Fire Detection In Different Color Models

V. Burak Celen , M. Fatih Demirci
Computer Engineering Departmant, TOBB University of Economics and Technology, Ankara, Turkey

Abstract— *Detecting forest fire is a highly active research area in the field of pattern recognition and computer vision as a number of existing methods available in the literature. The purpose of the proposed study is to select the most suitable color space, features and classifiers for the fire classification. Our approach begins by finding the likelihood of every pixel value. The fire is then defined by multiplying pixel channel value's likelihood. By using a simple thresholding schema, the fire pixel classification process is performed. Our experimental study demonstrates which color space, features and classifiers are most suitable for fire detection.*

Keywords: Fire and Smoke Detection, Pattern Recognition

1. Introduction

According to recent statistics [1], about 5 million hectares of land in the world and about 550 thousand hectares of land in Europe have been damaged every year by forest fire. The results of this terrible incident vary from the destruction of wildlife, the loss of life and goods to deforestation and carbon emissions. Both efficient and effective detection methods for forest fire are therefore necessary for several aspects.

A number of previous approaches on forest fire detection use motion information captured by one or more static cameras. Such approaches, e.g., [10][11][12] usually consider the change of potential fire regions in consecutive images. Toreyin et al. [7] describe a framework using color, motion, and fire frequency to find fire regions in videos. For each frame, this work computes the difference from its previous frame to determine whether moving pixel regions have a frequency of 10Hz. The approach then adapts Hidden Markov Model-based modelling to classify the fire regions.

Although promising results have been reported by motion-based fire detection systems, these systems are unable to detect fire which cannot be seen clearly from the current camera positions. For the early detection of forest fire which is not visible to the camera in some specific locations, one may consider installing cameras on mobile platforms, such as unmanned aerial vehicles (UAV).

In [13], a UAV based forest fire detection algorithm is presented. Heterogeneous UAVs detect and localize fire regions by employing some pattern recognition techniques. Both infrared and visual images are used for fire detection and for geolocation gps and other sensors are used. The fire segmentation process in infrared images is performed through a thresholding method and a rule-based system is adopted to perform this segmentation in visual images. Fire pixel characteristics used in this work include intensity values in red component and the ratio between the red component and the blue and green components.

The major problem of detecting forest fire on mobile platforms is the unavailability of using motion information. In addition, a fast change of lighting conditions and the visibility of both fire and smoke only for a short period of time are the other difficulties which present with systems working on mobile platforms.

In this paper, we propose a framework for detecting forest fire. Our framework is applicable to cases where motion information is not available. More specifically, our study considers still images and focuses on selecting the best features in different color models using various techniques. We then employ a number of classifiers with the best features to detect the forest fire. We compare the performance of different feature selection and different classification techniques for a forest dataset of 529 still images.

Various studies in the literature have been proposed in this field. Commonly, existing systems use color, shape, and motion to detect fire and smoke. Since motion is not applicable to mobile platforms, we will focus on color and shape information in this paper. Using color, a pixel in general is considered to be a fire pixel, if its color intensity values lie within a predetermined range.

According to the algorithm presented in [2], pixel P located at (x, y) in the image is classified as fire if the following rules hold:

$$R(x,y) > R_{mean} \tag{1}$$

$$R(x,y) > G(x,y) > B(x,y) \tag{2}$$

where R_{mean} is the mean of the red component of the image, R(x, y), G(x, y), and B(x, y) represent red, green and blue values for P, respectively.

In [3], the authors present a different rule-based system in the RGB color space to detect fire pixels. In particular, the following rules are defined:

Rule 1 : R(x, y) > RT
Rule 2 : R(x, y) $\geq$ G(x, y) > B(x, y)
Rule 3 : S $\geq$ ((255 - R(x, y)) * ST / RT)

if (Rule 1) AND (Rule 2) AND (Rule 3)
Fire Pixel
else
Non Fire Pixel

where R(x,y), G(x,y), and B(x,y) correspond to Red, Green and Blue values as before, RT and ST are the threshold values for the Red component and saturation, and S is the overall saturation of the image.

