Real-Time Fire Detection for Video-Surveillance Applications Using a Combination of Experts Based on Color, Shape, and Motion

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***Abstract*— In this paper, we propose a method that is able to detect fires by analyzing videos acquired by surveillance cameras. Two main novelties have been introduced. First, complementary information, based on color, shape variation, and motion analysis, is combined by a multiexpert system. The main advantage deriving from this approach lies in the fact that the overall performance of the system significantly increases with a relatively small effort made by the designer. Second, a novel descriptor based on a bag-of-words approach has been proposed for representing motion. The proposed method has been tested on a very large dataset of fire videos acquired both in real environments and from the web. The obtained results confirm a consistent reduction in the number of false positives, without paying in terms of accuracy or renouncing the possibility to run the system on embedded platforms.**

***Index Terms*— Fire detection, multiexpert system, video surveillance.**

I. Introduction

In recent years, several methods have been proposed, with the aim to analyze the videos acquired by traditional video-surveillance cameras and detect fires or smoke, and the current scientific effort [1], [2] focused on improving the robustness and performance of the proposed approaches, so as to make possible a commercial exploitation.

Although a strict classification of the methods is not simple, two main classes can be distinguished, depending on the analyzed features: color based and motion based. The methods using the first kind of features are based on the consideration that a flame, under the assumption that it is generated by common combustibles, such as wood, plastic, paper, or others, can be reliably characterized by its color, so that the evaluation of the color components in RGB (Red, Green, Blue), YUV (Luminance, Chrominance) or any other color space is adequately robust to identify the presence of flames. This simple idea inspires several recent methods: for instance, in [3] and [4], fire pixels are recognized by an advanced background subtraction technique and a statistical RGB color model: a set of images have been used and a region of the color space has been experimentally identified so that if a pixel belongs to this particular region, then it can be classified as fire. The main advantage of such algorithms lies in the low computational cost allowing the processing of more than 30 frames/s at Quarter Common Intermediate Format (176×144) image resolution. Differently from [3] and [4], Yu *et al.* [5] experimentally define a set of rules for filtering fire pixels in the HSV (Hue, Saturation, Intensity) color space. The introduction of the HSI color space significantly simplifies the definition of the rules for the designer, being more suitable for providing a people-oriented way of describing the color. A similar approach has been used in [6], where a cumulative fire matrix has been defined by combining the RGB color and HSV saturation in particular, starting from the assumption that the green component of the fire pixels has a wide range of changes compared with red and blue ones, this method evaluates the spatial color variation in pixel values to distinguish nonfire moving objects from uncontrolled fires.

The common limitation of the above mentioned approaches is that they are particularly sensitive to the changes in brightness, thus causing a high number of false positive due to the presence of shadows or to different tonalities of the red. This problem can be mitigated by switching to a YUV color space. In [7], for instance, a set of rules in the YUV space has been experimentally defined to separate the luminance from the chrominance more effectively than that in RGB, so as to reduce the number of false positives detected by the system. In [8], information coming from the YUV color is combined using a fuzzy logic approach to consider the implicit uncertainties of the rules introduced for thresholding the image. A probabilistic approach based on YUV has been also exploited in [9], where the thresholding of potential fire pixels is not based on a simple heuristic but instead on a support vector machine (SVM), able to provide a good generalization without requiring problem domain knowledge. Although this algorithm is less sensitive to variations in the luminance of the environment, its main drawback compared with other color-based approaches lies in the high computational cost required as soon as the dimensions of the support vector increase.

In conclusion, it can be observed that the methods using color information, although being intrinsically simple to configure, can be successfully used only in sterile areas, where no objects generally move inside. Their main limitation concerns about the number of false positives when used in normal populated areas: the persons with red clothes or red vehicles

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might be wrongly detected as fire only because of their dominant color. To face this issue, in the last years, several approaches have been proposed: they start from the assumption that a flame continuously changes its shape and the disordered movement of red regions can help in distinguishing it from rigid objects moving in the scene. For instance, in [10], the physical properties of the fire are used to build a feature vector based on an enhanced optical flow, which is able to analyze in different ways both the dynamic texture of the fire and its saturated flame. Dynamic textures have also been used in [11], where a two-phase texture detection process has been proposed to speed up the segmentation step, very useful to extract a wide set of shape-based features, and making possible the detection of the fire in a reasonable time. In [12], the irregularity of the fire over time is handled by combining the capabilities of finite-state automata with fuzzy logic: variations in wavelet energy, motion orientation, and intensity are used to generate probability density functions, which determine the state transitions of a fuzzy finite automaton.

The wavelet transform has been also used in [13] to properly detect the temporal behavior of flame boundaries. It is worth pointing out that the methods based on the wavelet transform, differently from those based on the color, cannot be used on still images and, in general, require a frame rate sufficiently high, higher than 20 frames per second (fps), to guarantee satisfactory results, thus limiting their applicability.

In [14], frame-to-frame changes are analyzed and the evolution of a set of features based on color, area size, surface coarseness, boundary roughness, and skewness is evaluated by a Bayesian classifier. The wide set of considered features allows the system to consider several aspects of fire, related to both color and appearance variations, thus increasing the reliability in the detection. In [15], the thresholding on the color, performed in the RGB space, is improved by a multiresolution 2-D wavelet analysis, which evaluates both the energy and the shape variations to further decrease the number of false positive events. In particular, the shape variation is computed by evaluating the ratio between the perimeter and the area of the minimum bounding box enclosing the candidates' fire pixels. This last strategy is as simple and intuitive as promising if the scene is populated by rigid objects, such as vehicles. On the other side, it is worth pointing out that the shape associated with nonrigid objects, such as people, is highly variable in consecutive frames, think for instance, to the human arms that may contribute to significantly modify the size of the minimum bounding box enclosing the whole person. This evidence implies that the disordered shape of the person may be confused with the disordered shape of the fire, thus consistently increasing the number of false positives detected by the system.

Therefore, in conclusion, the main limitation of motion based approaches lies in the fact that the performance improvement is often paid from different points of view: 1) in most of the cases, several sensitive parameters need to be properly set for the application at hand and 2) the motion and the shape of the flame are somehow dependent on the burning material as well as on the weather conditions (think, for example, a strong wind moving the fire).

In [16], a novel descriptor based on spatiotemporal properties is introduced. First, a set of 3-D blocks is built by dividing the image into 16×16 squares and considering each square for a number of frames corresponding to the frame rate. The blocks are quickly filtered using a simple color model of the flame pixels. Then, on the remaining blocks, a feature vector is computed using the covariance matrix of 10 properties related to color and to spatial and temporal derivatives of the intensity. Finally, an SVM classifier is applied to these vectors to distinguish fire from nonfire blocks. The main advantage deriving from this choice is that the method does not require background subtraction and thus can be applied also to moving cameras. However, since the motion information is only considered by considering the temporal derivatives of pixels, without an estimation of the motion direction, the system, when working in nonsterile areas, may generate false positives due to flashing of red lights.

