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A Novel Approach for Video based Fire Detection System using Spatial and Texture Analysis

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Abstract

Objectives: A novel video based fire detection algorithm based on rule base technique using RGB and HSV color space and spatial analysis based on wavelet analysis is proposed. **Methods/Statistical Analysis**: Rule base technique utilizing RGB and HSV color space for extraction of fire pixels in the frame was used. Threshold based spatial energy methodology is used for differentiating fire and fire like objects. Wavelet analysis is performed for calculation of spatial energy. Texture analysis using Local Binary Pattern (LBP) is also performed when fire or fire like candidate having spatial energy near to threshold of fire pixel. **Findings:** The usage of RGB color space alone for identification of fire in the video frames is not sufficient as they suffer from false detection. Two novel rules based on HSV plane is proposed which have improved the detection ability of system when compare to previous studies. But still suffers from false detection. Spatial energy methodology based on differentiating fire and fire like objects performs well and has achieved greater efficiency with low false detection rate of 4% on standard datasets. Texture analysis using Local Binary Pattern (LBP) is also performed in rare case when fire candidate is having spatial energy near to that of fire like object category. This has helped in reducing the computational complexity of the system. The system shows 100% accurate results. **Improvements:** The results obtained for different standard datasets using the proposed hybrid spatial and texture base analysis shows 100% accuracy with zero false positive and false negative rates which is not observed in any of the present articles.

Keywords: Fire Detection, Local Binary Pattern (LBP), Spatial Analysis, Texture Analysis, Wavelet Analysis

1. Introduction

Fire is a boon to human society but is also causes loss of economy and ecological damage frequently in every part of world. On February 14, 2016 fire broke in Knitwear Company in Ludhiana, which causes lose in corers of rupees. 25 people were killed when fire broke out in furniture factory in Egypt on 15th July 2015. Thus fire detection has become a burning issue especially in public places for safety. There is need of monitoring devices, which will detect fire in early stages. Fire detection using smoke sensor doesn't tell the amount of fire spread and its reaction time is late. Anything visuals are more reliable as compared to others. Hence during last decade fire detection through video has gained attentions of researchers. Cameras are very common in public places. CCTV camera having automatic fire detection systems will also save additional installation of systems for fire detection[1]. Fire has different characteristics. It may be from red to blue. Fire detection using video suffers from challenges to differentiate between fire and fire like candidate. Aim of this study is to present a robust fire detection system with low false positive rate.

1.1 Research Methodology

Fire detection has become an important part of research since last decade. A three step fire detection algorithm for

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forest fire detection is proposed[2]. Region segmentation is performed to segment fire from elements of forest using Fast Fourier Transform (FFT). Variations of segmented region are observed using DFT and wavelet transform to differentiate between fire and non-fire region. Flame flicker having 10 Hz as characteristics frequency is selected as fire region. A pixel intensity based fire detection method is proposed by utilizing lookup table[3]. Lookup table is created using k-means clustering consist of standard deviation and centroid of RGB channel. Based on this lookup table, fire candidates are predicted. To rectify false detection histogram analysis of red channel is performed. It is observed that majority of histogram is concentrated on right hand side. Accuracy of this system was found to be 83%. Markov model (HMMs) is utilized to distinguish between flame and non-flame portion of fire regions[4]. Wavelet analysis |W (n)| is performed. Two thresholds T1 and T2 are selected for deciding the present state of HMMs. Although results still suffers from false detection but better results were observed compared to existing methods. Fire detection is performed by identifying irregular boundaries and spatial wavelet analysis of fire flame[5]. Statistical data like energy, entropy, contrast, correlation and inverse difference moment is calculated along with local binary pattern to detect region of fire. Efficient result is observed but having higher computational cost[6]. Class conditional probability density function for flame identification is utilized for fire detection[7]. RGB color space base rule modeled is also combined to make the decision. Region growing is performed to find out whole flame region. False detection is observed in the result which is shown in latter part of paper. Statistical (energy, entropy, contrast, homogeneity) analysis along with color space based rule analysis is also useful for fire flame detection[8]. RGB as well as HSV plane is used. Results show better flame detection when compared to existing one at that time. Smoke variation pattern is analyzed[9] using spatial-temporal analysis using db4 wavelet transform. A different algorithm is developed especially for detection of outdoor smoke. Fire classification from background can be performed using Support Vector Machine (SVM)[10]. Feature vector contain 7 parameter is calculated before classification. These featured vector consists of results from color space and statistical (energy, entropy) analysis. This algorithm is having a reduced false detection of fire pixel. Rule based algorithm using RGB, YCrCb color space containing 9 rules have been made to identify fire pixel along with region growing operation[11]. Correlation is used as classifier. False negative classification was observed in result of proposed algorithm. A spatial-temporal flame modeling along with dynamic texture analysis for fire detection[12]. The proposed algorithm shows zero false positive rates. But this suffers from a high computational complexity.

2. Proposed Algorithm

This study proposes a video based fire detection system. From the literature reports, a fire detection can be divided into: i) rule base techniques; ii) Statistical and texture based techniques; iii) Spatial based techniques. Conventional rule based algorithm, based on color appearance, is computationally less complex but suffers from high false positive rate. Statistical based techniques are on higher side of complexity and even though after involving different parameter (energy, entropy, heterogeneity, etc.) these techniques are unable to remove false alarm in many cases which is shown in later half (Figure 4c). On other hand spatial analysis and texture analysis shows successful results in literature and removes false positive rate when compared to color space dependent rule base algorithm. But both of algorithm are computationally complex especially texture analysis. The main aims of the system are as follows.

1. Proposed system tries to develop a system which is less complex. Rule based fire detection algorithm system along with spatial variation analysis is considered. As fire is continuously keep on changing hence moving object detection is taken as first step.
2. Rules based system using RGB and HSV color spaces have been applied to mark out fire like pixels. The main aim behind using rule base algorithm was to reduce the operational space during spatial variation analysis. As many objects like sun, materials have same appearance as that of fire. Hence further analysis is required.
3. To avoid false detection due to rule base system further analysis is required. Spatial variation analysis using wavelet filter is performed to improve the detection rate. It is observed that fire have more spatial energy compared to materials with fire like appearance. Thus calculation of spatial energy will help to avoid false detection.
4. Fire continuously changes from time to time. Hence fire can be seen as texture which continuously changes

hence can be also known as dynamic texture. This makes fire detection possible by using dynamic texture analysis. Local Binary Pattern (LBP) has been used to perform texture analysis. SVM classifier has been used as classifier. As texture analysis is complex hence it is avoided in many cases. Texture analysis is performed only in special cases which are discussed later.

5. The main aim of the proposed algorithm was to remove false positive rate along with higher efficiency.

Figure 1 shows the flowchart for the proposed algorithm. It must be noted that there was no moving object detection in the case when only single images were taken. Rest of the operation remains the same.

2.1 Moving Object Detection

Fire pattern keeps on changing from time to time. Its pixel values also keep on changing. This property can be utilized to differentiate fire from the background. The background is created using Adaptive median method; frame subtraction is performed to identify moving region[12]. Creation of background will add further complexity in algorithm. Another difficulty associated is that if fire is there for longer period of time then fire is taken as part of background only. Frame difference between every 10th frames have been calculated which is shown in Figure 2. Frame difference is been converted into binary image using Otsu's threshold method. The created mask is being taken as moving region.