Philip et al. [4] design a system trained by some manually labelled data. Specifically, the training dataset is used to create a look up table. This is accomplished by creating a Gaussian smoothed three color histograms; one for each channel of RGB. Each histogram is divided into bins, where each bin denotes the probability of its pixels belonging to fire regions. Given an R,G,B triple of a pixel, the algorithm then computes a Boolean value indicating if the pixel is classified as a fire pixel.

Instead of using the RGB space, [5] employs the CIE L*a*b* color space for the detection of fire pixels. In particular, the following rules are applied.

Rule 1 : L*(x, y) $\geq L*_{mean}$
Rule 2 : a*(x, y) $\geq a*_{mean}$
Rule 3 : b*(x, y) $\geq b*_{mean}$
Rule 4 : b*(x, y) $\geq$ a*(x, y)
Rule 5 : P(L*(x, y) , a*(x, y) , b*(x, y)) $\geq \alpha$

if (Rule 1) AND (Rule 2) AND (Rule 3) AND (Rule 4) AND (Rule 5)
Fire Pixel
else
Non Fire Pixel (4)

where L*(x, y), a*(x, y), and b*(x, y) are L*, a* and b* values at CIE L*a*b* color space for a pixel located spatially at (x, y). $L*_{mean}$, $a*_{mean}$, $b*_{mean}$ are averages of the corresponding color channels. Here, Rule 5 is defined as P(L*, a* , b*) = P(L*,a*) P(L*,b*)P(a*,b*) where P(L*, a*), P(L*, b*), and P(a*, b*) are the likelihoods that (L*, a*), (L*, b*), and (a*, b*) belong to the fire, respectively. Likelihoods are computed using the look up table created from the training data. In this work, pixels whose likelihood values are higher than a threshold are marked as fire pixels.

Instead of working in the spatial domain, some alternative fire detection algorithms operate in the frequency domain.Che-Bin Lee and Narendra Ahaju [14], present spectral, spatial and temporal models of fire regions in video files. Fire regions are first detected based on spectral and spatial models. Boundaries of the potential fire regions are then represented as Fourier coefficients, which in turn are used to estimate the auto regressive (AR) parameter. Both Fourier coefficients and AR parameters are used together to form the feature vector given to the classifier.

Systems using the shape information usually compute the boundary roughness of the potential fire region to improve the fire detection rate. Borges et al. presents [6] a unified approach where after finding the potential fire regions based on the color information, boundary roughness, area size, variance, and skewness are computed for the final selection of fire regions. The approach then uses Bayes Classifier to classify the pixels.

Although finding fire pixels is an important step for forest fire detection, one should consider both fire and smoke pixels to improve the effectiveness of systems in fire detection. In this paper, we present a forest fire detection system which takes into consideration both fire and smoke pixels for 7 different color spaces: RGB, CIE L*a*b*, CIE L*u*v, CIE XYZ, HLS, HSV, YCrCb. The reason for studying such a various color spaces instead of focusing on only one space as done by many previous approaches is to investigate the most suitable color space for the forest fire detection. For each color space, we extract a set of features and determine the best feature set using different feature selection algorithms, e.g., PCA, K-Means, and Relative Entropy[9]. Finally, the input image is classified as either fire or non-fire through various classification methods, such as SVM, K-Nearest Neighbor, and Neural Networks. The experimental results demonstrate that more than 90% of correct fire classification ratio is achieved when the best selected feature set is used with appropriate classifiers

2. Proposed Work

Generally, vision-based fire and smoke detection systems are based on hybrid model which use color, geometry, and motion. Since motion is not applicable to mobile platforms, we consider only color and geometry in this paper. The overview of our approach is shown in Fig.1.

