FiSmo: A Compilation of Datasets from Emergency Situations for Fire and Smoke Analysis

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Abstract. *In this work, we present FiSmo, a compilation of datasets from emergency situations, composed of images, videos, regions of interest (ROIs), annotations, and features. These datasets were employed in the context of the RESCUER Project; they were used in the experimental analysis of techniques created in a set of works carried out at the Databases and Images Group (GBDI) of the University of Sao Paulo. These works were focused on the analysis of images and videos regarding the presence of fire, smoke, and explosions in emergency situations. The available data is composed of four image and two video datasets: fire/smoke detection in images; fire segmentation in images; smoke segmentation in images; content-based image retrieval; temporal segmentation of fire segments in videos; and fire detection in videos. All datasets were preprocessed according to the involved context, including annotation steps carried out by a set of subjects, training images and ROIs. Furthermore, the extracted feature vectors are also available, providing features of color and texture. FiSmo can be employed for experimentation of computational techniques and systems designed to work with images and videos from emergency situations.*

1. Introduction

Digital images and videos have been used in many fields of study. Nowadays, a massive number of image data is available on the internet due to the explosion of mobile devices, which captures and uploads images and videos to the cloud. To take advantage of this, the RESCUER Project[1] was developed to support the analysis of information regarding crises in large scale events using crowd-sourced data: images, videos, and text captured and sent by users. The Databases and Images Group (GBdI)[2], from the Institute of Mathematics and Computer Science of the University of Sao Paulo (ICMC-USP), is responsible for the image and video analysis functionalities of the RESCUER architecture. The computational system has to work in real-time to produce accurate and reliable information. Late responses or decisions based on inaccurate information may lead to financial losses

[1]RESCUER Project: Reliable and Smart Crowdsourcing Solution for Emergency and Crisis Management – www.rescuer-project.org

[2]GBdI: Databases and Images Group – www.gbdi.icmc.usp.br

and/or injuries. Therefore, the most relevant images and videos have to be identified as soon as possible. The relevant images and videos are the ones that pose emergency situations and can effectively assist in decision making. Defining the proper dataset to evaluate fire, smoke and explosion detection algorithms is a crucial step.

In this paper, we divulge a compilation of datasets of images and videos that present emergency scenarios called FiSmo[3]. Considering the high cost of making simulations in emergency scenarios to take pictures and make videos, we assume that images and videos gathered from social media website were suitable to reflect the real case scenario of emergency situations. Our dataset is composed of images retrieved from the Flickr[4] social media under the Creative Commons license; videos obtained from YouTube; and simulations carried out during the RESCUER project. These data were labeled according to the presence or absence of fire/smoke. Therefore, the datasets provide a proper material for the validation of the algorithms developed for emergency image and video analysis.

Subsets of the FiSmo have been used in a series of works, where in each work, the subset was adapted according to its needs:

- Fast Fire Detection -FFireDT [Bedo et al. 2015, Bedo et al. 2016]: combines low-level features and evaluation functions to support instance-based learning to detect fire in images and support similarity-enabled Relational Database Management Systems (RDBMS) in disaster-relief tasks [Oliveira et al. 2016];
- BowFire [Chino et al. 2015]: detects and segments fire in still images, by combining color features with texture classification on superpixel regions;
- SmokeBlock [Cazzolato et al. 2016]: segments and detects smoke in still images using superpixel segmentation and local color and texture features from images;
- SPATFIRE [Avalhais et al. 2016]: a fire event detection method that works with videos and takes advantage of spatial color modeling and motion pattern.

Additionally to the images and videos, the datasets are also composed of a set of features extracted from the images, regions of interest and annotations, obtained in preprocessing steps and manual efforts of aforementioned works.

FiSmo is divided into two main parts: FiSmo-Images, presented in Section 2, containing images datasets and information extracted from these images; and FiSmo-Videos, presented in Section 3, containing videos and annotations. In Section 4 we discuss the applicability, challenges, and limitations of the datasets, including the public location of the files. Finally, in Section 5 we present the conclusion of this work.

