A Forest Fire Detection System: The Meleager Approach

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***Abstract*—Forest fires cause immeasurable damages to indispensable resources for human survival, destroy the balance of earth ecology and worst of all they frequently cost human lives. In recent years, early fire detection systems have been emerged to provide monitoring and prevention of the disasterous forest fires. Among them, the Meleager[1] system aims to offer one of the most advanced and integrated technology solutions for fire protection worldwide by integrating several innovative features. This paper outlines one of the major components of the Meleager system, that is the visual fire detection sybsystem. Groundbased visible range PTZ cameras monitor the area of interest and a low level decision fusion scheme is used to combine individual decisions of noumerous fire detection algorithms. Personalized alerts and induced feedback is used to adapt the detection process and improve the overall system performance.**

***Keywords*-forest fire detection, decision fusion**

I. INTRODUCTION

Reliable fire detection systems with minimum detection latency are of great importance for fast reaction to prevent fire expansion and minimize damages. Traditional forest watch towers tend to be replaced by automatic detection systems that range from IR sensors [1], LIDAR (Light Detection and Ranging systems) [2], satellite platforms [3], to computer vision based systems [4,5] and WSN (wireless sensor network) systems) [6]. Aligned with the latter, the Meleager system aims to offer one of the most advanced and integrated technology solutions for fire protection worldwide by integrating the following important innovative features:

- A visual fire detection subsystem, which consists of high resolution cameras with embedded digital signal processing and machine vision algorithms.
- The simulation subsystem which has the unique feature of the "parallel" execution of multiple simulations for different scenarios of environmental parameters. The fire simulator handles the high variability of forest fires, by examining a set of environmental parameters (e.g., wind direction and speed) and creating dynamic hazard maps for the ongoing crisis. The fire simulator uses an innovative design that allows it to perform multiple snapshots of the perturbations from the average recorded values of environmental parameters.
- The data fusion subsystem that incorporates a two-tier data fusion scheme for better assessment of the field observations and for developing safer conclusions about the crisis and risk. The two-tier organization of the fusion scheme allows the scaling of the mechanism and the effective implementation of various versions of the Meleager system (large scale / prefectures, local authorities, private installations).
- Open protocols and interfaces: Meleager is based entirely on open standards for information exchange to ensure interoperability with existing systems, e.g., crisis management systems, GIS data, cartographic systems and systems for registration of land use.
- Crisis management with advanced algorithms - the part of crisis management incorporates applications based on spatial data (e.g., firefighting resource management). The dynamic positioning of various resources allows more efficient treatment of environmental risk and minimizes the impact on the lives and property of citizens and firefighting forces. This subsystem can optimize the firefighting equipment deployment and the citizen evacuation process of the affected region.
- Open GIS and interfaces. An innovative feature is the ability to record real-time information on the fire evolution, and reproduce at a later time and time scales selected by the system user (e.g., real-time reproduction, fast, slow, transition to a specific point in time).
- Implementation of personalized alerts / alarms and automatic activation of fire protection/sprinkler systems. The implementation of advanced technology and the major innovations incorporated in the system enhance the system functionality, usability, efficiency and interoperability while at the same time they can reduce costs.

This paper aims to describe the visual fire detection subsystem that was adopted by the Meleager project. Video-based fire detection has many advantages over traditional methods, such as low latency response and theoreticaly no space limits. Numerous techniques have been proposed that make use of the visual features of fire and smoke including color, motion, geometry, flickering and texture. Some of these techniques are summarized in Section 2, where related

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work on computer vision based wildfire detection methods is presented. Section 3 outlines the Meleager system architecture for the fire detection subsytem, whereas Section 4 presents some preliminary results. Finally, conclusions are drawn in Section 5.

II. Related Work

There is a lot of research for fire and smoke detection based on image processing. In general fire detection algorithms are mainly based on the analysis of motion and color information in video sequences to detect the flames [7]. In [8] authors use hidden markov models to detect flames in video. Color based detection methods are introduced in [9,10]. The fire detection method proposed in [11] adopts the RGB color chromatic model and uses disorder measurement. In [12] authors introduced the statistic color model for generic fire model and studied the fire detection method using foreground object information. Authors in [13] propose a system for fire detection at night, while in [14] a method is presented for forest fire detection using FFT and wavelets.