Now next step is to identify fire in the mask created after background subtraction. This step will reduce the search space and hence also reduce the computational time of the system.

2.2 Rule Base Analysis

Rule base analysis in RGB color space domain is the very first approach that can be was find in various literature[10,11,13–21]. Our initial step was to identify fire like pixels in the moving part of frame. Based on observed color of fire two rules have been made to decide the fire pixel candidate.

Rule 1:- R[1](p, q) = 1 ; if I(p,q,1) > I(p,q,2)>I(p,q,3) (1)
Else R [1] (p, q) = 0;

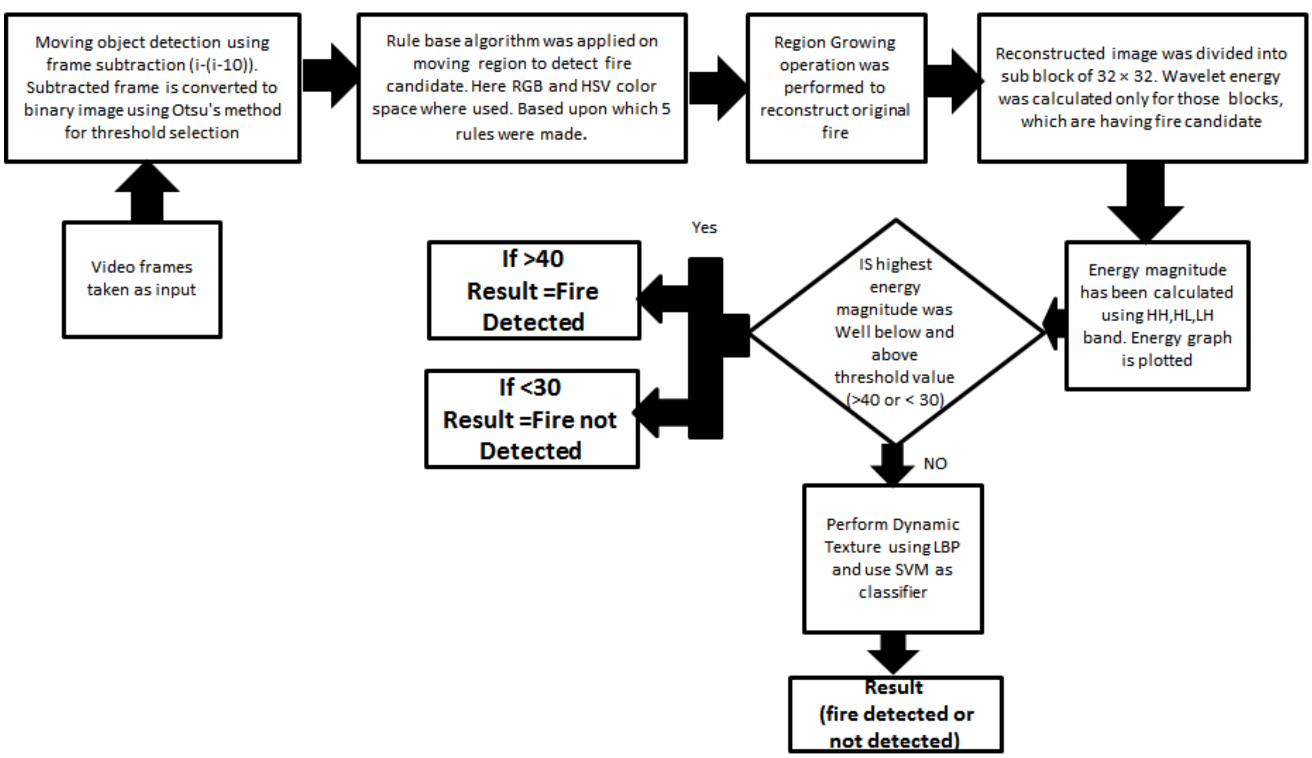
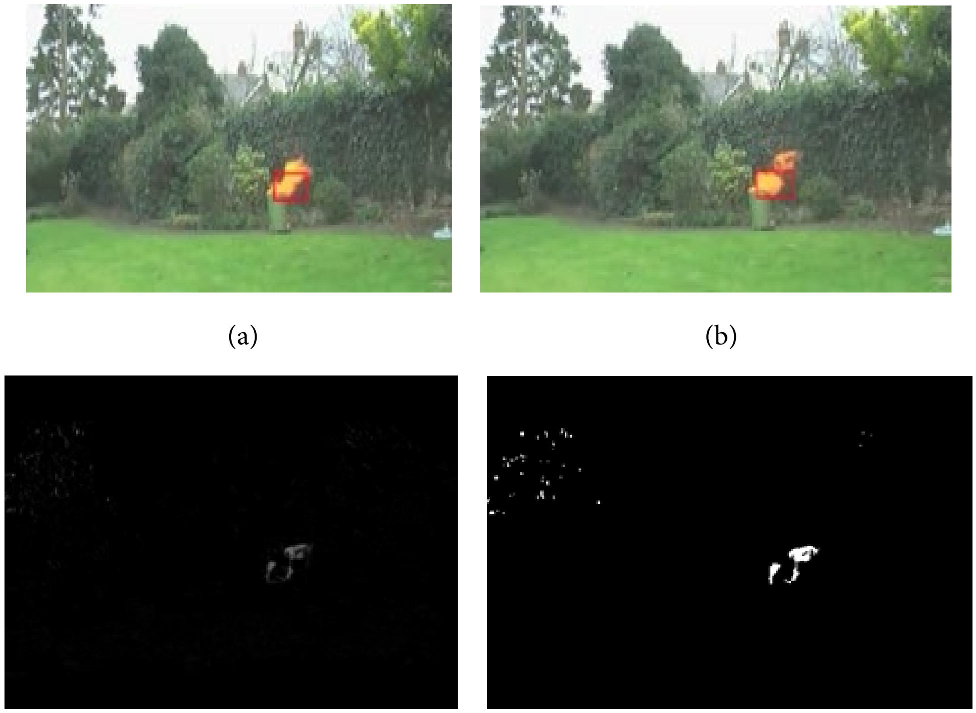


Figure 1. Flowchart for proposed algorithm.



(a) (b) (c) (d)

Figure 2. (a) and (b) Frame from video; (c) Frame difference (d) Results After applying Otsu's threshold method.

Where I (p, q) represents pixel value of RGB image (1 for red, 2 for green, 3 for blue plane)

Rule 2:- R[2](p, q) =1; if I(p,q,1) > 140 && I(p,q,2)> 80 && I(p,q,3) <150 (2)
Else R [2](p, q) = 0;

Where I (p, q) represents pixel value of RGB image

R (p, q)=1; if R[2](p, q) && R[1](p,q) = 1; else 0; (3)

The mask R (p, q) is created and it is used to predict fire candidate. If value of pixel is 1 then that pixel is predicted as fire. The result after applying Rule 1 and 2 is shown in images.

