Thesis for the Degree of Master of Engineering

Vision-Based Fire Detection Using the Improved Segmentation Algorithm and ADBM Information

by

FengJiPiao

Department of Electronic Engineering

The Graduate School,

Pukyong National University

August 2011

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개선한 분할 알고리즘 및 ADBM 정보를 사용한 비디오 기반 화재검출

Advisor: Prof. Ji GooRyu

by
FengJiPiao

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A dissertation

By

FengJiPiao

Approved by:

Kwang-Seok Moon

(Chair man)

Ji-Goo Ryu

(Member)

Jong-Nam Kim

(Member)

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FENGJI PIAO

부 경 대 학 교 대 학 원 전 자 공 학 과

요약

우리나라는 전국토의 65%가 산지이고 산림상태는 불에 잘 타는 침엽수가 전체의 42% 차지하고 있다. 이러한 특성 외에 최근의 기상이변 현상으로 산불 재난이 점차로 대형화 되고 있다. 화재감지 시스템은 화재 상황을 대처할 수 있도록 지원함으로써 피해규모를 축소시킬 수 있다. 현재의 화재 경보 시스템은 센서 기반의 감지기들이 대부분이며 이들 감지기는 화재가 발생한 후 일정한 시간이 지나 열이나 연기가 확산되어야 감지가 가능하므로 조기진화에 어려우며 개방된 공간 에서는 그 성능이 떨어지게 된다. 이에 반하여 비디오 기반 화재감지 시스템은 연기의 확산을 기다릴 필요 없이 카메라를 통하여 원격지에서 즉각적인 감지가 가능하다. 카메라를 이용한 화재감지 시스템의 장점에도 불구하고 이와 관련된 연구는 미비한 실정이다. 기존의 문제들을 극복하기 위하여 본 논문에서는 개선한 분할 알고리즘 및 ADBM 정보를 사용한 비디오 기반 화재검출 알고리즘을 제안하였다. 제안한 방법은 첫째, RGB, YCbCr 칼라공간을 사용하여 칼라기반 각 픽셀을 분류한다. 둘째, 연속된 프레임간 픽셀 값 차이의 절대값에 대한 평균을 이용하여 평균차이 배경모델(Average Difference Background Model)을 생성한다. 셋째, 학습된 평균차이 배경모델을 이용하여 전경과 배경영역으로 분할한다. 넷째, TFF(Texture Filter Functions)를 사용하여 지역의 픽셀 값의 변화의 정도를 나타내는 영상을 획득한다. 다섯째, 연결된 구성요소(Connected Components)를 이용하여 전경과 배경이 분할된 영상을 깨끗이 정리한다. 이 방법은 잡음이 포함된 영상을 마스크 영상의 형태로 입

력 받는다. 그리고 Morphology Open연산을 수행하여 작은 크기의 잡음을 제거하고, Morphology Close영산을 수행하여 영역들을 복원시킨다. 그런 다음 남아 있는 영역들을 찾고 Box 그려 준다. 실생활 환경에서 촬영된 화재 영상에 대해 실험한 결과 검출율은 99.9%로 이전의 비전기반 화재감지 알고리즘에 비해서 좋은 결과를 나타내는 것을 보여준다.

Vision-Based Fire Detection Using the Improved Segmentation Algorithm and ADBM Information

PIAO FENGJI

Department of Electronic Engineering, The Graduate School,
Pukyong National University

Abstract

About 65% of the whole Korea's land are surrounded by mountains. The majority of whole forests is in general pine forests which is likely to be burnt with ease. Recently, the fire is frequent and getting larger. The fire monitoring application systems can reduce the damage of properties by providing earlier warning for possible fire situation. Most of the fire alarm system using sensor-based detector. But these sensors, after the fire happened, when fire smoke spread to certain degree, can be detector fire. Instead, video-based fire detection system, does not have to wait for the spread of smoke, through the camera can immediately detector fire. Although, used a advantages, there are few related research. In order to overcome the existing problems, In this paper, we proposed a new vision-based fire detection algorithm. First, color-based segmentation using the RGB and YCbCr color space. Second, The absolute value of the successive inter-frame pixel value difference using average for the Average Difference Background Model to generate. Third, segment the image into foreground and background regions using the Average Difference Background Model. Fourth, acquired the degree of change in pixel values using the Texture Filter Functions. Fifth, clean up the raw segmented image

using connected-components analysis. This form of analysis takes in a noisy input mask image. It then uses the morphological operation open to shrink areas of small noise to 0 followed by the morphological operation close to rebuild the area of surviving components that was lost in opening. Thereafter, we can find the contours of the segments. The experimental results using real world videos show that our system can indeed improve detection performance compared to previous research.The detection rate achieved was 99.9%.

I. Introduction

Fire detection system are one of the most important components in surveillance systems used to monitor buildings and environment as part of an early warning mechanism that reports preferably the start of fire. Currently, almost all fire detection systems use built-in sensors that primarily depend on 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.

Due to the rapid developments in digital camera technology and video processing techniques, there is a big trend to replace conventional fire detection techniques with computer vision-based systems. In general computer vision-based fire detection systems employ three major stages.[1-4]First stage is the flame pixel classification; the second stage is the moving object segmentation; the last part is the analysis of candidate regions. This analysis is usually based on two figures of merit; shape of the region and the temporal changes of the region.

The fire detection performance depends critically on the performance of the flame pixel classifier which generates seed areas on which the rest of the system operates. The flame pixel classifier is thus required to have a very high detection rate and preferably a low false alarm rate. There exist few algorithms which directly deal with the flame pixel classification in the literature. The flame pixel classification can be considered both in grayscale and color video sequences.

Visual fire detection can be useful in conditions whereconventional fire detectors cannot be used. Particle and temperature sampling, and air transparency testing aresimple methods that are frequently used for fire detection [5-6]. These methods require close proximity to the fire. In addition, these methods are not always reliable, as they donot always detect the combustion itself. Most of them detect smoke, which could be produced in other ways.

Existing methods of visual fire detection rely almostexclusively upon spectral analysis using rare and usuallycostly spectroscopy equipment. This limits the fire detectionto those individuals who can pay high prices for expensivesensors that are necessary for these methods. Moreover,these methods still produce false alarms in the case of objects whose colors are almost the same with fire,especially sun.

