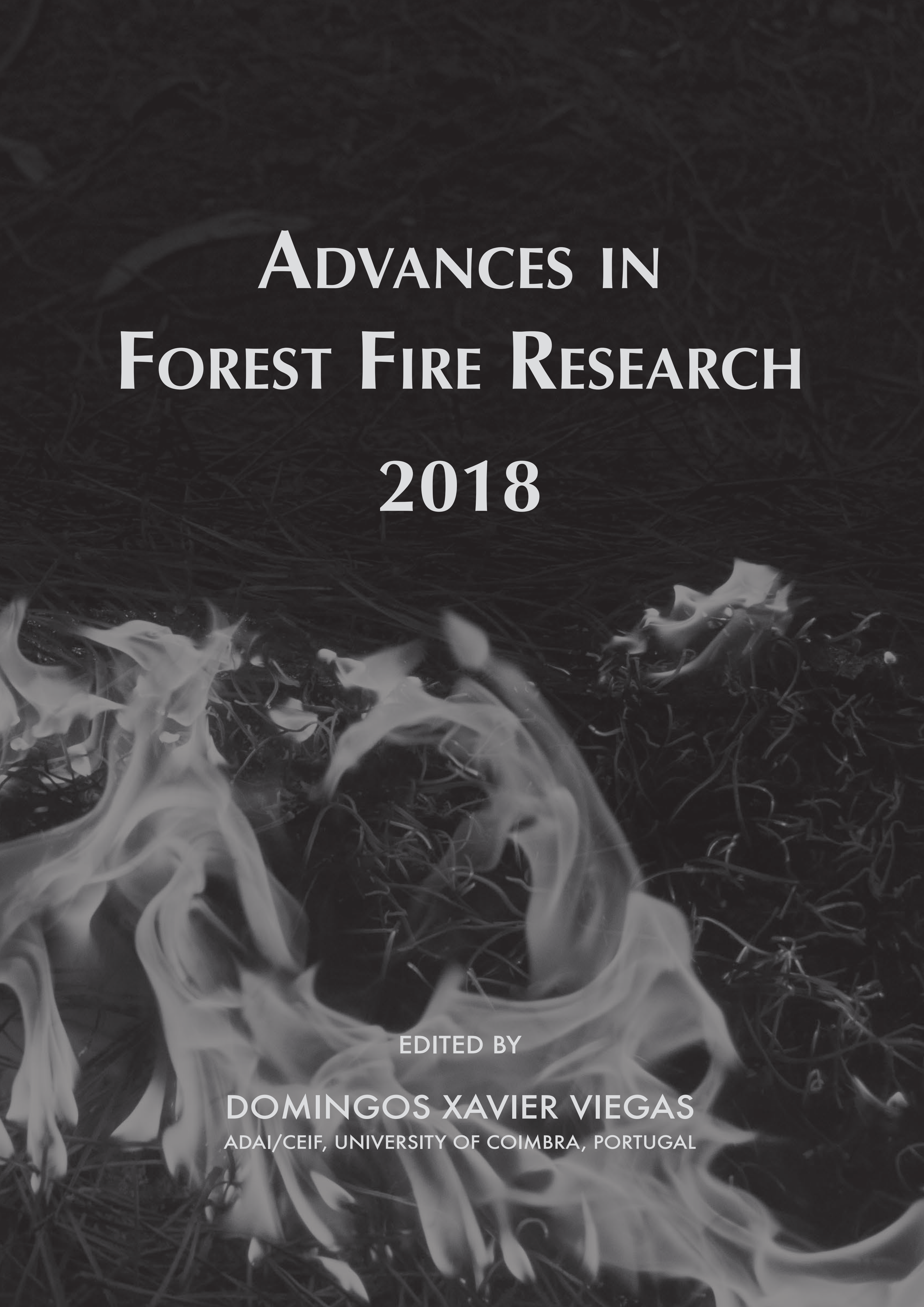

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DOMINGOS XAVIER VIEGAS

ADAI/CEIF, UNIVERSITY OF COIMBRA, PORTUGAL

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Non-Rigid Feature Extraction Methods in Real Time Forest Fire Detection Algorithms

Azarm Nowzad*[1,2]; Andreas Jock[1];Ralf Reulke[2]

[1]*IQ wireless GmbH, Berlin, Germany, {azarm.nowzad@iq-wireless.com, andreas.jock@iq-wireless.com}*

