Wavelet-Based Smoke Detection in Outdoor Video Sequences

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***Abstract*— In this paper an approach to detect smoke columns from outdoor forest video sequences is proposed. The approach follows three basic steps. The first step is an image pre-processing block which resizes the image by applying a bicubic interpolation algorithm. The image is then transformed to its intensity values with a gray-scale transformation and finally the image is grouped by common areas with an image indexation. The second step consists of a smoke detection algorithm which performs a stationary wavelet transform (SWT) to remove high frequencies on horizontal, vertical, and diagonal details. The inverse SWT is then implemented and finally the image is compared to a non-smoke scene in order to determine the possible regions of interest (ROI). In order to reduce the number of false alarms, the final step of the proposed approach consists on a smoke verification algorithm, which determines whether the ROI is increasing its area or not. These results are combined to reach a final decision for detecting a smoke column on a sequence of static images from an outdoor video. Experimental results show that multi-resolution wavelet analysis is more accurate than the traditional low-pass filters on this application.**

I. INTRODUCTION

Conventional smoke detector sensors have difficulties to detect smoke in large outdoor areas because they are based on the analysis of some particles that are transported from the fire to the detector as smoke. Recently smoke detection using surveillance cameras has become more active mainly because smoke, temperature or infrared sensors require a closer proximity to the smoke/fire (compared to cameras and image processing systems). Also smoke appears most of the times before flames on forest fires, and it is important to detect forest fires in their early stages to minimize fire damage (economical, environmental impact, human lives, etc). The optical land-based smoke identification procedure is selected, out of various possible detection methods for forest fires, as the most reliable, effective and accurate [1,2].

Still the video smoke detection has great technical challenges since its current performance is inferior to those of traditional particle-sampling based detectors in terms of detection rate and false alarm rate, mainly due to the variability in smoke density, scene illumination, diverse background, interfering objects and mainly because smoke is difficult to model and most of the common image processing methods does not characterize smoke well [3].

Although there are several existing techniques to detect smoke [4-7], the work reported in this paper is based on the idea that smoke gradually smoothens the edges in an image, such as the observed by [4] where Töreyin et al. extracted image features such as motion, edge-blurring to segment moving, flickering, and edge-blurring regions out from video. The method to extract these features was background subtraction, temporal wavelet transformation, and spatial wavelet transformation. Other works, such as the reviewed in [5] is based on the energy variations of an intensity image after being evaluated by means of the discrete wavelet transform (DWT) resulting on energy lowering at high frequencies on the presence of smoke which smoothens edges of the images. In addition the work of Kim and Wang [6] propose that a pan/tilt camera needs to ensure no movement to detect the areas of change in the current input frame against the background image and then locate ROI by connecting component analysis to finally use the k- temporal information of its color and shape to determine the presence of smoke or not. Based on these ideas we consider to ensure no movement of the camera which takes the video sequence and analyzing the ROI's on several frames to confirm the smoke regions.

In this paper an automatic smoke detection method on land-based cameras and image processing on video signals is presented. The video is assumed to be captured from a static CCD camera. This approach is based on the area detection of ROI's using the SWT transform and comprises three main steps. The first step is a "pre-processing" of an image obtained from a frame of the video sequence. The image is resized by a bicubic interpolation method and transformed to its intensity values (gray-scale), and finally two images from this frame are indexed with two different levels of indexation. The second step consists in removing the high frequency horizontal, vertical and diagonal details after applying the SWT to the

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gray-scaled image. The inverse SWT is then performed and finally the image values are grouped in areas of similar values by indexing the image. Finally the indexed image is analyzed to seek for ROI's which are the high-intensity areas inside larger areas (as it would be a smoke column inside a forest) or low-intensity areas inside larger areas (as can be objects moving on the scene or possible dark smoke from a different fuel type source). These detected areas are compared to a non-smoke image defined for that same video to determine the pixels which are different from a non-smoke scene, keeping only those pixels which are different from one image to another, concluding that those pixels kept are the possible smoke ROI's. The third step is a smoke verification algorithm which verifies if the ROI is increasing its area, denoting a growing smoke region produced by a forest fire. The remainder of this paper is organized as follows. Section 2 presents the proposed smoke detection approach including the image pre-processing block, the detection algorithm and the smoke verification algorithm. Section 3 presents the experimental results, and Section 4 contains the concluding remarks and future work.

