A Segmentation Method Based on Dynamic Programming for Breast Mass in MRI Images

Jihong Liu[1,2], Weina Ma[1], and Soo-Young Lee[2]

[1] College of Information Science and Engineering, Northeastern University, Shenyang, 110004 China
[2] Brain Science Research Center, Korea Advanced Institute of Science and Technology, Daejeon 305-701, Korea
liujihong@ise.neu.edu.cn

Abstract. The tumor segmentation in Breast MRI image is difficult due to the complicated galactophore structure. The work in this paper attempts to accurately segment the abnormal breast mass in MRI(Magnetic resonance imaging) Images. The ROI (Region of Interest) is segmented using a novel DP (Dynamic Programming) based optimal edge detection technique. DP is an optimal approach in multistage decision-making. The method presented in this paper processes the object image to get the minimum cumulative cost matrix combining with LUM nonlinear enhancement filter, Gaussian preprocessor, non-maximum suppression and double-threshold filtering, and then trace the whole optimal edge. The experimental results show that this method is robust and efficient on image edge detection and can segment the breast tumor area more accurately.

1 Introduction

Breast cancer has affected one of every eight women in United States and one of every ten women in Europe[1]. Early diagnoses of breast cancer are important. However, early diagnosis requires an accurate and reliable diagnostic procedure that allows physicians to distinguish benign breast tumors from malignant ones.

The goal of breast mass segmentation is to separate suspected masses from surrounding tissue as effectively as possible. It is extremely important in the diagnostic process, while it is a pre-processing step of Computer Aided Diagnosis (CAD). Over the years researchers have used many methods to segment masses in mammograms or ultrasonic. Petrick et al. [2] used a filtering method called the Density Weighted Contrast Enhancement (DWCE) method. Karssemeijer and Brake implemented a discrete dynamic contour model [3]. Furthermore, many researchers have implemented methods based on maximum likelihood analysis [4,5]. Forbes F et al. [6] proposed an ROI selection method that combines model-based clustering of the pixels with Bayesian morphology. Wismuller A et al. [7] suggested that the minimal free energy vector quantization neural network had the potential to increase the diagnostic accuracy of MRI mammography by improving sensitivity without reduction of specificity. An essential issue for CAD researchers is the ability to properly obtain the boundaries of masses, because these boundaries are often obscured by surrounding breast tissue.

D. Zhang (Ed.): ICMB 2008, LNCS 4901, pp. 307–313, 2007.

Image segmentation can be divided into parallel method and serial method. Parallel method based on the check point itself and its neighbors for edge detecting, mainly includes a few of local differential operator, such as Roberts gradient operator, Sobel gradient operator, Laplacian second order difference operator and so on. This method has the advantage of high speed, but the structural information is always discontinuous and fragmentary. Whether the check point is an edge point of image in serial method depends on its surrounding checked points, which is multistage decision process. Thus we can checkout the single-track, consecutive structural information of the ROI. However, the speed of this serial method is slow.

DP (Dynamic Programming) is a powerful tool for image segmentation to solve the optimization of multistage decision process. After examining the local discontinuity of the image, it joins the boundary using serial search method and then the edge detection is achieved successfully. Lie W N et al. [8] proposed a skyline image detection for navigation of mobile vehicles or planes in mountainous environments using DP algorithm can get a fast processing speed. We present a novel DP-based optimal edge detection method to segment the breast tumor in MRI image.

2 A DP-Based Optimal Edge Detection Method

In order to obtain the optimal edge, the whole process presented in this paper is divided into several sections.

2.1 Image Pre-processing

The detecting outcome of the optimal path in DP algorithm highly depends on the quality of the edge image. However, in most medical images as the gray level reflected the body internal structure changes smoothly, the available single filter is rather difficult to satisfy the demands of removing noise while simultaneously enhancing edges.

