Algorithm Detecting Point Microcalcifications Using Matlab for Breast Cancer

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***Abstract*-** Goal of this research is to improve the capability of ultrasound images for detecting breast microcalcifications (MCs) and remove the major barriers of ultrasound for early breast cancer detection. The low detection rate of MCs with ultrasound is due to the low spatial resolution of the ultrasound images and to the presence of speckle noise, which masks the tiny microcalcifications. The first objective of this project is to investigate the efficiency of time reversal multiple signal classification (TR-MUSIC), algorithm in detecting breast microcalcifications and we did our experiments on numerical phantoms for detecting point microcalcifications and got the simulated results.

I. INTRODUCTION

Breast cancer is the most common nonskin malignancy in women and the second leading cause of female cancer mortality after lung cancer. Women in the United States have one of the highest incidence rates of breast cancer in the world, with about 1,665,540 new cases of breast cancer diagnosed in 2014 and 585,720 deaths happened in US [1]. Men are also affected by this disease. In 2014 about 2,360 new cases of invasive breast cancer was diagnosed among men in the United States [2]. Early detection is the major key to surviving this disease. The earliest indication of potential breast cancer detectable by current screening methods is the presence of microcalcifications (MCS). They are small crystal calcium apatite's that form in human tissue through a number of mechanisms, and that range in size up to several mm. They are the first sign of breast cancer in more than half of all breast cancer cases and they are sometimes the only indication of malignancy, making their detection critical. Ultrasound imaging is a non-ionizing technique and is a safer method for breast microcalcifications detection. However, current state-of-the-art clinical ultrasound imaging systems can only reliably detect tumors of at least several millimeters in size . This limitation is due mainly to their low-resolution, the presence of speckle noise in their images, phase aberration, and attenuation. Ultrasound has played a very important role for detecting microcalcifications for dense tissue and it has greater impact because non ionizing radiation, low cost, available and portability. Microcalcifications detection is affected by spatial resolution of the imaging system, speckle noise in the image and phase aberration. Proper arrangements of transducer elements are very important to get ultrasound images. To detect microcalcifications numbers of transducer elements have to be greater than the number of microcalcifications. For low number of transducer elements image artifact will appear which will increase the cost for adding filters to reduce these kind of artifacts like anti-aliasing image filters. To build the algorithm for microcalcifications detection we have to set proper value for transducer width, kerfs, pitch and element length. Without proper setting of this elements value we will get poor image resolution. Many techniques such as artificial neural networks (ANN) [3], linear discriminant analysis (LDA) [3], and support vector machine [4], [5] and Bayesian neural can be used for mass detection and classification [6]. These computer aided systems uses large amount of samples to construct models [7]. Using artificial neural network for mass detection and classification a multilayer feed-forward neural network can be used for classifier, extendibility, heftiness and consistency of the proposed computer aided algorithm. Multilayer neural network used for variance contrast and auto correlation contrast depending on input features corrected by back propagation error. Fuzzy logic also can be used for global and local information enhancement by avoiding noise amplification [8]. Using this technique edge and textural information can be extracted from ultrasound image and contrast ratio can be modified, computed and enhanced using this technique [8]. To enhance the ultrasound images defuzzification can be used [8]. Support vector machine normally used for differential analysis of breast microcalcifications detection [5]. In this process block difference of local correlation co-efficient, simplistic textural features block variation of converse probabilities and auto-covariance matrix is applied to detect microcalcifications [4]. Support vector machine is also used for image recognition, bioinformatics [4]. In trajectory based deformation rectification for ultrasound images classification of tissue deformation, pixel dislocation assessment was performed among ultrasound images under different contact forces [9]. Information of contact force and the subsequent pixel displacements permitted the edifice of a trajectory field of subject beneath an ultrasound scan. Depending on the contact force pixel coordinates were plotted. Trajectory field and extrapolation algorithm was applied on each pixel-trajectory for rearranging the pixel to where it would have been without any contact force to get the tissue form [9]. Their apparition is inadequate by a number of factors including speckle noise, phase deviation, the system spatial resolution, attenuation, display parameters, and perception of human on the displayed image. If those limitations can be removed detection of microcalcification can be significantly improved. Depending on acoustic impedance of hydroxyapatite which is the most common element of microcalcification their amplitude reflection can be 0.9 inside tissue. So to get better resolution sub resolution model can be used to get bright reflector point under ultrasound. By increasing the aperture size resolution of the system can be increased. Using synthetic receive aperture imaging large aperture imaging can be reduced and which also reduces the system complexity associated with the imaging technique. Compared to single transmit aperture SRA system transmits into the same region of interest. When the sound wave is transmitted from the transducer echo signals are received in different sub aperture level. This signals are then added to create a large effective receive aperture and more channels are needed to receive signals in sub aperture level. The investigation of MC detectability is restricted by the reduced classification of their acoustic properties based on the theoretical radiation patterns of stiff and resilient spheres and clinically calculated speckle noise levels.

