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Improved Real-time Wildfire Detection using a Surveillance System

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Abstract— **Wildfire detection is an active and challenging research topic in computer vision. Wildfires can cause damage to valuable natural resources and can harm people and their communities. In this paper, we present CICLOPE, a tele-surveillance system that can perform remote monitoring and automatic fire and smoke detection. The CICLOPE system currently covers about 1.300,000 hectares of mainland Portugal enabling the monitoring of large areas at a very low cost per hectare. The goal of this paper is to present an assessment and evaluation of three of CICLOPE's eleven automatic fire and smoke detection algorithms. Concretely, we aim to determine the potential benefits of three CICLOPE's legacy algorithms: ADBACK, BEFORT, and BESTEST. ADBACK uses background subtraction techniques and a quasi-connected components method to detect smoke and fire while BEFORT and BESTEST use active learning techniques to update an auxiliary database of non-fire occurrences. We compare these three algorithms against one approach from the literature as a means to draw comparisons between the existing techniques. We also propose a number of performance metrics important to measure in a system of this kind, focusing on the consistent detection of smoke plumes and fire incidents over time, while achieving a low false positive rate. Using these evaluation measures, we show that our proprietary algorithms can attain the best performance on a dataset of 75 real wildfires over 3 months of surveillance.**

Index Terms—**Computer Vision, Smoke, and Fire detection, Surveillance Systems**

I. INTRODUCTION

Recently there has been increasing interest in developing real-time algorithms to automatically detect wildfire using surveillance systems [1]-[14]. Wildfire represents one of the most relevant problems nowadays both from a social and environmental standpoint; particularly, in Portugal where arson fires are the main cause of forest destruction [15]. The development of efficient and robust fire detection systems is an active research area. Here, video-based detection can be adopted as a viable alternative to traditional smoke sensor detectors [16], as a single camera can surveil a large area from a distance, being able to detect smoke much earlier than a traditional sensor if a robust computer vision algorithm is used.

Even though video-based detection is a promising alternative to traditional smoke sensor detectors, there are a number of challenges in the field [17]. Smoke plumes and flames are difficult to model due to its dynamic shape and texture features. Unstable cameras, obstacles and shadows, dynamic backgrounds and meteorological conditions also pose major obstacles to efficient smoke detection.

To address the previous challenges, we present CICLOPE, a system which allows for (1) implementation of state-of-the-art fire and smoke detection algorithms, (2) numerical performance evaluation and (3) result visualization to understand the detection outcome. More specifically, CICLOPE is a tele-surveillance system developed by a team of INOV researchers, with a background in the design of remote monitoring and control systems. INOV is a private nonprofit institution with a clear commitment in the area of video surveillance such as automatic fire detection, intrusion detection, traffic control, and suspicious behavior. Concretely, CICLOPE is an effort in the field of automatic fire detection.

Due to the characteristics of the equipment used, CICLOPE enables remote monitoring of large areas from a distance at a very low cost per hectare. The system currently covers about 1.300,000 hectares of mainland Portugal. Simultaneous or individual use of video cameras in the visible and infra-red range, as well as LIDAR, allows for daytime and nighttime observations in almost all weather conditions. The CICLOPE system is designed to be able to operate in any location, with completely autonomous power supply and communications systems.

The CICLOPE system currently includes eleven distinct algorithms, of which the following three legacy algorithms are considered in this paper: ADBACK, BEFORT, and BESTEST. The first algorithm is inspired by [1]. ADBACK uses adaptive backgrounds and a quasi-connected components scheme to detect potential targets. BEFORT uses a similar scheme to ADBACK to decide on a fire incident but trains their adaptive backgrounds using a database of past images. BESTEST uses another approach by performing a statistical analysis of the RGB channels of the image over time.

Even though the topic of automatic fire and smoke detection is a fairly mature field of research, there is some lack of agreement in the community on how to present and compare results. For instance, the fact that authors tend to use different

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performance metrics leads to a lack of uniformity and standards that ultimately delay progress in the field and has an overall negative impact. Accordingly, and as a secondary contribution of this paper, we describe a set of performance measures used to evaluate this kind of systems.