Our works in this thesis focus on image analysis. The purpose of this introduction is to provide an idea what this thesis is about and what you will learn from it. Having a background in Image Processing will help you read this thesis.[18]

1. Contribution

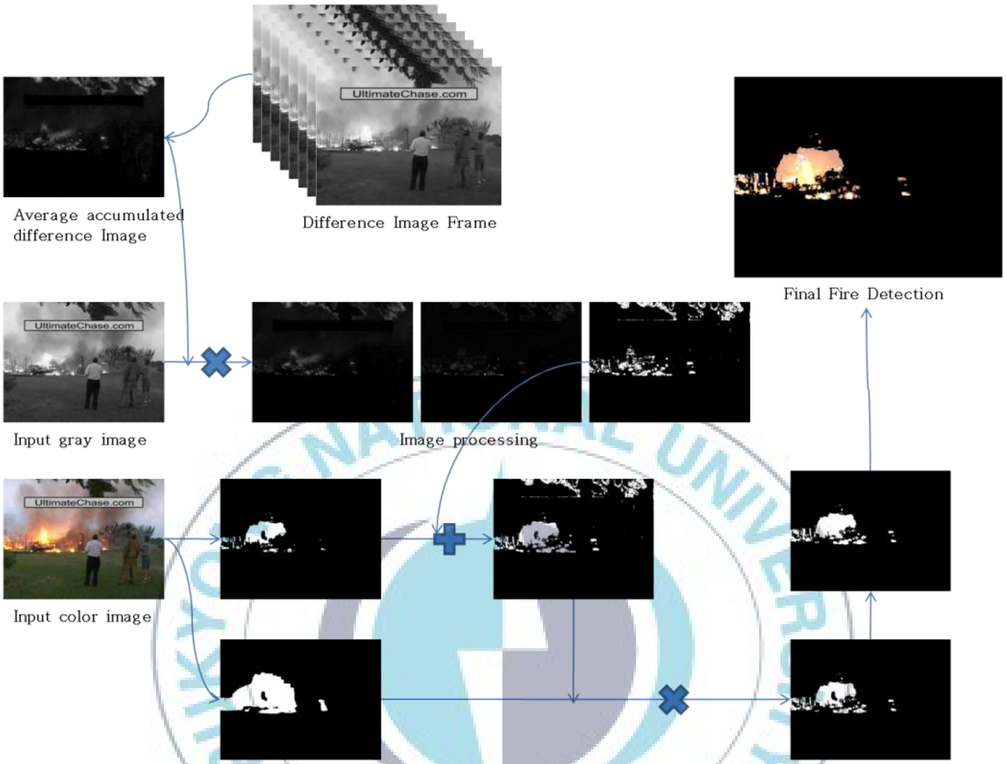


Figure 1.1 The flow chart of proposed algorithm

In this paper, we proposed a new vision-based fire detection algorithm. At first, we using the RGB and YCbCr color space for color-based segmentation. Next, The absolute value of the successive inter-frame pixel value difference using average for the Average Difference Background Model to generate. Later, segment the image into foreground and background regions using the Average Difference Background Model. At last, acquired the degree of change in pixel values using the Texture Filter Functions. Then, we using Morphology for the clean up the raw segmented image.

This form of analysis takes in a noisy input mask image. It then uses the morphological operation open to shrink areas of small noise to 0 followed by the morphological operation close to rebuild the area of surviving components that was lost in opening. Thereafter, we can find the contours of the segments. The experimental results using real world videos show that our system can indeed improve detection performance compared to previous research.

2. Organization

The rest of this thesis is organized as follows:

In chapter II, we briefly review some of the color-based image segmentation techniques and background removal analysis techniques and pixel classification techniques and statistical features techniques in the literature and present their reported results. In chapter III, we using some MATLAB function to do adjusting light intensity of the image, next, using the RGB and YCbCr color space for color-based segmentation, later using advanced background removal method to do background removal, then, using morphology for the clean up the foreground.In chapter IV, we present experimental results according to those proposed methods and compare them with the recent schemes in the literature. In chapter V, we present the conclusions about the above proposed method.

II. Related Work

1. Introduction

Conventional point smoke and fire detectors are widelyused in buildings. They typically detect the presence of certain particles generated by smoke and fire by ionization orphotometry. Alarm is not issued unless particles reach thesensors to activate them. Therefore, they cannot be used inopen spaces and large covered areas. Video based firedetection systems can be useful to detect fire in large auditoriums, tunnels, atriums, etc. The strength of using videoin fire detection makes it possible to serve large and openspaces. In addition, closed circuit television (CCTV) surveillance systems are currently installed in various publicplaces monitoring indoors and outdoors. Such systemsmay gain an early fire detection capability with the use ofa fire detection software processing the outputs of CCTVcameras in real time.[3]

2.General Fire Detection Algorithm

2.1 Statistical Features Algorithm

The system uses low-cost CCD cameras operating in the near infra red range todirectly detect fire and hotspots. In addition, LED illumination units are appropriately switched on and off, and the obtained images areanalyzed to detect smoke. Fusion of image processing results with temperature and humidity readings allows reliable detection of true fires and elimination of false alarms due to fog and dust. It was necessary to create a suite of fire sensitivity and false alarm immunity testsapplicable to these vision-based fire detection systems.

This method in statistical features, based on grayscale video frames, including mean pixel intensity, standard deviation, and second-order moments, along with non-image features such as humidity and temperature to detect fire in the cargo compartment. The system is commercially used in parallel to standard smoke detectors to reduce the false alarms caused by the smoke detectors.[7]

2.2 Color Model Based Algorithm

The RGB color model, the basic idea of the proposed of fire-detection in to adopt a RGB(Red, Green, Blue) model based chromatic and disorder measurement for extracting fire-pixels and smoke-pixels. The decision function of fire-pixels is mainly deduced by the intensity and saturation of R component. The extracted fire-pixels will be verified if it is a real fire by both dynamics of growth and disorder, and furtherly smoke.[8]

The YUV color model for the representation of video data, where time derivative of luminance component Y was used to declare the candidate fire pixels and the Chrominance components U and V were used to classify the candidate pixels to be in the fire sector or not. In addition to luminance and chrominance they have incorporated motion into their work. They report that their algorithm detects less than one false alarm per week; however, they do not mention the number of tests conducted.[9]

The HSI color model to roughly segment the fire-like regions for brighter and darker environments. Initial segmentation is followed by removing lower intensity and lower saturation pixels in order to get rid of the spurious fire-like regions such as smoke.[10]

2.3 Frame Differencing Algorithm

The very simplest background subtraction method is to subtract one frame from another(possibly several frames later) and then label any difference that is “big enough” theforeground. This process tends to catch the edges of moving objects.

