iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 2 **Issue:** V **Month of publication:** May 2014

DOI:

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

Survey on Video Based Fire Detection Systems

Micky James

Department of Computer Science, MG University, Kerala

M.Tech Student, Viswajyothi College of Engineering & Technology, Vazhakulam, Kerala

Abstract— ***Detecting break out of fire rapidly is vital for prevention of material damage and human casualties. Traditional point sensors detect heat or smoke particles and are quite successful for indoor fire detection. They will raise alarm only when particles produced as a result of combustion reach the sensors. Video detection approach geared toward these scenarios where point sensors may fail. This is an exhaustive survey over various video based fire detection systems. In addition to covering a wide viewing range, video cameras capture data from which additional information can be extracted. Some systems are making use of only flame based fire detection while, some are making use of smoke based detection. There are also some systems existing which will detect fire by making use of both fire flame and smoke. This work also includes a detailed analysis of the pros and cons of each system.***

Keywords— optical flow, vision based detection, smoke detection, optimal mass transport, support vector machine

I. INTRODUCTION

Fire detection systems are one of the most important components in surveillance systems, which are used to monitor buildings and environment as part of an early warning mechanism that reports preferably the start of fire. Detecting the break-out of a fire rapidly is vital for prevention of material damage and human casualties. This is a particularly serious problem in situations of congested automobile traffic, naval vessels, and heavy industry. Fire detection systems based on built-in sensors primarily depend on the reliability and the positional distribution of the sensors. The sensors should be distributed densely for a high precision fire detector system. In a sensor-based fire detection system, coverage of large areas in outdoor applications is impractical due to the requirement of regular distribution of sensors in close proximity. Conventional point smoke and fire detectors are widely used in buildings. They typically detect the presence of certain particles generated by smoke and fire by ionization or photometry. Alarm is not issued unless particles reach the sensors to activate them. Therefore, they cannot be used in open spaces and large covered areas. Video based fire detection systems can be useful to detect fire in large auditoriums, tunnels, atriums, etc. The strength of using video in fire detection makes it possible to serve large and open spaces.Vision-based detection is composed of the following three steps. Preprocessing (1) is necessary to compensate for known sources of variability. Feature extraction (2) is designed for the detection of a specific target. Classification algorithms (3) use the computed features as input and make decision outputs regarding the target's presence.

II. VIDEO BASED FIRE DETECTION SYSTEMS

The detection of fire and smoke in video is particularly applicable in industrial monitoring and surveillance. Detection that is performed by point detectors use ionization and light scattering. They are not effective in large, open spaces and have an inherent delay because of the time it takes for combustion particles to reach the sensor. Many fire detection systems are making use of either fire flame features or smoke based features for fire detection. But there are certain systems making use of both fire flame and smoke for fire detection.

A. Fire Detection Using Statistical Color Model in Video sequences

This method [1] is a real-time fire-detector that combines foreground object information with color pixel statistics of fire. Simple adaptive background model of the scene is generated by using three Gaussian distributions, where each distribution corresponds to the pixel statistics in the respective color channel. The foreground information is extracted by using adaptive background subtraction algorithm, and then verified by the statistical fire color model to determine whether the detected foreground object is a fire candidate or not. A generic fire color model is constructed by statistical analysis of the sample images containing fire pixels.

ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

The background is modeled with unimodal Gaussian, with mean and covariance matrix extracted from incoming image where incoming image is composed of Luminance, Chroma-Blue and ChromaRed (YUV) components. In this method, incoming image is composed of Red, Green, and Blue (RGB) components. The distributions of color channels of the each pixel are assumed to be independent, and modeled using a unimodal Gaussian whose parameters are settled in the training phase of the system.

A global generic model for fire colors is being used. Color clues that identify the fire are combined with change detection map CM(x,y) in order to identify the fire pixels in a video sequence.

