Fire Technology

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Multi Feature Analysis of Smoke in YUV Color Space for Early Forest Fire Detection

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Abstract. An image processing approach for detection of smoke in video using multiple features is proposed in this paper. It is assumed that the camera monitoring the scene is stationary. Video smoke detection methods have many advantages over traditional smoke detection methods due to large coverage area, fast response and non-contact. In order to reduce a false alarm rate, we propose a novel method to detect smoke by analyzing its multiple features. It consists of three stages. In the first stage, color filtering is performed in YUV color space to segment the candidate smoke region. In the second stage, spatio temporal and dynamic texture analysis is performed on the candidate smoke region to extract the spatial and temporal features; these features include wavelet energy, correlation and contrast of smoke. In the third stage, the extracted features are used as input feature vectors to train the Support Vector Machine (SVM) classifier, which is used to make decision about candidate smoke region. The proposed algorithm has been tested using news channel videos and videos captured by surveillance CCTV camera and shows impressive results in terms of detection accuracy, error rate and processing time.

Keywords: Smoke detection, Image processing, Wavelet transform, Gray level co-occurrence matrix, SVM, YUV color space

1. Introduction

Numerous fires threaten human lives and property throughout the world every day, so we need a reliable fire detection technique. Video-based Fire Detection (VFD) techniques detect fire by recognizing either smoke or flame anywhere within the field of view of the camera. Also, VFD helps to reduce detection time compared to the currently available sensors [1]. Smoke is the initial sign of disastrous forest fire; hence VFD techniques use recognition of smoke for early fire detection [2, 3]. The reason for developing smoke detection method is the fact that smoke spreads faster and will appear much quickly in the field of view of the

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cameras. Mainly in forest, the smoke produced by fires is visible much before the fire flames. Also, the toxic gases of smoke such as carbon monoxide, carbon dioxide, hydrogen sulfide etc., are very harmful to human beings and animals [4]. Hence the approach proposed in this paper focuses on the detection of smoke for early fire detection.

Many researchers use color, movement and texture properties of smoke for video-based detection. In order to improve the detection rate some researchers [5, 6] use soft computing techniques. Gubbi et al. [7] described a block-based approach, in which the statistical parameters such as geometric mean, arithmetic mean, standard deviation, skewness, kurtosis and entropy are determined from the discrete cosine transform and discrete wavelet transform coefficients. Finally, SVM classifier is trained for extracted features to make a decision.

Lee et al. [8] developed an approach for smoke detection using spatial and temporal analysis. Initially motion features are used to segment candidate smoke from the input image. Then the energy-based and the color-based features are analyzed in spatial, temporal and spatio temporal domains. All the extracted features are used as input for trained SVM. Gebejes and Huertas [9] analyzed texture using second order statistical measurements based on grey level co-occurrence matrix. The features used to analyze texture are contrast, homogeneity, dissimilarity, energy and entropy. Chen et al. [10] proposed a combination of block-based inter frame difference and local binary pattern from three orthogonal planes to analyze the dynamic characteristics of smoke. This method reduces false alarm by registering recent classification of smoke block with the help of smoke histogram image. It uses Support Vector Machine (SVM) for the classification of smoke block.

Chunyu et al. [11] used texture analysis for smoke detection based on Gray Level Cooccurance Matrix (GLCM). Here, smoke features are distinguished from other non-smoke disturbances using the parameters determined from GLCM. Agrawal and Mishra [12] detect smoke by analyzing the texture of smoke using Local Binary Pattern (LBP). In this technique moving region is segmented as candidate smoke region. Then histogram of LBP is computed and given as input vector for AdaBoost (which is one of the machine learning techniques) to classify smoke and non-smoke. Tung and Kim [13] proposed a four stage smoke detection algorithm. In the first stage, moving region is segmented using approximate median method, in the second stage Fuzzy C-Means Clustering (FCM) algorithm is used to cluster the candidate smoke region, in the third stage spatial and temporal characteristics of candidate smoke region are extracted and in the final stage the candidate regions are classified as smoke or non-smoke by SVM classifier. This technique requires more time to process each frame of the input videos. Meng-Yu et al. [14] presented their algorithm based on discrete wavelet transform and correlation analysis for smoke detection. They used discrete wavelet transform to separate low and high frequency content of the image. Then high frequency information is analyzed using correlation analysis.

Tian et al. [15] proposed smoke detection in video using sparse representation, local smoothness and blending parameters. Here the image is assumed to be a linear blending of smoke component and back ground image. Favorskaya and Levtin [16] developed an early smoke detection using spatio temporal clustering. In this method, after segmenting the moving region, color and texture analysis are carried out. Finally, fractal properties of smoke are used for confirming the candidate region. Jerome and Philippe [17] presented a technique to recognize smoke by analyzing the smoke plumes velocity. In this analysis energy of velocity distribution for smoke plume is higher than many other landscape phenomena except clouds. For clouds, standard deviation of velocity distribution is lower than smoke. The main criterion is that they use minimum energy and standard deviation threshold. Feiniu Yuan [18] proposed an accumulative motion orientation model based on integral image by fast estimating the motion of smoke. Using accumulation of motion, this technique can discriminate artificial lights and non-smoke moving objects from smoke.

Toreyin et al. [19] detected smoke by analyzing the back ground of the scene. When the smoke is present in the image frame, its edges lose their sharpness. This produces local extrema in the wavelet domain. A decrease in the value of local extrema is an indicator of smoke. Toreyin and Yigithan [20] described a technique where the periodic behavior of the smoke boundaries is analyzed using Hidden Markov Model (HMM). Also, smoke flicker can be modeled by high frequency nature of the boundaries of smoke region.

Ye et al. [3] used surfacelet wavelet transform and HMT model to extract texture features of smoke. Initially image is divided into number of blocks. For each block surfacelet transform is applied and the coefficients are calculated along various scales, directions and locations. From these coefficients, 3D-HMT model is constructed to estimate the dynamic texture features. Finally, SVM classifier is trained for the extracted texture features which can then classify the fire. This method has lower computational efficiency because of block by block processing of image. Benazza-Benyahia et al. [21] proposed a method to detect smoke that measures the local fractal feature of smoke areas using DCT coefficients. Here recursive DCT is employed to increase the detection rate. Cui et al. [22] describe early fire detection by analyzing the smoke texture using wavelet and gray level co-occurrence matrices. Finally, two layer back propagation neural network is used to discriminate smoke texture and non-smoke texture.

Truong and Kim [23] provide an early smoke detection system which determines the candidate block using moving block and smoke colored block of the input image. Finally, smoke is confirmed by estimating the motion vector. Kim and Wang [24] presented a method to detect smoke from video. This approach segments the Region of Interest (ROI) by connected component analysis and then the various features of ROI such as color, shape and edge informations are measured and compared with K-temporal information. Result of comparison gives decision about the existence of smoke.

