WILDFIRE DETECTION USING LMS BASED ACTIVE LEARNING

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ABSTRACT

A computer vision based algorithm for wildfire detection is developed. The main detection algorithm is composed of four sub-algorithms detecting (i) slow moving objects, (ii) gray regions, (iii) rising regions, and (iv) shadows. Each algorithm yields its own decision as a real number in the range [-1,1] at every image frame of a video sequence. Decisions from sub-algorithms are fused using an adaptive algorithm. In contrast to standard Weighted Majority Algorithm (WMA), weights are updated using the Least Mean Square (LMS) method in the training (learning) stage. The error function is defined as the difference between the overall decision of the main algorithm and the decision of an oracle, who is the security guard of the forest look-out tower.

***Index Terms*—** Least mean square methods, active learning, wildfire detection

1. INTRODUCTION

Manned lookout posts are commonly installed in forests all around the world. Surveillance cameras can be placed on to the surveillance towers to monitor the surrounding forest for possible wild fires. Furthermore, they can be used to monitor the progress of the fire from remote centers.

In this paper, a computer vision based method for wildfire detection is presented. Currently, average fire detection time is 5 minutes in manned lookout towers. Guards have to work 24 hours in remote locations under difficult circumstances. They may get tired or leave the lookout tower for various reasons. Therefore, computer vision based video analysis systems capable of producing automatic fire alarms are necessary to reduce the average forest fire detection time.

There are several approaches on automatic detection of forest fires in the literature. Some of the approaches are directed towards detection of the flames using infra-red and/or visible-range cameras whereas some others aim at detecting the smoke due to wildfire [1]-[4]. There are also recent papers on sensor based detection of forest fires [5, 6]. Infrared cameras and sensor based systems have the ability to capture the rise in temperature however they are much more expensive compared to regular pan tilt zoom cameras.

It is almost impossible to view flames of a wildfire from a camera mounted on a forest watch tower unless the fire is very near to the tower. However, smoke rising up in the forest due to a fire is usually visible from long distances. A snapshot of a typical wildfire smoke captured by a look-out tower camera from a distance of 5 Km is shown in Fig.1.

Guillemant and Vicente based their method on the observation that the movements of various patterns like smoke plumes produce correlated temporal segments of gray-level pixels. They utilized fractal indexing using a space-filling Z-curve concept along with instantaneous and cumulative velocity histograms for possible smoke regions. They made smoke decisions about the existence of smoke according to the standard deviation, minimum average energy, and shape and smoothness of these histograms [4].

Fig. 1. Snapshot of a typical wildfire smoke captured by a forest watch tower which is 5 km away from the fire (rising smoke is marked with an arrow).

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Our method also detects smoke due to forest fires. Automatic video based wildfire detection algorithm is based on four sub-algorithms: (i) slow moving video object detection, (ii) gray region detection, (iii) rising video object detection, (iv) shadow detection and elimination. Each sub-algorithm decides on the existence of smoke in the viewing range of the camera separately. Decisions from sub-algorithms are combined using an adaptive Weighted Majority Algorithm (WMA). Initial weights of the sub-algorithms are determined from actual forest fire videos and test fires. They are updated using the least mean square (LMS) algorithm during initial installation. The error function in the LMS adaptation is defined as the difference between the overall decision of the compound algorithm and the decision of an oracle. In our case, the oracle is the security guard. The compound decision algorithm will obviously produce false alarms. The system asks the guard to verify its decision whenever an alarm occurs. In this way, the user actively participate in the learning process.

The paper is organized as follows: Section 2 describes briefly each one of the four sub-algorithms which make up the compound (main) wildfire detection algorithm. Adaptive weighted majority algorithm is described in Section 3. In section 4, experimental results are presented. Finally, conclusions are drawn in Section 5.

2. BUILDING BLOCKS OF WILDFIRE DETECTION

Wildfire detection algorithm is developed to recognize the existence of wildfire smoke within the viewing range of the camera monitoring forest regions. Smoke at far distances ($> 100m$ to camera) exhibit different temporal characteristics than nearby smoke and fire [7], [8]. This demands specific methods explicitly developed for smoke detection at far distances rather than using nearby smoke detection methods described in [7]. The proposed wildfire smoke detection algorithm consists of four main steps: (i) slow moving video object detection, (ii) gray region detection, (iii) rising video object detection, (iv) shadow detection and elimination.

2.1. Detection of Slow Moving Objects

Video objects at far distances to the camera seem to move slower (px/sec) in comparison to the nearby objects moving at the same speed (m/sec). Assuming the camera is fixed, two background images, B_{fast} and B_{slow} corresponding to the scene with different update rates are estimated [9]. Slow moving objects within the viewing range of the camera are detected by comparing Y-channel values of two background images. If there exists a substantial difference between the two for some predetermined period of time, then an alarm for slow moving regions is raised, and the region is marked.

