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GLOBAL CHANGE REACTIVE BACKGROUND SUBTRACTION

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ABSTRACT OF THESIS

GLOBAL CHANGE REACTIVE BACKGROUND SUBTRACTION

Background subtraction is the technique of segmenting moving foreground objects from stationary or dynamic background scenes. Background subtraction is a critical step in many computer vision applications including video surveillance, tracking, gesture recognition etc. This thesis addresses the challenges associated with the background subtraction systems due to the sudden illumination changes happening in an indoor environment. Most of the existing techniques adapt to gradual illumination changes, but fail to cope with the sudden illumination changes. Here, we introduce a Global change reactive background subtraction to model these changes as a regression function of spatial image coordinates. The regression model is learned from highly probable background regions and the background model is compensated for the illumination changes by the model parameters estimated. Experiments were performed in the indoor environment to show the effectiveness of our approach in modeling the sudden illumination changes by a higher order regression polynomial. The results of non-linear SVM regression were also presented to show the robustness of our regression model.

KEYWORDS: Background Subtraction, Illumination change, Regression, Illumination compensation, Least squares, Event detection

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GLOBAL CHANGE REACTIVE BACKGROUND SUBTRACTION

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THESIS

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The Graduate School
University of Kentucky

2011

GLOBAL CHANGE REACTIVE BACKGROUND SUBTRACTION

THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Science in the
College of Engineering
at the University of Kentucky
By

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2011

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This work is dedicated to my mom, dad and sister

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Chapter 1

Introduction

Background Subtraction is a widely used approach for identifying moving objects in a video sequence, where each and every frame in the sequence is compared against a reference model. The reference model is commonly known as *Background Model* with no moving objects in the scene. The most important and fundamental task for background subtraction algorithms is to correctly identify the foreground pixels from a static or dynamic backgrounds. Pixels that differ significantly from the background model are usually considered to be foreground pixels. Background subtraction becomes a basic and critical step for numerous computer vision applications such as video surveillance and tracking, traffic monitoring, human gait and gesture recognition. There are several challenges that a good background subtraction must be able to handle. The most common problems are sudden illumination changes, motion changes such as camera oscillations, swaying tree branches, sea waves and changes in the background geometry like parked vehicles. A background update algorithm to cope with the real world environment is a challenging task especially for real time tracking applications. In this thesis, we identify those challenges associated with the sudden, fast illumination changes and build a regression model as a compensation to update the background model.

1.1 Sudden Illumination Changes

Illumination changes often occur in both indoor and outdoor environments. These illumination variations are gradual and fast variations depending on the speed in which they change the background scene. The gradual illumination changes like moving clouds, long shadows are common in outdoor environments. The sudden illumination changes often happen in indoor scenes due to human interferences such as opening curtains or blinds to control the natural lighting coming into the room, switching artificial lights from high to low or vice versa. Figure 1.1 shows consecutive frames of a walking person video sequence taken from a single camera. In figure 1.1(a) we can observe the illumination of the scene changes from high to low between two frames. Similarly figure 1.1(b) shows the illumination level of the scene changes from low to high. These sudden variations in the scene can cause the background subtraction systems to incorrectly identify the moving object resulting in poor tracking for surveillance applications. The background model needs to be periodically updated adhering to these changes to preserve good segmentation. So it is imperative to develop a compensation algorithm to handle these problems

1.2 Computer Vision Applications

With the advent of tracking and surveillance systems, world has been made a safer place to live in. Most of the tracking applications involve continuous monitoring of the scene and therefore the background model must be quickly updated during the sudden illumination changes. Object tracking will be impossible unless the background model is accurate for detecting the foreground objects in realistic scenarios. Poor background



Figure 1.1: Sudden Illumination changes in a indoor tracking environment: a) the top 2 figures show the change in illumination level from high lights to low. b) the bottom 2 figures show the change in illumination level from low to high when lights are switched on

subtraction leads to false and missing objects which directly affect subsequent steps to object tracking. By applying our proposed regression model during the illumination variations, a better foreground detection and accurate tracking is possible. Due to recent advancement in gesture recognition technology, there has been a significant increase in the use of gesture in interface design. People generally prefer human gestures such as eye blinks, head and body motions like face, hand etc compared to inputs from keyboard and joysticks. Good segmentation is a key factor for the gesture

recognition softwares to interpret the human gestures correctly. Most applications are bound to be affected by sudden illumination changes happening in the real time environment. Human gestures can be processed better if the algorithm can handle the inconsistent lighting.

1.3 Our Contributions

In this thesis, we identify the problems associated with background subtraction techniques in indoor environments. One of the main challenges is to make the background subtraction algorithms adapt quickly whenever the scene undergoes a sudden illumination change. Most of the existing techniques adapt to gradual illumination changes, but fail to cope with the sudden illumination changes. We propose a novel background subtraction technique to model the illumination change as a regression function of spatial coordinates. Our key contribution is developing a computationally efficient model for background replacement, thereby avoiding the background model to be learned again during the illumination changes. We present a fast and robust background subtraction system to handle these problems in real time without any prior information.

1.4 Organization

This thesis is organized as follows: In chapter 1 we discuss the importance of having a robust background subtraction for computer vision applications and a brief motivation for this research work is proposed. Chapter 2 analyzes the existing literature of background subtraction systems handling the sudden illumination changes. In chapter 3, we explain the motivation for background pixel modeling and introduce a

linear regression mathematical model to explain our approach for solving the sudden illumination change problem in real world scenarios. Chapter 4 gives us an overview of the entire system and discusses the real time implementation of the proposed approach. In chapter 5 we present our experimental results of the regression model and also evaluate our proposed scheme. The thesis concludes in chapter 6, where the scope of future work is discussed.

Chapter 2

Literature Review

In this section we review existing techniques for background subtraction systems. We also analyze the different approaches and provide relevant work for the sudden illumination changes in background subtraction algorithms. To motivate our approach we also review different illumination models and their illumination equations.

2.1 Background subtraction algorithms for changing illuminations

Before we discuss about the earlier approaches, we provide a brief survey about the background subtraction techniques.

Cheung et.al [1] discuss about the challenges for the background subtraction algorithms and classifies the functional flow of it into four components namely preprocessing, background modeling, foreground detection and data validation. The authors compare various background subtraction techniques like frame differencing, adaptive median filtering, Kalman filtering and mixture of Gaussians for detecting moving vehicles and pedestrians in urban traffic video sequences. Radke et.al [2] provides a detailed survey of common preprocessing techniques and decision rules in image change detection algorithms. The author also present a number of intensity adjustment methods used as preprocessing step to precompensate the illumination variations between images. Piccardi in [3] compares the background subtraction methods based on factors like speed, memory requirements and accuracy. The author discusses the practical implementations of both the simple and complex methods resulting in

a tradeoff of accuracy with memory and computational complexity. Parks et.al [4] evaluate seven popular background subtraction algorithms with different post processing techniques like noise removal, morphological closing, area thresholding, saliency test, optical flow test etc. The author demonstrates the impact of these techniques to improve the performance of the background subtraction algorithms. Background modeling forms a key step in choosing a model to be robust against all the environmental conditions. There are a number of algorithms to solve the illumination problem in background subtraction systems. We discuss only a few based on the approach and relevance to the work presented here. We broadly classify them into two different categories

1. Illumination invariant features - color normalization, intensity normalization, texture are used to build the background model
2. Background update - algorithms use illumination compensation techniques to update the background model

2.1.1 Illumination invariant features

In this section we discuss some of the illumination invariant feature based approaches for illumination change in background subtraction algorithms. Gevers et.al [5] used RGB channels to compute illumination invariant color coordinates l_1, l_2, l_3 and given by

$$l_1 = (R - G)^2/D; l_2 = (R - B)^2/D; l_3 = (G - B)^2/D \quad (2.1)$$

where $D = (R - G)^2 + (R - B)^2 + (G - B)^2$

Matsuyama et.al [6] developed a background subtraction system for varying illu-

minations. The authors propose two methods for the background subtraction process. The first method compares the background image and the observed image using illumination invariant feature normalized vector distance (*NVD*). The statistical characteristics like mean and variance of the normalized vector distance of the image blocks were analyzed by adaptively varying the threshold value. The spatial properties of the variation in a block are evaluated to enhance normalized vector distance. This method works under the assumption that the brightness variation due to moving object is concentrated in a specific area within a block. The second method estimates the illumination conditions of the image block using eigen image analysis using an illumination cone model. The detection and the accuracy of the background subtraction system improves when both the methods were integrated. Noreiga et.al [7] proposed illumination invariant background subtraction using local kernel histograms and contour based features. Contour based features are robust compared to color during the illumination changes.