II. METHODOLOGY

To detect Point like targets using ultrasound image processing Multiple Signal Classification (MUSIC) has promising outcome [10]. To derive the equation for multiple signal classification (MUSIC) time reversal matrixes T and inter element transfer matrix can be used. Normally when transducer elements receives the back propagated waves from targets time reversal image is created [10]. In time reversal multiple signal classification coherent point spread function helps to get axial and lateral resolution. Time reversal matrix can be written as T=M*M where M is the multi-static response matrix [11]. Where Green function vector is orthogonal to noise subspace and eigen value is zero.

$$<\alpha_{m0},g^*_m>=<\alpha_{m0},g^*_m>0 \qquad 1$$

Here, m=1,2,3,...,M and m0=M+1,...,N, and α_{m0} is the eigen vector having zero eigenvalue [11].

Algorithm of pseudo-spectrum can be written as,

$$E(Y_p)= 1/\sum_{m0=M+1}^{n} | < \alpha m0 *, gp > |2$$

Where α_{m0} is the m_0'th eigenvector with zero eigen value.

$$g_p(\omega)=\{G(R_l,Y_p)\}=[G(R_1,Y_p), G(R_2,Y_p),...., G(R_N,Y_p)]^T \qquad 3$$

Where $g_p(\omega)$ is the steering vector. For a test location Y_p steering vector can be found from green function vector. Because here signal subspace is orthogonal to the noise subspace and will disappear for test location Y_p becomes equal to reallocation of targets Y_m for non resolved as well as resolved targets. So pseudo spectrum E will rise towards infinity (theoretically) for each target location when $Y_p=Y_m$, m=1, 2, 3...M. Here equation (2) is multiple signal classification for time reversal imaging [11]. After defining variables for getting ultrasound images we have to do trace shaping for the desired images. For that we have to set image specification and process the ultrasound images for each element. After setting variables and other parameters for numerical phantoms we have to save the data in matrix to do further image processing for microcalcification detection.

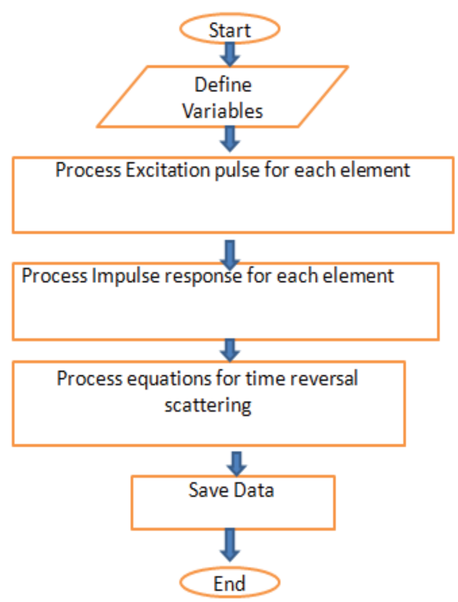

Fig.1. Flow chart for detection of microcalcifications.

Ultrasound images can be low in contrast. Preprocessing of the image reduces the noise and increases the contrast between the apprehensive areas and breast tissue background. We changed different parameters of ultrasound images to increase the image contrast to detect microcalcifications of numerical phantoms of the simulations. We used multiple signal classification algorithms for classifying the numerical phantoms for miocrocalcification detection [12]. Depending on the parameters selected in preprocessing level accuracy, sensitivity, specificity, positive predictive value, and negative predictive value are used to evaluate the classification results for microcalcification for a specific region of interest for numerical phantoms. The higher the five measurements are, the more reliable and valid detection will be. We also experimented the receiver operating characteristic and parameter to evaluate the performances of the proposed approach.