Thismethod is much too simple for most applications other than merely indicating regions ofmotion. For a more effective background model we need to keep some statistics about themeans and average differences of pixels in the scene.[19]

(a) (b) (c)

Figure 2.1 (a) Frame1 (b) Frame2 (c) Frame3 = Frame1 - Frame2

2.4 Background Based Algorithm

The averaging method basically learns the average and standard deviation (or similarly,but computationally faster, the average difference) of each pixel as its model of thebackground.[19]

The averaging method makes use of routines:

(1) Accumulate imagesover time.

(2) Accumulate frame-to-frame image differences over time.

(3) Segment the image (once a background model has been learned) intoforeground and background regions.

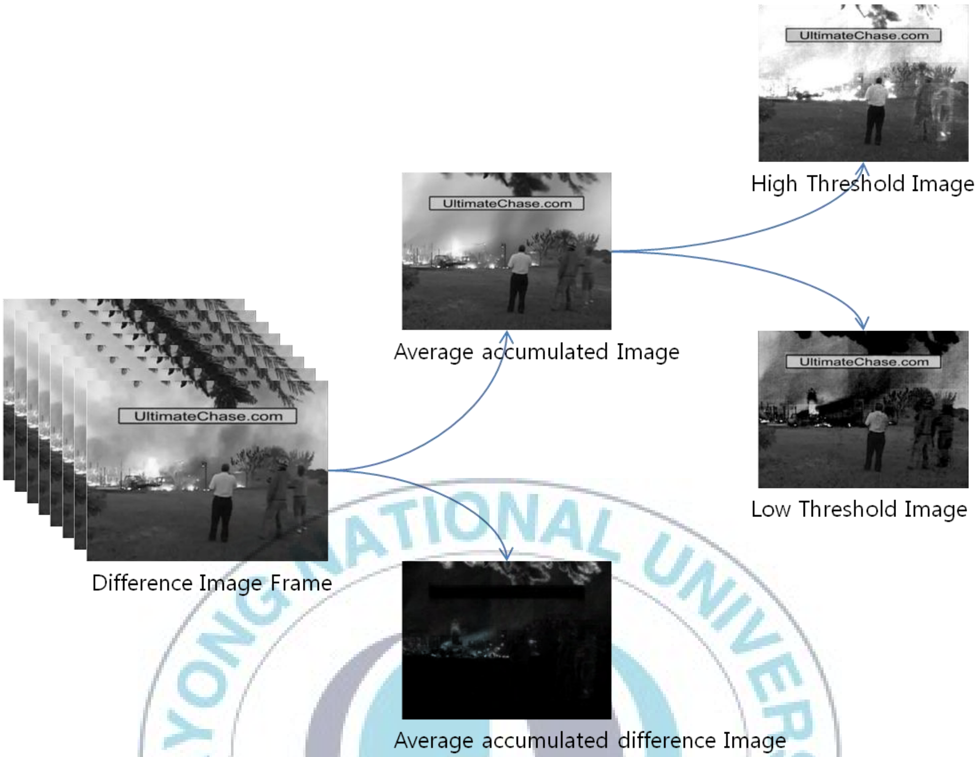


Figure 2.2 The flow chat of averaging background algorithm

Within this range around thepixel's average value, objects are considered to be background.Once we have our background model, complete with high and low thresholds, we useit to segment the image into foreground (things not "explained" by the background image)and the background (anything that fits within the high and low thresholds of ourbackground model).

We'vejust seen a simple method of learning background scenes and segmenting foregroundobjects. It will work well only with scenes that do not contain moving backgroundcomponents (like a waving curtain or waving trees). It also assumes that the lightingremains fairly constant (as in indoor static scenes)

3. Summary

We have discussed four algorithm of fire detection techniques in this chapter. The first method named Statistical Features Algorithm. The system also provides visual inspection capability which helps the aircraft crew to confirm the presence or absence of fire. However, the statistical image features are not considered to be used as part of a standalone fire detection system. Most of the works on flame pixel classification in color video sequences are rule based. The second method named Color Model Based Algorithm.However, none of these color spaces are directly related to the intuitive notions of hue, saturation, and brightness.This resulted in the temporary pursuit of other models. The third method named Frame Differencing Algorithm. The average difference method simple and quick, but using this method processed image is not very clean and clear. The fourth method named Background Based Algorithm. The resolution is very accurate, but because of the big amount of calculation, The time complexity is very high. In this paper we propose to use the RGB and YCbCr color space and improved background removal algorithm. In addition to translating the rules developed in the RGB andnormalized rgb to YCbCr color space, new rules are developed inYCbCr color space which further alleviate the harmful effects ofchanging illumination and improves detection performance.

