Fire Technology

Manufactured in The United States
DOI: 10.1007/s10694-017-0665-z

Deep Belief Network For Smoke Detection

Arun Singh Pundir, Department of Computer Science and Engineering, IIT, Roorkee, Roorkee, India*

Balasubramanian Raman, Department of Computer Science and Engineering, IIT, Roorkee, Roorkee, India

Received: 16 December 2016/**Accepted:** 13 June 2017

Abstract. Forest fire is an serious hazard in many places around the world. For such threats, video-based smoke detection would be particularly important for early warning because smoke arises in any forest fire and can be seen from a long distance. This paper presents a novel and robust approach for smoke detection that employs Deep Belief Networks. The proposed method is divided into three phases. In the pre-processing phase, the region of high motion is extracted by background subtraction method. During the next phase, smoke pixel intensities are extracted from the Red, Green and Blue and Luminance; Chroma:Blue; Chroma:Red color spaces for foreground regions. Subsequently, second feature which is based on texture is computed for detecting smoke regions in which Local Extrema Co-occurrence Pattern, an improved version of local binary patterns are extracted from different foreground regions which compute not only texture of smoke but also intensity and color of smoke using Hue Saturation Value color space. Finally, Deep Belief Network is employed for classification. The proposed method proves its accuracy and robustness when tested on different varieties of scenarios whether wildfire-smoke video, hill base smoke video, indoor or outdoor smoke videos.

Keywords: Smoke detection, Deep belief networks, Color spaces, Motion detection, Local extrema co-occurrence pattern

1. Introduction

One of the calamitous event that nature facing nowadays is the destruction caused by wildfire. Hence, detection of such wildfire at an early stage becomes crucial to prevent disasters caused by wildfire and thereby prevent global warming, rescue human life and their properties from destructions. Previously [3, 7, 11, 12], research was focused on detecting the fire but from last few years, it has been shifted to detection of smoke at an early stage since smoke is an early indication of fire. Hence, detecting smoke can warn the people much earlier than detecting fire.

There are different approaches for detecting fire and smoke that is with the help of computer vision techniques which uses non-optical sensor including cameras or with the help of smoke and fire alarms. Fire and smoke alarms are optical smoke detectors. These contain light-emitting diode (LED), a photocell and a base opening for entrance of smoke particles. In this, a light beam is constantly shoot out

* Correspondence should be addressed to: Arun Singh Pundir, E-mail: asp24.dcs2014@iitr.ac.in

Published online: 26 June 2017

between the LED and photocell, which shows the indication of complete circuit inside the alarm. When fire burst out, smoke enter from the base opening of alarm and interrupt the circuit, which is consider as a condition for triggering the alarm. Fire and smoke detection using these alarms can always give accurate results but there are many disadvantages related to it. Firstly, their vicinity is limited to a room or a hall hence not suitable for detecting wildfire smoke. Secondly, smoke and fire alarms work well when some carbon particle will reach their sensors, then only alarm will be triggered. Hence, it is not feasible to install the alarms in widespread environment area like in forests, hills etc.

While, in case of vision based smoke detection, this technique can detect the smoke instantaneously by capturing the images from surveillance cameras. Surveillance cameras when mounted on a hill top or some mobile tower can cover few kilometers for detection of smoke at an early stage. Another advantage of using such setup is that it is cheaper and easy to install as compared to sensor based detection system.

From the last few decades there have been various methods proposed for video based smoke and fire detection. Since, smoke has very precise characteristics which can distinguish it from other worldly objects like its color, texture and its state of motion. Hence, various motion based model, models based on colors and spatial and temporal features were employed for finding the features of smoke.

In this work, our approach mainly focuses on employing the three main characteristics of smoke that is motion, texture and color of smoke. Background subtraction algorithm is used for extracting the regions of high motion. On that particular region, we find the color based features with two different color sub spaces. LECoP given by Verma et. al. [21] are then employed for extracting not only texture of smoke but also intensity and color of smoke using HSV color space.

One of our main contribution in this work is using DBNs for classification purpose and using LECoP for finding texture and intensity of smoke simultaneously. Also, to the best of our knowledge, deep belief network has never been used for smoke detection.

2. Related Work

2.1. Color or Intensity Based Smoke and Fire Detection

The very first video based techniques that were used to detect video based smoke and fire detection were significantly based on color of smoke and fire. Chen et al. [5] used RGB color model along with disorder measurement for extracting the smoke and fire pixels. They gave decision functions based on the saturation and intensity values of the red component of the RGB model. Qi et al. [20] along with color and motion attributes of fire, also analyzed the time related and space related variation and intensity of fire. They found high frequency component of luminance flicker with the help of time based derivative matrix. They made use of RGB and HSV color space for finding the features of fire in each frame.

Habiboglu et al. [12] adopted Gaussian Mixture Model (GMM) for extracting the motion attributes. Color filtering algorithm was then used to classify the candidate region and non-candidate region for flame. Günay et al. [11] detected the variation in color of fire by enumerating the wavelet transform of the motion based colored region. They applied the Markov model to distinguish between the motion of fire and motion of non-fire moving objects. Phillips et al. [18] created a Gaussian-smoothed color histogram for computing the fire pixels and then found a temporal variations in pixels to discriminate among fire and non-fire pixels. Their main contribution was to give a method which is independent of, or insensitive to camera motion.