Given an input image, we apply the following procedure for generating its feature set. Since one of our objectives in this paper is to select the suitable color space for our application, we first convert the input RGB image into 6 other color spaces. For each color space including RGB, we create the lookup table, which denotes the likelihood of each pixel belonging to fire. Based on this information, we mark potential fire regions. Given a set of potential fire regions, we then generate the following features: the average likelihood values, number of pixels, boundary roughness, and variance. The feature set of the image then includes these 5 features: the average likelihood, the

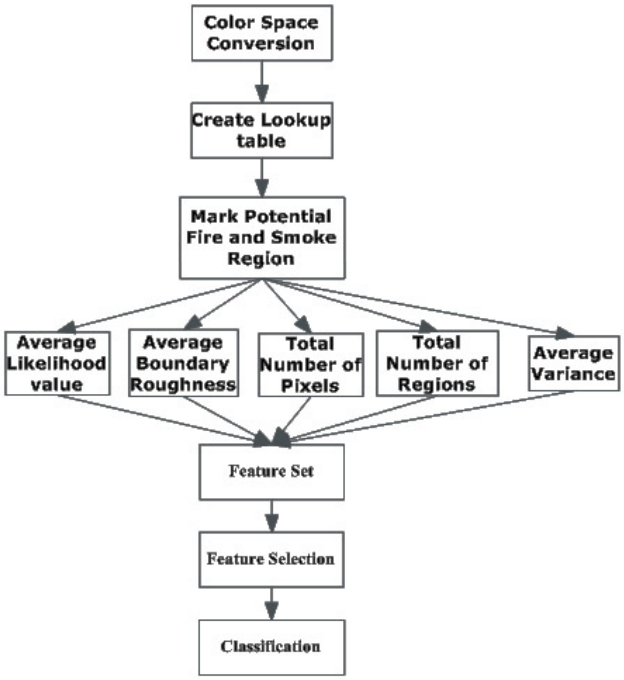

Fig. 1: Block Diagram of the proposed system. After generating different features for both fire and smoke regions, the most important set of features is selected. Different classification techniques are then applied for final fire and smoke region classifications.

average boundary roughness and the average variance for all marked fire regions, the total number of fire pixels and the total number of potential fire regions in the image. Since finding smoke in an image also indicates potential fire, this process is repeated and as a result the same feature set is generated for smoke regions. Having represented an image as a 7x10=70 dimensional feature vector (10 features for each of the color spaces), we can directly apply feature classification techniques. However, because of the curse of dimensionality, which affects the efficiency of the overall system, we first use feature selection methods to compute the most important features. Finally, selected features are classified using different classification techniques. Because the other main objective in this paper is to find the most suitable feature classification methods, the performance of different classifications techniques are also computed in this paper.

The proposed system is described in more detail below.

2.1 Color Space Conversion

Most cameras available in the market provide the RGB output. In order to work with different color spaces, an RGB image must be converted into other color spaces. As noted before, we consider 7 color spaces in this study; RGB, CIE L * a * b *, CIE L * u * v *, CIE XYZ, HLS, HSV, and YCrCb. Our objective for working with all these models instead of one model is to determine the suitability of each model for our application. The conversion between color spaces is done using standard computations, which are out of scope of this paper. The reader is referred to [8] for details.

2.2 Creating the Lookup table

A lookup table shows the likelihood that a pixel belongs to fire (or smoke). Using the training dataset, where fire, smoke, and non-fire regions are manually labeled, a histogram is created for each color channel in each color space. Each histogram is normalized between 0 and 1 to show the likelihood for each intensity value. To provide satisfactory results, similar likelihood values are grouped. These groups are then stored in lookup tables. Each row of a lookup table shows the intensity range of the corresponding pixels and the likelihood that the pixel group belongs to fire (or smoke).

2.3 Marking Potential Fire and Smoke Regions

Pixel intensity values for fire and smoke regions cluster within a specific range as observed by existing approaches. Most of the existing fire detection algorithms use this information only for a single color space and define heuristic rules for fire detection.

