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# Smoke Detection in Compressed Video

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## ABSTRACT

Early detection of fires is an important aspect of public safety. In the past decades, devices and systems have been developed for volumetric sensing of fires using non-conventional techniques, such as, computer vision based methods and pyro-electric infrared sensors. These systems pose an alternative for more commonly used point detectors, which suffer from transport delay in large and open areas. The ubiquity of computing and recent developments on novel hardware alternatives, like memristor crossbar arrays, promise an increase in the number of deployments of such systems. Existing video-based methods have been developed for the analysis of uncompressed spatio-temporal sequences. In order to respond the growing demand of such systems, techniques specifically aimed at analyzing compressed domain video streams should be developed for early fire detection purposes. In this paper, a Markov model and wavelet transform based technique is proposed to further improve the current state-of-the-art methods for video smoke detection by detecting signs of smoke existence in the MJPEG2000 compressed video.

**Keywords:** Smoke detection, fire detection, compressed domain cognition, compressed domain video analysis, MJPEG2000, computer vision, Markov model, crossbar memristor array.

## 1. INTRODUCTION

Global warming is here, happening now and its effects are witnessed everyday [1]. The average temperature of Earth's land surfaces rises each year all around the world [1]. This temperature rise results in higher risks for fire and/or wildfire outbreaks [2], [3]. Wildfires spread not only in conventionally hot and dry parts of the world, such as, countries around the Mediterranean coast, and southwest of the US, but also, in relatively humid and rather cold regions, like, the arctic [4].

Early detection of fires is vital for containing them in a timely fashion. Fire detection technology for outdoor spaces and/or large and spacious indoors, shifted from limited-capacity point detectors to volumetric sensors, such as visible-range/IR cameras, and passive infrared sensors (PIR) [5]. Point detectors commonly installed in buildings and rooms get activated once smoke reaches them. This takes unacceptably long time to trigger an alarm, if at all possible. On the contrary, volumetric sensors react instantaneously, once they "see" the existence of fire at a distance [6], [7]. Other visual modalities, such as hyperspectral imaging, are utilized for detecting fires remotely, as well [8].

In the past decade, computer vision based fire detection approaches gained remarkable popularity, due to advances in computer vision, image and video analysis techniques, as well as, progress in enabling technologies, such as, semiconductor device design and fabrication [5]. These developments pave the way for embedded computer vision systems equipped with lenses and cameras attached to computing platform which process acquired sequence of images [9]. Acquired image sequences are compressed on-the-fly, most of the time [10]. A natural approach for any computer vision application would be to achieve cognition in compressed domain, rather than sifting through each and every pixel in the reconstructed image sequence.

To that end, compressed domain video analytics literature exhibits an exponential growth [11]-[13]. Having said that, there exists no algorithms for fire detection in compressed domain. In this paper, a subband analysis and Markov model based smoke detection method for MJPEG2000 coded video sequences is proposed. In section 2, details of this particular method is presented. Results of initial tests are given in Section 3. The paper is concluded with the final section on a brief discussion about possible implementation of the proposed method on memristor crossbar arrays, as well as, other future directions.

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# 2. METHOD

The proposed method for smoke detection in compressed video has two assumptions: 1) the video is captured using a fixed camera, and 2) it is compressed using MJPEG2000 codec [14]. The first assumption makes it possible to detect moving video objects by estimating the background image. The second one, on the other hand, enables the proposed method to utilize motion estimation and moving video object analysis in the wavelet domain. Details of the method is presented in the sequel.

