VISION-BASED SMOKE DETECTION

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ABSTRACT

The vision-based smoke detection system is a pattern recognition technique that makes use of smoke patterns for the purpose of using up to the second level of the classifier. In this study, a novel method of recognition of smoke component had been considered by using a combination of support vector machine and Hamming distance for classification after the motion in the smoke video is detected. To improve the performance, Gabor filter is used additionally to remove noise and reduce false fire alarms. The moving objects are identified using Gaussian mixture model. Secondly, Haar-like features were extracted from integral images. Finally, support vector machine along with Hamming distance technique as a secondary classifier is used for classification purpose.

Keywords—Smoke Detection, Noise removal, Support Vector Machine, Hamming Distance.

INTRODUCTION AND RELATED WORK

Development in technology has raised the significance of surveillance. Along with the development of science and its techniques, development of environment & society should be emphasized. Security plays a vital role in the development of society & technology. Video surveillance has drawn the attention of most of the researchers. Surveillance systems are developed not only for monitoring the activities, behavior or changing information of any object but also for influencing, managing, or protecting them against any destroying results.

An existing surveillance system can be classified into following categories:

1. Indoor surveillance system
2. Outdoor surveillance system
3. Airborne surveillance systems
4. Single/Multiple surveillance systems

A major part of surveillance covers for detection of fire. Most of the buildings are secured by automatic fire alarm equipment which detects fire using conventional devices called detectors like heat detector, smoke detector or flame detector. Smoke detection has many potential applications. It is mainly used for early warning of fire events & alarm triggering for accidents in the tunnel. This task was done earlier using smoke detectors. The drawbacks in using point smoke detectors are as follows:-

1. Smoke detectors needed a close proximity of smoke.
2. These detectors could not provide any additional information about fire such as its location, density, and direction.

For the purpose of resolving these drawbacks, vision-based smoke detection has come into existence. Existing vision-based smoke detection methods make use of motion, color, edge or texture of smoke regions. Starting with the era of 20's, Toreyin et. Al (2005) extracted motion features of the image; he also segmented moving, flickering and edge-blurring regions out from the video. Adaptive Gaussian mixture model was used by Genovese et. Al (2011) to segment the moving objects, and area of decreased high-frequency energy component was identified as smoke using wavelet transformations. Genovese et al. combined state features of color, edge with a dynamic feature of region growing. Phillips et al. (2003) recognized color model based on Gaussian-smoothed color histogram distribution. A video-based smoke detection algorithm based on wavelets and support vector machine (SVM) was identified. Maruta et al.(2012) studied the texture features of smoke & applied SVM for classification.
Again , SVM based smoke detection method was proposed by Ye et al. & Zhao et al.(2015) which used Hidden Markov tree(HMT) derived from coefficients of the dual-tree complex wavelet transform(DT-CWT) in local regions of image sequences. Yuan (2011) proposed local binary pattern (LBP) and local binary pattern variance

(LBPV) for video-based smoke detection. But this algorithm is sensitive to changes between the background and foreground. Chenebert et al. (2004) combined texture and color-based feature descriptor and given as input to a trainer classifier based detection. Standard smoke sensors including with results of the smoke detection method was proposed by Maruta et al (2010).
In the proposed work, a combination of two classification method is proposed rather than single method. After motion detection by GMM background subtraction method, Gabor filter is applied for noise removal. Haar wavelet decomposition up to level 3 is used for feature extraction. Lastly, for classification purpose, support vector machine is used as the main classifier with Hamming distance is used as a secondary classifier.

MOTION DETECTION

Motion detection is the foremost phase in many approaches for smoke detection. Moving pixels were identified by subtracting the current image from the background image and thresholding. It is necessary to analyze further these moving regions for determining whether the motion is due to smoke or other ordinary moving object.
Smoke has a feature of being dynamic in nature, i.e.; it changes its shape and direction. The proposed algorithm uses motion with blob analysis and contrast as a key feature for the purpose of smoke detection.
There are various methods of motion detection such as frame differencing, optical flow, background subtraction. Post-processing with Gabor filter increases the performance by removing noise and reducing false alarms.

PROPOSED SMOKE DETECTION APPROACH

A flowchart of the proposed smoke detection method is shown in Figure 1.

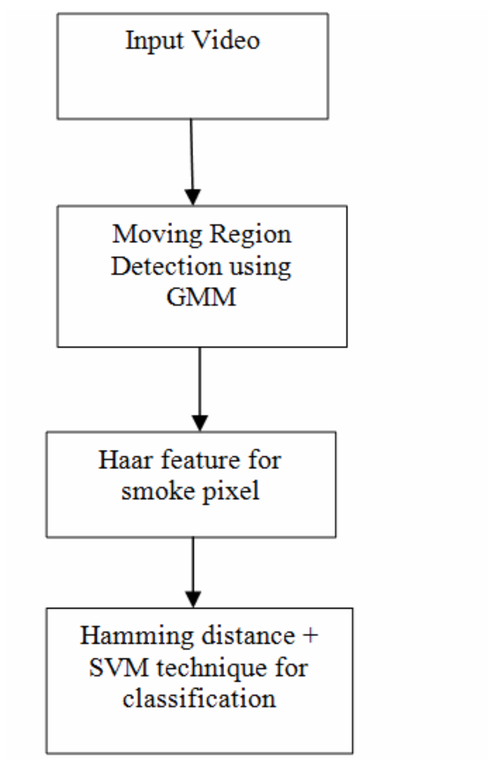

Figure 1: General Block representation of proposed work.

