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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

(a) (b) (c)

Fig. 1. Example of images of the database taken with the multi-spectral camera. (*a*) Image of the visible spectra, (*b*) image of the near infrared spectra and (*c*) ground truth based on the image (*a*).

Table 1
Global properties descriptors. Listed are the field variables, their type and a description of their meaning.

General information		
< Id >	Number	Unique image identifier
< Sequence >	Number	Sequence number
< NumIm >	Number	Image number in the sequence
< Owner >	Text	Author of the image
< Date >	Text	Date of the acquisition
< GPS >	Text	GPS position
< Place >	Text	Name of the place of shot
< Region >	Text	(Region, Country) of shoot
< Name Vis >	Text	Name of the visible spectra image
< Name IR >	Text	Name of the associated IR spectra image (if exists)
< Name GT >	Text	Name of the corresponding ground truth image
Acquisition settings		
< Material >	Text	Camera model
< Focal >	Number	Focal length of the visible camera
< Sensibility >	Number	ISO Sensitivity
< Exposure >	Number	Exposure time
< Spectra >	NIR/SWIR/MWIR/ LWIR	IR spectral domain (if IR image exists)

sequence (which are non-zero if the image belongs to a sequence). Another annotations list information on location and date. The last descriptors of this sub-group give the names of the visible image, the associated infrared image (if it exists) and the ground truth image.

The *Acquisition settings* fields give information about the equipment and settings used to obtain the images: the descriptor < Material > gives the camera model used, < Focal > indicates its focal length, < Sensibility > presents its ISO sensitivity and < Exposure > contains the exposure time used.

If an infrared image is associated to a visible image, the field < Spectra > indicates its spectral domain: near-infrared (*NIR*), short wavelength infrared (*SWIR*), medium wavelength infrared (*MWIR*) or long wavelength infrared (*LWIR*).

2.2.2. Fire and environment descriptors

The purpose of the proposed database is to specify the different parameters of the fire and the environment that can be important for detection purposes. These annotations are listed in Table 2 and are separated in two groups. The *Fire descriptors* group concerns the annotations specific to fire pixels and the *Background descriptors* group is about environment pixels. Most of these data were computed automatically with image processing algorithms and the ground truth images. The description and the computation of these descriptors are explained in the following.

Concerning the *Fire descriptors*:

The < Occupation > field is the percentage of fire pixels in the image. It is computed by dividing the number of fire pixels (pixels labeled "fire" in the ground truth image) by the total number of pixels of the image. In Table 2, [0– 100] indicates that this indicator is between 0 and 100.

Table 2
Fire and background descriptors. Listed are the field variables and their possible values.

Fire descriptors	
< Occupation >	[0–100]
< Color >	Red/Orange/Yellow-White/Other
< Smoke Superposition >	[0–100]
< ColorSmoke >	Black/Grey/White
< Texture >	0/1
< Dist F/C >	Near/Far
< Direction >	Right/Left/Moves close/Moves away
Background descriptors	
< Luminosity >	[0–100]
< Time >	Day/Night
< Vegetation >	Crimp wood/Low maquis shrubland/High maquis shrubland/ Trees
< Presence >	Men/Trunk/None/Other
< Clouds >	0/1

The < Color > field indicates the dominant color of fire pixels in the image. The possible value of this descriptor is *Red*, *Orange*, *Yellow-White* and *Other*. Each fire pixel is labeled to one of these colors using the *HSI* color space (see Ref. [31] for computation details). The dominant color is the color of the majority of fire pixels. An example of images of the database CFDB with different principal color is shown in Fig. 2.

The < Smoke Superposition > field indicates the percentage of fire pixels which are superimposed with smokes. A learning has been done with support vector machine in order to automatically classify fire pixels with and without smoke. The smoke pixels that not superimpose fire are not considered since only fire pixels given by the ground truth are processed. The field < ColorSmoke > indicates the color of the smoke. Its value can be *Black*, *Grey* or *White* and is annotated manually.