Li et al. [25] use dual background modeling method to get the moving object and then the movement features are extracted. This method is insensitive to variation of lighting conditions. Calderara et al. [26] presented a smoke detection technique based on image energy and color information. Here Mixture of Gaussion (MoG) model is constructed based on the statistical parameters of wavelet energy and color information to detect the possible smoke region. Cetin et al. [1] presented various video fire detection methods based on spectral range of the camera, whether smoke or flame detection and range of the system. Qureshi et al. [2]

developed a system for early fire detection using flame and smoke analysis, in which candidate region are analyzed through turbulence flow rate analysis of smoke and growth and flow rate information of flame. Anushikha et al. [27] detect glaucoma disease from the digital fundus image. Here wavelet features are extracted and compressed using Principle Component Analysis (PCA). PCA considers only two main principle components for classification. YongHua and JinCon [28] identified defects in wood based on texture analysis. They used GLCM, wavelet, LBP and histogram based approaches for analysis. Among the discussed smoke detection techniques in the literature, majority of the techniques focuses on color and shape characteristics together with the temporal behavior of smoke like changeable shape, velocity etc. Due to the variability of color, shape, motion and patterns of smoke, many of the existing video-based smoke detection techniques are still vulnerable to false alarms.

In this research, a new video-based smoke detection algorithm is investigated, where smoke is analyzed in consecutive video images in YUV color space, because the different features calculated in this color space are luminance independent. Both static and dynamic features are considered to reduce false alarm rate and computational complexity.

2. Smoke Detection Algorithm

The proposed method uses three stages for detecting smoke from the input video. The first stage is the color filtering in YUV color space. In this stage candidate smoke region is segmented from the background, based on the rules formed in YUV color space. The second stage is analysis of candidate smoke region using spatio temporal and texture analysis. During analysis, wavelet energy and texture properties using Gray Level Co-occurrence matrix (GLCM) are measured for candidate smoke region. Finally in the third stage, real smoke is identified by SVM classifier. The third stage has two phases, namely training phase and classification phase. In the training phase, SVM is trained for the extracted spatial and temporal features. In the classification phase, trained SVM is used to distinguish between smoke and non-smoke based on the extracted features. The various stages of the algorithm are shown in Figure 1.

2.1. Color Filtering

Color is the static feature of smoke. It is one of the basic features to identify smoke, because many objects in the background also have the same color as smoke. At low temperature, the color of the smoke ranges from bluish white to white and it changes to greyish black and black when the temperature increases [13]. Many researchers [21, 24, 3] analyzed smoke in different color spaces. The result of color based smoke pixel classification varies in each color space due to different background illuminations and environmental conditions. It is noticed that in YUV color space, color information does not suffer from illumination changes and hence, color filtering is performed in YUV color space. In YUV color space, Y represents luminance and U and V are chrominance components.

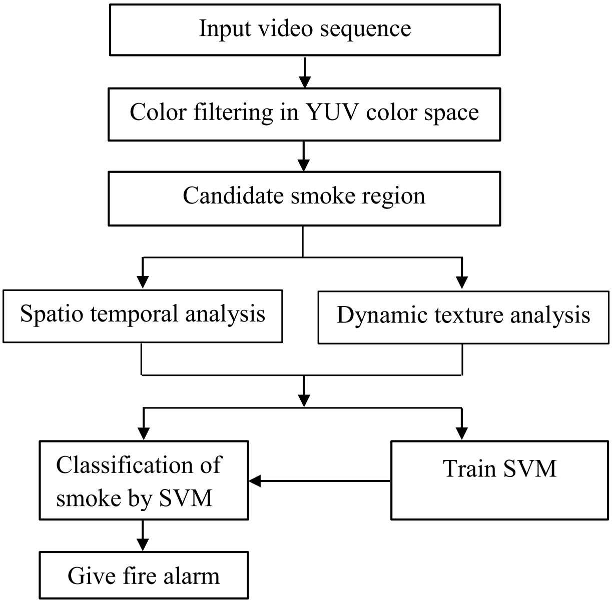


Figure 1. Smoke detection algorithm.

2.1.1. RGB to YUV Color Space Input video sequence obtained through video camera contains a number of frames, each frame is represented in RGB color space. The value of each pixel in the image with coordinates (x,y) is denoted by f(x,y) with triple (R,G,B),where R, G and B are intensities of R,G and B components respectively. Conversion from RGB to YUV color space is linear and the standard formula to convert RGB to YUV color space is given in the Eqs. (1 to 3) [1].

$$Y = 0.299R + 0.587G + 0.114B \tag{1}$$

$$U = -0.1687R - 0.3313G + 0.5B + 128 \tag{2}$$

$$V = 0.5R - 0.4187G - 0.813B + 128 \tag{3}$$

where Y, U and V are luminance and chrominance components of each pixel in the RGB image and they represent separate planes (Y plane, U plane and V plane). 'Y' takes the values in the range [0, 255]. Chrominance components 'U' and 'V' are increased to 128 so that they also take the values from 0 to 255.

2.1.2. Conditions in YUV Color Space To segment the smoke colored pixels in YUV color space, smoke images are analyzed in the different planes of YUV

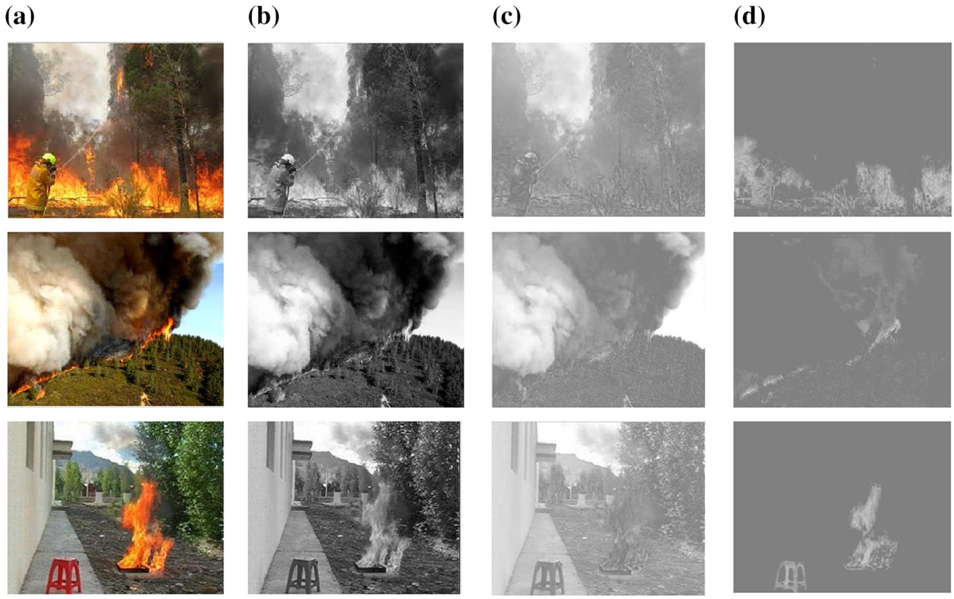


Figure 2. Input image in Y, U and V plane (a) RGB image, (b) Y component, (c) U component, (d) V component.

color space. Generally, the color of the smoke varies from bluish white to white (at low temperature) and then to greyish black and black (high temperature). In order to explain this concept clearly, we picked some sample images. And we have separated the Y component, U component and V component from the input image as shown in the Figure 2. It is observed that all the pixels in the smoke region have much higher value of chrominance component (U) compared to other non-smoke regions like fire flame, mountain, grass, trees etc. Also in smoke colored regions, differences between U and V components (U-V) are much greater than other non-smoke colored regions. Figure 3 shows histogram of (U-V) intensity image for smoke colored and non-smoke colored region. From the histogram it is clear that (U-V) intensity spreads in the range from (0 to 40) for non-smoke region and (40 to 130) for smoke colored region. These concepts are observed for thousands of images collected from the internet and depicted as rules given in Eqs. (4) and (5). Even though color filtering in YUV color space segments smoke regions, it allows non-smoke but smoke colored regions like clouds, sky and white colored objects.

$$\text{Rule I} : S^{1}_{color}(x,y) = \begin{cases} 1 & if\ |U(x,y) - 128| > T_U \\ 0 & Otherwise \end{cases} \tag{4}$$

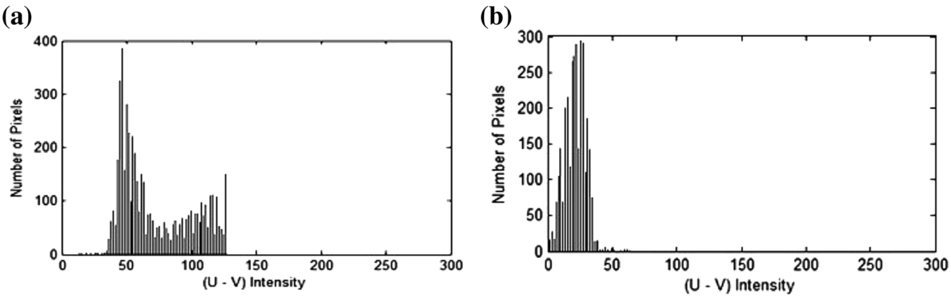


Figure 3. Histogram of (U-V) (a) smoke colored region, (b) non-smoke colored region.

$$\text{Rule II} : S^2_{color}(x,y) = \begin{cases} 1 & if\ |U(x,y) - V(x,y)| > T_{UV} \\ 0 & Otherwise \end{cases} \tag{5}$$

where, $U(x, y)$ and $V(x, y)$ are the intensity of U and V components at each pixel location $(x,y).T_U$ and T_{UV} are the threshold values selected through number of experiments. The values of T_U and T_{UV} are chosen as 60 and 40 respectively. $S^1_{color}(x,y)$ and $S^2_{color}(x,y)$ are the pixels satisfying rule I and II respectively. Finally, smoke colored pixels can be determined by using Eq. (6).

$$S_{color}(x,y) = \begin{cases} I(x,y) & if\ S^1_{color}(x,y) = 1\ (OR)\ S^2_{color}(x,y) = 1 \\ 0 & Otherwise \end{cases} \tag{6}$$

where $I(x, y)$ is the intensity of input RGB image in the pixel location (x,y). $S_{color}(x, y)$ is the pixel in the smoke colored region called candidate smoke region. Figure 4 shows the result of color filtering in YUV color space. This smoke colored region also includes regions which have similar color as smoke like sky, white colored wall, cloud, white colored car, etc. Hence, further analysis of candidate smoke region is needed. It is obvious that color alone cannot be used to detect smoke because of the smoke like colored objects in the input image. However, the color information can be used as a part of a more sophisticated system.

2.2. Analysis of Candidate Smoke Region

Segmented smoke region using color filtering called 'candidate smoke region' not only includes smoke regions but also some smoke like colored regions (sky, white colored wall, cloud etc.). From the result of color filtering, it is observed that the objects have the same color as smoke can also be segmented as smoke. Hence, it is necessary to analyze these 'candidate smoke regions' further to determine whether it is a real smoke or smoke colored region. The two methods proposed for analysis are (i) using spatial wavelet analysis (ii) using dynamic texture analysis.

Figure 4. Result of color filtering (a) Input RGB image. (b) Pixels satisfying Eq. (6).

2.2.1. Spatial Wavelet Analysis Wavelet transform is a fast linear invertible orthogonal transform used to analyze non-stationary signals. It provides time and frequency representation of a signal. Wavelet allows complex information to be decomposed into elementary form at different positions and scales.

Discrete wavelet transform is based on sub band coding and it uses digital filtering techniques. Wavelet transform decomposition is computed by successive low pass and high pass filtering of discrete time signals. Wavelet decomposition results-one low frequency sub band and three high frequency sub bands are shown in Figure 5. Low frequency components in an image reflect the whole structural information while the high frequency components reflect the edge information. Figure 6 shows the single level wavelet decomposition of input image in YUV

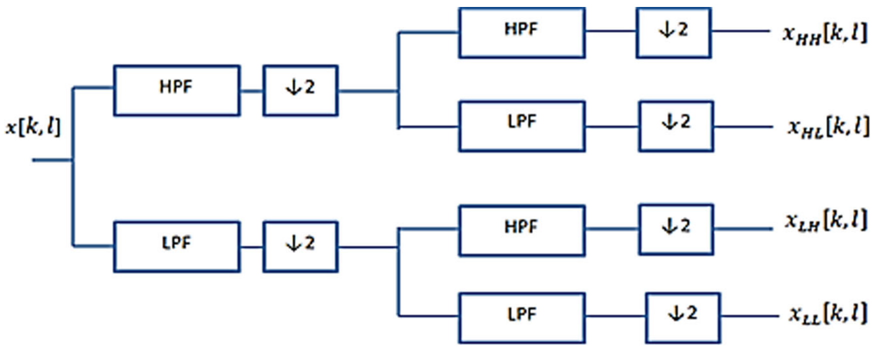


Figure 5. Two dimensional wavelet decomposition.

color space and the resulting four subimages (compressed image $x_{LL}[k.l]$, horizontal coefficient image $x_{HL}[k.l]$, vertical coefficient image $x_{LH}[k.l]$ and diagonal coefficient image $x_{HH}[k.l]$).

Wavelet sub images result from the spatial variation of pixel values in the input image. In the ordinary smoke colored region, there will be a little spatial variation of pixel value. On the other hand, there will be a significant spatial variation of pixel value in real smoke region. In the proposed method, wavelet transform is applied on the image in YUV color space because there is greater variation in the intensities of wavelet subimages in the real smoke region than in RGB color space as shown in Figure 7. This intensity variation results in high spatial wavelet energy in the real smoke region. The spatial wavelet energy is calculated by using Eq. (7).

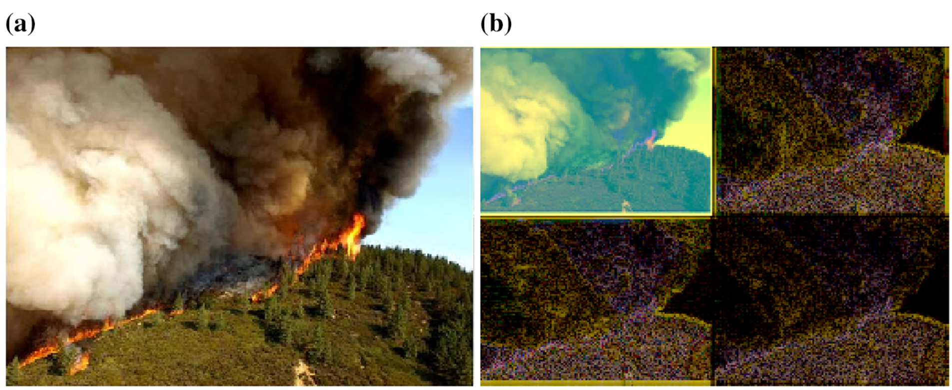


Figure 6. Discrete wavelet transform of image in YUV color space (a) Original image. (b) Wavelet transformed image: *top left* compressed image ($x_{LL}[k.l]$), *top right* horizontal coefficient image ($x_{HL}[k.l]$), *bottom left* vertical coefficient image ($x_{LH}[k.l]$), *bottom right* diagonal coefficient image ($x_{HH}[k.l]$).