Liyuan et.al [8] proposed a Bayesian framework to incorporate spatial, spectral and temporal features for complex background models. Principal features for different background objects are used. For stationary background pixels, the color and gradient features are used. For dynamic background pixels, color-cooccurrences are used as principal features. The statistics of the principal features are periodically updated for the gradual and once off background changes. Tian et.al [9] used three Gaussian mixtures [10] to model the background and integrated texture information to remove the false positive areas affected by the lighting changes. Zhao et.al [11] used Markov random field based probabilistic approach for modeling the background. The sudden

illumination changes are handled by fusing the intensity and texture information in an adaptive way. Xue et.al [12] proposed a background subtraction based on pixel phase features and distance transform. Phase features are extracted and modeled independently by Gaussian mixtures and distance transform is applied to get the foreground detection. Pilet et.al [13] proposed a statistical illumination model to replace the statistical background model during sudden illumination changes. The ratio of intensities between the background image and the input image is modeled as Gaussian mixtures in all three channels. The drawback of this model is that it relies on similar texture prior information and the spatial dependencies are not handled on texture-less regions.

2.1.2 Background update algorithms

Most of the background subtraction algorithms update the background during the illumination changes in the scene. These algorithms can be classified into slow and fast update algorithms. Comparatively all algorithms handle the slow changes very well. The sudden and fast changes are difficult to handle. The slow update algorithms are typically like the running average given by

$$B_t = \alpha \cdot I_t + (1 - \alpha)B_{t-1} \quad (2.2)$$

where B_t is the previous average of the pixel values, I_t is the current pixel value and α is the learning rate.

Toyama et.al proposed [14] the Wallflower algorithm for background maintenance. The algorithm uses three component system for background maintenance; pixel, region and frame level. The pixel level background maintenance is based on Weiner

prediction filter that uses past pixel values to predict the next pixel value in time. Pixels which deviate from the predicted value are classified as foreground. Frame level component detects the sudden and global changes in the image and swaps with alternate background models. The alternate background models are collections of many pixel level models predicted using Weiner filtering. The algorithm chooses background model via k -means clustering, where k defines the number of states for which the background is changing. Wallflower algorithm becomes complex in real time and performs better when the value of k is small, since it has smaller dataset of past pixel values to choose from. The system fails if no model matches with the new illumination conditions.

One of the earlier methods for illumination invariant change detection is accomplished by matching the intensity statistics like mean and variance of one image into another. The images are divided into small subregions and normalized independently based on the local statistics of each region [15]. The intensity of the second image $\tilde{I}_2(x)$ is normalized to have the same mean and variance of the first image $I_1(x)$.

$$\tilde{I}_2(x) = \frac{\sigma_1}{\sigma_2} \{I_2(x) - \mu_2\} + \mu_1 \quad (2.3)$$

Intensity change at any pixel is due to the varying illumination and the light reflected by the objects present in the scene. For Lambertian surfaces, the observed intensity at a pixel is modeled as a product of I_l illumination component and I_r reflectance component.

$$I(x) = I_l \cdot I_r \quad (2.4)$$

The illumination invariant change detection is performed by taking natural logarithms

and filtering out the illumination component separately [16].

$$\ln(I(x)) = \ln(I_l) + \ln(I_r) \quad (2.5)$$

The drawback of the model is it assumes the illumination changes are always slowly varying and cannot accommodate fast and sudden changes.

Messelodi et.al [17] proposed a background update algorithm based on Kalman filtering. The global illumination changes are measured and modeled as median of distribution of ratios by Kalman filtering framework. Parameswaran et.al [18] represented the global and local illumination changes as an illumination transfer function and used rank order consistency to remove the outliers present in the transfer function. Tombari et.al [19] used a non-linear parametric approach to model the sudden illumination changes on a neighbourhood of pixel intensities. Vijverberg et.al [20] modeled the global illumination changes as histogram of the difference image by fitting multiple Gaussian and Laplacian distributions. The assumption is that the foreground is small over the entire frame and results in a uniform histogram of the difference image. This assumption may not hold as the foreground could be lost during the illumination compensation over the entire image.

2.2 Illumination models

To model the interaction of light with the surface to determine the brightness and color at a given point, illumination models are used. Illumination models can be classified into two main categories, local illumination and global illumination models [21]. Illumination model can be invoked for every pixel or only for some pixels in the image. Many computer vision algorithms use simple illumination models because they

yield attractive results with minimal computation. Simple illumination models take into account for an individual point on a surface and the light sources illuminating it. The global illumination model take into account the interaction of light from all the surfaces in the scene. Modeling the reflection, refraction and shadows requires additional computation and hence increases the complexity. In this section, we shall see some simple illumination models for calculating the intensity at a given surface point.

2.2.1 Ambient light model

The simplest illumination model, which has no external light source describing unrealistic world of non reflective and self luminous objects. Ambient light is the result of light reflecting off other surfaces in the environment. The illumination equation of this ambient model is given by

$$I = I_a k_a \tag{2.6}$$

where I_a is the intensity of ambient light and k_a is the ambient reflection coefficient.

2.2.2 Diffuse light model

Diffuse reflection model illuminates an object by a point light source and reflects with equal intensity in all directions. This type of reflection is called Lambertian reflection. The diffuse illumination equation is based on Lambert's law and is given by

$$I = I_p k_d \cos \theta \tag{2.7}$$

where I_p is the intensity of point source, k_d is the diffuse reflection coefficient and θ is the angle between the surface normal \vec{N} and the light vector \vec{L} . Equation (2.7) is rewritten as

$$I = I_p k_d (\vec{N} \cdot \vec{L}) \quad (2.8)$$

The ambient light is added to diffuse reflection component to produce a more realistic illumination equation

$$I = I_a k_a + I_p k_d (\vec{N} \cdot \vec{L}) \quad (2.9)$$

2.2.3 Specular reflection model

Specular reflection produces bright spots on shiny surfaces, due to light being reflected unequally in all directions. Phong developed an illumination model for specular reflection [22], assuming maximum specular reflectance occurs when α is zero and falls off as α increases. Phong illumination model is given by

$$I = I_a k_a + I_p k_d (\vec{N} \cdot \vec{L}) + k_s \cos^n \alpha \quad (2.10)$$

where k_s is the material's specular reflection coefficient and α is the angle between the reflected light \vec{R} and viewpoint \vec{V} .

Chapter 3

Regression for Background Modeling

In this chapter we propose a regression function to model the illumination changes in the background subtraction system. The regression model is applied as a compensation whenever the background undergoes a sudden or gradual illumination changes. Handling the illumination changes can be considered as a prediction problem. In section 3.1 we provide the motivations for using a spatially adaptive illumination model to cope with sudden change in illumination. In section 3.2 we discuss how the illumination component is modeled into a regression function. By modeling the intensity ratios of background pixels before the light change and the background pixels after the light change as a function of spatial coordinates, a linear regression problem is formed. Following this in section 3.3 we discuss the formulations involved in building the regression model. We also discuss about the algorithm for generating higher order terms in the independent variable vector and least squares approximations to estimate the prediction parameters. Finally in section 3.4 we discuss about minimizing the error function in non-linear SVM regression.

3.1 Spatially-adaptive Illumination Modeling

In this section, we motivate the use of a spatially-adaptive illumination model to cope with sudden change of indoor illumination. Consider a small fixed Lambertian surface patch of area dA on a planar surface. This patch is at distance d from a fixed camera C with pixel size dP . The patch is projected onto the camera plane at the

homogenous image coordinate \mathbf{X}_I . Before the change of illumination, we assume this patch is illuminated by an ambient light source with radiant flux G steradians and N point light sources with radiant flux E_1, E_2, \dots, E_N steradians. After the change, the patch is illuminated by the same ambient light source and a new set of M point light sources with radiant flux F_1, F_2, \dots, F_M steradians. The situation is illustrated in Figure 3.1.

