A progressive processing method for breast cancer detection via UWB based on an MRI-derived model*

Xiao Xia(肖 夏)†, Song Hang(宋 航), Wang Zong-Jie(王宗杰), and Wang Liang(王 梁)

School of Electronic Information Engineering, Tianjin University, Tianjin 300072, *China*

(Received 2 September 2013; revised manuscript received 22 December 2013; published online 15 May 2014)

Ultra-wideband (UWB) microwave imaging is a promising method for breast cancer detection based on the large contrast of electric parameters between the malignant tumor and its surrounded normal breast organisms. In the case of multiple tumors being present, the conventional imaging approaches may be ineffective to detect all the tumors clearly. In this paper, a progressive processing method is proposed for detecting more than one tumor. The method is divided into three stages: primary detection, refocusing and image optimization. To test the feasibility of the approach, a numerical breast model is developed based on the realistic magnetic resonance image (MRI). Two tumors are assumed embedded in different positions. Successful detection of a 3.6 mm-diameter tumor at a depth of 42 mm is achieved. The correct information of both tumors is shown in the reconstructed image, suggesting that the progressive processing method is promising for multi-tumor detection.

Keywords: breast cancer detection, multi-tumor, progressive processing, MRI-derived model

PACS: 41.20.–q, 41.20.JB, 87.85.–d, 87.85.Pq **DOI:** 10.1088/1674-1056/23/7/074101

1. Introduction

Breast cancer is one of the malignant cancers for women. Early detection can help improve the patient's survival and comfort. At present, X-ray mammography is the most commonly used technique for breast cancer detection. However, this technique has a number of limitations including exposure to ionizing radiation, relatively high missed- and false-detection rates, and involves uncomfortable compression of the breast.[1,2]

Recently, the ultra-wide band (UWB) microwave imaging technique has become very attractive for early breast cancer detection, which relies on the high dielectric contrast between the malignant tumors and the surrounding normal breast tissues.[3,4] This technique has many obvious advantages, such as being safe, accurate, inexpensive, highly sensitive and painless. By using the UWB signals, both the necessary imaging resolution and an adequate penetration depth can be ensured.[5] During detection, the microwave radiated by the antenna illuminates the breast and there is a significant reflection from the tumor. The reflected signals are captured by the receiving antennas for reconstructing the breast image to show if there are tumors embedded in the breast. Some benign tumors may also have a high dielectric permittivity and could produce a backscatter response similar to that generated by malignant tumors. These benign tumors can be detected by this approach as well. Currently, distinguishing between malignant and benign tumors is principally based on the biological properties of the tumors.[6–8] There are also research groups engaging in studying the electromagnetic properties of the tumors,[9,10] expecting that the backscatter responses from malignant and benign tumors can be differentiated with a microwave detection technology.

In most clinical cases, breast cancer is unifocal,[11] which is considered as one tumor being present. Here we consider the case of two tumors. In this case, conventional imaging methods may fail to clearly identify the two tumors simultaneously. In this paper, a progressive processing method is proposed which can effectively detect all embedded tumors. In order to test the feasibility of the method, we use a numerical breast model extracted from the magnetic resonance image (MRI) as the simulation model. This model includes various breast tissues with two tumors inserted. A compact UWB antenna is employed to transmit and receive UWB signals. Both the conventional and the proposed methods are applied to the image reconstruction and their performances are demonstrated and compared.

This paper is organized as follows. Section 2 describes the MRI-derived breast model and the imaging setup. Section 3 presents the progressive processing method. Section 4 demonstrates the corresponding results. The feasibility is confirmed by the successful detection of small tumors in different locations. Finally, the conclusions are summarized in Section 5.

2. Breast model and imaging setup

2.1. MRI-derived breast model

Before clinical application, the UWB breast cancer detection technique requires rigorous testing. Thus, rather

*Project supported by the National Natural Science Foundation of China (Grant No. 61271323) and the Open Project from State Key Laboratory of Millimeter Waves, China (Grant No. K200913).

