this sense, the present work aims to bring a public test database called Corsican Fire Database (CFDB) and presents its use. The dataset consists of 500 visible images of wildfire collected worldwide, 100 multi-modal (visible and near infrared) images, and 5 sequences of about 30 multi-modal images of outdoor experimental fires captured by the authors. Each image is associated with a black and white (binary) ground-truth image, annotations and descriptors. This database is an evolving one, as its content increases with the images that are deposited online.

The paper is organized as follows. Section 2 gives information about publicly fire image datasets. Section 2.1 informs about the origin of the visible images of the Corsican Fire Database, their selection and the acquisition protocol of the multi-modal fire images and sequences. Section 2.2 presents the scheme of the manual annotation of the full collection of the database and the descriptors obtained by using image processing. Section 2.3 describes the handling of the new database. The way by which the data associated to the images are made available is described. Information is also given concerning how users of the database can create their own test subset selections for their specific research purposes. Finally, the conclusion appears in Section 4 with a summary of the main characteristics of this database and the prospects for its future extensions.

2. Wildland fire image dataset

Our research has shown that there was no large public database for wildland fire images. The vast majority of the research uses Internet collected images [32,33] or in house developed datasets of fire images non-available publically. This makes it very difficult to benchmark the different algorithms developed for the study of forest fires. A recent work by Bedo et al. [39] permitted the development of a Flickr-based Fire database. It contains about two thousand pictures; half of them have fire flames in different environments (vegetation, urban, car, etc.). These images were taken from Flickr (a web site for picture and video sharing). The database is under the Creative Commons license that guarantees free public use. Each image has been annotated manually as "fire" or "non fire" by seven human experts but no specific information about the fire pixels areas is given.

Another database is Dyntex [40]. This database is very well organized and its contents properly characterized. It offers a collection of six hundred and fifty high quality dynamic video texture sequences. The sequences contain images of size 720×576, with a frame rate of 25 images per second, and a duration of at least ten seconds. Each sequence comes with general information (name, date, place, etc.), information about acquisition conditions (camera settings, indoor or outdoor) as well as information about the image texture properties in the sequence (dynamic and spatial properties). However, this database does not contain wildland fires.

Considering what was interesting in the cited datasets and what was to improve, the Corsican Fire Database was developed. It contains images captured in the visible and near infrared spectrum, video sequences, annotation and details about the image characteristics, the environment, etc. Additionally it was built to be an evolving database ready for outside contributions.

2.1. Origin of the images

In order to build the database, a call for wildland fire images was made and more than 2000 images captured on the visible spectra were collected from partners and researchers. These images came from different parts of the world, have different formats and were acquired from cameras with different parameters. 500 images were selected in this set in order to have heterogeneous fire colors and textures, environments, light conditions and vegetation. For each image, a ground truth was built with a manual segmentation of the fire in the image by an expert. This part of the database was used in Ref. [30].

The database also contains 100 multi-modal fire images and 5 multi-modal sequences of fire in propagation. The multi-modal images were obtained using the JAI AD-080GE camera. This prism based 2-CCD multi-spectral camera acquires simultaneously an image in the visible spectra and an image in the near infrared (NIR) spectra (700 nm - 900 nm) through the same optic. An example of visible and near infrared images taken simultaneously is shown in Fig. 1 (a) and (b). The multi-modal images obtained directly from the JAI AD-080GE camera are not aligned due to the fact that the visible and NIR sensors are not exactly co-aligned. An image registration based on homography matrix transform computation was done in order to align multi-modal images that are available in the database. The camera shutter time was chosen according to the environment luminosity and the focal length was set to 6 mm. The sequences were kept with a frame rate of 1 fps. Images of both spectrum have a size of 1024×768 pixels.

All the images of the database are in a lossless png format.

2.2. Image descriptors

Each image of the database is annotated using several descriptors. Some of them were annotated manually and others automatically using an image processing procedure. The descriptors are divided into two main categories, *global descriptors* and *fire and environment descriptors*. The annotations have two purposes: (i) they can assist users in retrieving particular properties; for example, fires with a particular Color or Texture and (ii) it allows the user to quickly tailor test sets for specific research purposes; for example, to test or develop detection algorithms for specific fire conditions. A number of tools to assist in this selection process are described in Section 5. Some descriptors are missing if this information was not given by the image owner.

2.2.1. Global descriptors

The global descriptors give general information on the image. They are listed and described in Table 1. They are separated in two sub-groups, *General information* and *acquisition settings*.

The *General information* are administrative descriptors such as a unique identifier, the sequence number and the image number in the