The background subtraction process is the first step in the algorithm. The changes detected by the background subtraction stage are supplied to color verification process. Pixels that are detected by the algorithm as foreground object, and have a fire-like color classified by the rules defined are grouped into blobs with respect to their spatial connectivity. A time analysis of each fire-like blob is considered, and if it grows in size or changes its center location, then each fire blob is considered as a fire candidate.

The first step of the algorithm removes the background and detects possible foreground objects that are mainly caused from either temporal changes in the background or an object motion into the scene. The second step is applied if foreground pixels detected with fire-like colors. The output of this step mainly removes foreground objects, which do not have fire-like colors. There are some pixels, which are classified as foreground fire-like objects caused from the noise. In order to remove such a noise, remove connected component pixel groups of size less than 5 pixels. Second step is followed by the third step that aims the detection of foreground blobs where each blob is detected using connected component labeling algorithm. In connected component labeling algorithm 4-connectivity is used.

Detection of each blob is followed by construction of guard area which is rectangular area that covers each blob and used to observe the behavior of enclosed blob in consecutive frames in order to decide whether it is fire object or not. In each guard area two measures are carried out; the first one is the spatial mean of the blob in guard area, which is used to measure the behavior of fire which should be changing because the fire has property of swinging. The second measure is spatial area of detected pixels in guard area. It should be either getting larger or smaller in consecutive frames.

1) Advantage: The frame-processing rate of the detector is about 40 fps. The detection rate is in the order of 98.89%.

2) Disadvantage: Error in detection occurs when there is sudden change in lighting conditions.

B. Fire Detection in Video Sequences Using a Generic Color Model

This is a flame based fire detection method [2]. Here, a rule based generic color model for flame pixel classification is being used. System uses YCbCr color space to seperate luminance from the chrominance more effectively than other color spaces. YCbCr color space is used to construct a generic chrominance model for flame pixel classification. In addition to translating rules developed in the RGB and normalized rgb to YCbCr color space, new rules are used in YCbCr color space which further alleviate harmful effects of changing illumination and improves detection performance. RGB color space has disadvantage of illumination dependence i.e, if illumination of image changes, fire pixel classification rules cannot perform well.

Chrominance can be used in modeling color of fire rather than modeling its intensity. When translating RGB color space to one of the color spaces separation between intensity and chrominance is more discriminate. Because of the linear conversion between RGB and YCbCr color spaces, YCbCr color space is used to model fire pixels. Y is luminance, Cb and Cr are Chrominance Blue and Chrominance Red components, respectively.

For a given image, the mean values of the three components in YCbCr color space can be defined as,

$$Y_{mean} = \frac{1}{K}\sum_{i=1}^{K} Y(x_i, y_i)$$

$$Cb_{mean} = \frac{1}{K}\sum_{i=1}^{K} Cb(x_i, y_i)$$

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

$$Cr_{mean} = \frac{1}{K}\sum_{i=1}^{K} Cr(x_i, y_i)$$

where *(xi, yi)* is the spatial location of the pixel, Y_{mean}, Cb_{mean}, and Cr_{mean} are the mean values of luminance, Chrominance Blue, and Chrominance Red channels of pixels, and *K* is the total number of pixels in image.

The rules defined for RGB color space, i.e. R ≥ G ≥ B, and R ≥ R*mean*, can be translated into YCbCr space as

$$Y(x,y) > Cb(x,y)$$

$$Cr(x,y) > Cb(x,y)$$

where *Y(x,y)*, *Cb(x,y)*, and *Cr(x,y)* are luminance, Chrominance Blue and Chrominance Red values at the spatial location *(x,y)*. Flame luminance should be greater than Chrominance Blue and Chrominance Red should be greater than the Chrominance Blue. Since the flame region is generally the brightest region in the observed scene, the mean values of the three channels, in the overall image Y_{mean}, Cb_{mean}, and Cr_{mean} contain valuable information. For the flame region the value of the Y component is bigger than the mean Y component of the overall image while the value of *Cb* component is in general smaller than the mean *Cb* value of the overall image. Furthermore, the *Cr* component of the flame region is bigger than the mean *Cr* component. These observations are formulated as the following rule:

$$F(x,y) = \begin{cases} 1 & if\ Y(x,y) > Y_{mean}; Cb(x,y) > Cb_{mean}; Cr(x,y) > Cr_{mean} \\ 0 & otherwise \end{cases}$$

where *F(x,y)* indicates that any pixel which satisfies condition given above is labeled as fire pixel.

1) Advantages: Proposed model outperforms the model which uses rgb values both in detection rates and false alarm rate. Produces higher detection rate upto 99% fire detection. Also the system is cheap in computational complexity. YCbCr color space is better in discriminating the luminance from the chrominance, hence is more robust to the illumination changes than RGB or rgb color spaces

2) Disadvantage: Not taking into account the flickering nature of fire.

C. Fire and Smoke Detection in Video with Optical Mass Transport Based Optical Flow and Neural Networks

This method [3] proposes the use of optimal mass transport (OMT) optical flow for the detection of fire flame and smoke in video. The detection process is posed as a supervised Bayesian classification problem with spatio-temporal neighborhoods of pixels. Feature vectors are composed of OMT velocities and R,G,B color channels. The classifier is implemented as a single-hidden-layer neural network. The classifier can successfully distinguish between smoke and similarly colored white wall, as well as fire flame from a similarly colored background.

Computing optical flow for an image sequence rather than simple frame differencing allows one to take into account expected properties of the process being imaged. Optical flow based on optimal mass transport (OMT) is calculated for fire and the Horn and Schunck optical flow for smoke region classification.

Optical flow is a computational procedure to compute the motion between a set of images taken within a short time difference. The main idea is that the gray values of each image do not change between two images. This leads to the optical flow constraint.

$$I_t + \vec{u}.\nabla I = 0$$

where *I* is the image and $\vec{u}$ = [*u*, *v*] is the flow field. Given two images taken in a short time interval, it is possible to solve for the optical flow field $\vec{u}$ by solving the following optimization problem.

$$\min_{\vec{u}} \frac{1}{2}\|I_t + \vec{u}.\nabla I\|^2 + \alpha R(\vec{u})$$

where $R(\vec{u})$is a regularization operator, typically chosen to be the gradient of $\vec{u}$ and α is a regularization parameter. Under this assumption an object's brightness is constant from frame to frame. This assumption holds for rigid objects with a Lambertian surface, but fails for fluid and gaseous materials. In computer vision, these are modeled by so-called dynamic textures. The dynamic textures typical of smoke and fire

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

possess intrinsic dynamics and so cannot be reliably captured by the standard optical flow method. Also, the fire/smoke region tends to flow much faster than the area around it which may cause the model given by above equation to produce erroneous results.

One way to obtain better optical flow field models for fire and smoke do so is to base the optical flow on the physical attributes of these processes. One simple attribute is that fire and smoke tends to approximately conserve intensity taken as a generalized mass and move the mass in an optimal way. Thus, an appropriate mathematical optical constraint is not intensity preserving but rather mass conservation or brightness conservation. This model can be written as,

$$I_t + \nabla . \vec{u} \mathrm{I} = 0$$

The problem of smoke detection is posed as a two class system that must decide if a given pixel belongs to class smoke or class non-smoke. Neural Networks compute a least-squares model fit to Baye's discriminant functions; the output is a probability of a pixel belonging to a particular class, thus the choice of threshold level for classifying a pixel as smoke/non-smoke directly corresponds to the desired confidence level.

1) Advantages: Successfully distinguish between smoke and similarly colored white wall. Also the system can successfully distinguish fire from a similarly colored background.