The idea of combining several classifiers to obtain a more reliable decision has been generalized and extended in a theoretically sounder way in the pioneering paper [17]. Fire-colored pixels are identified using a hidden Markov model; temporal wavelet analysis is used for detecting the pixel flicker, spatial wavelet analysis is used for the nonuniform texture of flames, and finally, wavelet analysis of the object contours is used to detect the irregular shape of the fire. The decisions taken by the above mentioned algorithms are linearly combined by a set of weights that are updated with a LMS strategy each time a ground-truth value is available. This method has the advantage that during its operation, it can exploit occasional feedback from the user to improve the weights of the combination function. However, a drawback is the need to properly choose the learning rate parameter to ensure that the update of the weights converges and that it does so in a reasonable time.

The paper is organized as follows. Section II describes the rationale of our approach. In Section III, the proposed method is detailed: after a description of the multiexpert system (MES) in Section III-A, the three different experts, based on color, shape variation, and motion, are described in Sections III-B–III-D, respectively. In Section IV, the results obtained by testing the proposed approach over a wide dataset are shown before drawing the conclusion in Section V.

II. Rationale of the Method

Up to now, the efforts of the research community have been mainly devoted to the definition of a representation of both color and movement, so as to discriminate fire from nonfire objects; this inevitably leads to high-dimensional feature vectors. How to manage high-dimensional feature vectors is a well-known problem in the communities of machine learning and pattern recognition: in fact, as shown in [18], employing a high-dimensional feature vector would imply a significant increase in the amount of data required to train any classifier to avoid overspecialization and to achieve good results. Furthermore, independently of the particular features extracted, in most of the above mentioned methods, the high variability of fires as well as the large amount of noise in data acquired in fire environments prevents the systems from the achievement of a high recognition rate. More generally, it has been shown in [19] that increasing the performance of a system based on the traditional combination feature vector–classifier is often a very expensive operation: in fact, it may be required to design a new set of features to represent the objects, to train again the classifier, or to select a different classifier if the performances are not sufficiently satisfactory. Furthermore, this effort could be paid back by only a slight improvement in the overall accuracy, and so this approach may be proved to be not very convenient.

To overcome the above mentioned limitations, one of the solutions coming from [19] is to split the feature vector and, consequently, to adopt a set of classifiers, each tailored on a feature set and then trained to be an expert in part of the feature space. The main idea of this kind of paradigm, usually referred to as multiexpert system, is to make the decision by combining the opinions of the different individual classifiers (hereinafter *experts*), so as to consistently outperform the single best classifier [20]. This latter paper explains on the basis of a theoretical framework why a MES can be expected to outperform a single monolithic classifier. Most classifiers, given an unlimited amount of training data, converge to an optimal classification decision (in a probabilistic sense); but on a finite training set, their output is affected by an error (additionally with respect to the inherent error due to ambiguities in the input data), which is either due to overspecialization or to the choice of reducing the classifier complexity to avoid the loss of generalization ability. Kittler [20] shows that under some assumptions satisfied very often in practical cases, a suitably chosen *benevolent* combining function can make the overall output of the MES less sensitive to the errors of the individual classifiers.

MESs have been successfully applied in several application domains, ranging from handwriting recognition [19] and biomedical images analysis [21], [22] to face detection [23] and movie segmentation [24]. Starting from a preliminary study [25], in this paper, we propose the employing of a MES for detecting the fire in both indoor and outdoor environments: three different experts, complementary in their nature and regarding their errors, are combined with relatively little effort so as to make possible the improvement of the overall performance. It is evident that the successful implementation of a MES requires both the adoption of complementary sets of features feeding the different experts and the choice of a reliable combination rule.

Regarding the first aspect, we considered three different experts able to analyze the same problem from different points of view, based on color, movement, and shape variation, respectively. The main advantage deriving from this choice lies in the fact that the experts are very simple to configure, and so making the proposed system particularly suited for deployment in real environments.

As for the experts based on color and shape variations, two algorithms widely adopted by the scientific community and providing very promising results have been considered; they are based on a thresholding in the YUV space and on the variation of the shape in terms of minimum bounding box enclosing the detected moving object, respectively. In particular, the expert based on color aims to discriminate *red* from *nonred* objects and is particularly suited for sterile environments, while the one based on shape variation is very effective for distinguishing fire, usually having a strongly variable shape, from rigid objects moving in the scene, such as vehicles.

Finally, the expert based on movement evaluation is based on the assumption that fire has a disordered movement, much more disordered compared with any other object usually populating the scene. To exploit this property, a novel descriptor for representing the movement is proposed in this paper: the main idea is to adopt a bag-of-words approach for evaluating the direction of some salient points detected in the moving objects. The main advantage deriving from this choice is that the representation is very robust with respect to the noise introduced both during the extraction of the salient points and the evaluation of the direction of their motion.

Once obtained the decisions from the three different experts, the system needs to properly combine them: the idea is that each classifier should have different voting priorities, depending on its own learning space. For this reason, the combination rule adopted in this paper is based on weighted voting, where the weights depend on the prediction confidence of each class the system has to recognize [20].

The main original contributions of the paper are: 1) the proposition of a novel system for characterizing the movement of the flame; 2) the use of a multiexpert approach based on three complementary experts; and 3) a wide characterization of performance on a standard dataset of videos, made available at http://mivia.unisa.it.

III. Proposed Architecture

An overview of the proposed approach is presented in Fig. 1. Objects moving in the scene are first detected using the algorithm we recently proposed in [26], which proved to be very effective both from a qualitative and a computational point of view: a model of the background (which represents the scene without any object moving inside) is maintained and properly updated (*background updating*) so as to deal with the changes of the environments during the day; then, a background subtraction strategy is applied to obtain the foreground mask, encoding the objects moving in the scene (*foreground mask extraction*). Finally, the *blobs*, each one being associated with an object, are obtained by a connected component labeling analysis [27] (*connected component labeling*).

Three different experts have been introduced for evaluating the blobs: 1) based on color [color evaluation (CE)]; 2) analyzes the shape of the blobs detected in the current frame with respect to the ones detected in previous frame [shape variation (SV)]; and 3) evaluates the movement of the blobs in two consecutive frames [movemente evaluation (ME)]. The decisions taken by the experts are combined by a MES classifier based on a weighted voting rule, which finally assigns a class to each blob.

A. Multiexpert Evaluation

As mentioned before, one of the main choices determining the performance of a MES is the combination rule.