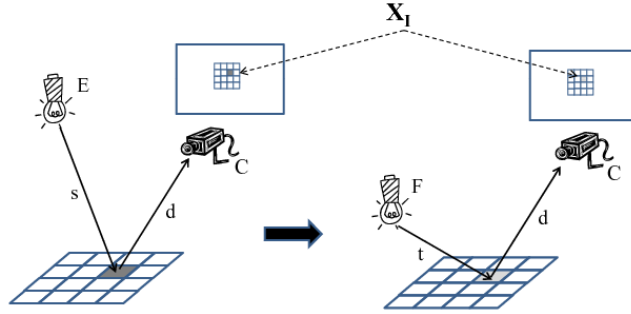


Figure 3.1: *Change of Illumination on a surface patch*

The radiance $L_{\text{before}}(\mathbf{X}_I)$ at pixel location \mathbf{X}_I can be calculated as follows:

$$L_{\text{before}}(\mathbf{X}_I) = \frac{\rho \cdot dA \cdot \gamma_C \cdot dP}{d^2} \cdot \left(G + \sum_{i=1}^N \frac{E_i \cdot \alpha_i}{s_i^2} \right) \quad (3.1)$$

where ρ is the surface reflectance, γ_C is the foreshortening factor between the camera and the incoming light ray from the patch, α_i and s_i are the foreshortening factor and the distance between light source E_i and the surface respectively. The radiance $L_{\text{after}}(\mathbf{X}_I)$ after the change of illumination is analogously given below:

$$L_{\text{after}}(\mathbf{X}_I) = \frac{\rho \cdot dA \cdot \gamma_C \cdot dP}{d^2} \cdot \left(G + \sum_{i=1}^M \frac{F_i \cdot \gamma_i}{t_i^2} \right) \quad (3.2)$$

where γ_i and t_i are the foreshortening factor and distance between light source F_i and the surface respectively. The ratio between the two radiances before and after is

given by

$$R(\mathbf{X}_I) = \frac{L_{\text{after}}(\mathbf{X}_I)}{L_{\text{before}}(\mathbf{X}_I)} = \frac{G + \sum_{i=1}^M (F_i \cdot \gamma_i) / t_i^2}{G + \sum_{i=1}^N (E_i \cdot \alpha_i) / s_i^2} \quad (3.3)$$

By considering only the ratio between intensities, we eliminate the dependence on the surface reflectance and the specific camera position and pose. Just as the color or texture of an object is independent of the camera, the homogeneity of common object surfaces supports the notion of using a smooth spatial function in modeling their appearances on a camera image. If the intensity ratios of a portion of the surface can be directly measured, one can interpolate the intensity ratios of the rest of the surface based on the image coordinate. To illustrate this idea, we consider a simple situation in which there is only a single light source being switched on. Equation (3.3) becomes

$$R(\mathbf{X}_I) = 1 + \frac{F \cdot \gamma}{G \cdot t^2} \quad (3.4)$$

Denote the 3D homogeneous location of the light source as \mathfrak{X}_S , the pseudo inverse of the camera projection matrix as P^+ and the depth of the surface as λ , we have

$$\begin{aligned} R(\mathbf{X}_I) &= 1 + \frac{F \cdot \gamma}{G \cdot \|\mathfrak{X}_S - \lambda \cdot P^+ \mathbf{X}_I\|^2} \\ &= 1 + \frac{F \cdot \mathfrak{N}^T \cdot (\mathfrak{X}_S - \lambda \cdot P^+ \mathbf{X}_I)}{G \cdot \|\mathfrak{X}_S - \lambda \cdot P^+ \mathbf{X}_I\|^3} \end{aligned} \quad (3.5)$$

In Equation (3.5), we replace the foreshortening factor γ with its definition as the inner product between the surface normal \mathfrak{N} and the unit direction from the source to the surface patch $\mathfrak{X}_S - \lambda \cdot P^+ \mathbf{X}_I$. The depth λ homogenizes the back projection so that we can obtain the actual 3-D distance using the 4-D homogenous coordinates. The factors F , G , P^+ and \mathfrak{X}_S are all constants. The surface normal \mathfrak{N} is the same for the entire planar surface and the depth of the surface from the camera cannot change

abruptly. As such, $R(\mathbf{X}_I)$ can be represented as a continuous function of \mathbf{X}_I and can be directly estimated given adequate training data to estimate all the constant factors. Our proposed approach uses the available intensity ratios over the confirmed background regions to fit a smooth regression function on \mathbf{X}_I , which can then be used for compensation in possible foreground areas. If there are significant variation in depths or the surface is not planar, we can still approximate it by segmenting it into multiple constant-depth planar surfaces and fit a regression function for each surface. Even in the presence of specular reflection on non-Lambertian surfaces, such an divide-and-conquer approach allows us to minimize problematic areas and adequately compensates the background for the change in appearance.

3.2 Background pixel modeling

The frame differencing model is one of the simplest techniques for foreground extraction. A background frame $B(i, j, t)$ with no foreground objects at time t is estimated. We replace \mathbf{X}_I with explicit coordinates i and j so as to highlight our model dependence on i and j . The new frame $I(i, j, t)$ is subtracted from the background frame. A global threshold value is applied to the difference image to get the foreground mask. This model works relatively well as long as there are no illumination changes in the background scene. The regression model update algorithm proposed here handles both sudden and gradual changes in the background scene. In our proposed approach we model the luminance as a function of spatial coordinates of a image. Due to the effects of sudden illumination changes on global thresholding we model the image $f(i, j)$ as a product of the illumination component and the

reflectance component. The illumination component is characterized by the type of illumination source and the reflectance component by the characteristics of the imaged objects. Let us denote $I(i, j, t)$ as a background pixel at time t . This is given by

$$I(i, j, t) = L(i, j, t) \cdot R(i, j) \quad (3.6)$$

where $L(i, j, t)$ is the illumination function and $R(i, j)$ is the reflectance of the material. The luminance function is a piece wise continuous function. Each pixel in a background image is modeled as a function of spatial coordinates (i, j) in a 2-d image plane.

$$I(i, j, t) = a(i, j) \cdot L(i, j, t - 1) \cdot R(i, j) \quad (3.7)$$

The time averaged background pixel before the illumination change $B(i, j, t - 1)$ and the background pixel after the illumination change $I(i, j, t)$ is modeled as a simple linear function $a(i, j)$. We begin our discussion using a first order polynomial which has a i, j and a constant term. The second order polynomial would contain i^2, j^2 , the cross product term ij, i, j and the constant term. However higher order polynomials could be used to model the background pixel. For the theory and results shown, we limit the discussion till fifth order due to numerical stability constraints.

$$a(i, j) = Ai + Bj + C \quad (3.8)$$

Combining equations (3.6) and (3.7)

$$a(i, j) = \frac{L(i, j, t)}{L(i, j, t - 1)} \quad (3.9)$$

The $a(i, j)$ is expressed as the ratio of illumination of background pixel after the change to the illumination of background pixel before the change. We update the background model based on these functions, where the spatial parameters are taken into consideration.