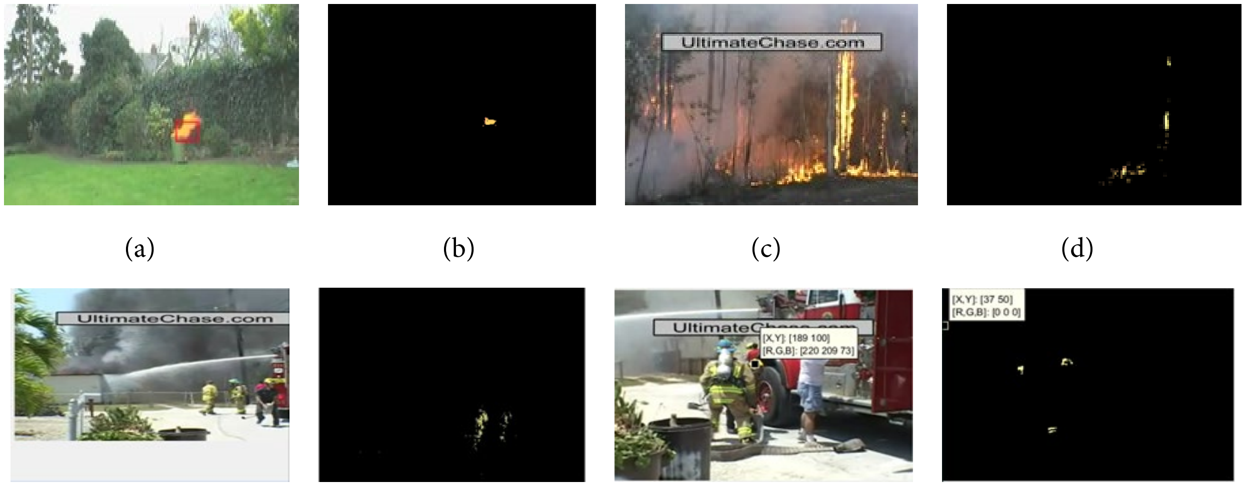
Detection of fire using only RGB color space led to false detection. As in daily life many things have same appearance as that of fire, for example object having reddish color like bag, wall, sun etc. Figure 3 shows the result by applying rule base algorithm for fire detection using RGB color space.

Here person was takes as fire image after applying rule based algorithm on RGB color space. These make RGB color space as not a reliable method for color detection. If we change the rule and set up higher threshold then it is observed that some fire pixels in frames are left out which will affect the accuracy of the system in further assessment. Hence other color space like HSV, YCrCb can be looked as replacement. To increase the accuracy, HSV color space is involved along with RGB for fire detection. It is observed that the fire in HSV plane is having higher value of luminance ('V'-plane). Using this property along with saturation value is used to filter out the fire pixels along with RGB color space. Based upon HSV color space, two novel new rules are introduced. These are given by rule 3 & 4.

Rule 3:- R[3](p, q) =1; if Im(p,q,2) > ((255- I(p,q,1)) × avg_s)/avr_r (3)
Else R [3](p, q) =0;

Where avg_s & a vr_r are the average value of saturation in HSV and Red in RGB color space

Rule 4:- R [4] (p, q) =1; if Im(p,q,2) < .65 (on scale of 1) (4)
Else R [4](p,q) =0;



(a) (b) (c) (d)

(e) (f) (g) (h)

Figure 3. (a), (c), (e) and (f) Frame having fire and fire like candidate; (b), (d), (f) and (h) Results after applying RGB color space.

Where im(p,q,2) represents pixel value of S plane in HSV colour space

Rule 5:- R[4](p, q) =1; if Im(p,q,3) > .97 (on scale of 1) (5)
Else R[4](p,q) =0;

Where im(p,q,3) represents pixel value of V plane in HSV colour space

R(p, q)=1; if (R[2](p, q) && R[1](p,q) && R[3](p, q) && R[4](p, q) && R[5](p, q))= 1; (6)
Else R (p, q)= 0;

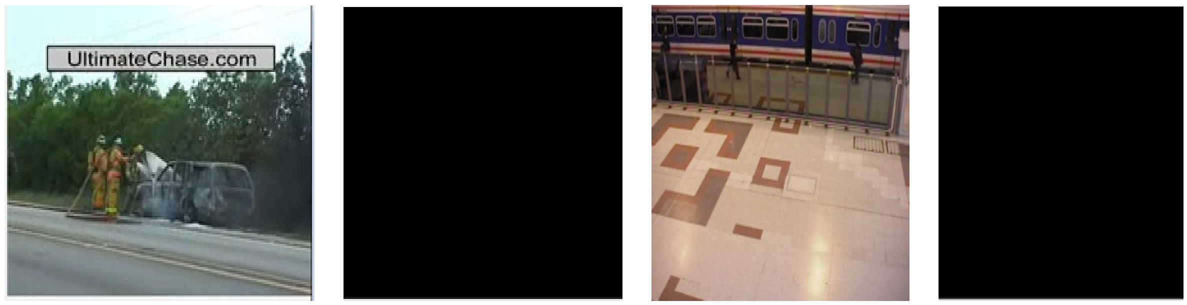
Results after applying rules 1-6 in HSV and RGB color space can be identified in Figures 4,5 and 5. It is observed that the system is able to eliminate false color pixel quiet efficiently when compared to earlier proposed methodology (Figure 4(c)).

2.3 Region Growing

From Figure 3(b) it can be observed that due to frame subtraction and rule based algorithm the fire candidate pixels are reduced than that of actual fire. This may lead to reduce the accuracy of systems. Hence it is required to

(a) (b) (c)

Figure 4. (a) Frame having Fire and fire like candidate (b) Results After applying HSV and RGB color space here false fire candidate is removed when compared to (c); (c) Result of algorithm proposed by [21].



(a) (b) (c) (d)

Figure 5. (a) And (c) Frame having Fire and fire like candidate (b) and (d) Results after applying HSV and RGB color space.

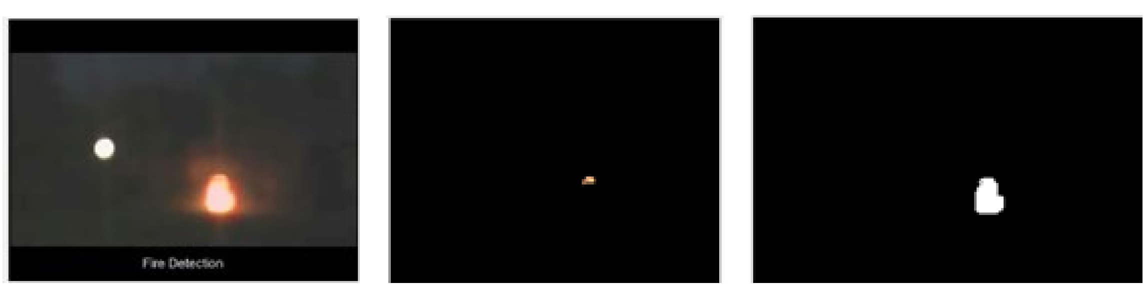
reconstruct the actual fire area. Region growing operation is applied. To decide seed point brightest pixel is picked. The fire pixel having value of red plane more than 251 and green value more than 170 is taken as seed point. It is very important to decide the threshold for performing region growing. Small threshold may lead to half reconstruction of fire region. High threshold value may reconstruct background part also as fire region. For this paper, threshold was varied from 0.010 to 0.020 (on scale of 1). Threshold value is decided depending upon count of fire candidate pixels. For high count low threshold value (.010) is used and for low count higher threshold value (.02) is selected.

