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指導教授：黃育仁 博士

磁振造影之多視角乳房腫瘤輪廓描繪

Multi-View Contouring for Breast Tumor on Magnetic Resonance Imaging

研究生：張耀文

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Multi-View Contouring for Breast Tumor on Magnetic Resonance Imaging

Advisor

Prof. Yu-Len Huang

Department of Computer Science of

Tunghai University

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召 集 人 胡育誠 簽章

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指 導 教 授 黃育仁 簽章

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摘要

腫瘤組織的形狀和輪廓特徵已被證明可以幫助醫生用來有效的判斷乳癌腫瘤的良惡性，然而病變的腫瘤區域是依賴臨床醫師根據經驗所描繪的，但在乳房磁振造影（MRI）中描繪腫瘤輪廓是困難且費時的。因此，自動乳房腫瘤切割可輸出輪廓，用於協助醫師做出正確的診斷並節省大量時間。隨著乳房磁振造影愈來愈廣泛被使用，自動切割乳房腫瘤輪廓變得重要，在臨床上應用很迫切。本研究中提出了一種多視角的腫瘤切割方法，用於描繪乳房磁振造影中腫瘤的輪廓，所提出的方法先使用前處理降低雜訊，並保留乳房腫瘤的形狀和對比度，在切割方面使用等位函數（Level-set）法在二維（2D）情況下從橫向、冠狀面和矢狀面擷取腫瘤輪廓。本研究評估十個惡性腫瘤病例，結果顯示此方法可得到精確的輪廓，並可節省大量的處理時間。

關鍵字： 乳癌，磁振造影，影像切割，等位函數法，多視角輪廓

ABSTRACT

The shape and contour of the lesion is shown to be effective features for physicians to identify the breast tumor as benign or malignant. The region of the lesion is created by the physician according their clinical experience. Contouring tumors on breast magnetic resonance imaging (MRI) is difficult and time-consuming. For this purpose, automatic contouring for breast tumors may assist physicians in making correct diagnoses. As breast MRI becomes more widespread used, a functional automatic contouring method is essential and its clinical application is becoming urgent. This study presents a multi-view segmentation method for detecting contours of breast tumors in MRI. The preprocessing of the proposed method reduces the any amount of noises but preserves the shape and contrast of breast tumor. The two-dimensional (2D) level-set segmentation method extracts precise contours of breast tumors from transverse, coronal and sagittal planes. This study evaluates ten malignant tumor cases. The simulation results show that the proposed contouring method could save much of the time required to sketch a precise contour.

Keywords: breast cancer; MRI; image segmentation; level-set method; multi-view contouring

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CHAPTER 1

INTRODUCTION

The top ten cancer result in death, the one of cancer is breast cancer. Breast is the important secondary sex characteristic of women. When the breast lesion happened, most of patients will lose their confidence and even lead to death. Breast cancer death rates decreased in the past years, because of the improved diagnostic methods. It could early detect the breast tumors. The breast cancer occurrence rates for woman are expected to increase in worldwide annually. According to the report from American Cancer Society (ACS), the prevalence of breast cancer increase every year [1]. In 2013, American women with breast cancer compare with 2010's data is increase 10%. However, because of advances in medical technology and people's increasing concern about health, making breast cancer mortality is declining. In 2013, the women's deaths due to breast cancer in United States which compare with 2010's data is decrease 2%. Early detection and early treatment can reduce breast cancer mortality.

Breast cancer is a tumor emerged from growing mammary epithelial cells or lobular, due to the loss of control growth cancer will invade and destroy neighboring tissues and organs, or metastasis to other organs via the blood and lymphatic system.

One of the popular way to detect breast cancer is MRI examination. MRI has many advantages such as non-invasive, no radiation damage and multi-view section. Thus breast MRI now become more widespread used and play a complementary efficacy [2-5]. In the past, the examination of breast tumor always make use of the mammogram which is sometimes difficult to discern the tumor because of the ointment at the patient's skin before the examination. Mammogram sometime employed other method to aid with examination, such as MRI or ultrasound imaging. However, MRI has wider shot angles and obtained tumor region is clear than that of ultrasound.

In recent years, the rapid development of computer technology, the image evolved from the original analog signals to digital signals. Through digital signal would carry out a series of image processing. Digital image partitioning into multiple segments is called image segmentation. The goal of image segmentation is making the image more meaningful and easier to analyze [6]. However, the segmentation has been a very complex and difficult problem in image processing field, due to the image texture features, edge features, noise, resolution and other factors would affect the segmentation results. In recent years, several image segmentation methods were applied to the medical imaging which can help for physician to clinical diagnose.

Many segmentation methods have been employed in various medical imaging.

Threshold image segmentation [7] also called histogram thresholding method which relied on the change of the grayscale or color value to partition. The Otsu's method [8] is one of the classical threshold segmentation. The method based on the change of the grayscale and divided image into two parts, the background and objectives. The optimal threshold is calculated according to background pixels and objectives pixels. The method would get defected result and image which result when the grayscale of image was distributed average.

Moreover, segmentation by using edge detection depends on the change of the gradient to partition [9]. The method utilized anisotropic diffusion to preserve the edge junctions, it makes thinning and linking of the edges unnecessary. The shape and position are preserved at every single scale so it does not require complicated comparison of images at different scales [10]. The method performed this characteristics to partition of image edge region. The result of edge detection is influenced by noise easily. The region-based segmentation method divided image into many regions [11]. Region growing, one of the simple region-based image segmentation method, is based on predefined criteria for growth into larger regions by grouping pixels or sub-regions. The region growing method needs to select optimal seed points and control the growing the number of times. The main disadvantage of the method is that relied on seed points and growing time.

Active contour model [12] also called snakes is a delineating contour in possibly noisy two-dimensional (2D) image. However, snakes deformation is dependent on initial estimate of contours. The drawback is that the method is very time-consuming and working on single target only. The level-set method is the evolution of snakes. Compare level-set method with snakes, level-set method less dependent on initial estimate of contours. When region of interest (ROI) manually sketched by different physicians. It will not influence the results. The level-set method is ameliorate of snake method defect. This study performed level-set characteristics to expand the boundary of tumor and then obtained a precise contour of the tumor.

As breast MRI becomes more widespread used, a functional automatic contouring method is essential and its clinical application is becoming urgent. This study presented a multi-view segmentation method for detecting contours of breast tumors in MRI. Chapter 2 explains the proposed method and steps. Chapter 3 shows the result of proposed method and evaluation of contour. Finally, Chapter 4 concludes this study.

CHAPTER 2

MATERIALS AND METHODS

2.1 Data Acquisition

Breast MR imaging was performed with the patient in the prone position. Examinations were performed with a 3.0-T commercially available system (Verio®; Siemens AG, Erlangen, Germany) and use of a dedicated 16 Channel breast coil. Imaging sequences included a localizing sequence, an axial tse_T1 weighted (3 mm), tse_T2_tirm, pre, during, and post-Gd 3D-FSPGR (1mm) with fat saturation images, before and five times after rapid bolus injection of 0.1 mmol/L gadobenate dimeglumine (Multihence®; Bracco, s.p.a., Milano, Italy) per kilogram of body weight at a rate of 2 ml/s; followed by a saline flush, acquired at 60 second intervals were obtained. All obtained images were stored on the hard disk and transferred to a personal computer using a DICOM (Digital Imaging and Communications in Medicine) connection for image analysis.

2.2 Flowchart of Segmentation Scheme

The aim of this study is to develop a practical segmentation scheme for breast MRI. However, the image segmentation which directly used three-dimensional (3D) level-set method was a very time-consuming work. Moreover, 2D presentation conforms to human vision seen. Hence this study utilized the 2D level-set method to segment MRI image. The 2D level-set method could save a lot of time in segmentation procedure and set optimum parameters easier. The proposed method segment MRI images within three angles, *i.e.* transverse, coronal and sagittal sections, it could efficiently segment 3D MRI breast tumor. Figure 1 shows the flowchart of the proposed method.