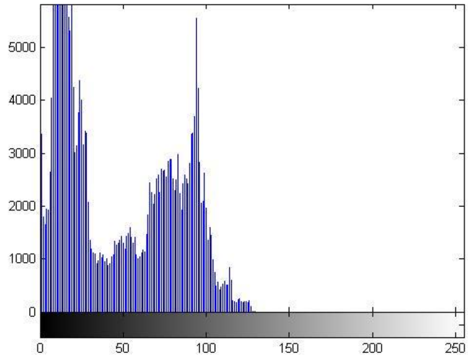
III. Proposed Algorithm

1. Image Adjusting

Nowadays, film cameras are already replaced by digitalcameras. Digital cameras capture and store photographsdigitally, and people can design methods to enhancepictures. If the output results are not good enough, thevery common problem is underexposure.[19]

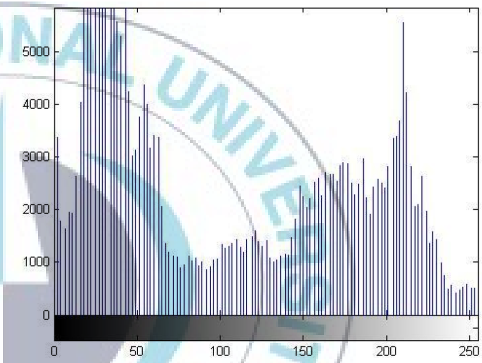
Adjust increases the contrast of the image by mapping the valuesof the input intensity image to new values. Image adjusting means changing image properties. Properties include, darkening images, lighting images, resizing images, cropping images etc.Image enhancement techniques are used to improve an image, where "improve" is sometimes defined objectively, and sometimes subjectively.Intensity adjustment is an image enhancement technique that maps an image's intensity values to a new range. To illustrate, this figure shows a low-contrast image with its histogram. Notice in the histogram of the image how all the values gather in the center of the range.

(a)



(b)

(c)



(d)

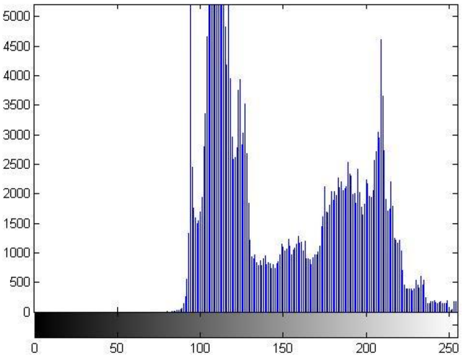
Figure 3.1 Original dark image and its histogram

(a) Original dark image

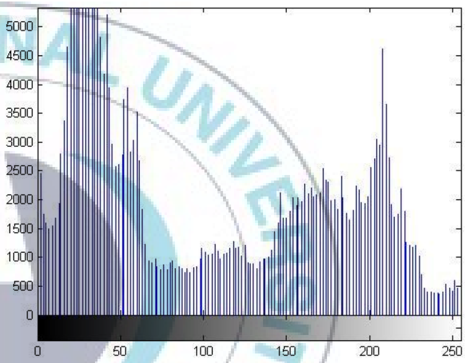
(b) Histogram of original dark image

(c) Adjusted image

(d) Histogram of adjusted image



(a) (b)



(c) (d)

Figure 3.2 Original light image and its histogram

(a) Original light image

(b) Histogram of original light image

(c) Adjusted image

(d) Histogram of adjusted image

(a) (b)

Figure 3.3R, G, and B channels of original dark image in column(a), and R, G, and B channels of adjusting images in column(b).

(a) (b)

Figure 3.4R, G, and B channels of original light image in column(a), and R, G, and B channels of adjusting images in column(b).

2. Color-Based Segmentation Using a Generic Color Space

In this paper, a rule-based generic color model for flame pixel classification is proposed. The proposedalgorithm uses RGB and YCbCr color space to separate the luminance from the chrominance. Because of the linear conversion between RGB and YCbCr color spaces, we conversion from RGB to YCbCr color space is formulated as follows(1):

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.2568 & 0.5041 & 0.0979 \\ -0.1482 & -0.2910 & 0.4392 \\ 0.4392 & -0.3678 & -0.0714 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} \ldots\ldots\ldots\ldots\ldots\ldots\ldots.(1)$$

Where Y is luminance, Cb and Cr are chrominance Blue and Chrominance Red component, respectively.

$$\mathcal{F}_{\tau}(x, y) = \begin{cases} 1, & \text{if } |Cr - Cb| \geq \tau \\ 0, & \text{otherwise} \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(2)$$

Where τ is a constant.

The value of τ is determined using a receiver operating characteristics analysis of Eq. (2) on an image set consisting of many images.

Figure 3.5 shows the three channels of YCbCr images for a representative image containing fire in more detail. The rule in (2) can be easily verified.

(a) (b)

(c) (d)

Figure 3.5 Original images and its Y, Cb and Cr channels

(a) Original image

(b) Y channels

(c) Cb channels

(d) Cr channels

For a given image, one can define the mean values of the three components in RGB color space as

$$R_{mean} = \frac{1}{K}\sum_{i=1}^{k} R(x_i, y_i) \ldots \ldots \ldots \ldots \ldots (3)$$

$$G_{mean} = \frac{1}{K}\sum_{i=1}^{k} G(x_i, y_i) \ldots \ldots \ldots \ldots \ldots (4)$$

$$B_{mean} = \frac{1}{K}\sum_{i=1}^{k} B(x_i, y_i) \ldots \ldots \ldots \ldots \ldots (5)$$

Where (x_i, y_i) is the spatial location of the pixel, R(x, y), G(x, y), and B(x, y) are Red, Green and Blue values for a pixel located spatially at (x, y), R_{mena}, G_{mean}, and B_{mean} are the mean values of Red, Green, and Blue channels of pixels, and K is the total number of pixels in image.

Since the flame region is generally the brightest region in the observed scene, the mean values of the three channels, in the overall image R_{mena}, G_{mean}, and B_{mean} contain valuable information. For the flame region the value of the Rcomponent is bigger than the $\frac{3}{2} \times R_{mena}$, the G component is bigger than the $\frac{3}{2} \times G_{mena}$, the B component is bigger than the $\frac{3}{2} \times B_{mena}$. These observations which are verified over countless experiments with images containing fire regions are formulated as the following rule:

$$R > \frac{3}{2} R_{mean} \quad \ldots\ldots\ldots\ldots \quad (6)$$

$$G > \frac{3}{2} G_{mean} \quad \ldots\ldots\ldots\ldots \quad (7)$$

$$B > \frac{3}{2} B_{mean} \quad \ldots\ldots\ldots\ldots \quad (8)$$

Figure 3.6 shows the three channels of RGB images for a representative image containing fire in more detail. The rule in (6-8) can be easily verified.