Çelik et al. [4] used RGB and HSV color models for smoke detection and implemented YCbCr color space for fire detection. Fuzzy logic concepts were adopted for making classification more accurate and statistical analysis was carried out for extracting different color spaces. Calderara et al. [2] along with motion and color also find the texture of smoke colored regions. The temporal behavior of the smoke was inferred with the help of Mixture of Gaussians (MoG) in wavelet domain. They described the blending function which was used to determine the color based features of smoke and a Bayesian model is defined at block level in which texture features were used to give the complete scenario for global evaluation of the entire frame.

2.2. Motion Based Smoke and Fire Detection

Another feature other than color that characterizes smoke is its state of motion hence motion detection is commonly used in video based smoke detection. For analyzing whether a moving object is smoke or non-smoke, further analysis of the high motion area is needed.Commonly, moving object detection algorithms that were employed by many researchers were optical flow analysis, temporal differencing and background subtraction.

Xu et. al. [23] computed features for motion detection by extracted disorder, growth, local wavelet energy, self-similarity and frequent flicker in boundaries of a moving region and created a normalized joint feature and then employed artificial neural network(ANN) to categories smoke and non-smoke pixels. Piccinini et. al. [19] employed a background suppression approach specifically Statistical And Knowledge-Bases Object Tracker (SAKBOT) to carried out the moving object segmentation. Other techniques such as ghost suppression, object validation and background bootstrapping were carried out for improving the accuracy of segmentation. Kopilovic [15], found that there are irregularities in the motion of smoke hence they considered the non-rigid property of the smoke. Two adjacent regions containing smoke were employed for computing the optical flow, the entropy of the distribution of the motion directions is then estimated to differentiate among smoke and non-smoke.

Vicente et. al. [22] made use of multi-dimensional temporal embedding space which consists of cluster analysis of points, for extracting the local motions which on further used to track local dynamic cluster of pixels. Velocity distribution histogram were used to compute the feature vectors which further employed to differentiate smoke from similar smoke looking objects like as clouds and wind-tossed trees which may create such clusters. Celik et. al. [3] employed adaptive background subtraction method for extracting foreground object information in which color pixel statistics were combined with foreground object information. Adaptive background model was generated with three different Gaussian distributions where pixel statistics were represented by these distributions in the corresponding channel for color. The fire pixels that were contained in the region of high motion were segmented using adaptive background subtraction method.

2.3. Texture Based Smoke Detection

Liu et. al. [16] made use of uniform local binary pattern (ULBP) and the YCbCr color space along with saliency based algorithm for fire detection. Cui et. al. [7] determined the texture of smoke by the fusion of Gray Level Co-occurance Matrices (GLCM) and and wavelet analysis tools. Ye et. al. [24] proposed a new dynamic texture descriptor for smoke detection along with Hidden Markov tree (HTM) and surfacelet transform. Various texture based models have been applied for smoke and fire detection. Apart from static texture, various dynamic texture based techniques [1, 6, 8, 10, 10, 25] has also been used for smoke detection.

3. Proposed Method

The proposed method consists of following major steps:

1. The moving targeted region is determined by using a background subtraction technique.
2. Smoke color detection: the smoke color pixels that are present in the region of high motion are determined by fusing RGB color space and YCbCr color space.
3. For foreground objects region, we have computed the LECoPs that give texture and intensity feature for smoke.
4. Finally, DBN is used for classification of smoke and non-smoke pixels.

The proposed method is shown in Figure 1.

3.1. Moving Target Detection

Background subtraction algorithm specifically frame differencing method [3] is employed for computing the regions of high motion. The key intuition behind using background subtraction technique is that, motion is a specific characteristics of smoke unlike other similar objects like clouds and fog that may be similar in texture and appearance. Therefore, background subtraction method incorporates the important property. The approach behind this algorithm is to detect the moving objects by computing the difference between the current frame and the reference frame. In this method, we have estimated the absolute difference between current image frame I_{n+1} and reference image frame I_n for recursively computing a background image B_{n+1} at time instant $n+1$ is as follows:

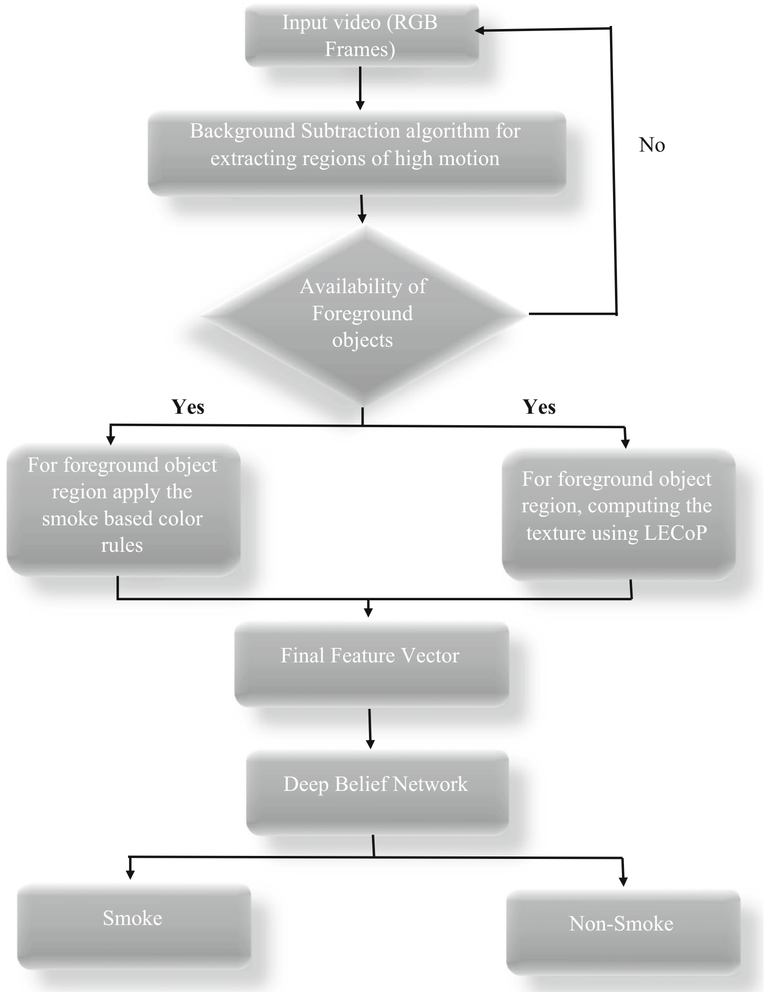

Figure 1. Block diagram of the proposed method.

$$B_{n+1} = |I_{n+1} - I_n| \tag{1}$$

where n is the total number of frames. This motion determining algorithm is not sufficient for deciding the presence of smoke, hence other properties of smoke are also considered like color and texture of smoke. Figure 2 shows the background subtraction method in four different scenarios.

3.2. Color Detection

One of the additive color models, designated by the name of RGB [5, 20], constitutes the combination of true colors (red, blue and green) in a broad range. Rep-

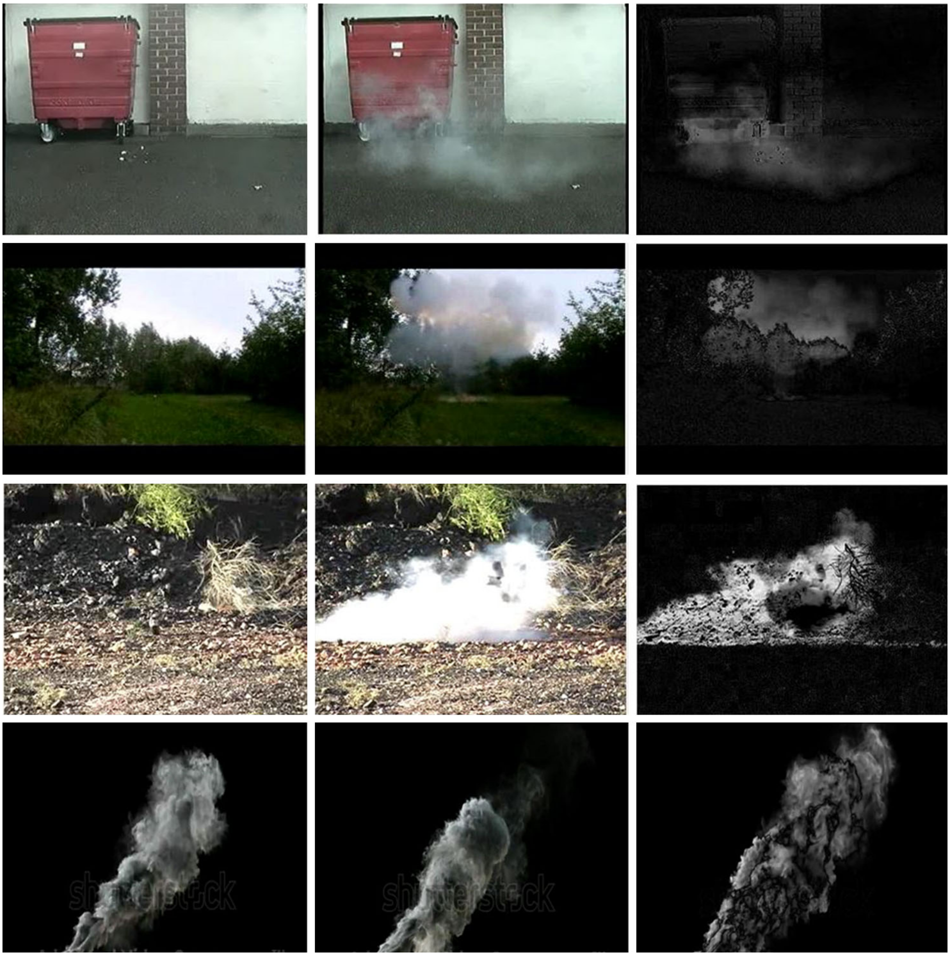

Figure 2. Background subtraction: first column in figure shows reference frames, second column shows the current frames and third column shows the background subtraction.

resentation of images in various electronics systems such as monitors, mobile phones etc. delineates the usage of RGB color model. The effectiveness of RGB color model is intensified with the association of spectral content. While RGB color model is one of the most popular color model and used in many applications, high redundancy and correlation are the problems associated with them. Here, the term correlation refers to stress on luminance information such that coding efficiency is reduced significantly. YCbCr [16] is another color model which is considered to be very closely related to human vision system. Here, luminance and chrominance sensitivity are equally specified and this property of YCbCR model is considered as added advantage over other color models. The three components of YCbCr color model are luminance, chroma-blue and chroma-red represented by Y, Cb and Cr respectively. While the component luminance is well-known, chroma-blue and chroma-red specifies the blue and red differences from luminance respectively.