[2]*Department of computer science, Humboldt-Universität zu Berlin, Berlin, Germany, {reulke@informatik.hu-berlin.de}*

Abstract

In this paper a smoke detection algorithm for real time forest fire detection is proposed. The scene complexity in open-air environment and the non-rigid nature of the smoke cause high false positive alarms in many detection algorithms. To increase the efficiency of the algorithm, a multi features smoke approach is presented in this work. To segment the possible smoke regions, a change detection method is applied to the image. Afterwards, static and dynamic features of smoke are analyzed. Merging the extracted smoke features and applying morphological processes, region(s) with the highest probability of having smoke pixels are extracted. Two complementary texture features, Gabor filter and Local Binary Pattern (LBP), are applied to the input images. The input image sequence are first characterized by bank of Gabor filters covering the spatial- frequency domain. As multichannel filtering approach, Gabor filters extract features at different orientations and scales. By segmenting the energy image, smoke candidates are extracted and examined using An eXtended Center-Symmetric Local Binary Pattern (XCS-LBP). The image is converted to an array of integer labels as feature vectors for further analysis on smoke and non-smoke classification. The smoke area shows a blurred and smooth texture characteristic compared to the non-smoke areas. This criterion is examined using the histogram of LBP. A number of 5000 labelled smoke blocks are applied to the XCS-LBP operator and the average histogram is calculated and normalized as a priori variable. Applying spectral analysis, a fuzzy logic decision process is implemented on a chromatic analysis enhanced in the HSI (Hue-Saturation-Intensity) color mode. To define the fuzzy rules, empirical analysis is applied on a set of image data. A trial and error method is then used to reduce the failures. The algorithm is tested on a natural scene forest fire data set, collected from three different sits in Germany. Experimental results show high performance accuracy in smoke classification.

Keywords: Non-Rigid object detection, Forest fire detection, smoke features, smoke classification, fuzzy logic smoke detection, smoke texture analysis

1. Introduction

Imaging techniques are the main processing element of fire detection technologies and have been developed to extract information from images and, ultimately, to detect fires. Since the effectiveness of any fire detection system is measured by its speed in reporting a fire to the authorities, image-based fire detection systems prioritize the reliability of early stage fire detection and real-time performance.

The majority of image-based techniques search the images for traces of smoke as pre-fire indicators, therefore allowing the discovery of a fire as soon as its smoke signature is visible, enabling a prompt intervention and an easy extinction.

Several solutions have been proposed to handle the early detection of forest fires. Detecting real smoke with low false alarm occurrences and a high detection rate is still a challenging problem, especially in complex natural environments, like forests. Smoke is semi-transparent at the beginning of a fire. The background manifold, natural scene illumination conditions, cloud shadows, wind, and various natural phenomena can drastically degrade the reliability of the detection systems.

Therefore, improvements in the detection rate as well as in the classification of the smoke features are still a topic of research.

The reliability and efficiency of a detection algorithm is strongly connected to the number of smoke features handled by the algorithm. Many image techniques focus on vision capabilities and have been developed to combine visualization fire properties with some extra features such as motion, flicker, heat and chemical characteristic of aerosols.

Camera-based automated smoke detection systems use image processing algorithms to detect smoke by analyzing typical features of smoke signatures, such as local changes of brightness, contrast, transparency and direction of smoke movement. Each of these smoke features is addressed by a specific algorithm individually.

In this study different smoke feature extraction methods and classification approaches are presented by using the data from a ground-based forest fire surveillance system. Change detection is applied to segment the possible smoke regions in the image, followed by static and dynamic analysis of the smoke features. Combining the extracted smoke features and applying morphological processes, Regions of Interest (ROIs) are extracted as region(s) with the highest probability of having smoke pixels.

2. Non-uniform illumination

Non-uniform illumination is an indivisible part of the natural scene environments. Barrow & Tenenbaum (1978) present recovering intrinsic scene characteristic from images as reflectance and illumination components. To do so, assumptions about the nature of the scene and the physics of image processing need to be taken. The physics consists of many unknown parameters such as camera parameters and lighting characteristic of the scene (Stainvas and Lowe 2003). In image processing, a simplification of physics is applied, which represents the intensity values of the image as the product of the illumination of the scene and the reflectance of the objects.

$$I(x,y) = L(x,y)R(x,y)$$

where $L(x,y)$ is the illumination and $R(x,y)$ is the reflectance.

The illumination of a scene is characterized by low frequencies and the lightening conditions, whereupon the reflectance arises by high spatial variations, especially at object edges. The main idea is to remove the illumination component as multiplicative noise signal, to achieve a uniform illumination scene.

Homomorphic filtering, an image enhancement technique, is applied to remove the multiplicative noise signal from the input images. The procedure is shown in Figure .

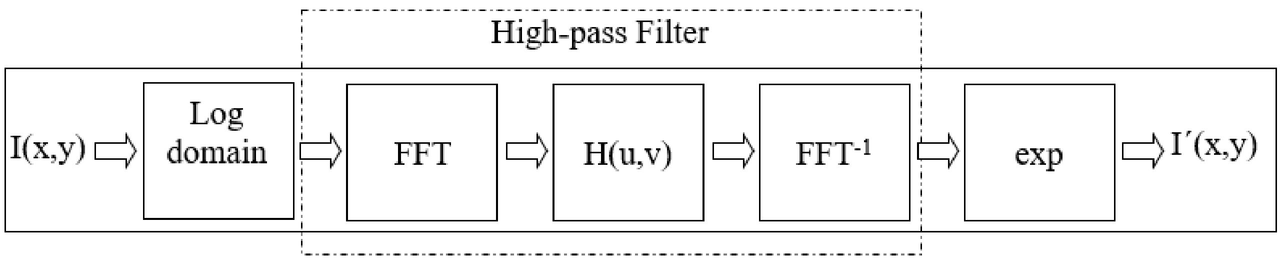


Figure 1 - Homomorphic filtering process in frequency domain

The illumination component is considered as additive component in log-transformed image and is filtered out using a high-pass filter. A frequency-domain high pass filter is constructed to amplify high frequency components. The exponential function is then applied to invert the log-transformed image. The result is a homomorphic filtered image including reflectance components.

3. Change detection

Change detection is one of the main steps in computer vision applications such as object detection, video surveillance and remote sensing systems. A common approach in detecting foreground pixels in an image is the inter-frame subtraction method, which is affected by environmental conditions and is sensitive to noise.

As the first viable step, background subtraction algorithm must be in the position to extract all possible changes, including semi-transparent smoke pixels.

By applying inter-frame subtraction and combining the result with a binary AND operation, pixels of moving regions are extracted. Considering smoke characteristics, in particular the semi-transparency, high frequency signals of the background are affected. Difference of Gaussian (DoG) is computed for background frame $B(x, y)$, by convolving image with a Gaussian kernel (Hsu et al. 2016) as

$$B_{DOG}(x, y) = (G_{\sigma 1}(x, y) - G_{\sigma 2}(x, y)) * B(x, y)$$

where $G_{\sigma}(x, y)$ is a Gaussian kernel with variance σ^2 and zero mean.

The DoG image of the background includes high frequency information such as edges and textures. A local entropy image is calculated on a 9x9 neighborhood. By thresholding the entropy image, the result of the background subtraction is examined on high frequency areas.

The segmented ROIs contain false positive incidences, which is filtered out in further analysis.

4. ROI classification

Understanding the natural scene environment helps to extract extra information to segment the target. The classification is observed as a non-trivial problem in natural scene due to the dynamic changes and topographical variations. Methods based on spatial relationships besides intensity changes are preferred for complex scene analysis. To analyze complex scene scenarios, more than one feature is required to extract classification information of the scene.

4.1. Texture descriptors

Texture descriptors are visual features for characterizing image texture and are used for classification purposes .Gabor filters and Local Binary Pattern (LBP) are two rich texture features with complementary characteristics. While LBP extracts small texture details, Gabor filters encodes texture analysis in a broader range (Tan X and Triggs B 2007).

For subsequent classification purposes, Gabor filters are widely used with the advantage of being invariant to illumination, translation and orientation changes to some extent (Sun Z et al. 2002).

Local Binary Pattern operator, introduced by Ojiala et al.1996, is a mean of summarizing local gray-level structure as feature vectors and converting an image into an array of integer labels. The statistics of the labels, mostly histograms, are used for image analysis.

4.1.1. Gabor filter bank

Gabor filters are a multichannel filtering approach that extracts features at different orientations and scales. As a matter of fact, dominant spatial frequency components of different textures are unequal. Image texture is defined as a Gaussian modulated sinusoid, which can model the texture orientation and the spatial frequency. The filter characteristic must be set in a proper set up to best capture texture information. To cover the spatial-frequency domain, multiple filters can be generated by tuning the frequency and angle. The filter position (F_x, F_y:center frequency, ɵ: orientation) and the standard deviations (σ_x, σ_y) of the Gaussian envelope needs to be assigned correctly to extract texture information (Al-Kadi 2017).

A two dimensional spatial Gabor function along the x-y axis is given by (Weldon and Heggins 1999)

$$g(x,y) = a(x,y)c(x,y)$$

where

$$a(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\{-\frac{1}{2}\left[\frac{x^2}{{\sigma_x}^2}+\frac{y^2}{{\sigma_y}^2}\right]\}$$

is the gaussian component and

$$c(x,y) = \cos(2\pi(F_x x + F_y Y))$$

is the sinusoidal component.

The radial frequency of the filter, with a width of N_c pixels, is assigned as follows

$$1\sqrt{2}, 2\sqrt{2}, 4\sqrt{2}, \ldots, \left(\frac{N_c}{4}\sqrt{2}\right)\frac{cycle}{image\ width}$$

which ensures that the passband of the highest frequency lies inside the image. The sampling orientation is in steps of 30 degrees, leading to 6 different orientations. Figure shows an example of applying Gabor filter on a real smoke image.

Figure 2 - Real smoke image (left), resulted energy image (right)

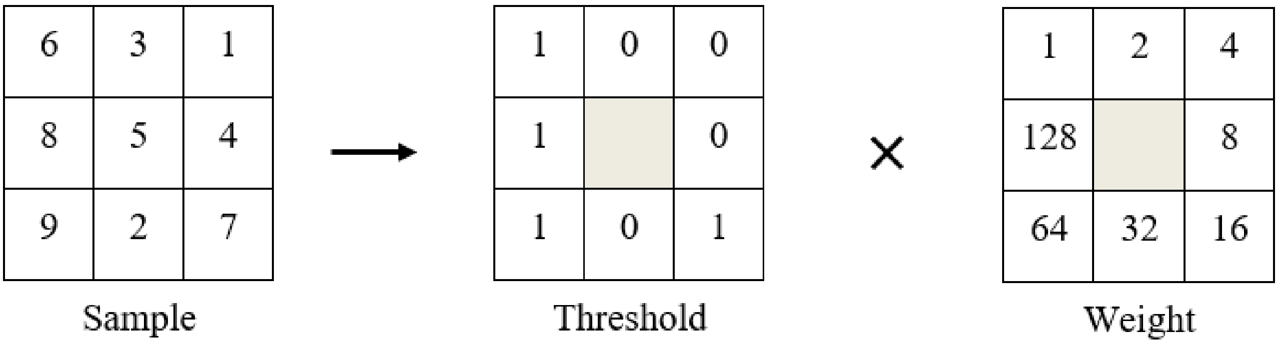
4.1.2. Local Binary Pattern

Local Binary Pattern (LBP) is a local texture descriptor, which is gray scale invariance. A binary number is formed by thresholding the neighborhood of each center pixel in a cell which is created by dividing the examined window. A normalized histogram is then computed for each cell. The LBP for texture analysis, proposed in by Ojala et al.1996 can be defined as

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p,\ \ s(x) = \{^{1\ ,x\geq 0}_{0\ ,x<0},$$

where g_p and g_c represent the gray values of center pixel and neighbouring pixels respectively. R is the circle radius and P is the total number of sample points in the neighborhood.

Figure shows a 3x3 neighborhood sample and the computation of LBP with P= 8 and R= 1.



$$LBP = 1 + 16 + 64 + 128 = 209$$

Figure 3 - Calculation of LBP

The neighboring pixels are multiplied by the binomial weights after thresholding. The LBP for each cell is then calculated by summing up the values. An input image with LBP result and the corresponding histogram is illustrated in Figure .

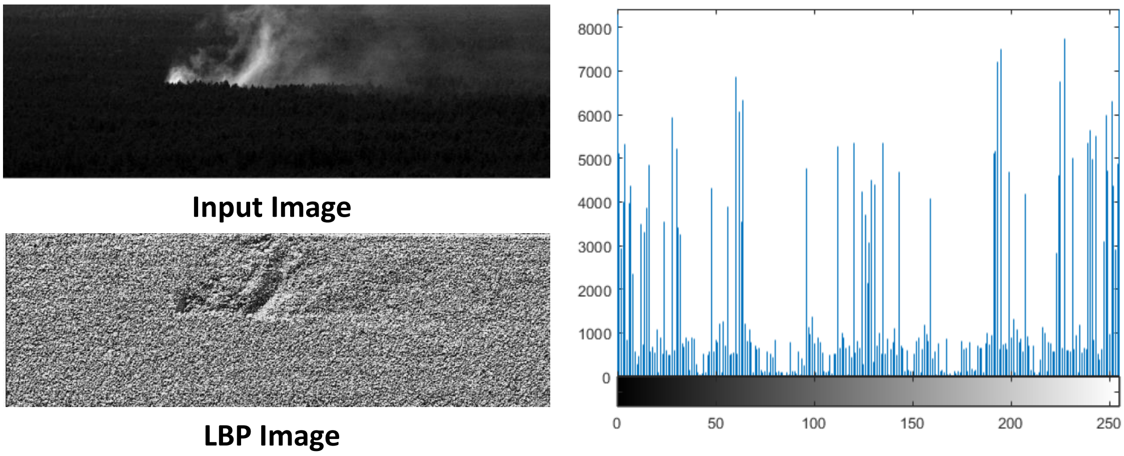


Figure 4 - Example of an input image, the corresponding LBP image and Histogram

As a local operator, LBP converts an image in to an array of integer labels which can be uses as feature vectors for further analysis of smoke and non-smoke classes.

4.2. Spectral analysis

Monochrome detectors are widely used in many video based detection systems. In comparison to color sensors, the light sensitivity, the spatial and optical resolutions and the dynamic range of these detectors exceed the color sensor function. However, the lack of color information increases the likelihood of falsely detected smoke and may degrade the system efficiency.

Input images, in Red, Green and Blue channels are converted into HSI color map, describing color in hue, saturation and brightness, which decouples brightness from the chroma components.

The color of the smoke is categorized in a wide range of dark gray (D_1, D_2) and light gray (L_1, L_2) based on many variables such as combustion material and burning temperature. The brightness component is used to describe these two different gray level regions. By assigning a fix threshold for the gray color of smoke, the range of the dark and light gray are defined based on statistical data.

Barring the variation given by a constant α, the intensity (I) of a gray colored pixel in RGB channels is almost the same. The decision function rules display as:

$$R \pm \alpha = G \pm \alpha = B \pm \alpha$$

$$L_1 \leq I \leq L_2 \,;\, D_1 \leq I \leq D_2$$

The values of α, D_1, D_2, L_1 and L_2 are assigned by empirical analysis of test frames. The main drawback of this method is the failure in smoke recognition, whenever the smoke intensity range exceeds the predefined range.

A reliable "Yes" and "No" decision for the smoke is replaced with a fuzzy logic based process in the proposed method to deal with uncertain and vague information.

As presented in Nowzad A et.al 2014, by evaluating the saturation and the intensity value ranges of the smoke and non-smoke pixels in natural environment, a fuzzy set is built to show how likely a given pixel belongs to a smoke class.

In fuzzy set theory, image A is defined as

$$\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left[x_{ij}, \mu\left(x_{ij}\right)\right], \forall x \in A, i = 0,1, \ldots, M-1, \qquad j = 0,1, \ldots, N-1$$

Where x_{ij} is the pixel value at (i,j) and $\mu(x_{ij})$ donates as membership value in the range of [0,1].

To specify the likelihood of an input pixel to the smoke class, (P_f(i,j)) is defined as fuzzy output. The higher the value of (P_f(i,j)), the more likely belongs the pixel to the smoke class.

Input (Saturation (i,j), Intensity (i,j)) and output (P_f(i,j)) variables are defined by membership functions. To build an interface between input and output variables, a series of IF-THEN rules are defined by analyzing the image dataset.

Table shows the rule table for the fuzzy inference system, which represents the final decision in a linguistic term.

Table 1 - Rule table for fuzzy inference system

		Intensity (i,j)		
	P_f(i,j)	PS	PM	PB
Saturation	PS	Medium	High	Medium
	PM	Low	Low	Medium
	PB	Low	Low	Low

PS, PM and PB stand for “Positive Small”, “Positive Medium” and “Positive Big” respectively, which are the membership functions of the input channels.

