www.ijecs.in
International Journal Of Engineering And Computer Science ISSN: 2319-7242
Volume 5 Issue 11 Nov. 2016, Page No. 19019-19022

Auto Contour Initialization of Breast Masses in Contrast Enhanced Breast CT

Harmandeep Kaur[1], Neeraj Julka

[1]ASRA College of Engineering & Technology,Bhwanigarh,Punjab
harmandeepk.sandhu@gmail.com

[2]ASRA College of Engineering & Technology,Bhwanigarh,Punjab
asranc22014@gmail.com

Abstract: Dedicated breast CT (bCT) produces high-resolution 3D tomographic images of the breast, fully resolving fibroglandular tissue structures within the breast and allowing for breast lesion detection and assessment in 3D.Various techniques have been used for detecting cancer in women. Previous studies have worked on providing a manual seed point for evaluating the area of tumor. In this study, we present a method for auto initialization of seed point enhancing the quality of detection. First, image enhancement techniques are used which is then followed by detection of circular areas in image and choosing the best out of them. In next step, centroid of the finest circle is used as the seed point. Further, 3D radial-gradient index segmentation is used to obtain a crude initial contour, which is then refined by a 3D level set-based active contour algorithm. The algorithm is run for a number of iterations to get the enhanced results.

Keywords: Dedicated breast CT, 3D segmentation, Active contour algorithm, Radial-gradient index.

1. Introduction

Breast cancer is the second-most common cause of cancer death among women and early detection of this plays an important role in reducing cancer related deaths in the world. The emphasis on the early detection of breast cancer in women, the desire not to miss even a malignant lesion in the early stage of disease, and the medical environment encouraged a biopsy approach to breast problems. But the positive biopsy rate for cancer is low, between 10% and 31%, which means 70%–90% of breast biopsies are performed in women with benign disease [1]. Therefore, both the mammographic and sonographic methods have been used in order to reduce the negative-to-positive biopsy ratio, and therefore, the cost to society by improving feature analysis and refining criteria for recommendation for biopsy [2], [3].

The screen-film mammography is being used by radiologists to detect cancer at an early stage. In this method, four images are obtained, two corresponding to the right breast and two to the left breast of the projections cranio-caudal (CC) and medio-lateral oblique (MLO). This use of CC and MLO images improves visualization of breast tissue and improving the chances of detecting the presence of non-palpable breast cancer. During the examination, the radiologist combines information from these two views to increase the chances of determining a priori regions with abnormalities defined as true positive (TP) and reduce the number of regions without abnormalities, i.e., reduce false positive (FP) regions [4].Screen-film mammography is a repetitive task which makes radiologists prone to oversight errors. As a result, radiologists fail to detect from 10% up to 30% of malignant lesion on mammograms [5].

Recent researches have been on developing dedicated breast CT (bCT) systems, which produce 3D images of the breast and mitigate superimposition effects in mammography [6–9]. This surfacing technology not only produces excellent morphologic details but also provides higher tumor contrast. Initial clinical reports showed that breast CT has better conspicuity in mass visualization over mammography and concluded that bCT is promising and is likely to play a significant role in future breast cancer screening and diagnosis [10, 11]. Figure 1 shows a labelled mammogram.

Recently, Computer-Aided Detection (CADe) and Computer-Aided Diagnosis (CADx) have used for mammographic images to assist radiologists on lesions analysis such as microcalcification, mass and architectural distortions [12].

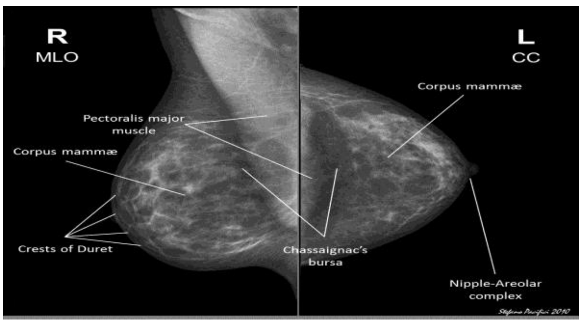


Figure1: A Mammogram image composes of image background, pectoralis muscle, corpus mamme, nipple- areolar complex, chassaignac's bursa and crests of duret.

DOI: 10.18535/ijecs/v5i11.52

Mass detection is a more complex exercise, because the mass is frequently indistinguishable from adjacent tissues.: (a) very conspicuous in size, shape and density; (b) poor in image contrast; (c) highly connected to the surrounding parenchymal tissue density, particularly for speculated lesions and (d) surrounded by no uniform tissue background with similar characteristics [13]. That makes progress be considerably slow for reliable detection of masses.

Figure 2 shows general framework of CAD system for lesion detection and classification in CT breast images.