3.3 Linear regression model

Linear regression often used as a predictive approach, models relationship between known observed data points and unknown parameters to be estimated from data. Due to sudden illumination changes in the scene, the background model needs to be updated to have a good foreground estimation. The regression analysis estimates the conditional expectation of the dependent variable vector Y_i given independent variable vector X_i . Assuming the background pixel before and after the light change is linear, the first order regression function is given by

$$I(i, j, t) = a(i, j) \cdot B(i, j, t - 1) \quad (3.10)$$

Substituting equation (3.8) in (3.10)

$$I(i, j, t) = (Ai + Bj + C) \cdot B(i, j, t - 1) \quad (3.11)$$

Combining equations (3.10) and (3.11)

$$I(i, j, t) = Ai \cdot B(i, j, t - 1) + Bj \cdot B(i, j, t - 1) + C \cdot B(i, j, t - 1) \quad (3.12)$$

The independent variable vector and the dependent variable vector for the above linear equation (3.12) is given by

$$X_i = [i \quad j \quad 1] \quad (3.13)$$

$$Y_i = \left[\frac{I(i, j, t)}{B(i, j, t-1)} \right] \quad (3.14)$$

In Matrix notation we rewrite as

$$\begin{pmatrix} \frac{I(0,0,t)}{B(0,0,t-1)} \\ \frac{I(0,1,t)}{B(0,1,t-1)} \\ \frac{I(0,2,t)}{B(0,2,t-1)} \\ \vdots \\ \vdots \\ \frac{I(m,n,t)}{B(m,n,t-1)} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 2 & 1 \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ m & n & 1 \end{pmatrix} \begin{pmatrix} A \\ B \\ C \end{pmatrix} \quad (3.15)$$

Independent variable vector X_i for the regression model consists of $(m \times n) \times p$ input vectors and the dependent variable vector consists of $(m \times n) \times 1$ output vectors where m and n are the height and width of the given background image. We estimate the parameters by least squares approximation.

3.3.1 Independent variable vector

In this section we describe how the higher order independent variable vector X_i is generated. We define a n^{th} order degree polynomial containing n^{th} order terms, $(n-1)^{th}$ order terms, $(n-2)^{th}$ order terms and so on. Let k denotes the degree of the i^{th} term in the polynomial and m denotes the degree of the j^{th} term in the polynomial, where i and j being the coordinates of the image. For any polynomial of order n , the degree of i^{th} polynomial term varies from 0 to n and degree of j^{th} polynomial term varies from 0 to $n-k$. The independent variable vector polynomial

terms are generated by the following equation

$$X_i = \sum_{k=0}^n \sum_{m=0}^{n-k} i^k j^m \quad (3.16)$$

Hence the independent variable vector consists of i coordinate term, j coordinate term, combination of (i, j) coordinates and a constant term. Choosing the right degree polynomial is important for this curve fitting problem. Higher the polynomial degree chosen, closer the fit is. Let us denote the degree of the polynomial be n . The number of terms in the polynomial P_t is given by

$$P_t = \frac{n^2 + 3n + 2}{2} \quad (3.17)$$

Number of terms in the degree polynomial denotes the number of parameters to be estimated.

3.3.2 Approximation using least squares

Least squares approximation is a standard technique for estimating the unknown parameters and for fitting the data to a line or a polynomial. Modeling the illumination changes could be considered as a data fitting problem. We try to fit a function to a set of data which minimizes the sum of squares between the measurements and the predicted values. For the linear regression model $Y_i = X_i \hat{\beta} + \epsilon$, the ordinary least squares method minimizes the sum of squared residuals to find the unknown parameter $\hat{\beta}$, which is a p dimensional vector

$$\hat{\beta} = (X'X)^+ X'y \quad (3.18)$$

Solving the above equation by taking pseudo inverse or using QR decomposition gives the least square estimates. The regression coefficient $\hat{\beta}$ is multiplied with the independent variable vector X provides us the predicted value \hat{y}

$$\hat{y} = X \cdot \hat{\beta} \quad (3.19)$$

The difference between the actual value y and the predicted value \hat{y} provides us the residual or error value. We compute the residual sum of squares RSS by summing up the squared difference between the actual value and the predicted value for the total number of data points and given by

$$RSS = \sum_{i=1}^n (y - \hat{y})^2 \quad (3.20)$$

3.4 Support Vector Machine Regression

In this section we motivate the use of non-linear SVM regression model to cope with the sudden illumination change problem. In linear regression for a given a set of data points $(x_1, y_1), (x_2, y_2) \dots (x_N, y_N)$, the estimator $E(Y|X)$ is linear. When fitting polynomial functions the choice of the degree polynomial has to be made before hand. Also the function estimated for higher order polynomial becomes ill-conditioned easily and may not give a accurate solution for overdetermined systems. To prevent this, we use a kernel regression method to model the functional relationship between the independent variable vector X_i and the dependent variable vector Y_i nonlinearly. Support vector machines are characterized by usage of kernels, where non linear functions are learned by mapping data points in linear space into high dimensional induced feature space. The kernel is defined by $k(x, y) = \langle \phi(x), \phi(y) \rangle$, where $\phi(x)$

and $\phi(y)$ are the non-linear feature space vectors. The kernel function assign weights to each data point and estimates the predicted points ($y(x_n)$) by minimizing the error function. For our model we choose a Gaussian Kernel given by

$$k(x, y) = \exp(-\|x - y\|^2/2(\sigma)^2) \quad (3.21)$$

Let t_1, t_2, \dots, t_N be the target values for the corresponding training input data points x_1, x_2, \dots, x_N , the quadratic error function is replaced with a ϵ -insensitive error function E_ϵ having linear cost.

$$C \sum_{i=1}^N E_\epsilon(y(x_n) - t_n) + \frac{1}{2} \|w\|^2 \quad (3.22)$$

where C and $\frac{1}{2} \|w\|^2$ is the regularization and the conditioning parameter. Slack variables ζ_n and $\hat{\zeta}_n$ for each data point is introduced to allow the points lie outside the ϵ tube. We empirically fine tune these parameters in our model to minimize the error function.

Chapter 4

Fast and robust real time background subtraction

In Chapter 3, we presented a mathematical model for solving the problem of sudden illumination changes that occur in the background scene. We assumed that the illumination variations can be modeled as a function and developed a regression model to fit the background regions affected by the illumination changes. In section 3.2 we described these polynomial functions are expressed as a ratio of illumination of background pixels before the change to illumination of background pixels after the change. In this chapter, we describe our proposed fast and robust real time background subtraction technique to the challenges mentioned in section 1.1. In section 4.1, we present a overview of our real time background subtraction system to compensate the sudden illumination changes. We discuss about the background modeling and foreground detection in section 4.2. In section 4.3, we discuss the details of our real time application and explain how the regression model is applied. In section 4.4, we introduce our event detection algorithm to make the system understand the sudden and gradual illumination changes in the indoor environment.

4.1 Overview of the Background Subtraction system

In this section, we present an overview of our proposed background subtraction system. We assume that the scene consists of a stationary background with moving foreground objects. Our system has a simple frame differencing model for the background subtraction and the background is updated by a compensation model if the

background scene undergoes illumination changes. Figure 4.1 shows the schematic diagram of the proposed robust background subtraction system. The incoming video

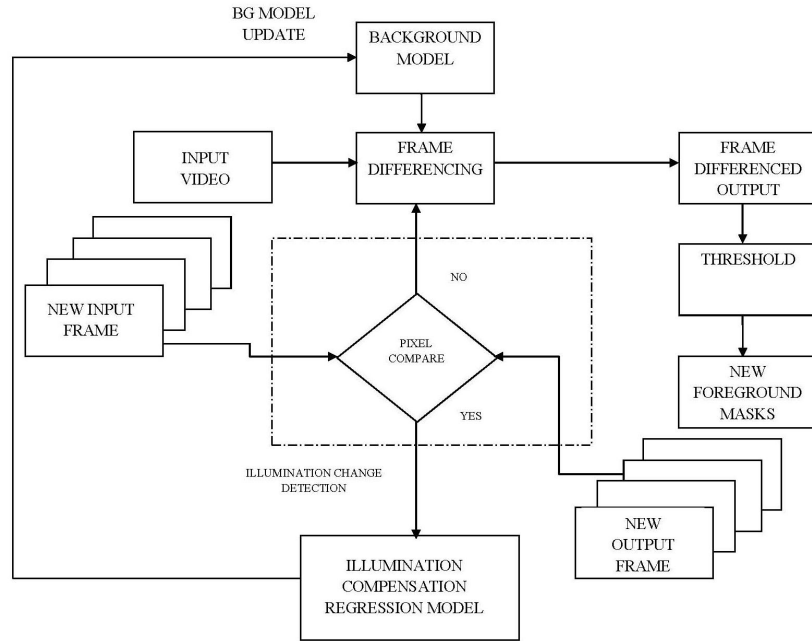


Figure 4.1: Schematic diagram of the proposed background subtraction system with compensation module

frames are subtracted from the background model and thresholded to give the foreground masks. Background model affected by the illumination changes are updated by a linear regression model. We have implemented a event detection mechanism to make the system understand when the compensation model needs to triggered. We have also implemented a twin comparison approach in the event detection for detecting the sudden and gradual illumination changes. We detect the illumination changes in the background subtraction using a two step process. In the first step we calculate the average count of the foreground pixels from the buffer. In the second step, decision is taken if the event is detected or not. The event is detected if the difference between the foreground pixel count of the incoming frame and the average

foreground pixel count of all the frames in the buffer is large. Our compensation algorithm computes the model parameters based on the regression function and updates the background model.