†Corresponding author. E-mail: xiaxiao@tju.edu.cn

© 2014 Chinese Physical Society and IOP Publishing Ltd

than the square or ellipse model used in many research literatures,[12–14] more realistic breast models in terms of shape, size and electrical properties are highly desired. MRI images are commonly employed to create models of this kind. Figure 1(a) shows a breast tissue MRI image. Since the MRI images are usually saved in grayscale, a breast model can be extracted based on the grey value of each pixel. Figure 1(b) shows the model we derived from the MRI image in Fig. 1(a). This model is applied in our UWB breast cancer detection. The MRI images are segmented to identify the interior of the breast and are filled with fatty tissues. The skin layer placed around the breast model has a varying thickness (between 2 mm and 3 mm). The glandular tissue and the chest wall are selected by setting thresholds for the pixel intensities of the MRI images. Two tumor simulants are assumed to be embedded in the breast. One tumor with a diameter of 3.6 mm is located at position (80 mm, 65 mm) in the x–y plane and at the depth of 42 mm. The other one with a diameter of 4 mm is located at position (100 mm, 56 mm) and at the depth of 35 mm. The electrical properties extracted from Ref. [15] are assigned to the tissues. The convolution perfectly matched layer (CPML) is employed as the absorbing boundary, which is very effective to prevent reflections from the breast model.[16]

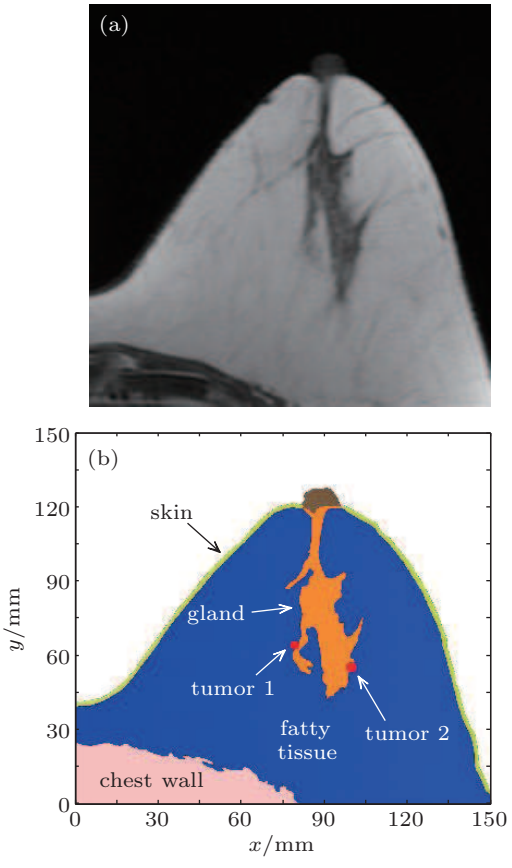


Fig. 1. (color online) MRI-derived breast model: (a) a magnetic resonance image, (b) geometry configuration of the breast model derived from the MRI scan.

2.2. UWB antenna

The antenna design is the key part for UWB imaging. To gather sufficient information for improving the image quality, the antennas must be able to operate over a wide band of frequencies and also be as small as possible so that enough antennas can be arranged in the array. In this paper, a slot on-body UWB antenna is chosen. This antenna has a very compact size with overall dimensions of 11 mm×13 mm. The bandwidth and the center frequency of the antenna are 12.5 GHz and 6 GHz, respectively. A description of the detailed design of the antenna was reported in Ref. [17].

2.3. Simulation process

In a UWB microwave imaging system, the resolution is determined by the bandwidth. However, losses in tissues increase with the frequency. The Gaussian monocycle pulse given in Eq. (1) with the center frequency of 5 GHz is employed in this study, which allows the signals to propagate a depth of a few centimeters into the breast without excessive attenuation, providing an adequate breast examination.[18,19] The excitation signal is of the form

$$V(t) = -\sqrt{e}\left(\frac{2\pi}{\tau}\right)(t - T_{\rm c}) \times \exp\left(-\frac{1}{2}\left(2\pi\frac{t - T_{\rm c}}{\tau}\right)^2\right), \quad (1)$$

where $T_{\rm c}$ is the time shift factor, and τ is the impulse width. The bandwidth of the impulse is 9 GHz. This bandwidth represents a trade-off between the resolution and the tissue penetration, which guarantees both good imaging quality and adequate detection depth.

