Regularization of Image Reconstruction in Ultrasound Computed Tomography

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***Abstract*– We propose two regularizations techniques for a bent-ray (BR) tracing algorithm to reconstruct the speed of sound maps of breast tissues in an Ultrasound Computed Tomography (USCT) system. When high frequencies are employed, the use of BR is a good approximation to describe the propagation of the front of the pressure wave. The quantitative accuracy of the images reconstructed with the BR algorithm was evaluated without any kind of regularization, and with two regularization methods. The regularizations were based on some available *a priori* information, namely the known higher and lower values of the speed of sound expected in the breast tissues, and the maps of the internal structures obtained from the standard reflection ultrasound (US) imaging. The use of the proposed regularizations in the implemented algorithm improves the convergence and quality of the resulting images, although further improvements are still possible. These methods will help obtaining quantitative US images in a reasonable amount of time, expanding the possibilities and applications of this technique.**

I. INTRODUCTION

Ultrasound computed tomography (USCT) is a non-invasive imaging technique with promising capabilities of being used for population screening of breast cancer. In its most common scheme, the patient lays face-down on a couch with the breast inside a water tank surrounded by an array of ultrasound transducers. When a transducer emits an ultrasound pulse, the other transducers record the transmitted and reflected signals. These signals are analysed and processed to recover the acoustical properties of the medium they went through. The reflected signals provide information of the changes in the acoustic impedance (the product of the density and the speed of sound in each tissue) and the concentration of scatterer points. This information, which is related to the tissue boundaries, is the one obtained in standard US imaging. On the other hand, the transmitted signals give information of the speed and attenuation of the sound in the different tissues. This information can be correlated with tissue density and stiffness [1], so it can be used to estimate the risk of malignancy of a suspicious tissue. The use of a ring of transducers in an USCT system allows all possible angles to be covered, so the images obtained have isotropic resolution, a high level of detail of the internal breast structure and far less noise and speckles than standard US images.

Several methods have been proposed for reconstructing USCT images from the recorded signals. Full-wave methods [2], [3] obtain the best results in terms of accuracy, resolution and artefacts control, but their high computational cost makes them currently unsuitable for clinical practice. Even with a cluster of computers, it is very difficult to reach reconstruction times shorter than several hours when high frequencies are employed. There are faster reconstruction methods based on approximate models, such as the Born or Rytov linearization of the full-wave physics [4], or ray-tracing algorithms [5]. The best resolution achievable with these approximate methods is theoretically bounded by half wavelength of the ultrasound in the medium, although this value is difficult to achieve in practice. This is an ill-posed problem with uncertainties not only in the measurements but also in the propagation models and reconstruction methods. Besides, the convergence of these algorithms is slow, so in order to obtain really fast reconstructions, it is necessary to use strategies to speed it up.

In this work we propose and evaluate the use of two regularization techniques for a bent-ray tracing algorithm to reconstruct speed of sound maps of breast tissue in an USCT system operating in the range of a few MHz [6]. At these high frequencies, it is valid to assume that acoustic energy travels along the lines perpendicular to the equal-phase wave fronts. Therefore, the use of bent-rays is a good approximation for the propagation of the front wave in tissue [7]. The quantitative accuracy of the images reconstructed with the algorithm without any regularization is first investigated, and then, improvements obtained with regularization are evaluated. The proposed methods are based on *a priori* information, such as the known range of the speed of sound present in breast tissue and the maps of the internal structures obtained with the reflection modality.

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II. METHODS

A. Iterative Reconstruction

We first implemented the iterative reconstruction algorithm ML-EM [8] (1) to obtain the estimation of the speed map:

$$f_j^{it+1} = f_j^{it} \frac{\sum_i A_{ij} \frac{y_i}{\sum_{j'} A_{ij'} f_{j'}^{it}}}{\sum_i A_{ij}} \tag{1}$$

where f_j^{it} is the inverse of the speed of sound values (slowness) at voxel j estimated at iteration it, y_i is the experimental TOF value at emitter-receiver pair i, and A_{ij} are system matrix coefficients obtained by means of the Fast Marching Method (FMM) [9] which was employed in the forward and backward propagation in the optimization algorithm. $\sum_{j'} A_{ij'} f_{j'}^{it}$ represents the estimated TOF. FMM provides the solution of the Eikonal equation (2), which describes the advance of the front wave according with the current speed map and subsequently it is possible to extract the delays map T.

$$|\nabla T|^2 = \frac{1}{c^2} \tag{2}$$

The gradient of the delays map are employed to guide the rays through the shortest trajectories and obtain the TOF values between the emitter and the receivers. The coefficients A_{ij} are obtained from these trajectories.

B. Regularizations

The large amount of noise and artifacts in the reconstructed images of this ill-posed problem motivates the use of pre-conditioning and regularization methods based on *a priori* information.

B.1 Using the known range of speeds

The composition of the breast could vary between patients, but the range of the speed of sound in the tissues of the breast is generally bounded by the values in the skin and the fat, which frequently represent the higher and lower speed values respectively. The maximum and minimum possible TOF values can be used as a pre-conditioning method to accelerate convergence and reduce the appearance of artefacts. To this end, we modified the optimization code by replacing the conventional OSEM by the AB-OSEM [10] to take those values into account in the reconstruction process. The maximum and minimum TOF values (TOF_{max} and TOF_{min} respectively) were calculated as the TOF values that would be obtained if all the tissues in the field-of-view (FOV) were fat or skin, respectively.

B.2 Edge-preserving filter based on the reflectivity map.