Figure 6 shows result after region growing. It can be observed that almost all fire region is reconstructed after region growing operation. Figure 6(b) also proves the robustness of the system where torch light which may act as fire candidate is eliminated after rule base operation.

From the result of Figure 7 (b, d) we can observed that even after using rule base algorithm, there is still chance of false detection. Hence further analysis is required to remove false detection. Hence we have decided to follow spatial analysis on fire candidate to remove false alarm.

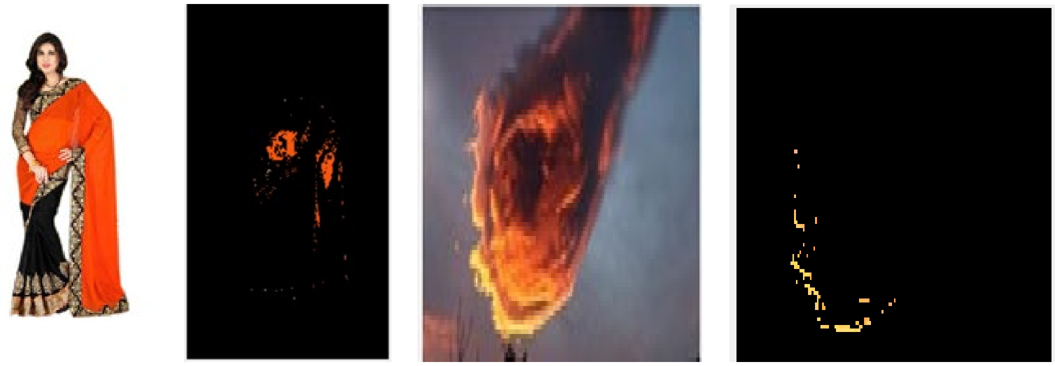
2.4 Spatial Analysis using Wavelet

Fire has a unique property to be kept on changing from one instance to another. Thus its spatial characteristics also changes simultaneously. This variation can also be seen as distinguishable features. Edge detection method is also used to identify spatial variation. Wavelet analysis has been used to detect fire flames[12]. Fourier descriptor along with wavelet transform for finding out the variations[2]. Variance has been calculated to detect fire region. It is observed that region belonging to fire shows high variance when compared to background. This paper also used wavelet analysis for finding out the variations in spatial domain. On previous work it is observed that wavelet analysis is performed on whole image. This will cause the computation cost on higher end, this paper performs spatial analysis only on fire candidate region. This will reduce



(a) (b) (c)

Figure 6. (a) Fire and torch light in same frame (b) After applying HSV and RGB color space rules (c) Mask of fire candidate region after region growing.



(a) (b) (c) (d)

Figure 7. (a) and (c) Fire like candidate (b) & (d) Results after applying RGB color space rules.

the computation. Simple wavelet filter is selected to compute wavelet transform. Filter value selected for low pass filter and high pass filter are (.25, .5, .25) and (-.25, .5, -.25). Fire has a tendency to keep changing with respect to time and due to its irregular shape. It is desire to retain high frequency components of the image. Spatial energy for pixel i,j has been calculated by

$$E(i,j)= HH(i,j)^2 + HL(i,j)^2 + LH(i,j)^2 \qquad (7)$$

Where E(i,j) is spatial energy of pixel i,j, HH,HL,LH represent the high-high, high-low and low-high band of wavelet transform of fire region. Total energy of block is the mean of addition of all the pixel energy.

$$E(x) = \sum_{\substack{1\le i\le m \\ 1<j<n}} \mathrm{E}(\mathrm{i},\mathrm{j}) E(x) = \qquad (8)$$

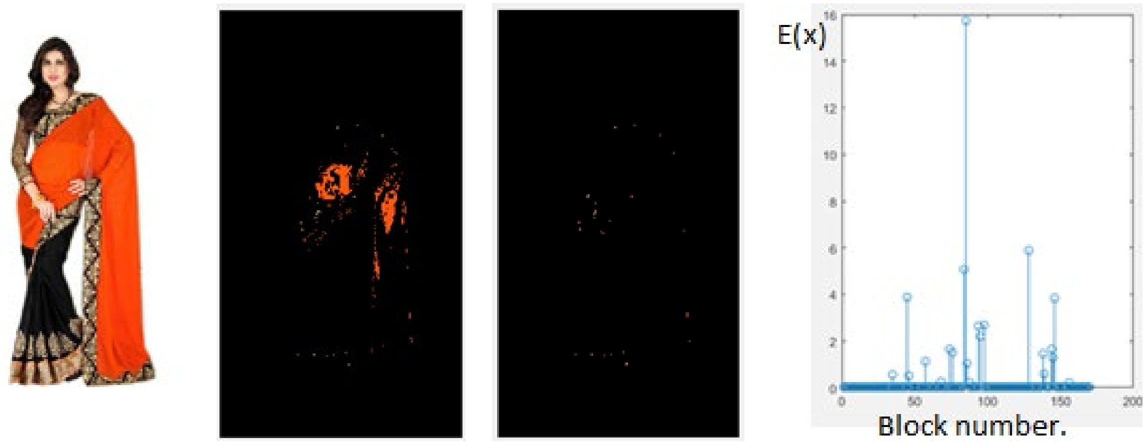
E(x) is the energy of the block X. Here n and m are size of block (n=32, m=32)

Figures 8-10 shows the result of result of spatial analysis. Initially fire candidate is estimated from the rule based algorithm and then the image is divided into a block of 32 × 32 and energy of each block is calculated and plotted.bv.

Conclusion can be drawn from Figures 8-10 that, block energy belongs to fire pixel is higher when compared to pixels from fire like object. This spatial analysis will play an important role to remove false fire candidate. From the experiments it is decided that block is declared as fire if energy is more than threshold value of 35. When it comes to video, same algorithm is applied on individual image. Algorithm is applied to every 10th consecutive frame of video. For spatial analysis the frame contains fire candidate after rule base algorithm and region growing is considered for spatial wavelet analysis. Single frame is divided into block of 32 x32 pixels. Wavelet filter is applied to block which contains fire candidate. Corresponding energy is calculated. Each frame contains many block, block having highest energy magnitude when compared to other block is considered as energy magnitude of

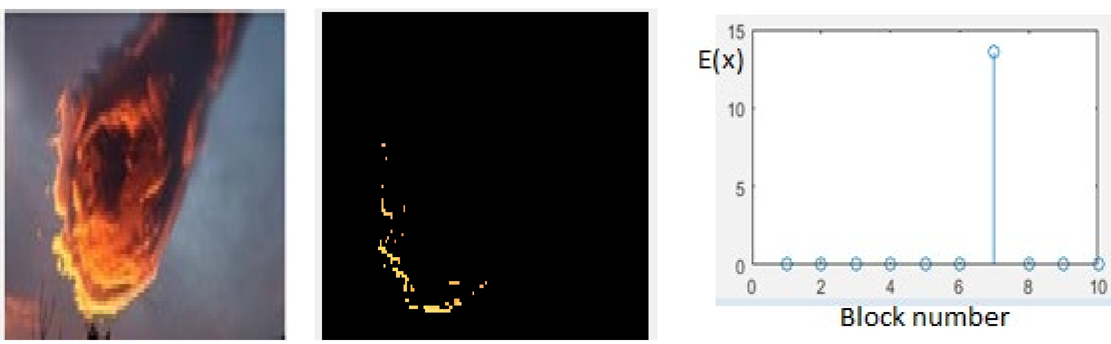
(a) (b) (c)

Figure 8. (a) Fire frame (b) After applying HSV and RGB color space rules (c) Energy of 32× 32 blocks is plotted, it can be seen that fire region is having energy varies from 30 to 45(ii region) and non-fire having range below 30 (region i).