The contribution of this work is therefore twofold. First, we propose a wildfire smoke detection method based on image processing techniques that are specifically designed to be applied in a great variety of environments and weather conditions. Secondly, we describe relevant performance metrics.

The remainder of this paper is organized as follows. In Section 2 we describe related work. In Section 3 the CICLOPE system is described in detail. In Section 4, we describe the algorithms that are considered in this paper evaluation. In Section 5 we introduce the used performance measures. In Section 6 results are presented. Section 7 contains some final remarks.

II. RELATED WORK

There are roughly two kinds of smoke detection systems: (i) systems based only on classical machine vision techniques and (ii) systems based on deep learning techniques. It is still not clear if deep learning can outperform the first class of algorithms and therefore research is still ongoing in both areas. We start by reviewing the most relevant contributions to the field in (i) and then in (ii). We also review what has been done in the field of benchmark systems and evaluation measures for fire and smoke detection systems.

One of the first methods proposed in the field is the Lehigh Omnidirectional Tracking System (LOTS) by Boult et. al. [1]. The system aims to detect small moving targets by the use of two adaptive models that capture slow background changes using two distinct thresholds. A quasi-connected components (QCC) analysis is used as a final processing detection step.

Jerome and Philippe [2, 3] propose a real-time fire detection system for video-based surveillance stations. The main idea of their approach is to capture the energy of the velocity distribution of smoke and contrast it with another natural phenomenon such as clouds or shadows. They use fractal embedding and linked list chaining to segment the image into potential smoke regions. The method is used in the commercial system “ARTIS FIRE” from the company “T2M Automation”.

Another approach to wildfire detection is by Gomez-Rodriguez et. al. in [4]. The authors use the optical flow algorithm for motion detection and Wavelet decomposition to solve the aperture problem in the optical flow. After a potential smoke target is detected with optical flow and segmented, different characteristics, such as speed, height, gray level, and inclination angle are extracted using sequential video frames to make the final decision.

In their approach, Damir et. al. [5] investigate several color space transformations and feature classifiers to perform a histogram-based segmentation of potential fire region. They evaluate histograms in YCrCb, CIELab, HSI, and HSI color spaces. They use two different naive Bayes classifiers to classify the histograms. The best performances are achieved with HSI and RGB color spaces. The method described is used in the commercial system iForestFire (https://www.lama.hr/en/solutions/integral-solutions/iforest-fire/) to monitor the coastline of Republic of Croatia.

A method for smoke detection at long ranges is proposed in [6] by Qinjuan and Ning. The method uses multi-frame temporal difference and OTSU thresholding to find the moving areas. Observing the color and area growth clues the system verifies the existence of smoke.

In [7,8], Töreyin et. al. also relies on background subtraction to perform detection but use wavelet analysis. In [9] the same authors propose a long-range smoke detection based on a real-time learning method that updates its decision based on human supervision (security guard at the watchtower). The approach uses four sub-algorithms for detecting (i) moving objects using background subtraction, (ii) gray regions using YUV color space, (iii) rising regions using hidden Markov models (HMM), and (iv) shadows using RGB angle between image and the background. The Least Mean Square (LMS) fuses the results of these methods.

A video-based wildfire detection system based on spatio-temporal correlation descriptors is presented in [10]. The proposed method uses background subtraction and color thresholds to find the moving regions. These regions are then divided into spatiotemporal blocks and correlation features are extracted from these blocks. A support vector machine (SVM) classifier is trained and tested with these descriptors obtained both from image data containing smoke and non-smoke objects.

A similar work to [10] is in [11]. In this work, a spatiotemporal bag-of-features (BoF) and a random forest classifier are used to detect smoke. First, candidate regions are detected using frame differences and non-parametric color models. Then, spatiotemporal regions are built by combining the candidate regions in the current frame and the corresponding regions in previous frames. A histogram of the gradient (HOG) is extracted as a spatial feature, and a histogram of optical flow (HOF) is extracted as a temporal feature. Here the authors assume that the diffusion direction of smoke is generally upward. Using these spatiotemporal features, a codebook and a BoF histogram are created. A random forest classifier is then built using the BoF histogram.