We can also use the hypothesis that all pixels of the same tissue should have locally the same speed of sound, in order to regularize the reconstruction. We used this hypothesis together with the information of the regions obtained from the reflection modality. Based on this, we can filter the noise with a low-pass filter preserving the boundaries between tissues, and then homogenize the speed in the different structures iteratively using a median filter. This kind of regularization is important to do it with caution, and always using a small sized kernel and a reasonable number of iterations to avoid removal of small structures which may be not visible in the reflexion modality.

The description of the methods employed in our USCT system to obtain the reflectivity map can be seen in [6]. The reflectivity map (which can be obtained in several seconds), is used to detect the edges of the structures in the breast, and then we filter the images after each iteration until a reasonable amount of speckles and noise are eliminated.

C. Numerical breast phantom.

The proposed method was evaluated with a numerical breast phantom (see Fig. 1A). It corresponds to a case with a large amount of fibro-glandular tissue, which has a density closer to the tumors. The values of c in each tissue were taken from [11]. To obtain simulated data we employed a full-wave algorithm [12] with 1 MHz central frequency and a FOV of 128 mm. The radius of the ring array was selected as 54 mm and a 128 × 128 pixels grid (pixel size 1 mm^2) was employed. We reconstructed the data without performing any pre-

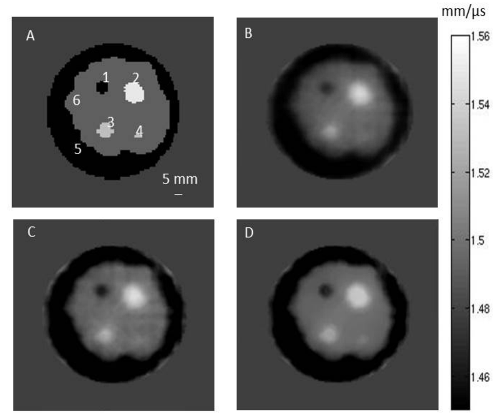

Fig. 1 A) Numerical breast phantom, B) OSEM reconstruction with bent rays. C) AB-OSEM reconstruction with bent rays. D) AB-OSEM + reflectivity filter based on the reflectivity map.

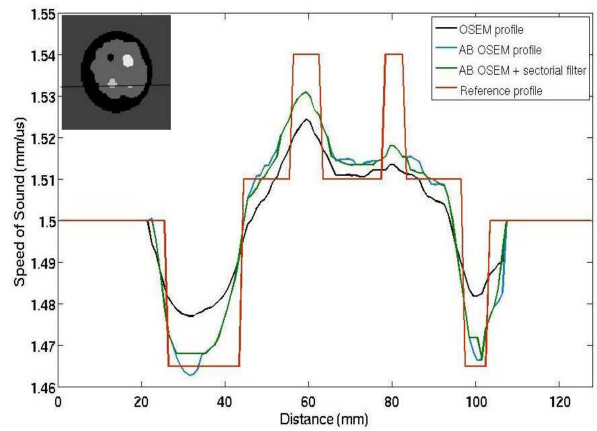

Fig. 2 Comparison of profiles between OSEM, AB-OSEM, AB-OSEM + reflectivity filter based on the reflectivity map.

conditioning and regularization on one hand, and implementing the above mentioned strategies on the other. A comparison between the mean and expected values in the structures of Fig. 1A was employed to test the quality of the obtained images.

III. RESULTS

Figs. 1B, 1C and 1D show the image reconstruction with no correction, the correction with the speed of sound range, and correction with both the speed of sound range and the reflectivity filter, respectively. As starting guess in each of these reconstructions it was employed a homogeneous map of water. The reconstruction time for 2 iterations and 20 subsets was around 14 minutes using a single core of an Intel Xeon 16-CPU @2.4GHz (the code is not parallelized). The regularization and preconditioning employed do not add significant time of computation in the reconstruction process. It is remarkable the improvement in the image quality obtained with these techniques. As it can be seen in Table 1, the mean values in the different structures correspond better with expected values when the regularization is applied. As can be seen in Figs, 1B and 1C, the correction of the speed of sound range produces better definition of edges than the conventional OSEM algorithm. Besides, in those cases, noise and speckles are significantly reduced. On the other hand, the reflectivity filter combined with the limited range of the speed of sound yields less noise, better definition of edges and better recovery of small structures (see Fig. 1D and Fig. 2).

TABLE 1 Expected and mean values in the structures of Fig 1A. All mean values were obtained defining ROIs of equal size as the structures in the numerical breast phantom.

		Mean value (mm/µs)	SD (%)	Expected Value (mm/µs)
OSEM	1	1.498	0.200	1.470
	2	1.530	0.392	1.550
	3	1.520	0.197	1.530
	4	1.510	0.040	1.530
	5	1.479	0.068	1.465
	6	1.507	0.066	1.510
AB-OSEM	1	1.485	0.269	1.470
	2	1.540	0.325	1.550
	3	1.528	0.262	1.530
	4	1.517	0.059	1.530
	5	1.468	0.136	1.456
	6	1.511	0.053	1.510
AB-OSEM + reflective filter	1	1.495	0.268	1.470
	2	1.538	0.260	1.550
	3	1.527	0.196	1.530
	4	1.517	0.059	1.530
	5	1.467	0.068	1.465
	6	1.511	0.040	1.510

IV. CONCLUSIONS

Two regularization methods based on *a-priori* information were developed for a BR image reconstruction code for USCT. These regularizations improve the convergence and quality of the resulting images. Although, the code should be optimized and parallelized to improve the current computation times and in this way facilitate the use of the code in the clinical practice. We are confident that these methods will enable obtaining quantitative US images in a reasonable amount of time and they will expand the possibilities and applications of this new technique.

V. REFERENCES

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