FIRE DETECTION AND 3D FIRE PROPAGATION ESTIMATION FOR THE PROTECTION OF CULTURAL HERITAGE AREAS

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ABSTRACT:

Beyond taking precautionary measures to avoid a forest fire, early warning and immediate response to a fire breakout are the only ways to avoid great losses and environmental and cultural heritage damages. To this end, this paper aims to present a computer vision based algorithm for wildfire detection and a 3D fire propagation estimation system. The main detection algorithm is composed of four sub-algorithms detecting (i) slow moving objects, (ii) smoke-coloured regions, (iii) rising regions, and (iv) shadow regions. After detecting a wildfire, the main focus should be the estimation of its propagation direction and speed. If the model of the vegetation and other important parameters like wind speed, slope, aspect of the ground surface, etc. are known; the propagation of fire can be estimated. This propagation can then be visualized in any 3D-GIS environment that supports KML files.

1. INTRODUCTION

Early detection of any fire always leads to its easier suppression and minimization of its consequences. Early detection of fire is traditionally based on human surveillance. This can either be done using direct human observation by observers located at monitoring spots (e.g. lookout tower located on highland) (Fleming, 2003) or by distant human observation based on video surveillance systems. Relying solely on humans for the detection of forest fires is not the most efficient method. A more advanced approach is automatic surveillance and automatic early forest fire detection using either (i) Space borne (satellite) systems, (ii) Airborne or, (iii) Terrestrial-based systems.

Some advanced forest fire detection systems are based on satellite imagery, e.g. the Advanced Very High Resolution Radiometer (AVHRR, 2010), launched by the National Oceanic and Atmospheric Administration (NOAA) in 1998 and Moderate Resolution Imaging Spectroradiometer (MODIS) (MODIS, 2010), put in orbit by NASA in 1999, etc. However, there can be a significant amount of delay in communications with satellites, because orbits of satellites are predefined and thus satellite coverage is not continuous. Furthermore, satellite images have relatively low resolution due to the high altitude of the satellite, while their geo-referencing is usually problematic due to the high speed of the satellites. In addition, the accuracy and reliability of satellite-based systems are largely affected by weather conditions. Clouds and precipitation absorb parts of the frequency spectrum and reduce spectral resolution of satellite images, which consequently degrades the detection accuracy.

Airborne systems refer to systems mounted on helicopters (elevation<1km) or airplanes (up to 2 to 10 km above sea level). They offer great flexibility, short response times and they are able to generate very high-resolution data (typically few cm). Also, geo-referencing is easier and much more accurate than the satellites. Drawbacks include the increased flight costs, flight limitations by air traffic control or bad weather conditions and limited coverage. Turbulences, vibrations and possible deviations of the airplane from a pre-planned trajectory due to weather conditions are additional problems. However, recently, a large number of early fire detection projects use Unmanned Aerial Vehicles (UAVs), which can alleviate some of the problems of the airborne systems e.g. they are cheaper and are allowed to fly in worse weather conditions.

For the above reasons, terrestrial systems based on CCD video cameras, sensitive in visible and near IR spectra, are today the most promising solution for realizing automatic surveillance and automatic forest fire detection systems. Especially in case of cultural heritage sites, efficient protection from the risk of fire can be achieved with only a small number of cameras. To this end, in this paper we present a computer vision based algorithm for wildfire detection, which is composed of four sub-algorithms detecting (i) slow moving objects, (ii) smoke-coloured regions, (iii) rising regions, and (iv) shadow regions. Besides detection, early intervention is also very important in fire fighting. If the fire-fighters knew where the fire will be a few minutes later, it would be easier for them to fight it. Therefore a big need for simulating the fire behaviour exists. In this paper we are proposing a system that can simulate the propagation of fire in time. Also this system can visualize the propagation of fire in any 3D-GIS environment that accepts KMZ as a file format.