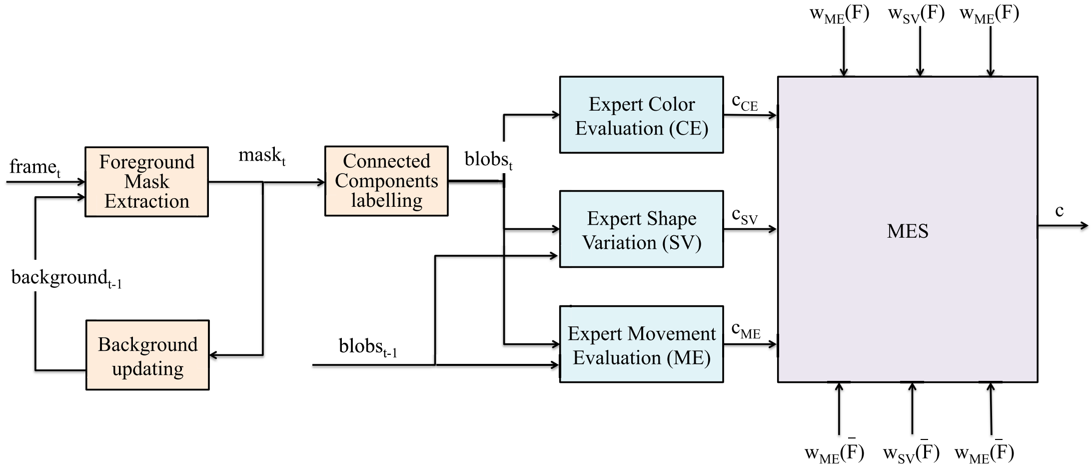


Fig. 1. Overview of the proposed approach. The blobs are detected by a background subtraction algorithm; the decision is taken by combining the information coming from three different experts, which are respectively, based on color, shape variation, and motion that analyze every input blob. Note that the last two experts need to be supplied with the blobs detected at the current frame and the previous frame.

Although several strategies have been proposed in the last years [28], it has been proved that one of the most robust to the errors of the combined classifiers (both when combining the classifiers based on the same features and when using different feature subsets in each classifier) is the weighted voting rule [20]. The main idea is that each expert can express its vote, which is weighted proportionally to the recognition rate it achieved for each class on the training set. For instance, suppose that both CE and the ME classify the blob b as fire and that the percentage of fires correctly detected on the training set is 0.8 and 0.7 for the two experts, respectively. Then, the two experts' votes for the class fire will be weighted 0.8 and 0.7.

In a more formal way, the generic kth expert, being $k \in \{\mathrm{CE}, \mathrm{SV}, \mathrm{ME}\}$, assigns to the input blob the class $c_k(b)$ chosen between the labels (F for *fire*, $\overline{F}$ for *nonfire*); this can be formulated as a vote to the generic class i as

$$\delta_{ik}(b) = \begin{cases} 1, & \text{if } c_k(b) \text{ gives the class } i \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

in other words, if the output corresponds to the class, then the vote will be 1, otherwise it will be 0.

As suggested in [19], the weights $w_k(i)$ are dynamically evaluated by a Bayesian formulation to lead to the MES highest recognition rate. In particular, this formulation considers the performance of each expert on the training set of each class. More formally, given the classification matrix $C^{(k)}$ computed by the kth expert on the training step, $w_k(i)$ can be determined by evaluating the probability that the blob b under test, belonging to the class i, is assigned to the right class c_k by the kth expert

$$w_k(i) = P(b \in i | c_k(b) = i) = \frac{C_{ii}^{(k)}}{\sum_{i=1}^{M} C_{ij}^{(k)}} \tag{2}$$

M being the number of classes and $C_{(ij)}$ the value of the classification matrix in the position (i, j).

The final decision is taken by maximizing the reliability of the whole MES in recognizing that particular class. In particular, the reliability $\psi(i)$ that the blob b belongs to the class i is computed by a weighted sum of the votes

$$\psi(i) = \frac{\sum_{k \in \{\mathrm{CE,SV,ME}\}} \delta_{ik}(b) \cdot w_k(i)}{\sum_{k \in \{\mathrm{CE,SV,ME}\}} w_k(i)}. \tag{3}$$

The decision for the class c is finally taken by maximizing the reliability over the different classes

$$c = \arg\max_i \psi(i). \tag{4}$$

B. CE: The Expert Based on Color Evaluation

This expert evaluates the color by analyzing its properties in the YUV color space; as already mentioned, YUV has been widely adopted in the literature since it separates the luminance from the chrominance and so is less sensitive to the changes in brightness. In particular, as proposed on [7], this expert is based on the combination of six different rules, denoted as $r_1^c, \dots, r_6^c$, able to model the color of the flames.

In more detail, as for r_1^c and r_2^c, the idea is related to the experimental evidence that in most of flames, the pixels exhibit a red channel value greater than a green channel value, as well as a green channel value greater than a blue channel value [29]

$$R(x, y) > G(x, y) > B(x, y). \tag{5}$$

Such conditions can be equivalently expressed in the YUV plane, by adopting the well-known conversion rules [30], so that we obtain for the generic pixel (x, y) of the image

$$r_1^c : Y(x, y) > U(x, y) \tag{6}$$
$$r_2^c : V(x, y) > U(x, y). \tag{7}$$

On the other side, r_3^c and r_4^c are based on the assumption that the red component of fire pixels is higher than the mean red component in the frame. Expressed in the YUV space, it implies that a fire pixel has the Y and V components higher

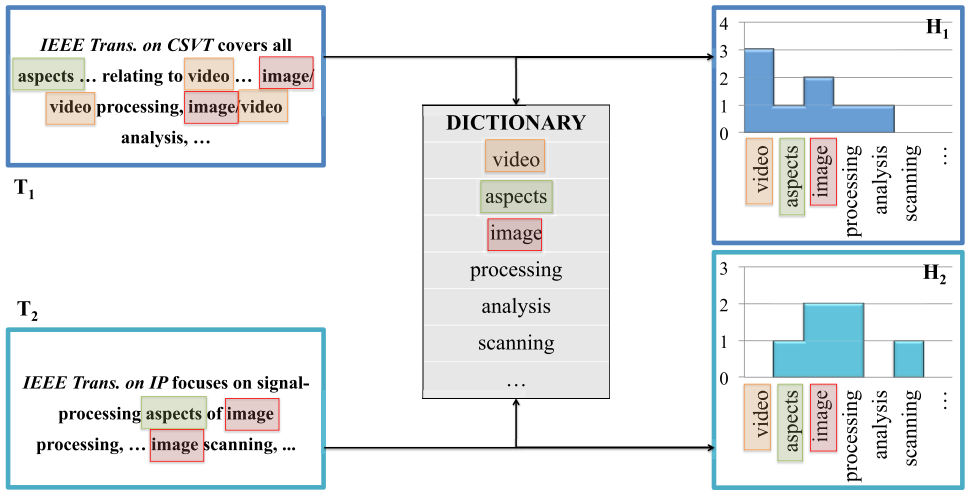


Fig. 2. Rationale of the bag-of-words approach applied to text classification: the occurrences, in a document, of a predefined set of words included into a dictionary are used for building up a histogram of occurrences. See the histograms H_1 and H_2 associated with the texts T_1 and T_2, respectively.