Figure 2: General framework

Remarkable amount of research has been done in detecting lesions in breast ultrasound images [14]. Different types of features have been proposed for extracting useful information from the breast tissue. Auto-covariance coefficients [15], features computed from Gray Level Co-occurrence matrix like contrast, correlation [16], Harr-like features[17], etc. are some examples of texture features computed from the entire image or ROIs using the gray level values. Local characteristics of the lesion like edge characteristics, nodule darkness [18], lesion area, circularity [19], lesion margin features like sharpness, echogenicity [20] also provide useful information.

MATERIAL AND METHODS:

Our method of approach consists of a number of steps. The detail of the different steps are discussed in the following sub-sections.

Dataset

The dataset of image included various contrast-enhanced breast CT images that has tumor.

Image Filtering and De-noising

The images obtained have been filtered using wavelet tranformsand defining levels. Following techniques were used:-

1. Decomposition:- Image resizing was performed and approximation and detailed coefficients were obtained.
2. Thresholding:- Soft thresholding was used to further enhance the quality of image.
3. Reconstruction:- Image was reconstructed to obtain the approximation coefficients and denoise the image for better results.

   Figure 3 shows a flow chart of implementation which is being proposed.

Image Enhancement

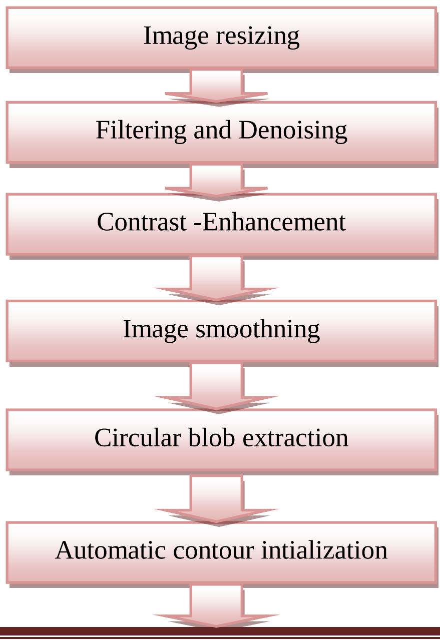
Image obtained after de-noising is further enhanced for feature extraction using histogram equalization. This provides more precision in highlighting the intensity which helps in extraction of affected area.

Image Smoothing

Gaussian filter is used for smoothing the input image keeping in view the edge extraction for circular blob detection. Gaussian filtering g is used to blur images and remove noise.

Circular Blob Extraction

Circle detection technique is used to detect all possible circles in image. Various measurements are applied to extract these circular area as radius, sensitivity and edge parameters. Further best five circles are chosen discarding the irrelevant areas that has been taken as circular. Based on intensity circular area having minimum intensity is chosen and radius and centroid of the circle are calculated.



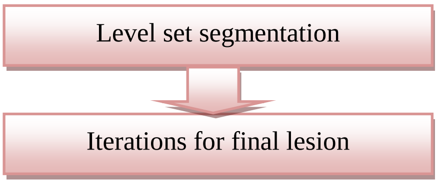


Figure 3 : Flowchart describing Implementation

Automatic Contour Initialization

For automatic initialization the centroid point is used as seed point. RGI segmentation is a seeded lesion segmentation technique [21]. Reiser et al. extended it into 3D and showed that it can be applied on dedicated breast CT images [22].
In this algorithm, the standard deviation of the Gaussian constraint function was 10 mm, based on Reiser et al.'s study [22]. Further, to ensure that the initial contour is completely contained within the lesion before the second segmentation stage, morphological erosion is applied to shrink the RGI segmented lesion contour by using the MATLAB function "imerode" with a cubic structuring element. The side length of the structuring element was one ninth of the cube root of the RGI segmented lesion volume. The resulting contour then served as the initial contour for the subsequent active contour segmentation.

Level-set Model

The level set-based propagating fronts theory for delineating shapes on an image was introduced in 1988[23]. The central Idea of a level set method is to express the contour as the zero level set of a higher-dimensional function, the so-called level Set function.

Final lesion

The applied algorithm is run for a number of iterations for extracting the final lesion which give the best result.

CONCLUSION

In this paper, we present a two-stage 3D lesion segmentation method combining RGI segmentation with an active contour model. The RGI segmentation generates an approximate contour, which serves as initial contour for the subsequent contour evolution. The automated lesion segmentation algorithm was evaluated by computing the centriods of the extracted circular blob.

REFERENCES:

[1] J. E. Meyer, T. J. Eberlein, P. C. Stomper, and M. R. Sonnenfeld, "Biopsy of occult breast lesions: Analysis of 1261 abnormalities," *J. Amer. Med.Assoc.*, vol. 263, pp. 2341–2343, 1990.

[2] E. A. Sickles, "Periodic mammographic follow-up of probably benign lesions: Results in 3,184 consecutive cases," *Radiology*, vol. 179, pp. 463–468, 1991.