The work presented in this paper is part of the FIRESENSE (Fire Detection and Management through a Multi-Sensor Network for the Protection of Cultural Heritage Areas from the Risk of Fire and Extreme Weather Conditions) project, which is co-funded by European Union's 7th Framework Programme Environment (Including Climate Change). The objective of FIRESENSE project is to develop a multi-sensor early warning system to remotely monitor areas of archaeological and cultural interest from the risk of fire and extreme weather conditions. The FIRESENSE system will take advantage of recent advances in multi-sensor surveillance technologies, using a wireless sensor network capable of monitoring different modalities (e.g. temperature, humidity), optical and infrared cameras, as well as local weather stations on the deployment site. Pilot deployments will be made in five cultural heritage sites in i) Thebes, Greece, ii) Rhodiapolis, Turkey, iii) Dodge Hall, Istanbul, Turkey, iv)

Temple of Water, Tunisia, v) Monteferrato-Galceti Park, Prato, Italy.

2. WILDFIRES IN CULTURAL MONUMENTS

The majority of cultural heritage and archaeological sites, especially in the Mediterranean region, are covered with vegetation or situated close to forest regions. Therefore they are exposed to increased risk of forest fire. Such fires may break out from within the site and spread towards nearby forests and other wooded land, or conversely start in nearby forests and spread to archaeological sites.

For example, in 2007, Ancient Olympia, which is a UNESCO world heritage site and the birthplace of the ancient Olympic Games, was seriously endangered by a fast-moving wildfire. The local archaeological site contains the remains of the ancient stadium, temples, the museum and administrative buildings. The fire reached the hill overlooking ancient Olympia and it was stopped just before entering the archaeological site, but not before reaching a historic pine-covered hilltop above the renowned stadium.

More recently in 2009, a multi-front wildfire raged the northeast of the greater Athens area and burnt 21,000 hectares of pine forest, olive groves, shrub land and farmland. Among the damaged areas was Marathon, site of one of history's most famous battlegrounds between the Greeks and the Persians in 490 B.C. and an area of supreme natural beauty. The wildfire encircled the museum of Marathon and closed in on the archaeological site of Rhamnus, which is home to two 2,500-year-old temples, the Marathon battle site, the Tomb of the Marathon Warriors and the Tomb of the Plataeans. The antiquities linked to the battle of Marathon were not directly damaged; however the physical setting of the sites was destroyed. Earlier in 2009, a fire in Boeotia threatened the Mycenaean citadel of Gla (13th century BC).

Other archaeological and cultural heritage sites that were threatened by wildfires in the last decades include: the ancient Kameiros, Rhodes Island in 2008, the temple of Epikouros Apollo in 1998, three Monasteries of Mount Athos in 1990 and a large fire at mountain Olympus that burned the scenic scoots-pine forest and the Dion antiquities in 1994 (Dimitrakopoulos, 2002).

Recent wildfires have caused significant damage to many archaeological and heritage sites in Turkey as well. In July 2007, the 2nd century BC theatre and the necropolis of the antique city of Notion (Ahmetbeyli, Aegean coast, 50 km south of Izmir) were partially destroyed by a wildfire. In February 2008, three houses in the Camiatik, a district of Kusadasi near Ephesus, were burned. These houses were classified as 1st degree heritage sites. A fire destroyed one hectare of pine trees in the Sulucahoyuk, which is an archaeological area in Nevsehir province in 2006. The site has been inhabited by people since the Neolithic age and it also contains remains from the Assyrian, Hittite, Phrygian, Hellenistic and late-Roman periods. In June 2008, a fire destroyed 2km^2 of land covered with shrubs in the ancient city of Laodikia in Denizli province. This bush fire also damaged some marble ruins. During summer of 2007 a forest fire broke out near the Ancient City of Ephesus and the House of the Virgin Mary (Mt. Koressos) at Selcuk Turkey. Luckily, fire fighters were able to control the fire and the ancient city of Ephesus did not suffer any harm.

As it is shown from all these incidents, wildfires are one of the main causes of the destruction of cultural monuments in recent years. The increase in seasonal temperatures has caused an explosion in the number of self-ignited wildfires in forested areas. Fanned by the dry winds, and fuelled by dry vegetation, some of these fires have become disastrous for many cultural heritage sites. Thus, beyond taking precautionary measures to avoid a forest fire, early warning and immediate response to a fire breakout are the only ways to avoid environmental and cultural heritage damages.