than the mean Y and V values in the frame respectively, while the U component lower than the mean U value in the frame

$$r_3^c : Y(x, y) > \frac{1}{N} \cdot \sum_{k=1}^{N} Y(x_k, y_k) \tag{8}$$

$$r_4^c : U(x, y) < \frac{1}{N} \cdot \sum_{k=1}^{N} U(x_k, y_k) \tag{9}$$

$$r_5^c : V(x, y) > \frac{1}{N} \cdot \sum_{k=1}^{N} V(x_k, y_k) \tag{10}$$

N being the total number of pixels in the image.

Finally, in [7], it has been experimentally evaluated that fire pixels are characterized by a considerable difference between U and V components. Thus, the last rule can be defined as

$$r_6^c : |V(x, y) - U(x, y)| \geq \tau_c. \tag{11}$$

In our experiments, τ_c has been set to 40, as suggested in [7].

The classifier decision c_{CE} is finally taken by evaluating the above mentioned rules. In particular, if all the conditions are verified, then the blob is assigned to the fire class

$$c_{\text{CE}} = \begin{cases} F, & \text{if } r_1^c \wedge r_2^c \wedge r_3^c \wedge r_4^c \wedge r_5^c \wedge r_6^c \\ \overline{F}, & \text{otherwise.} \end{cases} \tag{12}$$

C. Expert Based on Shape Variation

This expert (SV) analyzes the variation of the blob shape across two consecutive frames to exploit the observation that the shape of flames changes very quickly. In particular, as in [15], the algorithm computes, for each blob, the perimeter P_t and the area A_t of the minimum bounding box enclosed it. Such values are then used to compute the perimeter-area ratio r_t, which is an indicator of shape complexity

$$r_t = \frac{P_t}{A_t}. \tag{13}$$

The shape variation s_v^t is then evaluated by comparing the shape measure computed at the frame t with the one obtained by the nearest blob detected at the previous frame $(t-1)$

$$s_v^t = \left| \frac{r_t - r_{t-1}}{r_t} \right|. \tag{14}$$

The score s_v^t is finally analyzed; if it is higher than a given threshold, then the class fire is assigned to the input blob

$$c_{\text{SV}} = \begin{cases} F, & \text{if } s_v^t > \tau_v \\ \overline{F}, & \text{otherwise.} \end{cases} \tag{15}$$

D. Expert Based on Movement Evaluation

ME is based on a novel descriptor that adopts a bag-of-words approach [31], introduced in this paper to characterize the cluttered movement of fire. The rationale of this expert is based on the empirical observation that the parts of a flame appear to move at the same time in several different directions in a rather chaotic and unpredictable way; by contrast, the parts of a rigid or articulated object show at each instant a quite limited set of motion directions. For translating this observation into an effective description and classification system, we have chosen a bag-of-words approach.

Bag-of-words has been successfully applied in several application domains, ranging from text classification to audio event detection and action recognition. The underlying idea is that the pattern to be classified is represented by the occurrences of low-level features (words) belonging to a dictionary, and such occurrences are used to build a high-level vector; the generic component is associated with a word and its value is given a counting to the occurrences of that word in the input pattern (see Fig. 2 for an example).

To apply the bag-of-words strategy to our problem, the following main steps need to be dealt with: the extraction of the low-level representation, the definition of the dictionary that determines the construction of the high-level representation, and the paradigm adopted for the classification.

An overview of the proposed approach is shown in Fig. 4, while a more detailed explanation of the above mentioned phases will be provided in the following.

1) Low-Level Representation: To capture the motion of the different parts of a foreground blob, salient points are extracted and matched across consecutive video frames. The set of salient points is extracted using the scale invariant feature transform (SIFT) [32] descriptors. At a given time instant t, the high-speed corner-detection algorithm proposed in [33] is used to extract the set C_t of $|C_t|$ corners

$$C_t = \left\{c_t^1, \ldots, c_t^{|C_t|}\right\}. \tag{16}$$

Each corner is then represented by measuring the local image gradients in the region around it, thus obtaining the set of corresponding SIFT descriptors

$$V_t = \left\{v_t^1, \ldots, v_t^{|V_t|}\right\} \tag{17}$$

in which $|V_t| = |C_t|$.

Given the corner points extracted in two consecutive frames (t and $t-1$) and the corresponding set of descriptors (V_t and V_{t-1}), the algorithm computes a set of matchings by pairing each point at time t with the one at time $t-1$ that is closest according to the Euclidean distance between SIFT descriptors

$$M = \{m_1, \ldots, m_{|M|}\} \tag{18}$$

where

$$m_j = \left(v_t^a, v_{t-1}^b\right) \tag{19}$$

such that

$$b = \arg\min_i \left\|v_t^a - v_{t-1}^i\right\| \text{ and } \left\|v_t^a - v_{t-1}^b\right\| < \tau_M. \tag{20}$$

For each matching m_j, we consider the vector connecting the two corresponding corner points c_t^a and c_{t-1}^b and extract the angle ϕ_j of this vector with respect to the x-axis.

Fig. 4 clarifies this concept: the corner points c_{t-1} and c_t, represented as red and blue circles, respectively, are associated to their descriptors v_{t-1} and v_t. The matching m_j is represented by the green line connecting such points, while ϕ_j is the angle that m_j build with the x-axis (black line).

2) Dictionary: According to the proposed low-level representation, the space of the possible words is the round angle (0°–360°). To obtain a adequately small finite set of words, we decide to uniformly partition the space into $|D|$ sectors d, thus obtaining the dictionary D as

$$D = \left\{d_k | k = 1, \ldots, |D|; d_k = \left]k\frac{2\pi}{|D|}, (k+1)\frac{2\pi}{|D|}\right]\right\}. \tag{21}$$

$|D|$ has been experimentally set in this paper to 6: it implies that the resolution of the direction is 60°, which represents a good tradeoff between a suitable representation of the movement and the immunity to the noise.