The < Texture > field indicates if the fire is textured or not accordingly to the entropy of fire pixels (see Ref. [31] for computation details). The value "0" informs that the fire is not textured and the value "1" indicates that it is textured. For example, the fire area that appears in Fig. 2 (*b*) is considered textured unlike the fire region that appears in the Fig. 2 (*c*).

The < Dist F/C > field gives an indication on the distance from the fire with respect to the camera. Its value can be near or far. A fire is considered near to the camera when the distance is lower than 200 meters. This field is completed manually, given by the owner of the image from observation or field measurement.

The < Direction > field indicates the direction of the fire compared to the camera. This field is completed manually and given by the owner of the image. The possible values are: right, left, moves close and moves away.

Concerning the *background descriptors*:

The field < Luminosity > gives an information relating to the brightness of the environment. An automatic procedure computes an

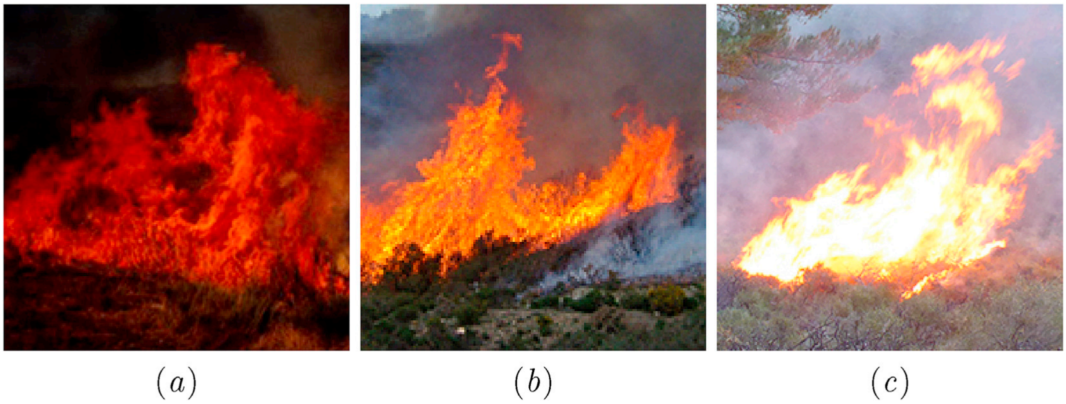

Fig. 2. Example of images of the database that have different value for the <Color> descriptor. The value computed for these images are *Red* for (*a*), *Orange* for (*b*) and *Yellow-White* for (*c*). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

average of channel *I* of *HSI* color space of the non-fire pixels (see Ref. [31] for computation details). The value of this field is a value between 0 and 100. Fig. 3 shows three images that have different luminosity values.

The following descriptors are annotated manually.

The field <Time> indicates if the picture has been captured during the day or the night.

The <Vegetation> field gives information about the vegetable fuel that appears in the image. The possible values are: crimp wood, low maquis shrubland, high maquis shrubland and trees.

The <Presence> descriptor indicates the presence of potential false positives area like the ones corresponding to fire men or trucks.

Finally the field <Clouds> indicates if clouds are visible in the sky that can also generate false fire detections especially when processing infrared images. The value "1" indicates the presence of clouds and the value "0" their absence.

2.2.3. Distribution of the dataset pixels

Table 3 gives the image pixel distribution by category. It shows the heterogeneity of the pixels in the dataset.

Table 3
Distribution of the dataset pixels by category.

			Number of pixels	Percentage
Fire Pixels	Red	Smoke	19 334 066	8.1%
		No Smoke	43 373 644	18.2%
	Orange	Smoke	32 812 298	13.8%
		No Smoke	115 227 509	48.4%
	White-Yellow	Smoke	18 519 389	7.8%
		No Smoke	2 426 830	1.0%
	Other	Smoke	578 832	0.2%
		No Smoke	5 332 683	2.2%
	All		237 950 619	100%
Non-fire Pixels	Low Intensity		170 088 686	21.9%
	Medium Intensity		259 874 877	33.5%
	High Intensity		345 107 529	44.5%
	All		775 071 092	100%

2.3. Database on internet

The Corsican Fire Database is available online at the following URL: http://cfdb.univ-corse.fr/. After registration, the images and sequences can be downloaded for research purposes via a customized interface. It gives to the user the possibility to download the entire database or to choose specific elements according to the descriptors detailed in the previous section. A screenshot of the browsing interface is shown in the upper part of Fig. 4.