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

Figure 3.6 Original RGB color images and its Red, Green and Blue channels:

(a) Original RGB image

(b) Red channels of original RGB image

(c) Green channels of original RGB image

(d) Blue channels of original RGB image

Figure 3.7 shows the fire detection mechanism for an image. Figure 3.7(a) shows the original image over which our generic model is applied to segment fire pixels. Figure 3.7(b) shows the binary image, where pixels that in line with the rule(2) are labeled with white. It is remarkable that, the assumption for the fire pixels having higher red components than the surrounding environment holds, but produces to many false positives. Figure 3.7(c) shows the binary image, where pixels that in line with the rule(6-8) are labeled with white. The resultant binary image shows that rules through (6), (7) and (8) are suitable for efficient segmentation of the fire.

(a) (b)(c)

Figure 3.7 Fire pixel segmentation in image using generic fire model

(a) Original image

(b) (b)Fire segmentation using only (2)

(c) Fire segmentation using (6), (7) and (8)

3. Advanced Background Removal Algorithm

In this chapter we examine algorithms thatdeal with finding, filling and isolating objects and object parts in an image. We startwith separating foreground objects from learned background scenes.[20]

Because of its simplicity and because camera locations are fixed in many contexts, backgroundsubtraction is probably the most fundamental imageprocessing operation for video security applications. Toyama, Krumm, Brumitt, andMeyers give a good overview and comparison of many techniques [Toyama99]. In orderto perform background subtraction, we first must “learn” a model of the background.Once learned, this background model is compared against the current image and thenthe known background parts are subtracted away. The objects left after subtraction arepresumably new foreground objects.

Of course “background” is an ill-defined concept that varies by application. For example,if you are watching a highway, perhaps average traffic flow should be consideredbackground. Normally, background is considered to be any static or periodicallymoving parts of a scene that remain static or periodic over the period of interest. Thewhole ensemble may have time-varying components, such as trees waving in morningand evening wind but standing still at noon. Two common but substantially distinctenvironment categories that are likely to be encountered are indoor and outdoor scenes.We are interested in tools that will help us in both of these environments.

Although the background modeling methods mentioned here work fairly well for simplescenes, they suffer from an assumption that is often violated: that all the pixels areindependent. The methods we describe learn a model for the variations a pixel experienceswithout considering neighboring pixels. In order to take surrounding pixels intoaccount, we could learn a multipart model, a simple example of which would be anextension of our basic independent pixel model to include a rudimentary sense of thebrightness of neighboring pixels. In this case, we use the brightness of neighboring pixelsto distinguish when neighboring pixel values are relatively bright or dim. We thenlearn effectively two models for the individual pixel: one for when the surrounding pixelsare bright and one for when the surrounding pixels are dim. In this way, we have amodel that takes into account the surrounding context. But this comes at the cost oftwice as much memory use and more computation, since we now need different valuesfor when the surrounding pixels are bright or dim. We also need twice as much data tofill out this two-state model. We can generalize the idea of “high” and “low” contextsto a multidimensional histogram of single and surrounding pixel intensities as well asmake it even more complex by doing all this over a few time steps. Of course, this richermodel over space and time would require still more memory, more collected data samples,and more computational resources.

In general, a scene model might contain multiple layers, from “new foreground” to olderforeground on down to background. There might also be some motion detection so that,when an object is moved, we can identify both its “positive” aspect (its new location)and its “negative” aspect (its old location, the “hole”).

In this way, a new foreground object would be put in the “new foreground” object leveland marked as a positive object or a hole. In areas where there was no foreground object,we could continue updating our background model. If a foreground object does notmove for a given time, it is demoted to “older foreground,” where its pixel statistics areprovisionally learned until its learned model joins the learned background model.

For global change detection such as turning on a light in a room, we might use globalframe differencing. For example, if many pixels change at once then we could classify it asa global rather than local change and then switch to using a model for the new situation.

In this chapter, we proposed the absolute value of the successive inter-frame pixel value difference method.

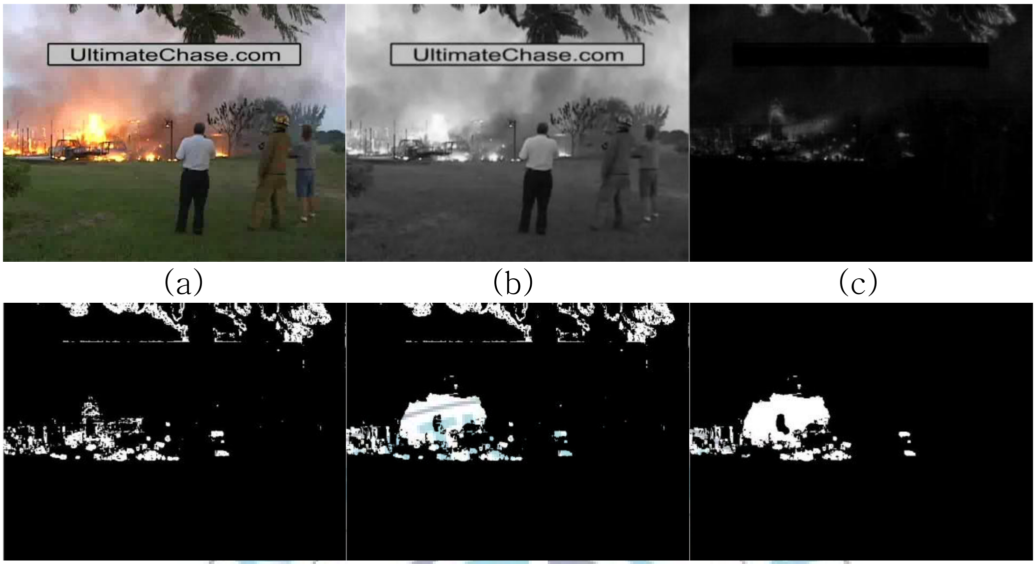
The averaging method makes use of three routines:

(1) Accumulateimagesover time.

(2) Accumulateframe-to-frame image differences over time.

(3) Segment the image (once a background model has been learned) intoforeground and background regions.

Figure 3.8 shows the background removal an image. Figure 3.8(a) shows the original image over which our generic model is applied to segment fire pixels. Figure 3.8(b) shows the gray scale image of original image. Figure 3.8(c) shows the gray scale image of image (b) add average different frame image. Figure 3.8(d) shows the binary image of image (c).Figure 3.8(e) shows the binary image of image (d) addFigure 3.7(c). Figure 3.8(f) shows the final background removal image.