The aim of this proposed work is to develop a recognition system to detect an occurrence of fire via detecting smoke. Smoke detection process is one of major sub-problems in the monitoring systems, in which the object of main focus is to detect smoke. As shown in Figure 1 following are the main steps to do in order to get characteristics feature extraction of smoke.

1. Background Subtraction

Background Subtraction is a popular method of moving object detection, especially under those situations with relatively static background. There are numerous approaches for this problem. Gaussian mixture model has been chosen because of its robust nature and fast feature. In this method, a pixel in the current frame is checked against the background model by comparing it with every Gaussian in the model until a matching Gaussian is found. If a match is found, the mean and variance of matched Gaussian is updated.

Gaussian mixture models (GMM) are composed of k multivariate normal density components, where k is a positive integer.

2. Haar feature Extraction

Wavelets can be used to analyze the data in the smoke region in multi-resolution mode. Wavelets have the advantage over traditional Fourier transform as the frequency data is localized in wavelet, allowing features which occur at the same position and resolution to be matched up. In our work HAAR wavelet is applied to the image of size 365 ^{x} 138 at three different levels successively for feature extraction. The wavelet transform has been performed and the image is divided into four sub-regions LL, HL, LH, and HH.

For an N x M image size, the first conversion step decomposes the signal into four sub-images of size N/2 x M/2, representing the sub-bands in the frequency domain. The obtained sub-images are labeled as LL; LH ; H L; H H, where L and H represent low- and high-frequency information, respectively. The second transformation level decomposes the LL sub-image, obtaining four images of size N/4 x M/4, and so on.

Most of the energy is contained in LL (low frequency) region of image, since the extracted region has contained major information on the image; this LL region (sub-image) is provided as an image to be newly processed so that we can again apply the wavelet transform to the relevant region. The HAAR wavelet transform is repeatedly performed in order to reduce information sizes as shown in Fig. 2 & Fig. 3. In this way, the characteristic values of further reduced region such as LL3 are obtained (Patil & Patilkulkarani, 2009).

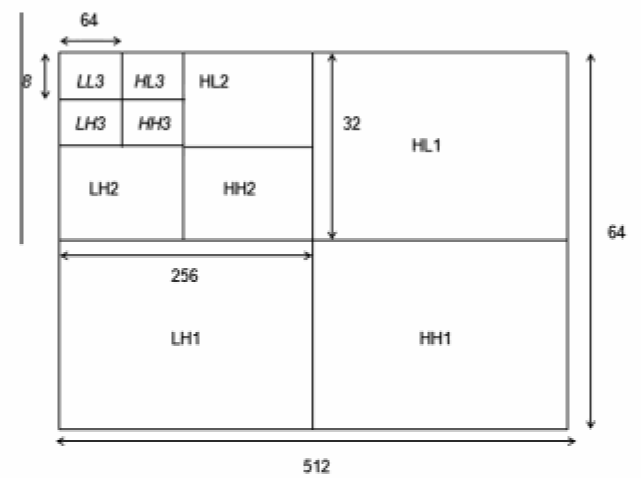

Figure 2: Haar wavelet decomposition up to level 3.

3. SVM and Hamming Distance

In the matching process, any smoke containing image is given input to the combined SVM and Hamming distance based classification approach. When any smoke comes into the system we extract 512 most important feature of that smoke using HAAR wavelet. These features are used for training and testing of the SVM. If correct classification is not done by SVM then Hamming distance is used for further classification. For doing classification through SVM, various SVM models have been developed in training phase.

SVM are a set supervised learning techniques introduced by Vapnik, which analyzes data and recognizes pattern. SVMs are capable of learning high dimensional spaces, and can provide high performance with a limited training

data set. Several techniques have been proposed to improve the classification performance and the time cost of SVMs.
The performance of SVM is calculated in terms of false acceptance rate (FAR) and false rejection rate (FRR). These two are defined below.

- False Acceptance Rate (FAR):- The probability of identifying an outsider as an enrolled user.
- False Rejection Ratio (FRR):- The probability of rejecting an enrolled user, as if he is an outsider

EXPERIMENTAL STUDY

The proposed work was implemented using MATLAB 8.5.0 (2015a) of MathWorks, Inc, USA in the Windows7 operating system with Intel Core i3 Processor, 2.20 GHz and 4 GB RAM.

After the moving region are identified using GMM background subtraction method, Haar wavelet decomposition is done. First level decomposition is shown in Figure. 3.

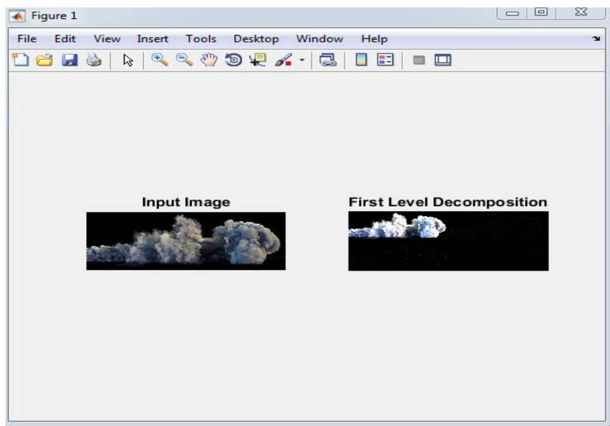

Figure 3: First level Haar wavelet decomposition.

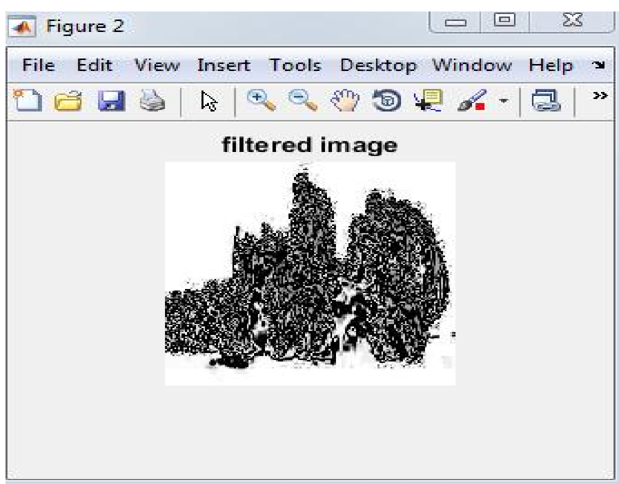

Figure 4: Gabor filtered image.

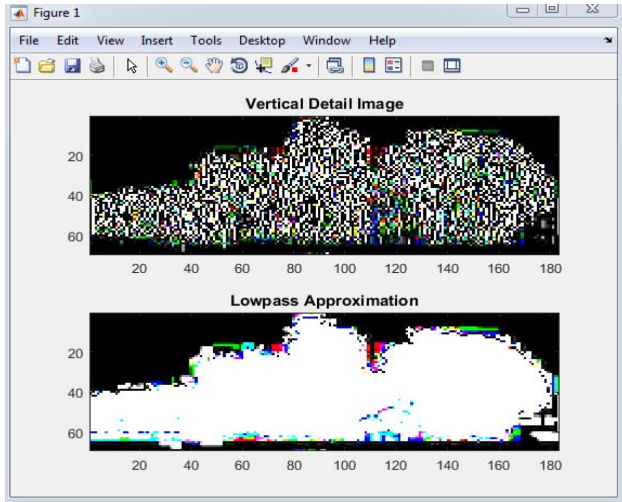

Figure 5: Detail characteristics of smoke pixels after Haar transform.

After determining the candidate region by background subtraction and haar decomposition, we can calculate the feature parameters of smoke, i.e. mean and variance of intensity of all pixels of that candidate region.

M_i and V_i be the mean value and variance value of i^{th} training data set $\mathbf{sv_i}$ extracted from training images. The test was performed using nine images with 320 ^{x} 240 image size.

The recognition accuracy of SVM combined with that of hamming distance is compared as follows:

Table 1 : Recognition accuracy with different feature vector

Methodology	False acceptance rate	False rejection rate	Accuracy
SVM(only)	0.11	2.3	97.38%
Hamming distance	0.22	0	99.7%
Proposed (SVM +hamming)	0.10	0	99.8%

The recognition rate is increased to 99.81% when combined both SVM and Hamming distance techniques are used with Haar feature as input.

CONCLUSION

In this paper, an effective smoke detection algorithm in images is proposed. The proposed work applies a combination of two classification method, rather than single method. After motion detection by GMM background subtraction method, Gabor filter is applied for noise removal. Haar wavelet decomposition up to level 3 is used for feature extraction. Lastly, for classification purpose, support vector machine is used as the main classifier with Hamming distance is used as a secondary classifier to distinguish between smoke and non-smoke, which gives an accuracy of 99.8 %. In future work, we will evaluate the performance of proposed work over wider variety of video imagesExperiment was done using LINGO software for simulation of GP. Various MCDM methods were applied first to find out ranks of indices considered for the research and then GP was applied to diversify the fund in various stocks of selected index with expected rate of return and risk. As stated above entire process was carried out in two different steps as below:

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