International Journal of Computer science engineering Techniques-– Volume 2 Issue 5, July - Aug 2017
RESEARCH ARTICLE OPEN ACCESS

A study of Edge Detection Techniques

[1]MS. Nabanita Basu ,[2] Prof.Samir Kumar Bandyopadhyay
Department of Computer Science and Engineering, University of Calcutta, JD Block Salt Lake, Sector III, Kolkata, 700098, India

Abstract:

An edge is a sharp discontinuity or a significant change in local intensity of an image. The process for tracking the edge of various components in an image is referred to as edge detection. Edge detector operators is classified into two basic types, namely, Gradient based or first order derivative based edge detectors and second order derivative based edge detectors. This paper describes these two algorithms in detail along with stepwise image examples.

Keywords **— Edge Detection, Sobel Edge Detector, Marr Hildrith edge detector.**

Introduction

An edge is defined as a sharp discontinuity or a significant change in local intensity of an image. The sharp change in pixel intensity value in an image is referred to as edge. The technique of tracking the edge of various components in an image is referred to as edge detection. Edge detection is aimed at marking out continuous lines in an image. The objective of most computer vision algorithms is to undertake imagesegmentation in order to identify the specific components in a given image. Edge detection often plays an integral role in demarcating image component/s of relevance. The component/s of interest is referred to as the Region of interest within the image processing/Computer Vision domain. Edge detection essentially partitions an image into non-overlapping regions, thereby, contributing to the process of Region of Interest extraction.

Edge-based segmentation finds application in different image analysis domains, namely medical and biomedical image analysis such as abnormality detection, tissue measurement, surgical planning and simulation, biological feature identification etc. Edge detection algorithms also find application in Geographical Information systems, remote sensing images and industrial machine vision problems.

Edge detector operators can particularly be classified into two basic types, namely, Gradient based or first order derivative based edge detectors and second order derivative based edge detectors. The gradient vector for each point in a 2D image is calculated for the horizontal and vertical direction. The gradient vectors are combined to obtain the gradient for each point. The Sobel edge detector, which is an improvement on Robert's edge detector algorithm, is a gradient based edge detector. The Laplacian of Gaussian or Marr Hildrith edge detector relies on second order derivative for edge detection. Slope of the zero crossing points of the second order derivative of the image is used to estimate the edges for the image. The threshold value tuning for both the edge detector algorithms is susceptible to vary from one image to another.This paper illustrates these two algorithms in detail along with stepwise image examples.

Review Works

The basic task for edge detection process is to reduce the amount of data to be processed while at the same time storing useful information about object boundaries [1-2]. The high pass filters are used in the process of identifying the image by locating the sharp edges which are discontinuous. These discontinuities changes in pixels intensities which define the boundaries of the object[3]. The edge detection aims to identify points in a digital image at which the image brightness changes sharply or abruptly. Image edge detection mainly deals with extracting edges in an image by identifying pixels where the intensity variation is very high.[4] Edges are used to measure the size of objects in an image; to isolate particular objects from their background; to recognize or classify objects.[4-5]

Methodology

Sobel edgedetector algorithm coupled with Otsu's threshold selection methodology was used to mark out the edges of images from 3 datasets, namely, Berkeley Segmentation Dataset and Benchmark BSDS500, Shapes database, In-House Natural Images database. Again, Marr-Hildrith algorithm was used for edge detection on the 3 datasets.

Dataset Selected/Developed

The Berkeley Segmentation Dataset consists of varied RGB colored images (particularly outdoor images) along with the segmentation ground truth. Size of each RGB image is 481 by 321. The edge detection algorithms, Sobel and Marr-Hildrith were tested on a total of 200 test images. Unlike the BSDS database, the Shapes database developed consisted of images of homogeneous coloring and illumination. Each image was of size 298 by 200. Dataset 3 consisted of in-house images extracted frame-wise from a motion video. Each image/video frame extracted from the video is of size 720 by 1280.