2. FiSmo-Images: Still Images from Social Media

In this section we present FiSmo-Images (**Fi**re and **Smo**ke Images), which is composed of four datasets: Flickr-FireSmoke, Flickr-Fire, BoWFire, and SmokeBlock. In the following subsections, we describe the process of collecting the images , preprocessing the data and the annotation task. Then, for each specific task, we present the modifications made in the data, in order to provide enough information for experimental analysis steps.

[3] FiSmo datasets are available at `https://goo.gl/uW7LxW`

[4] `https://www.flickr.com/`

2.1. Data Collection and Preprocessing

The collection of the images was carried by using the Flickr API[5], in August of 2014. All images downloaded were available under Creative Commons license. A total of 5,962 images were retrieved, using a set of textual keywords presented in Table 1.

Table 1. List of keywords used to retrieve images using Flickr API.

Keywords used to collect images using Flickr API				
fire	smoke	emergency	flames	burning
protest	boston marathon	car fire accident	criminal fire	fire department
firefighter	urban fire	house burning	criminal fire	fire car accident

Removing duplicated images: A similarity comparison between the images was carried, in order to identify duplicate images. The resulting 406 images identified as duplicated were removed, resulting in a dataset composed of 5,556 images.

Annotation of images according to the emergency scenario: Figure 1 shows examples of images from this dataset. Despite the keywords used during the acquisition, part of the images (e and f) do not have fire and/or smoke, and others (g and h) have fire and/or smoke, but are not from emergency scenarios (e.g. lightening purposes).

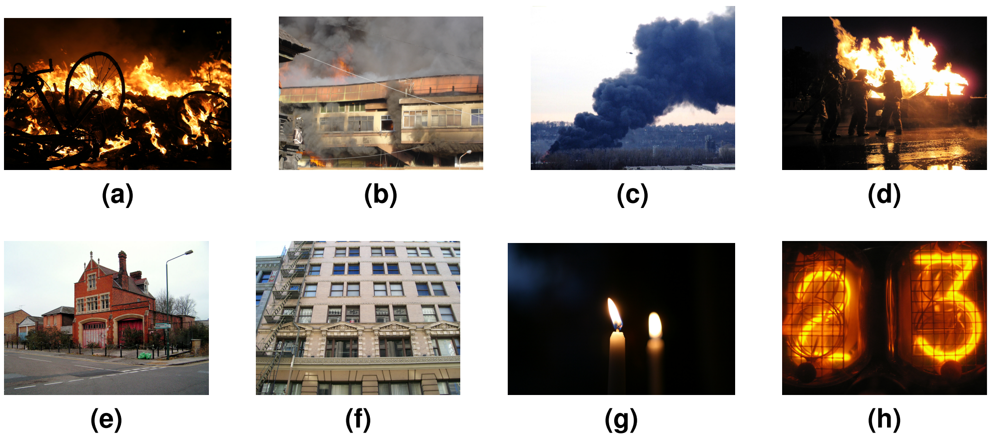

Figure 1. Sample images from the gathered dataset: (a-d) present fire and/or smoke; (e-f) do not present fire and/or smoke; and (g-h) present fire and/or smoke; but not from emergency situations.

As shown in Figure 1, not all of the retrieved images contain visual traces of fire/smoke. Thus, the next preprocessing step carried was the manual annotation of the images. For this task, we asked seven subjects to perform the annotation, all of them between 20 and 30 years old and familiar with the subject. We observed a disagreement between what is considered fire/smoke. For example: can the image showed in Figure 1-g be considered as "fire"? Part of the subjects considered fire for lightening purposes as "not fire" since it was not related to an emergency scenario. The same disagreement applies for the annotation as "smoke", for example when the smoke was coming out of the exhaust pipe of a car. Considering this scenario, all subjects were oriented to annotate the images according to the following questions:

[5] The Flickr API: `www.flickr.com/services/api/`

- Does the image contain fire from an emergency situation? (yes/no)
- Does the image contain smoke from an emergency situation? (yes/no)

The set of 5,556 non-duplicate images was divided into subsets constructed in a way that each image was annotated by at least two subjects. After the first round of annotation, all images with disagreement (i.e. different annotations) were submitted to a second round, performed by a third subject. After this process, we obtained the first dataset of FiSmo-Images, called **Flickr-FireSmoke**. This dataset contains 5,556 images classified as fire (y/n) and smoke (y/n), and its class distribution is described in Table 2. It was used as the basic ground truth for the experimental analysis of works regarding the detection of fire and smoke. For each specific task, the dataset was adapted in order to provide the proper information regarding the application context, resulting on specific datasets. In the next subsections, we present these variations.