4.2 Background modeling

In this section we discuss about the background modeling and the foreground detection. We have implemented the robust background subtraction system using a simple frame difference model. An initial background model estimate is obtained from the first few frames of the input video. These frames are stored in a video queue and are time averaged to give the initial background model. We use a video queue for storing 30 frames to compute the mean and standard deviation. Subsequent frames are subtracted from the background model and threshold is set to classify the foreground regions from the background. Each pixel in the incoming frame is classified as a foreground pixel or a background pixel based on the threshold computed by minimizing the standard deviation.

$$F_t(x, y) = \begin{cases} 1 & I(x, y, t) - I(x, y, t - 1) > Th \\ 0 & otherwise \end{cases} \quad (4.1)$$

The pixels greater than the threshold value are set to be foreground. Although the frame differencing model does a good foreground segmentation in indoor environments, the background model does not adapt itself to the sudden and gradual illumination changes in the background. In such cases, the background model is updated by a regression model to compensate for the illumination changes in the background scene.

4.3 Regression model

To update the background model during sudden and gradual illumination changes in the background scene, we employ our proposed regression modeling approach. We specify the assumptions on which our background subtraction algorithm work effectively. The regression model applied as a compensation for background subtraction systems during the sudden illumination variations is suited well for indoor environments. In section 3.2, we discussed how the background pixel is modeled as a function of luminance for illumination changes. If we include the reflectance component along with the illumination function, the segmentation process will be really difficult during single thresholding. We assumed that the background pixel can be modeled as a function of illumination as defined by equation (3.9). We begin to explain our algorithm implementation by finding a relationship between the background model frame and the frame where the illumination change occur. From now on, lets call the background model frame as frame A and the frame which undergoes the illumination change as frame B. Since we are looking at only the intensity information of an image, we convert both frame A and frame B into gray-scale images. Here frame A and frame B are expressed as ratio in the dependent vector and the independent variable vector is expressed in terms of the spatial coordinates of the 2-d image. The size of independent variable vector is $(m \times n) \times p$, where p is the number of terms in the polynomial. To estimate the transform parameters, we begin by computing the powers of the polynomial terms for a given order N defined by equation (3.16). A large bounding box containing the foreground region is cropped out from the previous frame before the illumination change, so that we include only the background

regions for estimating the model parameters. For all the test sequences shown, the value of N is varied from 2 to 5 to get a good foreground estimate. The model parameters $\hat{\beta}$ are computed by least squares method as defined in equation (3.18). we update the background model by multiplying the regression coefficient $\hat{\beta}$ with the old background. The regression model compensates for the illumination change in the subsequent frames by computing the necessary parameters to model these changes.

4.4 Event detection system

In this section we discuss about the event detection system used in our real time background subtraction system. Automated event detection is a critical process for video surveillance systems in uncontrolled environments. Motion and illumination changes are the common examples of the scene changes in real world scenarios. In an adaptive real time background subtraction system, the background model should be updated based on these scene variations by a event detection algorithm. We have used twin comparison approach to check if the background is affected by sudden or gradual illumination changes. Detecting these changes correctly is an important practical application in segmentation algorithms. The event detection algorithms are useful to find whether the frame is significantly different from the previous frames. Some of the common event detection algorithms are based on edge change ratio, histogram differences, standard deviation of pixel intensities, edge-based contrast, pixel differences etc. The implemented algorithm uses pixel differences as a metric to detect the sudden and gradual illumination changes. Lets now discuss about the algorithm implementation of the event detection system in detail. Figure 4.2 shows

the schematic diagram of our event detection system. Let FB be the frame buffer to store n consecutive frames and f_c be the frame count respectively. The frame buffer FB stores the foreground extracted frames in it. For every new incoming frame, the buffer gets filled if the frame count f_c is less than or equal to n . In the process a new frame is fetched simultaneously. Once the frame buffer is filled, we compute the average foreground pixels Fg_{av} over $n - 1$ frames. The foreground count of the frames gets accumulated in a Fg_{acc} accumulator. Fg_{acc} is averaged over frames to give Fg_{av} . We then check for the relative change for the new incoming frame. The buffer is updated using first in first out(FIFO) process. The frame buffer value is set

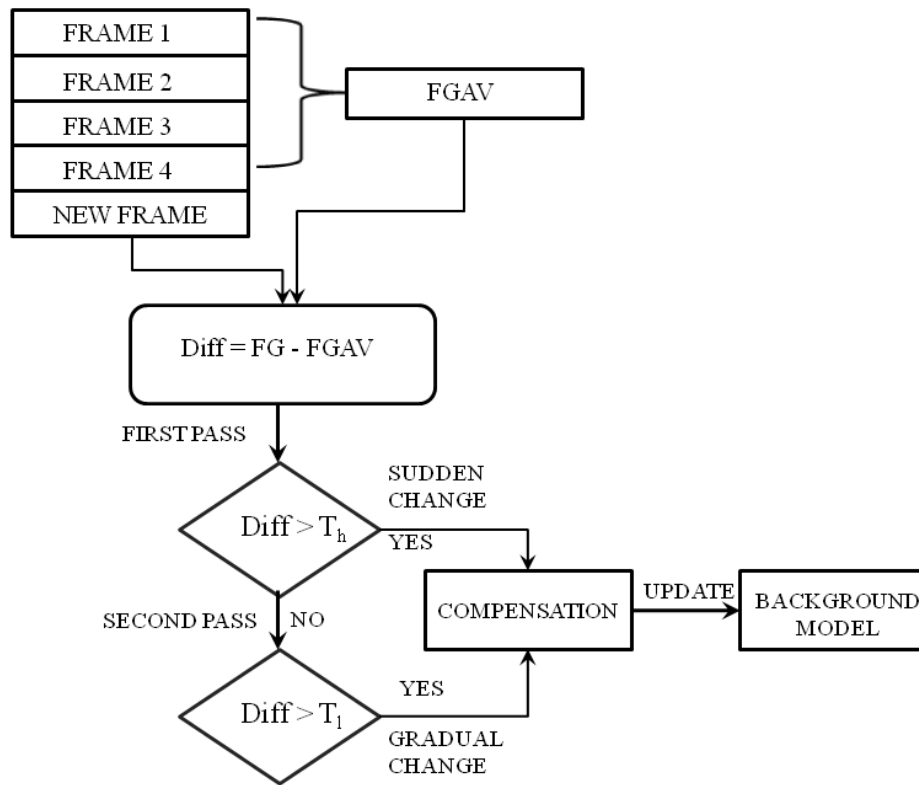


Figure 4.2: Overview of the event detection system using twin comparison method to five for our real time experiments. The first four frames in the buffer are averaged and compared with every new incoming frame. If the average foreground count in

the buffer is certain percentage higher than the new incoming foreground count, the event detection triggers the regression model to update the background frame.

4.4.1 Twin Comparison approach

To identify the sudden and gradual illumination changes, we employ the twin threshold or twin comparison approach. The idea is to have a common background and similar objects of interest between the two compared frames. The simplest way of detecting a event is to use a single threshold. This approach mainly detects the sudden illumination changes and are not suitable to detect gradual illumination variations. To detect both these changes we adopt the following decision rule

$$|Fg - Fg_{av}| = \begin{cases} > T_h & \text{Sudden illumination changes} \\ > T_l & \text{Gradual illumination changes} \end{cases} \quad (4.2)$$

Where T_h is set to a higher threshold and T_l is set to a lower threshold value. In the first pass, the event detector checks if the difference between the foreground pixel count in the new frame and the accumulated foreground pixel count in the buffer is higher than T_h . This is to ensure that the sudden illumination changes are accurately detected. If there is no such change, during the second pass the event detector checks for gradual illumination changes if difference pixel count is higher than T_l . If any of the above conditions are satisfied, then background model is compensated by the regression model. Figure 4.3 and 4.4 shows the sudden illumination changes detected by the event detection system.