Edge enhancement and sharpening have traditionally been accomplished using linear techniques. These techniques include Wiener filtering, high-pass filtering, and unsharp masking. The nonlinear filters usually considered are the lower-upper-middle (LUM) filter, the comparison and selection (CS) filter and the weighted majority of samples with minimum range (WMMR) filter. In our study we use LUM filters [9] to avoid many of the shortcomings of conventional linear edge-enhancing filters. In particular, LUM filters can intensively decrease levels of additive noise and remove impulsive-type noise while simultaneously enhancing edges. Furthermore, it does not cause any over-sharp. With an appropriate choice of parameters, LUM filters can function as smoothers. Before presenting the filters, we define some notation as follow:

Consider a discrete sequence $\{ x(n) \}$ where the index $n = [n_1, n_2, ..., n_d]$. Also, consider a moving window that spans N samples at each location n, where N is assumed to be odd. These samples can be indexed and written as a vector $x(n) = [x_1(n), x_2(n), ..., x_N(n)]$. The middle sample in the observation widow is denoted

$x_{(N+1)/2}(n)$ and the filter estimate at this location is denoted $y(n)$. The rank ordered or sorted observation samples are written as

$$x_1(n) \le x_2(n) \le ... x_N(n) \tag{1}$$

The output of the LUM filter with parameters k and l is given by

$$y(n) = \begin{cases} x_k & x_{(N+1)/2} < x_k \\ x_l & x_l < x_{(N+1)/2} \le t_l \\ x_{N-l+1} & t_l < x_{(N+1)/2} < x_{N-l+1} \\ x_{N-k+1} & x_{N-k+1} < x_{(N+1)/2} \\ x_{(N+1)/2} & others \end{cases} \tag{2}$$

Where t_l is the midpoint between x_l and x_{N-l+1} and $1 \le k \le l \le (N+1)/2$. The parameters k and l can be considered tuning parameters that allow the LUM filter to have a variety of characteristics. In the case where $l = (N+1)/2$ and k is varied, the LUM filter acts as a smoothing filter. As k is increased more smoothing can be expected, and if $k = l = (N+1)/2$, then the output of the LUM filter is simply the median. In the case where k =1 and l is varied, the LUM functions as a sharpener. As l is decreased, x_{N-l+1} and x_l move toward the upper and lower extreme values, respectively. This leads to an increased edge enhancing effect. When $1 < k \le l < (N+1)/2$, sharpening and outlier rejection can be achieved simultaneously. The parameter k can be increased to improve the impulse rejection characteristics of the LUM filter. The parameter l, on the other hand, controls the level of edge enhancement. This parameter is decreased to give more enhancement and increased to reduce enhancement. Finally, the filter performs an identity operation when $k = 1$ and $l = (N+1)/2$.

The image has a significant edge and higher signal-noise ratio after nonlinear filtering. But the false edge of the object image results from the DP algorithm entered the fork in the backward tracking due to the intersection or fork at the edge of image as well as the surplus noise .Therefore, in this paper we use a double-threshold gaussian filter to enhance the edge of low quality image, to reduce the effect of false edge. Based on this, filtering with 3×3 gauss template, the gradient image which includes all information of the edge is calculated.Non-maximum suppression is done on the gradient image to thin the edge.

In order to acquire a more efficient boundary, we propose a double-threshold suppression on the image which is clearly processed by above methods. While the main outline, after processing with double-threshold filtering, is relatively clear, the mixed false edge caused by inhomogeneous gray scale and noise is preferably removed. Then the processed image can be used for iteration of the initial cost matrix in DP algorithm, calculating the minimum cumulative cost matrix. Compared with normal local differential coefficient operator, our experience with proposed methods presents

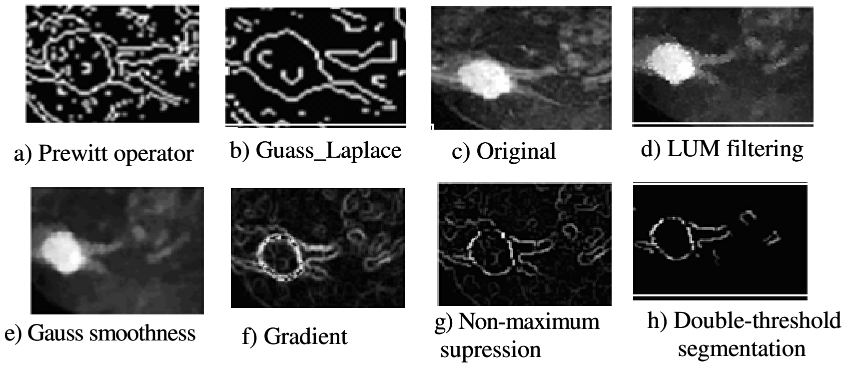

Fig. 1. Results gotten from the pre-processing and the traditional methods. a) Prewitt operator. b) Guass-Laplace. c) Original. d) LUM filtering. e) Gauss smoothness. f) Gradient. g) Non-maximum. h) Double-Threshold segmentation.

the more effective and clear results. In Fig.1 a) and b) are gotten by traditional operators, c) to h) are gotten by above pre-processing method in this paper.

2.2 The DP Algorithm for Image Edge Detection

In order to obtain the minimum uncertainty in the final output of medical imaging system, optimal criterion is necessary in edge detection. Especially in some cases it is essential to get the local boundary, and the DP algorithm based on interaction can process the object image perfectly.

When the image edge detection is considered as an optimal problem, it can be formulated in two aspects: (a) The optimal value M of the target function defined as $V = V(x_0, x_1, \cdots, x_N)$, where M is chosen from value of max or min and where $0 \le x_i \le n_i,\ \ i = 0,1,\cdots,N$. (b) The variable $(\bar{x}_0, \bar{x}_1, \cdots, \bar{x}_N)$ up to optimal target.

When there are different demands on target function and the variable is scattered, the whole problem will include a considerable solution space. Suppose the target function is presented as:

$$V(x_0, x_N) = V_0(x_0, x_1) + V_1(x_1 + x_2) + \cdots + V_{N-1}(x_{N-1}, x_N) \tag{3}$$

Then, the recursion formula of multistage optimization procedure can be applied:

$$f_0(x_0) = 0 \tag{4}$$

$$f_{k+1}(x_{k+1}) = \underset{0 \le x_k \le n_k}{opt} \ [V_k(x_k, x_{k+1}) + f_k(x_k)] \tag{5}$$

Where $k = 0,1,...N-1$, and $f_{k+1}(x_{k+1})$ is an intermediate variable. By the end of the recursion we have,

$$M = \underset{x_N}{opt} \ f_N(x_N) \tag{6}$$

Equation (4) actually is the solution to part(a), and the optimal variable of part(b) is given as follow,

$$\overline{x}_N = m_N = \arg \underset{x_N}{opt} f_N(x_N) \tag{7}$$

$$\overline{x}_k = m_{k+1}(\overline{x}_{k+1}), \qquad k = N-1, \cdots, 0 \tag{8}$$

Where, $m_{k+1}(\overline{x}_{k+1})$ denotes the value of $\overline{x}_k$ reaching to optimizing after $\overline{x}_{k+1}$ is given. Hence, through reverse recursion, the optimal variable is obtained.

In DP model for edge detection, the target function is given by the cumulative cost $cum(x_N, y_N)$ from starting point (x_0, y_0) which is the convergence of edge line or has a large curvature with the feature points on edge line to the end point (x_N, y_N). As a result the optimal value is namely the minimum cumulative cost matrix of stop point.

The demands of local gradient information and global edge cumulative cost information are needed in dynamic programming algorithm using for edge detection, which is just the reason that we get the global optimal solution. Using 8-neighbor connective method as an example, Fig. 2 shows the edge image applied DP algorithm after getting the local points.

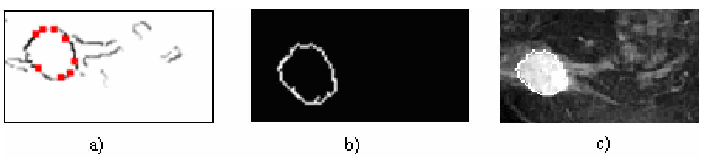

Fig. 2. ROI segmented using DP algorithm. a) Getting points. b) Edge extraction. c) Combination

3 Experimental Results

We tested our algorithm among 120 images of breast MR. Comparing with the traditional edge detection methods, we use above approach to segment abnormal region in breast MRI image and get the similar results with the diagnosis of doctor. One of the experimental results is shown in Fig. 3. It is obvious that this method is particularly helpful when the masses have ill-defined borders.

The threshold segmentation have a good effection on CT slices, simple algorithm and quick calculation, but it must be used according previous experiences or tried time after time, then being adjusted. Comparing with threshold segmentation, the algorithm of interactive segmentation based on DP is good for the object that have a smooth edge, which only need lesser degree to achieve accurate segmentation, although it also must spend time and interactive degree in bad edge image.