2.2. Detection of Gray Regions

Smoke due to forest fires is mainly composed of carbon dioxide, water vapor, carbon monoxide, particulate matter, hydrocarbons and other organic chemicals [10]. The grayish color of the rising plume is primarily due to water vapor in the output fire composition. This color can be identified by setting thresholds in the YUV color space. The chrominance values should be very low in a smoke region. Unfortunately, cloud shadows also have very low U and V values.

2.3. Detection of Rising Regions

Wildfire smoke regions tend to rise up into the sky. This characteristic behavior of smoke plumes is modeled with three-state Hidden Markov Models (HMM). Temporal variation in row number of the upper-most pixel belonging to slow moving regions are used as feature signals and fed to the Markov models in Fig.2. One of the models correspond to genuine wildfire smoke regions and the other one correspond to regions with clouds and cloud shadows. Transition probabilities are estimated off-line. The state S1 is attained, if the row value of the upper-most pixel in the current image frame is smaller than that of the previous frame (rise-up). If the row value of the upper-most pixel in the current image frame is larger than that of the previous frame, then S2 is attained and this means that the region moves-down. No change in the row value corresponds to S3.

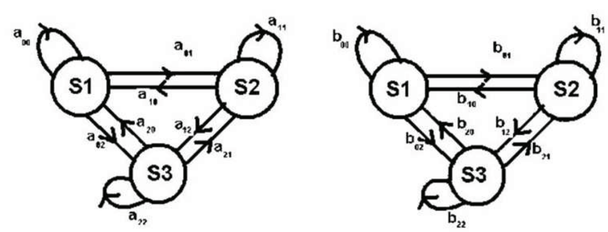

Fig. 2. Markov models corresponding to wildfire smoke (left) and clouds (right). Transition probabilities a_{ij} and b_{ij} are estimated off-line.

2.4. Shadow Detection and Removal

Shadows of slow moving clouds are major source of false alarms for video based wildfire smoke detection. Shadow regions are detected as in [11]. Average RGB vectors are calculated for slow moving regions both in the current and background images. For shadow regions, the directions of these vectors should be close to each other whereas the magnitude of the vector in the current image should be smaller than that of the vector in the background image. This is because shadow regions retain a representation of the underlying texture and color.

3. LMS BASED ADAPTATION FOR WEIGHTS OF SUB-ALGORITHMS

Let the compound algorithm is composed of N-many detection algorithms: $D_1, ..., D_N$. Upon receiving a sample input x, each algorithm yields a decision $D_i(x) \in \{-1, 1\}$. The type of sample input x may vary depending on the algorithm. In our case, for every detection algorithm, each pixel at the location x of incoming image frame is considered as a sample input. The compound algorithm can be arranged in the form of a weighted majority algorithm (WMA) given the correct classification result y from the oracle as in Algorithm 1. In

Algorithm 1 Weighted Majority(x,n)

> **for** i = 1 to N **do**
> $w_i(0) = \frac{1}{N}$, Initialization
> **end for**
> **if** $\sum_{i:d_i(x,n)=1} w_i(n) \geq \sum_{i:d_i(x,n)=-1} w_i(n)$ **then**
>   return 1
> **else**
>   return -1
> **end if**
> **for** i = 1 to N **do**
>   **if** $d_i(x,n) \neq y$ **then**
> $w_i(n+1) \leftarrow \frac{w_i(n)}{2}$
>   **end if**
> **end for**

contrast to the original WMA update mechanism, weights are updated according to the LMS algorithm which is the most widely used adaptive filtering method [12]. Another innovation that we introduced in this paper is that individual decision algorithms do not produce binary values 1 (correct) or -1 (false). They produce a real number between 1 and -1, i.e., $D_i(x) \in [-1, 1]$.

Let $\mathbf{D}(x,n) = [D_1(x,n)...D_N(x,n)]^T$, be the vector of decisions of the algorithms for the pixel at location x of input image frame at time step n. The weight adaptation equation is as follows:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \frac{e(x,n)}{||\mathbf{D}(x,n)||^2} \mathbf{D}(x,n) \qquad (1)$$

where $\mathbf{w}(n) = [w_1(n)...w_N(n)]$, is the current weight vector. We define

$$\hat{y}(x,n) = \mathbf{D^T}(x,n)\mathbf{w}(n) = \sum_i w_i(n) D_i(x,n) \qquad (2)$$

as an estimate of the correct classification result $y(x,n)$ of the oracle for the pixel at location x of input image frame at time step n, and the error $e(x,n)$ as $e(x,n) = y(x,n) - \hat{y}(x,n)$. The adaptive algorithm converges, if $D_i(x,n)$ are wide-sense stationary random processes and when the update parameter μ lies between 0 and 2 [13]. The computational cost can be reduced by omitting the normalization by the norm $||\mathbf{D}(x,n)||^2$ by selecting a μ close to zero.

Algorithm 2 LMS Based Active Decision(x,n)

> **for** i = 1 to N **do**
> $w_i(0) = \frac{1}{N}, Initialization$
> **end for**
> $\hat{y}(x,n) = \sum_i w_i(n) D_i(x,n)$
> **if** $\hat{y}(x,n) \geq 0$ **then**
>   return 1
> **else**
>   return -1
> **end if**
> $e(x,n) = y(x,n) - \hat{y}(x,n)$
> **for** i = 1 to N **do**
> $w_i(n) \leftarrow w_i(n) + \mu \frac{e(x,n)}{||\mathbf{D}(x,n)||^2} D_i(x,n)$
> **end for**

The proposed algorithm is presented in Algorithm 2. The weights are unconditionally updated using LMS adaptation in Eq 1. The user participate actively in the learning process by disclosing her/his classification result, y, on the sample pixel at location x of input image frame. For the automatic video based wildfire detection algorithm, the decision results, $D1$, $D2$, $D3$ and $D4$ of the four sub-algorithms described in Section 2 corresponding to each pixel at location x of every incoming image frame at time step n, are determined as:

(i) Detection of Slow Moving Objects: The difference between the Y-channel values of the background images B_{fast} and B_{slow} determines the decision value, $D_1(x,n)$. It is -1, if the difference is lower than or equal to T_{low}, which is an experimentally determined threshold. It is 1, if the difference is higher than or equal to T_{high}. It takes real values in the range (-1,1) if it is in between the two thresholds $T_{high} > T_{low}$.

(ii) Detection of Gray Regions: $D_2(x,n)$ is -1, if Y-channel value for (x,n) couple is below a threshold and chrominance values are high. It takes values closer to 1 as the chrominance value gets lower and the brightness increases.

(iii) Detection of Rising Regions: A Markov model based system would give a "smoke decision", when the probability value corresponding to smoke Markov model were higher than that of cloud model. The ratio of smoke model probability to cloud model probability determines the value of $D_3(x,n)$. If the ratio is higher than an experimentally determined threshold, it is 1, and if the ratio is lower than another threshold, it is -1. The range of ratio values in between these thresholds are linearly mapped between 1 and -1.

(iv) Shadow Detection and Removal: The angle between the color vectors of the background and the current image of the video determine the decision function $D_4(x,n)$. The higher the angle between the two images, the closer the decision value is to 1.

The threshold values in all of the decision functions are chosen in such a way that they produce positive values for all of the wild fire video recordings that we have. The final decision must also yield a non-negative value when the decision functions produce positive values. In the proposed method, if any one of the weights happens to be negative then it is set to zero in order to have a non-negative final decision value when individual decisions are positive.

4. EXPERIMENTAL RESULTS

The proposed LMS based active learning method is implemented on a PC with an Intel Core Duo CPU 1.86GHz processor and tested with forest surveillance recordings captured at 5 fps from cameras mounted on top of forest watch towers near Antalya and Mugla in Turkey. The installed system successfully detected three forest fires in the summer of 2008.

Three types of approaches are compared with each other in the experiments: (a) WMA based scheme, (b) LMS based scheme, and (c) Weights are fixed and equal. Comparative tests are carried out with 6-hour-long forest surveillance recordings consisting of actual forest fire and test fire sequences as well as sequences with no fires. Fire alarms are issued by all three methods at about the same time after smoke become visible. However, there are substantial performance differences among the schemes for videos with false alarm.

When a false alarm is issued by the compound algorithm, the learning process is much faster for LMS based scheme in comparison to WMA based approach. This is reflected in the average learning durations and is presented in Table 1. $Learning\ duration$ is defined as the duration in number of frames necessary for a learning method to adapt its parameters in order to yield the desired output. It is infinite for the scheme with fixed and equal weights.

Table 1. Average learning durations in No. of frames (seconds)

Method	Average Learning Durations No. of frame (sec.)
WMA Based	32 (6.4)
LMS Based	11 (2.2)

The proposed LMS based method also produces the lowest number of false alarms among the three methods. We have 6 hours of forest videos. We selected five extremely hard video clips in which false alarms are issued by the WMA and 'fixed-weights' algorithms. Active fusion method LMS Number of image frames in which false alarms are issued by different methods are given in Table 2.

Table 2. Number of false alarms issued by different methods to video sequences without any wildfire smoke. Video sequences are 500 to 1000-frame long.

Video Sequence	Number of frames with false alarm		
	WMA Based	LMS Based	Fixed Weights
V1	28	0	116
V2	19	0	41
V3	24	2	59
V4	32	1	67
V5	52	2	84

5. CONCLUSION

An automatic video based algorithm for wildfire detection using an LMS active learning capability is developed. The compound algorithm comprises of four sub-algorithms yielding their own decisions as a real number in the range [-1,1]. Decision fusion is realized by the LMS based Weighted Majority Algorithm. Guards participate actively in the learning process of the algorithm. Experimental results show that the learning duration is decreased with the proposed active learning scheme. It is also observed that false alarm rate is decreased compared to WMA based and fixed weights schemes. The current system produces 0.25 false alarms in an hour. This is an acceptable rate for a look-out tower.

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