Comparative and Efficient Analysis of Gradient Based Edge Detection Technique in Medical Images

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Abstract
Boundary detection is the process of identifying two dissimilar regions in an image. In recent years, there have been several new methods to solve the problem of boundary detection like active contour model, geodesic active contour model, active contours without edges, etc. But still the difficulty exists in processing images with concave boundary and noisy regions. The proposed Gradient Edge Detection (GED) technique can detect the boundaries of images in noisy images using the intensity and texture gradient features. The performance and robustness of the method have been tested in synthetic noisy images and medical images including knee joints in MR images and aortas in cardiovascular MR images. The efficiency and the effectiveness of the GED technique can be analyzed by comparing the result with the existing active contour models. The results show that the proposed GED technique yields better performance than the active contour models.
Keywords - Boundary Detection, Gradient Edge Detection, MR Images, Texture.

I. INTRODUCTION
Medical images are often noisy and too complex to expect local and low level qualifiers to generate perfect boundary regions. This work proposes an edge detection technique called GED based on the intensity and texture pattern occurring in the medical image. This method can separate boundary with improved accuracy without prior knowledge about the gradient noise present in the image. The proposed technique outperforms the classical contour models like active contour model, geodesic contour model and snake contour model, especially for images with concave boundary regions like the heart and knee joint MR images. The major objective of this paper is to use the GED technique to detect and map the ill-defined edges in medical images with high accuracy. The purpose of this paper is also to achieve better way of detecting the boundary regions comparing with other classical edge detecting contour models.

The problem of edge detection is the presence of noise that results in random variation in level from pixel to pixel. Therefore, the ideal edges are never encountered in real images [1], [2]. A great diversity of edge detection algorithms have been devised with differences in their mathematical and algorithmic properties such as Roberts, Sobel, Prewitt, Laplacian, and Canny, all of which are based on the difference of gray levels [3]–[6]. The difference of gray levels can be used to detect the discontinuity of gray levels. On the other hand, region-based approaches are based on similarity of regional image data. Some of the more widely used approaches are thresholding, clustering, region growing, and splitting and merging [7]. However, the performance evaluation of image segmentation result is still a challenging problem as they fail to extract the correct boundaries of objects in noisy images. In recent years, there have been several new methods to solve the problem of boundary detection, e.g., Active Contour Model (ACM), Geodesic Active Contour (GAC) model, Active Contours Without Edges (ACWE), Gradient Vector Flow (GVF) snake model, Vector Field Convolution (VFC) snake model, etc. The snake models have become popular especially in boundary detection where the problem is more challenging due to the poor quality of the images. The ACMs also known as snakes are curves defined within an image domain that can be moved under the influence of the internal energy and external energy [8]–10].

Though many algorithms for boundary detection have been developed to achieve good performance in field of image processing, most algorithms for detecting the correct boundaries of objects have difficulties in medical images in which ill-defined edges are encountered [11]–[13]. Medical images are often noisy and too complex to expect local, low level operations to generate perfect primitives. The complexity of medical images renders the incorrect boundary detection. To remedy this problem, a new technique for boundary detection for ill-defined edges in noisy images is proposed.

II. GRADIENT EDGE DETECTION TECHNIQUE
The GED based edge detection technique involves mainly three steps: Edge Mapping, Average Edge Field and GED technique. Figure 1 shows the different steps present in the proposed edge detection technique.

A. Edge Mapping
Edge map is used to identify edges of objects in an image which is derived from Law’s texture and Canny edge detection. It gives important information of the boundary of objects in the image that is exploited in a decision for edge following. This involves two sub-concepts, namely, Law’s Texture and Canny edge detection.

Figure 1. Overview of proposed Edge Detection Techniques

1) Law's Texture

Law's Texture is applied by convolving the input image with the texture mask. This is achieved by determining texture properties by assessing average gray level, edges, spots, ripples and waves in texture. The measures are derived from three simple vectors. L3 = (1,2,3) which represents averaging; E3 = (-1,0,1) calculating first difference (edges); and S3 = (-1,2,-1) corresponding to the second difference (spots). After convolution of these vectors with themselves and each other, five vectors result: Level L5 = [1, 4, 6, 4, 1], Edge E5 = [-1,-2, 0, 2, 1], Spots S5 = [-1, 0, 2, 0,-1], Ripples R5 = [1, -4, 6,-4, 1], Waves W5 = [-1, 2, 0,-2,-1]. The input noisy image and the Law's texture image are shown in figure 2 and figure 3.

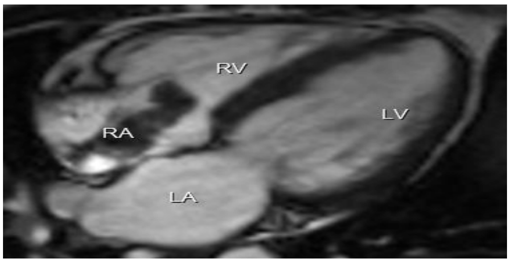


Figure 2. The input Image (Heart)

2) Canny Edge Detection

The Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images. Canny also produced a computational theory of edge detection explaining why the technique works. The first step of Canny edge detection is to convolve the output image obtained from the forementioned Law's texture t(i, j) with a Gaussian filter. The second step is to calculate the magnitude and direction of the gradient. The third step is non maximal suppression to identify edges. The broad ridges in the magnitude must be thinned so that only the magnitudes at the points of the greatest local change remain. The last step is the thresholding algorithm to detect and link edges. The double threshold algorithm is used to detect and link edges as shown in figure 4.

B. Average Edge Field

Average edge vector model is obtained by calculating the average of the entire vector field. Each component is the convolution between the image and the corresponding difference mask.

$$M_x(i,j) = -G_y \times f(x,y) \tag{1}$$

$$M_y(i,j) = -G_x \times f(x,y) \tag{2}$$

Where G_x and G_y are the Gaussian mask applied on the image with respect to x and y axes respectively.

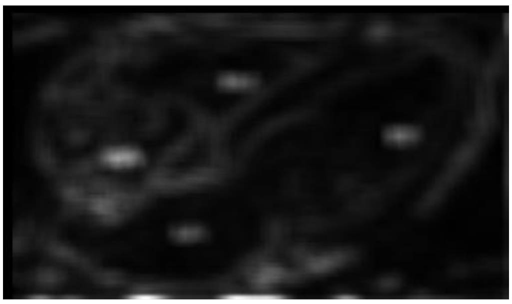


Figure 3. Law's Texture

Figure 4. Output of Edge mapping

$$G_x(x,y) = \frac{1}{\sqrt{2\Pi}\sigma}\left(\frac{x}{\sqrt{x^2+y^2}}\right)\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{3}$$

$$G_y(x,y)=\frac{1}{\sqrt{2\Pi\sigma}}\left(\frac{y}{\sqrt{x^2+y^2}}\right)\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right) \tag{4}$$

C. Gradient Edge Detection technique

The GED technique determines the boundary of an object. At the initial position (i, j) of an image, the successive positions of the edges are then calculated by a 3 × 3 kernel matrix. Here fractional pixels are needed during the transform.

$$L_{ij}(r,c)=\alpha M_{ij}(r,c)+\beta D_{ij}(r,c)+\varepsilon E_{ij}(r,c) \qquad 0\le r,c\le 2 \tag{5}$$

where α, β, and ε are the weight parameters that control the edge to flow around an object. The larger value of an element in L_{ij} indicates the stronger edge in the corresponding direction. The 3 × 3 matrices M_{ij} , D_{ij} and E_{ij} are calculated as follows:

$$M_{ij}(r,c)=\frac{M(i+r-1,\, j+c-1)}{\max_{i,j} M(i,j)} \tag{6}$$

$$D_{ij}(r,c)=1-\frac{\left|D(i,j)-D(i+r-1,\, j+c-1)\right|}{\pi} \tag{7}$$

$$E_{ij}(r,c)=E(i+r-1,\, j+c-1),\ 0\le r,c\le 2 \tag{8}$$

III. Experimental Results and Discussions

The output of the GED technique is compared with the existing models like Robert, Sobel, Prewitt, Canny and Active contour model to check the efficiency and the accuracy of the proposed method. The performance improvement and accuracy can be notably seen in the gradient edge detection technique. Figure 5 and 6 shows the output of active contour model (existing method) and gradient edge detection technique. Figure 7 and Figure 8 show the significance of using GED technique, it detects the boundaries accurately even at zoomed-in position.