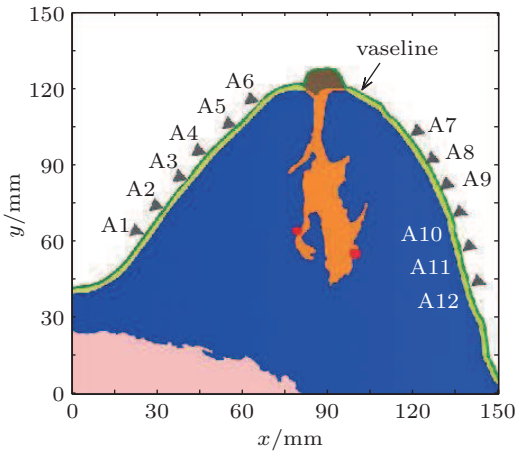


Fig. 2. (color online) Array configuration consisting of 12 antennas.

As shown in Fig. 2, a 12-element antenna array (from A1 to A12) is formed around the surface of the breast. A matching medium vaseline, which has a dielectric constant of 2.2, is applied to the skin for improving the performance of the antenna. During the detection, the GMP is emitted from one antenna alternately and the backscattered signals are collected by the

other antennas. This step is repeated for all the antennas. The recorded signals include direct waves, skin backscatter signals, tumor backscatter signals and clutter signals due to the heterogeneity of the breast tissue. The tumor response can be extracted by subtracting the reference signals for the tumor-free case from the recorded signals. These post-processed signals will be employed for image reconstruction.

3. Progressive processing method

Two distinct methods are commonly employed for UWB microwave imaging, called the confocal microwave imaging (CMI)[20] and the robust capon beaming (RCB).[21]

The CMI method involves time-shifting and summing the signals to create a synthetic focus. If a tumor exists at the focal point, the waveforms will add coherently. The clutter signals will add incoherently. Therefore, the tumor backscatter signals are enhanced while the clutter signals are suppressed. The RCB method exhibits higher resolution and better noise suppression than the CMI. The principle of RCB is to find the best weight vector to reduce the noise power.[22]

Both the aforementioned methods are effective when only one tumor exists. However, in the case of multiple tumors, it may be difficult to clearly identify all tumors from the reconstructed image simultaneously. The main reasons for this are shown as follows.

1) It is more difficult to capture the tumor response from a deeper embedded tumor as the attenuation of the signal is very large in human tissue.

2) The distances between the tumors and the antennas are different. The tumor that is embedded more closely to the antenna array is expected to be more easily identified.

3) The contrast between a tumor and the surrounding tissues differs in diverse regions since the realistic breast is heterogeneous and the attenuation coefficients vary for different surrounding tissues. The tumor which has larger contrast and lower attenuation surrounding reflects the signal more strongly.

Therefore, the response intensities from different tumors are dissimilar. Tumors with relatively strong response can be detected, while tumors with relatively weak response may be treated as the clutter.

In order to solve this problem, we propose a progressive processing method. The main idea of this method is that employing partial antennas to focus on one certain tumor so that the tumors in different places can be detected respectively. This method consists of three stages: primary diagnosis, refocusing and image optimization.

In the primary diagnosis stage, the antennas are positioned on the skin covering the breast. All recorded signals are used to reconstruct the breast image by using the CMI algorithm. Based on the reconstructed image, the suspected tumor regions can be recognized as the primary diagnosis results. However, these regions cannot be confirmed to be tumors or noise. The next stage is to confirm the suspected tumor region.

In the refocusing stage, a limited number of antennas are employed as an array pointing toward one certain region where the tumor is suspected to exist. In this stage, the following steps are taken.

1) Pick out the pixels whose intensities are greater than 70% of the maximum value. These pixels will form some isolated pixel groups.

2) For each group in step 1), find $x_{\min}$, $x_{\max}$, $y_{\min}$, $y_{\min}$ of the pixels. The central point of this pixel group is defined as $P(x_P, y_P)$, where $x_P = (x_{\min} + x_{\max})/2$ and $y_P = (y_{\min} + y_{\max})/2$. Assume there are M central points.

3) For P_m, which is the m-th central point, calculate the distances between the antennas and the central point as follows:

$$D_{\mathrm{A}_n P_m} = \sqrt{(x_{\mathrm{A}_n} - x_{P_m})^2 + (y_{\mathrm{A}_n} - y_{P_m})^2}, \tag{2}$$

where A_n is the n-th antenna. Find the minimum $D_{\mathrm{A}_n P_m}$, the corresponding antenna is defined as $\mathrm{A}_{\min}$.

4) Select enough antennas surrounding $\mathrm{A}_{\min}$ to form an array. These antennas in the array must satisfy the following condition: the angle, whose vertex is P_m, formed by P_m and any two antennas is less than 90°. It can be expressed as

$$\arccos \frac{(x_{\mathrm{A}_p} - x_{P_m}) \cdot (x_{\mathrm{A}_q} - x_{P_m}) + (y_{\mathrm{A}_p} - y_{P_m}) \cdot (y_{\mathrm{A}_q} - y_{P_m})}{D_{\mathrm{A}_p P_m} \cdot D_{\mathrm{A}_q P_m}} < 90^\circ. \tag{3}$$

5) Signals received by the selected array are employed to create a breast image using the CMI algorithm. According to the reconstructed image, if the intensity in this region is very strong, a tumor is confirmed to exist in this region. If there is no significantly strong intensity, no tumor exists.

6) Repeat step 3) to step 5) for all the central points in turn. The reconstructed images are employed to confirm the presence of tumors in the corresponding positions.

In the image optimization stage, the RCB algorithm is applied to the case in which the tumor has been identified in order to improve the clarity of the reconstructed image.

4. Results

In this section, the performance of the proposed progressive processing method is demonstrated by comparing with the CMI and the RCB algorithms. Figure 3 shows the images obtained via the CMI and the RCB algorithms. In Fig. 3(a), tumor 1 can be clearly identified from the reconstructed image. However, tumor 2 cannot be confirmed since its response is not strong enough. There is a possibility that this information is treated as noisy when comparing with the response of tumor 1. In Fig. 3(b), it is obvious that the clutter signals are better

suppressed when compared with those in Fig. 3(a). Nevertheless, only tumor 1 can be recognized, while it fails to detect the other tumor.

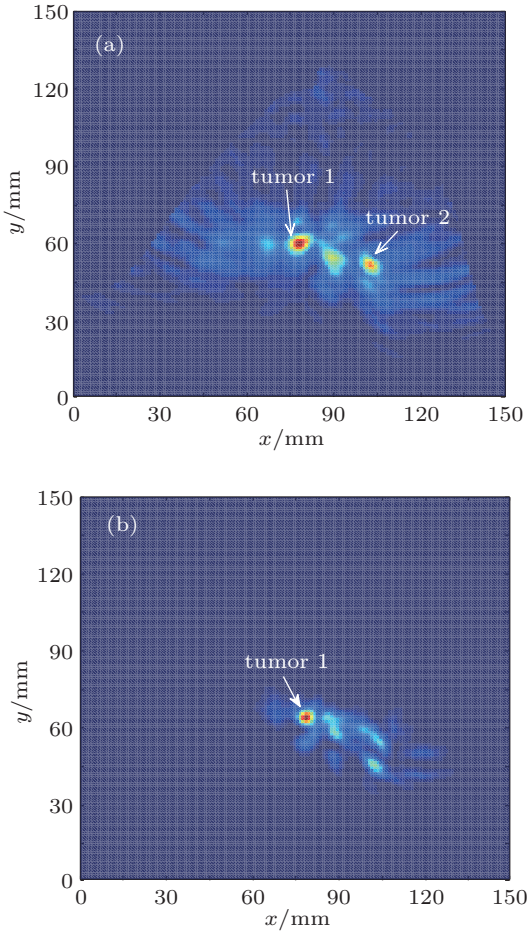


Fig. 3. (color online) Images reconstructed by employing signals obtained from all antennas: (a) CMI algorithm, (b) RCB algorithm.

In the progressive processed method, figure 3(a) is considered as the primary diagnosis image. In the second stage, the 12 antennas are divided into two groups. Group 1 is formed by antenna 1 to antenna 6 pointing towards the region where tumor 1 is suspected to exist. Group 2 is formed by antenna 7 to antenna 12 pointing towards the region where tumor 2 is suspected to exist. Figure 4 displays the reconstructed images using antenna group 1 and antenna group 2 respectively, in which both tumors can be confirmed. In the third stage, for obtaining high-quality images, the RCB algorithm is applied to suppress noise. The reconstructed image is shown in Fig. 5. Both tumors can be clearly observed. Define the position of the maximum pixel value as the tumor location. Then the estimated positions of tumor 1 and tumor 2 are (79 mm, 64.5 mm) and (101 mm, 51 mm) in the x–y plane, respectively, which show good agreement with their true locations.

The imaging results show that both CMI and RCB are ineffective to detect all the tumors, while the progressive processing method is proved to have the capability of detecting multiple tumors.

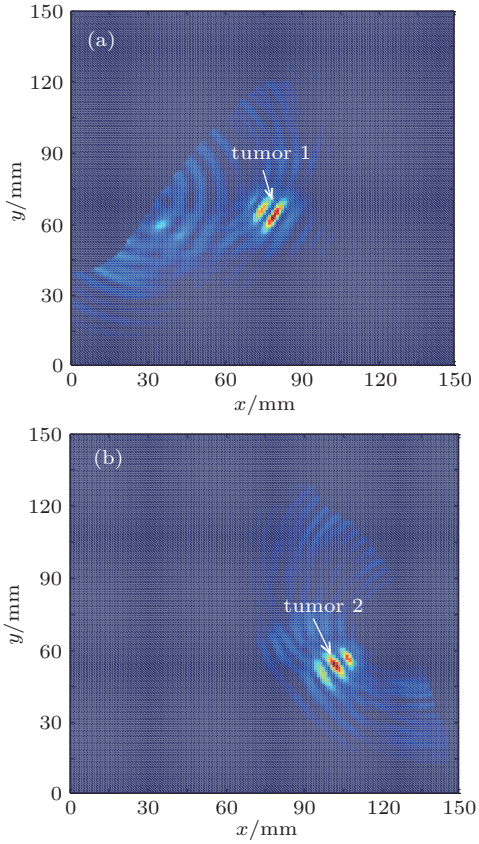


Fig. 4. (color online) Image reconstruction by CMI algorithm employing a partial antenna array: (a) for the case with antenna group 1 (from A1 to A6), (b) for the case with antenna group 2 (from A7 to A12).

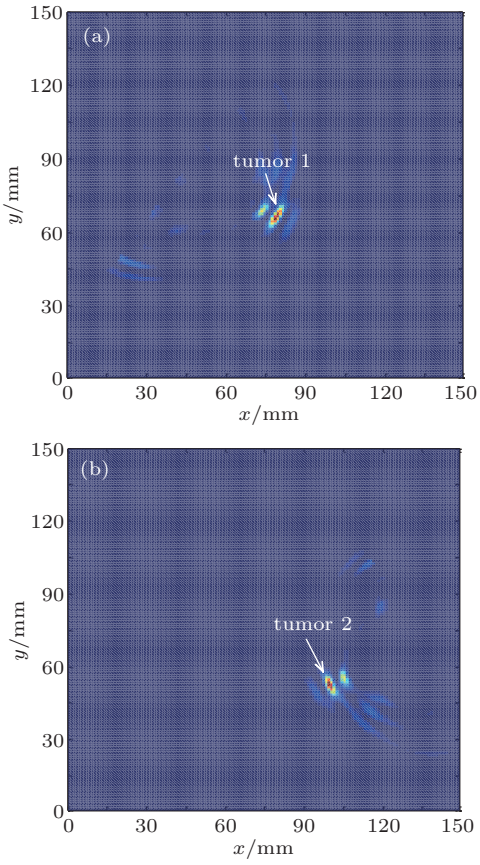


Fig. 5. (color online) Image reconstruction by RCB algorithm employing a partial antenna array: (a) for the case with antenna group 1 (from A1 to A6), (b) for the case with antenna group 2 (from A7 to A12).