III. RESULTS

We did our experiments on numerical phantoms to get simulated results. We did experiments for different sampling frequencies and sound speeds. For higher sampling frequencies point microcalcifications are more detectable than lower frequencies. We did our experiments for sampling frequencies 25MHz, 30MHzz, 35Mhz, 39MHz and 41MHz. It was found for sampling frequency 41MHz point microcalcifications are more detectable than other sampling frequencies.

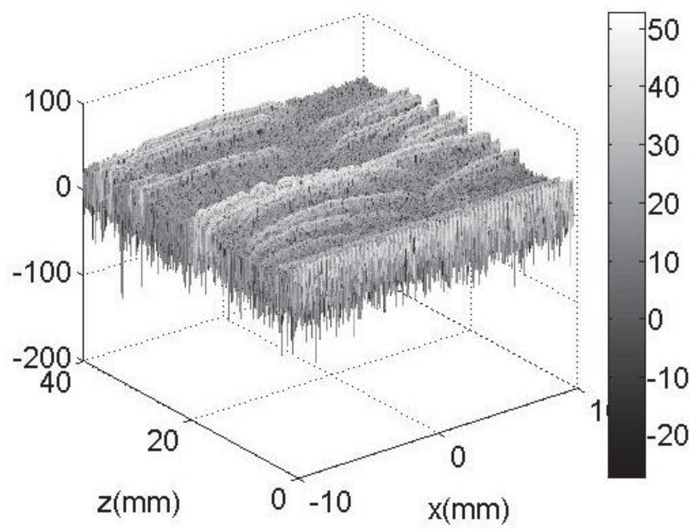

Fig.2 Detection of microcalcifications at 25MHz.

We gradually increased our sampling frequency from 25MHz to 41MHz to observe point microcalcifications become more detectable or not and to increase the precision level. For higher sampling frequencies we get less penetration but image resolution increases so point microcalcifications become more distinguishable. We can also vary the lateral and axial distance between the point scatters to change the wave length between them. In fig.4. sharp spikes of the reflected ultrasound waves distinguishes point microcalcifications more clearly.

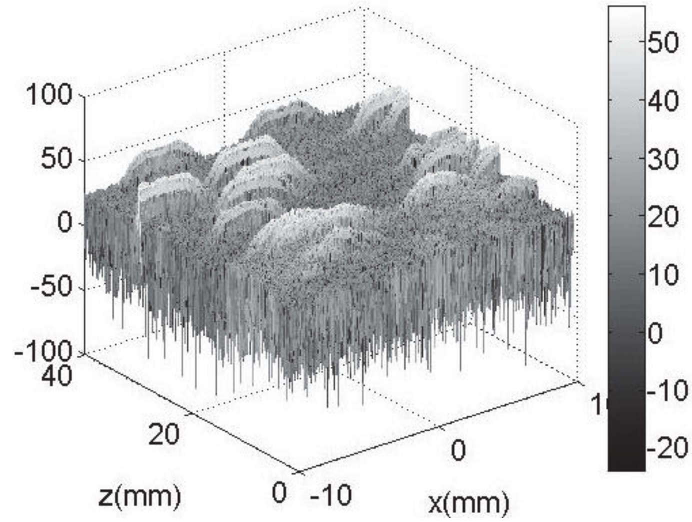

Fig.3. Detection of microcalcifications at 35MHz.

Distances between point scatters were decided depending on the wave length of the ultrasound frequency. When doing our simulated experiments using MATLAB we considered all the scatters is in one single plane.

