FIRE PIXEL CLASSIFICATION USING FUZZY LOGIC AND STATISTICAL COLOR MODEL

Turgay Çelik[*], *Hüseyin Özkaramanlı, Hasan Demirel*

Department of Electrical and Electronic Engineering, Eastern Mediterranean University , Gazimağusa, TRNC, Mersin 10, TURKEY, [*]turgay.celik@emu.edu.tr

ABSTRACT

In this paper, fuzzy logic enhanced generic color model for fire pixel classification is proposed. The model uses YCbCr color space to separate the luminance from the chrominance more effectively than color spaces such as RGB or rgb. Concepts from fuzzy logic are used to replace existing heuristic rules and make the classification more robust in effectively discriminating fire and fire like colored objects. Further discrimination between fire and non fire pixels are achieved by a statistically derived chrominance model which is expressed as a region in the chrominance plane. The performance of the model is tested on two large sets of images; one set contains fire while the other set contains no fire but has regions similar to fire color. The model achieves up to 99.00% correct fire detection rate with a 9.50% false alarm rate.

Index Terms— Fire detection, fuzzy logic, color model

1. INTRODUCTION

Due to the rapid developments in digital camera technology and developments in content based video processing, more and more vision based fire detection systems are introduced. Vision based systems generally make use of three characteristic features of fire: color, motion and geometry. Phillips et al. used color predicate information and the temporal variation of a small subset of images to recognize fire in video sequences [6]. A manually segmented fire set is used to train a system that recognizes fire like color pixels. The training set is used to form a look-up table for the fire detection system. The authors offer the use of generic look-up table if the training set is not available. Chen et al. used chromatic and dynamic features to extract real fire and smoke in video sequences [3]. They employ a moving object detection algorithm in the preprocessing phase. The moving objects are filtered with fire and smoke filter to raise an alarm for possible fire in video. They used a generic fire and smoke model to construct the corresponding filter. Töreyin et al. proposed a real-time algorithm for fire detection in video sequences [8]. They combined motion and color clues with fire flicker analysis on wavelet domain to detect fire. They have used a mixture of ten three dimensional Gaussians in RGB color space to model a fire pixel using a training set. Töreyin et al. proposed another algorithm for fire detection which combines generic color model based on RGB color space, motion information and Markov process enhanced fire flicker analysis to create an overall fire detection system [7]. They have employed the fire color model developed by Chen et al. Recently, Celik et al. proposed a generic model for fire color [1-2]. The authors combined their model with simple moving object detection in order to detect fires in video.

Almost all the vision based fire detection systems use some sort of a hybrid model which combines motion, geometry and color information. In general, fire detection systems use color clues as a precondition to generate seed areas for possible fire regions since it is the most discerning feature. An effective color model for fire pixel classification is thus essential for almost all vision based fire detection systems.

In this paper we propose a fuzzy logic enhanced approach which uses luminance and chrominance information to replace the existing heuristic rules. First the rules developed in the RGB and rgb color spaces (R>G>B) are translated to YCbCr color space. It is observed that the developed rules fall short in describing an exact mathematical model for fire color. The implicit fuzziness or uncertainties in the rules obtained from repeated experiments and the impreciseness of the output decision can be encoded in a fuzzy representation that is expressed in linguistic terms. The single output decision quantity will then give a better likelihood that a pixel is a fire pixel. The fuzzy model achieves better discrimination between fire and fire like-colored objects. As a result, it helps reduce false alarm rate. Further discrimination between fire and non fire pixels are achieved by a statistically derived chrominance model.