Table 2. Class distribution of the 5,556 images from Flickr-FireSmoke dataset.

Flickr-FireSmoke Dataset	
class	***# images***
fire and smoke	527
only fire	1,077
only smoke	369
none	3,583

2.2. The Flickr-Fire Dataset

In emergency situations, urban and crowded scenarios may contain a vast amount of information to be processed in a short interval of time. During an explosion in a stadium, for example, many users can use send pictures, short movies and text messages to social media websites, and it is important to process and filter all this information for the rescue forces. To address this problem, Bedo *et al.* [Bedo et al. 2015, Bedo et al. 2016] proposed the FFireDt method, that classifies a given input image based on past cases (pre-annotated images), relying on a content-based image retrieval module. FFireDt is able to select similar images, helping to filter the information and build an overview of the emergency scenario for the authorities. In this work, the authors used a subset of Flickr-FireSmoke, in order to obtain a balanced dataset, called **Flickr-Fire**, composed of:

- 2,000 images, 1,000 labeled as *"fire"* and 1,000 labeled as *"not fire"*;
- Six files containing low-level features, extracted from the 2,000 images, and the corresponding classes. The Feature Extractor Methods (FEM) used were: Color Layout, Scalable Color, Color Structure, Color Temperature, Edge Histogram and Texture Browsing.

Oliveira *et al.* [Oliveira et al. 2016] also employed this dataset on a system to support civilian crisis situations relying on a RDBMS.

2.3. The BoWFire Dataset

Several methods regarding the problem of fire detection on videos have been proposed in the last years [Celik and Demirel 2009, Zhang et al. 2014]. To detect fire on videos, the methods explore color features on the video frames and refine their output using temporal features of the videos. There are also a few works that detect fire on still images based on color. These works achieved good results on forest fire or controlled environments because the fire contrasts with the background. However, when changing the emergency scenario to urban regions, the images may also contain reddish/yellowish objects, which can be mistaken as fire. This problem was studied by Chino *et al.* [Chino et al. 2015], where the authors proposed the BoWFire, a method based on color and texture analysis.

In order to train and validate the BoWFire method, the authors constructed the **BoWFire** dataset. The BoWFire dataset is a subset of the Flickr-FireSmoke dataset, with images from emergency situations with fire in urban scenarios. The BoWFire dataset also has images with no visible fire containing reddish or yellowish objects and sunsets, which can be mistaken as fire. To validate the method, the authors constructed a ground truth composed of masks of the fire regions in the images. Figure 2 shows examples of the BoWFire images and their respective masks. The BoWFire dataset has a second dataset used as a training set. This second dataset consists of images classified as fire and non-fire. It is important to note that non-fire images also contain red or yellow objects. Figure 3 shows examples of the training set. In summary, the BoWFire dataset consists of:

- 226 images, 119 labeled as "fire" and 107 labeled as "not fire";
- 226 masks of the regions containing fire, that were used as ground truth;
- 240 images (regions of interest – ROIs) of 50x50 pixels resolution, 80 labeled as *"fire"* and 160 *"not fire"*. These images were used for training purposes.

Figure 2. Sample images and the corresponding mask of the fire regions.

Figure 3. BoWFire ROIs with fire (1st row) and without fire (2nd row).

2.4. The SmokeBlock Dataset

Many computer vision methods in the literature address the problem of detecting smoke. However, they usually rely on the movement present on videos to differentiate smoke regions from background objects, such as trees and clouds [Cazzolato et al. 2016]. The existing methods that work with still images propose the classification of pixels analysing only the color of pixels, mainly considering smoke regions as depicting grayscale colors. However, in real scenarios smoke regions depict different colors considering many factors, e.g. illumination, temperature and the material being burned. To overcome these problems Cazzolato *et al.* [Cazzolato et al. 2016] proposed the SmokeBlock, a smoke detection method using color and texture patterns.