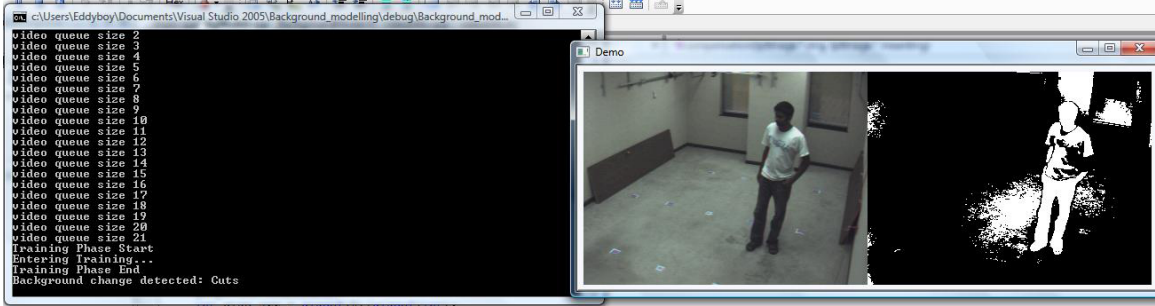


Figure 4.3: Background change detection: low to high



Figure 4.4: Background change detection: high to low

4.5 Time Complexity analysis

In this section, we analyze the time complexity of our algorithm to compensate the illumination changes in the background. Our algorithm was implemented in MATLAB version 7.0 and the real time implementation was done in C++. The best case analysis of regression algorithms have a $O(n^3)$ complexity [26], but a probabilistic speed up of the algorithm could result in much lesser complexity. Let us assume that the image $I(i, j)$ with N pixels is affected by the changing illumination, the computational complexity of the compensation algorithm depends on the polynomial function used to fit the background. The complexity of generating the independent vector X for the compensation algorithm in equation (3.16) is linear in terms of the regression parameters. Hence the overall cost of the compensation algorithm depends only on the data points N and is given by $O(N)$.

Chapter 5

Experiments and discussion

In this chapter we present our results of the proposed global change reactive background subtraction by modeling the illumination changes as a regression function. The algorithm presented in the section 4.3 are tested on different indoor video sequences. Each of the sequences presented here demonstrate the effectiveness of our algorithm including scenarios like lights turn on and off from low to high, high to low etc. Figure 5.1 shows the video sequence of a person walking in a indoor environment captured from a stationary camera. The scene contains various reflective objects in the background making them difficult to model the spherical and diffuse reflections. We do not include any priori information about the type of illumination change that could potentially happen. Also our model did not include any of the Phong's model assumptions considering these reflections. In section 5.2 we evaluate our proposed scheme using statistical classifications like recall and precision etc.

5.1 Foreground detection during different illumination conditions

In figure 5.1 the first row shows two frames from the input video sequence. The first frame of the first row is the frame before the illumination change. The second frame of the first row shows the impact of segmentation where the actual illumination change occurs. The second and third row shows the compensated output using different orders of the regression function. As discussed, the regression model doesn't have any assumptions on Phong's model to handle the specular reflections and also

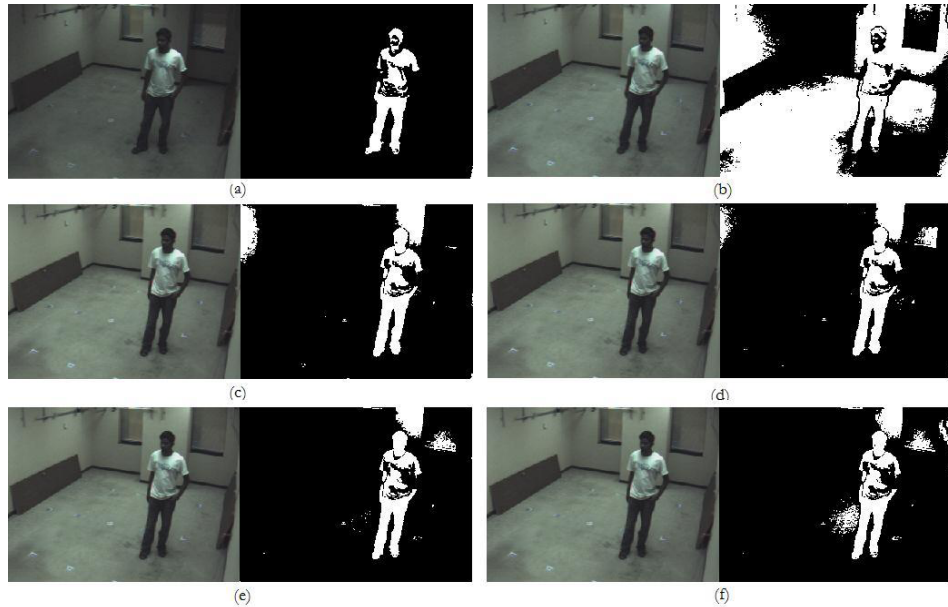


Figure 5.1: Illustration of compensation using regression polynomial 2^{nd} to 5^{th} order: a) frame before illumination change. b) illumination change from low to high. c) compensation by second order. d) third order. e) fourth order. f) fifth order

the shadows. From the figure 5.1, we show the results of segmentation with a constant threshold which improves till the 4^{th} order. This is illustrated by mean square error analysis in figure 5.2. The graph shows the mean square error values of different orders of the polynomial. The compensation is better for the 4^{th} order, due to the numerical properties of the 5^{th} order polynomial. This is due to the presence of too many predictor variables in comparison with the number of the observations, the matrix becomes rank deficient. Table 5.1 shows the mean square error values of the video sequences presented in this section.

The Figure 5.3 shows the input sequence of the same video, with the lights switched back from high to low. The results of the compensation for second order, third order and fourth order are presented in each row. The first column shows the frame before the illumination change. The second column shows the effect of

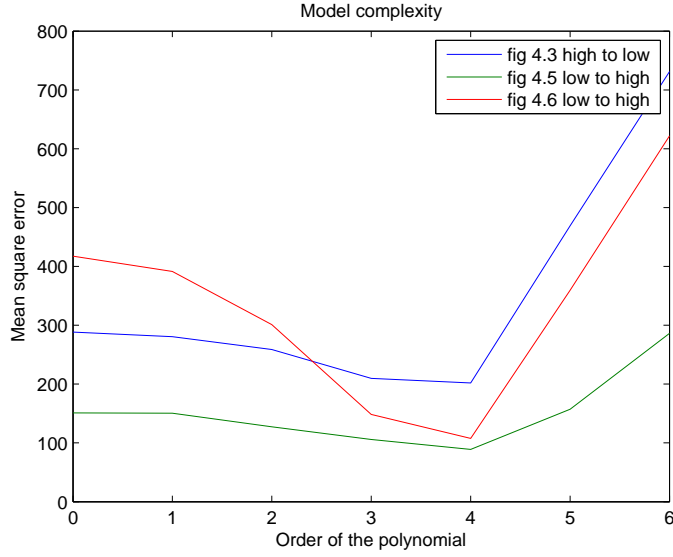


Figure 5.2: Mean square error

Table 5.1: Mean square error analysis

Mean Square error			
Polynomial order	fig 5.1	fig 5.3	fig 5.4
0	288.37	151.04	417.51
1	280.43	150.58	391.42
2	258.62	127.24	301.13
3	209.61	105.69	148.38
4	201.94	88.94	107.58
5	468.99	157.34	359.47
6	731.27	286.19	621.92

illumination change on background subtraction. The third column shows the effect of compensation by 2^{nd} , 3^{rd} and 4^{th} order polynomial.