A number of works have been using deep learning techniques to address the problem of smoke and fire detection [12]-[14]. For instance, in [12] the authors propose the use of convolutional neural networks (CNNs) for CCTV surveillance cameras, which can detect fire in varying indoor and outdoor environments.

In [13] a CNN is proposed for smoke detection. The authors use a potential target area extraction before deep learning. Then, the extracted feature maps of candidate areas are classified by the designed deep neural network model based on CNN.

In [14] a smoke detection algorithm is proposed based on the motion characteristics of smoke and a CNN architecture. The authors use an object detection algorithm based on background dynamic update and dark channel prior. Then, the features of suspected regions are extracted automatically by a CNN and detection is performed.

Despite the promising results of deep learning approaches, the training of CNNs relies on large datasets containing numerous images where the fire must be present (which are difficult to acquire) and it is still not clear how they behave in extreme conditions such as long-range detection.

Some efforts have been made to measure the existing smoke and Some efforts have been made to measure the existing smoke and fire detection algorithms across some of the previous perspectives. For instance, the detection performance of the system proposed in [18] was compared against that of the state-of-the-art Töreyin algorithm [7] using 9 online video sequences downloaded from http://signal.ee.bilkent.edu.tr/VisiFire. Despite using a standard test data set, only three metrics were evaluated, namely false positives, true positives and detection rate (true positive rate over false positive rate). A comparison of selected algorithms for fire monitoring was proposed in [19], using data from the NOAA Advanced Very High-Resolution Radiometer (AVHRR). The performance of the methods was characterized according to true and false positive rates as a function of fire temperature and area, solar and viewing geometry, visibility, season and biome. A project of note in the field is the Fire Modelling Standards/Benchmark (FMSB) [20]. The FMSB aimed to demonstrate the major principles behind benchmarking systems of fire detection models. Another important work of note is that of [21] which reviews evaluation measures for this kind of systems. The proposed framework ignores however important metrics such as recall or precision.

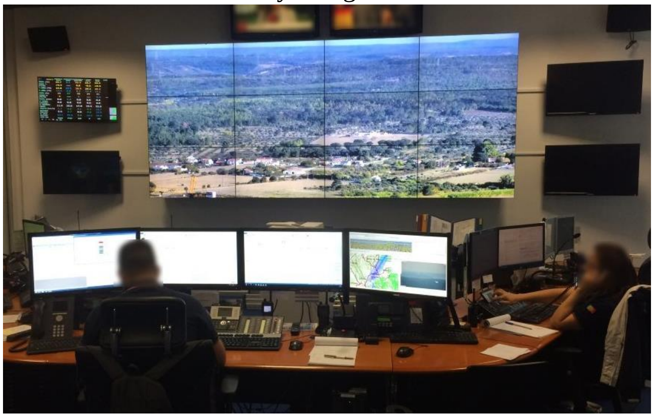

Fig. 1. Image of Control Room of Ciclope System at ANPC Control Center of Santarém.

III. CICLOPE PROJECT

CICLOPE is a distributed monitoring and control system that operates on around 60 surveillance towers in Portugal. These surveillance or "watch" towers are placed at different locations all over Portugal near risk areas. Surveillance cameras are placed in these watch towers to monitor the surrounding areas for possible wildfires. Cameras, once installed at watch towers, operate all year long.

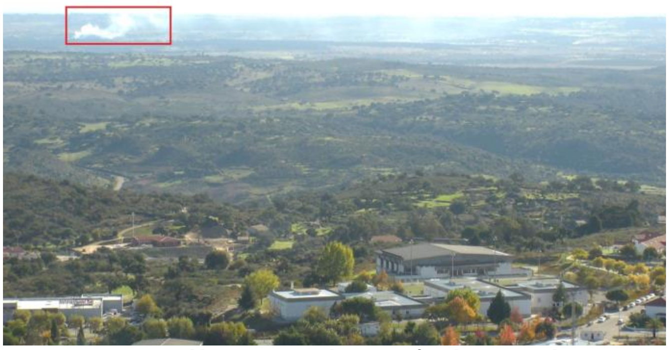

Fig. 2. Image captured by CICLOPE showing a fire detection at long-range.