To locate potential fire regions, we use the following equation, which computes the likelihood of pixel q belonging to fire.

$$P(ch0, ch1, ch2) = P(ch0) * P(ch1) * P(ch2) \tag{3}$$

where ch0, ch1, and ch1 correspond to q's intensity values in channel 0, channel 1, and channel 2. As mentioned before, likelihood values are calculated through the lookup table. Once the overall likelihood of a pixel is computed, we check whether this value is greater than a threshold. The threshold is selected using the training dataset and its value is different for each color space. Pixels whose overall likelihood values are big enough are marked as fire. Since existence of smoke is an important indication for fire, this procedure is repeated for smoke, resulting in potential marked fire and smoke pixels in the input image.

2.4 Feature Generation

Once the potential fire and smoke regions are determined, we generate the features for each image in each color space. To do this, we first focus on color, since it is the most common feature in the existing algorithms. Since likelihoods are computed based on the pixel intensity values, we calculate the average likelihood value using all potential fire and smoke regions in our approach.

Since neither fire nor smoke has a smooth and specific shape, we use the boundary roughness for both fire and smoke regions. Specifically, for each marked region, this feature is computed as:

$$BR = P_s / P_{CHS} \quad (4)$$

where P_s is the region perimeter and P_{CHS} is perimeter of the minimum convex hull containing the region. We take the average boundary roughness for all potential fire and smoke regions in the image.

Fire and smoke regions don't have specific textures. As can be seen in left of Fig.2, one may notice that the outer part of the fire is red and its inner part is light yellow. In addition, the smoke in the right looks similar in intensity. This observation suggests that the variance of the fire is usually high and that of the smoke is small. To use this feature in our approach, we compute the average variance over all potential fire and smoke regions.

Our next two features include the total number of potential fire and smoke regions and the total number of pixels in all such regions. According to our observations, an image having a number of fire and smoke regions is likely to have fire. Since database images come with different dimensions, we normalize the number of pixels in each image in our approach.

Fig. 2: Intensity values of fire regions vary from dark red to light yellow, while the that of smoke regions look similar.

2.5 Feature Selection

The feature generation step creates a total of 10 features (5 for fire and 5 for smoke) for each color space. Since we use 7 different color spaces, an image is represented as a 70 dimensional feature vector. Because of the curse of dimensionality, which has a negative effect on the efficiency of the overall system, we first use feature selection methods to compute the most suitable features for our application. The feature selection methods we used in this paper consists of Principal Component Analysis, top-2 with K-means, and Relative Entropy. These methods are briefly described below.

2.5.1 Principal Component Analysis

The purpose of the PCA is to convert a set of possibly correlated variables into a set of linearly uncorrelated variables (principal components). This conversion is performed in such a way that the first principal component has the largest variance, and the second principal component has the second largest variance, etc. Since the number of principal components is less than the number of original variables, PCA is often used for dimensionality reduction. In this paper, we apply PCA to reduce our 70-dimensional feature vector into lower dimensional spaces. PCA allows us to represent the most important features in the lower dimension first.

2.5.2 Top2 with K-Means

For this selection method, we reduce the dimension of the feature vector to two. Since one goal of the feature selection is to find the set of features which best separate the input data into fire and non-fire, we first need to select which two features are the most suitable for this purpose. To do this, we use all $\binom{70}{2}$ feature pairs, and for each feature pair we see how well the data is separated in two dimensional space using K-means clustering algorithm. Specifically, after the data is separated using one feature pair, two clusters are computed through K-means. For each cluster, we then find the average distance of each data point to its cluster representative. Ideally, this distance should be smaller for good separations. Overall, we select the feature pair which best separates the input data.

2.5.3 Relative Entropy

In this method, we employ the Kullback-Leibler Divergence for feature selection. This method is based on the average of the logarithmic difference between the input distributions. The author is referred to [8] for details.

2.6 Classifier

Once the feature selection process is done, we can proceed with classification. As noted before, we evaluate the selected features with different classifiers: SVM, K-NN, Feed Forward Back Propagation Artificial Neural Network and Perceptron. These classification techniques are briefly described below.