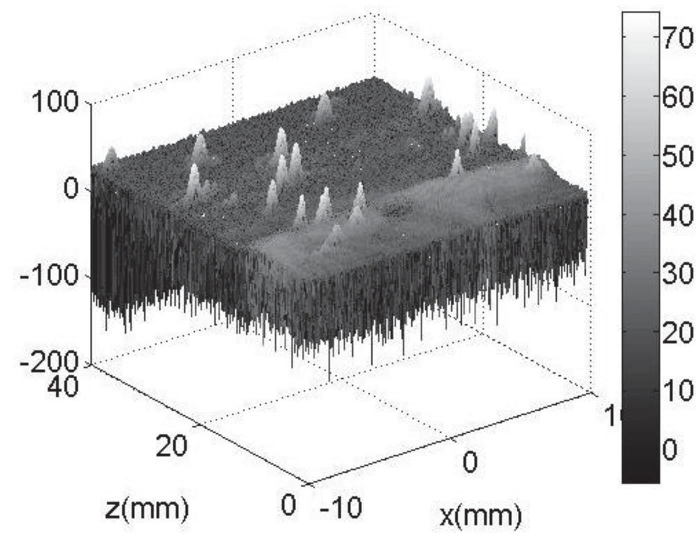

Fig.4. Detection of microcalcifications at 41MHz.

To get and measure ultrasound scatters signal Foldy-Lax [10] model was used. After processing the saved data for numerical phantoms we got the simulated results. Proper selection of sampling rate is very important when working with ultrasound images and without proper selection of sampling rate we will get poor image resolution. As our main purpose is to detect point microcalcifications of mm size, dimensions of simulated results in MATLAB is multiplied by 10^{-6}.

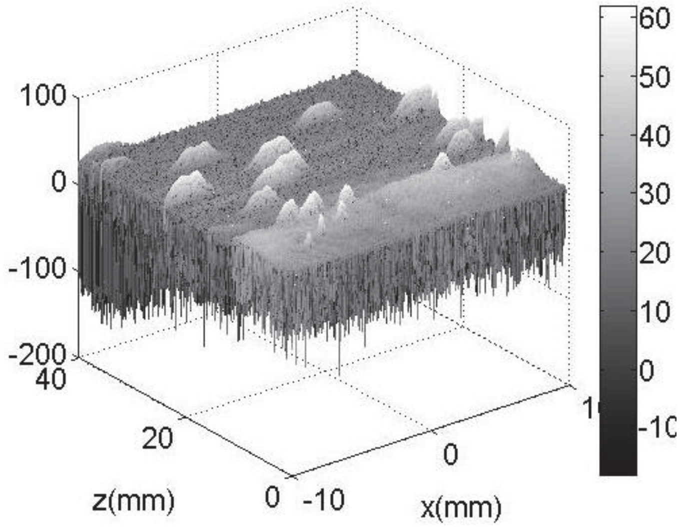

Fig.5. Detection of microcalcifications at 1380m/s.

In fig.4. we can see point microcalcifications are more distinguishable for sampling rate of 41MHz. But for sampling frequency 25MHz in fig.2. these point microcalcifications were more scattered. Without proper selection of sampling rate aliasing distortions occurs for frequency 25 and 35 MHz .When we increased and properly selected our sampling frequency that gives us the opportunity to detect point microcalcifications more precisely. Then we set out sampling frequency at 41MHz and varied the sound speed from 1380m/s to 1540 m/s. Because as we know inside human body velocity of sound wave varies from 1380m/s to 1540 m/s. Point microcalcifications were more scattered for sound speed 1380 m/s in fig.5. but in fig.6. those point microcalcifications were more distinguishable for sound speed 1540 m/s. After doing couple of experiments for different sampling rate and sound speed we found that best microcalcifications detection occurs at sampling rate 41MHz and sound speed 1540 m/s.

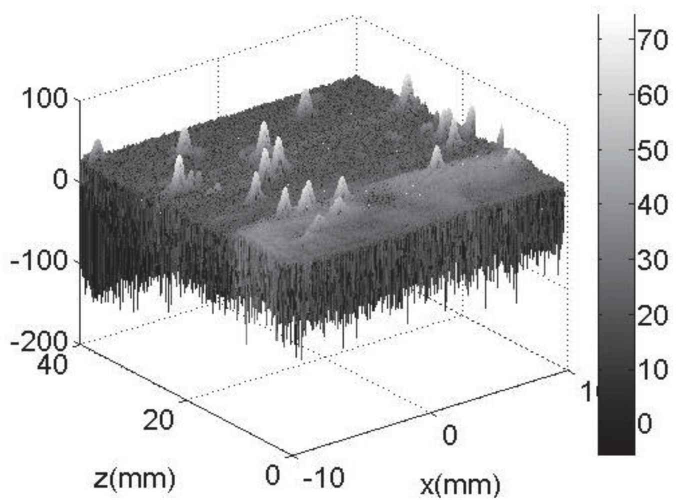

Fig.6. Detection of microcalcifications at 1540m/s.