SmokeBlock was trained with a set of ROIs depicting different colors and patterns of images, as presented in Figure 4. For each input image, the method classifies the image as smoke or not smoke, and outputs the segmented smoke regions of the image (if it was classified as smoke). The experimental analysis was carried out using a subset of the dataset Flickr-FireSmoke, named **SmokeBlock** dataset, which is composed of:

- 1,666 images, 832 labeled as *"smoke"* and 834 labeled as *"not smoke"*;
- 10 files containing the low-level features of the images and the corresponding classes. The FEM employed were: Color Layout, Color Structure, Color Temperature, Edge Histogram, Haralick, LPB, Normalized Histogram, Scalable Color, Texture Spectrum and Zernike.
- 103 images (ROIs), 43 labeled as *"smoke"* and 60 labeled as *"not smoke"*.
- Low-level features of the images and the corresponding classes. The FEM employed were: Color Layout and Haralick;

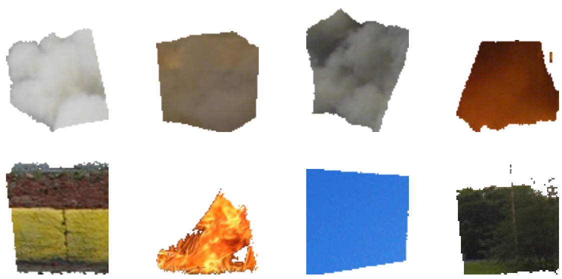

Figure 4. SmokeBlock ROIs with smoke (1st row) and without smoke (2nd row).

2.5. FiSmo-Images: Summarization

FiSmo-Images consists of a set of the image datasets Flickr-FireSmoke, Flickr-Fire, BoWFire and SmokeBlock, and it is summarized in Table 3. The images from all datasets are labeled, according to the purpose of the work, as fire/not fire and smoke/not smoke.

Table 3. Summarization of the FiSmo-Images datasets.

FiSmo-Images				
Dataset Name	Purpose	# images	Features	ROIs
FireSmoke	Fire and Smoke detection	5,556	No	No
Flickr-Fire	Global fire detection and content-based image retrieval	2,000	Yes	No
BoWFire	Fire detection and segmentation	226	No	Yes
SmokeBlock	Smoke detection and segmentation	1,666	Yes	Yes

3. The FiSmo-Videos: Unconstrained Videos for Event Segmentation

There has been an increasing interest from the computer vision community in researching about several video-related problems over the past two decades. One of the outcomes of this is the effort to make publicly available datasets with benchmarks, as an example, the multimedia event recognition (MED) dataset composed of high-level complex event categories provided by TREC Video Retrieval Evaluation (TRECVid) [6]. Notwithstanding, with regard to the fire emergencies scenario, there is a lack of standard benchmark datasets for fire detection publicly available.

The literature shows that, in general, previous studies focusing on fire detection constrain the domain of the problem through the assumption that the scenes are captured in a stationary set up [Töreyin et al. 2006, Celik and Demirel 2009, Zhang et al. 2014, Qureshi et al. 2016], or have a limited influence of camera motion [Habiboğlu et al. 2012]. The validation of these methods is usually based on datasets of short video clips acquired with static cameras. For instance, the *MIVIA*[7] [Di Lascio et al. 2014] dataset, one of the most used dataset for fire detection, is composed of 14 videos with fire and 17 which do not contain fire. More recently, Qureshi *et al.* [Qureshi et al. 2016] introduced the *QuickBlaze*[8] dataset, with a total of 30 short-duration videos in which 50% has fire.

Besides the fact that the existing datasets were built under the stationary camera constraint, there is also another limitation regarding the type of problems that can take advantage of them. Methods that focus on fire detection in videos with categoric binary output can assess their performance from such data. In fact, those are the most common task for video fire detection in the literature. However, if the problem is more complex, e.g., event segmentation where the focus is to detect the approximate time interval where the event of interest takes place, then these datasets are no longer adequate. This is because each video is usually a single sequence with fire or a single sequence without fire.