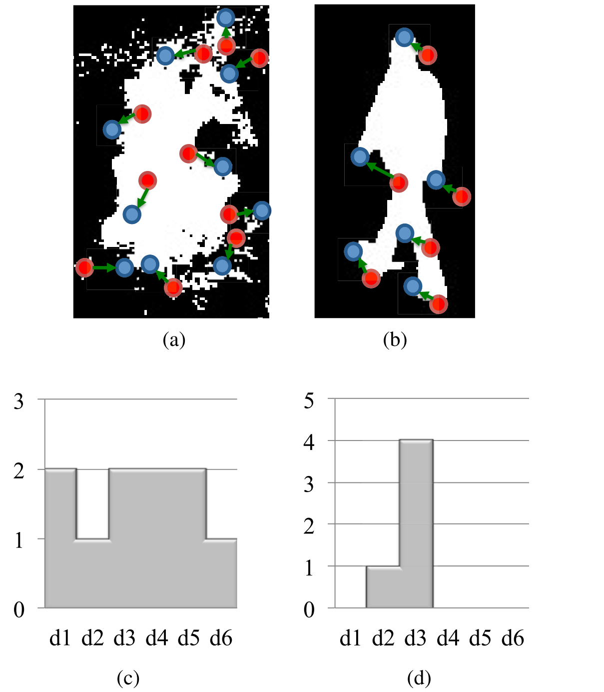


Fig. 3. Low level representation (a), (b) and high level representation (c), (d) of a fire (a), (c) and a non fire (b), (d) blob. Red and blue circles in (a) and (b) represent the salient points extracted at the frame t and $t-1$, respectively.

3) High-Level Representation: Given the dictionary D, for each blob, the algorithm finds the words of D that occur in the blob, i.e., the intervals d_k that correspond to the motion direction of the salient points; then the blob can be represented by the histogram H of the occurrences of such words. An example is reported in Fig. 3, where the low-level representation (a, b) and the corresponding high-level representation (c, d) for a fire (a, c) and a nonfire object (b, d) are shown.

In a more formal way, the generic angle ϕ_j is associated with the index s_j, depending on the word d_k it belongs to

$$s_j = |k : \phi_j \in d_k, \quad k \in \{1, \ldots, |D|\}|. \tag{22}$$

The set $S = \{s_1, \ldots, s_{|M|}\}$ associated with a generic blob b is then evaluated obtaining the histogram $H = \{h_1, \ldots, h_{|D|}\}$, whose generic element h_i can be computed as

$$h_i = \sum_{l=1}^{|M|} \delta(s_l, i), \quad i = 1, \ldots, |D| \tag{23}$$

$\delta(\cdot)$ being the Kronecker delta.

4) Classification: The main assumption used for designing the classifier is the evidence that the obtained feature vector is different for the two classes; in presence of fire, the movement is disordered, determining the occurrences of the words rather homogeneously distributed. Conversely, when a rigid or articulated object moves in the scene, we mainly obtain values concentrated on a single or a few bins. See Fig. 3 for an example.

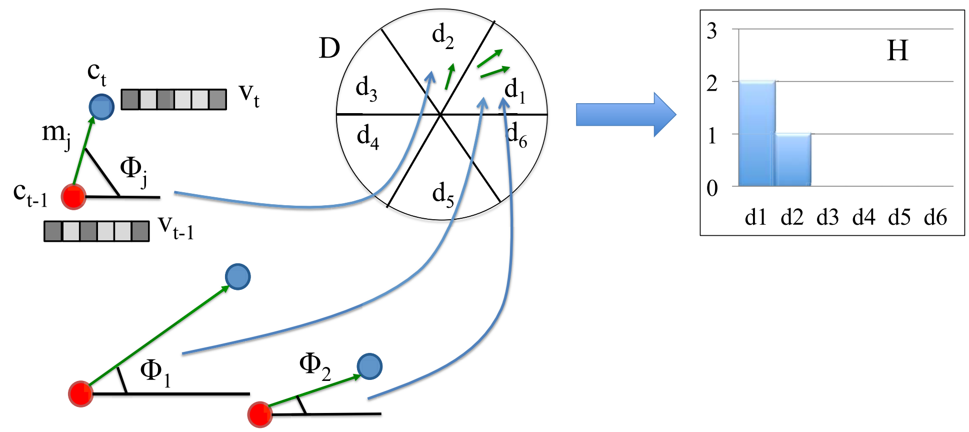


Fig. 4. Given the corner points c_{t-1} and c_t (red and blue circles, respectively), the matching m_j is obtained by minimizing the Euclidean distance between the corresponding descriptors v_{t-1} and v_t. The direction of the motion, encoded by the angle ϕ_j, is evaluated according the dictionary D, and the histogram of occurrences H is then built.

For this reason, we introduce a measure of the homogeneity hm of the histogram

$$\mathrm{hm} = 1 - \frac{\max(H)}{\sum_{k=1}^{|H|} h_k} \tag{24}$$

and, consequently, if it is higher than a given threshold, then the input is classified as fire and otherwise as not fire

$$c_{\mathrm{ME}} = \begin{cases} F, & \text{if hm} > \tau_m \\ \overline{F}, & \text{otherwise.} \end{cases} \tag{25}$$

IV. Experimental Results

Most of the methods in the literature (especially the ones based on the color evaluation) are tested using still images instead of videos. Furthermore, no standard datasets for benchmarking purposes have been made available up to now. One of the biggest collection of videos for fire and smoke detection has been made available by Töreyin *et al.* [13] and Cetin [34]. Starting from this collection, composed of approximately 31 250 frames, we added several long videos acquired in both indoor and outdoor situations, thus resulting in a new dataset composed of 62 690 frames and more than 1 h of recording. More information about the different videos are reported in Table I, while some visual examples are shown in Fig. 5.[1]

Note that the dataset can be seen as composed of two main parts: the first 14 videos characterized by the presence of fire and the last 17 videos that do not contain fires; in particular, this second part is characterized by objects or situations, which can be wrongly classified as containing fire: a scene containing red objects may be misclassified by color-based approaches, while a mountain with smoke, fog, or clouds may be misclassified by motion-based approaches.

Such composition allows us to stress the system and to test it in several conditions which may happen in real environments.

[1]The whole dataset can be downloaded from our website: http://mivia.unisa.it/datasets/video-analysis-datasets/fire-detection-dataset/.

The dataset has been partitioned into two parts: 80% has been used to test the proposed approach, while 20% for training the system by determining the weights of the MES.

An overview of the performance achieved on the test set, both in terms of accuracy and false positives, is summarized in Table II.

Among the three experts considered in this paper (CE, ME, and SV), the best one is the CE, which achieves on the considered dataset a very promising performance (accuracy = 83.87% and false positives = 29.41%). Note that such performance is comparable with the one reached by Celik and Demirel [7], where over a different dataset, the number of false positives is about 31%.