Sobel Edge Detector

The Sobel edge detection algorithm can broadly be classified into 4 basic steps, namely, Image derivative computation in the x-direction, Image derivative computation in the y-direction, Gradient magnitude computation and thresholding to obtain the Sobel edges of the image. Unlike conversion of an RGB image to grayscale, in the implemented algorithm each RGB image was represented as 3 grayscale images, one representing the Red Channel Values alone and the other two representing the Blue and Green color channel values respectively. For each color channel image, the aforementioned steps were independently executed. Otsu thresholding for each channel was independently performed and the edge image for each channel was merged to obtain the final edge map for the given image(Fig. 1). As opposed to the conventional method of converting an image to grayscale and then computation of horizontal and vertical convolution, the channel based method helps minimize information loss thereby facilitating clearer edge detection (Fig. 2)

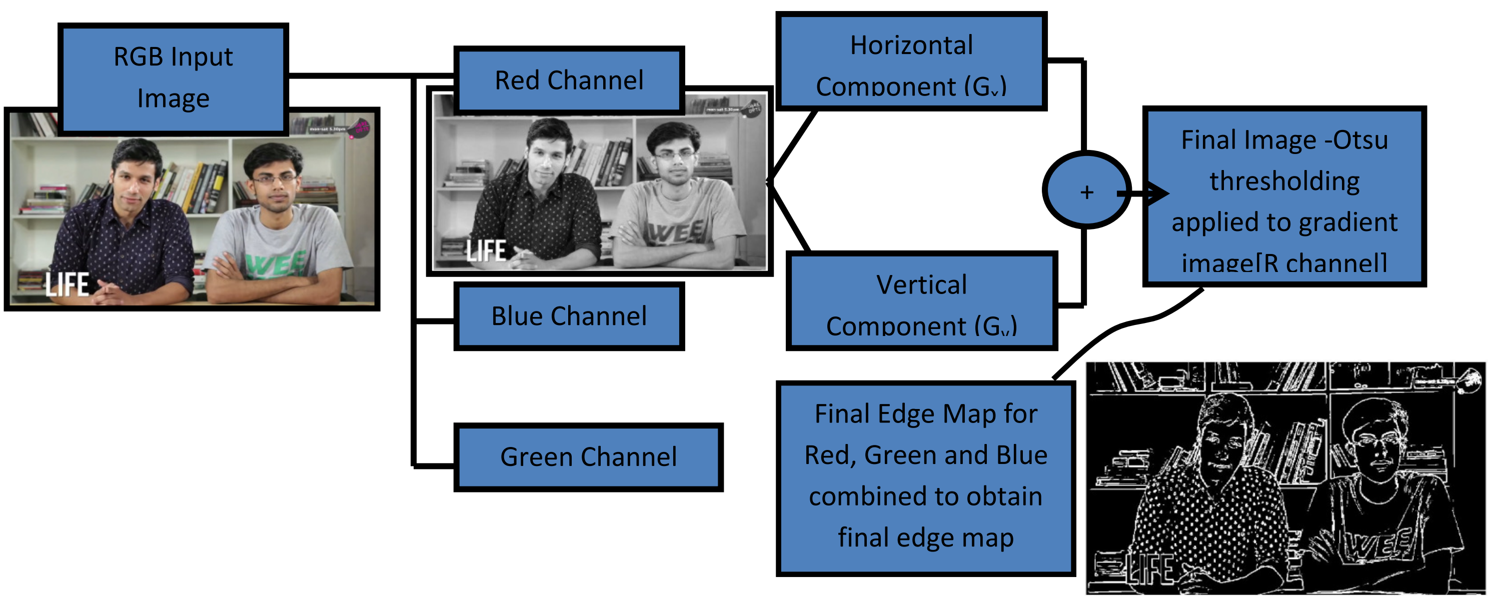


Figure 1: Graphical flow chart of the Sobel Edge detection algorithm implemented

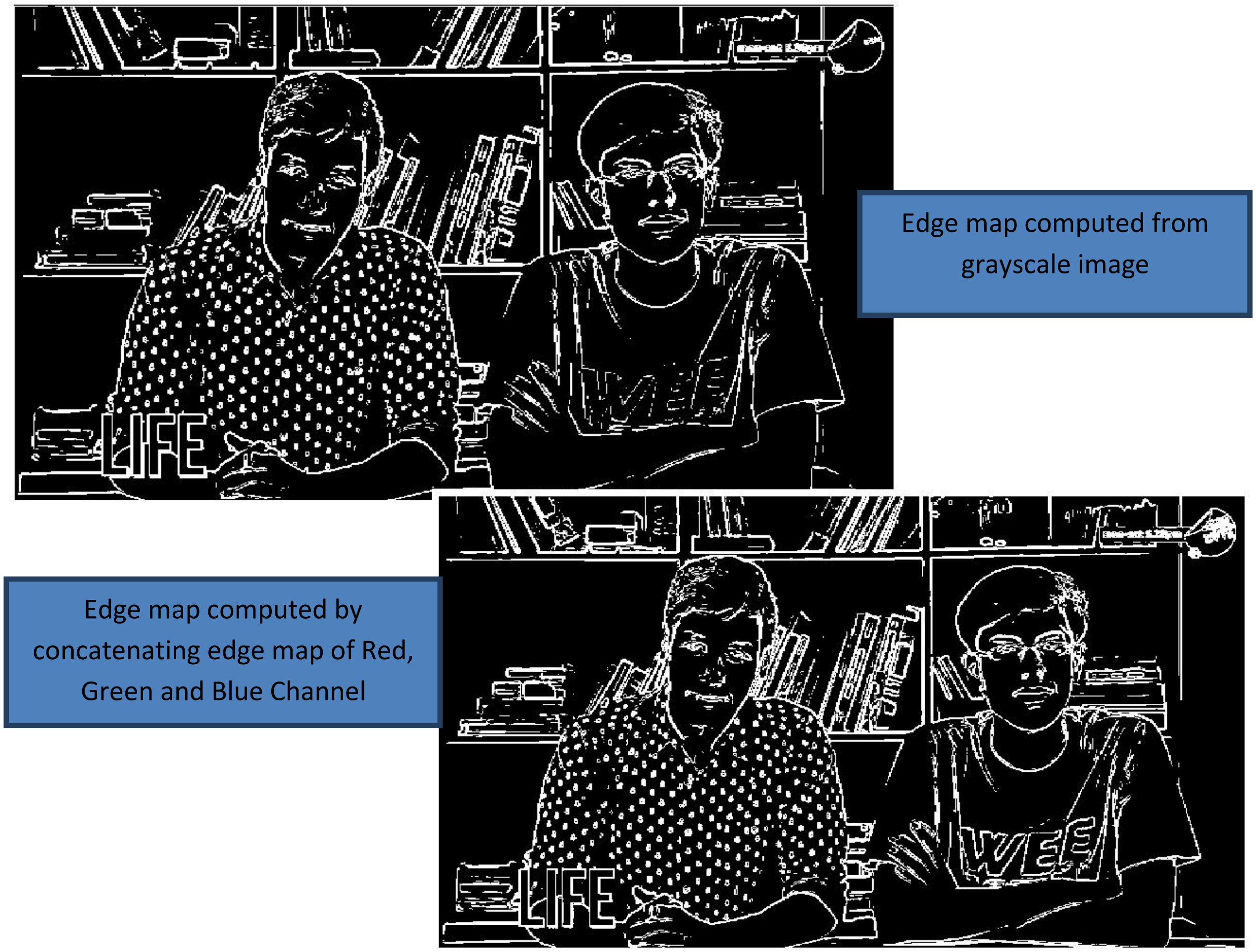


Figure 2: Each color channel was used to develop independent edge map as opposed to computing the edge map from grayscale version of the image in order to minimize information loss in the final edge map. The 'WEE' is much less clear in the grayscale based edge map

Image derivative computation in x-direction

With the use of matrix$S = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$ the horizontal gradient was computed. Each color channel of the RGB image was convoluted with the given matrix. Figure 3 represent the horizontal gradient for a randomly selected image from dataset 3. Similar technique could be used for horizontal gradient computation of a grayscale image.