[3] W. K. Moon, D. Y. Noh, and J. G. Im, "Multifocal, multicentric, and contralateral breast cancers: Bilateral whole-breast US in the preopera-tive evaluation of patients," *Radiology*, vol. 224, pp. 569–576, 2002.

[4] M. Elter, A. Horsch, CADx of mammographic masses and clustered microcalcifications: a review, Medical Physics 36 (2009) 2052–2068.

[5] M.L. Giger, H.P. Chan, J. Boone, Anniversary paper: history and status of CAD and quantitative image analysis: the role of medical physics and AAPM, Medical Physics 35 (2008) 5799–5820.

[6] Lindfors KK, Boone JM, Newell MS, D'Orsi CJ: Dedicated breast computed tomography: the optimal cross-sectional imaging solution? Radiol Clin N Am 48:1043–1054, 2010

[7] Glick SJ: Breast CT. Annu Rev Biomed Eng 9:501–526, 2007

[8] Kalender WA, Beister M, Bioone MJ, Kolditz D, Vollmar VS, Weigel CCM: High-resolution spiral CT of the breast at very low dose: concept and feasibility considerations. Eur Radiol 22:1–8, 2012

[9] O'Connell A, Conover DL, Zhang Y, Seifert P, Logan-Young W, Lin CFL, Sahler L, Ning R: Cone-beam CT for breast imaging: radiation dose, breast coverage, and image quality. AJR 195:496–509, 2010

[10] Lindfors KK, Boone JM, Nelson TR, Yang K, Kwan ALC, Miller DF: Dedicated breast CT: initial clinical experience. Radiology 246: 725–733, 2008

[11] Prionas ND, Lindfors KK, Ray S, Huang S, Beckett LA, Monsky WL, Boone JM: Contrast-enhanced dedicated breast CT: initial clinical experience. Radiology 256:714–723, 2010

[12] M.L. Giger, H.P. Chan, J. Boone, Anniversary paper: history and status of CAD and quantitative image analysis: the role of medical physics and AAPM, Medical Physics 35 (2008) 5799–5820.

[13] B.W. Hong, B.S. Sohn, Segmentation of regions of interest in mammograms in a topographic approach, IEEE Transactions on Information Technology in Biomedicine 14 (2010) 129–139

[14] H.D. Cheng, J. Shan, W. Ju, Y. Guo, and L. Zhang, "Automated breast cancer detection and classification using ultrasound images: A survey," *Pattern Recognition*, vol. 43, no. 1, pp. 299–317, 2010

[15] D.R. Chen, W.J. Kuo, R.F. Chang, W.K. Moon, and C.C. Lee, "Use of the bootstrap technique with small training sets for computer-aided diagnosis in breast ultrasound," in *Ultrasound in Medicine and Biology*, 2002

[16] W. Gomez, W.C.A. Pereira, and A.F.C Infantosi, "Analysis of co-occurance texture statistics as a function of

gray-level quantization for classifying breast ultrasound," *Trans. Medical Imaging*, vol. 31, no. 10, pp. 1889–1899, 2012

[17] J. Zhang, S.K. Zhou, S. Brunke, C. Lowery, and D. Comaniciu, "Database-guided breast tumor detection and segmentation in 2d ul-trasound images," in *SPIE*, 2010

[18] S. Joo, Y.S. Yang, W.K. Moon, and H.C. Kim, "Computer-aided diagnosis of solid breast nodules: Use of an artificial neural network based on multiple sonographic features," *Trans. Medical Imaging*, vol. 23, no. 10, pp. 1292–1300, 2004

[19] K. Zheng, T.F. Wang, J.L. Lin, and D. Li, "A new methodology based on q-entropy for breast lesion classification in 3-d ultrasound images," in *Eng. in Medicine and Biology*, 2006

[20] C.M. Sehgal, T.W. Cary, S.A. Kangas, S.P. Weinstein, S.M. Schultz, P.H. Arger, and E.F. Conant, "Computer-based margin analysis of breast sonography for differentiating malignant and benign masses," *Journalof Ultrasound in Medicine*, vol. 23, no. 9, pp. 1201–1209, 2004

[21] Kupinsiki M, Giger ML: Automated seeded lesioni segmentation on digital mammograms. IEEE Trans Med Imaging 17:510–517, 1998

[22] Reiser I, Joseph SP, Nishikawa RM, Giger ML, Boone JM, Lindfors KK, Edwards A, Packard N, Moore RH, Kopans DB: Evaluation of a 3D lesion segmentation algorithm on DBT and breast CT images. Proc SPIE 7624:76242N, 2010

[23] Osher S, Sethian JA: Fronts propagating with curvature-dependent speed: algorithm based on Hamilton–Jacobi formulations. J ComputPhys 79:12–49, 1998

Author Profile

Harmandeep Kaur pursuing M.Tech degree in Electronics and Communication Engineering from ASRA College of Engineering & Technology.