When we were working with the numerical phantoms we observed that sound wave scattering from different microcalcifications sent from transducer elements also depends on proper selection of sound speed. Because when sound wave propagates through human body it's characteristics changes due human body tissue. In our experiments we observed when we selected sound speed at 1380m/s the image resolution of the simulated ultrasound images were poor. But when we gradually increased our sound speed from 1380m/s to 1540m/s then the image resolution got better.

IV. DISCUSSION

Proper selections of ultrasound parameters are very important to get better image resolution. Slight variations of these variables will cause poor image. Because of that we will not be able to detect microcalcifications which are very tiny in size. Proper selection of equations in algorithms is also very important when working with sound wave. In our experiments we were more concerned about the wave equation to characterize the sound wave property when moving through the human body. More transducer element will increase the image resolution but that will also increase the cost. More sampling rate also gives better image resolution but is also increases the complexity and cost of the system. So we have to make a trade of between the demand and requirement. Otherwise one of the main reasons for using ultrasound to detect breast microcalcifications will have no meaning.

V. CONCLUSION

We had some positive as well as negative outcomes when trying to develop our algorithm for numerical phantoms. We tried to analyze the negative results and also tried to find out possible reasons and solution for that. Such as depending on variation of sound speed ultrasound image resolution changes due change of characteristic of sound wave when interacts with body tissue. We also observed that for not choosing the proper sampling rate aliasing distortion occurs. Other factors like pulse width duration, excitation pulse, attenuation co-efficient and impulse response also creates changes on ultrasound image resolution of B-mode scanning. We tried to set proper value of these parameters to get better result for detection of microcalcifications in breast cancer. Finally, wave equation reflection imaging and factorizing method have outstanding impact for increasing the image resolution of ultrasound images for microcalcifications detection to detect early breast cancer. Image speckles can be reduced effectively by using wave equation for further image processing when analyzing the received reflected or diffracted sound wave from different microcalcifications.

References

[1] *Breast Cancer Facts & Figures | American Cancer Society*.

[2] *U.S. Breast Cancer Statistics*.

[3] H. D. Cheng, J. Shan, W. Ju, Y. Guo and L. Zhang. Automated breast cancer detection and classification using ultrasound images: A survey. *Pattern Recognit 43(1),* pp. 299-317. 2010. . DOI: 10.1016/j.patcog.2009.05.012.

[4] N. Piliouras, I. Kalatzis, N. Dimitropoulos and D. Cavouras. Development of the cubic least squares mapping linear-kernel support vector machine classifier for improving the characterization of breast lesions on ultrasound. *Comput. Med. Imaging Graph. 28(5),* pp. 247-255. 2004. . DOI: 10.1016/j.compmedimag.2004.04.003.

[5] Y. Huang and D. Chen. Support vector machines in sonography: Application to decision making in the diagnosis of breast cancer. *Clin. Imaging 29(3),* pp. 179-184. 2005.

[6] D. Chen, R. Chang, C. Chen, M. Ho, S. Kuo, S. Chen, S. Hung and W. K. Moon. Classification of breast ultrasound images using fractal feature. *Clin. Imaging 29(4),* pp. 235-245. 2005.

[7] D. Chen, R. Chang and Y. Huang. Breast cancer diagnosis using self-organizing map for sonography. *Ultrasound Med. Biol. 26(3),* pp. 405-411. 2000.

[8] Y. Guo, H. Cheng, J. Huang, J. Tian, W. Zhao, L. Sun and Y. Su. Breast ultrasound image enhancement using fuzzy logic. *Ultrasound Med. Biol. 32(2),* pp. 237-247. 2006.

[9] S. Sun, B. W. Anthony and M. W. Gilbertson. Trajectory-based deformation correction in ultrasound images. Presented at SPIE Medical Imaging. 2010, .