## 2.1 Motion detection in wavelet compressed domain using hybrid background subtraction

Fixed camera assumption guarantees that the background image may be estimated using a background subtraction method. In this paper, motion detection using hybrid background subtraction is utilized [15]. For that purpose, the wavelet coefficients corresponding to a particular subband image at the n-th frame, $L_n(i,j)$ and subband image at the (n-1)-st image frame are compared with respect to a threshold specifically defined for that particular location (i,j):

$$|L_n(i,j) - L_{n-1}(i,j)| > T_n(i,j) \tag{2.1}$$

If the expression in (2.1) is satisfied, then the wavelet coefficient at (i,j)-th location is classified as a "moving pixel"('s wavelet coefficient). On the other hand, if that expression is not satisfied, then it's called a "non-moving pixel". Both background $G_n(i,j)$ and threshold $T_n(i,j)$ coefficients corresponding to (i,j)-th location at the n-th frame, are estimated in an iterative manner, for those pixels corresponding to non-moving pixels:

$$G_n(i,j) = a.G_{n-1}(i,j) + (1-a)\, L_{n-1}(i,j) \tag{2.2}$$

$$T_n(i,j) = a.T_{n-1}(i,j) + (1-a)b|L_{n-1}(i,j) - G_{n-1}(i,j)| \tag{2.3}$$

where a is a real number, $0 < a < 1$, and b is a positive integer. At any instant of time, the moving blob is estimated using:

$$|\, L_n(i,j) - G_n(i,j)| \tag{2.4}$$

followed by connected component analysis and binary morphological operations steps [16]. Hence, candidate smoke regions are determined by extracting moving video objects by just analyzing subband images. Note that, number of subband images utilized for the first step may be adjusted according to the desired sensitivity level. One should include more subband images into the calculations in order to estimate moving objects more accurately.

## 2.2 Subband energy analysis

Moving blobs estimated in Section 2.1, are treated as candidate smoke regions. Current step of the algorithm further analyzes wavelet coefficients corresponding to background and current image frames, $G_n(i,j)$'s and $L_n(i,j)$'s, respectively. Following observations are made for smoke video objects: 1) they degrade local subband energies, and 2) fire flicker results in "random oscillations" in energy-ratio of wavelet coefficients corresponding to background and current image frame, namely, $G_n(i,j)$'s and $L_n(i,j)$'s, respectively [5].

In order to assess the existence of smoke video objects at a given location (i,j), high-subband energy, E, corresponding to that particular location (i,j) at a given frame n, is evaluated:

$$E(n, (i,j)) = H_n^2(i,j) + V_n^2(i,j) + D_n^2(i,j) \tag{2.5}$$

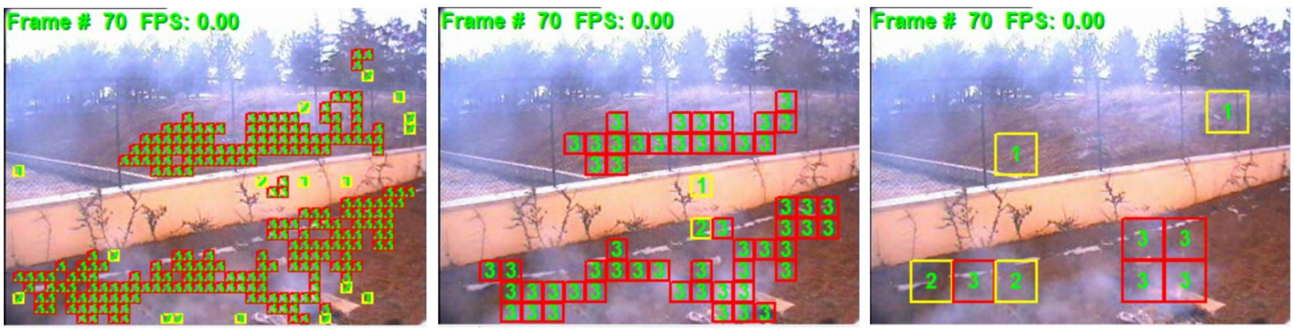
where, E(n, (i,j)) is the total high-subband energy corresponding to a location (i,j) at the n-th frame, H, V, and D, are the horizontal, vertical and diagonal subbands in a two dimensional wavelet (subband) decomposition. Note that, these wavelet coefficients are readily available in MJPEG2000 compressed video [14].