3. FIRE DETECTION AND PROPAGATION ESTIMATION LITERATURE REVIEW

Flames and smoke produced during a wildfire behave in a chaotic manner. For this reason, a typical wildfire does not have a specific identifiable shape that could be recognized using classical pattern recognition techniques. In the following an overview of existing approaches flame a smoke detection will be provided. In addition, the most popular fire propagation estimation models will be reviewed.

3.1 Video Flame Detection Techniques

A feature that is most identifiable by a video flame detection method is its colour. The colour of the flame is not a reflection of the natural light, but it is generated as a result of the burning materials. In some cases, the colour can even be white, blue, gold or even green depending on the chemical properties of the burnt material and its burning temperature. However, in the cases of organic materials such as trees and brush, the fire has the well-known red-yellow colour. Many natural objects have similar colours as those of the fire (including the sun, various artificial lights or reflections of them on various surfaces) and can often be mistakenly detected as flames, when the decision takes into account only the colour criterion.

For this reason, additional criteria have to be used to discriminate between such false alarm situations and real fire. Many researchers use motion characteristics of the flame as well as the special distribution of fire colours in the scene. The use of spatio-temporal criteria in the flame detection algorithm may significantly increase the computational complexity, since multidimensional image processing is needed. Four dimensions due to position, pixel luminance information and time (x,y,Y,t) exist in the case of greyscale images or 6 dimensions (x,y,r,g,b,t) exist in the case of colour images having red, green and blue components. Therefore, to keep the complexity low, most works in the literature use either a) purely spatial or b) purely temporal criteria or c) a two-step approach combining results obtained the above criteria.

A recent review of video fire detectors can be found in (Xiong, 2009). The methods can be broadly categorized as follows:

• *Change (including Motion) Detection (Chen, 2004):* In most flame detection algorithms, a pre-processing step exists, focusing on regions of interest where there is a temporal change in the scene. This can significantly reduce the computational burden for the subsequent processing by reducing the video processing only in moving regions. Some of the techniques used for this task include: a) simple temporal differencing, b) background estimation and subtraction, and c) optical flow based motion detection techniques.

• *Colour Detection (Phillips, 2000), (Celik, 2009):* Colour is a very important criterion of the fire that is used in most of the currently available methods. Usually, chromatic analysis of the images to search for regions with fire colours uses one or more decision rules in a colour space. Usually, the RGB colour space is used but other colour spaces as HIS or YUV have also been used in the literature. In some cases look-up tables and/or neural networks are also used for this task. Look-up tables can reduce the computational complexity but have high memory requirements.

• *Shape/Geometry/Contour Cues (Zhang, 2006):* Specific features of the candidate regions of interest in video such as its shape, geometry and/or contour are examined and an effort is made to identify particular characteristics, patterns or models that are consistent with the presence of flames (e.g. random contour shape etc).

• *Temporal Analysis (Zhang, 2008):* Temporal cues leading to strong high frequency content in video, due to the flame flickering process, are identified in the video. This is a good indication of the presence of a wildfire. The Fast Fourier Transform (FFT), wavelet analysis or simpler mathematical rules can be used for the task of identifying rapidly changing regions in video.

• *Spatial Analysis (Toreyin, 2007):* Flame colours may follow certain models or spatial distribution patterns, which can be identified, e.g. fractal models, wavelet models in multiple spatial resolutions. Such models are used to discriminate flames from other natural or man-made moving objects in video.

3.2 Video Smoke Detection Techniques

The rapid development in computer industry in the last two decades has enabled integration of intelligent algorithms in video based surveillance systems. Most surveillance systems already have built-in simple detection modules (e.g. motion detection, event analysis). In recent years there has been significant interest in developing real-time algorithms to detect fire and smoke for standard surveillance systems (Toreyin, 2009b).

Most commercially available smoke detectors are point sensor type detectors. These sensors are actuated when the smoke plume gets close to the sensor. Therefore there is always a transport delay until the smoke reaches the sensor. Video based smoke detection can be used to remedy this situation, since a single camera can monitor a large area from a distance and can detect smoke earlier than a traditional point detector if a robust detection algorithm is used. Although video based smoke detection is a promising alternative to traditional smoke detectors, it has some drawbacks that need to be resolved before a reliable system is realized. Smoke is difficult to model due to its dynamic texture and irregular motion characteristics. Unstable cameras, dynamic backgrounds, obstacles in the viewing range of the camera and lighting conditions also pose important constraints to the smoke detection problem.