3.1. Video Data Acquisition

In order to provide support to the task of detecting events of fire from unconstrained videos, we have collected videos from two distinct sources. The first subset was extracted from YouTube, and the second was provided by the RESCUER Project partners after a fire simulation in an industrial park. More details are described in the following sections.

3.1.1. The FireVid Dataset

The FireVid dataset was collected from YouTube , using an adapted version of the crawler tool TubeKit [9]. This tool works by making periodically requests with queries that use previously selected keywords. For this purpose, the set of keywords showed in Table 4 was selected. 97 videos were downloaded, from which 27 were selected for the annotation task totalizing $83,675$ frames. The videos are unconstrained in respect to several aspects:

[6] http://trecvid.nist.gov

[7] http://mivia.unisa.it/datasets/video-analysis-datasets/fire-detection-dataset

[8] http://vgl-ait.org/cvwiki/doku.php?id=quickblaze:main

[9] http://www.tubekit.org

- Video quality: resolution, frame rate, encoding algorithm;
- Point of view: ground level shooting and aerial videos captured by drone and from a helicopter;
- Scene lightening: several lightening conditions such as sunny, dusk, night, shade;
- Scale and distance: different distances to the subjects and presence of distance variation in a single video;
- Camera motion: mostly hand-held shooting with different amount of motion.

Table 4. Keywords used to retrieve videos.

Keywords used to collect videos from YouTube		
fire	smoke	explosion
flames	burning	blaze
campfire	bonfire	combustion
ignite	wildfire	firefighters

3.1.2. The RESCUER Video Dataset

Specialists working on the RESCUER Project in a partnership with experts from several areas and companies belonging to a chemical industrial park located in Camaçari, Brazil, had performed a fire exercise simulation with victims. During this simulation, videos were shot with different handheld mobile devices. The scenes captured the firefighters extinguishing the fire from different angles of view and distances. Besides, there is reasonable variability regarding the amount of movement from the camera handler perspective, light conditions, resolution, and duration. Shooting the videos while taking into account these diversities is important in order to simulate the scenario where people with different camera devices, shooting skills, local position and motion behavior would be more likely to represent a real situation. A total of $29,895$ frames from 61 videos were annotated in this dataset. Figure 5 shows a sample of frames from the FireVid and RESCUER datasets.

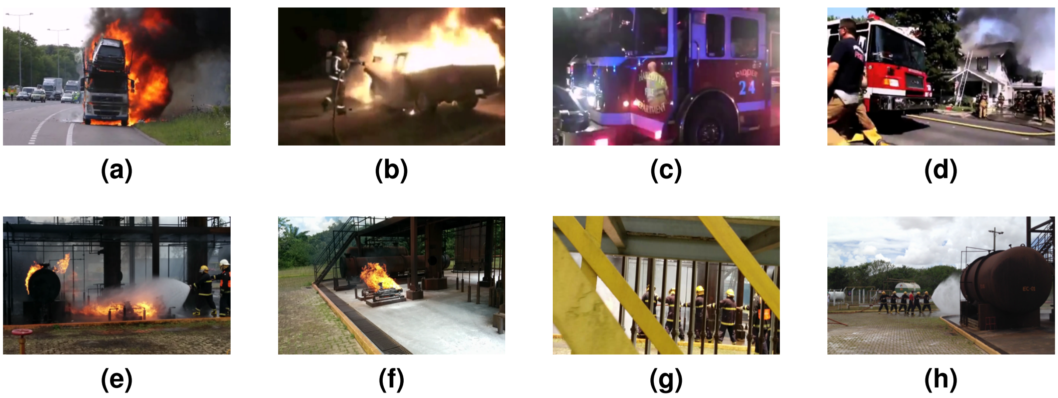

Figure 5. Sample frames from the video dataset: (a-b) fire segment, (c-d) non-fire segment on FireVid datatset; (e-f) fire segment and (g-h) non-fire segment on RESCUER videos dataset.