(a) (b) (c)

(d) (e) (f)

Figure 3.8 The background removal an image

(a)Original image

(b)Gray scale image

(c)Image (b) add average different frame image

(d)Binary image of image (c)

(e)Image (d)add Figure 3.7(c)

(f)Final background removal image

4. Connected Components for Foreground Cleanup

we should pause todiscuss ways to clean up the raw segmented image using connected-components analysis.This form of analysis takes in a noisy input mask image; it then uses the morphologicaloperation *open* to shrink areas of small noise to 0 followed by the morphologicaloperation *close* to rebuild the area of surviving components that was lost in opening.Thereafter, we can find the “large enough” contours of the surviving segments and canoptionally proceed to take statistics of all such segments. We can then retrieve either thelargest contour or all contours of size above some threshold.[11]

Binary images in general will contain more than one object. In order to identify orclassify the objects in the image, we must first identify the connected components, that isthe distinctly connected blobs that correspond to each object in the image. At this stage,we are assuming that each object is isolated from the others, that is, there is no occlusion.The sequential scanlabelling algorithm we describe comes from Horn's book [12].

We then go on to describe the technique of mathematical morphology for low-level imageanalysis. The notes in this section follow closely those of Gonzalez and Woods.

Given a binary image we wish to scan through it, identify distinct `blobs' and labeleach one uniquely. Connectivity will be described using a left-skewed 6-connectednessneighbourhood scheme, as shown in figure 3.9

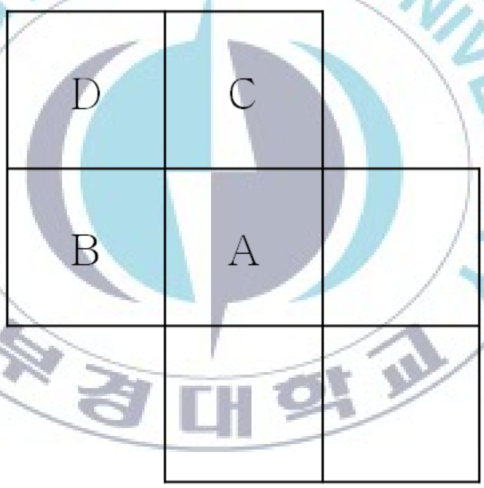


Figure 3.9 The 6-connected neighbourhood

Mathematical Morphology is a tool for extracting image components that are useful forrepresentation and description. The technique was originally developed by Matheronand Serra [13] at the Ecole des Mines in Paris. It is a set-theoretic method of imageanalysis providing a quantitative description of geometrical structures. Morphology can provide boundaries of objects, their skeletons, and their convex hulls. Itis also useful for many pre- and post-processing techniques, especially in edge thinningand pruning.

Generally speaking most morphological operations are based on simple expanding andshrinking operations. The primary application of morphology occurs in binary images,though it is also used on grey level images. It can also be useful on range images.

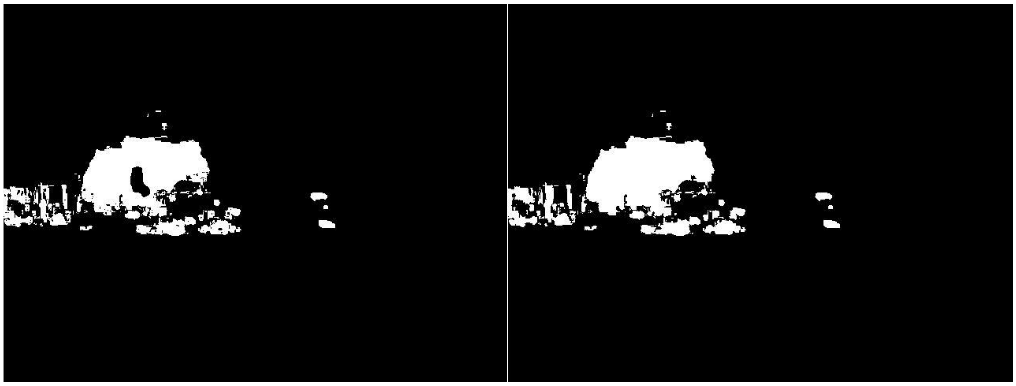
Morphological reconstruction has a broad spectrum of practical applications, each characterized by the selection of the marker and mask images. For example, let I denote a binary image and suppose that we choose the marker image, F, to be 0 everywhere except on the image border, where it is set to 1-I:

$$\mathcal{F}(\mathrm{x},\mathrm{y}) = \begin{cases} 1-\mathrm{I}, & \text{if } (\mathrm{x},\mathrm{y}) \textit{ is on the border of } I \\ 0, & \text{otherwise} \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(9)$$

Then,

$$\mathrm{H} = [R_{I^c}(\mathcal{F})]^c \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(10)$$

Figure 3.10 shows the foreground cleanup an image. Is a binary image equal to I with all holes filled, as illustrated in Figure 3.10(b)



(a) (b)

Figure 3.10The foreground cleanup

(a)The background removal image

(b)Clean up image (a)

IV. Experimental Results

We compared the image segmentation rate using generic color spaces. And we analyze the average difference frame background model removing the background of image. Our Systems used for implementation and experiment as follows. The spec of PC are Intel(R) Core(TM)2 Duo CPU, 2.93GHz, 4.00GB Ram and Windows 7, MATLAB 2010 were set up to make up the program. Experimental images shown in Figure4.1, still images and video images respectively.

Figure 4.1 shows the experimental images. As experimental data from the various images on the internet, we use the images that can be divided into image of the day and image of the night region.

Figure 4.2 show the original dark and light image in column (a), and adjusting imsge in column (b).

Figure 4.3 shows the Different frame image and its average accumulated image, average accumulated different image.Figure

4.3(a) shows theDifferent frame image. Figure 4.3(b) shows the averageaccumulated image.Figure 4.3(b) shows the average accumulateddifferent image.