[10] A. J. Devaney, E. A. Marengo and F. K. Gruber. Time-reversal-based imaging and inverse scattering of multiply scattering point targets. *J. Acoust. Soc. Am. 118*pp. 3129. 2005.

[11] A. J. Devaney. Super-resolution processing of multi-static data using time reversal and MUSIC. *J. Acoust. Soc. Am.* 2000.

[12] F. K. Gruber, E. A. Marengo and A. J. Devaney. Time-reversal imaging with multiple signal classification considering multiple scattering between the targets. *J. Acoust. Soc. Am. 115*pp. 3042. 2004.

[13] M. E. Anderson. The detection of breast microcalcifications with medical ultrasound *J. Acoust. Soc. Am. 101(1),* pp. 29. 1997. . DOI: 10.1121/1.417973.

[14] D. Chen, R. Chang, W. Kuo, M. Chen and Y. Huang. Diagnosis of breast tumors with sonographic texture analysis using wavelet transform and neural networks. *Ultrasound Med. Biol. 28(10),* pp. 1301-1310. 2002.

[15] L. Chen, Y. Chen, X. Diao, L. Fang, Y. Pang, A. Cheng, W. Li and Y. Wang. Comparative study of automated breast 3-D ultrasound and handheld B-mode ultrasound for differentiation of benign and malignant breast masses. *Ultrasound Med. Biol.* 2013.

[16] G. Clement, J. Huttunen and K. Hynynen. Superresolution ultrasound imaging using back-projected reconstruction. *J. Acoust. Soc. Am. 118*pp. 3953. 2005.

[17] B. E. Hashimoto. Sonography of ductal carcinoma in situ. *Ultrasound Clinics 1(4),* pp. 631-643. 2006.

[18] L. Huang, Y. Labyed, F. Simonetti, M. Williamson, R. Rosenberg, P. Heintz and D. Sandoval. High-resolution imaging with a real-time synthetic aperture ultrasound system: A phantom study. Presented at SPIE Medical Imaging. 2011.

[19] J. A. Jensen, S. I. Nikolov, K. L. Gammelmark and M. H. Pedersen. Synthetic aperture ultrasound imaging. *Ultrasonics 44*pp. e5-e15. 2006.

[20] B. Liu, H. D. Cheng, J. Huang, J. Tian, X. Tang and J. Liu. Fully automatic and segmentation-robust classification of breast tumors based on local texture analysis of ultrasound images *Pattern Recognit 43(1),* pp. 280-298. 2010. . DOI: 10.1016/j.patcog.2009.06.002.

[21] E. A. Marengo, F. K. Gruber and F. Simonetti. Time-reversal MUSIC imaging of extended targets. *Image Processing, IEEE Transactions on 16(8),* pp. 1967-1984. 2007.

[22] P. M. Morse and K. U. Ingard. *Theoretical Acoustics* 1968.

[23] I. Reiser, R. Nishikawa, A. Edwards, D. Kopans, R. Schmidt, J. Papaioannou and R. Moore. Automated detection of microcalcification clusters for digital breast tomosynthesis using projection data only: A preliminary study. *Med. Phys. 35(4),* pp. 1486-1493. 2008.

[24] A. P. Sarvazyan, M. W. Urban and J. F. Greenleaf. Acoustic waves in medical imaging and diagnostics. *Ultrasound Med. Biol.* 2013.

[25] C. M. Sehgal, S. P. Weinstein, P. H. Arger and E. F. Conant. A review of breast ultrasound. *J. Mammary Gland Biol. Neoplasia 11(2),* pp. 113-123. 2006.

[26] Y. Su, H. Wang, Y. Wang, Y. Guo, H. Cheng, Y. Zhang and J. Tian. Speckle reduction approach for breast ultrasound image and its application to breast cancer diagnosis. *Eur. J. Radiol. 75(1),* pp. e136-e141. 2010.

[27] C. J. Vyborny, M. L. Giger and R. M. Nishikawa. Computer-aided detection and diagnosis of breast cancer *Radiol. Clin. North Am. 38(4),* pp. 725-740. 2000. . DOI: 10.1016/S0033-8389(05)70197-4.