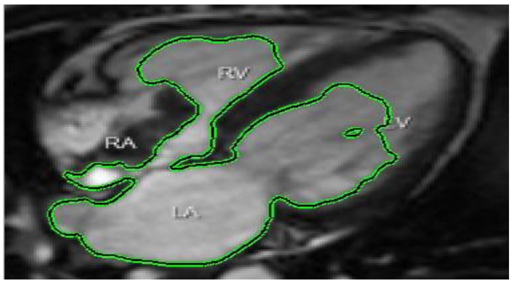


Figure 5. Active contour model (Existing)

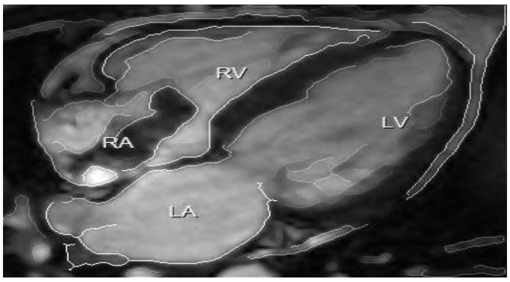


Figure 6 The GED technique output image

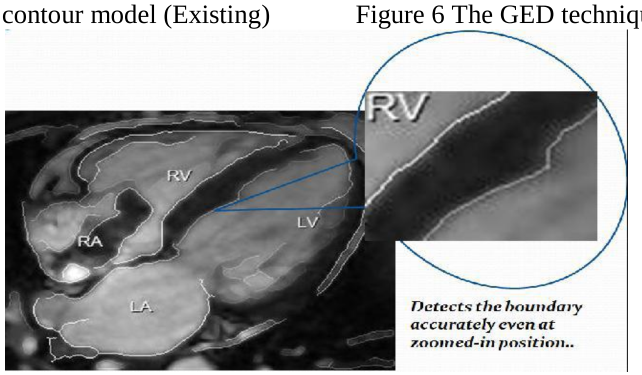
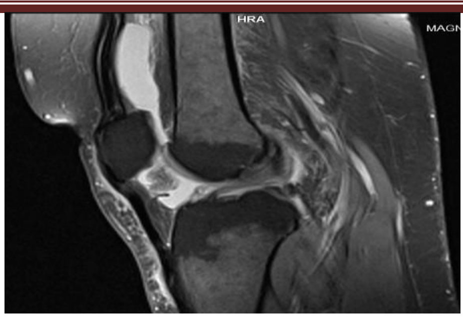
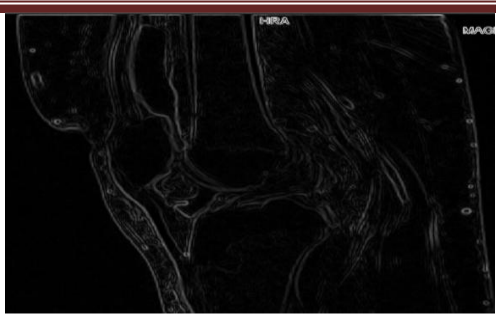


Figure 7. Boundaries at zoomed-in image

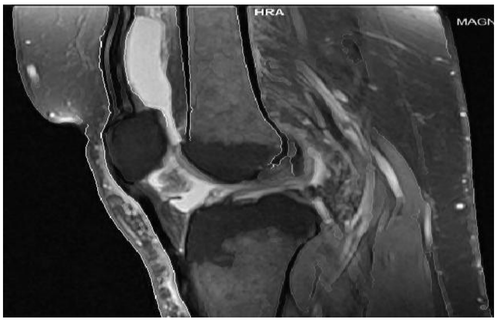


Input Image



Law's Texture

Output of Edge Mapping



The GED technique output image

Figure8. Boundary Detection of Knee joint image by GED Technique

IV. CONCLUSION

In this paper, the Gradient Edge Detection technique is proposed for boundary detection. The proposed edge following technique can detect the boundaries in complex medical images with high accuracy comparing with the existing contour models. Hence it can be useful for doctors and physicians for boundary extraction and detection of deforms in the body. The edge following technique can detect the open boundary regions in images. It can be improved in such a way to detect the closed and localized regions in the image.

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