Figure 4.4 shows Using different method for the fire detection. Figure 4.4(a) shows Using HIS color space. Figure 4.4(b) shows Using RGB color space. Figure 4.4(c) shows Using YCbCr color space. Figure 4.4(d) shows Using RGB and YCbCr color space, proposed.

Figure 4.5 shows the fire detection in different frame sequences.

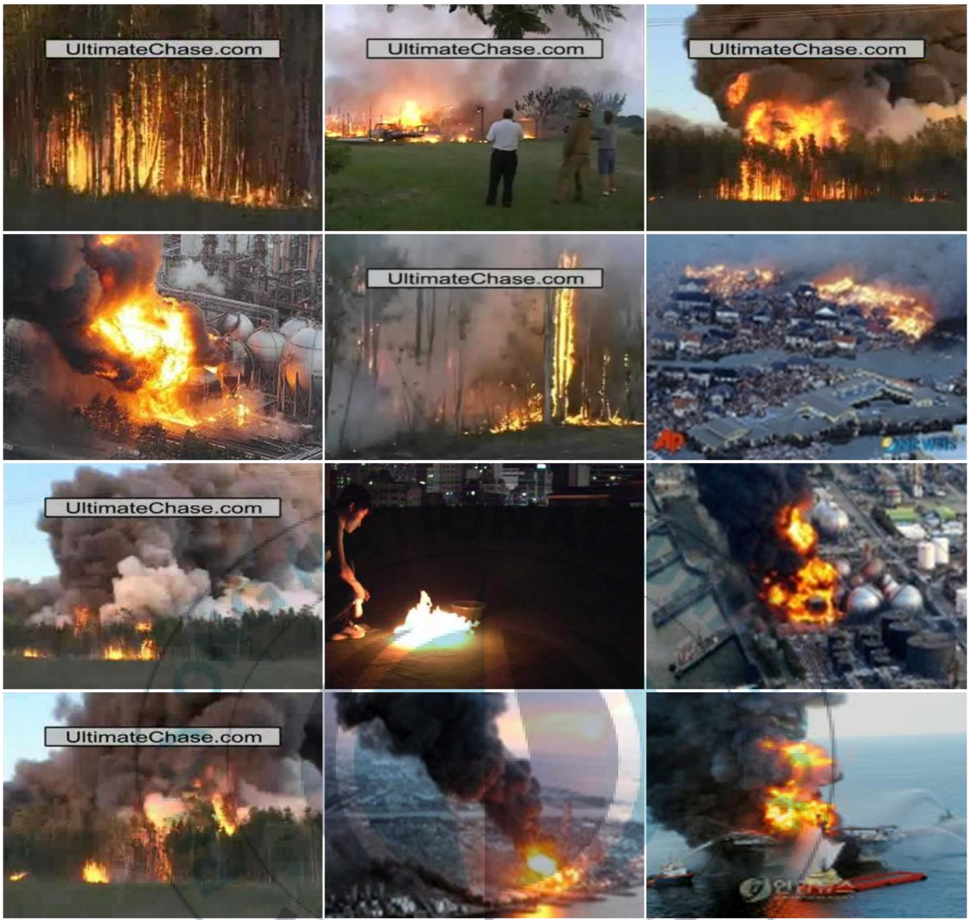


Figure 4.1 Experimental Image

(a) (b)

Figure 4.2 Original dark and light image in column (a), and adjusting imsge in column (b)

(a) (b) (c)

Figure 4.3 Different frame image and its average accumulated image, average accumulated different image

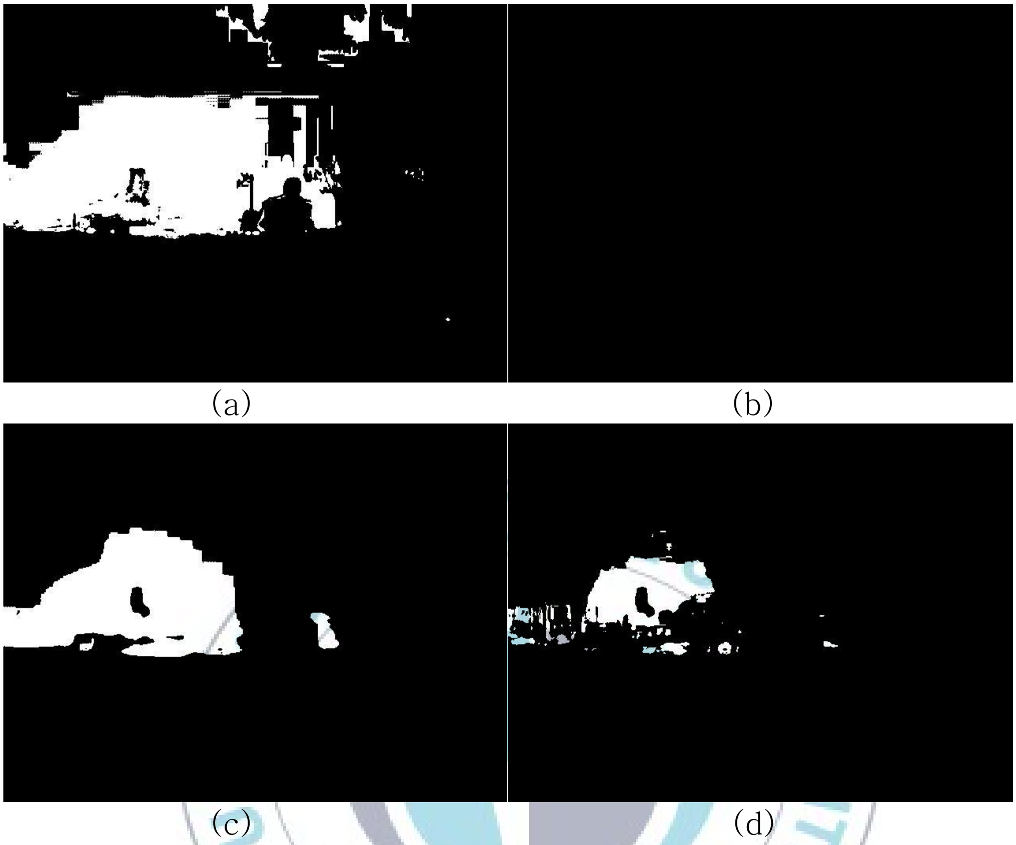


Figure 4.4 Using different method for the fire detection

(a) [15]used HIS color space

(b) [16]used RGB color space

(c) [17]used YCbCr color space

(d) Using RGB and YCbCr color space, proposed.