Fig. 3 a) is the initial image. Fig. 3 b) and c) show the pre-processing results. In Fig.3 d) shows a gradient image whose gradient line has more than one pixel. In Fig.3 e), it only keeps the middle pixels after non-maximum suppression, and accordingly the ridge of single pixel wide is obtained. Fig.3 f) shows the clear boundary without false edge using double-threshold segmentation. The quality of threshold affects the result of image segmentation directly. However, we can not find a uniform threshold for adjusting due to large and obvious differences existing among the medical imaging, so in processing program the exact threshold is obtained according the user's observation and experience. As in Fig.3 g), in order to prevent the DP algorithm entering the wrong edge line in backward tracking process, we get several feature points which are in the convergence area of edge line or have a large curvature. The edge points are identified via backward tracking minimum cost path, as it shown in Fig .3 h). Fig.3 i) shows the initial image combined with the edge.

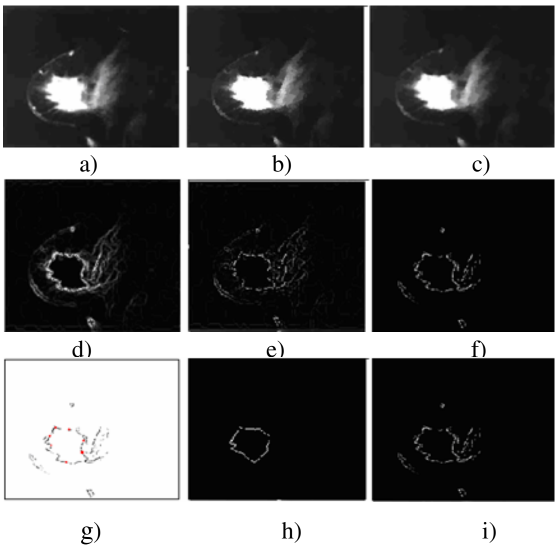

Fig. 3. The experimental results of DP method. a) Original image. b) LUM filtering. c) Guass smoothing. d) Gradient image. e) Non-maximum suppression. f) Double-threshold segmentation. g) Getting points. h) Edge extraction. i) Combined image.

4 Conclusions

We have developed a mass segmentation method that is capable of detecting the edge of the abnormal mass and marking its region. The ROI is segmented using a novel DP-based optimal edge detection technique. Dynamic programming is an optimal approach in multistage decision-making. The method presented in this paper processes the object image to get the minimum cumulative cost matrix combining with LUM nonlinear enhancement filter, Gaussian preprocessor, Non-maximum suppression and Double-threshold segmentation, and then traces the whole optimal edge. The experimental results show that this method is robust and efficient on image edge detection and can segment the breast tumor area more accurately.

References

1. Pandey, N., Salcic, Z., Sivaswamy, J.: Fuzzy logic based microcalcification detection. neural networks for signal processing X. In: Proceedings of the 2000 IEEE Signal Processing Society Workshop 2000, Sydney, NSW, Australia, pp. 662–671 (2000)
2. Petrick, N., Chan, H.-P., Sahiner, B., Wei, D.: An Adaptive Density-Weighted Contrast Enhancement Filter for Mammographic Breast Mass Detection. IEEE Transactions on Medical Imaging 15(1), 59–67 (1996)
3. Brake, G.M., te, K.N.: Segmentation of suspicious densities in digital mammograms. Medical Physics 28, 259–266 (2001)
4. Kupinski, M.A., Giger, M.L.: Automated Seeded Lesion Segmentation on Digtal Mammograms. IEEE Transactions on Medical Imaging 17(4), 510–517 (1998)
5. Kinnard, L., Lo, S.-C.B., Wang, P., Freedman, M.T., Chouikha, M.: Automatic Segmentation of Mammographic Masses Using Fuzzy Shadow and Maximum-Likelihood Analysis. In: Proceedings. IEEE International Symposium on Biomedical Imaging, pp. 241–244 (2002)
6. Forbes, F., Peyrard, N., Fraley, C., Georgian-Smith, D., Goldhaber, D.M., Raftery, A.E.: Model-based region-of-interest selection in dynamic breast MRI. Journal of Computer Assisted Tomography 30(4), 675–687 (2006)
7. Wismüller, A., Meyer-Bäse, A., Lange, O., Schlossbauer, T., Kallergi, M., Reiser, M.F., Leinsinger, G.: Segmentation and classification of dynamic breast magnetic resonance image data. Journal of Electronic Imaging 15 (2006)
8. Lie, W.N., Lin, T.C., Hung, K.S.: A robust dynamic programming algorithm to extract skyline in images for navigation. Pattern Recognition Letters 26(2), 221–230 (2005)
9. Hardie, R.C., Boncelet, C.G.: Gradient-based edge detection using nonlinear edge enhancing profilers. IEEE Trans Image Processing 4(11), 1572–1577 (1995)