(a)

(b)

(c)

Figure 3: Horizontal Gradient of the Image for the (a) Red (b) Green and (c) Blue Channel

Image derivative computation in y-direction

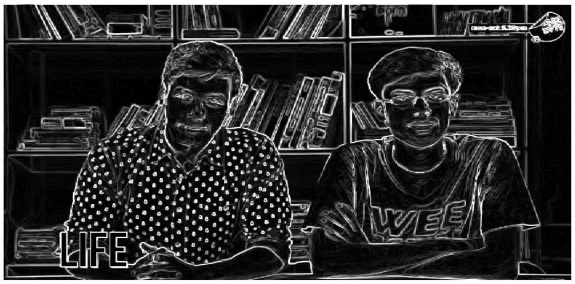
Transpose of matrix S (i.e.,$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$) was used to calculate the vertical gradient for each color channel of an RGB image. Figure 4a, 4b and 4c represent the vertical gradient for a randomly selected image from dataset 3. Vertical gradient computation of a grayscale image can be computed using the same techn*i*que.

(a) (b)

(c)

Figure 4: Vertical Gradient of the Image for the (a) Red (b) Green and (c) Blue Channel

Gradient magnitude computation and threshold value selection The gradient magnitude (G_{xy}) was computed using the equation $G_{xy} = \sqrt{G_x^2 + G_y^2}$ and it is shown in (Fig.5). After computation of the Gradient magnitude for each color channel in a RGB image. Otsu threshold was computed independently for the red, green and blue color channel respectively in a RGB image. Based on the threshold value, edge map corresponding to each color channel in a RGB image was computed. Another similar technique could be used for edge detection in a grayscale image. The final edge map for the RGB image was computed by concatenating the edge maps obtained for each color channel (Fig.6).

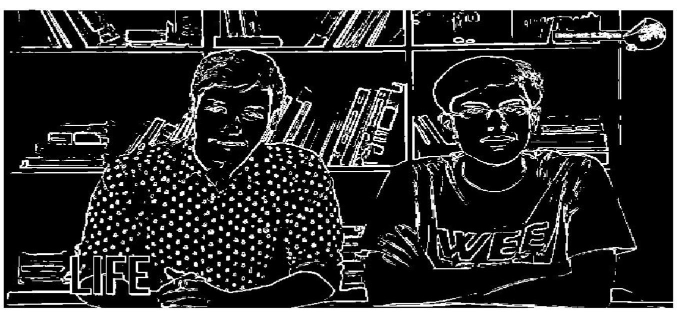


(a)

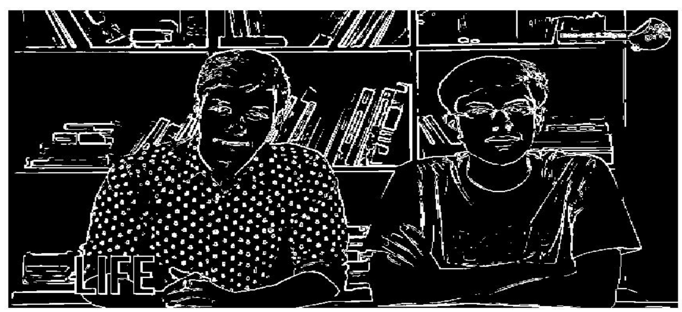
(b)

(c)

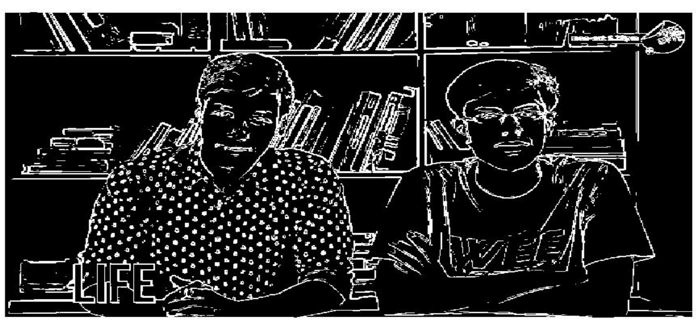
Figure 5: Combined Gradient of the Image for the (a) Red (b) Green and (c) Blue Channel



(a)



(b)



(c)

Figure 6: Edge Map of the Image for the (a) Red (b) Green and (c) Blue Channel

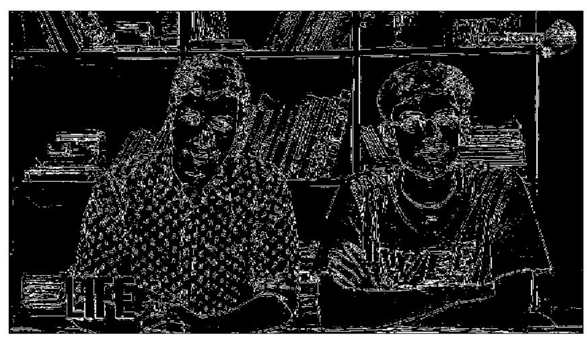
Marr-Hildrith edge detector

Unlike the Sobel operator, the Marr-Hildrith edge detector is sensitive to noise. So blurring or smoothening of an image using a 2D Gaussian filter is performed to minimize high frequency noise in an image. This step helps prepare the image for edge detection using the Laplacian of Gaussian technique. The Laplacian operator is applied to the filtered image. Owing to the associative nature of the convolution function, the output for convolving a Gaussian filtered image by a Laplacian kernel is by far similar to the application of Laplacian of the Gaussian to the convolution of an image. This requires fewer mathematical operations as the Laplacian and Gaussian kernel are by far much smaller in size as compared to the image. Again, pre-calculation of the Laplacian of Gaussian in advance calls for only one convolution at runtime.At the onset a squared Gaussian kernel is developed for a particular size(denoted by N) and standard deviation(denoted by sigma). The 2D Laplacian of Gaussian or the second derivative of the image centered on zero with standard deviation σ was computed using the equation

$$\Delta^2 G = -\frac{1}{\pi\sigma^4}\left[1 - \frac{x^2 + y^2}{2\sigma^2}\right] e^{-\frac{x^2+y^2}{2\sigma^2}}$$

The LoG kernel was normalized and discretized, so that all values of the LoG kernel lie in the [-255, +255]. Empirically a kernel size of 9 and standard deviation of 1.4 was selected for convolution of any image. Convolution of the same image with a kernel size of 3 and standard deviation of 0.6, kernel size of 7 and standard deviation 1 result in under-representation and over representation with inclusion of spurious edges respectively. Again, convolution of image with discrete Laplacian of Gaussian kernel of size 17 and standard deviation 1.4 results in inclusion of false/spurious edges. Figure 7 represents the edges identified by use of different kernel size (i.e. N) and σ values on a randomly selected image from dataset 3.

(a)



(b)

(c)

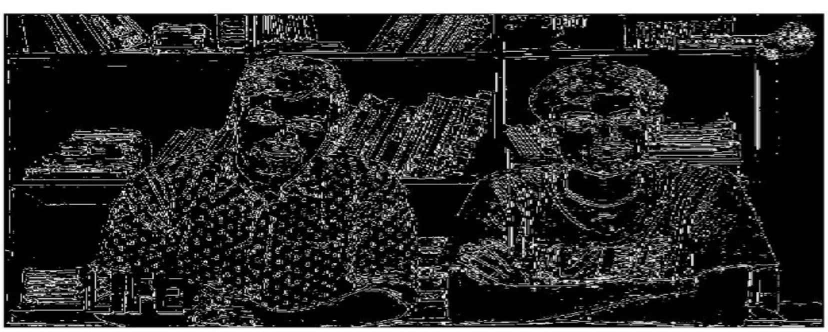


Figure 7: Marr Hildrith Edge Map of the Image for (a) N=3, sigma=0.6 (b) N=7, sigma=1 (c) N=17. Sigma=1.4

Again, by convention, for Marr Hildrith edge detection, a RGB image is converted to grayscale after which Laplacian of Gaussian operator is applied to the same. To preserve maximum image information and minimize information loss, convolution is independently performed for each of the 3 color channels using the same discrete Laplacian of Gaussian kernel. For the convolutions obtained, zero crossing positions are then marked out. Zero crossing positions can broadly be classified into two basic types, namely, real zero crossing points({-,0,+},{+,0,-}) and expected zero cross points({-,+},{+,-}). A zero cross point (i.e. real and expected) are marked with the slope of the crossover. For points of value 'a' and '–b', the slope was calculated as sum of the absolute value of 'a' and 'b'. Thereafter Otsu threshold value was calculated for each zero cross over map obtained for each color channel. After Otsu thresholding, the 3 edge maps were added to obtain the final Marr-Hildrith edge map for a given RGB image. A single channel based similar technique can also be utilized for a grayscale image. Figure 8 represents the channel based edges detected for each image randomly selected from dataset 3.

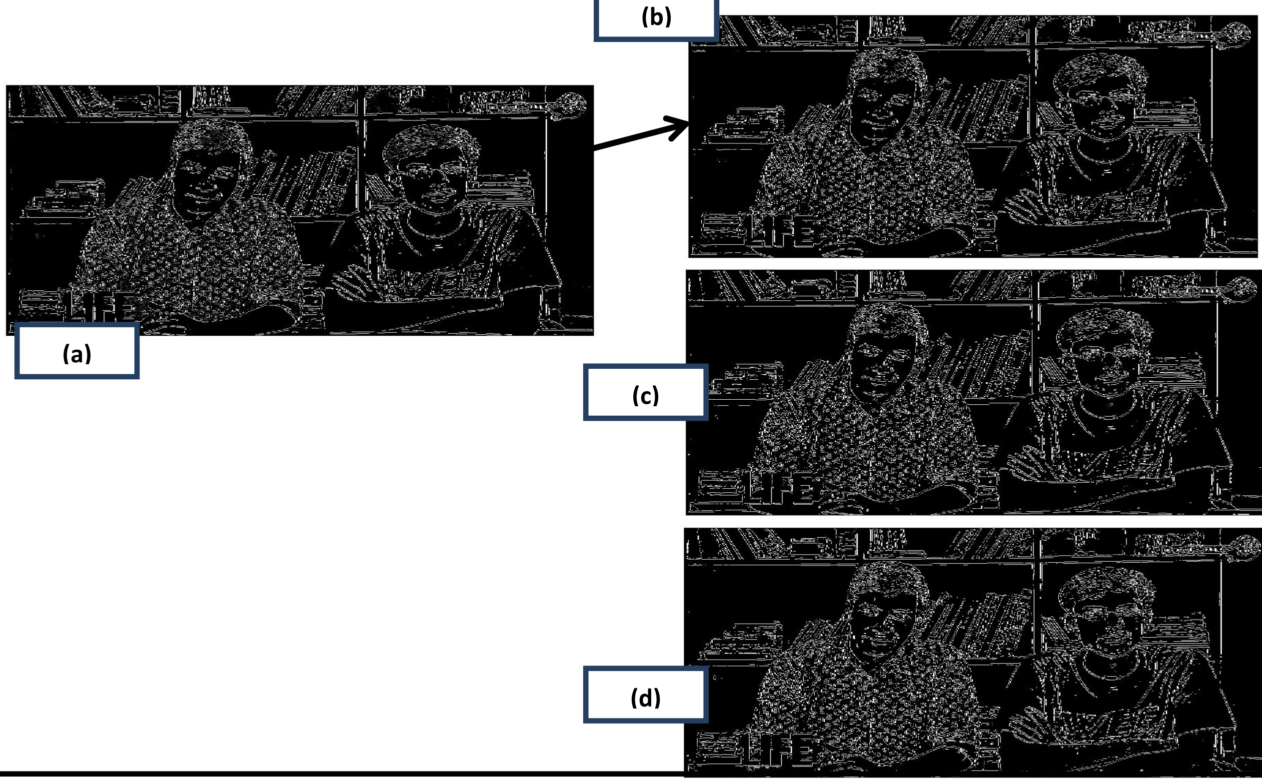
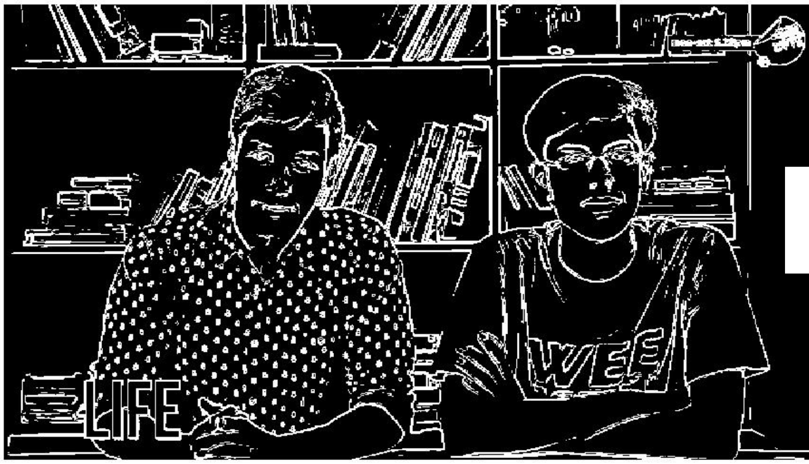