Most smoke detection algorithms start with motion detection (Gomez-Rodriguez, 2003). Different motion detection algorithms are developed for close range and long range smoke detection tasks. Motion detection reduces the area that is searched for smoke that in turn reduces the computational cost of the algorithm. Therefore, the detection quality of the method directly depends on the reliability of the motion detection algorithm. Although there are many motion detection algorithms that work well in practice, new algorithms can be developed to handle dynamic backgrounds and moving cameras.

After motion detection spatial and temporal image features that characterize smoke well are calculated. The calculated features are fed into a decision mechanism or a classifier (SVMs, neural networks, Bayesian) to find the final segmentation (Jayavardhana, 2009, Zhengguang, 2007, Krstinić 2009).

3.3 Fire Propagation Estimation and Visualization Techniques

Early detection of wildfires at cultural heritage sites or nearby forest areas is just the first step of the prevention. To encounter wildfires in places like this is unavoidable. After such an incident occurs, one major step in order to minimize the damages is early intervention by predicting the propagation direction and the rate of spread (ROS) of fire.

Governments of countries such as Canada, USA and Australia pioneered in this research area and developed several fire propagation estimation models. These models can be classified into three basic categories: empirical, semi-empirical and physical models. Empirical models are based primarily on the statistics collected by observation of experimental or historical fires and their application is only feasible to the areas for which the models have been created. On the other hand, physical models are based on fluid dynamics and laws of conservation of energy and mass. Physical models provide more accurate results; however, their use is limited, since they require high computational power and accurate input data. For these reasons semi-empirical models are considered as the most appropriate for fire simulation applications. Semi-empirical models combine the analytical formulation of physical phenomena with statistical information measurements. The most known semi-empirical models are: Rothermel model, Huygens model and Cellular Automata. The Rothermel model is the most popular model. It is the base of the widely used BEHAVE and FARSITE simulation programs.

The visualization of the propagation of fire is also a very important issue since it helps the fire department to plan the deployment of its forces (Köse, 2008). Geographical Information Systems (GIS) are widely used for this purpose. By using a propagation simulator with GIS support, a real-time decision support system can be developed (Kessel, 1991). Thus, the effectiveness of the fire fighting strategies is enhanced. GIS stores spatial information in a digital mapping environment that allows fire managers to quickly select and view data that can influence fire behaviour. Factors such as vegetation types, slopes, aspects, natural or man-made barriers, and historical weather patterns can be overlaid to determine fire hazards based on modelling potential fire behaviour (GIS Solutions, 2010).

4. PROPOSED FIRE DETECTION AND PROPAGATION ESTIMATION TECHNIQUES

Especially from long distance, smoke is observed first in wildfires. In the proposed system, the algorithm given in (Toreyin, 2009a) is used. The main properties of smoke are given as; (i) it moves slowly, (ii) its colour is gray, (iii) it moves vertically. Therefore smoke in the scene can be detected using these properties. On the other hand shadows of the objects in the scene, especially the clouds may show the same properties as smoke. Thus, as the last step of the smoke detection algorithm, smoke should be discriminated from shadow. For each property, a decision value is generated. These sub-algorithm decisions are then used to give the final “smoke” or “not smoke” decision.

Speed of movement in the scene can be defined as pixels per second (pix/sec). However, objects closer to the camera moves seem to move faster than the objects far away, even if their actual speed is same. Therefore one slow (B_{slow}) and one fast (B_{fast}) background image is generated from the scene (Cetin et. al. 2004). These background images are updated with different update rates. These two background images are subtracted from each other and then compared with two experimentally determined thresholds ($T_{1,low}$ and $T_{1,high}$). For each pixel (x,y) of each frame (n) of the scene, a decision value is determined as,

$$D_1(x,y,n) = \begin{matrix} 1, & where & \left|B_{fast} - B_{slow}\right| \geq T_{1,high} \\ -1, & where & \left|B_{fast} - B_{slow}\right| \leq T_{1,low} \\ (-1,1) & & o.w. \end{matrix}$$

The second decision value $D_2(x,y,n)$ is determined according to the colour of the pixels. $D_2(x,y,n)$ is equal to -1 if the Y channel of the background is below a threshold and the chrominance values are high. As the chrominance value decreases and the brightness increases, $D_2(x,y,n)$ takes values closer to 1.

A Hidden Markov model (HMM) is used to determine the third decision. The aim of this step is actually discriminating clouds and the smoke, both of which have the same moving speed and colour properties. Two HMMs are trained separately for each and the ratio of the outputs probabilities (P_{smoke} / P_{cloud}) of the HMMs is used as $D_3(x,y,n)$. The ratios are mapped between [-1,1] linearly, 1 being the ratio higher than a threshold $T_{3,high}$ and -1 lower than a threshold $T_{3,low}$. Again both thresholds are determined experimentally.

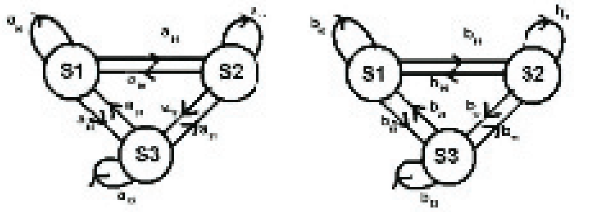

Figure 1: HMMs corresponding to smoke (left) and cloud (right). The models are trained off-line. Figure is taken from (Toreyin, 2009a).

The last decision $D_4(x,y,n)$ is made for shadow removal. The angle between the colour vectors of the background and current frames is used to generate this decision (Harwood, 1999). First the average RGB vectors are calculated for both the background and the current frame. Since the shadow regions retain the underlying texture and colour. In the shadow regions the direction of the vectors in the current frame are smaller than the vectors in the background. The higher the value is, the more the decision value is closer to 1. The overview of the smoke detection algorithm is given in (Toreyin, 2009b).

After smoke is detected, the next step is the determination of the possible propagation of fire. Research on 3-D fire propagation estimation and visualization techniques has been conducted, with the aim to simulate the spread of a wildfire and visualize it on a 3D display in 3D. The spread calculations are done using a library called 'fireLib'. fireLib was developed using BEHAVE (Andrews 1986) algorithm, by Collin D. Bevins, USDA Forest Service Rocky Mountain Research Station. According to BEHAVE, fire propagation depends on a number of parameters (e.g. ignition points, fuel model, humidity, wind, terrain data and other factors). These parameters are either measured or estimated and are used either directly or after modifications. However, these parameters for each cell are assumed to be constant with respect to time. When a cell is ignited, the calculation of the ignition times for its neighbouring cells is performed. The propagation of fire from one cell to another depends on the ignitability of the cell, which is done only once per cell. This calculation yields an ignition time instant as well as an estimated flame length. However as the time increases and fire propagates further, some of the parameters in some cells may change (e.g. wind, moisture, fuel type). This issue is not taken into account in fireLib model. To cope with this problem, we take into account the dynamically changing parameter values within a recursive computation of the ignition times. Flame length is calculated once when the cell is ignited. To have a more realistic visualization we scale the flame length with a function that is decaying in time after some maximum. By this way the calculation of the fire propagation on dynamically changing landscape is achieved.

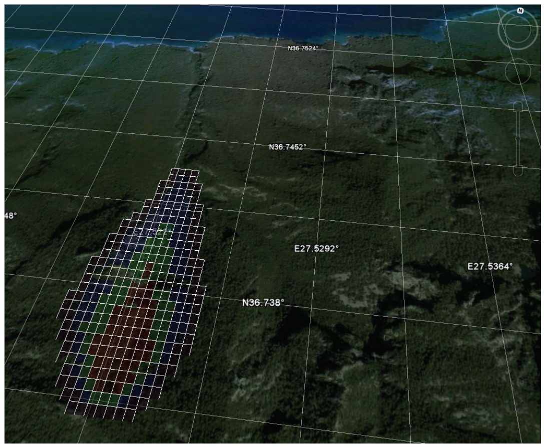

Figure 2: Colour-coded illustration of ignition times.