(a) (b) (c) (d)

Figure 9. (a) Fire like candidate (b) Results after applying RGB color space rules (c) After applying HSV and RGB color space (d) Energy of different block of images using wavelet transform.



(a) (b) (c)

Figure 10. (a) Fire like candidate (b) After applying HSV and RGB color space (c) Energy of different block of images using wavelet transform.

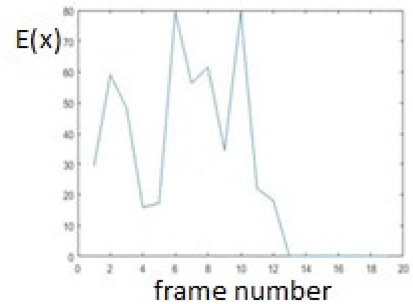
that frame. This is performed due to observation during the test that highest energy block was most likely to be belongs to fire region. Using this philosophy energy is plotted for whole video considering single energy value representing each frame.

Figure 11 shows the energy graph of video. It is observed that the right hand side of graph is zero this is due to fact that second half do not contains fire but contains fire like content (figure 3(e and g). This show how effective is the system towards elimination of false alarming situation. Other video and their results are shown in Figures 12 and 13. Video from Pets database[22] is also taken as in this database the frame contains reddish colors and represents daily life situation which is necessary to check for robustness of algorithm. It must be noted that in energy graph, X-axis represents the frame number of video and Y-axis represents the magnitude of energy (E(x)) for the corresponding frame. The actual frame in video was more than shown in graph due to fact that, algorithm was applied on every 10th consecutive frame.

It can be observed from the graph (Figure 13(a - j)) of all the video corresponding to fire is having energy well above threshold which is 35. On other hand for Pets Data set[23] which do not contain fire is having energy well below the threshold (Figure 13 (h and i)).

From Figure 14, it is observed that the energy on later part which corresponds to frames contains sun and reflections have lower magnitude when compared to right hand side which represents actual fire.

From the result of Figure 15 (a, b) it can be observed that energy associated with frame containing fire is quite less and it just crosses the threshold. In actual scenario it may happen that frame containing fire may be missed due to low value of energy. This happens because energy



(a) (b)

Figure 11. (a) Video from ultimatechase.com (Burning_ Vehicles_ Stream) Frame (b) Results after applying color space rule and its energy representation.

Boat_ Fire_ Stream Controlled_ Burn_ Stream controlled3 Controlled_ Burn_ Stream

forest_2

forest_4

Extreme_ Fire_ Scenes_ Stream

Object Tracking (PETS 2006)

Pets 2006

Ranch_ Fire_ Stream

Figure 12. Name of video taken to test the algorithm[22].

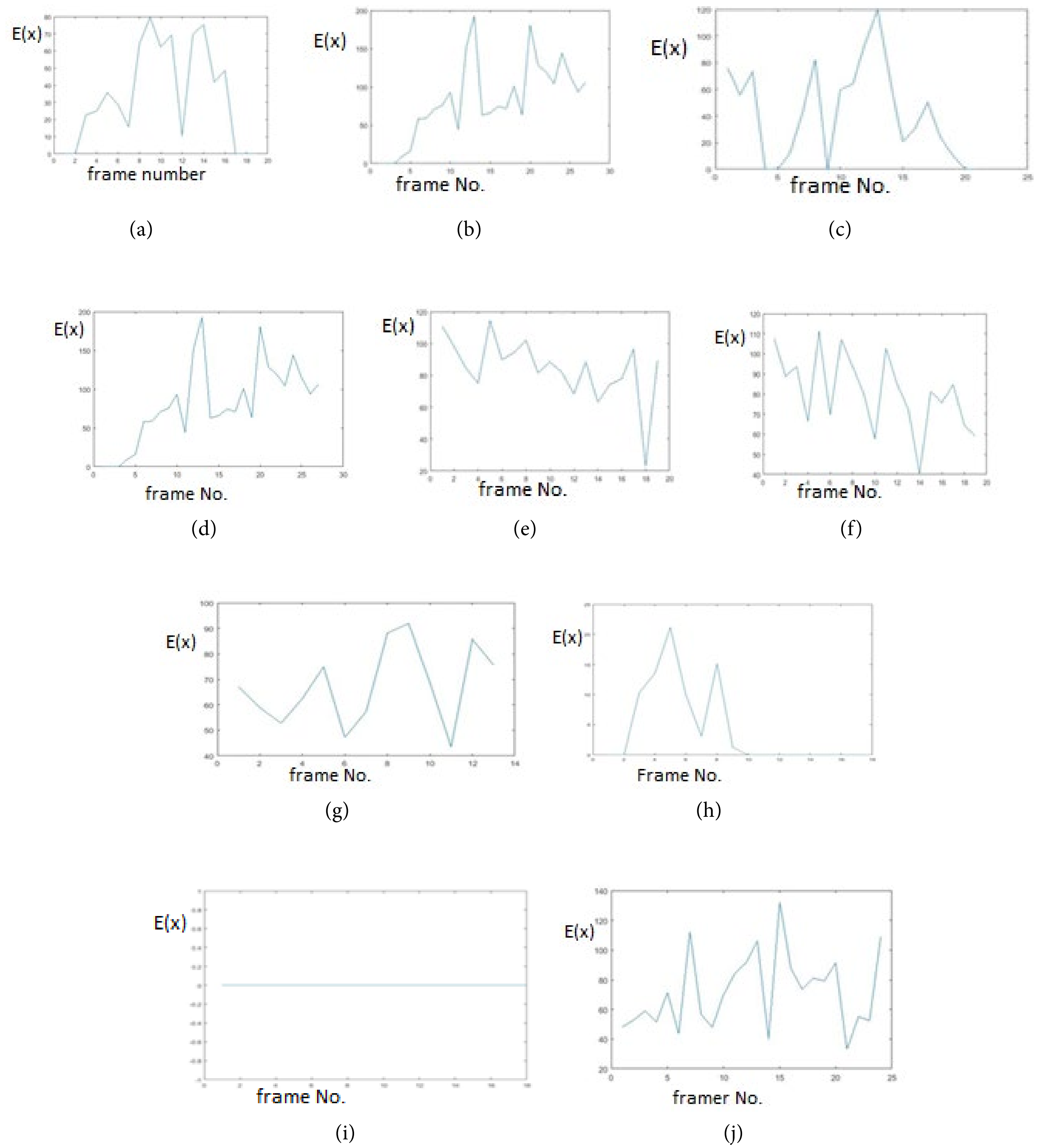
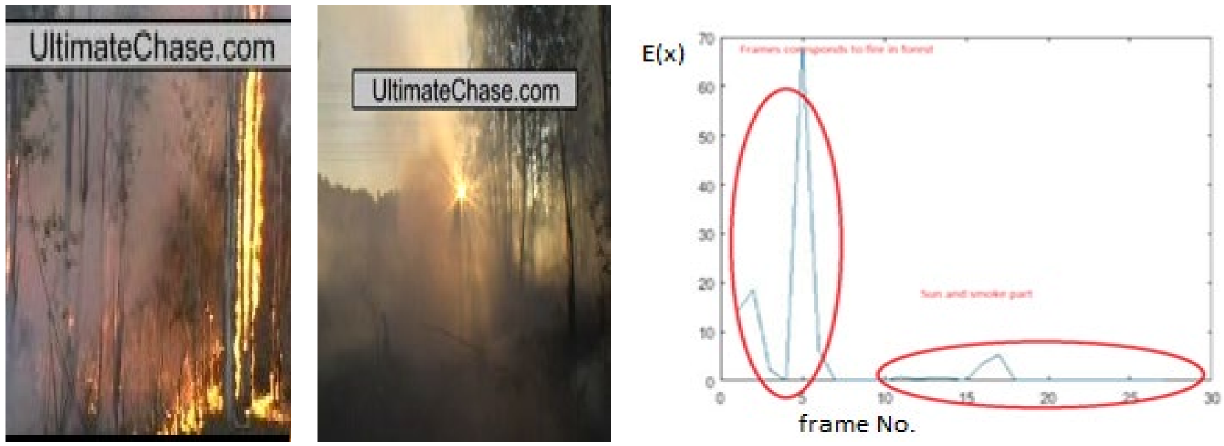