The values of the Occupation, Luminosity and Smoke Superposition descriptors are in the interval [0–100]. The research procedure is carried out by considering three sub-intervals that are: [0–20] (low),]20–45] (medium) and]45–100] (high).

The lower part of Fig. 4 shows part of the list of the information associated to the images selected with the following attributes: no specific region, no associated infrared image, not belonging to a sequence, without clouds, not textured, no specific false positive elements, no specific time, low percentage of fire pixels in the image and smoke-fire covering, dominant fire color that is orange, no specific smoke color, with a medium environment brightness, no specific vegetation type, no specific fire distance and no specific direction of fire propagation.

The browsing interface allows to download all the selected images or to select images by considering their information. By clicking on the eye icon it is possible to see the fire image and the associated IR image if

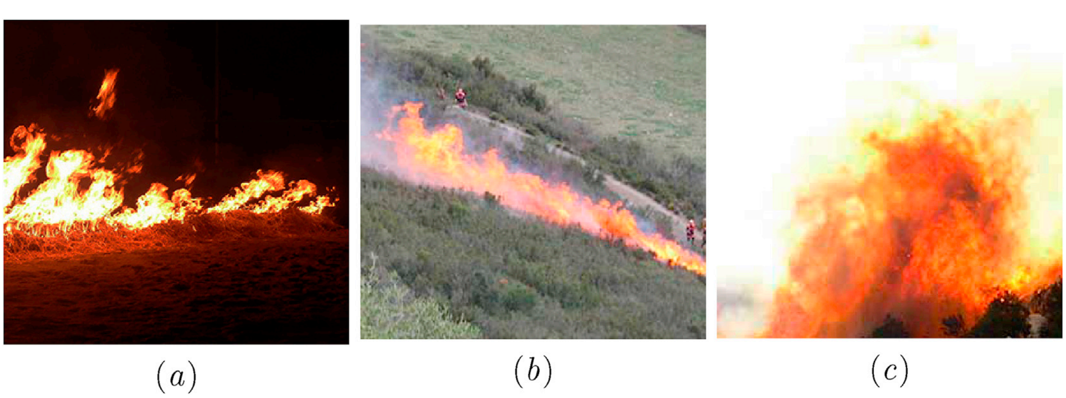

Fig. 3. Example of images of the database that have different value for the <Luminosity> descriptor. The value computed for these images are 10 for (*a*), 44 for (*b*) and 64 for (*c*).