Depending on the weight of each rule, qualified consequents are generated and aggregated. The output is then assigned by means of the “Defuzzification” interface.

5. Proposed algorithm

Consecutive frames in a rate of 1 frame per second are extracted from the stationary video surveillance camera. Preprocessing steps are applied on the input images to increase the performance of the detection algorithm.

A Gabor filter bank is designed using six different orientations (ɵ = 0, 30, 60, 90, 120,150) and the radial frequencies of ($2^2\sqrt{2}, 2^3\sqrt{2}, 2^4\sqrt{2}, 2^5\sqrt{2}, 2^6\sqrt{2}, 2^7\sqrt{2}, 2^8\sqrt{2}$), with orientation and frequency bandwidths of each filter be 30° and 1 octave, respectively. The bandwidths are assigned based on the ability of the human visual system and computational costs (Jain and Farrokhnia 1991). The Gabor magnitude features is then extracted and went through some postprocessing steps. First, a low pass Gaussian filter is applied to the energy image, to compensate local variations in constant texture regions. A map of spatial location is added to the Gabor features for classification purposes. For each pixel in the image, there are 42 Gabor features and two additional spatial locations. Principle Component Analysis (PCA) is applied to visualize the energy image from 44 D to 1 D intensity value per pixel. The magnitude features of the candidate areas are then extracted by segmenting the result image.

Applying the proposed change detection method on energy images, ROIs are extracted. The small objects in the foreground and the holes are removed, while the small islands in the image in close distance are combined together using morphological filters. The extracted ROIs are further analyzed by applying LBP descriptor.

The texture characteristic of the smoke area is blurred and smooth compared to the non-smoke areas. This can be checked using the histogram of LBP.

An eXtended Center-Symmetric LBP (XCS-LBP), presented in by Silva C et.al 2015, is computed for each image block is as a 16 dimensional feature vector. A number of 5000 labelled smoke blocks are applied to the XCS-LBP operator and the average histogram is calculated and normalized as a priori variable. The similarity of the histogram is defined by measuring the distance from a suspected ROI to smoke class. If the similarity measurement meets the predefined condition, the block will be conducted for spectral analysis.

The spectral analysis is implemented by converting the RGB image to HSI color map and applying fuzzy-based rules. A total number of 9 rules are defined to link the possible combinations of the input variables as shown in Table . To define the fuzzy rules, empirical analysis is applied on a set of image data. A trial and error method is then used to reduce the failures and makes adaptive changes to achieve best results.

6. Experimental results and discussion

The proposed method is evaluated on real set smoke image sequences (8 frames/ sequence) with 32 sequences of smoke and 20 sequences of non-smoke events. The images are taken from three different sites in Germany and a resolution of 512 ×1360 pixels.

Figure and Figure show some examples of the smoke and non-smoke forest images, under various illumination conditions and the detection results.

Figure 5 - Examples of image data set. The first two rows are smoke images

Figure 6 - Detection results on real scene images

As illustrated in Figure , the smoke detection algorithm detects and locates smoke regions within the frame. The last example in the second row shows a low density smoke event, which is not detected. The number of non-detected smoke events is only three, with two events of low transparency and a small smoke cloud at long distance.

7. Conclusion

In this paper, a texture and color-based smoke detection algorithm is presented. The efficiency of the algorithm is increased by implementing a multi features smoke approach. To segment the possible smoke regions, a change detection method is applied to the homomorphic filtered image sequence, including reflectance components.

Merging the extracted smoke features generated by static and dynamic analysis, morphological processes are applied to retrieve region(s) with the highest probability of smoke pixels.

A Gabor filter bank is designed covering the spatial-frequency domain. Texture information are segmented from the calculated energy image. Applying change detection, further analyses on fine texture changes, caused by smoke pixels, are done using an eXtended Center-Symmetric Local Binary Pattern (XCS-LBP). Finally, a spectral examination is performed on the suspected regions based on fuzzy-rules to classify smoke and non-smoke events. Experimental results show high performance accuracy in smoke classification. Most of the non-detected smoke events are caused by smoke transparency, which is a vague decision criterion. The sensitivity of the proposed smoke detection algorithm can be tuned to detect transparent smoke up to a defined level. However, higher sensitivity is directly connected to false positive misclassification.

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