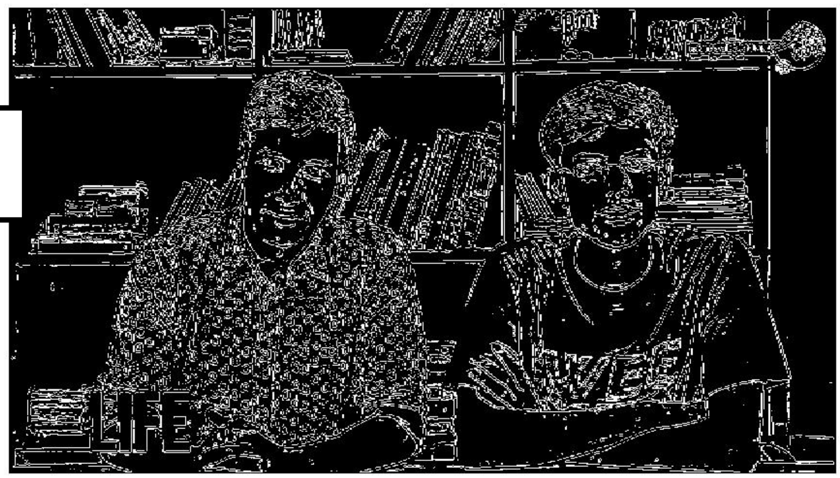
Figure 8: (a) Zero Crossing image for red channel of image (b) Otsu thresholding of zero crossing image for red channel (c) Otsu thresholding of zero crossing image for green channel (d) Otsu thresholding of zero

Results and Discussion

Figure 9 represents the image edge maps obtained for the same image using the Sobel operator and the Marr-Hildrith operator. Visual perception of the edge maps reveal that while Marr Hildrith preserves detailed edge information, Sobel operator concentrates more on preserving the strong edge information while neglecting the weaker ones. However, the Sobel operator or Marr-Hildrith application for edge detection is particularly based on the segmentation need of the concerned problem and color distribution of image.



Edge Map of Image obtained using Sobel Operator



Edge Map of Image obtained using Marr-Hildrith Operator

Figure 9: Edge maps for an image using Sobel operator and Marr Hildrithoperator (N=9, sigma=1.4)

Conclusions

The Sobel edge detector, which is an improvement on Robert's edge detector algorithm, is a gradient based edge detector. The Laplacian of Gaussian or Marr Hildrith edge detector relies on second order derivative for edge detection. Slope of the zero crossing points of the second order derivative of the image is used to estimate the edges for the image. These two are discussed in the paper.

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