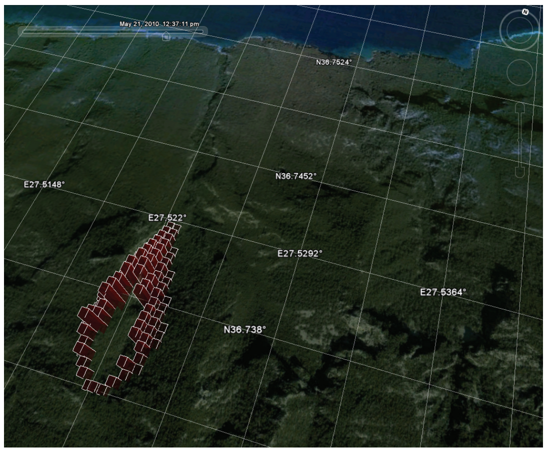

Figure 3: Screenshot from a flame length animation in Google Earth™

Another problem is that the 13 fuel models defined by fireLib are not representative of the fuel models usually found in the Mediterranean region. Currently, the most appropriate model among the 13 already defined models in fireLib is simply used as the vegetation model. However, it is planned to derive more accurate forest models of Turkey and Greece in the near future.

The next phase is the visualization of the fire propagation. This visualisation is important since (i) it enables early intervention of the fire and (ii) it helps to fire department to deploy its forces easily. The fire propagation software in the literature yield a 2D view (mostly a top view) of the fire-site, which may not provide a clear view of the situation to the persons responsible for the deployment of fire-fighting forces. In the FIRESENSE project, it is aimed to visualize this raw propagation data on a more user-friendly 3D-GIS environment. For this purpose Google Earth™ is used in the proposed system. The main reasons of choosing Google Earth™ are because it is public available and widely used by experts and non-experts. Also it allows the creation of impressive 3-D animations of the fire propagation, in addition to the static views.

Moreover, due to its layered design, Google Earth™ provides to the developer (and the user) enhanced flexibility to visualize various types of additional information on the map. For instance, the timeline of the propagation can be colour-coded and displayed. Positions of the deployed equipment, observation posts, fire-fighting units etc. can also be visualized on the map. Two example views of the visualizations that can be obtained by the proposed approach can be seen in Figure 2 (colour-coded illustration of Ignition times) and Figure 3 (Screenshot from a flame length animation).

5. EXPERIMENTAL RESULTS

A forest fire version of the proposed smoke detection system is currently being used by Directorate of Forests (OGM) at the forests of Turkey. Within the framework of the FIRESENSE project the system will be extended and used for the protection of cultural heritage monuments and it will be installed in five selected test sites, as mentioned in the introduction section.
During years 2007-2009, Manavgat, Marmaris and Aksehir in Turkey were destined as pilot sites for the smoke detection system. During 2008, two small and one big forest fires at Manavgat and one forest fire at Aksehir were detected using the proposed system.

Figure 4: Interface of the wildfire detection system used in the forests of Turkey

The proposed system not only detects wildfires early but also enables the wildfires to be watched from remote places. In 2008 the fight against big forest fire at Manavgat was commanded directly from OGM at Ankara, using the proposed system. Due to the success of the system, currently Turkish Government is installing the system to the other forest areas in Turkey. An example figure from the system interface is given in Figure 4.
A sample result from a detected fire at the region of Antalya is illustrated in Figure 5. As seen in Figure 5(a), first a candidate smoke region is determined. Then this candidate region is analyzed for a few frames and a final decision is provided according to this analysis (Figure 5(b)).

6. CONCLUSIONS

Early warning and immediate response to a fire breakout are the only ways to avoid great losses and environmental and cultural heritage damages. Hence, the most important goals in fire surveillance are quick and reliable detection and localization of the fire. It is much easier to suppress a fire when the starting location is known, and while it is in its early stages. Information about the progress of fire is also highly valuable for managing the fire during all its stages. Based on this information, the fire fighting staff can be guided on target to block the fire before it reaches cultural heritage sites and to suppress it quickly by utilizing the required fire fighting equipment and vehicles.

(a)

(b)

Figure 5: Sample results from a test fire at Antalya region. (a) The possible smoke area is detected; (b) alarm is given finally when the region of interest is decided to be smoke.

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