II. PROPOSED SMOKE DETECTION APPROACH

A flow chart of the proposed method is shown in Fig. 1. It can be seen that a low-level alarm is set when a change on the scene is detected. Although the smoke confirmation is only determined after reviewing frames from different interval times, the final decision comes only after verifying the smoke ROIs with the smoke verification algorithm. The smoke verification algorithm determines when there is an increase of area of the selected ROIs denoting that the smoke is incrementing and therefore reducing the false alarm rate by only considering as smoke alarms those ROI's which increase their area.

A. *Image pre-processing block*

The pre-processing block applies several signal processing techniques which increase the performance of the proposed detection algorithm and reduce false alarms. The pre-processing block comprises three stages. Image resize and super-resolution by the bicubic interpolation algorithm, grayscale transformation of the image, and image indexing. To resize the image the bicubic interpolation algorithm is selected because it is one of the most common interpolation methods in two dimensions [8]. Using this method the value of a function f at the point (x,y) is computed as a weighted average of the nearest sixteen pixels in a rectangular grid (4 x 4). In order to perform a wavelet transformation and image indexation, the color image is required to go under a color-to-grayscale transformation, which in its most common approach [9], retains the lightness information and discards the chroma and hue information. Assuming that components of an image (red, green and blue (R,G,B)) are signals in luminescence, (1) is essentially a close approximation of the luminescence of an image [9].

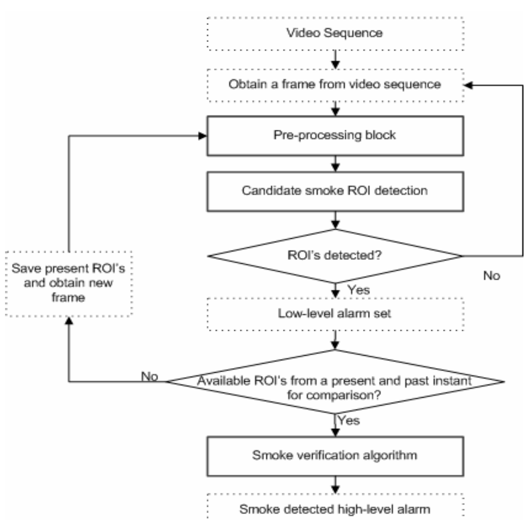

Figure 1. Proposed approach flow chart.

$$\text{GRAY} = 0.30\text{R} + 0.59\text{G} + 0.11\text{B} \quad (1)$$

B. *ROI Detection Algorithm*

The detection algorithm is based on the idea that smoke gradually smoothness the edges in an image. Based on that idea, after applying the SWT the high frequencies of an image are discarded and then the image is reconstructed by the inverse SWT to obtain an image with no details on the edges. By removing the high frequency details on an image, regions with smoke are not highly modified, as the smoke already smoothness those edges. On the other hand, the region which does not present smoke notoriously changes when removing these details.

The proposed detection algorithm is easily visualized in Fig. 2. It is observed that the smoke detection begins with the SWT transformation to remove high frequencies on the horizontal (H) vertical (V) and diagonal (D) details, followed by the inverse SWT to obtain a grayscale image with no high frequency details. At this point the algorithm saves two images with two different decomposition levels, J=3 and J=4, selected as the optimal levels for detection since the first two levels does not eliminate enough details generating false alarms and further levels from 4 discard also the smoke regions as discussed in Section 3. Although the SWT is computationally more complex than the DWT it is suitable for edge detection applications [10, 14] and the SWT does not apply decimation as the DWT does it, keeping the image of the same size as the original. It is important to note that wavelet analysis is selected over other image processing techniques on the basis that wavelet transform can be considered as a frequency analysis with different band-pass filters of different sizes (wide windows for low frequencies and narrow windows for high frequencies), making wavelet analysis a powerful tool in image processing. Also wavelet transforms have successfully improved the texture analysis and texture recognition applications [11], which can be closely related to detecting a smoke region on a forest.