Figure 13. (a)-(j). Energy corresponds to video mentioned in figure. 12. Video was taken from ultimatechase.com[16] and Pets Database[22].



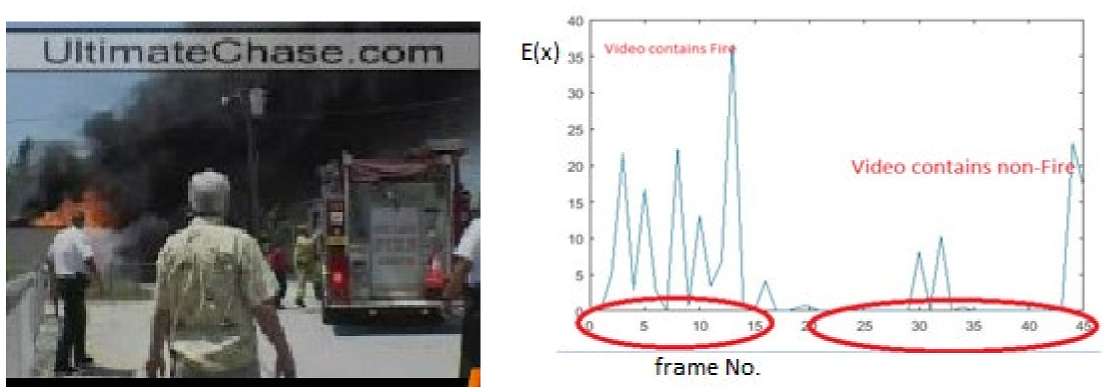
(a) (b) (c)

Figure 14. (a) Video from ultimatechase.com (Smoky_ Ground_ Stream) Frame contains sun and smoke (c) Results After applying color space rule and its energy representation.

is calculated for the block which only fire candidate. It may also happen that no of pixels taken as fire candidate is very less than the actual due to the rule base algorithm which mentioned above. Hence it is always preferred to go for further analysis so that system doesn't miss out on low values of energy. To avoid such scenario it was decided to go for texture analysis. But performing texture analysis will further increase the complexity. Hence this step is followed only when the highest energy magnitude in video is in range of 30-40 which was in +5 and -5 range of threshold.

2.5 Texture Analysis

Dynamic texture analysis is followed by many researchers for fire detection[23]. Applying texture analysis on each video frame will increase the computational cost of system. To overcome this problem, frame having higher energy (in range of 30-40) was only taken for texture analysis. Local binary pattern is used for texture analysis. To improve the accuracy of system generation of two binary patterns have proven to be quite efficient in past[24]. Hence same has been applied over here during texture analysis. Generation of binary patterns was explained in later half. To classify fire



(a) (b)

Figure 15. (a) Video from ultimatechase.com (Mobile_ Home_ Fire_ Stream) Frame (b) Results After applying color space rule and its energy representation .

and non-fire candidate SVM classifier is used. For training 4000 images is used in which 2000 corresponds to fire and rest are non-fire images. Matlab functions SVM classify and SVM train is used here for training and testing purpose.

To perform LBP analysis image is subdivided into small blocks. Local binary pattern can be applied on different block sizes 9×9, 5×5, 4×4. In our case block size of 5×5 is used. In this block binary pattern is computed between the center pixel (represented by b) and the boundary of the block (stored in matrix 'c') .the operation is shown in Gigure.16. Center is selected and is represented by 'b'.

The operations performed on the matrix is given by

$$D\ (i) = abs(c\ (i)-b) \tag{9}$$

$$Th = c\ (i)/16; \tag{10}$$

$$E\ (i) = 1 \quad ;\ If\ D(i) > th \tag{11}$$

$$Else\ E\ (i) = 0$$

Where 'b' represents center pixel and c(i) represents boundary element of matrix, 'th' represents the threshold value.

E(i) represents the binary pattern shown in Figure 16 (a,b). To increase the accuracy further we have made slightly modified the algorithm. It is observed that, introduction of another LBP pattern will increase the accuracy of system. Another matrix F(i) created which represents the binary pattern given by

$$F(i)=1 \quad If\ c(i) > b;\ else\ F(i)\ is\ zero \tag{12}$$

This local pattern is converted into unit integer (represented by s and t) using

$$s=s+(\ 1\times (2\text{^}(i-1)));\quad if\ E(i)=1;\quad \&\ t=t+ (1\times (2\text{^}(i-1)));\quad if\ F(i)=1; \tag{13}$$