The CICLOPE system is designed to be able to operate in any location, with completely autonomous power supply and communications systems. The cameras and all associated equipment, namely the positioning and control systems, are maintained by a team of specialized technicians and engineers. A CICLOPE installation consists of several watch towers (WT) and a Management and Control Center (MCC). It is from the MCC that all towers are controlled and to which all the images captured by the cameras arrive. The MCC has a powerful control application, with some innovative features, patented by INOV.

The entire CICLOPE system works over IP, from image acquisition to visualization and processing, which guarantees high performance, unlimited scalability and the use of any digital communication medium (Microwave, GPRS / UMTS, fiber optics, etc.).

CICLOPE is based on the client/server concept, allowing the towers to be controlled from different locations, for example from a Fire Station, Civil Protection, Police Point and so on. For instance, Fig.1 shows an image of a Civil Protection center in Santarém, Portugal.

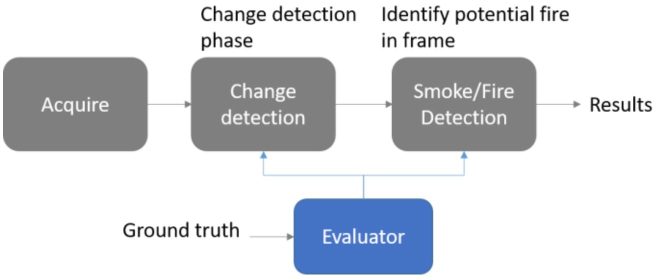

Fig. 3. Smoke/fire detection process implemented.

It is usually difficult to view fire flames from a camera mounted on a watch tower. However, smoke is visible at long distances. A snapshot of a typical wildfire smoke captured by a watch tower camera from a far distance is shown in Fig.2. Since smoke can be spotted before the flames themselves, smoke detection is usually the primary aim of the system.

The diagram of Fig. 3 shows the execution of a standard detection flow in the system. There is a first module responsible for acquiring video frames. The next module is responsible for detecting changes between frames. While not all changes between consecutive frames are necessarily fires, it is likely that a fire incident results from a change between two consecutive frames especially when the frame rate is low (as in the case of CICLOPE). The detection module is the core of the platform and implements the algorithms.

The evaluator is also an important building block of the system. The goal of this model is to evaluate and measure the performance of each of the algorithms. Here, it is important to evaluate not only if true hits occur but also if smoke plumes/fires in consecutive frames are being correctly tracked. A set of measures are related to this module: how long did it take to detect a fire, for how long was the fire detected, the number of missed hits for the same fire and others. We describe, in detail, how to evaluate image alignment and smoke/fire detection in the results section.

IV. ALGORITHMS

In the following, we describe three algorithms of CICLOPE for fire and smoke detection.

A. ADBACK

The first algorithm is based on ADaptive BACKground subtraction (ADBACK) and is inspired by the LOTS algorithm [1]. ADBACK uses two gray level background images (B_{light} and B_{dark}), that are initialized during an initial training process using a set of consecutive N frames, without target objects:

$$B_{light}(x,y) = max(I^t(x,y), t = 1,\dots,N) \quad (1)$$

$$B_{dark}(x,y) = \min(I^t(x,y), t = 1,\dots,N) \quad (2)$$

where $I^t(x,y)$denotes a frame at the time instant t.

Target objects are detected with two thresholds (T_L, T_H). The difference between each pixel and the closest background image is calculated and, if it exceeds a low threshold T_L, the pixel is considered active. A target is detected if a set of connected active pixels such that a subset of them verifies

$$\min_i |I^t(x,y) - B_i^t(x,y)| > T_H \quad (3)$$

where T_H is the high threshold. The low and high thresholds as well as the background images are updated dynamically as new frames come in.

