Automatic Forest Fire detection in Visible Spectra

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Abstract

Forest fire is natural phenomena with devastating consequences on ecological systems, infrastructure and human lives. Despite all technology and human forces, great fires are hard to control. Only effective way to fight forest fires is early detection and appropriate fast reaction, therefore great efforts are made to achieve early detection. We present automatic forest fire detection algorithm which is central part of the Intelligent Forest Fire Monitoring System based on the remotely controlled video cameras sensitive in visible spectra. Forest fires are detected in incipient stage using various autonomous advanced image analysis and understanding techniques. Video input is analyzed to find visual signs of forest fire, particularly smoke during the day and flames during the night. Post-processing algorithms based on meteorological and video data fusion are applied and decision about raising an alarm is brought by a voting based strategy where weight is assigned to the output of each detection algorithm. If the suspicious region in the visual range of the camera is detected the alarm is delivered to the human operator who makes the final decision about delivering the alarm to the fire fighters or discarding a false alarm.

1 Introduction

Forest fires represent a constant threat to ecological systems, infrastructure and human lives. According to the prognoses, forest fire, including fire clearing in tropical rain forests, will halve the world forest stand by the year 2030 [1]. Vegetation fires speed up the extinction of species, aggravate the greenhouse effect, and causes enormous economic damage.
Great fires are hard to fight despite all technology and human forces used. Only effective way to minimize damage is an early detection and appropriate fast reaction. Great efforts are therefore made in all regions to achieve early recognition. Different approaches and sensor inputs are used for the automatic detection of fire, ranging from the IR sensors to identify heat flux from the fire [2], light detecting and ranging (LIDAR) systems [3, 4] that measure the laser light backscattered by the smoke particles, detection of smoke on satellite images [5], to smoke plume detection with cameras in the visible spectra. Several platforms for surveillance activities have been tested in recent years. The individual method depends on the specific regional conditions and the financial budget.
Optical based systems often imply a high rate of false alarms due to atmospheric conditions (clouds, shadows, dust particles formations), light reflections and human activities. However, in time-critical local fire events in densely populated areas, smoke is a relevant feature for the early recognition of fire. In systems based on visible spectra images, automatic smoke plume detection can be combined with human operator monitoring multicamera system. Additionally, cost of the visual spectra camera equipment is often several times cheaper compared to IR cameras and other types of advanced sensors. This is especially important in rugged and indented areas like Dalmatian coast with its many islands, and small towns surrounded by dense pine forests, where structure of the terrain requests larger number of sensors to achieve satisfactory coverage. In the case of the real incident, video presence is useful in controlling the situation on the terrain and directing the efforts of fire fighters.

This paper presents intelligent video based monitoring system fore early detection of forest fires, implemented under the name iForestFire. Central part of the system is the module for automatic forest fire detection based on various autonomous advanced image processing, image analysis and image understanding techniques. Video input is analyzed automatically by several fire recognition algorithms, trying to find visual signs of forest fire, particularly smoke during the day and flames during the night. If suspicious region on the input image is detected, alarm is raised to the operator. The operator inspects suspicious image parts and brings the final decision about raising the alarm to the fire fighters.

2 System Architecture

iForestFire is Web Information System (WIS) [6]. All components and functionality of the system can be reached and administrated through dynamic and interactive web pages, as shown in Fig. 1. Real time video and meteorological data are shown on Web pages together with GIS data and interface for pan/tilt/zoom camera control when the system is in manual mode. To a user function of all components is presented as a part of web application, although some components like automatic fire detection are not web based application. The system hardware architecture is based on field units and a central processing unit. The field unit includes the day night, pan/tilt/zoom controlled IP based video camera and an IP based mini meteorological station connected by wired or wireless LAN to a central processing unit where all analysis, calculation, presentation, image and data archiving is done.