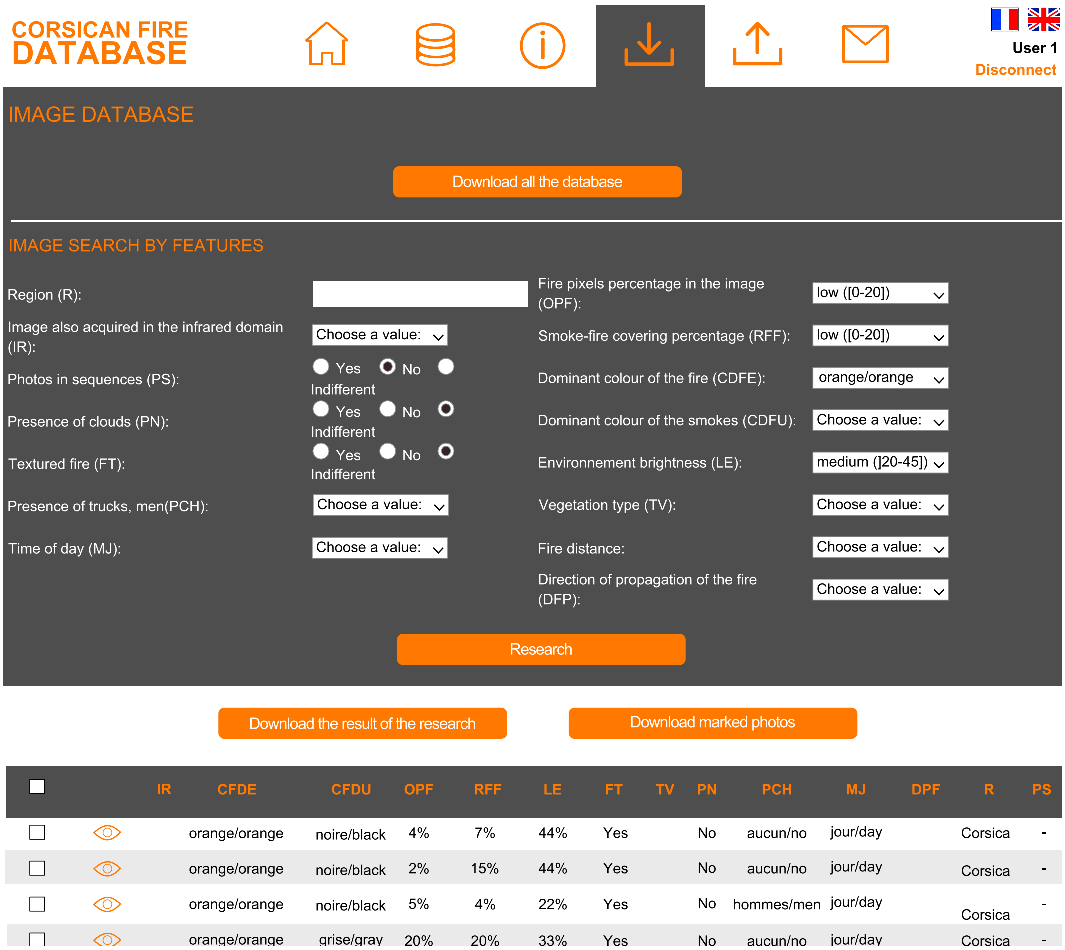

Fig. 4. Screenshot of the Corsican Fire Database browser.

it exists.

The user downloads a compressed repository that gathers folders and a csv file. A folder contains at least one visible image and its corresponding ground truth. It can also contain the associated infrared image if it exits. It has all the images (visible, ground truth and infrared) of the same sequence. The *csv* file gives all the descriptor values of each image identified by a specific number.

In order that this database evolves over time, the website proposes an interface for the upload of new images or sequences and the recording of the associated data (Fig. 5). These resources are not directly integrated with the database and follow a procedure of validation and image processing before their publication on the website. Thus, the database can grow in the future and contain more wildland fire images through users contribution.

3. Fire picture analysis

This section presents examples of processing and analysis that can be carried out using the dataset.