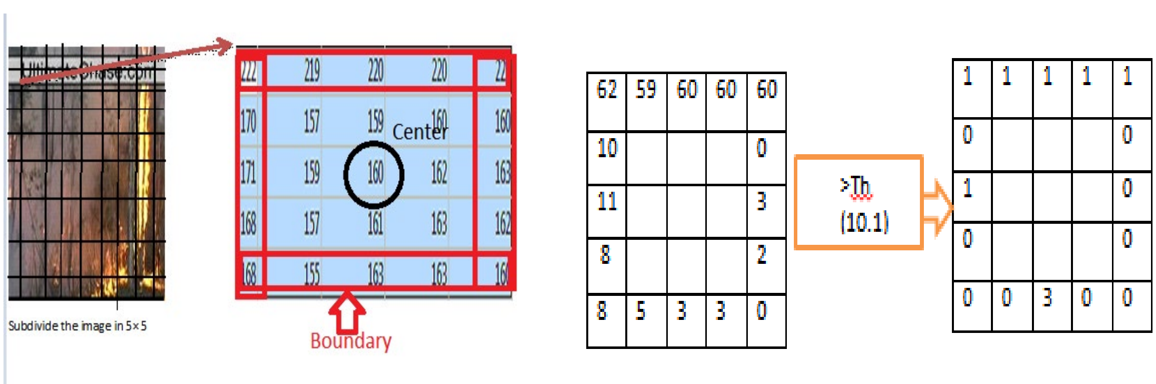
$$s=s+(\ 0\times (2\text{^}(i-1)));\quad if\ E(i)=0;\quad \& \quad s=s+(\ 0\times (2\text{^}(i-1)));\quad if\ F(i)=0; \tag{14}$$

Using equation 9-14 every 5 ×5 block is replaced by two integer value 's' and 't'. Image is converted into feature vector represented by integers. This feature vector is used to train the SVM classifier. The screenshot result from SVM classifier was presented in Figure 17. The frame is taken from video mentioned in Figure 15. The frame taken for texture analysis was that frame which has highest energy magnitude compared to the rest.

The results show the successful detection of fire. Hence texture analysis removes the false negative rate which was earlier present while using spatial wavelet analysis.

3. Results

Robust fire detection algorithm proposed and was tested on images and video containing fire and non-fire elements. The proposed algorithm performed on a PC with specifications of 8 GB RAM, Inteli3 processor which runs at 3.4GHz. Windows 7 is used as an operating system and Matlab 2015 has been used as computing tools. Standard data sets were used to test the fire detection algorithm. The video have resolutions of 400 × 256, 680 × 480 and 480 × 360. This shows the flexibility of the system and



(a) (b)

Figure 16. (a) Division of images and block representation. (b) Binary pattern observed after operation (If D(i) > 'th' then '1' else 0).

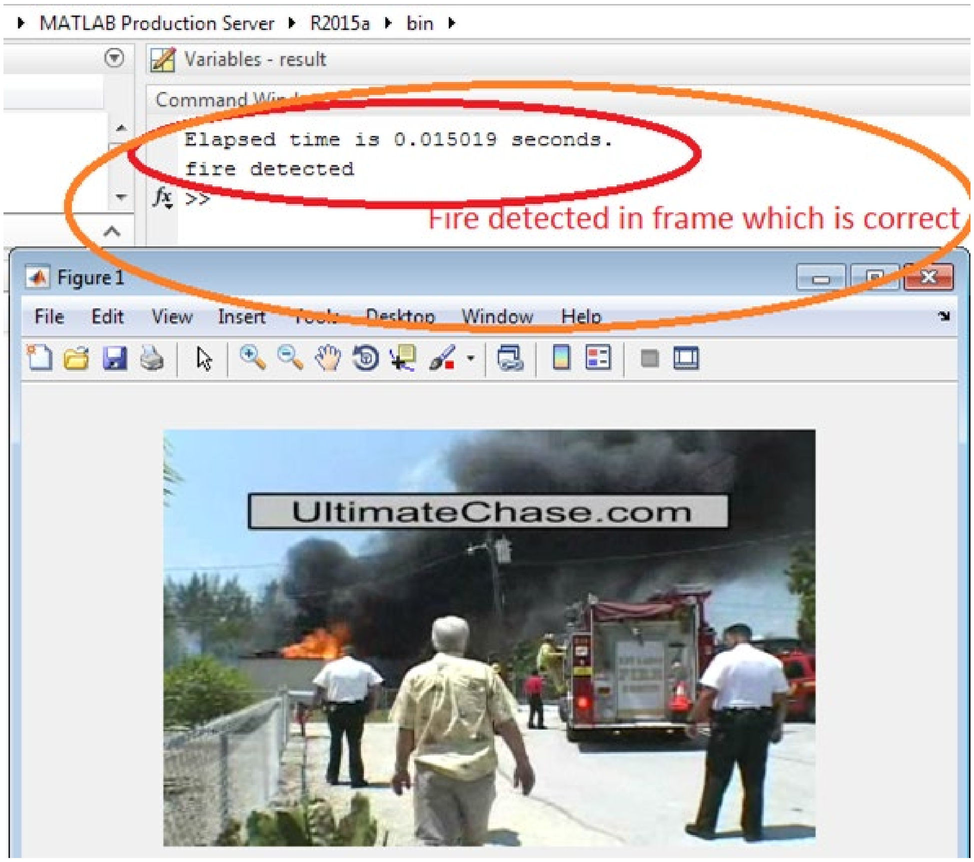


Figure 17. Screen shot of the result given by SVM classifier after LBP analysis. The result comes out as "fire detected" which was present in the frame. Frame taken from video (Mobile_Home_Fire_Stream[23]).

algorithm is designed independent of the size of frame. In video sequence, algorithm is applied after every 10 frames. It was suggested to have frame rate of 3.3 frame/sec (with no LBP) having resolution of 400 × 256 due to the required time of operation. It may be noted that the time of operation may vary if the fire content is more. In that case wavelet transform need to be applied on more number of blocks which may vary the computation time. The video sequence was declared fire if magnitude of energy exceeds the threshold value even may be for one frame only.

There are a total of 26 images which consist of both fire and fire like object to test proposed algorithm. Some of the sample images used was shown in Figure 18. To test the algorithm, initially each analysis was applied separately to check the efficiency of each algorithm. Then at the end both of them were combined to test the images. It was observed that rule base algorithm performs worst with as accuracy of 73.3% or false positive rate of 26.6%. Spatial analysis shows better accuracy of 86.6% with false positive rate of 13.3%. Proposed algorithm shows accuracy of 100% with zero false positive rates. It is to be noted that texture analysis was not done on sample images as proposed algorithm (rule base and energy analysis) have shown accuracy of 100%.In this result presence of fire means positive. False positive means detection of fire when it is not actually present.

Fire detection was performed on videos also. There are a total of 22 videos which consist of both fire and fire like object to test proposed algorithm. Some of sample video and results (magnitude of energy) were shown in Figure 12 and 13. To test the algorithm Rule based analysis was applied separately. Then at the end proposed algorithm was tested. It was observed that rule base algorithm performs worst having an accuracy of 77.2% and false positive rate of 22.8%. Spatial analysis along with rule based analysis shows better accuracy of 95.45% with false negative rate of 4.55% which can be identified in Figure 19. Proposed algorithm shows accuracy of 100%

Figure 18. (a)-(j) Sample images taken to test the algorithm.

with zero false positive rates. In this result presence of fire means positive. False positive means detection of fire when it is not actually present. The results are mentioned in Figure 20.

Some of the sample images for the video taken for algorithm testing have been already shown in Figure 12 along with results shown in Figure 13. The final results of individual videos are shown in Table 1.