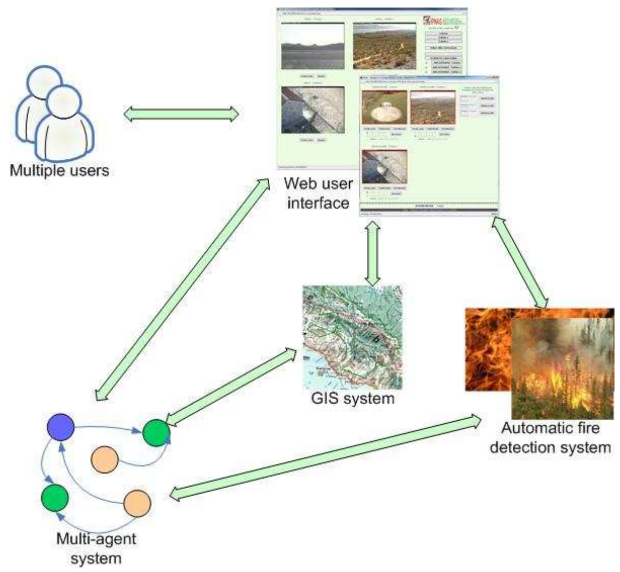


Figure 1: iForestFire software components

Monitoring station, shown in. Fig. 2 is equipped with pan/tilt/zoom controlled IP based video camera and an IP based mini meteorological station. Meteorological station measures important meteorological parameters like air temperature, relative humidity, air pressure, and wind speed and direction, which are used to reduce false alarms rate in automatic fire detection. All meteorological and other measured data are stored in a database and can be used for later analysis. Data gathering from video and meteo sensors in

Figure 2: iForestFire field unit

real time is done by a multi agent system. System is implemented using JADE [7] and running Rete [8] algorithm for reasoning and knowledge processing. A monitoring station is controlled with up to 20 agents depending on the monitoring station properties like number of cameras, number of preset positions per camera, etc.From the functional point of view, iForestFire system is built-up from the following components:

- Data gathering from video and meteo sensors in real time
- Automatic fire detection from acquired video data
- Data archiving for later analysis
- Geolocation information system
- Fire risk and spreading simulation

However, system architecture is highly modular. For example, if monitoring station is not equipped with a meteorological station, agents dedicated to collecting meteo data from each sensor of sensory network and storing it into data base are not activated.

3 Automatic fire detection

Early recognition of forest fire and appropriate fast reaction is the only way to minimize damage and threat to the infrastructure and human lives. The central part of the iForestFire is the component for the automatic detection of the fire. The detection is based on the visible signs of forest fire, as well as on the inputs from other sensors.

The fire itself in its early stages is usually not visible in daylight, especially if the monitoring spot is far from the location of the fire. However, smoke is the visible feature of the forest fire in densely wooded areas that can be used to detect fire in its incipient stage. Visible signs of fire are much easily recognized during the night, when the fire produces high contrast to the unenlightened landscape. The automatic detection system has two operational modes for the detection of the fire in daylight and during the night. The mode selection is automatic based on video input. Regardless of the operational mode, detection is carried out in up to 16 preset positions covering the entire field of view of the camera. The detection in single preset position takes about 15 seconds, resulting in up to 4 minutes interval between two detection cycles.

If the suspicious region in the visual range of the camera is detected the alarm is delivered to the human operator who makes the final decision about delivering the alarm to the fire fighters or discarding a false alarm. The sensitivity of the automatic fire detection can be adjusted using several parameters thus the system can be easily tuned for different landscapes and particular atmospheric and illumination conditions.

Variations in the smoke color tones, environmental illumination, atmospheric conditions (clouds, mist, shadows, dust), quality of images of wide outdoor areas and other problems make smoke detection a complex task. To detect smoke with reasonably low error rates, several algorithms based on different visual characteristics of smoke are implemented. Post-processing algorithms based on meteorological and video data fusion are applied and decision about raising an alarm is brought by a voting based strategy where weight is assigned to the output of each detection algorithm.