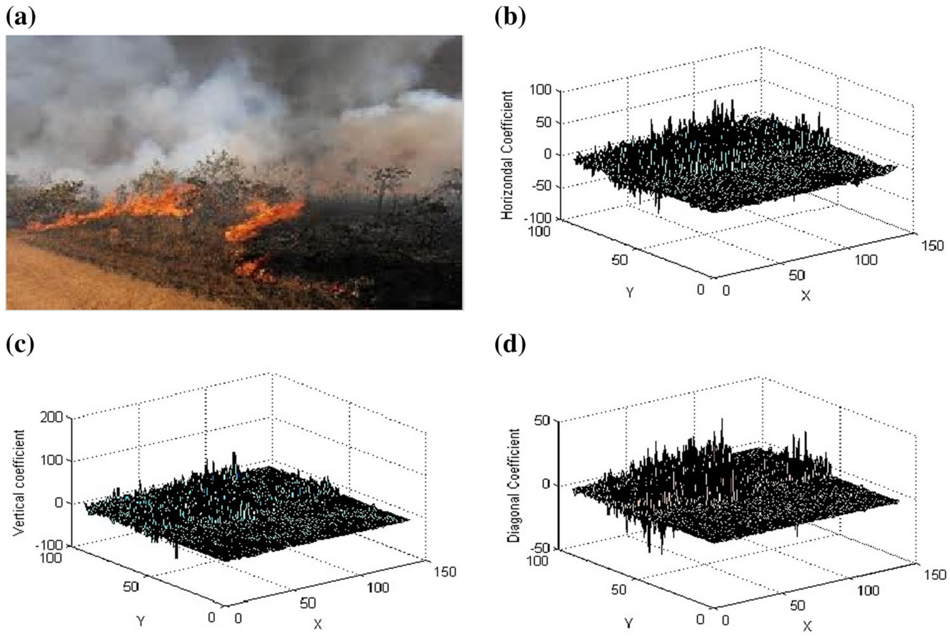


Figure 7. Plot of wavelet coefficients in YUV color space (a) Input RGB image. (b) Horizondal coefficient. (c) Vertical coefficient. (d) Diagonal coefficient.

$$e = \frac{1}{\mathrm{m} \times \mathrm{n}} \sum_{k,l} |x_{LH}[k,l]|^2 + |x_{HL}[k,l]|^2 + |x_{HH}[k,l]|^2 \quad (7)$$

where, $x_{LH}[k, l]$ is the low–high subimage, $x_{HL}[k, l]$ is the high-low subimage and $x_{HH}[k, l]$ is the high–high subimage in YUV color space respectively. m × n is the number of pixels in the candidate smoke region and '*e*' is the spatial wavelet energy. Figure 8 shows variations of wavelet energy with time for smoke and cloud regions. It is clear that there is a wide energy barrier between the wavelet energy calculated for smoke and cloud. For smoke, *e* is very low i.e., below 3.5E−04, but for cloud it is above 2.692E−2. Hence, for consecutive k number of frames wavelet energy in the 'candidate smoke region' is monitored. This feature can discriminate smoke and cloud effectively.

2.2.2. Dynamic Texture Analysis Texture properties are measured for each frame of input video. The texture analysis quantifies the intuitive qualities described by the terms such as rough, smooth silky or bumpy as a function of spatial variation of pixel intensities. Texture measures are generally computed using histograms (mean, standard deviation, moment etc.) which carry no information about the relative position of the pixels with respect to each other. One way to incorporate

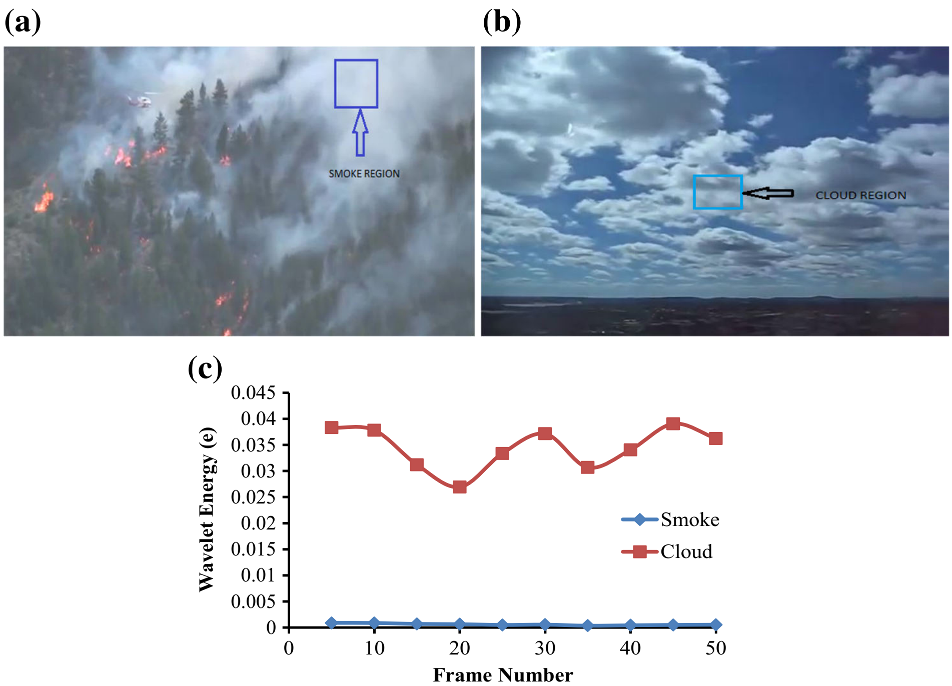


Figure 8. Wavelet energy (a) Smoke image. (b) Cloud image. (c) Variation of wavelet energy with time.

this information into texture analysis is to consider not only the distribution of intensities but also the relative position of pixels in an image.

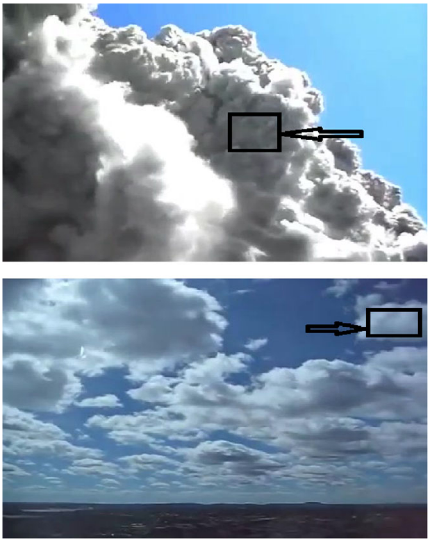
Consider an image $f(x, y)$ with L possible intensity levels. Let G be the matrix whose element g_{ij} is the number of times that pixel pairs with intensities, z_i and z_j occur in $f(x, y)$ in the position specified by O (O be an operator defines the position of two pixels relative to each other) where $1 \leq i, j \leq L$, a matrix formed in this manner is referred to as gray level cooccurrence matrix (GLCM) and is denoted as G. G represents the number of intensity levels L and inorder to choose the size of G manageable, L is chosen as '8'. Figure 9 shows the G for smoke and cloud texture using the value of L as '8' and a position operator O defined as one pixel immediately to the right.

If 'n' is the total number of pixel pairs satisfy 'O', then the probability that the pair of points satisfy O is P_{ij} and it is determined by using the Eqs. (8) and (9).

$$P_{ij} = \frac{n_{ij}}{n} \tag{8}$$

and

(a)



(b)

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	929	86	0	0	0	0
0	0	67	1451	5	0	0	0
0	0	0	1	11	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	300	6	0	0	0	0
0	0	3	671	5	0	0	0
0	0	0	17	1223	22	0	0
0	0	0	0	40	263	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

Figure 9. GLCM of smoke and cloud region (a) Input image. (b) GLCM of smoke and cloud region indicated as *arrow* in (a).

$$\sum_{1}^{k}\sum_{1}^{k} P_{ij} = 1 \tag{9}$$

where 'k' is row (or column) dimension of the square matrix G. The mean and standard deviation computed along row and colomn of G is denoted by m_r, m_c, σ_r *and* σ_c respectively and the formulas to calculate them are given in Eqs. (10 to 15) [9].

$$m_r = \sum_{i=1}^{k} iP(i) \tag{10}$$

$$m_c = \sum_{j=1}^{k} jP(j) \tag{11}$$

$$\sigma_r = \sqrt{\sum_{i=1}^{k} (i - m_r)^2 P(i)} \tag{12}$$

$$\sigma_c = \sqrt{\sum_{j=1}^{k} (j - m_c)^2 P(j)} \tag{13}$$

$$\text{Here, } P(i) = \sum_{j=1}^{k} P_{ij} \tag{14}$$

$$P(j) = \sum_{i=1}^{k} P_{ij} \tag{15}$$

Each of these quantities is scalar independent of the size of G. From gray level cooccurance matrix four parameters can be determined. They are contrast, correlation, energy and homogeneity. Among the four mentioned parameters only contrast and correlation show considerable deviation between smoke surface and cloud surface. Hence, both are used for dynamic texture analysis.

2.2.2.1. Correlation Analysis. Correlation is a measure of how each pixel is correlated to its neighbour over the entire range of an image. Correlation is considered as a number which can be used to describe the relation between two pixel values. Correlation is in the range from -1 to $+1$ corrosponding to perfect positive and negative correlated images. The correlation of an image is calculated by using the Eq. (16) [9].

$$Correlation\ (Q) = \sum_{1}^{k} \sum_{1}^{k} \frac{(i - m_r)(j - m_c) P_{ij}}{\sigma_r \sigma_c}, \quad \sigma_r \neq 0; \ \ \sigma_c \neq\leq 0 \tag{16}$$

where m_r and m_c are mean computed along row and column of the matrix G respectively and its value is given in Eqs. (10) and (11). σ_r and σ_c are standard deviation computed along row and column of matrix 'G' respectively and its value is given in Eqs. (12) and (13). Figure 10 shows the variation of correlation with time for a video with smoke texture and cloud texture. The particles of smoke spread faster than cloud, hence the relative intensity variations between adjecent pixels are high for smoke but less for cloud. As time elapses, the correlation between adjecent pixels decreases for smoke surface but is almost constant for cloud and other smoke colored surfaces.

2.2.2.2. Contrast Analysis. Contrast is a measure of intensity contrast between a pixel and its neighbour over the entire image. It is a difference in luminance or color that makes an image distinguishable. The range of contrast is from 0 to $(k-1)^2$. Contrast is '0' for a constant image. The image contrast is determined using Eq. (17) [9].

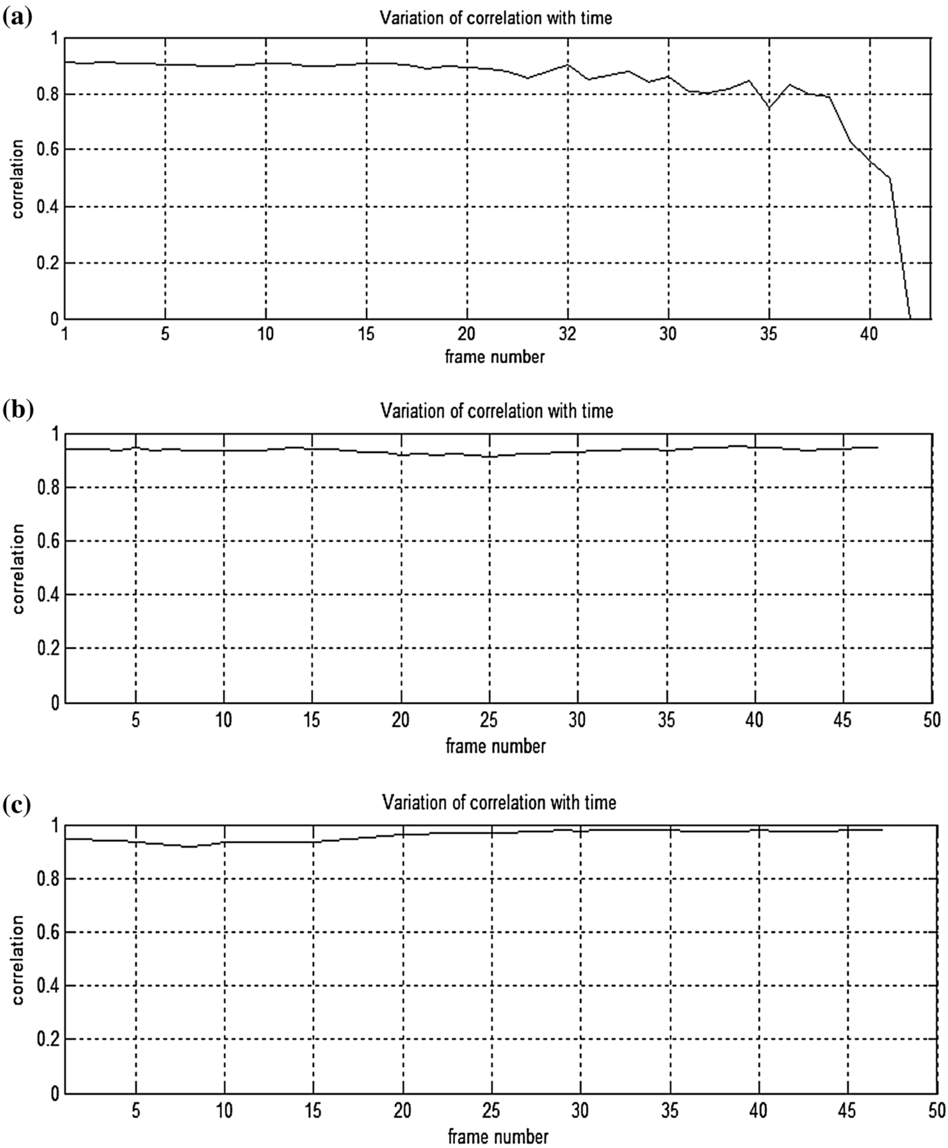


Figure 10. Variation of correlation with time (a) smoke region, (b) cloud region, (c) sky region.

$$Contrast(C) = \sum_{i=1}^{k} \sum_{j=1}^{k} (i-j)^2 P_{ij} \tag{17}$$

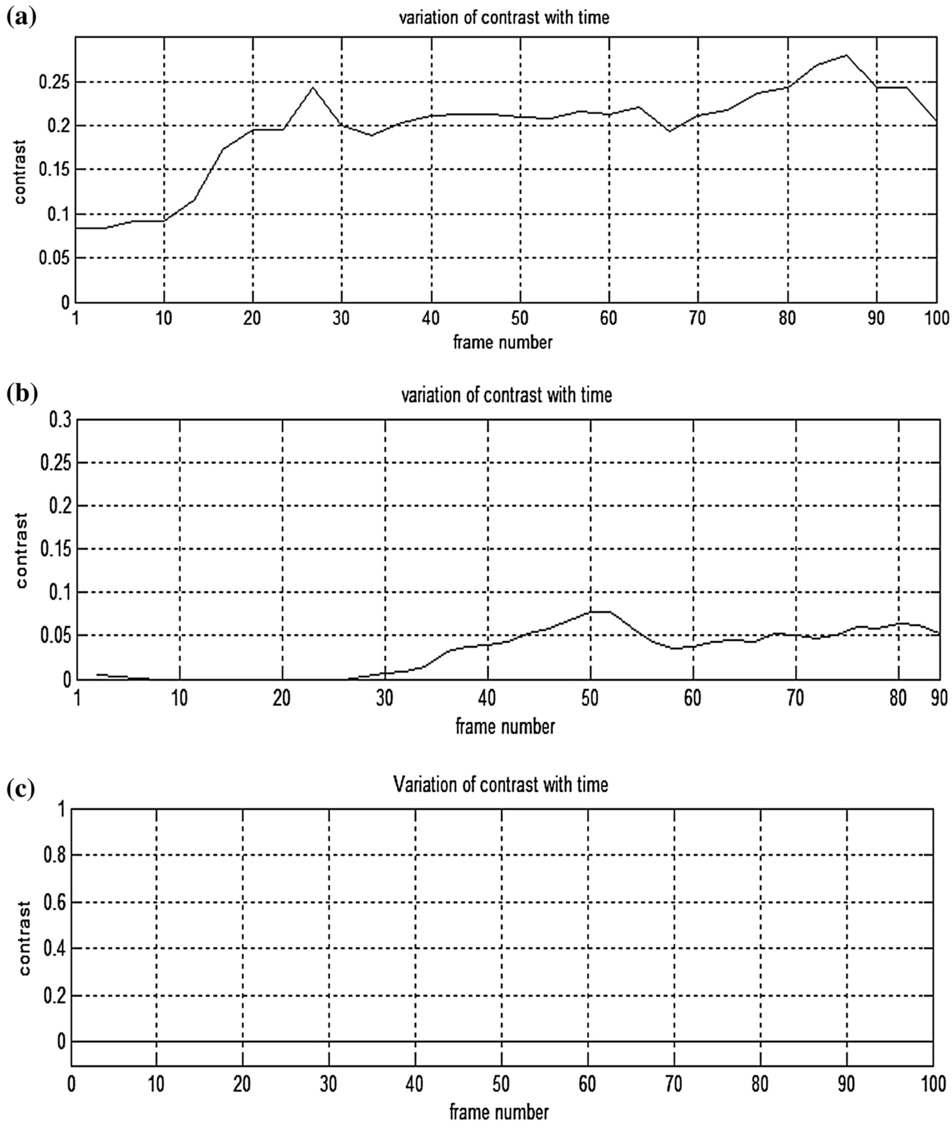


Figure 11. Variation of contrast with time (a) smoke, (b) cloud, (c) sky.

where P_{ij} is determined using Eq. (8). If high is the randomness, more will be the contrast. Smoke region in the consecutive frames of video exhibits more randomness. Hence, contrast increases with time for smoke as shown in Figure 11a. In Figure 11b contrast decreases with time for cloud surface, because of the smooth intensity level of adjacent pixels in the cloud region. But for a constant image like

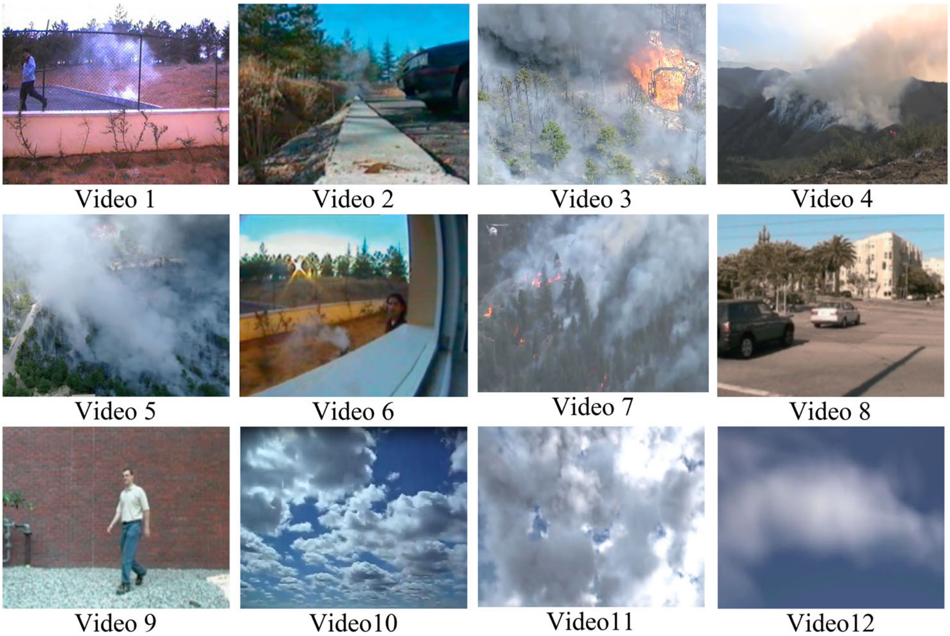


Figure 12. Examples of test videos: smoke (videos 1 to 7), non-smoke (videos 8 to 12).

sky region, contrast is ‘0’ due to the result of no intensity variation between the neighboring pixels as shown in Figure 11c.

2.3. Fire Verification Using Support Vector Machines

Support vector machines are supervised learning methods introduced by vapnik. SVM is applied mainly in the field of pattern recognition. Because of their high generalization ability over a wide range of applications and their excellent performance with limited training data set, SVMs have gained wide acceptance over traditional machine-learning methods, such as radial basis function networks and back-propagation neural networks. SVM can be either linear or non-liner SVM. Many data are not fully linearly separable; hence, we used non-linear SVM for smoke classification. In the proposed method, we used LIBSVM tool to classify smoke images. In the previous section we described three spatio temporal parameters (wavelet energy e, correlation Q and contract C) of smoke: $sv = [e, Q \; and \; C]$. During training the above three mentioned parameters are given as input feature vector, which is then used to generate smoke alarm. The training data set is obtained from lot of smoke, cloud and smoke colored moving scenes. In the training stage, selection of proper kernel function for the SVM classifier is important because it affects the accuracy of the classification. If the kernel function is appropriate for the dataset, the classification result is good, otherwise it is worse. We

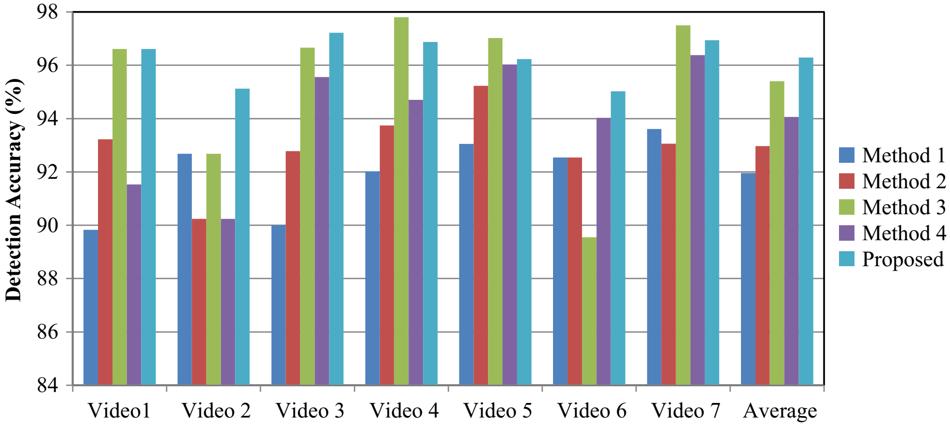


Figure 13. Smoke detection accuracy for existing and proposed methods in positive smoke videos.

selected radial basis function (RBF) as kernel through the analysis of number of smoke video clips. This kernel is defined in Eq. (18).

$$k(sv_m, sv_n) = exp\left(-\frac{sv_m - sv_n^2}{2\delta^2}\right) \tag{18}$$

where, $k(sv_m, sv_n)$ is the kernel function, sv_m and sv_n are the input feature vectors and δ is the width of the kernel function set by the user. If δ values are small, overtraining occurs and the kernel function is wrapped tightly around the data points. If δ values are large, kernel function forms oval around the data points

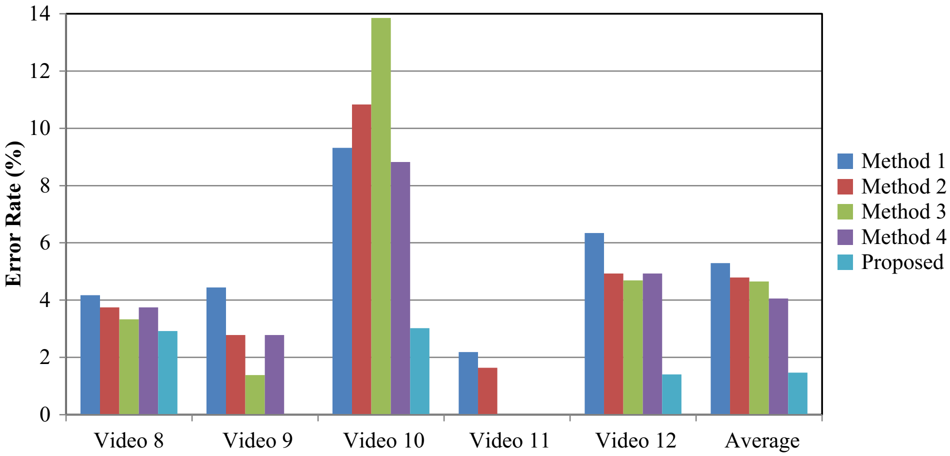


Figure 14. False smoke detection rate for existing and proposed methods in negative smoke videos.

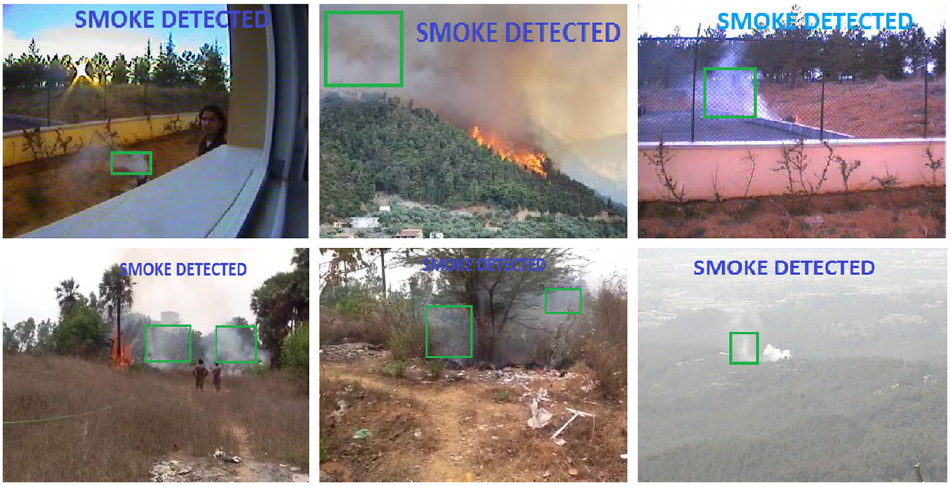


Figure 15. Examples of smoke detection by the proposed methods.

without defining the shape or pattern. The default value of δ is set as 10. In our proposed research, the value of δ was varied from 9 to 17.

3. Experimental Results and Discussion

The overall performance of the proposed multi feature smoke detection method is compared with those of four state-of-the-art algorithms: Smoke detection in video using wavelets and SVM (method 1) [7], an effective four-stage smoke-detection algorithm using video images for early firm-alarm systems (method 2) [13], quick blaze: early fire detection using a combined video processing approach (method 3) [2] and vision-based smoke detection system using image energy and color information (method 4) [26]. All the existing algorithms and proposed algorithm are implemented using MATLAB 7.11 and tested using Intel core 2.67 GHz PC platform.

The proposed algorithm is evaluated using more than 175 videos with 115 smoke videos and 60 non-smoke videos. Of these, some videos are collected from the internet (http://signal.ee.bilkent.edu.tr/VisiFire/Demo/SmokeClips/SmokeFar, http://signal.ee.bilkent.edu.tr/VisiFire/Demo/ForestSmoke/ and http://www.videezy.com/fire_and_smoke/2513_smoke) and some of them are obtained from videos captured by surveillance CCTV camera and also using news channel videos. These videos include real smoke, sky, smoke-colored moving regions like cloud, white colored car etc. Each has frame rate of 10 frames/s and image resolution is 360 $\times$ 638. Figure 12 shows smoke and non-smoke input videos used for testing. The SVM classifier is trained using 80 smoke videos and 45 non-smoke videos out of 115 smoke videos and 60 non-smoke videos respectively. After thorough analysis with smoke and non-smoke videos, the system parameters are set as threshold value $T_u = 60$, $T_{uv} = 40$ and scaling factor $\delta = 10$.

3.1. Performance Evaluation

For positive smoke videos, the true positive (TP) and false positive (FP) rate of proposed method are compared with the other four existing methods and tabulated in Table 1. Here, TP is the rate of correctly detecting real smoke as smoke and FP is the rate of identifying real smoke as non-smoke. In videos 1, 2 and 6, smoke is blurred in some frames of the video and it looks like the color of the wall. Hence, the accuracy of all the methods is relatively low except the proposed one. Even though the smoke is blurred, the proposed method considers the continuous dispersion of smoke with time and achieved perfect detection results. Along with smoke, some frames of video 1 includes person moving with smoke colored shirt. The proposed method correctly detects real smoke region, but not the smoke colored region.

Initial frames of video 4 do not contain any smoke and includes only dusk and evenings. These non-smoke regions are detected as smoke by most of the existing methods, but not by the proposed one. In videos 5 and 7, smoke appears clearly, so the detection rate is high for all the methods. From Figure 13 it is clear that for all the input smoke videos, the proposed method outperformed other techniques showing the average detection rate of 96.29% versus 91.96%, 92.97%, 95.4%, and 94.06% respectively.

The proposed and the existing four methods are also tested for smoke negative videos and their True Negative (TN) and False Negative (FN) are given in Table 2. TN is the rate of correctly recognizing non-smoke as non-smoke and FN is the rate of recognizing non-smoke as smoke. The videos 10, 11 and 12 contain moving cloud, which is recognized as smoke by most of the existing methods but the proposed method does not recognize it as smoke because of dynamic texture analysis, where the relative intensity variation of adjacent pixels is considered for consecutive frames. The videos 8 and 9 contain smoke colored moving car and the person moving with smoke colored shirt respectively. For these two videos, the proposed method performs better than the existing methods. From Figure 14, it is concluded that the proposed method outperforms the existing methods to reduce the FN rate and shows the average FN rate of 1.47% versus 5.29%, 4.79%, 4.65% and 4.06% respectively.

Overall, the proposed multi feature analysis of smoke detection method outperformed the existing smoke detection methods by increasing the smoke detection accuracy and decreasing the false smoke detection rate. Figure 15 shows some examples of smoke detection by the proposed method. In the proposed method, analysis is done in YUV color space because Y, U and V intensities differ greatly for smoke and non-smoke pixels. Also, YUV color space makes linear relation with RGB color space; hence, it is easy to convert RGB color space into YUV color space. Spatio temporal and dynamic texture analyses are also performed in YUV color space due to the enormous wavelet energy gap between smoke and smoke-colored region. The main intention of the proposed method is to detect smoke with little complexity. Many of the researchers developed video smoke detection techniques which use complex rules and hence, they take more time to complete the process [24, 18, 25]. Some methods lead to false smoke identification

Table 1
Smoke Detection Results of Existing and Proposed Methods for Positive Smoke Videos

		True positive (TP)										False positive (FP)									
		Method 1		Method 2		Method 3		Method 4		Proposed		Method 1		Method 2		Method 3		Method 4		Proposed	
Video	No. of frames	TP (frame)	TP (%)	TP (frame)	TP (%)	TP (frame)	TP (%)	TP (frame)	TP (%)	TP (frame)	TP (%)	FP (frame)	FP (%)	FP (frame)	FP (%)	FP (frame)	FP (%)	FP (frame)	FP (%)	FP (frame)	FP (%)
Video 1	59	53	89.83	55	93.22	57	96.61	54	91.53	57	96.61	6	10.17	4	6.78	5	8.47	5	8.47	2	3.38
Video 2	41	38	92.68	37	90.24	38	92.68	37	90.24	39	95.12	3	7.32	4	9.76	3	7.31	4	9.76	2	4.87
Video 3	180	162	90.00	167	92.78	174	96.66	172	95.56	175	97.22	18	10.0	13	7.22	6	3.33	8	4.44	5	2.78
Video 4	639	588	92.02	599	93.74	625	97.8	605	94.70	619	96.87	51	7.98	40	6.26	23	3.59	34	5.32	20	3.13
Video 5	504	469	93.05	480	95.23	489	97.02	484	96.03	485	96.23	35	6.94	24	4.76	18	3.57	20	3.97	19	3.77
Video 6	201	186	92.54	186	92.54	180	89.55	189	94.03	191	95.02	15	7.46	15	7.46	21	1.04	12	5.97	10	4.98
Video 7	360	337	93.61	335	93.06	351	97.5	347	96.38	349	96.94	23	6.39	25	6.94	9	2.5	13	3.61	11	3.05
Average			91.96		92.97		95.4		94.06		96.29		8.04		7.03		4.25		5.93		3.71

Table 2
Smoke Detection Results of Existing and Proposed Methods for Negative Smoke Videos

		True negative (TN)										False negative (FN)									
		Method 1		Method 2		Method 3		Method 4		Proposed		Method 1		Method 2		Method 3		Method 4		Proposed	
Video	No. of frames	TN (frame)	TN (%)	TN (frame)	TN (%)	TN (frame)	TN (%)	TN (frame)	TN (%)	TN (frame)	TN (%)	FN (frame)	FN (%)	FN (frame)	FN (%)	FN (frame)	FN (%)	FN (frame)	FN (%)	FN (frame)	FN (%)
Video 8	240	230	95.83	231	96.25	232	96.66	231	96.25	233	97.08	10	4.17	9	3.75	8	3.33	9	3.75	7	2.92
Video 9	360	344	95.56	350	97.22	355	98.61	350	97.22	360	100	16	4.44	10	2.78	5	1.38	10	2.78	0	0
Video 10	397	360	90.68	354	89.17	342	86.14	362	91.18	385	96.98	37	9.32	43	10.83	55	13.85	35	8.82	12	3.02
Video 11	183	179	97.81	180	98.36	175	95.62	183	100	183	100	4	2.19	3	1.64	0	0	0	0	0	0
Video 12	426	399	93.66	405	95.07	406	95.3	405	95.07	420	98.59	27	6.34	21	4.93	20	4.69	21	4.93	6	1.41
Average			94.71		95.21		94.46		95.94		98.53		5.29		4.79		4.65		4.06		1.47

Table 3
Processing Time of Existing and Proposed Smoke Detection Methods

Smoke detection methods	Average processing time per frame in seconds
Method 1	0.67
Method 2	1.04
Method 3	0.98
Method 4	0.97
Proposed	0.57

because of background illumination and sensitive system parameters [21, 22]. If the camera is far away from the smoke, the movement of smoke is very slow. Such a dynamic texture is also handled positively by the proposed method. The time taken by the system to process each frame of the input videos is the crucial factor in smoke detection system.

Table 3 shows the average processing time required to process each frame of input videos. In the proposed method, no complex rules are used and all the operations are carried out in YUV color space. Also conversion from RGB to YUV color space is linear. Hence, the proposed multi feature based smoke detection method takes less time of 0.57 s to process each frame of input videos compared to other smoke detection systems.

The proposed method can be used for the detection of smoke when its color varies from bluish white to white and then to greyish black. When the smoke color is apart from the specified color spectra (purely black), the system fails to work. In future the proposed method can be extended to cover the entire color spectra of smoke. Also, the system can be trained with multiple classifiers instead of a single classifier called SVM and hence, detection rate can be further improved. The proposed method can also be further enhanced by adding additional features of smoke by taken into account of smoke color which is outside the specified color spectra.

4. Conclusions

For early fire surveillance, a video-based smoke detection system is developed and it could have a great impact on raising the safety levels in urban areas. In most of the forest fires, smoke appears quickly to the field of view of the camera than flame. Hence, early fire detection can be easily achieved by video smoke detection. The proposed algorithm segments the candidate smoke region by color filtering in YUV color space. Then the spatio temporal and dynamic characteristics of smoke are extracted by wavelet transform and GLCM in YUV color space. Finally, SVM is trained for the extracted features to classify the smoke and non-smoke regions. The experimental results show that the proposed method provides high detection rates, low false smoke detection rates and less response time, when compared to the existing smoke detection methods. Moreover, we will use the proposed smoke detection method in real time surveillance and smoke detection.

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