3.2. Annotation Protocol and Ground-truth

We provide frame-level ground-truth, instead of a single label for each video. For each frame of a video, two different annotators assigned that frame to one of the labels: *"fire"*, *"notFire"* or *"ignore"*. Similarly to how the annotation was conducted for the Flickr-FireSmoke dataset, the annotators were asked to label a frame with *"fire"* if they were able to consider that, the frame isolated, has fire. The label *"notFire"* was assigned to every frame in which the annotators were confident that there was no fire in the frame. However, if a frame shows a fire like lightening but the annotator was not able to tell whether it is fire or any other lightening source, then he/she was instructed to assign the *"ignore"* label. The *"ignore"* label was also assigned to every frame that is part of any post-edition transition effect. We adopted the use of the last label to exclude from our analysis segments that are not useful to evaluate. For each frame that the two annotators did not agree, a third annotator was cast so to define the label.

After the manual annotation task, we process the frame annotation to create the ground-truth for each transition. For each subsequent pair of frames f_i and f_{i+1}, the transition label t_i represents a transition of a fire segment if f_i = *"fire"* and f_{i+1} = *"fire"*, then t_i = *"fire"*. If one of the frames is *"fire"* and the other is *"notFire"*, or both are *"notFire"*, then t_i = *"notFire"*. For the case in which at least one of the frames is *"ignore"*, then we assign t_i = *"ignore"*. This annotation scheme allows one to use both datasets to validate not only simple fire detections methods, but also temporal segmentation of fire methods, such as the work presented by [Avalhais et al. 2016].

4. Discussion

The effort to build FiSmo was made due to the lack of datasets of images and videos depicting real situations. In the literature is possible to find small sets of images and videos, generally of a restricted scenario (for example, forest fire), and without any additional information to be used as ground truth. FiSmo provides a feasible set of additional information that can be used as a basis for experimental analysis.

4.1. Applicability

FiSmo can be applied in the analysis of emergency scenarios, regarding the detection of fire and smoke in still images and videos. By providing a set of images retrieved from social media, the analysis can be carried using real data, with realistic characteristics such as different resolutions, illuminations, angles, and situations. The images and videos also contain labels, manually created, making it feasible for classification and clustering tasks. Additionally, the low-level features extracted from the images enable the use of this dataset for content-based image retrieval analysis.

4.2. Challenges and Limitations

One of the main challenges regarding the detection of fire and smoke is the subjectivity of the problem. During the annotation process, one may consider, for instance, a candle inside a cup as fire (Figure 4.2-a). However, one can label the image as not fire, since a candle is not related to an emergency situation. Also, a third opinion may lead a person to label the image as not fire, because the flame is not visible. Here we have three different points of view, and whether they are right or wrong is subjective, and it depends on the application scenario. Fire regions may be mistaken by objects like lights, flashlights, and sunset (Figure 4.2-b). Also, fire flames may present different colors, depending on the temperature, the material being burned, and the illumination.

The same issue can be applied to smoke. In some situations, even for the human eye, it is difficult to differentiate regions depicting smoke. In Figure 4.2-c is possible to observe smoke and water presenting similar texture and color patterns. Particularly, smoke detection has many challenges, for instance: regions may present transparency, leading to more difficulties during the detection; depending on the illumination, the temperature, and the material being burned, smoke can present different colors (Figure 4.2-d); and smoke is visually similar to other objects, such as mist, water, trees, and clouds.

(a) (b) (c) (d)

Figure 6. Challenges regarding fire and smoke detection in images: (a) fire can be used for lightening and (b) may depict different colors; (c) smoke can be mistaken by objects such as water, making it difficult to determine the region depicting only smoke and (d) can also present different colors.

4.3. Download and Citation Request

FiSmo is public for research, under the Creative Commons license, and available at `https://goo.gl/uW7LxW`. In case this dataset (or part of it) is used for scientific, industrial, or academic purposes, or in case it is publicly mentioned for whatever purpose, please include the citation to this work.

5. Conclusion

We presented the FiSmo compilation of images and videos datasets. FiSmo provides annotations, regions of interest and low-level features obtained from the data. This information can be used as a basis for experimental analysis of several works since it is built from real images and videos. The datasets can be used in several applications regarding the analysis of fire, explosion and smoke in emergency scenarios. The dataset is public for research, available online, and can be used under the Creative Commons license.

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