3.1. Construction of a pixel learning set

Some pixel detection methods like [18,19,21] needs labeled fire pixels for training. Following is the description of the method we have used in building the pixels learning set. Fifty images of the dataset were chosen randomly among the five hundred images. The fire pixels of these fifty images were sorted in six categories depending to the color of the pixels (red, orange, white-yellow) and the presence of smoke. The non fire pixels were classified using three levels of intensity (low, medium and high). 500 000 non fire pixels and 500 000 fire pixels were chosen as follows. For each category, each pixel was represented with a feature vector constructed from color features extracted using different color spaces. An average feature vector was computed for each category and the pixels were sorted based on the distance between their feature vectors and the average feature vector. The pixels were then sampled uniformly to obtain the desired number for each category. According to the observations of Table 3, the pixel distribution was built as follows: 50% of orange pixels, 33% of red pixels and 17% of white-yellow pixels for fire pixels, and 20% of low intensity pixels, 40% of medium intensity pixels and 40% of high intensity pixels for non-fire pixels. To make it convenient for the processing step, the learning pixels can be organized in order to create an image of size 1000×1000 whose upper half corresponds to the "fire" pixels and the lower half corresponds to the "non-fire" pixels. This image presented in Fig. 6 shows the different categories: region N°1 corresponds to the pixels "red with smoke", region N°2 contains the pixels "red without smoke ", region N°3 includes the "orange with smoke" pixels, region N°4 corresponds to the "smokeless orange" pixels, region N°5 represent "yellow-white pixels" with smoke and region N°6 corresponds to "smoke-free yellow-white" pixels. We can notice that the "non-fire" pixels of "low" and "medium luminosity" are composed of many pixels with green color (which can be assumed to originate from the vegetation in the images). The "non-fire" pixels with "high brightness" represent the color of the sky and the smoke.

3.2. Performance analysis of pixel detection methods

The dataset can be used to analyse the performance of fire pixel detection algorithms based on fire pixels and environment

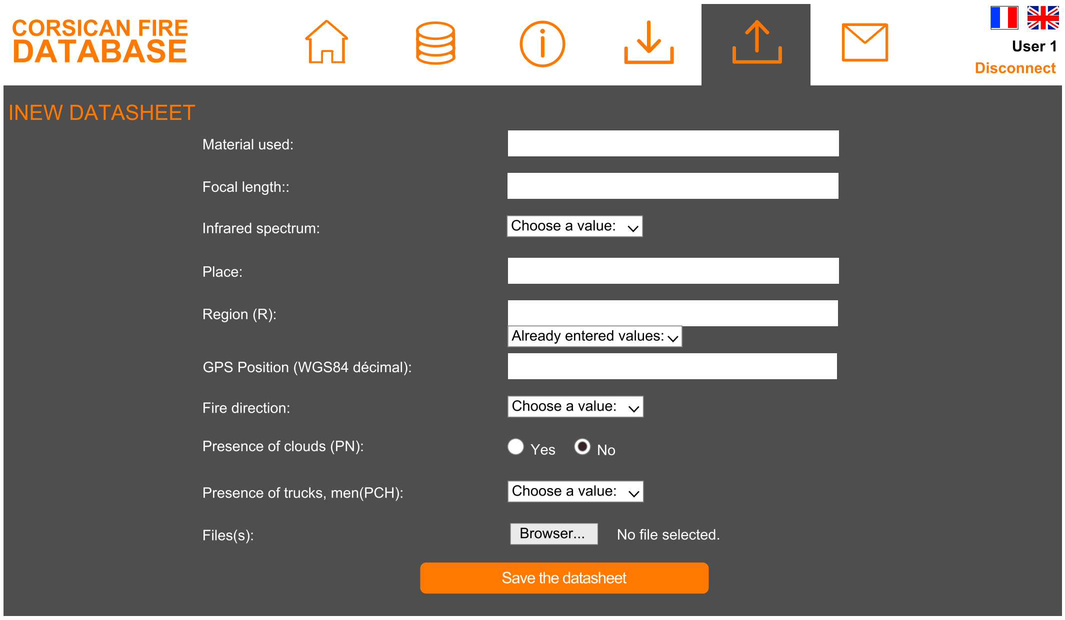

Fig. 5. Screenshot of the Corsican Fire Database browser page to upload images.

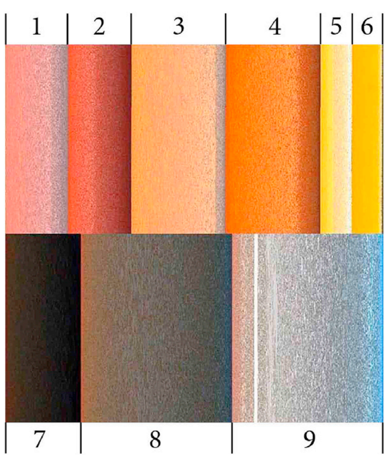

Fig. 6. Pixels of the pixel learning set. Nine categories are visible: (1) red with smoke, (2) red without smoke, (3) orange with smoke, (4) orange without smoke, (5) yellow-white with smoke, (6) yellow-white without smoke, (7) low brightness, (8) medium brightness and (9) high brightness. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Scores of three state-of-art fire detection methods.