Support Vector Machines (SVM) is a technique to maximize the margin of two group's closest points by finding the optimal separating hyperplane. K-Nearest Neighbour is a non-parametric classifier. An input data point is classified based on the classes of its k-nearest points. Feed Forward Back Propagation Artificial Neural Networks separates the space through non-linear hyperplanes. These neural networks have non-directional iterations between neurons. After each iteration, the coefficients of neurons are refined according to errors. In the proposed approach, the neural networks are composed of 1 input, 1 hidden, and 1 output layers. Perceptron is another supervised classification algorithm, which separates the space as 2 different classes. As a difference from the previous neural network approach, in this algorithm, input layers are directly connected to output layers.

3. EXPERIMENTAL RESULTS

For evaluating the proposed work we perform 3 tests. The first test is for finding the best color space for detection of fire and smoke regions. The second test is for finding the best feature set for classifying fire and finally the third test is for finding the best classifier. These tests are described in more detail in the following subsections.

Before presenting the experiments we will first describe the dataset of 529 forest fire images collected from the internet. These images have different size, exposure mode and day time. The day time of the images is the same as the real forest fire probability of day or night. This is about 12%. The dataset consists of 164 non-fire and 365 fire images, out of which 67 images have only fire, 55 images have only smoke and the rest of the 234 images has both fire and smoke regions.. At fig 3, there is a sample of night and day fire from database

Fig. 3: Sample of night and day fire from database

For each database image, fire and smoke regions are marked. We store 3 distinct copies of an image: the original, and the fire and smoke region labelled images.At fig 4, we see the 3 copies of images.

For the experiments, 50% of database images are used for training and the other 50% is used for testing. The system is evaluated using accuracy, precision, recall and specificity measures [9], which are computed as follows:

a b c

Fig. 4: (a) original image (b) fire region labelled image (c) smoke region labelled image

$$
\begin{aligned}
Precision &= \frac{tp}{tp+fp} \\
Recall &= \frac{tp}{tp+tn} \\
Accuracy &= \frac{tp+tn}{tp+tn+fp+fn} \\
Specificity &= \frac{tn}{tp+fp}
\end{aligned}
\tag{5}
$$

where tp, tn, fp and fn denote true positive, true negative, false positive and false negative rates, respectively.

3.1 Finding the Most Suitable Color Model

For testing the performance of each color model, a pixel based fire and smoke classifications are performed as described in section 2.3. The threshold used for determining the likelihood of fire and smoke regions is selected experimentally.

Table 1 and table 2 show the fire and smoke detection results, respectively.

Table 1: Comparison of color space detection rates for finding fire pixels. Acc. means accuracy, Re. means recall, Pre. means precision and Spe. means specificity. Other M. denotes the previous work [1] presented for fire detection.

Space	Acc.%	Re.%	Pre.%	Spe.%
CIE Lab	92	95	94	75
CIE Luv	82	99	82	3
CIE XYZ	84	99	84	13
HLS	87	87	97	89
HSV	87	99	87	33
RGB	86	98	87	31
YCrCb	90	96	92	62
Other M.	73	63	79	83

After examining the fire detection rates of Table 1, one may notice that the proposed approach achieves better rates for most of the evaluation criteria than the rule-based previous work. Based on the results, the best color models for detecting fire pixels are CIE L*a*b* and YCrCb. As the rates show, the least suitable color models are recorded

Table 2: Comparison of color space detection rates for finding smoke pixels.

Space	Acc.%	Re.%	Pre.%	Spe.%
CIE Lab	58	97	58	4
CIE Luv	68	86	68	40
CIE XYZ	68	68	74	68
HLS	63	82	64	36
HSV	62	75	64	40
RGB	58	98	58	4
YCrCb	62	84	62	31

as CIE L*u*v* and CIE XYZ.