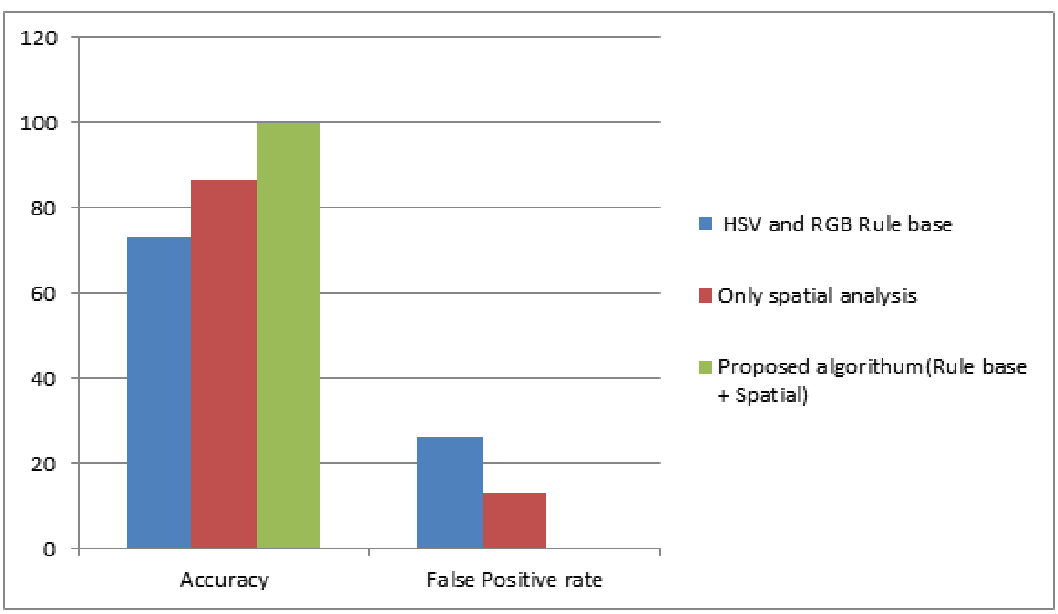


Figure 19. Accuracy and false positive rate of system when applied on sample images.

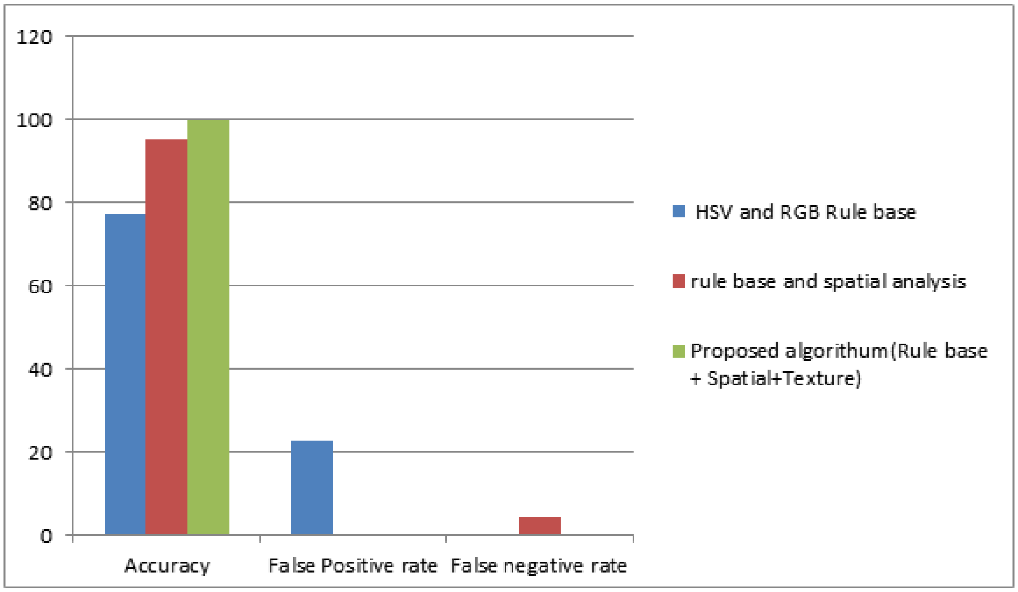


Figure 20. Accuracy, false positive and false negative rate of system when applied on sample videos.

Table 1. Result of different Video sequence and their result after applying proposed algorithm on video sequences. The video has been taken from standard data base (ultimatechase.com[16] and pet database[23])

Name of Video	Type (Fire or non-fire)	Result
Forest2	Fire	Fire
forest3	Fire	Fire
forest4	Fire	Fire
forest5	Fire	Fire
ForestFire1	Fire	Fire
Controlled_ Burn_ Stream	Fire	Fire
controlled1	Fire	Fire
controlled2	Fire	Fire
controlled3	Fire	Fire
Extreme_ Fire_ Scenes_ Stream	Fire	Fire
fBackYardFire	Fire	Fire
Boat_ Fire_ Stream	Fire	Fire
Boat_ Fire_ Stream	Fire	Fire
Sparking_ Wire_ Stream	Fire	Fire
Smoky_ Ground_ Stream	Fire	Fire
Video Analytics Sample (9) VCA - Fire Detection	Fire	Fire
RV_ Fire_ Stream	Fire	Fire
Ranch_ Fire_ Stream	Fire	Fire
Oil_ Refinery_ Stream	Fire	Fire
pets2006-4	Non-Fire	Non-Fire
Pets2006	Non-Fire	Non-Fire
Mobile_ Home_ Fire_ Stream	Fire	Fire

4. Conclusion

A robust fire detection alarming system is proposed in this paper. Moving object detection reduces the search space of fire candidate. It can be observed from initial results that the rule base algorithm is not effective for fire detection using RGB color space alone. After combining HSV color space rule false detection belongs to yellow and red color is removed this can be observed from Figure 4 & 5. But this rules are not able to remove the false detection having bright color and having 'V' plane value near to 1 (Figure 7). Rule based algorithm may leave some pixels due to the hard threshold this needs region growing operation to reconstruct whole fire candidate. Spatial energy analysis using wavelet transform shows robust results having overall accuracy of 98.87 % (25 images and 22 videos) with zero false positive rates. If the block size will reduce to 16 × 16 then this may lead to much higher energy magnitude but may increase the false positive rate. Energy analysis is highly efficient in discriminating fire and fire like candidate including sun (Figure 14). Fire shows higher magnitude of energy (Figure 13.a-f) when compared to other objects (Figure 9, 10, 13.h &13.i). LBP operation was used as texture analysis. Using LBP operation after spatial analysis have increase the accuracy of system to 100% with zero false positive as well as zero false negative rate. LBP operation is applied only when the frame energy is in near range of threshold (30-40), such occasions are quite less (only once among whole testing operation including 22 video & 26 images). Texture analysis is avoided due to the required time of operation (it doubles the whole operation time) which will increase the complexity and increase the system time required to respond in case of fire. System response time can be reduced if Matlab is used on Linux operating system. Open CV can be seen as replacing tool to reduce time of operation if researcher wants windows 7 only as operating system. As a future work this proposed algorithm can be implemented in hardware like Raspberry pi 2, Banana Pi etc. with attached camera to take input. Such system will solve purpose of CCTV monitoring with automatic fire detection ability. This will save additional sensors that need to be installed for fire detection.

5. References

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