			Phillips [19]	Chen [29]	Horng [26]
Red	Smoke	Low	0.95	0.80	0.87
		Medium	0.92	0.78	0.78
		High	0.89	0.73	0.86
	No smoke	Low	0.93	0.85	0.89
		Medium	0.90	0.83	0.80
		High	0.87	0.78	0.87
Orange	Smoke	Low	0.98	0.98	0.90
		Medium	0.95	0.96	0.81
		High	0.92	0.91	0.89
	No smoke	Low	0.97	0.97	0.78
		Medium	0.94	0.95	0.69
		High	0.91	0.90	0.76
Yellow	Smoke	Low	0.87	0.94	0.78
		Medium	0.85	0.92	0.69
		High	0.81	0.86	0.76
	No smoke	Low	0.97	0.98	0.58
		Medium	0.95	0.96	0.50
		High	0.91	0.91	0.56
All			0.91	0.88	0.78

characteristics. The performance of the methods are obtained by considering standard metrics that compare the fire areas obtained by pixel detection to the ones obtained manually (the ground truth). In this paper, the F-score [41] is used. As each tested image has associated descriptors, the scores of pixel detection methods can be obtained according to the images characteristics as it is shown in Table 4 for three different state-of-the-art techniques. From these experimental tests, we can see that for the red colored fires, the technique proposed in Ref. [19] is the best performing overall. For the orange colored fires the best performing techniques are [19] and [29]. For yellow fires [29], is the best performing. The global results on all this colored fires (with and without smoke) show that the best performing technique overall is [19] with an F-score of 0.91 followed by Ref. [29] with an F-score of 0.88.

This data are useful to identify the strengths and weaknesses of the algorithms and to benchmark them. If we need to benchmark fire pixel detection is a specific context images (for example fire pixels with red dominant color and medium smoke), it is possible to get the corresponding set of images using the web interface of the database.

4. Conclusion

The Corsican Fire Database aims to provide a common dataset of multi-modal wildfire images and videos. This dataset can be used for research and training. It also provides categories of fire and background properties. The proposed wildland fire images database was designed to be an evolving database over time. It contains visible spectrum and near infrared (NIR) images in its current form. Still it was designed to accommodate other spectrums in the future. The visible spectrum color images are by far the most used in current research in the area of forest fires and the proposed database provides a large number of images captured in this spectrum. Additionally, this database contains video sequences captured simultaneously in color and NIR spectrums. These image sequences can serve in the study of multispectral fusion algorithms, the analysis of the performance of fire segmentation in these spectrums, the use of motion for fire segmentation, etc. The user-friendly web interface permits the selection of a subset of images based on different criteria. The users can also contribute to the database by uploading their own images, image sequences (visible, infrared, etc.), corresponding ground-truth, and the image parameters. The newly added images are processed using algorithms developed by the authors for further categorization within the database. All these aspects make the proposed database an interesting tool for researchers and professionals in the field of wildland fire study.

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References

[1] Prométhée^2 : the Database on Forest Fire in Mediterranean Region in France. (Accessed le 13 August 2015).
[2] FAO, Enlisting Communities in Wildfire Prevention, 2010 (accd le 13 August 2015).
[3] EFFIS. European forest fire information system. http://forest.jrc.ec.europa.eu/effis/ . (accd le 13 August 2015).
[4] Peter L. Fuglem, Kelvin G. Hirsch, Canadian Council of Forest Ministers, Stratégie canadienne en matière de feux de forêt: synthèses de fond, analyses et perspectives, 2006.
[5] J. Ramiro Martínez-de Dios, Luis Merino, Aníbal Ollero, Fire detection using autonomous aerial vehicles with infrared and visual cameras, in: Proceedings of the 16th IFAC World Congress, 2005.
[6] D. Stipaničev, T. Vuko, D. Krstinić, M. Štula, L. Bodrozic, Forest fire protection by advanced video detection system-croatian experiences, in: Third TIEMS Workshop-improvement of Disaster Management System, Trogir, 2006.
[7] Steven Verstockt, Peter Lambert, Rik Van de Walle, Bart Merci, Bart Sette, State of the art in vision-based fire and smoke detection, in: 14th International Conference on Automatic Fire Detection, vol. 2, University of Duisburg-Essen. Department of Communication Systems, 2009, pp. 285–292.
[8] Ingram Thomas Loane, James Stanley Goul, Aerial Suppression of Bushfires: Cost-benefit Study for Victoria, National Bushfire Research Unit, CSIRO Division of Forest Research, 1986.
[9] G.F. George, C.W. Ewart, W.C. Friauf, Flir: a promising tool for air-attack supervisors, Fire Manag. Notes 50 (1989) 26–29.
[10] Yolanda Prez, Elsa Pastor, Eullia Planas, Matt Plucinski, Jim Gould, Computing forest fires aerial suppression effectiveness by IR monitoring, Fire Saf. J. 46 (1–2) (January 2011) 2–8.
[11] J.R. Martnez-de Dios, L. Merino, F. Caballero, A. Ollero, Automatic forest-fire measuring using ground stations and unmanned aerial systems, Sensors 11 (6) (2011) 6328–6353.
[12] Francisco Rodriguez, Amador Moreno Robles, D-09-04.The Infrared Imager: its Use for Wildland Fire Monitoring, Technical report, EUROFIRELAB, 2004.
[13] Lucile Rossi, Jacques Henri Balbi, Jean Louis Rossi, Thierry Marcelli, Antoine Pieri, Front fire propagation model: use of mathematical model and vision technology, Adv. Technol. Res. - Dev. - Appl. (July 2006) 745–760.
[14] A. Enis Çetin, Kosmas Dimitropoulos, Benedict Gouverneur, Nikos Grammalidis, Osman Günay, Y Hakan Habiboğlu, B.U. ğur Töreyin, Steven Verstockt, Video fire detection–review, Digit. Signal Process. 23 (6) (2013) 1827–1843.
[15] Paulo Vinicius, Koerich Borges, Joceli Mayer, Ebroul Izquierdo, Efficient visual fire detection applied for video retrieval, in: 16th European Signal Processing Conference, IEEE, 2008, pp. 1–5.
[16] Turgay Celik, Hasan Demirel, Huseyin Ozkaramanli, Mustafa Uyguroğlu, Fire detection using statistical color model in video sequences, J. Vis. Commun. Image Represent. 18 (2) (April 2007) 176–185.
[17] Jean-François Collumeau, Hélène Laurent, Adel Hafiane, Khaled Chetehouna, Fire scene segmentations for forest fire characterization: a comparative study, in: 18th IEEE International Conference on Image Processing (ICIP), 2011, pp. 2973–2976.
[18] Byoung Chul Ko, Kwang-Ho Cheong, Jae-Yeal Nam, Fire detection based on vision sensor and support vector machines, Fire Saf. J. 44 (3) (2009) 322–329.
[19] Walter Phillips III, Mubarak Shah, Niels da Vitoria Lobo, Flame recognition in video, Pattern Recognit. Lett. 23 (1) (2002) 319–327.
[20] B. Uğur Töreyin, Yiğithan Dedeoğlu, Uğur Güdükbay, A. Enis Çetin, Computer vision based method for real-time fire and flame detection, Pattern Recognit. Lett. 27 (1) (January 2006) 49–58.