B. BEFORT

BEFORT, the second algorithm is based on the same reasoning of ADBACK but uses a database of past images to construct the background light and dark. Concretely, for each new image, the algorithm analyses N previous images. For each pair of these images I_1 and I_2 creates the two gray level backgrounds

$$B_{light}(x,y) = \max\big(I_1(x,y), I_2(x,y)\big) \quad (4)$$
$$B_{dark}(x,y) = \min\big(I_1(x,y), I_2(x,y)\big) \quad (5)$$

Target objects are detected with two thresholds (T_L, T_H). The difference between each pixel and the closest background image is calculated and if it exceeds a low threshold T_L, the pixel is considered active. If a pixel is active for at least one pair of past images, then it is considered a target.

C. BESTEST

The BESTEST algorithm uses N previous images to create a statistical background model per pixel. For each new image I^t it calculates the average and standard deviation value of the component Red, Green and Blue. If a pixel is within a certain distance of the background it is considered active. This distance is computed using the standard deviation of the pixel for each color component:

$$|I_R^t(x,y) - B_R^t(x,y)| > \sigma_R(x,y) \vee$$
$$|I_G^t(x,y) - B_G^t(x,y)| > \sigma_G(x,y) \vee$$
$$|I_B^t(x,y) - B_B^t(x,y)| > \sigma_B(x,y) \quad (6)$$

When the red, green or blue distance is superior to the respective standard deviation of the pixel then the pixel is considered an active pixel. Quasi-connected components are used to determine the final targets.

V. PERFORMANCE MEASURES

In this section, we describe a set of general performance measures applicable to any smoke and fire detection method that can be of use both from an academic as well as a real-life standpoint.

A. Alignment Performance Measures

One of the most important steps of our algorithms is change detection. For successful change detection, it is important to have correct frame alignment. Alignment here refers to the ability to align two successive frames from the same scene. Concretely, alignment consists of moving, and potentially deforming, a template image to minimize the difference between the template and an input image [22]. In order to evaluate alignment, it is important to first determine what a correct alignment is: Suppose we are trying to align a template image T(x) to an input image I(x), where $x = (x,y)^{\mathrm{T}}$ is a vector containing the image coordinates. If the warp is denoted by W(x, p), where p =$(p_1, \dots\ p_n)^T$ is a vector of parameters, we assume that the goal of image alignment is to minimize:

$$\sum_{\mathrm{x}}\big[\mathrm{I}\big(\mathrm{W}(\mathrm{x};\mathrm{p})\big) - \mathrm{T}(\mathrm{x})\big]^2 \quad (7)$$

with respect to p, whereby the sum is performed over the range of pixels x in the template image T(x).
There is a vast range of alignment evaluation measures. In this section, we present one of the most popular measures: Pearson's correlation coefficient (PCC).

Pearson Correlation Coefficient

Pearson's Correlation Coefficient (PCC) is a widely used statistical measure used in pattern recognition and image processing. The PCC has the ability to output a single scalar from the comparison of two images. The coefficient takes value 1 if the two images are identical, 0 if they are completely uncorrelated, and -1 if they are anti-correlated, for example, if one image is the negative of the other.

A major advantage of PCC is that it is invariant to linear transformations of x and y. Accordingly, the method is mostly indifferent to uniform variations in brightness and contrast. The correlation coefficient between sequences $X = \{x_i \mid i = 1 \dots, n\}$ and $Y = \{y_i \mid i = 1 \dots, n\}$ is given by:

$$\mathrm{r} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2}\ \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\bar{y})^2}}} \quad (8)$$

where
$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$ *and* $\bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i$
which can also be written as:

$$r = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{(x_i-\bar{x})}{\sigma_x}\right)\left(\frac{(y_i-\bar{y})}{\sigma_y}\right) \quad (9)$$

or

$$\mathrm{r} = \frac{1}{n}\bar{X}^t\ \bar{Y} \quad (10)$$

This measure is compared against a threshold to determine if the alignment was a good or bad alignment. Over time, the system keeps track of the overall number of processed images and computes the percentage of aligned images. An aligned image is an image whose PCC is above a given threshold of alignment (PCC > $T_A = 0.65$)These figures are presented as a function of time.