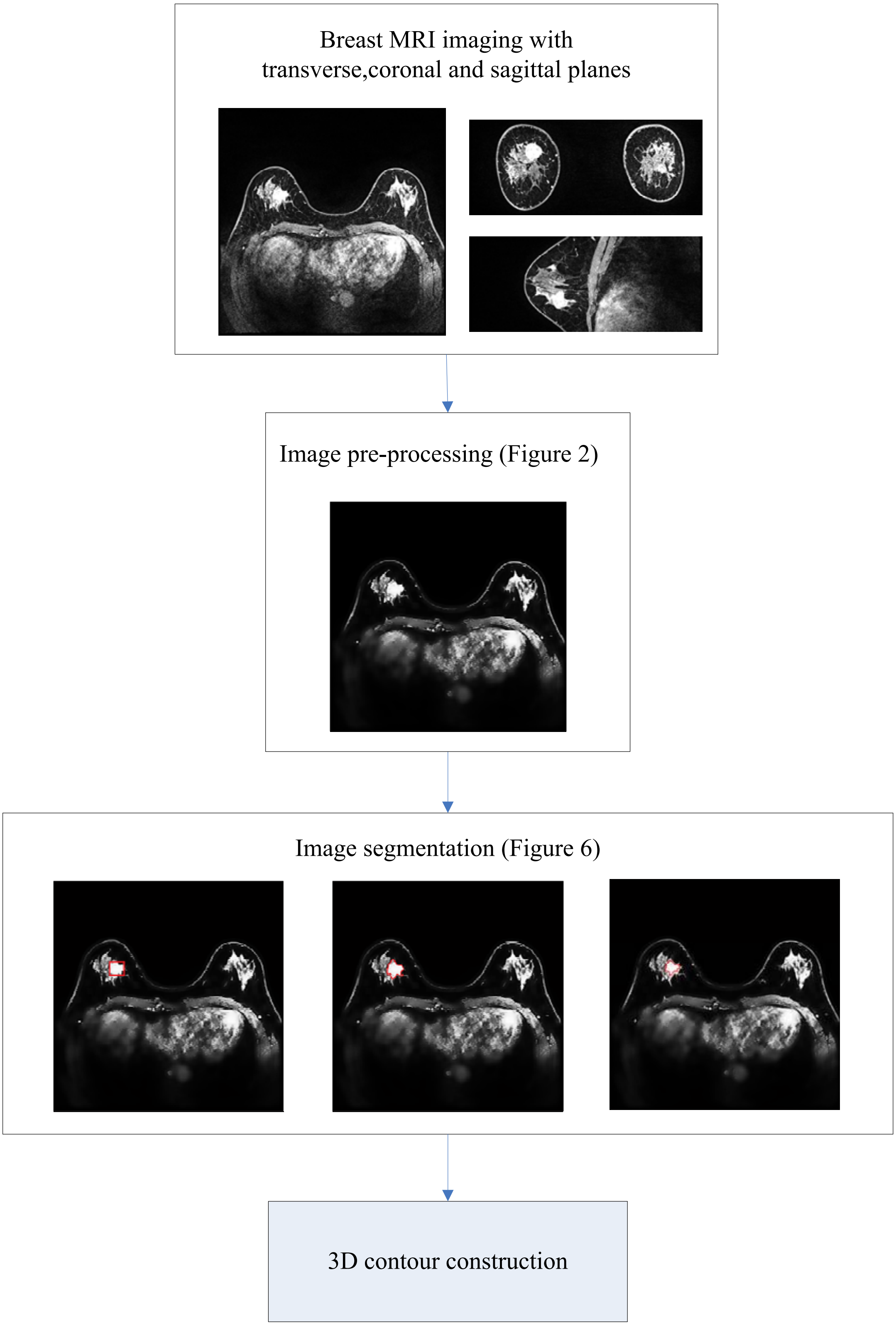


Fig. 1. Flowchart of the proposed method

2.3 Image Preprocessing

Preprocessing is a significant step before segmentation since breast MRI images always include noises, speckles and tissue textures that make contour segmentation difficult. In MRI imaging, the pixels of tumor cluster resemble neighborhood texture. The effective preprocessing method for contouring should aim to reduce noises and preserve the useful information, such as edge and boundary of the mass lesions. The anisotropic diffusion method which based on a partial differential equation is very practical not only in image de-noising but also in preserving the important boundary information. The proposed method combined the anisotropic diffusion filtering and grayscale adjusting method to reduce noise and enhance image contrast. Moreover, Gaussian blur method is effective to subtract noise for image processing. Just like watched to image through translucent screen, the method is effective to subtract noise and speckles. Anisotropic diffusion evolved the architecture from the basis a Gaussian blur. The method is effective to subtract noise, but not subtract to major part of image.

Formally, let $\Omega \subset$ denote a subset of the plane and $I(I, t)|\Omega|R$ be gray images of a family , then anisotropic diffusion is defined as where Δ represents the Laplacian, ∇ represents the gradient, represents

the divergence operator, and $c(x, y, t)$ represents the diffusion coefficient. The rate

of diffusion is controlled by $c(x, y, t)$. It often chosen as a function of the image gradient to preserve the edges of the image. P. Perona *et al*. proposed the idea of anisotropic diffusion [10] and defined two functions for the diffusion coefficient

$$c(\| \nabla I \|) = \frac{1}{1 + \left(\frac{\| \nabla I \|}{K} \right)^2}, \tag{3}$$

where the constant K controls the sensitivity of edges. In signal processing, the noise was filtered through wiener filter [13, 14]. Wiener filter needed to have noise spectrum of the original signal information. The purposed of wiener filter through statistics found that optimal of filter. The optimal of filter is effective to subtract major part of noise. In grayscale, the pixels of *n* bits grayscale image represented color by 0-*n*-1 grayscale value. The grayscale adjusting procedure could enhance the image contrast.

Image pre-processing in the proposed method included anisotropic diffusion, wiener filtering and grayscale adjusting method [15]. Figure 2 shows flowchart of the image processing. Figure 3 shows an example of the pre-processing results.

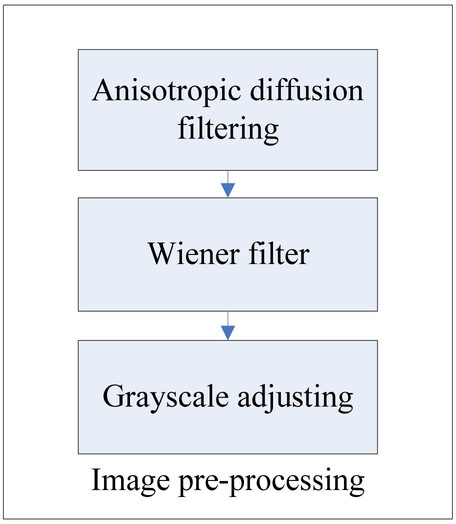
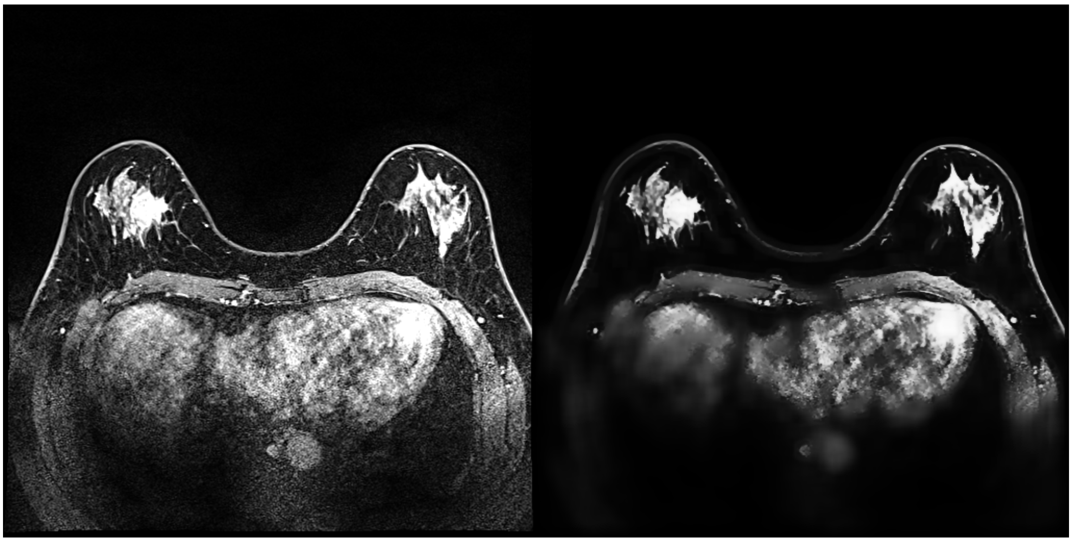


Fig. 2. Flowchart of the image preprocessing



(a) (b)

Fig. 3. Result of image preprocessing: (a) the original tumor image (transverse view), (b) the final preprocessed image of the proposed method

2.4 VOI Extraction & Initial Contour Generation

To extract the volume of interest (VOI) in MRI, a physician experienced in breast MRI examination defined and manually selected rectangular ROI including the tumor border in the three specified slices, *i.e.*, the first, middle and last slices from the transverse plane of breast MRI. The first, middle and last slices were the slice with appeared tumor, the largest diameter of the tumor and the tumor is tending to disappear, respectively. The ROI was specified by indicating a rectangular box that delimits the scene domain, and a VOI was constructed by describing the single target in a volume space. After the ROI regions in the three slices were defined, the VOI area was extracted from the 3D volume. Figure 4 presents the ROI data maps into VOI area. By using the extracted VOI region, the proposed method specified the initial contour as the ROI region in the middle slice.