2)Disadvantages: OMT basis analysis for flame detection and classification is capable of modeling fire with dynamic texture and not capable of modeling fire with saturated core.

D. SVM Based Forest Fire Detection Using Static and Dynamic Features

In SVM based forest fire detection [4] using static and dynamic features a new specific flame pattern is defined for forest, and three types of fire colors are labeled accordingly. With 11 static features including color distributions, texture parameters and shape roundness, the static SVM classifier is trained and filters the segmented results. Using defined overlapping degree and varying degree, the remained candidate regions are matched among consecutive frames. Subsequently the variations of color, texture, roundness, area, contour are computed, then the average and the mean square deviation of them are obtained. Together with the flickering frequency from temporal wavelet based Fourier descriptors analysis of flame contour, 27 dynamic features are used to train the dynamic SVM classifier, which is applied for final decision.

For segmentation of possible flame regions, color values of each pixel in an image are checked with a pre-determined color distribution, which represents the range of possible fire colors in a color model such as RGB space. For forest fire, a new definition to describe the flame pattern more properly is introduced: 1) The periphery of fire region is in orange or red color. 2) Only if the fire burns fully, there are one or more white-yellow color cores.

Based on the new definition for forest fire pattern, there may be three types of colors in the segmented fire region: white-yellow, orange, red. Thus the pixels in fire can be labeled with three corresponding marks. As pixels with whiteyellow color belong to the high bright flame regions, V value of the HSV color space is employed to help label such pixels. Since flames are often covered with smokes in forest, its bright value will be decreased with different degrees. It is not possible to use a fixed V value as the threshold. Therefore, an algorithm is proposed to self-adaptively calculate the threshold value of V for fire images. After color based segmentation, the possible flame regions are obtained in one single image. Areas that are not directly used as fire areas, but are further checked to filter out the false candidates based on some static features with trained support vector machine (SVM).The static features include color distribution, texture parameter and shape roundness. Before computing dynamic characteristics of varying fire, the corresponding candidate fire regions should be found among consecutive video frames, which is a problem of pattern matching. Although the camera may mildly wobble and the candidate flame regions may randomly flicker, locations and shapes of the corresponding candidate regions among consecutive video frames do not change seriously. Therefore, two parameters of overlapping degree and varying degree are defined to evaluate the matching of two regions in this approach.

Based on the matched results, dynamic features of the candidate fire regions from continuous video frames can be extracted, and used to further identify forest fire from the other fire like objects. In this method, the dynamic features include the variations of color distribution, texture, roundness,

ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

area, contour and the flickering frequency. Since the flickering frequency is a constant value of about 10 Hz, it can be directly used as one dynamic feature of forest fire. Together with the flickering frequency, the 27 dynamic features are used as input of SVM classifier, and the trained SVM is applied for the final decision.

1)Advantages: A total of 27 dynamic features are considered for SVM based final classification, and the features are computed from every 20 consecutive video frames. Therefore, except for accuracy, the detection algorithm can perform and give alarms in real time. For the segmented results from single frame, SVM trained on 11 static features is applied to filter out the false regions, and only the remained regions continue with the following steps. In this way the computational expense is saved obviously.

2)Disadvantages: The system has lower accuracy for fire with small regions. The performance is even worse for small fires covered by smoke.

E. Optical Flow Estimation for Flame Detection in Videos

In this method [5], instead of using classical optical flow based methods, two optical flow methods are specifically designed for the fire detection task: optimal mass transport (OMT) models fire with dynamic texture, while a data-driven (NSD) optical flow scheme models saturated flames.

In this method, first RGB frames in the video are converted to scalar valued frames by a transformation in which fire-like colors will be weighting high in the scalar valued frames. In order to improve the chance of good segmentation between foreground and background, a new model for the generalized mass is used based on flame color. The generalized mass of a pixel is represented by the similarity to a center fire color in the HSV color space. Scalar valued frames are used for optical flow computation. OMT flow fields computed from the generalized mass images. OMT has the ability to capture dynamic texture for the fire image and discriminate between the rigid object's flow field, which appears much more structured.