Once smoke emanates from a particular location and occludes with the high-band content presumably available at that very location, the ratio of E estimated for the background would be different than the E calculated for the current image frame. By keeping track of the ratio of these two energy values, one may fit a random model to assess the type of the candidate region as being affiliated with either a smoke or a non-smoke region. For that purpose, a three-state Markov model is trained for two types of data. Training phase includes estimation of state transition probabilities. In the test phase, the model yielding the highest probability is concluded to be the type of the candidate region. A similar approach was adopted to determine whether there is flame within the viewing range of a PIR sensor or not [7].

# 3. RESULTS

The proposed method is trained and tested using videos in [17]. Results indicate that, as more coefficients are used, the accuracy of smoke detection in compressed domain increase. On the other hand, the computational load of the proposed method is orders of magnitude lower than analyzing the whole data.

Sample images are presented in Figure-1. As images suggest, detected regions in the compressed domain are not as accurate as regions detected using the original, uncompressed video. Table-1, on the other hand, presents the smoke detection performances corresponding to analysis using uncompressed and compressed domains. According to the table, it is observed that, detection rate decreases as the data at hand is solely depending on compressed domain values, namely, wavelet coefficients.




(a) (b) (c)

Figure – 1: Sample output images corresponding to smoke detection using (a) original, uncompressed video, (b) first level wavelet coefficients, (c) second level wavelet coefficients. As the data size shrinks down from (a) to (c), the accuracy of detection seems to be decreasing.

Table – 1: Detection performance comparison for two different video types, namely, uncompressed, and compressed using MJPEG2000, where wavelet coefficients are readily available. Compressed domain analysis, makes it really fast, to detect smoke, in return of reduced detection rate.

| **Video Sequences** | **Number of Shots with Smoke** | **Number of Shots Detected as Smoke** | | **Description** |
|---|---|---|---|---|
| | | *Uncompressed* | *Compressed* | |
| Video 1 | 0 | 0 | 0 | A smoke-colored parking car |
| Video 2 | 5 | 5 | 4 | Fire in a garden |
| Video 3 | 5 | 5 | 4 | Fire in a snowy garden. |
| Video 4 | 7 | 7 | 5 | Burning box |
| Video 5 | 6 | 6 | 5 | Burning pile of woods |

# 4. DISCUSSION AND CONCLUSION

A smoke detection method for compressed domain video is proposed. The method is based on two assumptions. The first assumption is that the video is captured with a fixed camera, while the second one is that the video is compressed using MJPEG2000 codec.

These assumptions make it possible to access spatial wavelet coefficients of each and every frame of the video, and estimate a sequence of background images in the compressed domain. Using these coefficients, moving objects are detected. Carrying out a further analysis on the high-subband energies of background and current image frames, smoke blobs are determined. As an immediate follow-up, tests should be carried out on other publicly available fire datasets.

This particular contribution of smoke detection in compressed video may be regarded as an application of a more general research field of compressed domain video analysis. The main purpose of compressed domain video analysis is to develop and devise methods and algorithms that process much less amount of data than, say, a cloud based central unit. Hence, these algorithms are mostly targeted towards running on mobile and edge platforms. In that respect, new logic and memory unit design paradigms are very well suited for applying these compressed domain cognition type techniques. Therefore, apart from this particular algorithm's direct applicability to the existing transistor-based memory and logic units, it may also be realized and run on memristor crossbar array type logic and memory units. Similar artificial intelligence and image analysis applications are available on memristor crossbar arrays [18]-[20].

Memristor crossbar arrays exhibit brain-like non-volatility. Thanks to their inherent parallelism, O(1)-time-complexity matrix-vector multiplications may be performed [20]. As a result, possible implementation of compressed domain video analysis algorithms on memristor arrays may further enable edge-/pervasive-computing. Smoke detection in compressed video is a practical candidate to showcase the efficacy of memristor crossbar arrays.

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