2. FIRE PIXEL COLOR MODELING

For each pixel in a fire blob, the value of Red channel is greater than the Green channel, and the value of Green channel is greater than the value of Blue channel. Furthermore the fire color has very high saturation in the Red channel [1-3]. These rules defined for RGB space, i.e. $R \geq G \geq B$, and $R \geq R_{mean}$, can be translated into YCbCr color space as;

$$Y(x,y) > Cb(x,y) \quad (1)$$

$$Cr(x,y) > Cb(x,y) \quad (2)$$

where $Y(x,y)$, $Cb(x,y)$, and $Cr(x,y)$ are Luminance, ChrominanceBlue and ChrominanceRed values for a pixel located at spatial coordinates (x,y). Equations (1) and (2) imply, respectively, that fire Luminance should be greater than ChrominanceBlue and ChrominanceRed should be greater than the ChrominanceBlue. Equations (1) and (2) can be interpreted to be a consequence of the fact that the fire has saturation in red color channel (R). Fig. 1 shows a representative fire image with its Y, Cb and Cr channels.

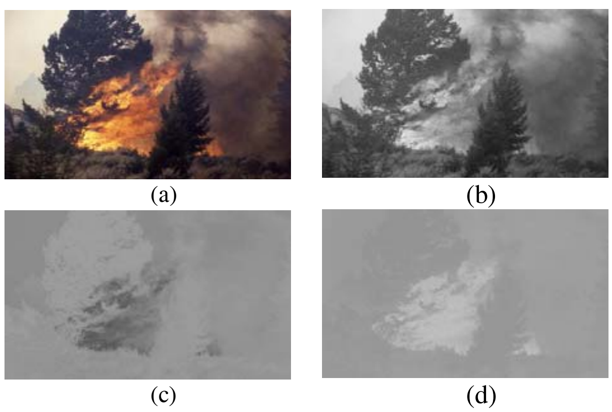


Fig. 1: RGB input image and it's Y, Cb and Cr channels, (a) Original RGB image (b) Y channel, (c) Cb channel, (d) Cr channel.

As can be observed from Fig. 1, for a fire pixel it is more likely that, $Y(x,y)$ is greater than $Cb(x,y)$. This is because the luminance information which is related to the intensity is naturally expected to be dominant for a fire pixel. Repeated experiments with fire images have shown that the greater the difference between $Y(x,y)$ and $Cb(x,y)$ components of a pixel, the higher the likelihood that it is a fire pixel. Fig. 1 also hints that $Cb(x,y)$ should be smaller than $Cr(x,y)$. Similarly, a higher discrimination between $Cb(x,y)$ and $Cr(x,y)$ means that corresponding pixel is more likely a fire pixel. However the rules fall short in coming up with a single quantitative measure which can indicate how likely a given pixel is a fire pixel. The implicit fuzziness or uncertainties in the rules obtained from repeated experiments and the impreciseness of the decision variable can be encoded in a fuzzy representation. This provides a way to express the output decision in linguistic terms. The single output decision quantity expressed as a number between zero and one will then give the likelihood that a pixel is a fire pixel. As will be shown later in the paper, this fuzzy output is also capable in better discriminating fire and fire-like colored objects with respect to rules defined in (1) and (2).

Let $P_f(x,y)$ be defined as a measure that shows how likely a pixel located at spatial location (x,y) belongs to fire pixel. Its range is $[0\,1]$, and it is a mapping of the observation defined in (1) and (2) to a quantity which describes the likelihood that a given pixel is a fire pixel. In order to evaluate $P_f(x,y)$, combination of triangular and trapezoidal membership functions are used both for the difference between $Cr(x,y)$ and $Cb(x,y)$, ($Cr(x,y)-Cb(x,y)$), and the difference between $Y(x,y)$ and $Cb(x,y)$, ($Y(x,y)-Cb(x,y)$). Fig. 2a, 2b and 2c show respectively membership functions which are used for $Y(x,y)-Cb(x,y)$, $Cr(x,y)-Cb(x,y)$, and $P_f(x,y)$. It should be noted that, Mamdani [4] type fuzzy inference system (FIS) is used with the rules defined in Table 1. The distribution of membership functions and rules defined in Table 1 is found using experimental analysis.

Table 1 show the rules used in our FIS. The rules are defined in such a way to reflect our expectation for a fire pixel. A total of 25 rules are constructed to account for all possible combinations of input variables. An example rule is as follows:

if $Y(x,y)-Cb(x,y)$ **is *NB* and** $Cr(x,y)-Cb(x,y)$ **is *NB* then** $P_f(x,y)$ **is *NB*.**

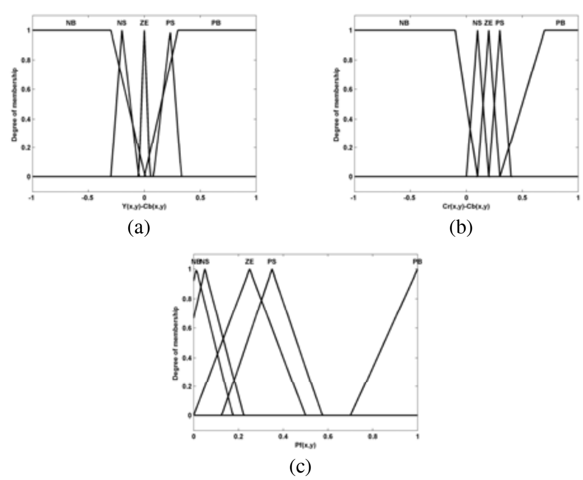


Fig. 2: Membership functions for (a) $Y(x,y)-Cb(x,y)$, (b) $Cr(x,y)-Cb(x,y)$, and (c) $P_f(x,y)$

	$P_f(x,y)$	*Cr(x,y) – Cb(x,y)*				
		NB	**NS**	**ZE**	**PS**	**PB**
Y(x,y)-Cb(x,y)	**NB**	*NB*	*NB*	*NB*	*NB*	*NB*
	NS	*NB*	*NB*	*NB*	*NB*	*NS*
	ZE	*NB*	*NB*	*NS*	*NS*	*ZE*
	PS	*NS*	*ZE*	*ZE*	*PS*	*PB*
	PB	*NS*	*ZE*	*PS*	*PB*	*PB*

Table 1: Rule table for fuzzy inference system.

Given a set of inputs from $Y(x,y)-Cb(x,y)$ and $Cr(x,y)-Cb(x,y)$, the *crisp* output of the fuzzy system is computed as follows: first, the inputs are fuzzified based on the membership functions shown in Fig. 2a and Fig. 2b. Then, the *min* implication operator [4] is applied on the fuzzy rules. Center of area defuzzification is applied on the union of all rule outputs in order to find a quantitative measure for $P_f(x,y)$ [4]. $Y(x,y)-Cb(x,y)$ and $Cr(x,y)-Cb(x,y)$ is normalized to $[-1 \;\; 1]$ before entering into FIS. The surface for 25 rules is shown in Fig. 3. The figure shows the likelihood $P_f(x,y)$ as a function of inputs $Y(x,y)-Cb(x,y)$ and $Cr(x,y)-Cb(x,y)$. The visual appearance of Fig. 3 is as expected and interpreted as follows; when $Y(x,y)-Cb(x,y)$ is less than zero, corresponding $P_f(x,y)$ approaches to 0, and if both $Y(x,y)-Cb(x,y)$ and $Cr(x,y)-Cb(x,y)$ gets closer to value of 1.0, the $P_f(x,y)$ approaches to 1.

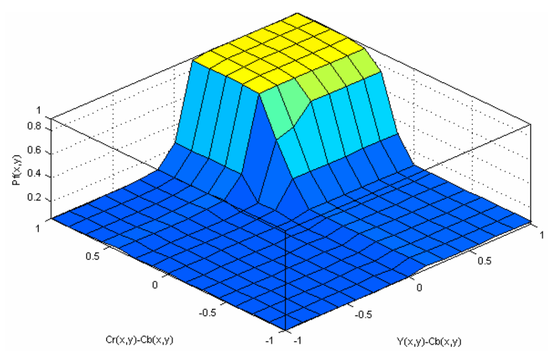


Fig. 3: View of rules given in Table 1 and used in FIS.

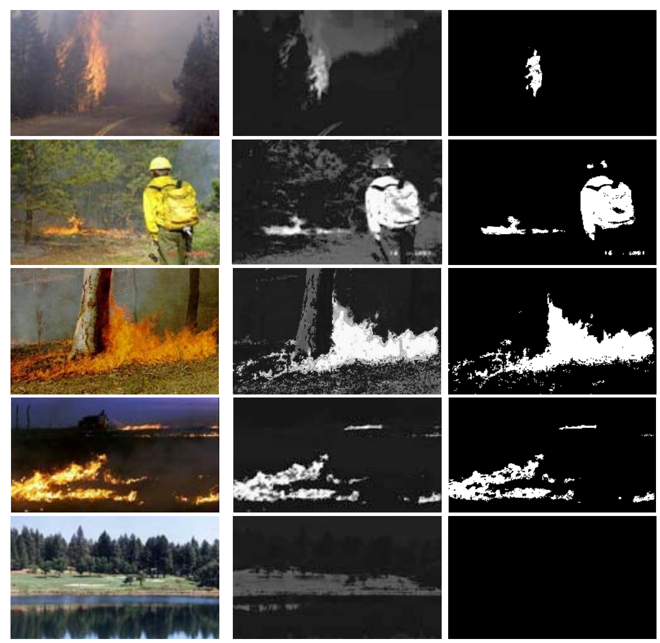
Let's define $B_f(x,y)$ as a binary image corresponding to $P_f(x,y)$ which shows fire pixels in the image. The binary image can be evaluated as follows;

$$B_f(x,y)=\begin{cases}1 & iff \quad P_f(x,y)\geq 0.5\\ 0 & otherwise\end{cases} \tag{3}$$

In (3) the value of 0.5 is intentionally selected with assumption that, any pixel is equally likely to be a fire pixel. Fig. 4 shows binary maps B_f and their corresponding P_f. It is clear that P_f gets higher values over fire regions and lower values over non-fire regions. It should be noted also that, the P_f is non-zero in non-fire regions which are fire-like colored.

In addition to the above fuzzy mechanism a statistical analysis of chrominance information in fire pixels over a large set of images is performed. For this purpose a set which consists of 1000 images at different resolutions are collected from internet. The collected set of images has a wide range of illumination and camera effects. The fire regions in the 1000 images are manually segmented and the histogram of a total of 16,309,070 pixels is created in the Cb-Cr chrominance plane. Fig. 5 shows distribution of fire pixels in Cb-Cr plane. The area containing fire pixels in Cb-Cr plane can be modeled using intersections of three polynomials denoted by $fu(Cr)$, $fl(Cr)$ and $fd(Cr)$. The equations for the polynomials are derived using least square estimation technique as (Mathews et al., 1999);

$$\begin{aligned}
fu(Cr) &= -2.6187x10^{-10}Cr^7 + 3.2731x10^{-7}Cr^6 - 1.7465x10^{-4}Cr \\
&\quad + 5.1568x10^{-2}Cr^4 - 9.0999Cr^3 + 9.5970x10^2 Cr^2 \\
&\quad - 5.6012x10^4 Cr + 1.3958x10^6 \\
fl(Cr) &= -6.7686x10^{-8}Cr^5 + 5.4981x10^{-5}Cr^4 - 1.7634x10^{-2}Cr^3 \\
&\quad + 2.7812Cr^2 - 2.1504x10^2 Cr + 6.6243x10^3 \\
fd(Cr) &= 1.8053x10^{-4}Cr^4 - 1.0207x10^{-1}Cr^3 + 2.1662x10Cr^2 \\
&\quad - 2.0474x10^3 Cr + 7.2883x10^4
\end{aligned} \tag{4}$$



(a) (b) (c)

Fig. 4: RGB input image and it's P_f and B_f. Column (a) RGB input image, Column (b) P_f for corresponding input image, Column (c) B_f for corresponding input image,

The region bounded by the three polynomials is depicted in Fig. 6. The boundaries of the region which correspond to the polynomials are shown in red. Once this region is obtained, it is easy to define a chrominance region for classifying the fire pixel. We formulate this as;

$$\begin{aligned}
&(Cb(x,y)\geq fu(Cr(x,y)))\cap(Cb(x,y)\leq fd(Cr(x,y))) \\
&\cap(Cb(x,y)\leq fl(Cb(x,y)))
\end{aligned} \tag{5}$$

Finally, fire pixel mask derived from equation (3) and chrominance region defined in (5).

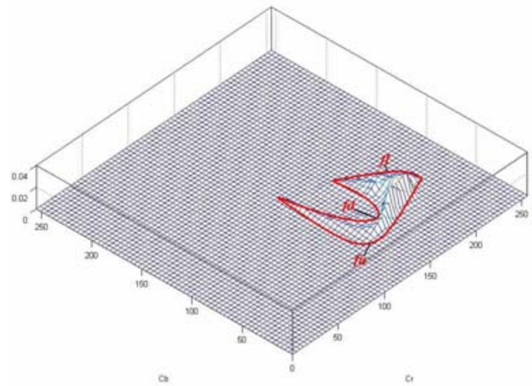


Fig. 5:3-D distribution of hand labeled fire pixels in Cb - Cr plane, and a fire region definition in Cb - Cr plane using three polynomials named with, fu , fd and fl .

3. PERFORMANCE ANALYSIS

For the comparison purposes, two sets of images are collected from Internet. One set is composed of images that consist of fire. Fire set consists of 332 images of size 256 by 256. The images in fire set show diversity in fire-color, and environmental Illuminations. The other set does not contain any fire but contains fire-like colored regions such as sun and other reddish objects. Non-fire set consists of 419 images, and they are again resized to 256 by 256.

The performance of the fuzzy logic enhanced generic fire model in the YCbCr color space is compared with previous models which were rule based and defined in other color spaces: RGB [1],[3], rgb [2] and YCbCr. YCbCr color space model is also a new model, and it uses the rules defined in (1) and (2), with the same chrominance model described in (5).

Two types of comparisons are carried out; one is for the evaluation of the correct fire detection rate and the other is for the false alarm rate. The following criterion is used for declaring a fire region: if the model achieves to detect at least 5 pixels of a fire region in a given image, then it is assumed as a correct detection. For the false alarm rate the same detection criterion is used with the non-fire image set.

In Table 2, we have tabulated fire detection results with false alarm rates. It is clear from Table 2 that, fuzzy logic enhanced YCbCr color based model outperforms the models developed in other color spaces both in high detection rate and low false alarm rate.

As it can be observed from Table 2, YCbCr color space outperforms other color spaces both in correct detection rate and false alarm rate. This is due to the ability of YCbCr color space to separate luminance from chrominance. The two models proposed in this work takes the advantage of this property and develops separate models in both luminance and chrominance planes. For the YCbCr model the rules fall short in describing a single quantitative measure which can indicate how likely a given pixel is a fire pixel. As a result, it becomes difficult to discriminate between fire regions and fire-like regions. The implicit fuzziness or uncertainties in the rules is encoded in a fuzzy representation. This provides a way to express the output decision in linguistic terms. As a result, the most needed discrimination between fire and fire-like regions is enhanced. This is clearly reflected in Table 2 with a 9.5 % false alarm rate, which is a reduction of 20.5 % compared to rule based YCbCr model.

Model	Detection Rate (%)	False Alarm Rate (%)
RGB, Chen et al. [3]	93.90	66.42
RGB, Celik et al. [1]	78.50	28.21
rgb, Celik et al. [2]	97.00	78.39
YCbCr	99.00	31.00
Proposed	99.00	9.50

Table 2: Performance comparisons of the models with respect detection rates, and false alarm rates.

4. CONCLUSIONS

We have developed two models: one based on predominantly on luminance and the other on chrominance. For the luminance model, concepts from fuzzy logic are used to replace existing heuristic rules and make the classification more robust in effectively discriminating fire and fire like colored objects. Further discrimination between fire and non fire pixels are achieved by a statistically derived chrominance model. The decision for classifying a fire pixel can be made combining the mask derived from fuzzy logic enhanced luminance model with the chrominance model. The model achieves up to 99.00% correct fire detection rate with a 9.50% false alarm rate.

5. REFERENCES

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