Accurate foreground detection becomes a difficult task if the background scene contains reflective objects. Figure 5.4 shows the effect of compensation on video sequences in the presence of many complex objects like white boards, iron bars etc. The 4^{th} order polynomial with least mean square error value has a better compensation. More noisy areas in the segmented image can be cleaned using morphological methods or by a median filter, which is beyond the scope of discussion of this thesis.



Figure 5.3: Illustration of illumination compensation from high to low : a) The first column shows the frame before the illumination change for 2nd, 3rd and 4th. b) The second column shows the actual illumination change. c) The third column shows the compensation by 2nd, 3rd and 4th.

The demo sequences are available in our project website at <http://vis.uky.edu/~edwin/demos.html>.

5.2 Evaluation of the regression model

In this section, we perform a quantitative evaluation of the performance of our algorithm compensated by 2nd, 3rd, 4th order polynomial function. In order to have a fair comparison, we select the frame after the illumination change of each video sequence and perform hand segmentation to estimate the ground truth. We then compute the precision and recall values from these frames for the video sequences shown in this section. Precision is the number of correctly identified foreground pixels by the regression algorithm to the number of foreground pixels detected by the regression algorithm. Recall is the number of correctly identified foreground pixels by the regression algorithm to the number of foreground pixels in the ground truth. Table 5.2, 5.3 and 5.4 summarizes the precision and recall values of the frames after

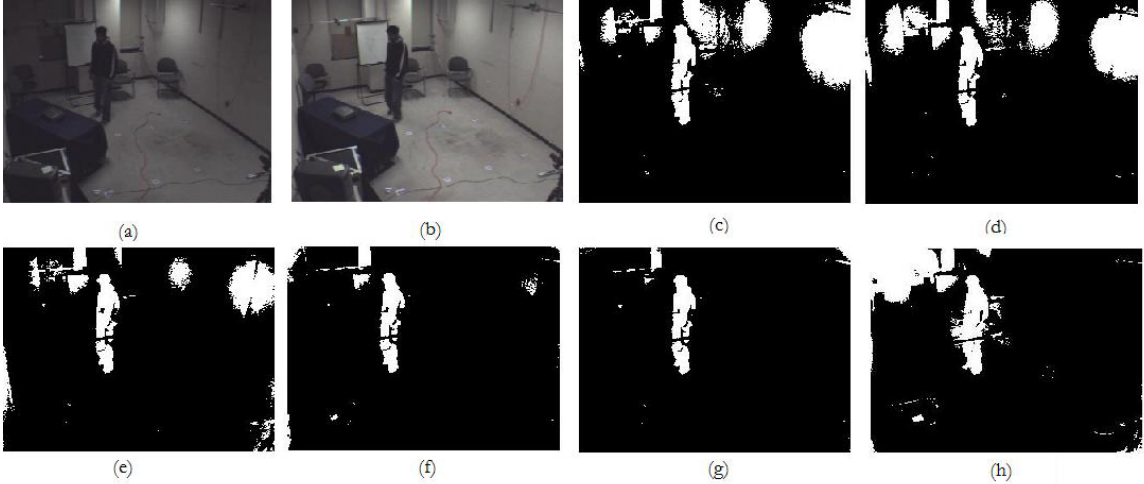


Figure 5.4: Illustration of compensation: a) frame before illumination change. b) illumination change from low to high. c) compensation by zero order. d) first order. e) second order. f) third order. g) fourth order. h) fifth order

illumination change.

Table 5.2: Precision and Recall values of the frames after illumination change in low to high sequence

Order	Precision	Recall
4	0.6779	0.6943
3	0.5988	0.7222
2	0.5678	0.7235

Table 5.3: Precision and Recall values of the frames after illumination change in high to low sequence

Order	Precision	Recall
4	0.9417	0.6142
3	0.1203	0.7607
2	0.1368	0.7613

From our experiments, visually and statistically we see a good precision and higher recall values for frames compensated by 4th order regression polynomial function. Figure 5.5 (a) and (b) shows the hand segmented and the ground truth of the low to high sequence. Figure 5.5 (c) and (d) respectively shows the foreground pixels detected

and correctly identified by the algorithm by 4th order regression polynomial function. Figure 5.6 (a) and (b) shows the hand segmented and the ground truth of the high to low sequence. Figure 5.6 (c) and (d) respectively shows the foreground pixels detected and correctly identified by the algorithm by 4th order regression polynomial function. Figure 5.7 (a) and (b) shows the hand segmented and the ground truth of the complex object sequence. Figure 5.7 (c) and (d) respectively shows the foreground pixels detected and correctly identified by the algorithm by 4th order regression polynomial function.

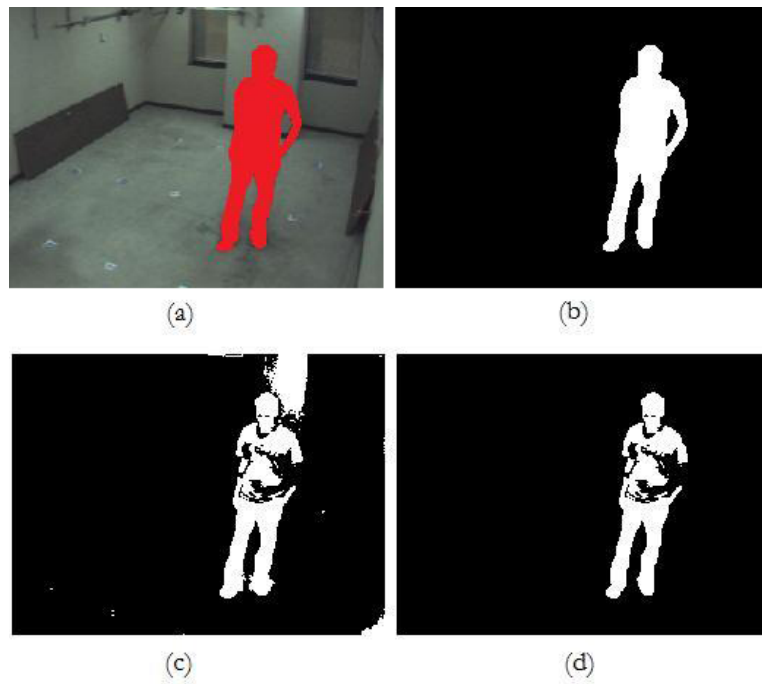


Figure 5.5: Foreground masks obtained - low to high sequence: a) Hand segmented image. b) Ground truth. c) Foreground pixels detected by 4th order regression model. d) Foreground pixels correctly identified by 4th order regression model.

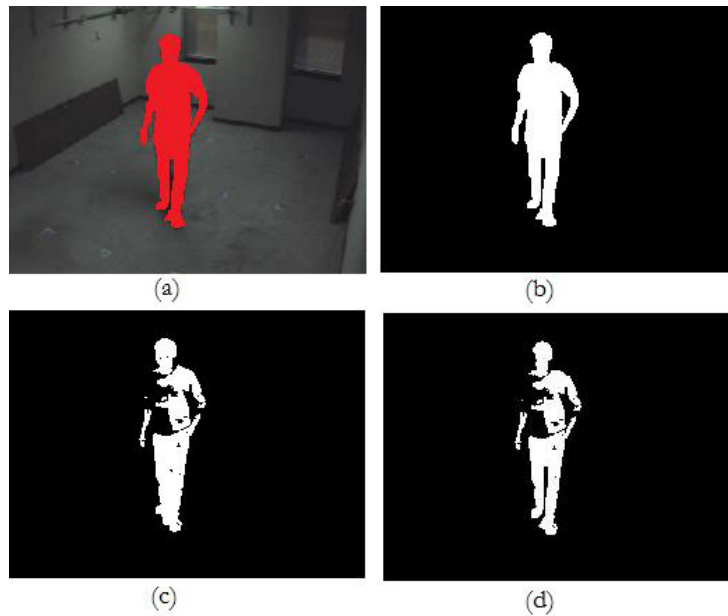


Figure 5.6: Foreground masks obtained - high to low sequence: a) Hand segmented image. b) Ground truth. c) Foreground pixels detected by 4^{th} order regression model. d) Foreground pixels correctly identified by 4^{th} order regression model.