The reason for this can better be understood by studying the CIE L*a*b* and CIE L*u*v* histograms given in Fig. 5. The CIE L*a*b* histograms are closer to the normal distribution and have small variances, resulting in a better fire detection model. Here, having a normal distribution and small variances imply that fire pixels are collected from small areas, thus the system assigns high likelihood values for fire pixels and low likelihood values for non-fire pixels. Since the histograms of the CIE L*u*v* color space is not closer the normal distribution and has high variances, this model gives every pixel almost the same likelihood value.

The results suggest that the color information is more suitable for detecting fire than smoke. While fire has a distinct color range, smoke do not. Mostly, smoke is transparent and has the same color as the cloud.

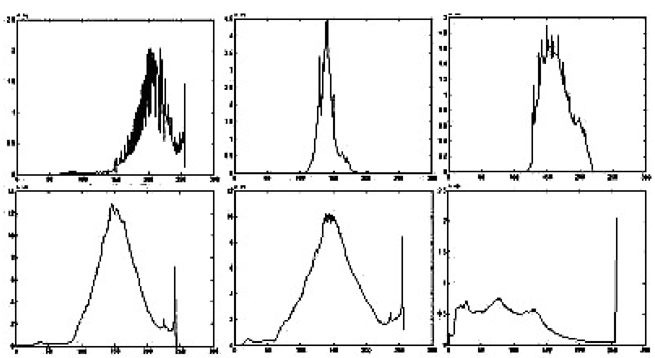

Fig. 5: The top row shows the CIE L*a*b* histogram for L*, a* and b* respectively, for fire regions. Second row CIE L*u*v* histogram for fire of L*, u* and v* respectively.

3.2 Finding Best Features Set

There are 3 different feature selection methods (PCA, K-Means, and Relative Entropy) in our system. To evaluate the feature selection methods, we reduce the number of features using each method and rank the selected features using different classifiers. According to our results, the Relative Entropy provides better feature selection over the other two techniques. The top 20 features we obtained for fire and smoke detections are given in Table 3.

Table 3: Selected best 20 features buy using relative entropy.

Color Space	Feature
CIE L*u*v*	Average Boundary Roughness of Fire
CIE L*u*v*	Average likelihood Value of Fire
CIE L*u*v*	Total Number of Fire Regions
CIE L*u*v*	Average Variance of Fire
RGB	Average Boundary Roughness of Fire
CIE L*u*v*	Total Number of Fire Pixels
HSV	Average Variance of Fire
HSV	Total Number of Fire Pixels
RGB	Total Number of Smoke Regions
RGB	Total Number of Fire Pixels
YCrCb	Total Number of Fire Pixels
CIE L*u*v*	Average Variance of Smoke
CIE XYZ	Total Number of Smoke Pixels
CIE L*u*v*	Average Boundary Roughness of Smoke
YCrCb	Total Number of Smoke Regions
HSV	Total Number of Fire Regions
CIE L*u*v*	Total Number of Smoke Pixels
YCrCb	Total Number of Smoke Regions
CIE L*u*v*	Total Number of Smoke Regions
CIE L*a*b*	Total Number of Fire Pixels

As can seen in Table 3, despite the low accuracy in finding fire and smoke pixels in CIE L*u*v color space, this space consists of the best features. This is because of the CIE L*u*v* spaceï£¡s high recall and low specificity. Finding the good threshold value for the other color spaces will indeed increase their performance. Note that fire-based features are better than those smoke-based since fire has distinct characteristic, such as color range. We record that boundary roughness and total number of pixels are good features for both fire and smoke regions.

3.3 Finding Best Classifier

There are 4 different feature selection methods that we use in our framework: SVM, K-NN, Feed Forward Back Propagation Artificial Neural Network and Perceptron. Top classification results are depicted in Table 4.

Table 4: Experimental result of feature selection method and classifier couple. Selection method means using feature selection method.

Selection Method	Classifier	Feature Number	Accuracy%
Relative Entropy	K-NN(k = 1)	16	92
Relative Entropy	SVM	18	86
PCA	SVM	16	76
PCA	KNN	24	75
Relative Entropy	Perceptron	16	74

Overall the results demonstrate that more than 90% of correct fire classification ratio is achieved when the features selected by Relative Entropy used with K-NN classifiers. As shown above, this rate is higher than the rule-based system presented in the literature.