Smoke detection is also vital for fire alarm systems. In an uncontrolled fire, smoke can be detected by a camera more easily than flames. This results in early detection of the fire. Various research activities for video smoke detection are available in the literature. In [15] the motion and color characteristics of the smoke are used for detection. A system that uses a fast accumulative motion orientation model is proposed in [16]. The method that is presented in [17] exploits techniques such as backround substraction, flickering extraction and contour classification. A similar contour based solution using wavelets is proposed in [18].

Most of the above mentioned methods for flames and smoke detection were tested in a limited experimental environment and are prone to increased false alarm rate according to the environmental conditions. Moreover, the majority of the systems detect either flames or smoke. Furthermore, heuristic fixed thresholds are used for the detection process. In this paper, a hybrid day/night system for flame and smoke detection is proposed. Hierarchical design approach and novel scene tile segmentation ensure early detection and reduced false alarm rate. Finally, user feedback and historical data are incorporated in the detection process thus making the system capable for automatic threshold calculation without empirical fixed threshold values.

III. System Architecture

A. System set-up

The flowchart of the Meleager fire detection subsystem is presented in Fig. 1. The scene is segmented in tiles as it is shown in Fig. 2 and the detection process is repeated for each tile in a round robin fashion.

This segmentation is critical for several reasons.

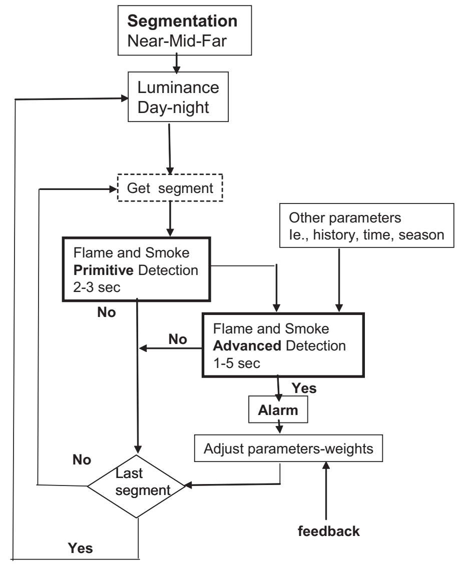

Figure 1. Fire detection subsystem flowchart

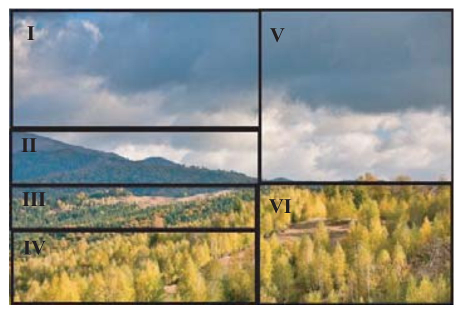

Figure 2. Scene tile segmentation

- First of all there are image segments where the presence of fire is impossible. This is for example the case of tiles I and V in Fig. 2 that contain regions of the sky. These tiles are prone to false alarms since clouds are often mistaken for smoke by a machine vision automatic detection system. By excluding these regions from further processing we not only speed up the detection process but we reduce considerably the false alarm rate. However, these segments are not totally worthless. There is always the possibility to search for smoke in these segments, since smoke tends to move upwards, and then fuse this information with the decision taken in the spatially lower tiles.
- By segmenting an image in small tiles we obtain a finer characterization of the scene. For example, in Fig. 2 tile II can be characterized as "far", tile III as "mid"- distanced, whereas tile IV can be characterized as "near". Although motion of flames and smoke is a key feature for fire detection, for distant objects motion is hard to be detected promptly. In this case, either

the sensitivity of the detection algorithms should be increased or their weight in the final decision should be decreased.

- Segmentation results in tiles with almost uniform texture. Therefore, fire detection techniques are more suitable than others for specific backgrounds. For example, in areas with swaying trees, a Mixture of Gaussian background model seems more appropriate to detect motion due to flames or smoke.
- Computational complexity reduction also justifies scene tesselation. Some methods, such as the eigenbackgrounds approach, are based on PCA (principal component analaysis) and are applied to whole images. Therefore, small size images reduce memory and processing requirements.

B. Primitive detection algorithms

Following the flowchart of Fig. 1, luminance conditions are taken into account before fire detection takes place. Smoke is not detectable at nights and flames are not always visible during the day especially in the first stages of the fire event. Thus, the type of algorithms and the various thresholds used depend heavily on the luminance conditions.

The primitive detection algorithms explore two basic features of flames and smoke, that is motion and color. Three techniques are employed for motion detection

- Temporal difference of two successive frames
- Background subtraction (needs background modeling)
- Optical Flow

Temporal difference schemes exhibit large noise disturbance and a dilation-erosion technique followed by deletion of small blobs is used to reduce noise. Alternatively, to reduce disturbance of noise we sum up pixels in a block (i.e 4×4) and then calculate difference of sums block by block as in [16]. Several background subtraction methods have been adopted for the Meleager sytem. The technique in [18] estimates the background using a first order IIR filter for each pixel in a sequence of frames. In [13] the same approach is used but two background images are created (day and night) depending on updating rates. A *running Gaussian average* [19] is another technique where each pixel is modeled as a Gaussian random variable. This method is suitable for unimodal backgrounds. An extension of this method that works with RGB and treats colors independenty [12] is also included in the pool of algorithms. To deal with multimodal backgrounds the Mixture of Gaussians model [21], has been also incorporated.

An approximation of the background pdf can be obtained by the histogram of the most recent pixels classified as background values. To avoid poor modeling due to the missing distribution tails, each sample is smoothed with a Gaussian kernel. This technique, which is referred as KDE (Kernel Density Estimation) [22], is also suitable for multimodal backgrounds. A method faster than KDE, with low memory requirements, is the Sequential Kernel Density Approximation (SKDA) [23]. The method uses the mean shift algorithm to detect the modes of the pdf, which are later propagated by adapting them with new samples. A different method of background modeling is the Cooccurence of image variations [24]. The method is based on the fact that neighboring blocks of pixels belonging to the background experience similar variations over time. Finally, a method termed Eigenbackground approach [25] has been also adopted by the Meleager system. The method is based on the Principal Component Analysis as applied to sequences of frames.

Regarding the optical flow motion detection schemes, we have incorporated the most representative one, that is the Lucas Kanade method, and its variant the pyramidal Lucas Kanade. The latter uses smaller resolution of images and it is appropriate to detect motion of nearby objects.

At the output of the motion detection process we should find connected regions (blobs) that represent the moving objects. These blobs will be tested for flame or smoke using color information. Three flame color detection schemes are used. The first was proposed in [12] and works in the RGB color space. Three conditions should be met simultaneously in order to classify a pixel as a fire pixel. The R component should be greater than R_{mean}, the double inequality $R > G > B$ should be satisfied, and the ratio of the G, B to the R compnent should be within certain limits. The second method [13], works in the LUV color space and uses brightness to detect fires during night. The third method [7] models fire color as a mixture of Gaussians in RGB space. The proposed number of Gaussians is 10. If a pixel color lies within $2 \cdot \sigma$ of the center (mean) of a Gaussian is classified as fire pixel.

Similarly to the flame color detection, three models are use for smoke. The first one, proposed in [11], classify a pixel as smoke if the following condition is met

$$\max\{R, G, B\} - \min\{R, G, B\} < \alpha \quad \text{AND} \quad k_1 \leq L \leq K_2$$

where L is the luminance and $\alpha = 15 - 20$. For dark gray smoke $K_1 = 80, K_2 = 150$ whereas for light gray smoke $K_1 = 150, K_2 = 220$. The second method [16] is similar to the previous one with an additional criterion in case of bluish color smoke:

$$\begin{aligned} B &= \max\{R, G, B\} \text{ AND} \\ &\max\{R, G, B\} - \min\{R, G, B\} < \beta \end{aligned}$$

where β is a suitably chosen thresold. Finally, the third method [26] uses the criteria

$$|R - G| < T, \quad |G - B| < T, \quad |R - B| < T$$

with suggested threshold value $T \in [15, 25]$. Additionally, for early detection, smoke low temperature induces a white-bluish to white color which means small saturation. Therefore an additional criterion is (working in HSV color space)

$$S \leq 0.1$$

C. Advanced detection algorithms

If some blobs pass the motion and color screen tests, then they are processed further in an effort to reduce the false alarm rate. The algorithms that the Meleager system uses, for this advanced detection, explore other features of flames and smoke such as the geometry and the spatial and temporal variability. Regarding geometry the pool of algorithms consists of four techniques. In the first technique we take advantage of the turbulant shape of flames and smoke as in [17]. If P is the perimeter of the cadidate fire blob and A its area, then we form the metric

$$T = \frac{P}{2\pi^{1/2} A^{1/2}}$$

The value of T for circular schemes, such as the bright areas of car headlights, is equal to 1. Deviations from this value is a strong indication for flames or smoke. The second algorithm [7] is also based on the roughness of the boundary of fire or smoke blobs. A 1-D signal is created using the distances from the center of mass of a cadidate fire or smoke blob to the points of its perimeter. In case of a rough boundary, this signal exhibits large variations which can be detected using a simple one stage wavelet filter. The third technique was originally proposed in [14]. We assume that the boundary of a cadidate region consists of N pixels, which in complex notation are written as $\{z_i = x_i + jy_i\}$. Using these points we find the DFT of the 1-D boundary signal. The first 2-3 dozens of the DFT coefficients are sufficient to describe the shape of the underlying blob. If flickering is present, due to fire or smoke, it can be detected by analyzing the variability of the DFT coefficients from frame to frame. This analysis can be achieved using simple wavelet filters. Finally, the fourth "geometry" detection algorithm has been proposed in [27] and it is based on the change of shape of fire or smoke regions from frame to frame. We may define the normalized area change, ΔA_i, from the $i-1$-frame to the i-frame as

$$\Delta A_i = \frac{|A_i - A_{i-1}|}{A_i}$$

and compare it with a suitably chosen threshold in order to decide for fire or smoke. Similarly, we can use the change of the perimeter ΔC_i of the cadidate blob instead of ΔA_i.

Many algorithms have been proposed for fire detection that are based on the spatial and temporal variance of fire regions. The Meleager system has adopted at least 10 methods but their assessment has not be done thoroughly yet. Next, we outline some of these methods. The chromimance components of fire blobs exhibit large spatial variance due to the random nature of fires. Experimental results [27] show that a standard deviation greater than 50 is a good indicator for the presence of fire. According to [9], the G component, in RGB images, exhibits large variations for fire blobs and therefore we can base decisions on the difference $\max G - \min G$ of adjacent pixels over small blocks.

Saturation of the G and R channel of fire pixels move the histogram of the corresponding values to the upper side. This phenomenon can be detected using a third order statistic, called skewness. The authors in [27] state that skewness obtains values less than -1 for fire blobs.

The significant spatial variance in fire areas can be explored using a 2-D wavelet filter. The authors in [7] base decisions on the sum of low-high, high-low and high-high wavelet images of fire-colored moving regions. Wavelet filters can also be used for temporal analysis. If a pixel at position $(k.l)$ belongs to a fire region, then its value (either the Y component in the YUV color space or the R component in the RDB color space) in successive frames will exhibit large variations. A two stage wavelet filter bank fed by the 1-D signal $x_n(k,l)$ (n is the frame index) can be used to detect such variations. The zero-crossings of the high frequency subband signals in a time window of 2-3 sec is a good indicator for the presence or not of fire. Flickering is also detected using the cumulative time derivative signal, estimated as

$$a_n(k.l) = wa_{n-1}(k,l) + (1-w)d_n(k,l)$$

where $d_n(k,l) = |Y_n(k,l) - Y_{n-1}(k,l)|$ is the time derivative of the luminance component (in the YUV space) at the (k,l) position. The authors in [9] proposed an improvement in the estimation, that further decreases false alarm rate. In their approach $d_n(k.l)$ is weighted by the factor $Y_n(k,l)I_{Y_n(k,l)>\delta}$, where I_A is an indicator function.

D. Decision fusion and user feedback

The final decision about a fire event will be based on both primitive and advanced algorithms. For each tile N frames are used for background modeling as it is shown in Fig. 3. N is a variable that depends on the motion algorithm used and ranges from 1, in case of the temporal difference algorithm, to 60-80, for more complex algorithms like the Mixture of Gaussian or the SKDA algorithm. There is no need to re-estimate the background model each time the process returns to the same tile. The parameters of the previously estimated model can be stored and then updated, in a selective or blind fashion, using more recent frames. After background estimation, a motion detection algorithm leaves G frames to pass, to increase detection probability for slowly moving objects, and then checks the following L frames for possible moving objects. Having detected the moving objects, color detection algorithms are applied. A moving object is characterized as fire blob if

$$\sum_i w_i c_i > T_c$$

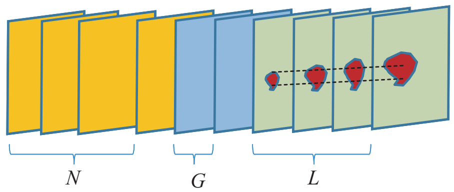

Figure 3. Motion and color based decision

where c_i are binary decisions for the existence of fire, w_i are normalized weights (initialized to the same value) and T_c is a suitably chosen threshold. Detected fire blobs in successive frames correspond to the same fire source if their convex hulls exhibit considerable overlapping. After the association of fire blobs in the L frames, a final decision is taken using the m out of L majority rule. That is, if at least m fire blobs (corresponding to the same fire source) exist in a sequence of L frames then we decide for fire event. Note that this decision, call it d_j, is binary and depends on the motion detection algorithm used. To increase system's reliability we can test more than one motion detection algorithms and combine the results. In this case, we allow d_j to take $L+1$ values, representing the number of fire blobs detected in the sequence of L frames, and we combine them in a linear fashion as

$$\sum_j p_j d_j > T_m$$

where p_j are weights summing to one and T_m is a predetermined threshold.

If the previous condition is satisfied then the control is passed to more sophisticated techniques as it is shown in Fig. 1. These algorithms operate on the fire blobs detected by the motion algorithm that maximizes d_j, that is

$$\hat{j} = \arg\max d_j$$

Geometry based decisions, g_j, and spatial/temporal variance decisions, v_j, are fused in a higher level to reach a final decision. In the framework of the Meleager project three fusion schemes are under investigation, that is

- A majority voting rule, using binary decisions g_j and v_j
- Thresholding of linear weighted sums, using soft decisions g_j and v_j
- Dempster-Shafer rule of combination, treating decisions g_j and v_j as beliefs.

A positive detection triggers an alarm and the end user is notified by sending him a number of frames containing detected fire blobs. The user replies and his feedfack is used to adjust the weights of the fusion process and the thresholds of the algorithms. In case of a true positive detection, all algorithms that favor the fire decision increase their weights. The rest of the algorithms lower their thesholds to become more sensitive. On the contrary, in case of a false positive (false alarm), all the algorithms favoring the fire decision increase their thresholds whereas the rest increase their weights. Two more situations may exist, that is true negative and false negative. These situations are detected by other means, ie. temperature sensors in the field, or periodic feedback regardless the presence of a fire event. For false negative, the detection algorithms that miss the event decrease their thresholds thus becoming more sensitive, while the rest increase their weights. On the other hand for true negative, detecting algoritms increase thresholds and non detecting algorithms increase weights. The process is summarized in the following table.

	Detecting Algorithms	Non Detecting Algorithms
True Positive	Weights $\uparrow$	Thresholds $\downarrow$
False Positive	Thresholds $\uparrow$	Weights $\uparrow$
True Negative	Thresholds $\uparrow$	Weights $\uparrow$
False Negative	Weights $\uparrow$	Thresholds $\downarrow$

Table I
ADJUSTMENT OF WEIGHTS AND THRESHOLDS

IV. EXPERIMENTAL RESULTS

In this section we present some initial experimental results. Algorithms for primitive detection of fire and smoke have been ported and mapped on a System on Chip, OMAP3530. The chip includes one general purpose processor, ARM Cortex A8, one special purpose processor, Texas Instrument TMS320C64x+ and one graphic accelerator. For the algorithm implementation both the generic purpose and the special purpose processor have been used. For primitive fire detection we implemented the algorithm proposed in [16] to detect motion. We have used blocks of 4x4 pixels. The output of this process, that represents connected regions (blobs) is fed to the next phase where the fire color detection technique proposed in [12] is applied. The results are depicted in the Figure 4. As we can see at the end of primitive phase the flames are detected successfully. However, some blocks that constitute false alarms are also present.