The selected wavelet applied to this work was from the biorthogonal family. On the biorthogonal case the filter bank has different filters for analysis and synthesis (see Fig. 3). These wavelets provide several benefits over orthonormal wavelets as perfect reconstruction, symmetry and smoothness (vanishing points) [12], making them appropriate for the

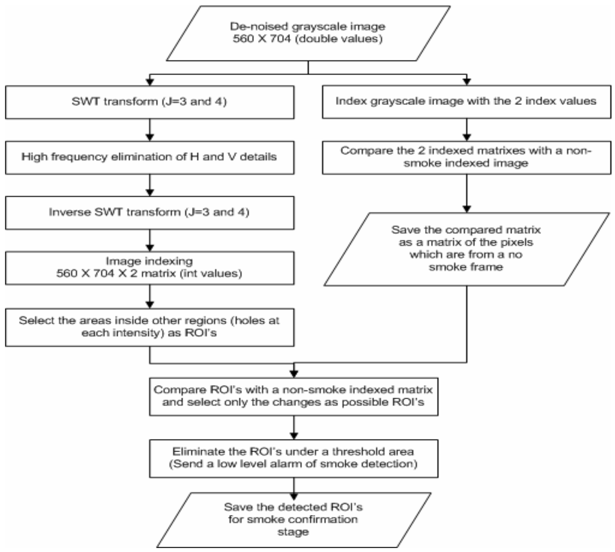

Figure 2. Proposed ROI detection algorithm.

application as a smooth wavelet is needed due to the characteristics of the smoothen edges caused by smoke. The degree of the filter coefficients selected for the biorthogonal wavelet are 6 and 8, proven to be suitable for the application as reviewed in Section 3, to keep the coefficients on a low order for lower execution time of the whole system and still have some smoothness from the wavelets. After smoothening the image on its grayscale format, by eliminating high frequencies, two indexed images at different levels of indexation are obtained to perform the detection algorithm. Image indexation consists on scaling and then rounding an intensity image. The purpose of the image indexation is to group the intensity colors which are close to each other. This is done because in an outdoor video sequences there would be a predominant area of green colors from trees, or a predominant area of high-intensity with color from the smoke or clouds. Thus, instead of having 255 intensity values on an image, the values are reduced to a desired range, grouping areas like could be the sky region, forest, plains, smoke regions, etc. The indexation levels are determined by analyzing the histogram of the grayscale image, and then calculating the elements of each value and selecting an indexation based on the values of the histogram. The indexation levels were tested on a large quantity of different videos with different conditions and the indexation technique proved to be trustable as reviewed in Section 3.

Another task of the algorithm consists in using the previously described indexation process to group the grayscale image and comparing it with a non-smoke frame from a data base, and selecting only those pixels which changed from one scene to another, as changing region. The indexation at this point is selected due to the fact that when comparing a full gray scale of 255 values with a non-smoke frame on an outdoor video sequence almost all of the pixels are different from one frame to another, mainly because of the slight movement of the camera or the movement of the objects (trees, grass, etc). On the other hand, when indexing the image the slight changes on the image are not considered as changing region of the image, because the indexed image has already grouped close values.

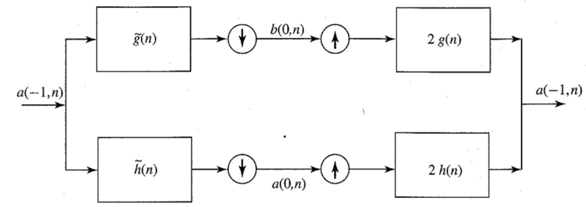

Figure 3. Biorthogonal wavelet filter bank

After the indexation of the image the ROIs are determined by selecting the intensity areas which are inside other areas (holes inside the grouped areas of each intensity value). These areas are selected by correlating the four images, from the two different wavelet decomposition levels indexed at two different levels, and keeping only those pixels which appear at the four different images. These images are then compared with the matrix that contains only those pixels which are different from a non-smoke frame. The pixels which are present on both images are kept as smoke detected ROI's. At the same time a low-level alarm is set indicating that some ROI did not take place on a non-smoke scene and as a result they have a high probability of being smoke regions. This indexation helps grouping the areas so the changes from a non-smoke scene to a smoke detection scene are minimized as in outdoor video sequences the pixels of moving objects are under a rigid-transformation (translation and rotation) much more than an indoor video. Finally the selected smoke possible ROIs are eliminated if they are under a specified threshold area, minimizing false alarm rate from small objects moving on the scene. The threshold area is determined for each application depending on the distance from the camera to region to detect the smoke, and it also depends upon the desired sensitivity of the system (selecting a small threshold area for early detection and large threshold area for minimizing the false alarm rate).