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B. Detection Performance Measures

There are four types of errors that can be made in detection. First, the system may indicate the presence of a smoke plume/fire in a place where the fire does not exist. The second type of error may occur when a fire or smoke plume exists somewhere in an image, but the system does not recognize it or indicates the presence of fire in the wrong location. Each of these errors can be referred to as respectively:

- Measure D-1: (FP) – False Positive in the frame. An estimate exists that is not associated with a ground truth object.
- Measure D-2: (FN) – False Negative in the frame. A ground truth object exists that is not associated with an estimate.

Two other fundamental measures which are often ignored in this field are precision and recall. They are often used in information retrieval but are rarely used to determine if and how well fire and smoke are being detected.

Recall. Given a collection of true positive samples (TP) and false negatives (FN)

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP+FN}}. \quad (11)$$

Recall assesses how much of the ground truth (fire data set) is covered by estimation (detection data set). It varies between 0 (no overlap) and 1 (full overlap). The recall is necessary for good detection quality as it measures how well a model detects all the relevant fires.

Precision, Given a collection of true positive samples (TP) and false negatives (FN)

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (12)$$

Precision assesses how much of the estimation covers the ground truth and can take values between 0 (no overlap) and 1 (full overlap). As a recall, precision alone is an important property but cannot guarantee a high-quality detection.

F-measure. To address the limitations of precision and recall it is possible to use the F-measure. The F-measure is expressed as

$$Fmeasure = \left(\frac{Precision * Recall}{Precision + Recall} \right). \quad (13)$$

This measure is a better indicator of good detection as it requires both high precision and recall values. We also use the standard measure of accuracy:

$$Accuracy = \left(\frac{TP+TN}{TP+TN+FP+FN} \right). \quad (14)$$

VI. RESULTS

In this section, we present the results of comparing CICLOPE's three algorithms against LOTS [1]. We divide this section into three subsections: (i) dataset description, (ii) alignment results and (iii) detection results.

A. Dataset

The smoke and fire detection algorithms are applied to a set of 6895 1920 × 1080 real-world images collected between October and December 2018 from a viewpoint of a watchtower in Castelo Branco, Portugal. The images were

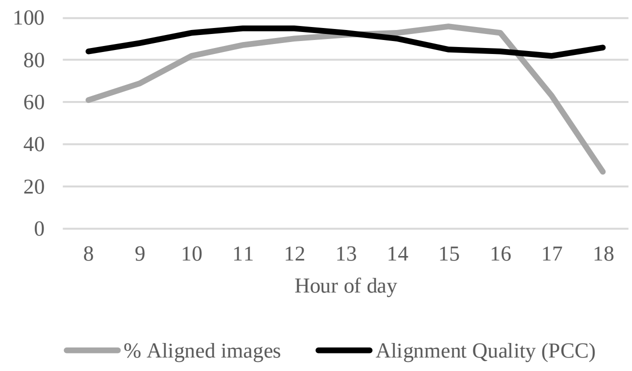

Fig. 4. Efficiency of the image aligner module measured per hour of day.

sampled every 5 minutes during daylight period from 7 A.M to 19 P.M. Overall, the dataset encompasses 50 critical days with at least one fire. Concretely, the set includes 438 images samples with smoke or fire representing 75 real fire incidents. Fires can be at a close, mid and long range.

B. Alignment Results

The results of applying the CICLOPE aligner to the 7000 images are summarized in Fig. 4. The chart of Fig. 4 shows the efficiency of the aligner measured in two perspectives: (i) % of aligned images and (ii) average correlation coefficient over time. As shown, the aligner works best under optimal lighting conditions i.e. between 12 and 16H. Here, the percentage of aligned images is always above 90% and the average correlation coefficient is consistently high (> 0.80).

These results suggest that CICLOPE's aligner could be improved during these hours.

C. Numerical Results

We ran our tests in a PC with Intel (R) Core (TM) i5-8400 CPU 2.80 GHz, 8.0 GB memory, 64 bits OS. The results of our experiments are shown in Table I. Here, a true positive (TP) or "fire observation" is defined as an image (video frame) that has at least one smoke/fire. We also show in column 2 (in parentheses) the number of fire incidents detected out of the 75.