Under unfavorable lighting conditions, especially in closed spaces, fire blobs are likely saturated, thus violating OMT's assumption that dynamic texture is present in fire. These blobs have boundary motion, which is characterized by Non-Smooth Data (NSD) optical flow.

Static or almost static image regions should be excluded from consideration. Given the flow vectors, four features are proposed to characterize the motion magnitude and direction. Magnitude feature f_1 and f_2 measure mean magnitude, whereas two features f_3 and f_4 analyze motion directionality. The first two features, will have high values for moving, fire-colored objects. The last two features distinguish turbulent fire motion from rigid motion by comparing flow directionality. Computing optical flow and extracting features from an entire frame is unfavorable for two reasons. First, computation time increases as the domain grows, and more importantly, the classification fails for scenes with more than one source of motion.

The simplest way of classifying a candidate region based on its feature vector is to threshold each of the features based on heuristically determined cutoff values and make a decision by majority voting. However, better results can be achieved by learning the classification boundary with a machine learning approach such as neural networks. Training the neural network (NN) means performing a non-linear regression in the feature space to best separate the labeled training data into classes.

During the training phase, training examples are provided. In the testing phase, a feature vector is supplied and the output is a probability that the feature vector is associated with a particular class i.e, fire or non-fire.

1) Advantages: Can successfully distinguish fire images from non fire images.

2)Disadvantages: Little false detections are observed in the presence of significant noise, partial occlusions, and rapid rotational motion.

III. CONCLUSIONS

Video based fire detection has emerged as an interesting topic due to the increased applications in industry and forest fire detection. Many fire detection techniques have been developed by various researchers. This work evaluated some of the selected video based fire detection techniques. A brief overview of the different methods, their advantages and disadvantages are included as part of the survey.

ACKNOWLEDGMENT

The author would like to thank the Department Head, Project Guide and Group Tutor, for their constructive

ISSN: 2321-9653

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE AND ENGINEERING TECHNOLOGY (IJRASET)

comments and informative suggestions that have helped to improve this paper.

REFERENCES

[1] T. Celik,H. Demirel,H. Ozkaramanli and M. Uyguroglu, "Fire Detection using statical color model in video sequences", in J. Vis. Commun. Image R., no 18, pp. 176-185, 2007

[2] T. Çelik and H. Demirel, "Fire detection in video sequences using a generic color model," *Fire Safety J.*, vol. 44, no. 2, pp. 147–158, 2009.