3.1 Background subtraction

First processing step in smoke detection is motion detection and background subtraction. Several methods have been proposed in the literature [9, 10]. Time and space complexity constraints enforced by simultaneous processing of several video inputs in real time impose the selection of an algorithm with low computational complexity and memory requirements. Further, system should adapt to significant changes that can arise in time interval between two visits to the same preset position due to environmental illumination. Moving pixels detection is based on the adapted background subtraction method proposed in [11]. A foreground blob of pixels b_n at time step n is defined by

$$b_n = \{x : |I_n(x) - B_n(x)| > T_n(x)\}, \tag{1}$$

where $B_n(x)$ is the background, $T_n(x)$ is threshold and $I_n(x)$ is the current frame value at the pixel x and time step n. Both the background B_n and the adaptive threshold T_n are recursively estimated from the sequence of frames $I_0, ..., I_{n-1}$:

$$B_n = \begin{cases} \alpha B_{n-1}(x) + (1-\alpha) I_n(x), & x \in b_n \\ B_{n-1}(x), & x \notin b_n \end{cases} \tag{2}$$

$$T_n = \begin{cases} \alpha T_{n-1}(x) + 5 \times (1-\alpha) D_n(x), & x \in b_n \\ B_{n-1}(x), & x \notin b_n \end{cases} \tag{3}$$

$$D_n(x) = |I_n(x) - B_{n-1}(x)|, \tag{4}$$

where α is a time constant that specifies how fast new frames are adopted in the background model. Initial background B_0 is taken to be the first frame in sequence and threshold T_0 is set to a predefined value.

We have adapted this method to the multiple position detection system with long time interval between two visits to the same position. To cope with the long pause between two subsequent frames, at the beginning of each detection cycle in the particular position, background model is updated with the first frame in the new cycle:

$$B_n(x) = \delta B_{n-1}(x) + (1-\delta) I_n(x) \tag{5}$$
$$\tfrac{2}{3}\alpha < \delta \leq \alpha$$

Equation (5) takes in to the account changes that have occurred as a result of deferent illumination or environmental conditions between two visits to the same preset position. Constant δ defines the influence of first frame in sequence to the previously adopted background model. If a new object enters the scene between two visits to the same position, it will still be detected. Even if the larger change is erroneously adopted to the background model, dynamic objects, like smoke, will be detected in the subsequent frames.

3.2 Pixel level classification

Suspicious regions disclosed by background subtraction are further processed by several algorithms based on different visual characteristics of the smoke. As the system is designed for monitoring wide areas, smoke can be detected several miles from the camera position thus the texture information content is usually low. However, color, histogram features and shape attributes, both intraframe and temporal can be used to distinguish smoke-like clusters of pixels from other artefacts in the input video stream.

Color and histogram characteristics are empirically acquired from the image collection gathered on the real forest fire monitoring sites [12] and images from the archive of the Professional Firefighting Brigade of the Split-Dalmatian county of the Republic of Croatia. Pixel level segmentation of smoke colored pixels [13] incorporates probabilistic model to classify a pixel into the *Smoke* class (ω_s) or into the *Non-Smoke* class (ω_{ns}). Pixels belonging to the *Smoke* class are assumed to have measurement vector x (color coordinates in *HSI* color space) distributed according to the distribution density function $p(x|\omega_s)$ and the distribution of the *Non-Smoke* class is defined with $p(x|\omega_{ns})$. Once the distributions have been estimated the Bayes theorem is applied to calculate the probabilities:

$$p(\omega_s|x) = \frac{p(x|\omega_s)p(\omega_s)}{p(x)} \tag{6}$$

$$p(\omega_{ns}|x) = \frac{p(x|\omega_{ns})p(\omega_{ns})}{p(x)} \tag{7}$$

where the prior probabilities $p(\omega_s)$ and $p(\omega_{ns})$ represent the probabilities of *Smoke* and *Non-Smoke* classes before observing the vector x. The newly encountered pixel, represented with the measurement vector x is classified as smoke if

$$\frac{p(\omega_s|x)}{p(\omega_{ns}|x)} > 1 \tag{8}$$

We use the prior probabilities as a user controllable parameter which controls the sensitivity of the smoke detection algorithm. This way the algorithm can be biased to minimize more expensive errors (it is obviously more serious to miss detect a real forest fire than to disturb the operator with the false alarm). Probability distributions for the *Smoke* and *Non-Smoke* classes are computed from the training set of images using the kernel density estimation technique based on the assumption that the probability distribution at a continuity point can be estimated using the sample observation that falls within region around that point [14–16].