In our method, we combine the properties from the two different color models to get strong smoke features from different approaches of color spaces. By observing many potential frames in videos, we get the conditions as represented by Equations 2, 3 and 4 in the RGB space,

$$\left|R_{x,y} - G_{x,y}\right| < \tau \tag{2}$$

$$\left|G_{x,y} - B_{x,y}\right| < \tau \tag{3}$$

$$\left|R_{x,y} - B_{x,y}\right| < \tau \tag{4}$$

where τ is a threshold. The value of τ is specified to 20 in our experiment. The above equations are used to find the color of smoke. Hence, after conducting various experiments we found that value 20 of threshold τ detected the grayish color of smoke more efficiently. After this, color based features have been extracted on behalf of Equations 2, 3 and 4.

The details for finding the color features of smoke are:

1. For the moving targeted region, we find the corresponding red, green and blue values that is RGB color space values based on the Equations 2, 3 and 4.
2. Using the above same conditions, we computed the luminance and chrominance values for smoke using the conversion from RGB to YCbCr color space.
3. Now, normalize the values of RGB and YCbCr color space to the range [0,1] by dividing the RGB and YCbCr color space values by 255 to make the vales in the range [0,1].
4. Finally merge the RGB color and the YCbCr color space values into a single feature matrix.

3.3. Texture and Intensity Detection using Local Extrema Co-occurance Patterns

For extracting the eminent features in an image, one of the renowned method in computer vision is texture analysis. Ripples on water, smoke, waving flags etc. are some of the examples of textures. In this paper, we have used LECoP features as given by Verma et al. [21] for determining the texture of the smoke along with HSV color space which is utilizes the intensity, color and brightness of images. LECoP are an improved version version of local binary patterns, LECoP used the local extrema patterns for extracting the local directional information and with the help of gray level co-occurance matrix, feature values are computed.

In LBPs, the center pixel value and its reference neighborhood values are compared based on intensity while in local extrema patterns, edge information is extracted in different directions along with local binary patterns. Pixel values are compared in 0°, 45°, 90° and 135° directions with the center pixel values and if the comparing pixels are in a definite direction that is either greater or less compared to center pixel, have been assigned a value equal to 1. Value 0 is assigned if the comparing pixels have values of opposite nature that is one pixel is less and another is greater than center pixel. Local extrema patterns are calculated as:

$$I_i'(\phi) = P_3(I_k', I_{k+4}') \tag{5}$$

where $k = (1 + \phi/45), \forall_\phi = 0°, 45°, 90°, 135°$ and $I_i' = I_i - I_c$

I_i represents neighboring pixel intensity value and I_c gives intensity value for center pixel.

$$P_3(I_k', I_{k+3}') = \begin{cases} 1 & I_k' \times I_{k+4}' \geq 0 \\ 0 & else \end{cases} \tag{6}$$

$$LEP(I_c) = \sum 2^{\phi/4} \times I_k'(\phi), \forall_\phi = 0°, 45°, 90°, 135° \tag{7}$$

$$H(L)|_{LEP} = \sum_{m=1}^{M} \sum_{n=1}^{N} P_2(LEP(m,n), L), L \in [0, 45] \tag{8}$$

Equation 7 is used to calculate local extrema patterns (LEPs) and Equation 8 compute the histogram of LEPs map and *phi* represents the angle of local extrema patterns.

3.4. Smoke Detection Using Deep Belief Networks

DBN was given by Hinton et al. [14] are high connected probabilistic generative models, having a plenty of hidden layers with strong correlation between them. This significant concept was based on layer-by-layer, greedy algorithm which was learnt in an unsupervised manner.

The basic idea behind DBN is a type of log-linear Markov Random Field (MRF) called Restricted Boltzmann machine (RBM), which treats each inner layer as a RBM. A RBM is a specific type of MRF containing two types of layers, one layer specifically Bernoulli consists of stochastic hidden type and another is stochastic visible layer (specifically Bernoulli or Gaussian). RBM restricts Boltzmann machine to have hidden-hidden and visible-visible connection.