5. Conclusion

In this paper, breast cancer detection is performed with an MRI-derived numerical model. A progressive processing method for detecting multiple tumors is proposed and described in detail. The imaging results obtained with the simulation demonstrate the successful detection of a tumor as small as 3.6 mm in diameter at a depth of 42 mm under the skin's surface. The correct locations of both tumors are found, suggesting that the presented method is a promising approach for multiple-tumor detection. Future work will involve using more complex realistic breast models both in 2D and 3D to optimize this method for accurate and rapid tumor detection; and experimental studies using tissue phantoms will be carried out to test the efficacy of the method.

References

[1] Xiao X, Xu L and Li Q W 2013 *Chin. Phys. B* **22** 094101
[2] Li X and Hagness S C 2001 *IEEE Microw. Wirel. Compon. Lett.* **11** 130
[3] Xiao X, Xu L and Liu B Y 2013 *Acta Phys. Sin.* **62** 044105 (in Chinese)
[4] Joines W T, Zhang Y, Li C X and Jirtle R L 1994 *Med. Phys.* **21** 547
[5] Xiao X and Kikkawa T 2008 *Jpn. J. Appl. Phys.* **47** 3209
[6] Kleer C G, Giordano T J, Braun T and Oberman H A 2001 *Mod. Pathol.* **14** 185
[7] Haka A S, Shafer-Peltier K E, Fitzmaurice M, Crowe J, Dasari R R and Feld M S 2002 *Cancer Res.* **62** 5375
[8] Breslin T M, Xu F S, Palmer G M, Zhu C F, Gilchrist K W and Ramanujam N 2004 *Ann. Surg. Oncol.* **11** 65
[9] Bindu G and Mathew K T 2007 *Microw. Opt. Technol. Lett.* **49** 2341
[10] Do C M and Bansal R 2013 *Proceedings of SPIE 8745 Signal Processing, Sensor Fusion, and Target Recognition XXII*, April 29, 2013 Baltimore, USA, p. 87451X
[11] Rezo A, Dahlstrom J and Shadbolt B 2011 *The Breast* **20** 259
[12] Lim H B, Nhung N T T, Li E P and Thang N D 2008 *IEEE Trans. Biomed. Eng.* **55** 1697
[13] De Rodriguez M E, Vera-Isasa M and Del Rio V S 2008 *IEEE Trans. Biomed. Eng.* **55** 2772
[14] Ryu K S and Kishk A A 2011 *IEEE Trans. Antennas Propag.* **59** 3788
[15] Xiao X and Kikkawa T 2008 *Appl. Surf. Sci.* **255** 597
[16] Roden J A and Gedney S D 2000 *Microw. Opt. Technol. Lett.* **27** 334
[17] Sugitani T, Kubota S, Toya A, Xiao X and Kikkawa T 2013 *IEEE Antennas Wirel. Propag. Lett.* **12** 733
[18] Fear E C, Hagness S C, Meaney P M, Okinoiewski M and Stuchly M A 2002 *IEEE Microw. Mag.* **3** 48
[19] Campbell M A, Okoniewski M and Fear E C 2010 *Microw. Opt. Technol. Lett.* **52** 1164
[20] Fear E C, Li X, Hagness S C and Stuchly M A 2002 *IEEE Trans. Biomed. Eng.* **49** 812
[21] Liu B Y, Xiao X and Liu X 2011 *International Conference on Control, Automation and Systems Engineering*, July 30–31, 2011, Singapore, p. 1
[22] Xie Y, Guo B, Xu L, Li J and Stoica P 2006 *IEEE Trans. Biomed. Eng.* **53** 1647