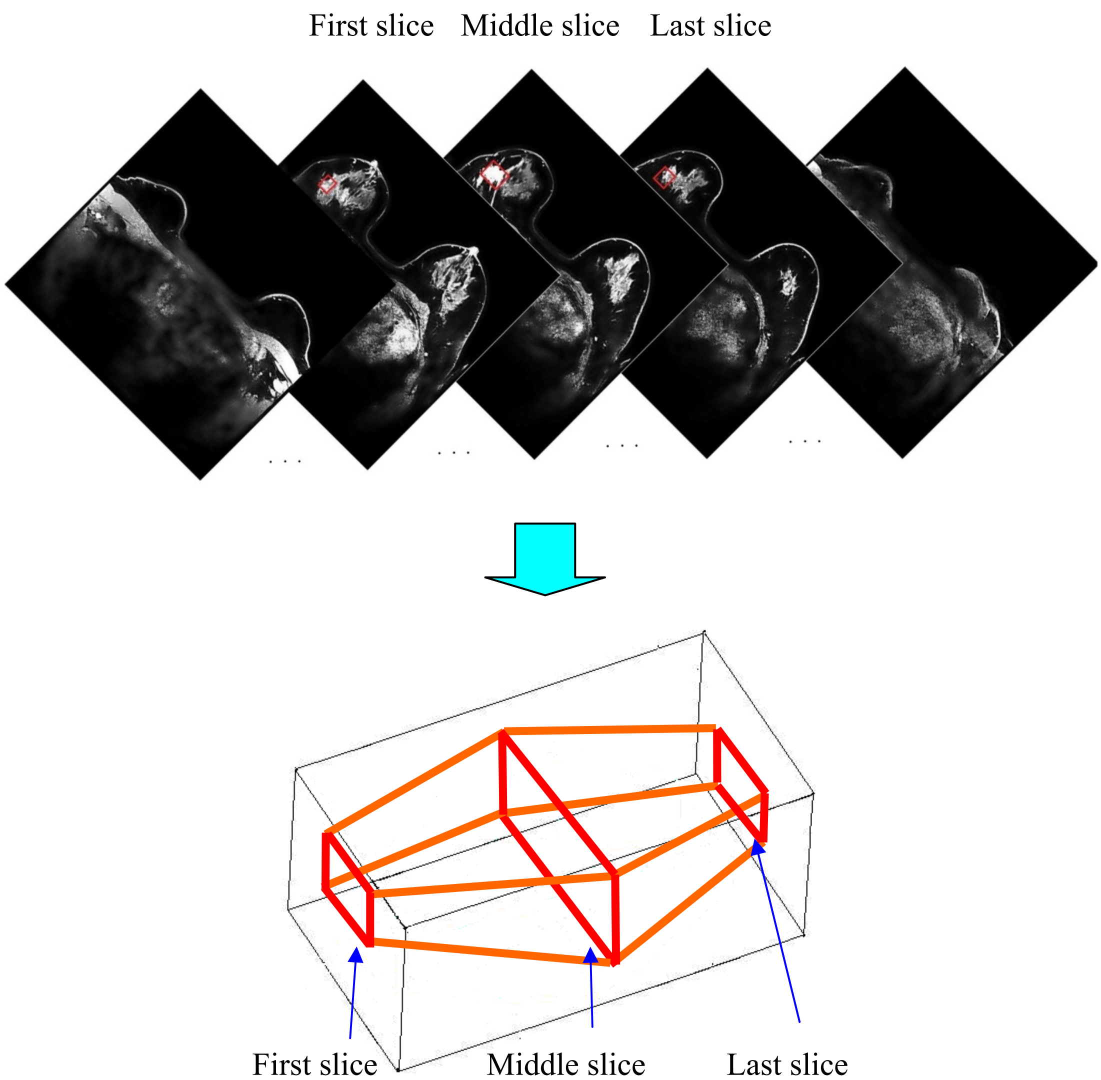


Fig. 4. Volume of interest (VOI) extraction in MRI images (transverse view)

2.5 Image Segmentation

The proposed scheme performed the 2D level-set method (LSM) as the prime segmentation procedure. The LSM, one of the most popular segmentation algorithms, is a numerical technique for tracking interfaces and shapes [16-21]. In short, the ideas of level-set is the method that the 2D continuous function surface the same function value curve φ (x, y) represent as the plane closed curve, when{φ = 0}, is called the zero level set and the φ(x, y) is also called level set function. The zero level-set contour of the function is defined by

$$\Gamma = \{(x, y) \mid (x, y) = 0\}. \quad (4)$$

Furthermore, the inside region and the outside region the curve defined as follows:

$$\begin{cases} \varphi(x, y) < 0 & \text{outside region} \\ \varphi(x, y) = 0 & \text{contour} \\ \varphi(x, y) > 0 & \text{inside region} \end{cases} \quad . \quad (5)$$

In level-set method, the contour that prefer to φ = 0, the internal region contour is φ > 0, and the external region contour is φ < 0 , and we can define the outline of its internal and external contour depending on the value of the function, as shown in Fig. 5.

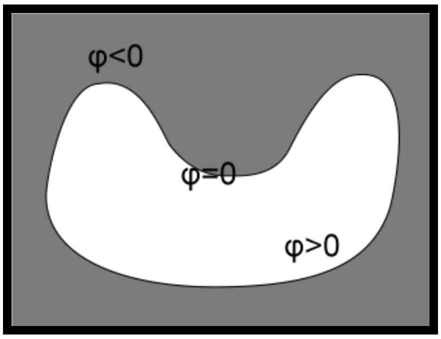


Fig. 5. The concept of level-set method.

This study utilized level-set method which is proposed by C. M. Li [19], the functionis updated as

$$\frac{\partial \phi}{\partial t} = -\delta_\varepsilon(\phi)(\lambda_1 e_1 - \lambda_2 e_2) + v\delta_\varepsilon(\phi)\mathrm{div}\left(\frac{\nabla \phi}{|\nabla \phi|}\right) + \mu\left(\nabla^2 \phi - \mathrm{div}\left(\frac{\nabla \phi}{\nabla \phi}\right)\right),$$

where δ_ε is the dirac delta function which used to smooth the contour. The and is level-set evolution rate. The term $-\delta_\varepsilon(\varphi)(\lambda_1 e_1 - \lambda_2 e_2)$ is called the data fitting term which obtained from the data fitting energy. This term is important for driving active contour toward object boundaries. The second terms $v\delta_\varepsilon(\varphi)\mathrm{div}\left(\frac{\nabla\varphi}{|\nabla\varphi|}\right)$ is in order to maintain the contour regularly. In the zero level contour of the second term has the effectiveness on smoothing. The third

term $\mu\left(\nabla^2\phi - \mathrm{div}\left(\frac{\nabla\phi}{\nabla\phi}\right)\right)$ maintain the level set function to regularity. Moreover, λ_1, λ_2, v and μ are parameters which adjust the weights of the three terms. The λ controls the length of contour. The λ sets bigger, the iteration times needs more. The v controls the speed of contour growth. The v sets bigger, the growth of contour is quicker. The μ sets smaller means it can segmentation to smaller region. This study utilized the results of the extracted VOI area as an initial contour, and then 2D LSM and an erosion post-processing procedure was performed to obtain the final contours. Figure 6 shows flowchart of the image segmentation. Figure 7 shows the results of image segmentation schematic diagram.

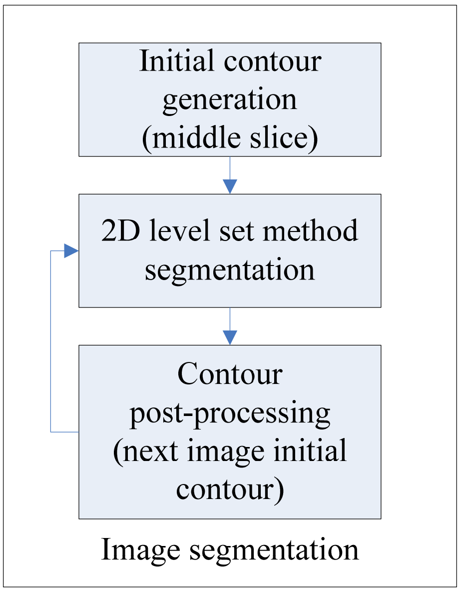
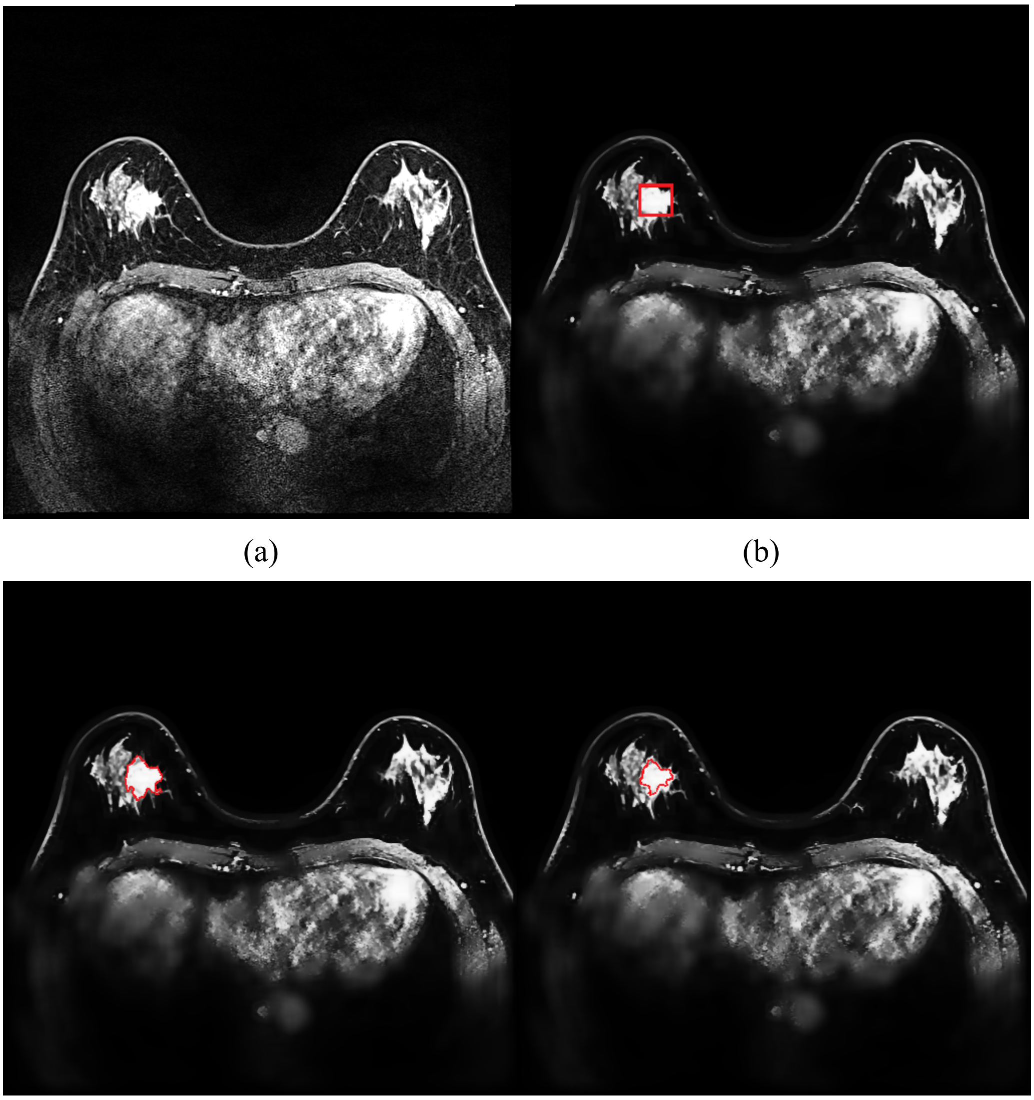


Fig. 6. Flowchart of the image segmentation



(a) (b)

(c) (d)

Fig. 7. Results of 2D level-set segmentation: (a) the original tumor image, (b) the pre-processed image with an initial contour, (c) the result of level-set method and (d) the post-processed result

2.6 Multi-View Contouring

The 2D LSM extracted precise contours of breast tumors from transverse, coronal and sagittal planes. The 3D contours generated from the transverse, coronal and sagittal planes denoted Con_T, Con_C and Con_S, respectively. Moreover, this study developed the intersection version and union version of the 3D contours from the three views. Con_{AND} denoted the contour of region that occurred simultaneously (such as AND operation) from Con_T, Con_C and Con_S. Con_{OR} denoted the contour of region that gathered (such as OR operation) from Con_T, Con_C and $Con_{S.}$ The proposed contouring modes could save much of the time required to sketch precise contours.

This study experimented 10 malignant case. Each case segmented tumor from transverse, coronal and sagittal sections, respectively. The proposed method obtained five tumor contouring results, i.e. Con_T, Con_C, Con_S. Con_{AND} and Con_{OR}. The result of Con_{AND} tumor is usually exact. The reason is the contour of region that occurred simultaneously from transverse, coronal and sagittal, respectively. The result of Con_{OR} tumor is usually inaccurate. The reason is the contour of region that gathered from transverse, coronal and sagittal, respectively.

2.7 Evaluation of Contour

Quantitative analysis of four practical similarity measures [22], the similarity index (SI), overlap value (OV), overlap fraction (OF) and extra fraction (EF), between the manually determined contours and the automatically determined contours comparison. SI is the similar degree between REF (manually sketched by an experienced physician) and SEG (segmented by the proposed method). The relationship between REF and SEG, overlap area which consists the area of the proposed segmentation method and manual sketching by physician, extra area is called the false positive area and missing area false is called negatives area. Figure 8 illustrates the relationship between the REF and SEG. The SI, OF, OV and EF are defined as

$$SI=\frac{2*(REF\cap SEG)}{REF+SEG}, \tag{7}$$

$$OF=\frac{REF\cap SEG}{REF}, \tag{8}$$

$$OV=\frac{REF\cap SEG}{REF\cap SEG}, \tag{9}$$

$$EF=\frac{\overline{REF}\cap SEG}{REF}. \tag{10}$$

When SI, OV and OF approach to 1, and EF computation approaches to 0, it means that the automatic segmentation and manual contours by physician with similar results. The overlap denotes the area of the intersection of the reference and the automated segmentation.

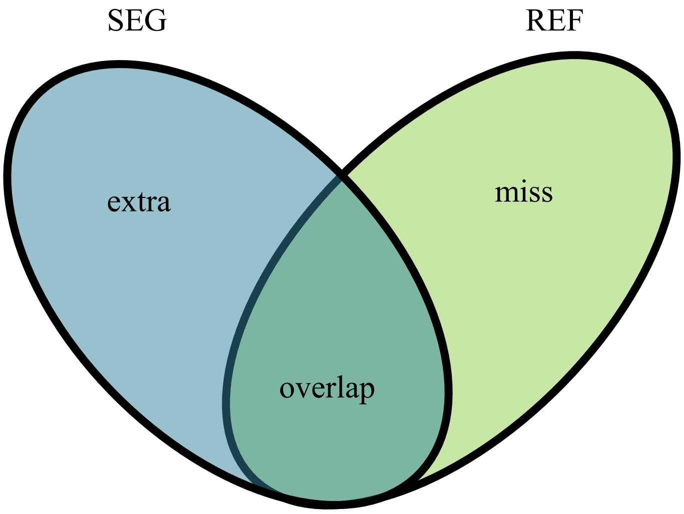


Fig. 8. The relationship between the tumor segmentation by SEG (segmented by the proposed method) and REF (manually sketched by an experienced physician)

CHAPTER 3

RESULTS

This section illustrates the evaluation of contours to analyze the effectiveness of the proposed method. This study totally used 10 malignant breast tumors (pathology-proven cases) with manual sketched contours to test the accuracy of the proposed contouring method. The virtual organ computer-aided analysis (VOCAL) [23-25] scheme within 4D View software (GE Medical Systems, Zipf, Austria), was performed to obtain an approximated 3D contour. The obtained contour (Con_V) was then saved in files for comparison with the automatically generated contours. The VOCAL scheme estimates 3D contours by a selectable degree of rotation. This study adopted a very common rotation degree 30^o, the Con_V utilized the six extracted tumor regions to build a 3D interested region volume. Figure 9 represents the tumor contour manually sketched with 30° rotation.

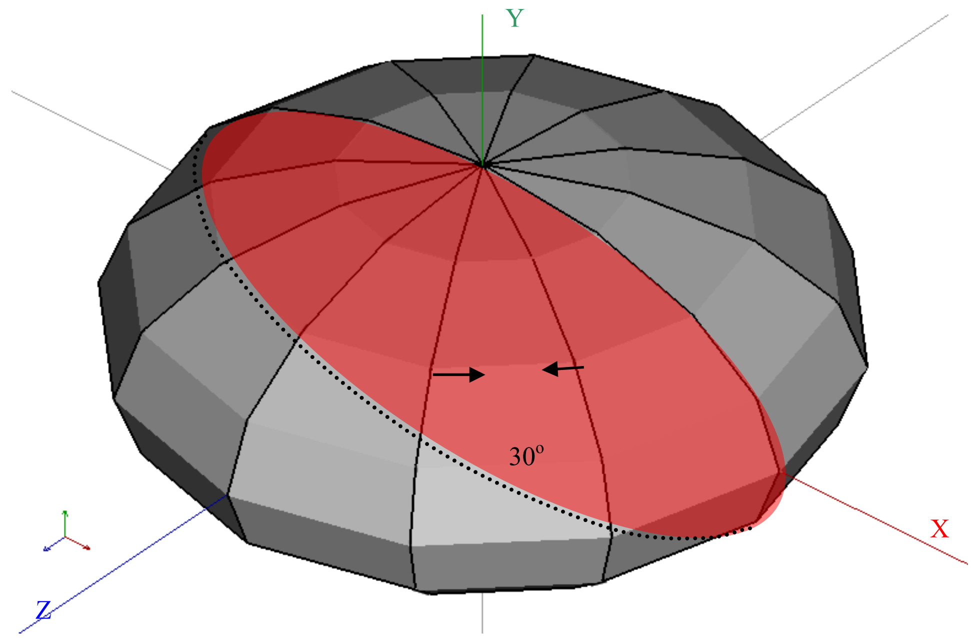
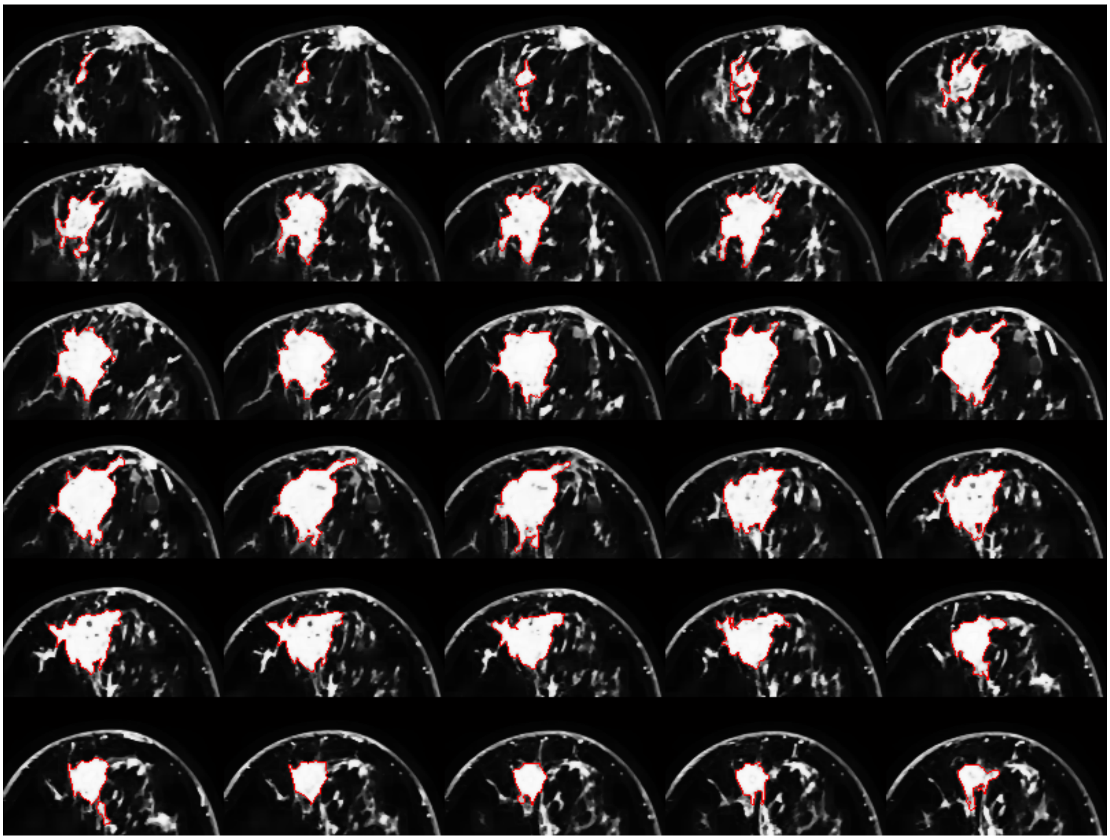


Fig. 9. The tumor contour manually sketched with 30° rotation by export

Before the execution of the LSM, the first step to reduce noise and preserve detail information of the breast tumor by pretreatment. Each case used selected VOI of middle slice as the initial contour. The parameters of LSM was $\lambda_1 = \lambda_2 = 1$, $v = 255^2 \times 0.001$ and $\mu = 1$ and number of iterations was experimentally set to 75. Figure 10 shows the results which applied the proposed segmentation method on MRI from transverse, coronal and sagittal planes. Figures 11 to 13 show the tumor contours by using the proposed method and the VOCAL method. Figures 11, 12 and 13 are the segmentation results of tumor contour in transverse, coronal and sagittal sections, respectively. Figures 11(a), 12(a) and 13(a) show the result of tumor contour drawn manually by physician; Figures 11(b), 12(b) and 13(b) show the result of tumor contour by using the proposed method; Figures 11(c), 12(c) and 13(c) are the contouring result by using VOCAL method. Figures 14, 15 and 16 show the tumor contour the result of the proposed method and the VOCAL method. Figures 14, 15 and 16 are the segmentation results Con_{AND} in transverse, coronal and sagittal sections, respectively.

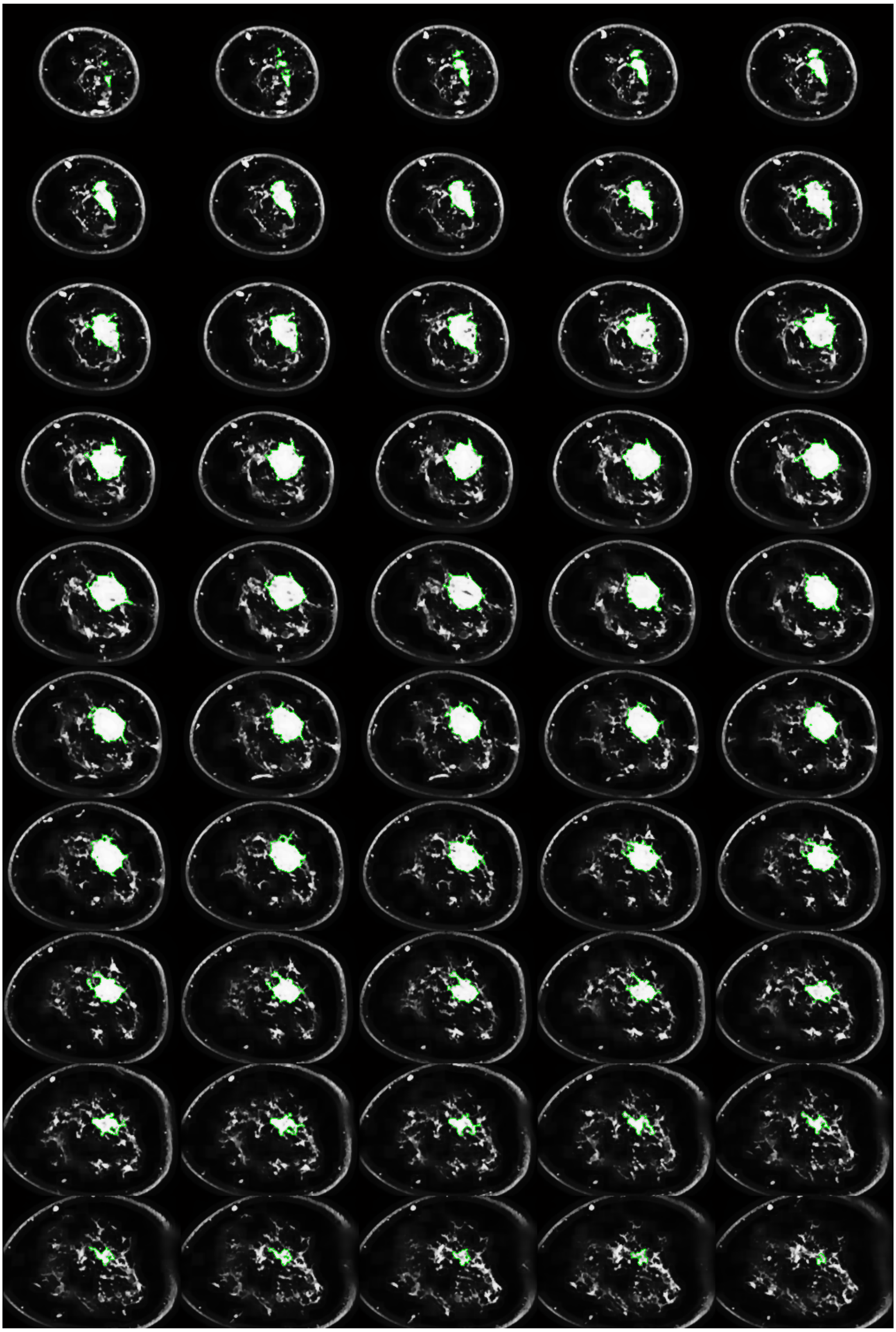
Tables 1 illustrates the assessment indices among the segmentation modes. The proposed method determined average of the measures (SI, OV, OF, EF) in transverse view were (0.900, 0.853, 0.817, 0.190). The proposed method determined average of the measures (SI, OV, OF, EF) in Con_{AND} were (0.920, 0.916, 0.868, 0.141). The VOCAL method determined average of the measures (SI, OV, OF, EF) were (0.796, 0.741, 0.664, 0.385). Compared with the proposed tumor contour segmentation method and VOCAL method, performance of the proposed method is much better than VOCAL method. The result of proposed method resemble manually sketch contour by physician, it can help for physician to clinical diagnose.

The simulations were made on a single CPU Intel(R) Core(TM) i7-2600 3.40GHz personal computer with Microsoft Windows 7 professional operating system and the program development environment was MATLAB (R2013.a) software (The MathWorks, Inc., Natick, MA). Average execution time for each view of case was 300 seconds(include image pre-processing and image segmentation). The run times of segmentation are clinically acceptable.



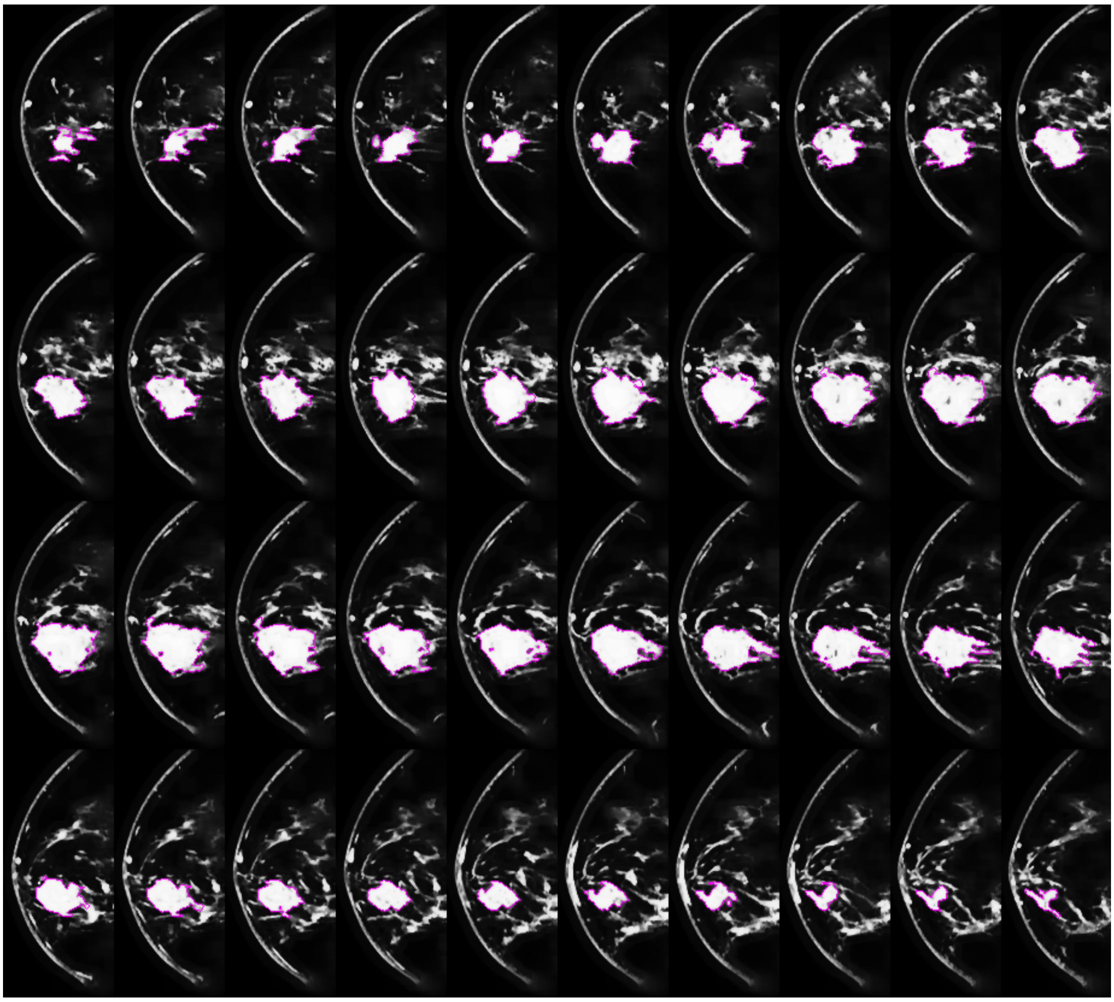
(a)

Fig. 10. Multi-view contouring desirable results obtained by the proposed method: (a) in transverse plane (Con_T), (b) in coronal plane (Con_C), and (c) in sagittal plane (Con_S) (continued)



(b)

Fig. 10. Multi-view contouring desirable results obtained by the proposed method: (a) in transverse plane (Con_T), (b) in coronal plane (Con_C), and (c) in sagittal plane (Con_S) (continued)



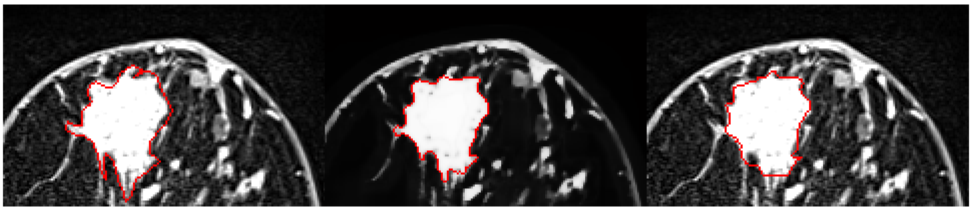
(c)

Fig. 10. Multi-view contouring desirable results obtained by the proposed method: (a) in transverse plane (Con_T), (b) in coronal plane (Con_C), and (c) in sagittal plane (Con_S)

Table 1. The contouring evaluations using the measurements

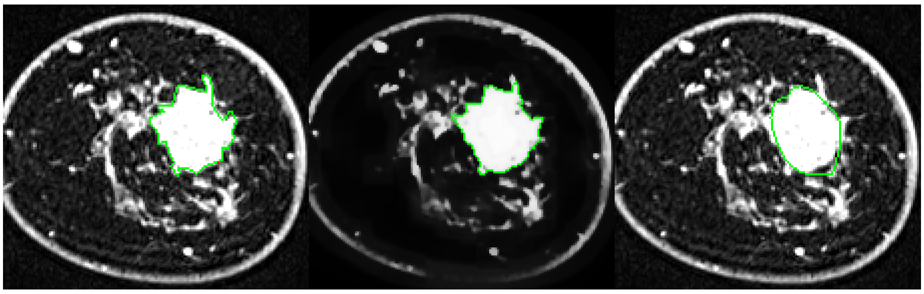
Contours	Average *SI*	Average *OF*	Average *OV*	Average *EF*
Con_T	0.900	0.853	0.817	0.190
Con_C	0.901	0.852	0.821	0.186
Con_S	0.877	0.827	0.782	0.231
Con_{AND}	0.920	0.916	0.868	0.141
Con_{OR}	0.857	0.780	0.755	0.255
Con_V	0.796	0.741	0.664	0.385

SI: similarity index; *OF*: overlap fraction; *OV:* overlap value; *EF*: extra fraction



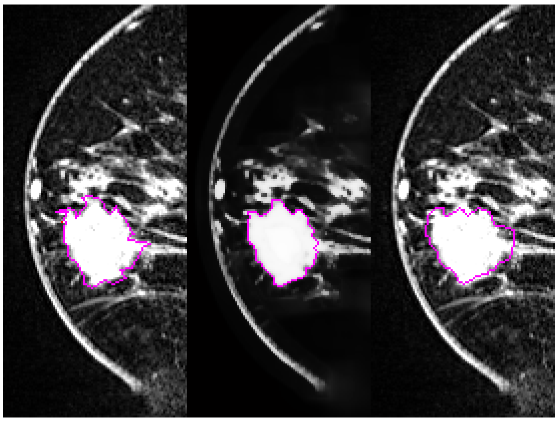
(a) (b) (c)

Fig. 11. The results of contour segmentation in transverse view: (a) physician, (b) the proposed method and (c) the VOCAL method



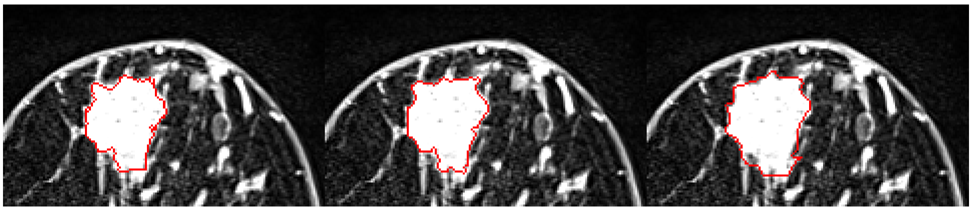
(a) (b) (c)

Fig. 12. The results of contour segmentation in coronal view: (a) physician, (b) the proposed method and (c) the VOCAL method



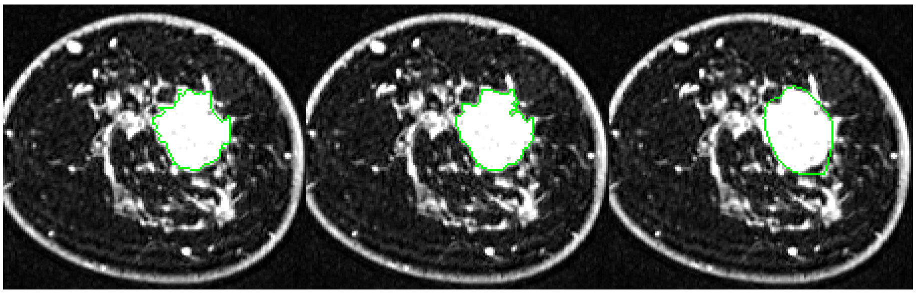
(a) (b) (c)

Fig. 13. The results of contour segmentation in sagittal view: (a) physician, (b) the proposed method and (c) the VOCAL method



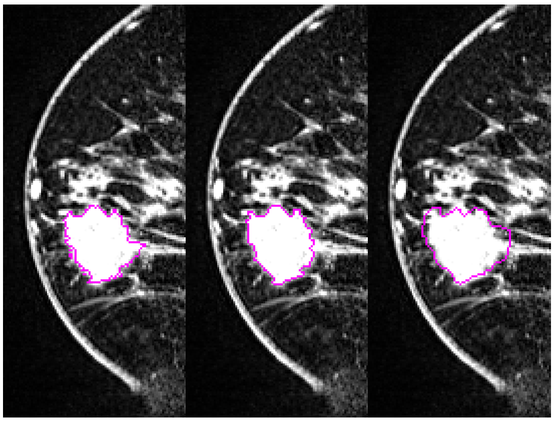
(a) (b) (c)

Fig. 14. The results of contour segmentation in transverse view (Con_{AND}): (a) physician, (b) the proposed method and (c) the VOCAL method



(a) (b) (c)

Fig. 15. The results of contour segmentation in coronal view (Con_{AND}): (a) physician, (b) the proposed method and (c) the VOCAL method



(a) (b) (c)

Fig. 16. The results of contour segmentation in sagittal view (Con_{AND}): (a) physician, (b) the proposed method and (c) the VOCAL method

CHAPTER 4

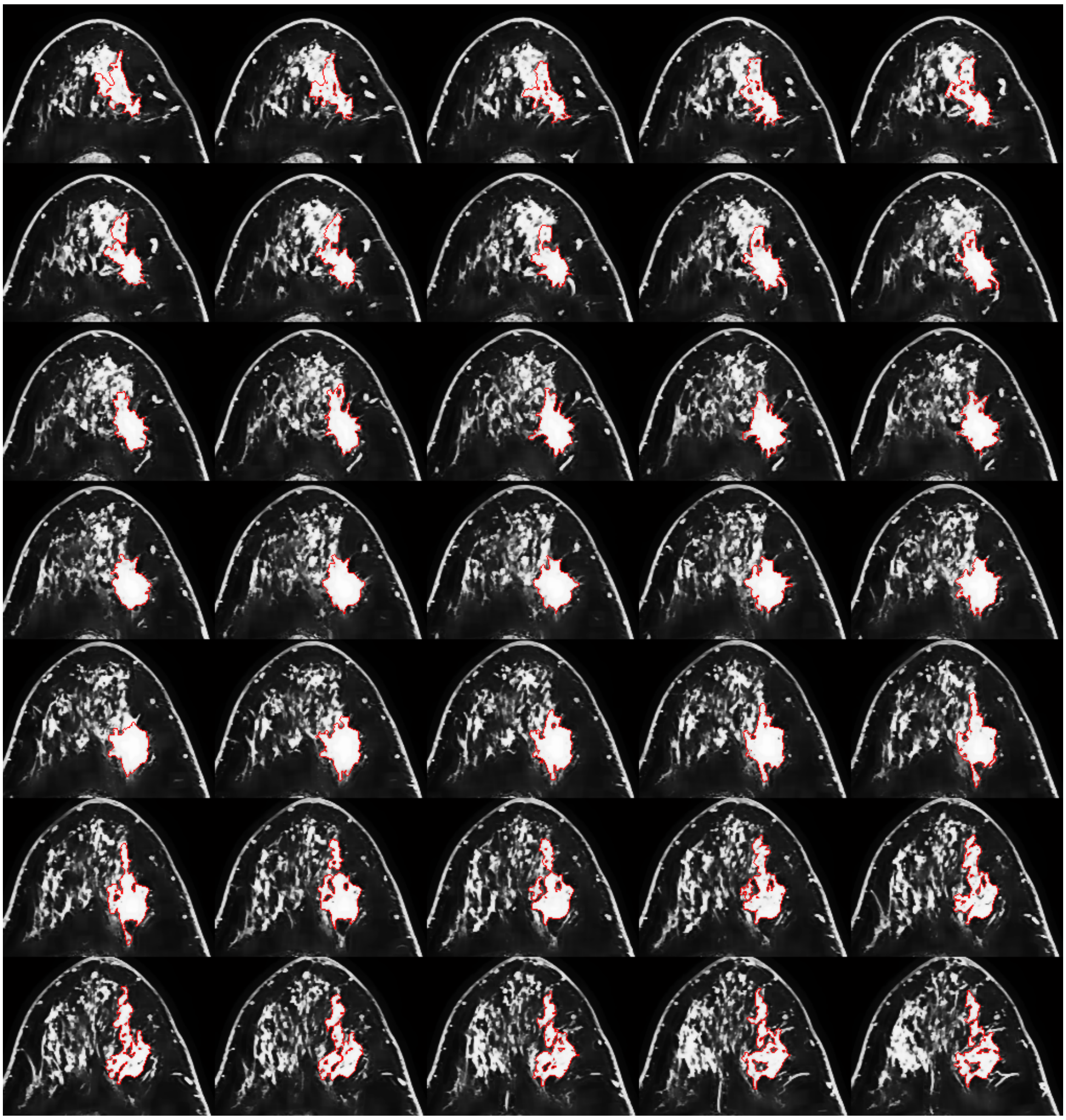
CONCLUSION

This study presented an efficient method for automatically detecting contours of breast tumors in MRI. The proposed method applied anisotropic diffusion filtering, wiener filtering and grayscale adjusting method as the preprocessing step. The selected ROI within the MRI slice was utilized as initial contour and then the deformation-based level-set segmentation automatically produces a precise contours of the tumor from transverse, coronal and sagittal planes. We found that the proposed method determines the contours of breast tumors that are very similar to manual sketched contours. The experimental results reveal that the proposed method can practically determine the contours of a breast tumor from MRI images.

This study evaluated 10 malignant cases which were segmented to generate tumor contour by using the proposed method. The quantitative analysis to examine the proposed method can effectively to segment MRI imaging of tumor contours. The SI can reach the average 0.920 in $Con_{AND.}$ The average EF of the VOCAL method and Con_{AND} is 0.385 and 0.141, respectively. It means that the segmentation by proposed method of tumor contour is more accurate than that of VOCAL method. In this study, each view of case run time required probably in 300 seconds. The proposed method is quicker than other segmentation methods.

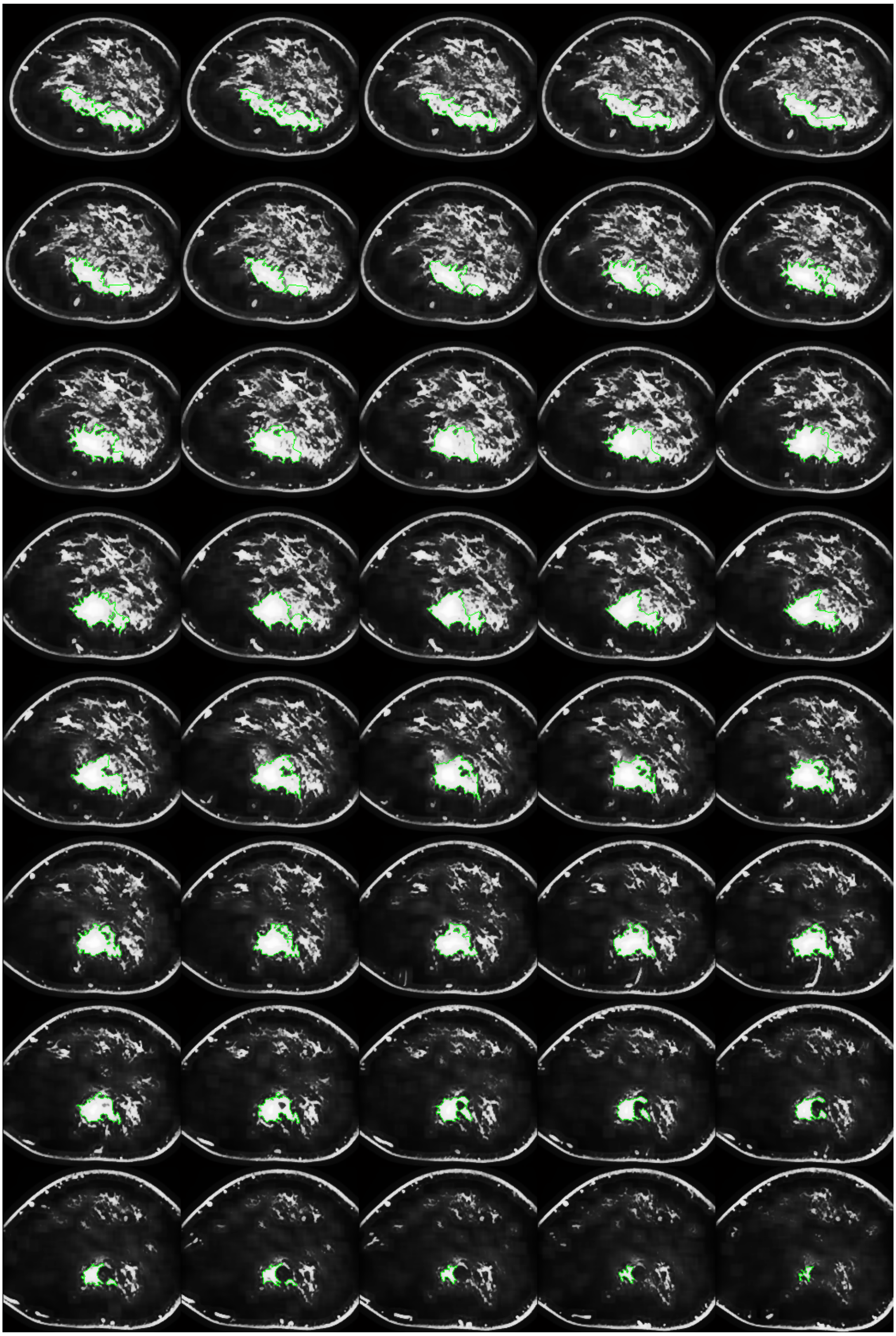
However, there are 2 cases of defected segmentation by using the proposed method. We found that the image pre-processing does not distinguish a region from a neighborhood pixels of tumor, as shown in Fig. 17. Therefore, we will try the adaptive image pre-processing method in the future. The adaptive image pre-processing combine with proposed method, it may increase the running time.

Shape based imaging diagnosis of breast tumor takes the advantage of nearly independent to the different machines. However, it always relies on physicians to manually segment tumors. A physician is hard to manually sketch the contours of tumors in an MRI which contained a great quantity 2D images. In this study, image pre-processing step performed the anisotropic diffusion and grayscale adjusting method to get a clear contour of breast MRI. The proposed method utilized the efficient LSM segmentation method for detecting contours of breast tumors in MRI images. The procedure of the proposed method save much time on sketching tumor. The segmentation results to examine tumor contour by four practical similarity measures evaluation. Superficial measure and shape information from 3D tumors could be used in clinical diagnosis. The results of computer simulations reveal that the proposed method always identified similar contours as were obtained by manual contouring of the breast tumor.



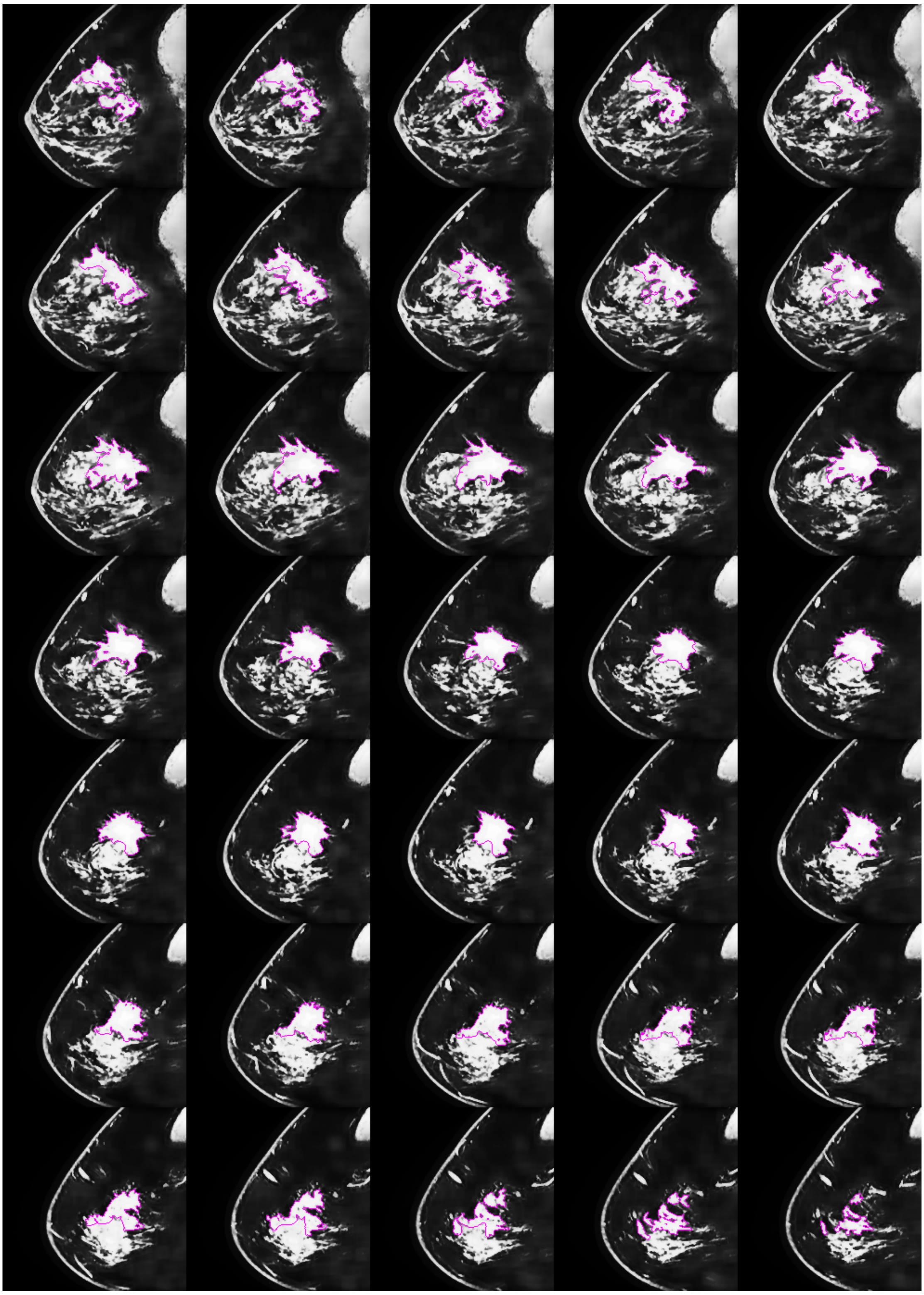
(a)

Fig. 17. Multi-view contouring defected results obtained by the proposed method: (a) in transverse plane (Con_T), (b) in coronal plane (Con_c), and (c) in sagittal plane (Con_s) (continued)



(b)

Fig. 17. Multi-view contouring defected results obtained by the proposed method: (a) in transverse plane (Con_T), (b) in coronal plane (Con_c), and (c) in sagittal plane (Con_s) (continued)



(c)

Fig. 17. Multi-view contouring defected results obtained by the proposed method: (a) in transverse plane (Con_T), (b) in coronal plane (Con_c), and (c) in sagittal plane (Con_s)

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