In RBMs, the energy function $E(v, h; \theta)$ is used to describe joint distribution $P(v, h; \theta)$ where v is the visible unit, h is the hidden unit and θ defines the given model parameter. The joint parameters are mathematically described in Equation 9

$$P(v,h;\theta) = \frac{exp(-E(v,h;\theta))}{Z} \tag{9}$$

Here, Z is the normalizing factor or partition function which is mathematically defined as $Z = \sum_v \sum_h exp(-E(v,h,\theta))$ and visible vector v is assigned a marginal probability which is mathematically described as

$$P(v;\theta) = \frac{\sum_h exp(-E(v,h;\theta))}{Z} \tag{10}$$

For RBM, based on Bernoulli (visible) and Bernoulli (hidden), the energy is given by

$$E(v,h;\theta) = -\sum_{i=1}^{V}\sum_{j=1}^{H} w_{ij}v_ih_j - \sum_{i=1}^{V} b_iv_i - \sum_{j=1}^{H} a_jh_j \tag{11}$$

where a_i and b_j are the bias terms and, v_i and h_j are the visible and hidden units respectively while w_{ij} corresponds to symmetric interaction term between v_i and h_j. The conditional probabilities can be mathematically computed as

$$P(h_j = 1|v;\theta) = \sigma(\sum_{i=1}^{V} w_{ij}v_i + a_j) \tag{12}$$

$$P(v_i = 1|h;\theta) = \sigma(\sum_{j=1}^{H} w_{ij}h_j + b_i) \tag{13}$$

where $\sigma(x) = 1/(1 + exp(x))$

Similarly, RBM based on Gaussian-Bernoulli, the energy is computed as:

$$E(v,h;\theta) = -\sum_{i=1}^{V}\sum_{j=1}^{H} w_{ij}v_ih_j + \frac{1}{2}\sum_{i=1}^{V}(v_i - b_i)^2 - \sum_{i=1}^{H} a_ih_j \tag{14}$$

and conditional probabilities to above become:

$$P(h_j = 1|v;\theta) = \sigma(\sum_{i=1}^{V} w_{ij}v_i + a_j) \tag{15}$$

$$P(v_i|h;\theta) = N(\sum_{j=1}^{H} w_{ij}h_j + b_i, 1) \tag{16}$$

where real values are given to v_i and Gaussian distribution is being followed with calculated mean as $\sum_{j=1}^{H} w_{ij}h_j + b_i$ and variance with value one. First Gaussian-

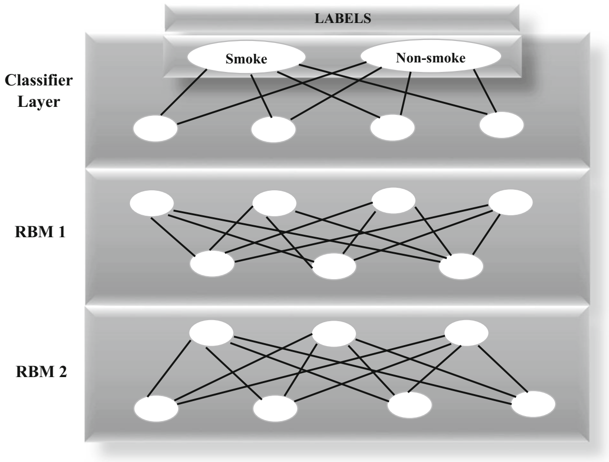

Figure 3. A DBN classifier with two RBM layers.

Bernoulli RBMs were used to build binary stochastic variables, which in term is further refined by using Bernoulli–Bernoulli RBM.

From the decoding prospective, a deep belief network can be seen as a perceptron with many layers that is a multilayer perceptron having many layers. The input frame is processed layer after layer to final layer according to Equation 15, then using softmax operation, its output is converted into a multinomial distribution.

In our method, we use the conventional frame-level DBN to train the weights. Specifically, we follow the method for DBN weight training as mentioned in [13, 14] The method adopted was to train the stack of RBMs and after that all the parameters are fine tuned with the back-propagation algorithm. The deep belief network with two RBM layers is shown in Figure 3.

4. Testing and Analysis

To test the algorithm, the method has been performed on the publicly available dataset from different sources.[1,2,3,4] For convenience in future research, the dataset are gathered and available on author's website.[5]

For purpose of training and testing, 10,000 frames are chosen from 17 videos, out of which 10 videos are smoke containing videos and 7 are non-smoke videos. From smoke containing videos, we have extracted 5000 frames and 5000 frames were taken out from non-smoke videos. Since the dataset consist of 10,000 frames

[1] http://cvpr.kmu.ac.kr/.
[2] http://www.openvisor.org.
[3] http://signal.ee.bilkent.edu.tr/VisiFire/Demo.
[4] https://www.shutterstock.com/video/search/smoke.
[5] https://sites.google.com/site/smokedataset/smokedataset.

Figure 4. Ten smoke videos that are used in our method in which above five are non-wild fire smoke videos and below five are wild-fire videos.

with equal distribution of smoke and non-smoke classes (Figures 4 and 5). Out of which, 70% of the frames has been used for training the system whereas rest of the frames are kept for testing. The selection criteria for both training and testing was such that the frames must be continuous so that the temporal information within the frame is retained and later retrieved as features. These frame sequences were then cropped and labelled as smoke and non-smoke. Now, total 10,000 frames are employed in our method out of which 7000 frames are used for training purpose and 3000 frames are used for testing purpose. The videos that are smoke-containing have different types of smokes ranging from very dense smoke like in wild-fire to very light smoke as in indoor or outdoor smoke. Non-smoke videos have background as similar to smoke-containing videos. The frame rate of the videos is 30 Hz while the size of each input frame is 320×240 pixels. The testing videos are described in Table 1. Figures 5 and 6 shows all the videos employed in the given method.

In most of the literature, researchers normally computed accuracy based at patch-level but in our work, we have evaluated accuracy based on image-level evaluation that is smoke and non-smoke image classification accuracy. Since, there is no standard dataset for smoke detection, we compared our results with two different classifiers of the same category that is Artificial Neural Network

Figure 5. Seven non-smoke videos that are used in our method.

Figure 6. Seven non-smoke videos that are used as a challenging dataset in our method which comprises of clouds, fog, sandstorm and steam.

(ANN) and autoEncoders with DBNs. For implementing ANN, autoEncoders and DBNs, we have utilized the toolboxes as given by Palm et al. [17].

In our experiments, we have used 100 hidden layers for each neural network based classifier and results are shown for different values of epochs. The results of different classifiers on the dataset are shown in Tables 2, 3 and 4 for epoch value 1, 20 and 50 respectively.

Results are shown for 100 hidden units and epoch value 50, DBN based classification give accuracy value of 99.51%. Figures 7, 8 and 9 are shown the total time taken and accuracy for different classifiers using epoch values 1, 20 and 50 respectively.

4.1. Evaluation of Proposed Method on Very Challenging Non-smoke Dataset

In this section, proposed method is evaluated on very challenging non-smoke dataset. These non-smoke videos are very similar to smoke containing videos.

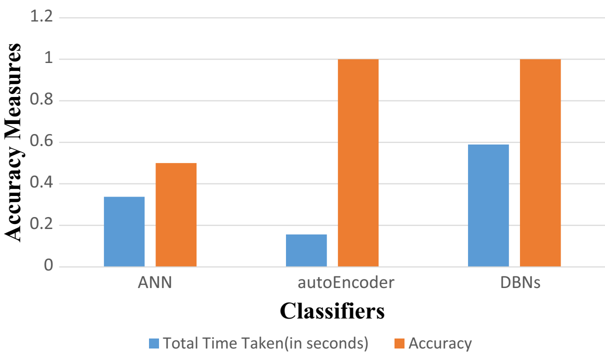

Figure 7. Time And accuracy measure of different classifiers for epoch value 1.

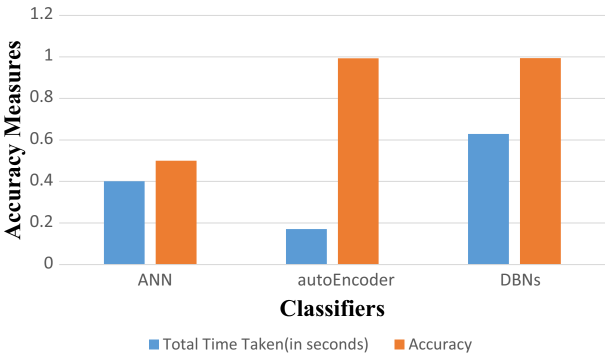

Figure 8. Time And accuracy measure of different classifiers for epoch value 20.

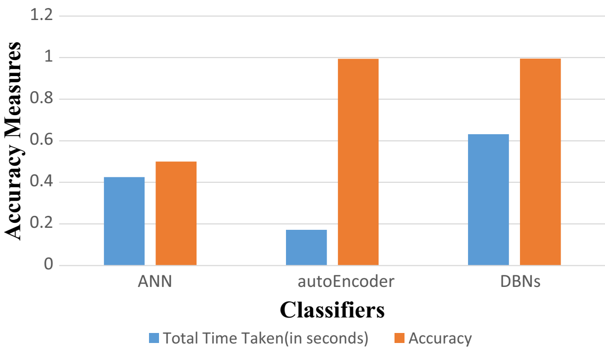

Figure 9. Time And accuracy measure of different classifiers for epoch value 50.

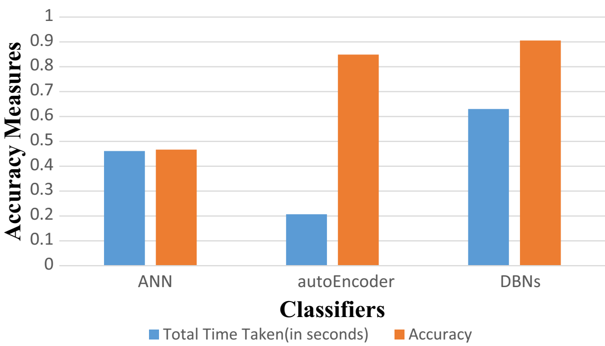

Figure 10. Time And Accuracy measure of different Classifiers on challenging dataset for epoch value 50.

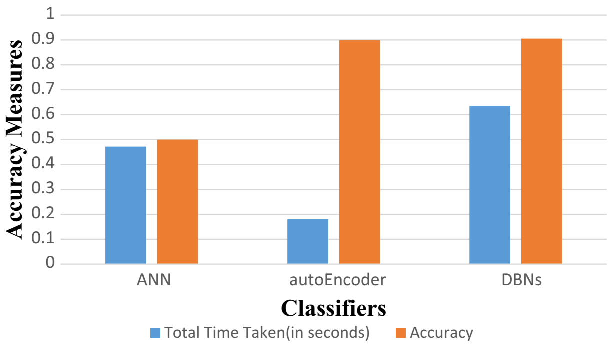

Figure 11. Time And accuracy measure of different classifiers on wildfire smoke for epoch value 50.

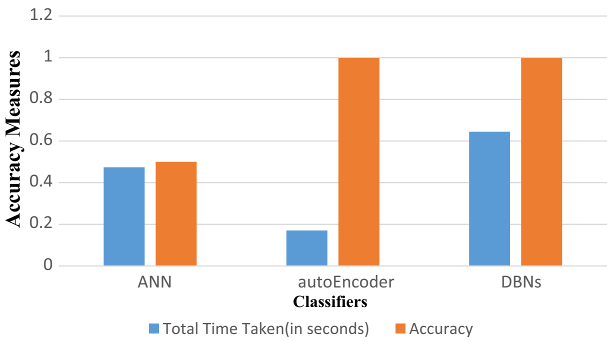

Figure 12. Time And accuracy measure of different classifiers on non-wildfire smoke for epoch value 50.

Table 1
Description of Smoke Containing Videos

Sr. No.	Description
1	Slow diffusion of dark smoke within black room
2	Slow diffusion of smoke from chimney in room
3	Smoke on road
4	Indoor slow spreading near smoke color wall
5	Smoke behind fence where men wearing smoke-color shirt is in motion
6	Very slow diffusion of smoke from a forest
7	Very rapid diffusion of smoke within a forest
8	Sudden smoke diffusion at ground within a forest
9	Wild-fire smoke from a hill top
10	Slow diffusion of smoke from hill foot

Table 2
Comparison of Results for Different Classifiers for Epoch 1

Classifiers	Total time taken (s)	Mini-batch mean squared error	Full-batch train error	Accuracy (%)
ANN	0.33773	0.489920	0.500000	50.00
autoEncoders	0.15624	0.0040993	0.004873	99.01
DBNs	**0.58928**	**0.0059987**	**0.000000**	**99.27**

The bold font depicts the performance of the system using our proposed methodology

Table 3
Comparison of Results for Different Classifiers for Epoch 20

Classifiers	Total time taken (s)	Mini-batch mean squared error	Full-batch train error	Accuracy (%)
ANN	0.40087	0.4893700	0.500000	50.00
autoEncoders	0.17034	0.0052808	0.004426	99.31
DBNs	**0.62859**	**0.0039561**	**0.000000**	**99.42**

The bold font depicts the performance of the system using our proposed methodology

Table 4
Comparison of Results for Different Classifiers for Epoch 50

Classifiers	Total time taken (s)	Mini-batch mean squared error	Full-batch train error	Accuracy (%)
ANN	0.42511	0.4854800	0.500000	50.00
autoEncoders	0.17137	0.0043302	0.003622	99.45
DBNs	**0.63113**	**0.0086365**	**0.000000**	**99.51**

The bold font depicts the performance of the system using our proposed methodology

Table 5
Evaluation of Proposed Method on Very Challenging Non-Smoke Dataset for Epoch 50

Classifiers	Total time taken (s)	Mini-batch mean squared error	Full-batch train error	Accuracy (%)
ANN	0.46116	0.485001	0.533323	46.67
autoEncoders	0.20671	0.154090	0.150892	84.91
DBNs	**0.63007**	**0.129900**	**0.090571**	**90.57**

The bold font depicts the performance of the system using our proposed methodology

Table 6
Evaluation of Wildfire Smoke Detection Accuracy for Epoch 50

Classifiers	Total time taken (s)	Mini-batch mean squared error	Full-batch train error	Accuracy (%)
ANN	0.47179	0.4759901	0.500000	50.00
autoEncoders	0.17993	0.0043177	0.003563	99.03
DBNs	**0.63551**	**0.0081879**	**0.000000**	**99.10**

The bold font depicts the performance of the system using our proposed methodology

Table 7
Evaluation of Near Distance Smoke Detection Accuracy for Epoch 50

Classifiers	Total time taken (s)	Mini-batch mean squared error	Full-batch train error	Accuracy (%)
ANN	0.47361	0.4852133	0.500000	50.00
autoEncoders	0.17030	0.0044711	0.003598	99.87
DBNs	**0.64431**	**0.0087636**	**0.000000**	**99.92**

The bold font depicts the performance of the system using our proposed methodology

Such videos comprise of fog, steam, sand storm and clouds. In this scenario, we have also follow the same procedure for training and testing as done in previous sections. Results for this section are shown in Table 5. Figure 10 shown the total time taken and accuracy for different classifiers using epoch valve 50 on this dataset. Results evaluated on this dataset indicate that there is reduction in accuracy since our method cannot differentiate between steam and smoke as both form have same color, texture and motion. While in other cases, like fog, cloud and sandstorm, our method perform well. This is because of an additional property of smoke that it is always in state of motion.

4.2. Accuracy Measures for Wildfire Smoke and Near-Distance Smoke Detection

In this scenario, we employed five videos of wildfire smoke and seven are non-smoke videos. From wildfire smoke videos, we incorporated 5000 frames and 5000 frames were extracted from non-smoke videos. These frames are consecutively taken out so that we can acquire the temporal information from the previous frame about regions of high motion. These frame sequences were then cropped and labelled as smoke and non-smoke. Hence, total 10000 frames are used in our method out of which 7000 frames are used for training purpose and 3000 frames are used for testing purpose. Similarly, we have follow the same procedure for near distance uncontrolled smoke. The results for this section are shown in Tables 6 and 7. Figures 11 and 12 have shown the total time taken and accuracy for different classifiers using epoch value 50 on wildfire and non-wildfire smoke respectively.