[21] Turgay Celik, Hasan Demirel, Fire detection in video sequences using a generic color model, Fire Saf. J. 44 (2) (2009) 147–158.
[22] De-Chang Wang, Xuenan Cui, Eunsoo Park, Changlong Jin, Hakil Kim, Adaptive flame detection using randomness testing and robust features, Fire Saf. J. 55 (January 2013) 116–125.
[23] Steve Rudz, Khaled Chetehouna, A. Hafiane, Hélène Laurent, Olivier Séro-Guillaume, Investigation of a novel image segmentation method dedicated to forest fire applications, Meas. Sci. Technol. 24 (7) (2013) 075403.
[24] Giuseppe Marbach, Markus Loepfe, Thomas Brupbacher, An image processing technique for fire detection in video images, Fire Saf. J. 41 (4) (2006) 285–289.
[25] Turgay Celik, Fast and efficient method for fire detection using image processing, ETRI J. 32 (6) (2010) 881–890.
[26] Wen-Bing Horng, Jian-Wen Peng, Chih-Yuan Chen, A new image-based real-time flame detection method using color analysis, in: Networking, Sensing and Control Proceddings, IEEE, 2005, pp. 100–105.
[27] Che-Bin Liu, Narendra Ahuja, Vision based fire detection, in: Proceedings of the 17th International Conference on Pattern Recognition,(ICPR), vol. 4, IEEE, 2004, pp. 134–137.
[28] Juan Chen, Yaping He, Jian Wang, Multi-feature fusion based fast video flame detection, Build. Environ. 45 (5) (May 2010) 1113–1122.
[29] Thou-Ho Chen, Ping-Hsueh Wu, Yung-Chuen Chiou, An early fire-detection method based on image processing, in: International Conference on Image Processing, (ICIP), vol. 3, IEEE, 2004, pp. 1707–1710.
[30] Tom Toulouse, Lucile Rossi, Turgay Celik, Moulay Akhloufi, Automatic fire pixel detection using image processing: a comparative analysis of rule-based and machine learning-based methods, Signal, Image Video Process. (2015) 1–8.
[31] Tom Toulouse, Lucile Rossi, Moulay Akhloufi, Turgay Celik, Xavier Maldague, Benchmarking of Wildland Fire Colour Segmentation Algorithms, IET Image Processing, August 2015.
[32] Forest health, natural resources, fire, trees, wildfire, silviculture photos. http://www.forestryimages.org/. (Accessed: 09 December 2015).
[33] Home of the wildland firefighter. http://www.wildlandfire.com/. (Accessed: 09 December 2015)..
[34] Nobuyuki Otsu, A threshold selection method from gray-level histograms, Automatica 11 (285–296) (1975) 23–27.
[35] T.W. Ridler, S. Calvard, Picture thresholding using an iterative selection method, IEEE Trans. Syst. Man Cybern. 8 (8) (1978) 630–632.
[36] Josef Kittler, John Illingworth, Minimum error thresholding, Pattern Recognit. 19 (1) (1986) 41–47.
[37] L. Rossi, T. Toulouse, M. Akhloufi, A. Pieri, Y. Tison, Estimation of spreading fire geometrical characteristics using near infrared stereovision, in: IS&T/SPIE Electronic Imaging, March 2013 pages 86500A–86500A.
[38] Tom Toulouse, Estimation par stéréovision multimodale de caractéristiques géométriques d'un feu de végétation en propagation (Ph.D. thesis), University of Corsica, November 2015.
[39] Marcos VN. Bedo, Gustavo Blanco, Willian D. Oliveira, Mirela T. Cazzolato, Alceu F. Costa, Jose F. Rodrigues Jr., Agma JM. Traina, Caetano Traina Jr., Techniques for effective and efficient fire detection from social media images, in: 17th International Conference on Enterprise Information System, 2015, pp. 34–45.
[40] Renaud Péteri, Sándor Fazekas, Mark J. Huiskes, DynTex : a comprehensive database of dynamic textures, Pattern Recognit. Lett. (2010).
[41] Cornelis J. Van Rijsbergen, Information Retrieval, second ed., Butterworth-Heinemann, London, 1979.