For smoke we use the same motion detection technique as before. For the subsequent color analysis the rule proposed in [27] is applied with the use of empirical thresholds. Again, the smoke region is detected successfully and the existence of blocks outside this region represents false alarms as depicted in Figure 5. The false alarm rate (false alarm blocks / total image blocks) at the end of primitive detection is less than 4% for the fire video and 5% for the smoke video. Such rates are extremely encouraging taking into account that we have implement one motion detection algorithm and one color detection algorithm. The primitive detection phase will incorporate more than one of similar techniques as described in the previous section.

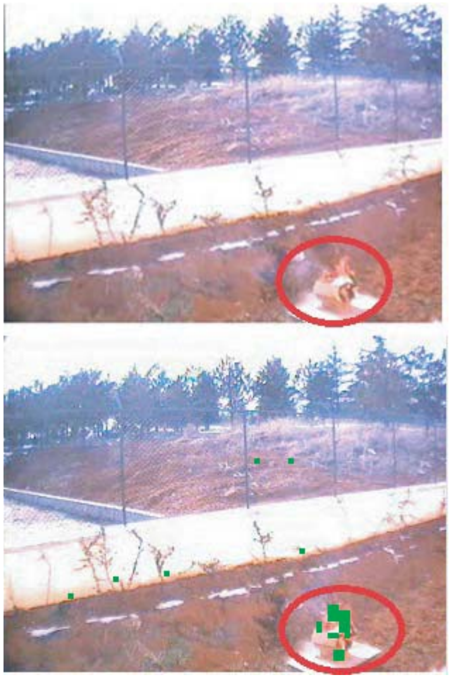

Figure 4. Flame detection in video. Initial video snapshot (top) and flames (green blocks) detected in primitive phase..

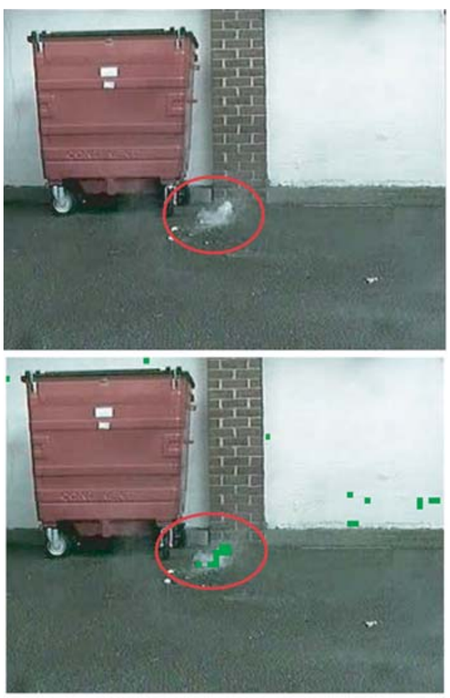

Figure 5. Smoke detection in video. Initial video snapshot (top) and smoke (green blocks) detected in primitive phase.

V. Conclusions

In this paper we presented the functionality of the visual component, as a part of the overall Meleager architecture, regarding the early detection of potential fires. The images are obtained from PTZ cameras that supervise an area of interest. To cope with various environmental conditions and deliver alarms with increased accuracy and confidence a layered hierarchical scheme has been adopted. Furthermore a scene segmentation technique is applied in order to facilitate and speed-up the detection process. On the primitive stage, motion and color detection algorithms are implemented. On the second stage, advanced algorithms are used in an effort to reduce the false alarm rate. The decision about flame or smoke presence is taken through various fusion schemes. Moreover, personalized alerts and induced feedback is used to adapt the detection process and improve the overall system performance. Algorithms for primitive detection of fire and smoke have been implemented on a DSP thus making the solution distributable. The first experimental results are encouraging in terms of detection rate.

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