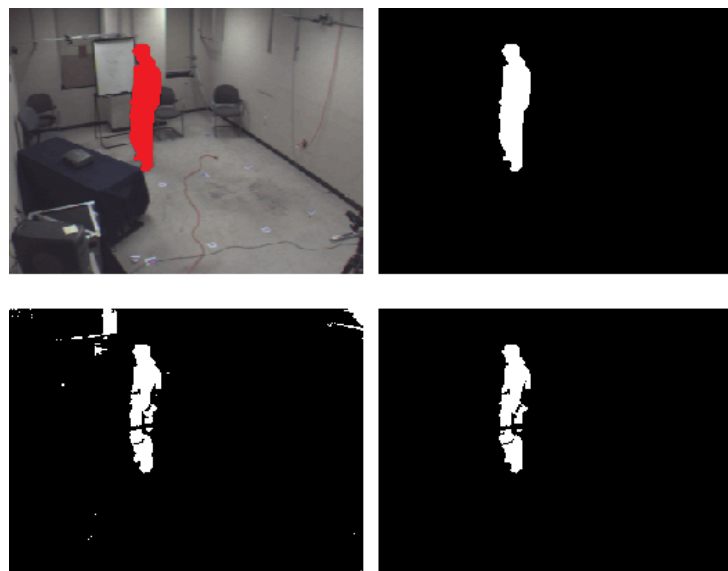


Figure 5.7: Foreground masks obtained - complex object sequence: a) Hand segmented image. b) Ground truth. c) Foreground pixels detected by 4^{th} order regression model. d) Foreground pixels correctly identified by the 4^{th} order regression model.

Table 5.4: Precision and Recall values of the frames after illumination change in complex object sequence

Order	Precision	Recall
4	0.7309	0.8237
3	0.5627	0.8152
2	0.2559	0.8188

5.3 SVM regression results

In this section we discuss our simulation results for the illumination compensation by SVM regression on the three sequences. This implementation is based on the toolbox [27] for the support vector machines. The training data for the model is built by cropping out a large bounding box containing the foreground region from the frame before the illumination change, to make sure we include more background pixels for the training. The model computes the support vectors list based on input training data and set of predefined parameters for SVM regression. We have selected the Gaussian Kernel function with conditioning parameter $\lambda = e^{-7}$, $\epsilon = .05$ and bound on the lagrangian multipliers value set as 1000 for our model. The model parameters are estimated from the regression analysis and the new background model is updated based on these values. Figure 5.8 shows the illumination compensation by SVM regression. The first column shows the frame after the illumination change and the second column shows the results of compensation on low to high, high to low and complex object sequences. Table 5.5 summarizes the precision, recall values for the results in figure 5.8.

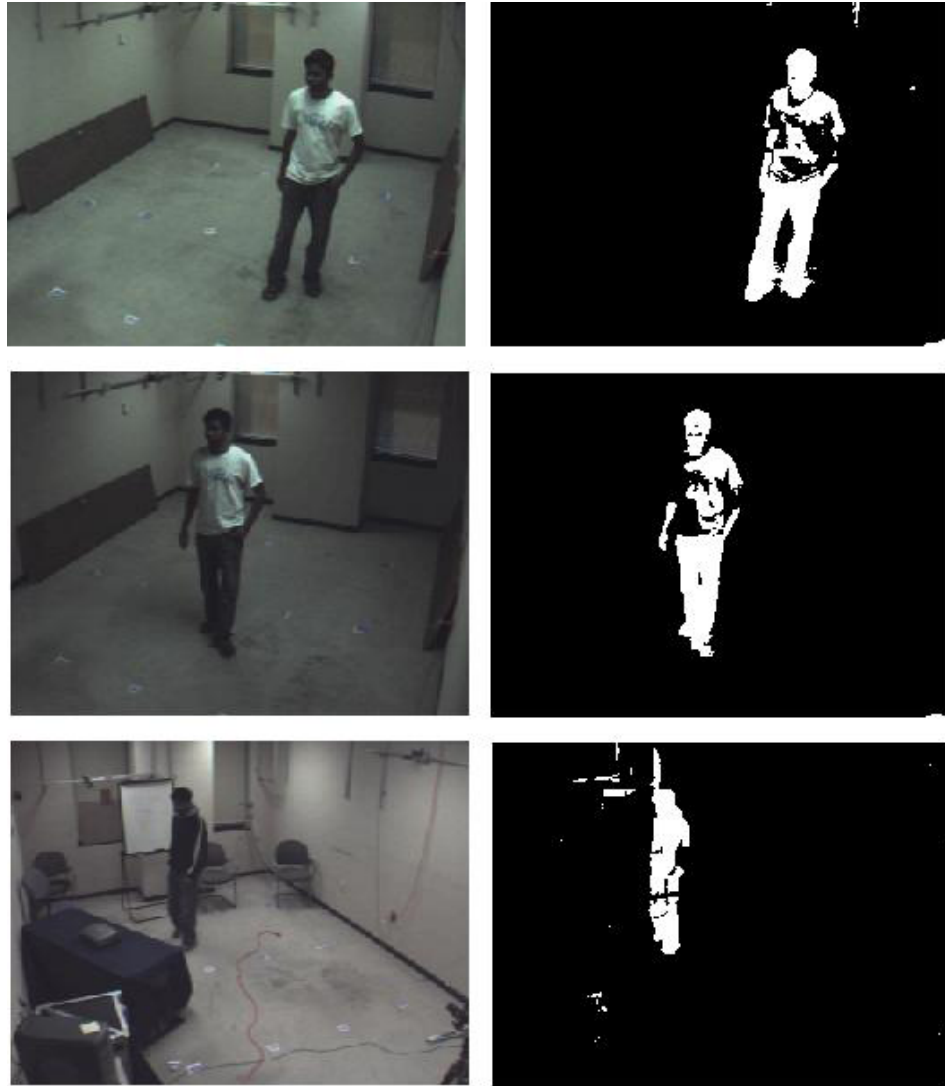


Figure 5.8: SVM regression compensation: The first column shows the frame after the illumination change. The second column shows the illumination compensation by SVM regression

Table 5.5: Precision and Recall values of sequences using SVM regression

Sequence	Precision	Recall
low to high	0.8796	0.7408
high to low	0.9611	0.6918
complex object	0.8424	0.8451

In section 5.2, we show the precision and recall values of the 4th order regression model was higher than the lower order polynomials. We also compare the results of the SVM regression with the 4th order regression model. There is an increase in precision value from 0.67 to 0.73 for the low to high sequence. For the high to low sequence the precision improves from 0.94 to 0.96. In the complex object sequence, modeling the sudden illumination changes by SVM regression shows a significant increase from 0.73 to 0.84. Recall values for the complex object and the low to high sequence shows a marginal increase from 0.82 to 0.84 and 0.69 to 0.74 respectively. For the high to low sequence the increase in recall is much higher from 0.61 to 0.69. From the results we conclude, the SVM regression model does a better job in compensating the illumination changes in different areas of the background scene.

Chapter 6

Conclusion and Future Work

In this thesis we have proposed a single regression model to compensate the fast and sudden illumination changes in the indoor environment. This thesis addressed the challenges due to light switch sequences associated with background subtraction techniques in indoor environments. We have modeled the intensity ratios as a function of spatial coordinates to handle these global and local illumination changes. We have developed a real time implementation of the proposed approach to demonstrate the effectiveness of our regression algorithm to handle these sudden illumination changes in a simpler background subtraction framework. We have experimentally and statistically shown that these changes are handled better by the higher order polynomials having the minimum mean square error. We have tested our algorithm on light switch sequences from low illumination to high illumination, high illumination to low illumination and also in the presence of reflective surfaces like white boards, shining rods etc.

We can extend our single regression framework to multiple regression model to better handle the real world scenarios. The objects in the real world are not perfectly lambertian and also cast shadows. A single regression model is not sufficient to fit the complex scenes due to depth discontinuities. We highlight a few possible research directions to make the regression framework to be more robust to these challenges. By segmenting the scene into multiple regions and each region could be fitted with a

single regression model. This is likely to provide a good illumination compensation compared to the single regression model for complex background scenes.

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