3.3 Local histogram features

In addition to pixel level color segmentation of smoke colored pixels, local histogram features, based on the histogram of a region of the image are also used to distinguish smoke-like objects from other disturbances isolated by background subtraction. Dispersion $\hat{\mu}_1$ and mean m_1 are computed as [17, p. 334]:

$$m_1 = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{9}$$

$$\hat{\mu}_1 = \frac{1}{N}\sum_{i=1}^{N} |x_i - m_1| \tag{10}$$

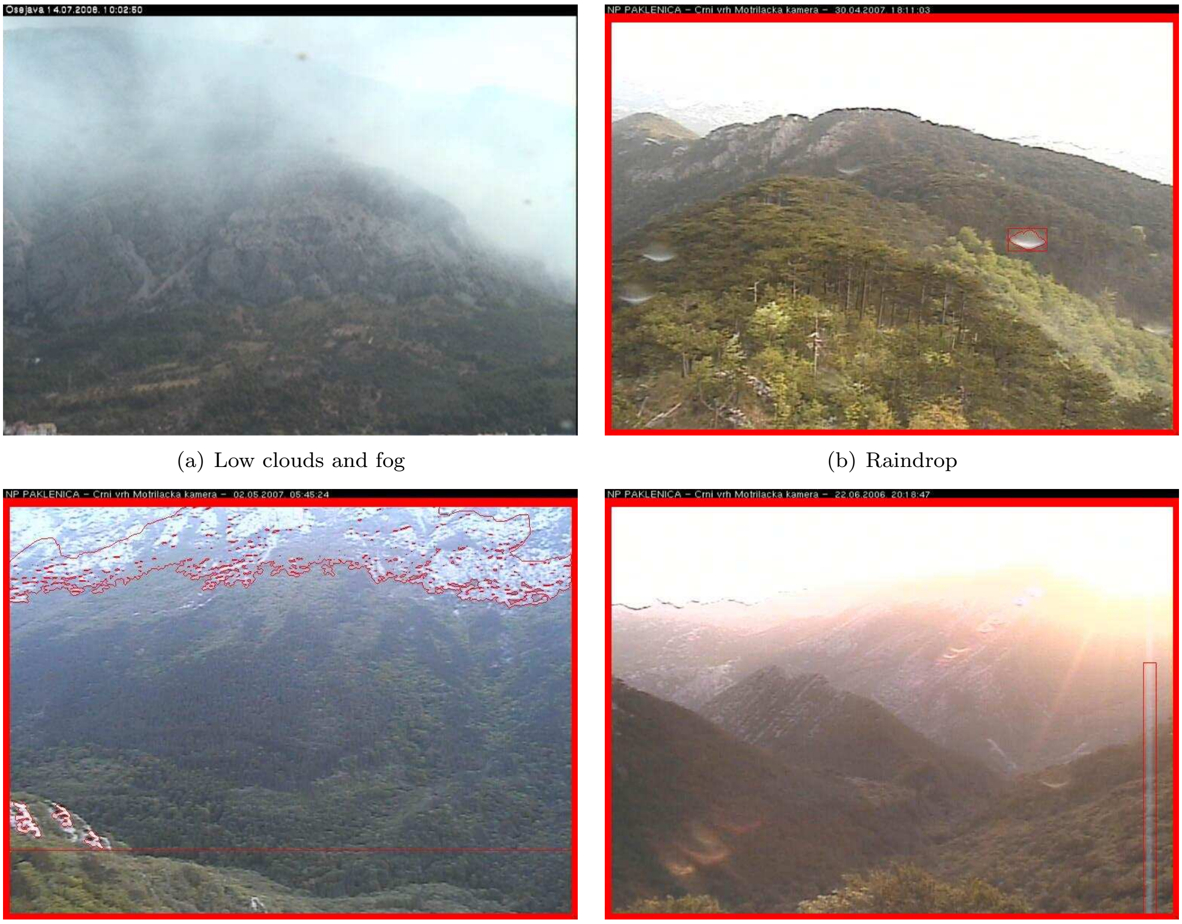
for the *intensity* and *saturation* components of the suspicious regions of the input image in *HSI* color space. Obtained values are compared to the ranges empirically acquired from the training data set.