Figure 4.5 The fire detection in different frame sequences

Table 4.1 Performance of the proposed color space compared with three similar color space in the literature

Color model	Detection rate in fire set
RGB[8]	93.9%
Rgb[4]	97.0%
YCbCr[1]	99.0%
RGB and YcbCr, proposed	99.9%

Table 4.2 Performance of the proposed algorithm of the fire detection

	Format	Dimension	Number of Frame	Number of Frame Detected Fire	Detection Rate
Movie A	AVI	400*256	208	208	100
Movie B	AVI	640*480	94	94	100
Movie C	AVI	400*256	219	219	100
Movie D	AVI	400*256	245	243	99.2
Movie E	AVI	640*256	152	152	100
Movie F	AVI	400*256	216	216	100

Table 4.1~4.2 shows the results using proposed color space is better in discriminating the luminance from the chrominance, hence is more robust to the illumination changes than RGB or rgb or YCbCr color spaces.

Table 4.3 Comparison of the some fire detection methods

Algorithm	Detection rate in fire set
Method [14]	33.3%
Method [8]	67.3%
Method [1]	46.9%
Method [15]	85.0%
Proposed	99.9%

In Table 4.3, our proposed method is compared with other methods. The proposed algorithm achieves 99.9% flame detection rate. The results are compared with other methods in the literature and the performance improvement of the proposed method both in correct fire detection rate and false alarm rate is demonstrated.

V. Conclusions

In this paper, we proposed a new vision-based fire detection algorithm.The proposed color model uses RGB and YCbCr color space, which is better in discriminating the luminance from the chrominance, hence is more robust to the illumination changes than only used RGB color space. The performance of the proposed color model is tested on two sets of images. One fire of day and fire of night. The proposed color model achieves 99.9% flame detection rate. Next, The absolute value of the successive inter-frame pixel value difference using average for the Average Difference Background Model to generate. Later , segment the image into foreground and background regions using the Average Difference Background Model. Then, clean up the raw segmented image using connected-components analysis. This form of analysis takes in a noisy input mask image. It then uses the morphological operation open to shrink areas of small noise to 0 followed by the morphological operation close to rebuild the area of surviving components that was lost in opening. Thereafter, we can find the contours of the segments. The experimental results using real world videos show that our system can indeed improve detection performance compared to previous research.The results are compared with two other methods in theliterature and the performance improvement of the proposedmethod both in correct fire detection rate and false alarm rate isdemonstrated.The proposed color model can be used in fire detection in videosequences. We have shown that the proposed algorithm performswell in segmenting fire regions in video sequences. In our futurework, we will make the time analysis of fire regions in videosequence by measuring spread in the fire regions. Furthermore,the flicker nature of fire will be considered as a future work.

Reference

[1] T. Celik, H. Demirel, "Fire detection in video sequences using a generic color model," in Fire Safety Journal, 2008.

[2] B.U. Toreyin, Y. Dedeoglu, A.E. Cetin, "Flame detection in video using hiddenMarkov models," in: Procedings of IEEE International Conference on ImageProcessing, 2005.

[3] B.U. Toreyin, Y. Dedeoglu, U. Gudukbay, A.E. Cetin, "Computer vision basedmethod for real-time fire and fame detection," Pattern Recognition Lett, 2006.

[4] T. Celik, H. Demirel, H. Ozkaramanli, "Automatic fire detection in video sequences," in: Proceedings of European Signal Processing Conference, 2006.

[5] T.Cleary,W.Grosshandler, 1999. Survey of firedetection technologies and system evaluation/certificationmethodologies and their suitability for aircraft cargocompartments. Us Department of Commerce,

TechnologyAdministration, National Institute of Standards and Technology.

[6] W.Davis,K.Notarianni, 1999. NASA fire detection study. US Department of Commerce, TechnologyAdministration, National Institute of Standards and Technology

[7] W. Krull, I. Wıllms, R.R. Zakrzewskı, M. Sadok, J. Shırer, B. Zelıff, “Design andtest methods for a video-based cargo fire verification system for commercial aircraft,”Fire Saf, 2006.

[8] T. Chen, P. Wu, Y. Chiou, “An early fire-detection method based on image processing,” International on Image Processing, 2004.

[9] G. Marbach, M. Loepfe, T. Brupbacher, “An image processing technique for fire detection in video images,” Fire Saf, 2006.

[10] Wen-Bıng Homg, Jım-Wen Peng, Chıh-Yuan Chen, “A new image-based real-time flame detection method using color analysis,” in: Procedings of IEEE Networking, Sensing and Control, 2005.

[11] R. C. Gonzales and R. E. Woods, "Digital Image Processing,"Prentice Hall, Upper Saddle River, NJ, 2002.

[12] Berthold Klaus Paul Horn, "Robot Vision," MIT Press, 1986.

[13] J. Serra, "Image Analysis and Mathematical Morphology," Academic Press, 1982.

[14] B. Lee and D. Han, "Real-Time Fire Detection Using Camera Sequence Image in Tunnel Environment," Proceedings of ICIC, 2007.

[15] B. Cho, J. Bae, and S. Jung, "Image Processing-based Fire Detection System using Statistic Color Model," International Conference on Advanced Language Processing and Web Information Technology, 2008.

[16] T. Celik, H. Demirel, H. Ozkaramanli, M. Uyguroglu, "Fire detection using statistical color model in video sequences," Visual Communication & Image Representation, 2006.

[17] 박봉희, 류지구, 문광석, 김종남, "YCbCr 칼라 모델에서 화재의 움직임 정보를 이용한 화재검출," 한국멀티미디어 추계학술발표대회논문집, 2010.

[18] http://www.mathworks.com/.

[19] http://www.oreilly.com

[20] http://www.cse.iitk.ac.in/users/vision/dipakmj/papers/OReilly%20Learning%20OpenCV.pdf