In regard to the TP measure the best model was ADBACK with a total of 388 TP in 438 fire samples (representing 69 detected fires in 75). Predictably, this model is also the one with the highest recall (88.58%) as it is the algorithm with by far the highest number of successful detections.

There may be situations where a high recall rate may be necessary, namely during fire danger season dates where the risk of fire is more likely and the potential for destruction is larger. In such cases having a more sensitive algorithm, such as ADBACK, eventually aided by human supervision, can be more of use than resorting to a more conservative method.

We consider a false positive as any image (video frame) where there are one or more false alarms. According to this metric, BEFORT excels the other algorithms with only 609 false alarms in the 6895 images. Please note that given the images' sample rate of 5 minutes, this figure means that every hour there will only be around 1.8 false alarms (on average), a very acceptable rate. The drawback of this algorithm is its conservativeness as it has a considerably low recall (5.71%)

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compared to ADBACK's recall (88.58%).

Another balanced algorithm is BESTEST. It shows an acceptable recall (16.67%), a not so low precision (6.75%) (close to the one of ADBACK), the highest accuracy (80.07%) and the second highest F-measure (9.60%). The ADBACK is, however, the best in recall (88.58%), precision (12.32%) and F-measure (21.63%).

It is important to discuss the relevance of F-measure to provide an overall view of the performance of models. It is clear from our example that the F-measure is better than the traditional metric of accuracy. For instance, consider the accuracy of LOTS, 84.12%, which is the second highest accuracy of the set. This metric does not translate the low recall attained by this method (2.51%) resulting from LOTS only detecting 7 fires out of the 75. In contrast, the F-measure gives the best scores to BESTEST, BEFORT, and ADBACK which makes sense as these methods show more balanced results.

As a final note please consider that the F-measure results were not remarkable (21.63% for the best case of ADBACK). This follows again from the fact that it is difficult to remove false alarms, especially given the low fps under which the system operates, resulting in a low precision rate. Environmental conditions, sudden light changes, fog, camera shifts, rain, and other factors contribute to a high number of frames with alarms. This, however, and as explained before, does not mean that a model with low precision and consequently low F-measure is necessarily a bad model in this context.

TABLE I
PERFORMANCE OF TESTED ALGORITHMS

Measure	LOTS [1]	ADBACK	BEFORT	BESTEST
True Positives (TP) (Detected fires)	11 (7 fires)	388 (69 fires)	25 (16 fires)	73 (31 fires)
False Positives (FP)	668	2762	609	1009
Precision (%)	1.62	12.32	3.94	6.75
Recall (%)	2.51	88.58	5.71	16.67
Accuracy (%)	84.12	59.22	85.17	80.07
F-measure (%)	1.96	21.63	4.66	9.60

I. CONCLUSION

In this paper, we present CICLOPE, a surveillance system that is able to perform remote detection of smoke and fire in real-time. We describe three of its legacy algorithms and compare them against LOTS [1], a similar model from the literature.

Our main contribution is showing how this kind of algorithms performs in challenging real-world datasets. Our dataset is challenging for several reasons. First, it comprises both close, mid and long-range fires. It is easier to detect fire and smoke at close or mid-range than at far-range especially when we consider tenths of kilometers away. It is problematic to define thresholds that can be applied both to detect close and long-range fires. In the future, a solution may be developed to take into consideration a depth map of the scene when defining the thresholds.

Second, the camera can shift considerably. For the purpose of background subtraction, it is important to have aligned images. Misaligned images can result in non-moving objects such as trees and houses being detected as moving objects and eventually generate false alarms. As future work, the CICLOPE aligner may be improved for its problematic hours.

Third, sudden light changes, fog, and rain as well as other environmental conditions can also lead to false detections. Note that we aim to detect smoke plumes/fires that can have very small dimensions (such as a minimal area of 10 pixels in a 1920 × 1080 image. Developing algorithms that can deal with these complex scenes is a non-trivial task. To this aim, it may be necessary to develop tailored algorithms/heuristics to solve each of these problems.

We also aimed to show how evaluation measures such as recall, precision, and F-measure can be of use to compare smoke and fire detection algorithms. We stress that it is important to analyze these measures as well as standard false positive and true positive rates and accuracy.

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