5. Conclusion

This paper proposes a system capable of detecting smoke based regions using a DBN. The three crucial features of smoke that is color, motion and texture have been employed to detect smoke based regions. The method can also be extended to fire detection and is robust enough for real time implementations. The superiority of proposed technique in comparison to other smoke detection techniques is that this method gives a classification accuracy of 99.51%.

References

1. Amiaz T, Fazekas S, Chetverikov D, Kiryati N (2007) Detecting regions of dynamic texture. In: International conference on scale space and variational methods in computer vision, pp 848–859. Springer
2. Calderara S, Piccinini P, Cucchiara R (2008) Smoke detection in video surveillance: a mog model in the wavelet domain. In: International conference on computer vision systems, pp. 119–128. Springer
3. Celik T, Demirel H, Ozkaramanli H, Uyguroglu M (2007) Fire detection using statistical color model in video sequences. J Vis Commun Image Represent 18(2):176–185. doi:10.1016/j.jvcir.2006.12.003
4. Çelik T, Ozkaramanli H, Demirel H (2007) Fire and smoke detection without sensors: image processing based approach. In: Signal processing conference, 15th European. Citeseer
5. Chen J, He Y, Wang J (2010) Multi-feature fusion based fast video flame detection. Build Environ 45(5):1113–1122. doi:10.1016/j.buildenv.2009.10.017
6. Chetverikov D, Péteri R (2005) A brief survey of dynamic texture description and recognition. In: Computer recognition systems pp 17–26. Springer
7. Cui Y, Dong H, Zhou E (2008) An early fire detection method based on smoke texture analysis and discrimination. In: Image and signal processing, congress on, vol 3, pp 95–99. IEEE
8. Doretto G, Chiuso A, Wu YN, Soatto S (2003) Dynamic textures. Int J Comput Vis 51(2):91–109. doi:10.1023/A:1021669406132
9. Enis Cetin A, Porikli F (2011) Special issue on dynamic textures in video. Mach Vis Appl 22(5):739–740. doi:10.1007/s00138-011-0325-0
10. Fazekas S, Amiaz T, Chetverikov D, Kiryati N (2009) Dynamic texture detection based on motion analysis. Int J Comput Vis 82(1):48–63. doi:10.1007/s11263-008-0184-y
11. Günay O, Taşdemir K, Töreyin BU, Çetin AE (2010) Fire detection in video using lms based active learning. Fire Technol 46(3):551–577. doi:10.1007/s10694-009-0106-8
12. Habiboglu YH, Gunay O, Cetin AE (2011) Real-time wildfire detection using correlation descriptors. In: Signal processing conference, 19th European, pp 894–898. IEEE
13. Hinton GE, Osindero S, Teh YW (2006) A fast learning algorithm for deep belief nets. Neural Comput 18(7):1527–1554
14. Hinton GE, Salakhutdinov RR (2006) Reducing the dimensionality of data with neural networks. Science 313(5786):504–507
15. Kopilovic I, Vagvolgyi B, Szirányi T (2000) Application of panoramic annular lens for motion analysis tasks: surveillance and smoke detection. In: Conference on pattern recognition, 15th international, vol 4, pp 714–717. IEEE

16. Liu ZG, Yang Y, Ji XH (2016) Flame detection algorithm based on a saliency detection technique and the uniform local binary pattern in the ycbcr color space. Signal Image Video Process 10(2):277–284. doi:10.1007/s11760-014-0738-0
17. Palm RB (2012) Prediction as a candidate for learning deep hierarchical models of data. Technical University of Denmark, p 5
18. Phillips Iii W, Shah M, da Vitoria Lobo N (2002) Flame recognition in video. Pattern Recognit Lett 23(1):319–327. doi:10.1016/S0167-8655(01)00135-0
19. Piccinini P, Calderara S, Cucchiara R (2008) Reliable smoke detection in the domains of image energy and color. In: Conference on image processing, 15th international, pp 1376–1379. IEEE
20. Qi X, Ebert J (2009) A computer vision based method for fire detection in color videos. Int J Imag 2(S09):22–34
21. Verma M, Raman B, Murala S (2015) Local extrema co-occurrence pattern for color and texture image retrieval. Neurocomputing 165:255–269
22. Vicente J, Guillemant P (2002) An image processing technique for automatically detecting forest fire. Int J Thermal Sci 41(12):1113–1120. doi:10.1016/S1290-0729(02)01397-2
23. Xu Z, Xu J (2007) Automatic fire smoke detection based on image visual features. In: International conference on computational intelligence and security workshops, CISW, pp 316–319. IEEE
24. Ye W, Zhao J, Wang S, Wang Y, Zhang D, Yuan Z (2015) Dynamic texture based smoke detection using surfacelet transform and hmt model. Fire Saf J 73:91–101
25. Yuan F (2011) Video-based smoke detection with histogram sequence of lbp and lbpv pyramids. Fire Saf J 46(3):132–139. doi:10.1016/j.firesaf.2011.01.001