C. *Smoke Verification Algorithm*

The smoke verification algorithm at this stage is a simple ROI area increment confirmation. The algorithm verifies the area increment on the same ROI from a second frame taken at a desired time interval. The ROIs detected at the first frame are kept as bounding boxes which are the smallest rectangle that can contain the whole smoke ROI's. These bounding boxes are then expanded to its sides as it is considered that the smoke region will grow and the confirmation analysis needs to be done to a larger area than the initial detected area. The expansion of the bounding boxes depends on each application mainly because of the zoom of the camera and the number and proximity of the ROIs as these areas cannot be too large to overlap two different ROIs. Afterwards the areas inside the bounding boxes are compared one to each other and if the area increased its size, a high-level alarms is set and the ROI is confirmed as a smoke region, because normally the smoke on a forest fire "grows" (elevates to the air), reducing false alarm rates.

III. EXPERIMENTAL RESULTS

The proposed method is assessed on a large variety of outdoor video sequences taken with static surveillance cameras including live and off-line videos with different conditions presenting and not presenting smoke. The videos are selected to be outdoor videos where only smoke, not flames, appear at a long distance on the forest, plains or the horizon. The average processing time depending on the possible ROI's on a Intel ® Core Duo E8400 at 3.00 GHz and 1.95 GB of RAM is about 15 seconds making the algorithm useless for real time smoke detection, but due the characteristics of the smoke verification and robustness of the algorithm it can be used on live videos detecting changes on the smoke at long distances accurately every working cycle (around 15 sec), minimizing false alarm rate.

Sample images showing the detected smoke regions are shown in Fig. 4 and Fig. 5, corresponding to movie 2 and movie 3 respectively. There are no false alarms presented after the smoke verification algorithm but the low-level alarm appeared at movie 1, 3 and 11. These low-level alarms indicate that a region different from a non-smoke scene was taking place. In movie 1 the false alarms were generated by the trees which are close to the camera and move because of the wind. Even though a false low-level alarm is presented, the smoke verification algorithm discards this ROI as smoke regions. In movie 3 the same false alarm shows because of the fog and luminosity of the video. Finally in movie 11 the low-level alarm was set because there was not a non-smoke scene at the data base. This was done with the purpose of proving that the algorithm can detect the moving smoke even if the non-smoke frame is wrongly taken, and the algorithm will detect the regions of the smoke which vary at a forest fire from one frame to another.

The pre-processing algorithm proved to be useful on images with considerate changing regions from a non-smoke scene as can be seen in movie 1 and 3. This pre-processing algorithm did not present a significant improvement on scenes with slight changes from a non-smoke scene, as movie 2, 5 or indoor video sequences. Some other super-resolution algorithms from reference [13] were tested proving better results but not programmed on the final application because of the computational complexity. The image indexation proved to be a trustable technique to detect smoke with the current restriction that the indexations levels are selected manually and not automatically, which can be done by studying the histogram patterns and defining indexation levels according to each histogram. The SWT multi resolution analysis is suitable for this application as the smoke needs to be detected on the early stages of its appearance. Table I presents a summary of the detection rate (DR) and false alarm rate (FAR) of the proposed approach with several wavelets and different decomposition levels on two segments from movies 2 and 3. Each segment corresponds to a section of each movie which has 10 frames where 5 of the frames do not have a smoke region and 5 frames have a fast growing smoke region corresponding to 10 seconds of video (one frame per second).

The sections of the video can be defined because these 3 video sequences represent controlled forest fire experiments where the event of the smoke region is known at the time and place of occurrence. The DR and FAR are described by (2) and (3) respectively and are the performance metrics defined in this work to easily visualize the efficiency of SWT and traditional low-pass filter techniques.

Figure 4. Sample image from movie 2 succesfully detecting smoke

Figure 5. Sample image from movie 3 succesfully detecting smoke

$$DR = \frac{\#of\_Detected\_frames}{\#of\_Smoke\_frames} * 100 \qquad (2)$$

$$FAR = \frac{\sum \#of\_Detected\_ROI's}{\#of\_Video\_frames} * 100 \qquad (3)$$

Table II is similar to Table I but the approach applies a low pass Gaussian filter, keeping the rest of the proposed approach identical in order to make a comparison between the SWT analysis and a traditional low pass filter. Four different low-pass filters are defined with different sizes (hsize, which is a row, column vector of the size of the filter) and the standard deviation value (sigma). The results from Tables I and II show that multi-resolution wavelet analysis is more accurate than the traditional low-pass filters in this application. Also the decomposition level J=3 is the appropriate level for the earliest smoke detection with the smallest false alarm rate and level J=4 is a suitable level for confirming a smoke region as the false alarm rate is minimum but the detection will come considerably later than with other decomposition levels. It is important to note that the wavelet selected was the biorthogonal 6-8 wavelet, as it keeps the computational processing time low with just a few coefficients and gives the same results as other high coefficient smoother wavelets such as the Symlet 20 or Daubechies 10 wavelets.

TABLE I. SMOKE DETECTION AND FALSE ALARM RATE FROM MOVIES 2 & 3 WITH SEVERAL WAVELETS AND DECOMPOSITION LEVELS

Wavelet type and number of filter coefficients	*Decomposition level*	*Movie 2*		*Movie 3*	
		DR	*FAR*	*DR*	*FAR*
Haar (2)	J=1	80%	0%	60%	0%
	J=2	60%	0%	60%	0%
	J=3	100%	0%	100%	10%
	J=4	60%	0%	20%	0%
Daubechies (10)	J=1	80%	0%	80%	10%
	J=2	80%	0%	60%	0%
	J=3	100%	0%	100%	10%
	J=4	60%	0%	40%	0%
Biorthogonal (6, 8)	J=1	80%	0%	80%	10%
	J=2	80%	0%	60%	0%
	J=3	100%	0%	100%	10%
	J=4	60%	0%	40%	0%
Symlet (20)	J=1	80%	0%	80%	10%
	J=2	80%	0%	60%	0%
	J=3	100%	0%	100%	10%
	J=4	60%	0%	40%	0%

TABLE II. SMOKE DETECTION AND FALSE ALARM RATE FROM MOVIES 2 & 3 WITH LOW-PASS GAUSSIAN FILTER

Low-pass Gaussian filter (hsize, sigma)	*Movie 2*		*Movie 3*	
	DR	*FAR*	*DR*	*FAR*
(10, 10 ,1)	80%	0%	80%	10%
(10, 10 ,5)	40%	0%	40%	10%
(100, 100 ,1)	100%	0%	80%	10%
(100, 100 ,5)	20%	0%	0%	0%

IV. CONCLUSIONS AND FUTURE WORK

A smoke detection approach is developed and proved to be useful on smoke detection in outdoor video sequences. The approach is considerably robust to reduce false alarms due to the smoke verification algorithm and suitable for outdoor video sequences from static surveillance cameras. It is based on the image indexation and SWT multi-resolution analysis to detect changing regions of the video and verifying the area increment of this ROI. Three main steps are followed by this algorithm. The first step is the image pre-processing, followed by the detection algorithm and finally a smoke confirmation algorithm. Automatic selection of the indexation levels can be deduced from the histogram of the image as a future improvement of the method. Multi-resolution wavelet analysis proved to detect smoke at earlier stages of its development than other traditional low-pass filters with this technique. Decomposition level J=3, on this technique, proved to detect smoke earlier on a forest fire on different sample videos. Computation speed seems to be an issue for smoke detection but an average of 15 seconds in smoke detection is a short time compared to the time that a forest fire brigade takes to arrive at the detected zone. In order to reduce the processing time, the proposed algorithm will be programmed on C# and also other less computational complex wavelet transforms, like the discrete wavelet transform or the dual tree complex wavelet transform, will be tested for the efficiency and processing time. Some of the parameters of the algorithm such as the indexation level and the threshold area are selected manually but we consider that these parameters need to be tuned automatically by selecting a suitable indexation level and threshold area for each scene based on the histogram representation of the image.

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