3.4 False alarm reduction

Background subtraction and confirmation based on color and local histogram can efficiently identify appearance of smoke in the controlled region with zero miss-rate. However, there are situation when the smoke does not exist in reality, but the automatic surveillance system recognizes characteristics typical to the phenomena which leads to an alarm that does not correspond to the real occurrence of forest fire. Examples are given in Fig. 3. Primary causes for false alarms are natural phenomena visually similar to smoke that at certain conditions can be misinterpreted as smoke even by a human observer. These include fog and clouds that are low to the ground (Fig. 3(a)), dust, rain drops on the camera (Fig. 3(b)), intense changes in environmental illumination (Fig. 3(c)) and sunlight reflections (Fig. 3(d)), etc. In fact, the largest number of false alarms occurs in periods of the dynamic changes in the environmental illumination, especially in dawn and dusk. Such dynamic changes can easily be detected as motion, which in turn triggers the process of detection. Most of these alarms can be easily dismissed by common sense reasoning of the human observer.

Different scenarios that can trigger false alarm have to be covered by specific methods. Thus several methods have been developed to reduce false alarm rate [18]. These methods are mainly based on spatial characteristics of objects segmented as possible smoke formations. Spatial attributes can be divided in intra frame attributes and temporal characteristics. Latter are mainly used to eliminate abrupt changes detected as smoke. While the appearance of smoke is gradual, dynamic changes in aerial illumination can result in large regions of image detected as smoke as shown in Fig. 3(c). Accordingly, if the ratio of object size vs. evolution time is above certain threshold, the segmented object is discarded.

Intra frame attributes are based on the geometry of suspicious objects detected on a single frame and the



(a) Low clouds and fog

(b) Raindrop

(c) Alarm triggered by abrupt change in illumination

(d) Sunlight effect

Figure 3: Different natural phenomena can trigger false alarms

observation that the smoke plumes have rather convex shape that is not over elongated. For all detected objects the axis of least moment of inertia (Fig. 4) is calculated, that corresponds to the intuitive length of the object which is used to calculate elongation factor [18], ratio of length vs. width of the object. Experimental values acquired from the training set of images showed that the smoke in the incipient stage of forest fire have elongation factor less than 3. Elongation factor is efficiently used to reject majority of alarms triggered by sunlight effects on camera as shown in Fig 3(d).

False alarms triggered by raindrops and filth on the camera objective can be rejected based on the observation that smoke has not compact shape, while objects like raindrops are rather circular and compact as shown in Fig. 5. Compactness factor [18] is calculates using the perimeter of the object and its area:

$$c = \frac{l^2}{4\pi A}, \tag{11}$$

where l is the perimeter of the object and A is the area of the object. Another feature that can be used to distinguish smoke form raindrops is the curvature

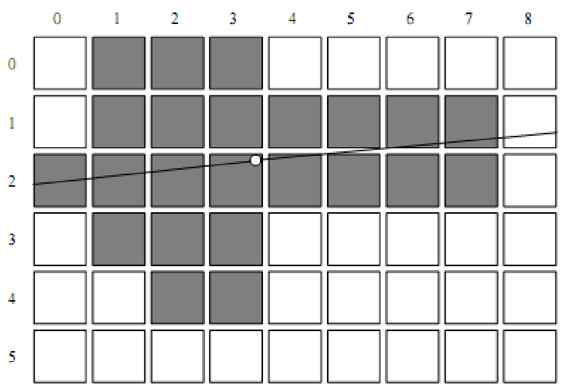


Figure 4: Axis of least moment of inertia

of the smoke shape, which by nature of its spread is rather distorted. Bending energy of the object shape is calculated according to:

$$B = \frac{1}{l} \sum \alpha^2, \tag{12}$$

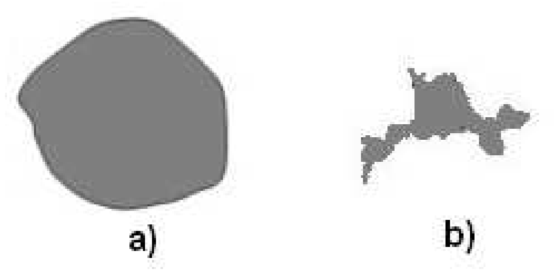


Figure 5: Detected objects: a) raindrop, b) smoke

where l is the perimeter of the object and α is the angle between two pixels whose distance is 3 from neighboring boundary pixels, as shown in Fig. 6.

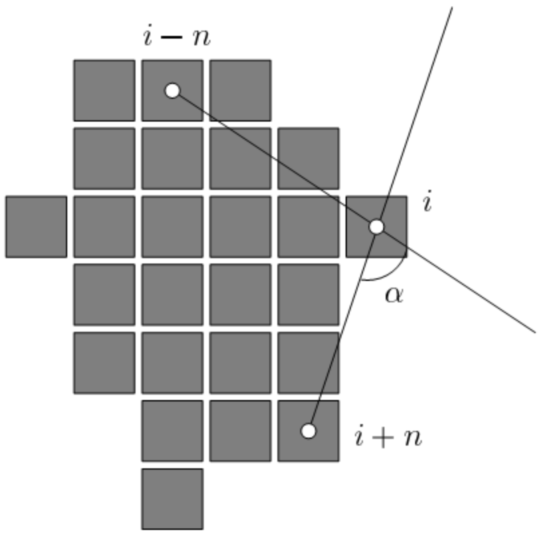


Figure 6: Angle α

Beside methods based solely on image processing and analysis techniques, alarms can also be discarded using more complex approaches based on sensor data fusion in combination with common sense reasoning. These methods combine information extracted from video input with meteorological information. Thus phenomena like raindrops and fog can be recognized using moisture detector. Temporal characteristics of smoke could be analyzed by comparing optical flow (Fig. 7) in suspicious regions in image with the wind direction and speed. However, extreme importance of keeping zero-miss rate in fire recognition suggests that no alarm should be dismissed based solely on meteorological information because they reflect meteorological situation on micro location where the equipment is mounted, while fire and smoke can be recognized several miles from the monitoring spot.

Figure 7: Optical flow

4 Conclusion

Environment protection is one of the most important tasks for the human kind. Hugh efforts in all areas of a society are directed to the preservation of natural heritage as much as possible. Information and communication technologies take up environment protection to a higher level. Intelligent environmental sensor networks provide the way of monitoring and controlling of physical environments. Information collected by these systems give new insights into the environment and provides data for modeling and simulation of environmental processes, while intelligent processing of the collected data in real time can reduce hazards of natural and man-made disasters by detection of dangerous situations and raising early warnings.

The presented system is based on a network of remotely controlled video cameras and meteorological stations integrated with the geolocation information system and intelligent data processing algorithms. Collected data is processed in real time to provide early detection of possible forest fire. In the case of real incident, video presence is used to guide the firefighters efforts on the terrain and to prevent dangerous situations, while the fire risk and spreading simulation module is used to anticipate development of the fire.

The main problem encountered in fire detection in visible spectra is high rate of false alarms. Different scenarios were developed in order to reduce the overall number of alarms. However, the false alarm rate is never expected to be zero, because in certain scenarios even human observers cannot distinct real and false alarms.

Forest Fire Monitoring system presented in this paper is installed on several location on the Croatian coast and islands. Currently best coverage is achieved in Istra county where complete coverage of the peninsula of Istra is achieved by 29 field units (cameras and mini meteorological stations) connected to 7 data processing centers. Systems installed on different locations have detected several real forest fire incidents. Video archive of the systems have also been used in police investigations about incidents.

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