4. Conclusions

In this paper, we present a forest fire detection system which takes into consideration both fire and smoke pixels for 7 different color spaces. . For each color space, we extract a set of features and determine the best feature set using different feature selection algorithms, e.g., PCA, K-Means, and Relative Entropy. Finally, the input image is classified as either fire or non-fire through various classification methods, such as SVM, K-Nearest Neighbor, and Neural Networks. The experimental results demonstrate that more than 90% of correct fire classification ratio is achieved when the best selected feature set is used with appropriate classifier.

As a result of this study, we decide that most suitable color space for modeling fire pixel is CIE L*a*b* and YCrCb. The best features are mostly fire features in CIE L*u*v* color space and the best classifier is K-NN.

For future work, the proposed system will be tested for different likelihood threshold values to maximize recall and specificity. For understanding the effect of the exposure mode, the system will be evaluated with images taken by cameras known parameter settings.

References

[1] FAO, 2006.Global Forest Assessment 2010.FAO forestry Food and Agriculture Organization of the UN, Rome, Italy.

[2] T. Celik, H. Demirel, H. Ozkaramanli, M. Uyguroglu, "Fire detection using statistical color model in video sequences", Journal of Visual Communication and Image Representation (2007) 176-185.

[3] T. H. Chen, C. L. Kao and S. M. Chang, "An Intelligent Real-Time Fire-Detection Method Based on Video Processing,"in Proceedings of the IEEE 37th Annual (2003) International Carnahan Conference on Security Technology, pp. 104-111,2003.

[4] W. Phillips III, M. Shah, and N. da Vitoria Lobo, "Flame Recognition in Video," in Proceedings of the Fifth IEEE Workshop on Applications of Computer Vision., pp. 224-229, 2000.

[5] Celik, Turgay. Fast and Efficient Method for Fire Detection Using Image Processing. ETRI Journal, Volume 32, Number 6, December 2010

[6] P. V. K. Borges, E. Izquierdo, "A probabilistic approach for visionbased fire detection in videos," IEEE. Trans. On Circuits and Systems for Video Technology, vol. 20, pp. 721 - 731, may 2010.

[7] B. U. Toreyin, A. E. Centin, "Online detection of fire in video," IEEE. Conf. on Computer Vision and Pattern Recognition, pp. 1 - 5, June 2007.

[8] S. Kullback and R. A. Leibler, On Information and Sufficiency, Ann. Math. Statist. Volume 22, Number 1 (1951), 79-86.

[9] D. Olson. Advanced data mining techniques. Springer Verlag, 2008

[10] Yuan Feiniu, "A fast accumulative motion orientation model based on integral image for video smoke detection", Pattern Recognition Letters, 2008:Vol.29, Issue 7, pp. 925-932.

[11] Ziyou Xiong, Rodrigo Caballero, Hongcheng Wang, Alan M. Finn, Muhidin A. Lelic, and Pei-Yuan Peng, "Video-based Smoke Detection: Possibilities, Techniques, and Challenges", IFPA, Fire Suppression and Detection Research and Applications - A Technical Working Conference (SUPDET), Orlando, FL, 2007.

[12] L. Merino, F. Caballero, J. R. M. de Dios, and A. Ollero, "Cooperative fire detection using unmanned aerial vehicles," in Proc. IEEE Int. Conf. Robot. Autom., Apr. 2005, pp. 1884âĂŞ1889.

[13] L. Merino, F. Caballero, J. R. M. de Dios, and A. Ollero, "Cooperative fire detection using unmanned aerial vehicles," in Proc. IEEE Int. Conf. Robot. Autom., Apr. 2005, pp. 1884âĂŞ1889.

[14] C. B. Liu and N. Ahuja,"Vision Based Fire Detection," in Proc. of Int. Conf. on Pattern Recognition, ICPR âĂŹ04, Vol. 4, 2004.