On the other hand, we can also note that the expert ME, introduced for the first time in this paper for identifying the disordered movement of fire, reveals to be very effective. We obtain a 71.43% accuracy and 53.33% false positives. It is worth pointing out that the considered dataset is very challenging for this expert: in fact, the disordered movement of smoke as well as trees moving in the forests can be easily confused with the disordered movement of the fire. This consideration explains the high number of false positives introduced using only the ME.

As expected, the best results are achieved by the proposed MES, which outperforms all the other methods, both in terms of accuracy (93.55%) and false positives (11.76%). The very low false positive rate compared with state-of-the-art methods is mainly due to the fact that ME and SV act, in a sense, as a filter with respect to CE. In other words, ME and SV are able to reduce the number of false positives introduced by CE without paying in terms of accuracy: this consideration is confirmed by the results shown in Fig. 7, where the percentage of the number of experts that simultaneously take the correct decision is reported. In particular, Fig. 7(a) details the percentage of the number of experts correctly assigning the class fire: we can note that all the experts correctly recognize the fire in most of the situations (69%), while two experts assign the class fire in the remaining 31%.

TABLE I
DATASET USED FOR THE EXPERIMENTATION

Video	Resolution	Frame Rate	Frames	Fire	Notes
Fire1	320x240	15	705	yes	A fire generated into a bucket and a person walking near it. Video downloaded from [34].
Fire2	320x240	29	116	yes	A fire very far from the camera generated into a bucket. The video has been downloaded from [34].
Fire3	400x256	15	255	yes	A big fire in a forest. The video has been acquired by [35] and downloaded from [34].
Fire4	400x256	15	240	yes	See the notes of the video *Fire3*.
Fire5	400x256	15	195	yes	See the notes of the video *Fire3*.
Fire6	320x240	10	1200	yes	A fire generated in a red ground. Video downloaded from [34].
Fire7	400x256	15	195	yes	See the notes of the video *Fire3*.
Fire8	400x256	15	240	yes	See the notes of the video *Fire3*.
Fire9	400x256	15	240	yes	See the notes of the video *Fire3*.
Fire10	400x256	15	210	yes	See the notes of the video *Fire3*.
Fire11	400x256	15	210	yes	See the notes of the video *Fire3*.
Fire12	400x256	15	210	yes	See the notes of the video *Fire3*.
Fire13	320x240	25	1650	yes	A fire in a bucket in indoor environment. Video downloaded from [34].
Fire14	320x240	15	5535	yes	Fire generated by a paper box. The video has been acquired by the authors near a street.
Fire15	320x240	15	240	no	Some smoke seen from a closed window. A red reflection of the sun appears on the glass. Video downloaded from [34].
Fire16	320x240	10	900	no	Some smoke pot near a red dust bin. Video downloaded from [34].
Fire17	320x240	25	1725	no	Some smoke on the ground near a moving vehicle and moving trees. Video downloaded from [34].
Fire18	352x288	10	600	no	Some far smoke on a hill. Video downloaded from [34].
Fire19	320x240	10	630	no	Some smoke on a red ground. Video downloaded from [34].
Fire20	320x240	9	5958	no	Some smoke on a hill with red buildings. Video downloaded from [34].
Fire21	720x480	10	80	no	Some smoke far from the camera behind some moving trees. Video downloaded from [34].
Fire22	480x272	25	22500	no	Some smoke behind a mountain in front of the University of Salerno. The video has been acquired by the authors.
Fire23	720x576	7	6097	no	Some smoke above a mountain. The video has been downloaded from [34].
Fire24	320x240	10	342	no	Some smoke in a room. Video downloaded from [34].
Fire25	352x288	10	140	no	Some smoke far from the camera in a city. Video downloaded from [34].
Fire26	720x576	7	847	no	See the notes of the video *Fire24*.
Fire27	320x240	10	1400	no	See the notes of the video *Fire19*.
Fire28	352x288	25	6025	no	See the notes of the video *Fire18*.
Fire29	720x576	10	600	no	Some smoke in a city covering red buildings. Video downloaded from [34].
Fire30	800x600	15	1920	no	A person moving in a lab holding a red ball. The video has been acquired by the authors.
Fire31	800x600	15	1485	no	A person moving in a labwith a red notebook. The video has been acquired by the authors.

The advantage in using a MES is much more evident in Fig. 7(b), which refers to nonfire videos. In this case, only 17% of videos are correctly classified by all the experts. On the other hand, most of the videos (61%) are assigned to the correct class by two experts, thus confirming the successful combination obtained thanks to the proposed approach.

To better appreciate the behavior described above, a few examples are shown in Fig. 6. In Fig. 6(a), the fire is correctly

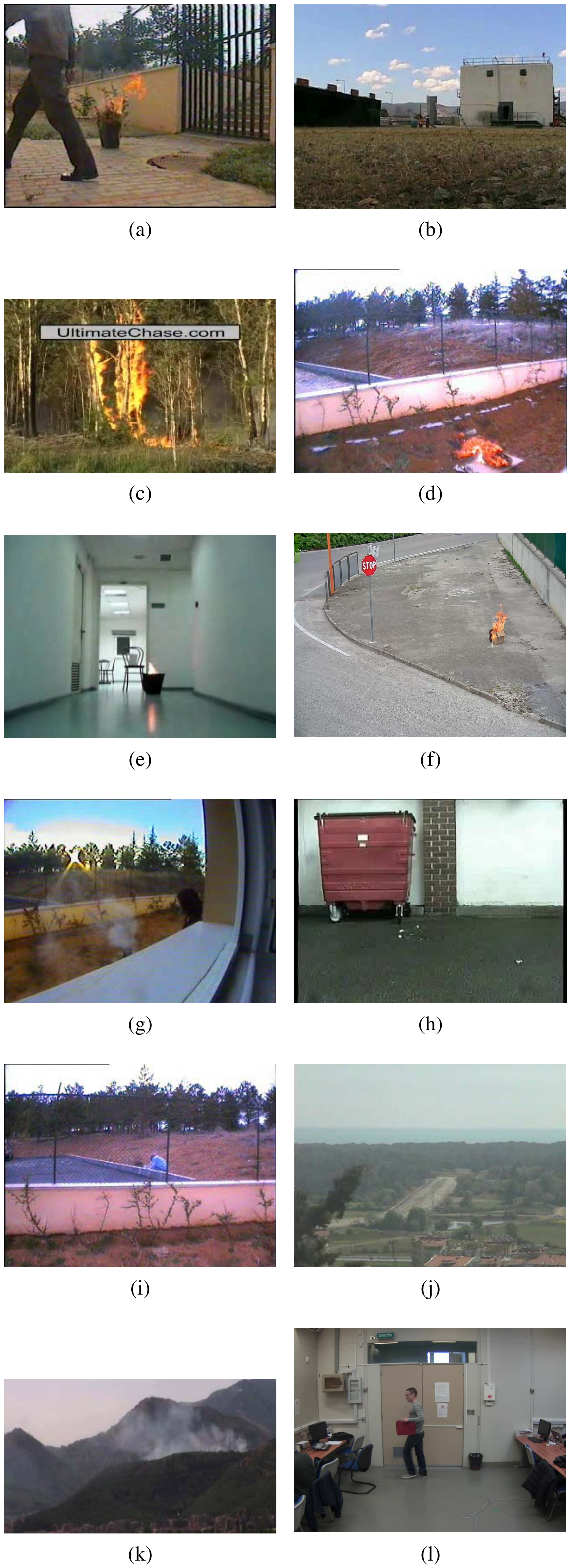


Fig. 5. Examples of images extracted from the videos used for testing the method. (a) Fire1. (b) Fire2. (c) Fire4. (d) Fire6. (e) Fire13. (f) Fire14. (g) Fire15. (h) Fire16. (i) Fire19. (j) Fire20. (k) Fire22. (l) Fire31.

recognized by all the experts: the color respects all the rules, the shape variation in consecutive frames is consistent, and the movement of the corner points detected is very disordered.

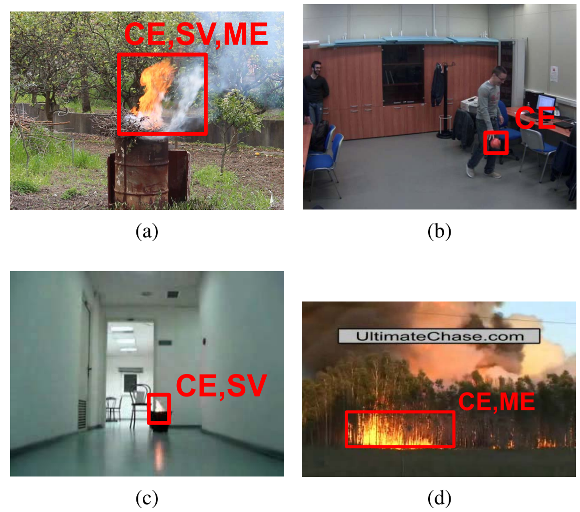


Fig. 6. Three experts in action; the red box indicates the position of the fire, while the letter on it refers to the expert recognizing the presence of the fire: (a) CE, SV, and ME. (b) CE. (c) CE and SV. (d) CE and ME.

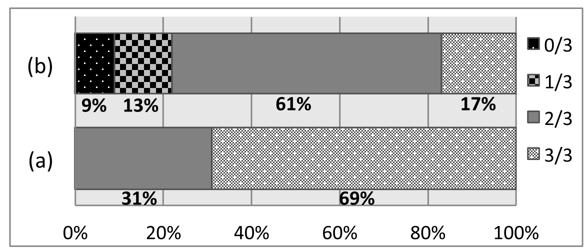


Fig. 7. Number of experts simultaneously taking the correct decision in (a) fire and (b) nonfire videos. For instance, 31% of situations are correctly assigned to the class fire by two experts over three, while in the remaining 69%, all the three experts correctly recognize the fire.

A different situation happens in Fig. 6(b), where the only classifier detecting the fire is the one based on the color: in this case, the uniform movement of the salient points associated with the ball as well as its constant shape allow the MES to avoid a false positive introduced by the use of a single expert. In Fig. 6(c) and (d), other two examples are shown: in particular, in the former, a small fire with a variable shape has both a uniform color and a uniform movement of the salient points. The combination of color and shape variation experts helps the proposed system to correctly detect the fire. The last example shows a very big but settled fire, whose shape is stable and so it is not useful for the detection. In this situation, the combination of the experts based on color and motion allows the MES to take the correct decision about the presence of fire.

Table II also shows a comparison of the proposed approach with three recent state-of-the art methodologies [15], [16], [29] that have been chosen, because they too are based on the combined use of color, motion, and shape information. For [15], we have used two different versions: the original one that, as proposed by its authors, analyzes the images in the RGB color space and a version modified by us, working instead in the YUV space; we have chosen this modification on the basis of [7], where it is shown experimentally that

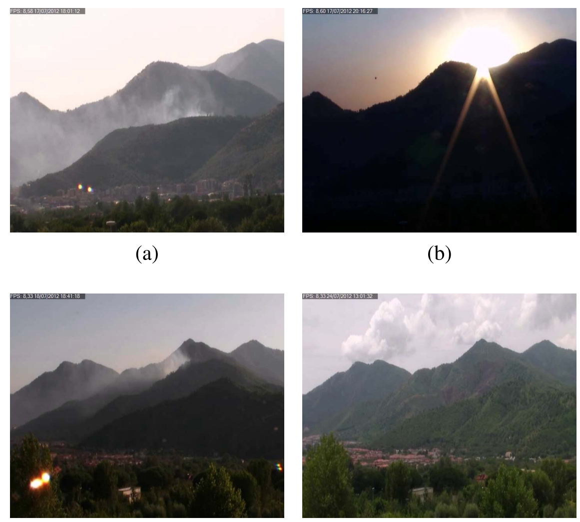
TABLE II
COMPARISON OF THE PROPOSED APPROACH WITH STATE-OF-THE-ART METHODOLOGIES IN TERMS OF ACCURACY, FALSE POSITIVES, AND FALSE NEGATIVES

Typology	Method		Accuracy	False Positives	False Negatives
Single Expert	**CE**	[7]	83.87 %	29.41 %	0 %
	ME	Proposed	71.43 %	53.33 %	0 %
	SV		53.57 %	66.67 %	21.85 %
MES	**CE + SV**		88.29 %	13.33 %	9.74 %
	CE + ME	[25]	92.86 %	13.33 %	0 %
	CE + ME + SV	Proposed	**93.55 %**	11.76 %	0 %
Other Methods	**RGB+Shape+Motion**	[15]	74.20 %	41.18 %	7.14 %
	YUV+Shape+Motion	[15]	87.10 %	17.65 %	7.14 %
	Color+Shape+Motion	[16]	90.32 %	**5.88 %**	14.29 %
	Color+Shape+Motion	[29]	87.10 %	11.76 %	14.29 %

color-based methods work better in the YUV than in the RGB, as confirmed by the results in Table II. The table shows that methods based on the combination of different kinds of information significantly outperform the single experts in terms of false positives; the difference in terms of false negatives is not so strong. Thus, the combination helps more to improve the specificity than the sensitivity of the system. The proposed approach overcomes all the other considered methodologies [15], [16], [29] in terms of accuracy (93.55% against 89.29%, 90.32%, and 87.10%, respectively). On the other hand, the best method in terms of false positives is [16] (11.76% of the proposed approach with respect to 5.88% of [16]). The better false positive rate of [16] is, however, balanced by an improved false negative rate of our method, which shows no false negatives (i.e., no fires are missed) versus a 14.29% false negative rate of [16]. While the difference between the two algorithms in terms of accuracy may not seem to be very large, the differences in the distribution of false positives and false negatives can make each of the two methods preferable depending on the requirements of the specific application.

A more detailed comparison for each of the considered videos is shown in Table I of the Electronic Annex: we can note that differently from the other considered approaches, our method achieves a 100% true positive rate, since it is able to also retrieve very small flames (as the ones in videos fire1, fire2, fire6, or fire13). This is mainly due to the introduction of the MES for taking the final decision about the event, which is able to detect the onset of small fires at an early stage when the amount of motion is still not very large. It is also evident that the method [16] is impressive for its reduced false positive rate, causing on the whole dataset just a single false positive.

To further confirm the effectiveness of the proposed approach, we also evaluated it over a second freely available dataset (hereinafter $D2$).[2] It is composed by 149 videos, each lasting approximately for 15 min, and so resulting in more than 35 h of recording; $D2$ contains very challenging situations, often recovered as fire by traditional color-based approaches:



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

Fig. 8. Some examples of the dataset $D2$, showing red houses in the wide valley (a,c,d), the mountain at sunset (b), and some lens flares (a,c).

red houses in a wide valley [Fig. 8(a) and (d)], a mountain at sunset [Fig. 8(b)] and lens flares [bright spots due to the reflections of the sunlight on lens surfaces, Fig. 8(a) and (c)].

Although the situations are very challenging, no false positives are detected by our MES. The result is very encouraging, especially if compared with CE, achieving on the same dataset 12% of false positives. It is worth pointing out that such errors are localized in approximately 7 h, mainly at sunset, and are due to lens flares. Such typology of errors is completely solved by the proposed approach able to take advantage of the disordered movement of the flames.

Finally, we have also evaluated the computational cost of the proposed approach over two very different platforms: the former is a traditional low-cost computer, equipped with an Intel dual core T7300 processor and with a RAM of 4 GB. The latter is a Raspberry Pi B, a Broadcom BCM2835 system-on-a-chip, equipped with an ARM processor running at 700 MHz and with a RAM of 512 Mbits. The main advantage in using such device lies in its affordable cost, around $35 U.S.

[2]The whole dataset can be downloaded from our website: http://mivia.unisa.it/datasets/video-analysis-datasets/smoke-detection-dataset/.

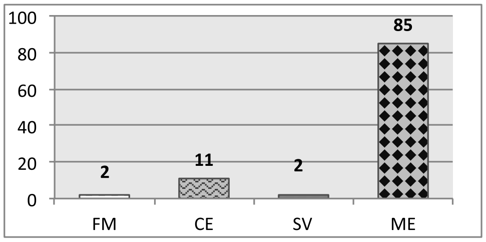


Fig. 9. Average execution time of our algorithm, in terms of percentage of the total time for any expert (CE, SV, and ME) and the preliminary low-level vision elaborations (FM).

The proposed is able to work, considering 1CIF videos, with an average frame rate of 60 frames/s and 3 frames/s, respectively, over the above mentioned platforms. Note that 60 frames/s is significantly higher than the traditional 25–30 frames/s that a traditional camera can reach during the acquisition. It implies that the proposed approach can be easily and very effectively used on the existing intelligent video-surveillance systems without requiring additional costs for the hardware needed for the images processing.

To better characterize the performance of the proposed approach, we also evaluated the time required by the different modules, namely, the three experts (CE, ME, and SV) and the module in charge of updating the background, extracting the foreground mask and labeling the connected components (FM). The contribution of each module is highlighted in Fig. 9: the average time required to process the single frame has been computed and the percentage of each module with respect to the total time is reported. We can note that SV only marginally impacts on the execution time; this is due to the fact that the search of the minimum bounding boxes enclosing the blobs and of its properties (in terms of perimeter and area) is a very low-cost operation. Although the introduction of SV only slightly increases the performance of the MES (from 92.86% to 93.55% in terms of accuracy), the small additional effort strongly justifies its introduction in the proposed MES.

On the other side, the higher impacts are due to ME and CE: as for the former (85%), it is evident that the computation of the salient points, as well as their matching, is a very onerous operation. As for the latter, it may appear surprising the big effort required by the CE with respect to FM (CE: 11%, FM: 2%). It is worth pointing out that FM's operations (such as background updating and connected component labeling) are very common in computer vision, and thus very optimized versions have been proposed in standard libraries such as OpenCV.

Finally, it is worth pointing out that the computation time is strongly dependent on the particular image the algorithm is processing. It is evident that pixel-based modules (such as FM and CE) need to process the whole image independently of the objects moving inside. On the other hand, it is evident that the more are the objects moving inside the scene, the higher is the effort required by FM for detecting and analyzing the salient points. It implies that the variance with respect to the overall time required for the computation is about 51% of the overall time. Note that the final combination of the decisions taken by the three experts has not been considered, since the time required is very small with respect to the other modules.

In conclusion, the obtained results, both from a quantitative and a computational point of views, are very encouraging since they allow the proposed approach to be profitably used in real environments.

V. Conclusion

In this paper, we propose a fire detection system using an ensemble of experts based on the information about color, shape, and flame movements. The approach has been tested on a wide database with the aim of assessing its performance both in terms of sensitivity and specificity. Experimentation confirmed the effectiveness of the MES approach, which allows one to achieve better performance in terms of true positive rate with respect to any of its composing experts. Particularly significant by the applicative point of view is its drastic reduction of false positives, from 29.41% to 11.76%. The comparison with other state of the art methods highlights its highest accuracy on the considered dataset; at the same time [16], although having a less true positive further reduces the false positive rate, conquering the best rank on this aspect. These considerations seem to suggest us that further investigations should be done in the direction of understanding how to put together the strength of the high accuracy of our method together with the strength of [16] of a really low false positive rate.

As for the execution efficiency, even though the system is made of three experts working simultaneously, its overall computational load is compatible with low cost embedded systems such as the Raspberry Pi; a carefully tuned implementation runs in real time at a frame rate of about 3 frames/s on images at a resolution of 320×240. A noteworthy additional outcome of this paper is the database prepared for the experimentations; a wide collection of videos containing fires filmed in different conditions and environments are completed with a significant number of nonfire videos, carefully selected among those highly confusable with scenes of fire. This made it possible to check the robustness of the system with respect to the generation of false positives. The database is publicly available at: http://mivia.unisa.it/datasets/.

Future work will be devoted to the integration in the same MES framework of a smoke detection algorithm and to the extension of the approach to operating conditions currently not covered, such as its execution directly on the board of the camera and its use on pan–tilt–zoom cameras.

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