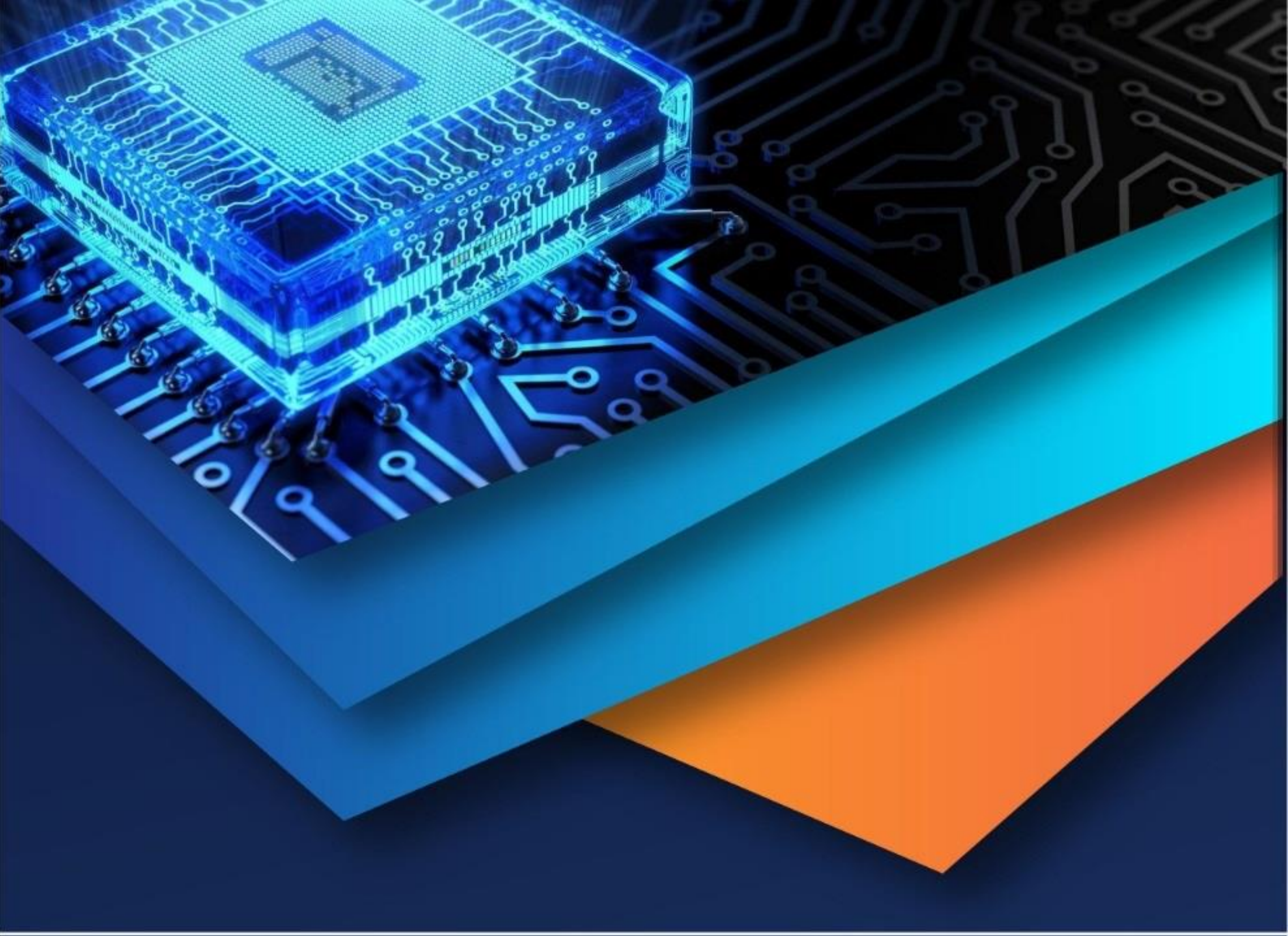
[3] Kolesov, P. Karasev, A. Tannenbaum, and E. Haber, "Fire and smoke detection in video with optimal mass transport based optical flow and neural networks," in *Proc. IEEE Int. Conf. Image Process.*, Sep. 2010, pp. 761–764.

[4] J. Zhao, Z. Zhang, S. Han, C. Qu, Z. Yuan, and D. Zhang, "SVM based forest fire detection using static and dynamic features," *Comput. Sci. Inf.Syst.*, vol. 8, no. 3, pp. 821–841, 2011.

[5] M. Muller, P. Karasev, and I. Kolesov, "Optical flow estimation for flame detection in videos", *in IEEE Trans. On Image Process.*, vol.2, no.7,pp. 2786-2797, 2013.

[6] W. Phillips, III, M. Shah, and N. da Vitoria Lobo, "Flame recognition in video," *Pattern Recognit. Lett.*, vol. 23, nos. 1–3, pp. 319–327, 2002.

[7] B. Toreyin, Y. Dedeoglu, U. Gudukbay, and A. Cetin, "Computer vision based method for real-time fire and flame detection," *Pattern Recognit. Lett.*, vol. 27, no. 1, pp. 49–58, 2006.



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY