

Edge Detection in Brain Images

Samir Kumar Bandyopadhyay

Dept. of Computer Sc. & Engineering, University of Calcutta
92 A.P.C. Road, Kolkata – 700009, India

ABSTRACT

In this paper problem of edge detection in digital images is considered. Particular attention is paid to brain magnetic resonance images. The new approach to edge detection is introduced. Results of proposed method are presented and compared with traditional approach.

In this work, a new contour detection method is studied for detecting brain tumor regions based on their gradient magnitude information. Gradient magnitude data, an edge detection method, is generated from the brain slice image intensity or perceived brightness information. Contour map of the brain tumor is generated by using the gradient magnitude differences of the template masks (cropped from brain slice tumor image) and the sample masks (traverses the image) raw pixel and perceived brightness (luminance) data. Then these differences are averaged and normalized to produce edge profiles of the brain tumor region contours. This data is used by the remote surgical devices for removing the tumor area.

Keywords Perceived brightness (luminance), gradient magnitude, contour profiling, and edge detection

Introduction

Edge detection is a critical element in image processing, since edges contain a major function of image information. The function of edge detection is to identify the boundaries of homogeneous regions in an image based on properties such as intensity and texture. Many edge detection algorithms have been developed based on computation of the intensity gradient vector, which, in general, is sensitive to noise in the image. In order to suppress the noise, some spatial averaging may be combined with differentiation such as the Laplacian of Gaussian operator and the detection of zero crossing.

Combining both spatial and intensity information in image, we present an MRI brain image segmentation approach based on multi-resolution edge detection, region selection, and intensity threshold methods. The detection of white matter structure in brain is emphasized in this paper. First, a multi-resolution brain image representation and segmentation procedure based on a multi-scale image filtering method is presented. Given the nature of the structural connectivity and intensity homogeneity of brain tissues, region-based methods such as region growing and subtraction to segment the brain tissue structure from the multi-resolution images are utilized. From the segmented structure, the region-of-interest (ROI) image in the structure region is derived, and then a modified segmentation of the ROI based on an automatic threshold method using our threshold selection criterion is

presented. Examples on both T1 and T2 weighted MRI brain image segmentation is presented, showing finer brain tissue structures.

Different Edge Detection Techniques

There are many ways to perform edge detection. However, the most may be grouped into two categories, gradient and Laplacian. The gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image. The Laplacian method searches for zero crossings in the second derivative of the image to find edges.

The facial features (eyes, nose, mouth) have very sharp edges. These also happen to be the best reference points for morphing between two images. Notice also that the Marr-Hildreth not only has a lot more noise than the other methods, the low-pass filtering it uses distorts the actual position of the facial features. Due to the nature of the Sobel and Prewitt filters we can select out only vertical and horizontal edges of the image as shown below. This is very useful since we do not want to morph a vertical edge in the initial image to a horizontal edge in the final image. This would cause a lot of warping in the transition image and thus a bad morph.

Canny [1] derived analytically optimal step edge operators and showed that the first derivative of Gaussian filter is a good approximation of such operators. An alternative to gradient techniques is based on statistical approaches. The idea is to examine the distribution of intensity values in the neighborhood of a given pixel and determine if the pixel is to be classified as an edge. In comparison with the differential approaches, less attention has been paid to statistical approaches. However, this method has been approached by some authors, e.g., Bovik et al. [2] and Yakimovsky [3]. In the past two decades several algorithms were developed to extract the contour of homogeneous regions within digital image. A lot of the attention is focused to edge detection, being a crucial part in most of the algorithms. Classically, the first stage of edge detection (e.g. the gradient operator, Robert operator, the Sobel operator, the Prewitt operator) is the evaluation of derivatives of the image intensity. Smoothing filter and surface fitting are used as regularization techniques to make differentiation more immune to noise. Raman Maini and J. S. Sobel [4] evaluated the performance of the Prewitt edge detector for noisy image and demonstrated that the Prewitt edge detector works quite well for digital image corrupted with Poisson noise whereas its performance decreases sharply for other kind of noise.

Davis, L. S. [5] has suggested Gaussian preconvolution for this purpose. However, all the Gaussian and Gaussian-like smoothing filters, while smoothing out the noise, also remove genuine high frequency edge features, degrade localization and degrade the detection of low-contrast edges. The classical operators emphasize the high frequency components in the image and therefore act poorly in cases of moderate low SNR and/or low spatial resolution of the imaging device. The awareness of this has led to new approaches in which balanced trade-offs are sought between noise suppression, edges, altogether resulting in operators acting like band-pass filters e.g. Canny. Sharifi, M. et al. [6] introduces a new classification of most important and commonly used edge detection algorithms, namely ISEF, Canny, Marr-ildreth, Sobel, Kirch and Laplacian. They discussed the advantages and disadvantages of these algorithms. Shin, M.C et al. [7] presented an evaluation of edge detector performance using a structure from motion task. They found that the Canny detector had the best test performance and the best robustness in convergence and is one of the faster executing detectors. It performs the best for the task of structure from motion. This conclusion is similar to that reached by Heath et al. [8] in the context of human visual edge rating experiment. Rital, S. et al. [9] proposed a new algorithm of edge detection based on properties of hypergraph theory and showed this algorithm is accurate, robust on both synthetic and real image corrupted by noise. Li Dong Zhang and Du Yan Bi [10] presented an edge detection algorithm that the gradient image is segmented in two orthogonal orientations and local maxima are derived from the section curves. They showed that this algorithm can improve the edge resolution and insensitivity to noise. Zhao Yu-qian et al. [11] proposed a novel mathematic morphological algorithm to detect lungs CT medical image edge. They showed that this algorithm is more efficient for medical image denoising and edge detecting than the usually used template-based edge detection algorithms such as Laplacian of Gaussian operator and Sobel edge detector, and general morphological edge detection algorithm such as morphological gradient operation and dilation residue edge detector. Fesharaki, M.N. and Hellestrand, G.R [12] presented a new edge detection algorithm based on a statistical approach using the student t-test. They selected a 5x5 window and partitioned into eight different orientations in order to detect edges. One of the partitioning matched with the direction of the edge in the image shows the highest values for the defined statistic in that algorithm. They show that this method suppresses noise significantly with preserving edges without a prior knowledge about the power of noise in the image.

Automated Edge Detection Technique

The automated edge detection technique is proposed to detect the edges of the regions of interest on the digital images automatically. The proposed technique consists of two algorithms, which are as follows:

In our experiment, 18 invasive brain tissues from different 18 patients and 8 noncancerous falsely

detected breast tissues from 8 different normal patients are considered. Each of the 24-bit BMP Image size is 640 x 480 Pixels.

24-bit Color Image to 256-color Gray Image

1. Take this 24-Bit BMP file as Input file and open the file in Binary Mode, (Size $M \times M$).
2. Copy the ImageInfo (First 54 byte) of the Header from Input 24-Bit Bmp file to a newly created BMP file and edit this Header by changing filesize, Bit Depth, Colors to confirm to 8-Bit BMP.
3. Copy the ColorTable from a sample gray scale Image to this newly created BMP at 54th Byte place on words.
4. Convert the RGB value to Gray Value using the following formula:
 - a. $blueValue = (0.299 * redValue + 0.587 * greenValue + 0.114 * blueValue);$
 - b. $greenValue = (0.299 * redValue + 0.587 * greenValue + 0.114 * blueValue);$
 - c. $redValue = (0.299 * redValue + 0.587 * greenValue + 0.114 * blueValue);$
 - d. $grayValue = blueValue = greenValue = redValue;$
5. Write to new BMP file.

Now 24-bit BMP color image is taken as input. Then convert it to 256-color Gray Scale image by following this algorithm. This 256-color Gray Scale image is the output of the algorithm. In this algorithm, first read the red, blue and green value of each pixel and then after formulation, three different values are converted into gray value, stated in Step 4.

256-color Gray Image to Bi-color (using Pixel Clustering on Threshold Value, T)

1. Open 256-color Image (Size $M \times M$)
2. Read a Pixel value
3. If the Pixel Intensity value less than or equal to T (128) then make it 0 Else make it 255 and write into same Pixel Location
4. Go to Step 2 until end of file
5. Close file

This algorithm is actually used here to convert the Gray Image to Bi-color (Monochrome Image).

This is the Edge Detection Algorithm set on a Threshold Value. Results are shown in Figure 1 and Figure 2.

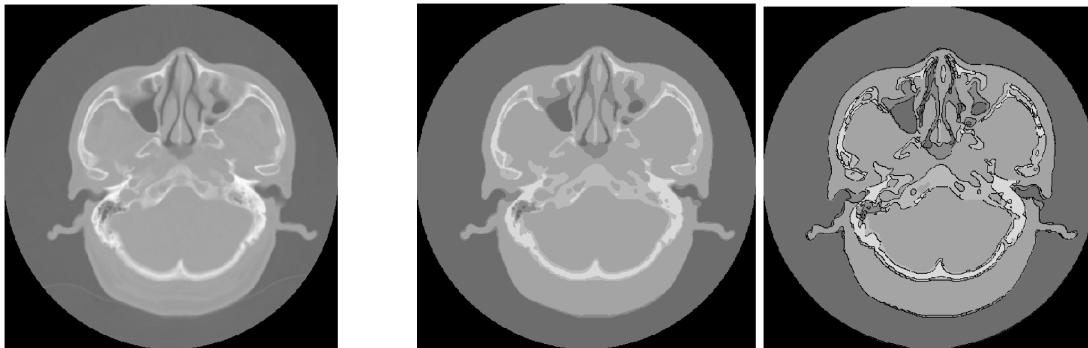


Figure 1 (a) Original image of brain image (b) Brain image (512x512) with noise (c) Brain Image after Noise Removal

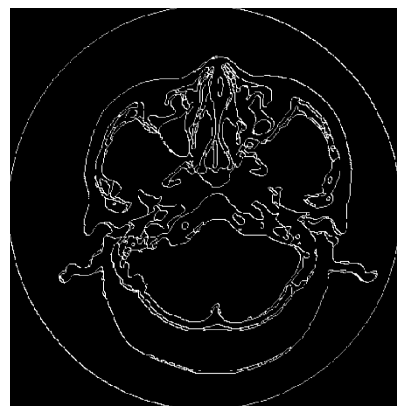


Figure 2 Brain Image after Edge Detection

Conclusions

Edges are one of the most important elements in image analysis and computer vision, because they play quite a significant role in many applications of image processing, in particular for machine vision. A lot of computer vision methods rely on edge detection as a pre-processing stage. However, no single edge detection

algorithm can successfully discover edges for diverse images and no specific quantitative measure of the quality for edge detection is given at present. In this paper, a new contour detection method is studied for detecting brain tumor regions based on their gradient magnitude information.

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