Computer modelling of iterative technique application for tissue thermal imaging

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Thermal therapies are effective methods used for cancer treatment. During thermal cancer treatment there are usually small temperature fluctuations of between 37°C and 43°C inside the human body. These fluctuations are very important to monitor accurately for quality cancer treatment, preferably with a non-invasive technique.

Through-transmission ultrasonic tomography is a convenient non-invasive technique, which allows internal cross-sectional images of acoustic properties to be obtained; acoustic properties change as the temperature changes, and this allows temperature fields in tissue to be measured.

Computer modeling of temperature fluctuation reconstruction using ultrasonic through-transmission tomography has been carried out. The model considers a fan-bean tomography scheme (60 sensors, 2160 rays in total) and iterative techniques for solving the inverse problem. It also assumes the 2D temperature is being reconstructed in an area of tissue of 60mm x 60mm size, and the temperature fluctuation size is ~6.5 mm in diameter. Such heated regions can appear, for example, during thermal treatment using high intensity focused ultrasound (HIFU). Algorithms for solving the inverse problem using algebraic iterative methods (including EM, ART and SART) have been investigated. Bilinear interpolation of temperature values was used in between the nodes, in which temperature is being reconstructed. The model takes into account electronic measurement noise and assumes increasing linear dependence of sound speed on temperature, which is approximately correct for the considered temperature range and non-fatty tissue. Circular and ellipsoidal heated regions have been investigated, along with multiple contrasts. It was shown that it is possible to reconstruct temperature fluctuations with a good accuracy.

A reconstruction technique was also investigated for regions of tissue which contain bones or other acoustically non-transparent objects, as these objects cause missing parts in the projection data. A special method for temperature distribution reconstruction from noisy projections with missing data was developed. The developed method reduces the number of unknowns by partial substitution of values obtained by iterative EM technique reconstruction. The accuracy of the developed method was investigated by computer modeling and compared with known expectation maximization methods. It was shown that the developed method gives higher accuracy and less distortion after reconstruction than the expectation maximization method. The developed method, therefore, may give a better opportunity to accurately monitor the thermal cancer treatment of more regions of the human body.

Keywords- iterative techniques, CT acoustical imaging, cancer thermal treatment, computer modeling

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I. INTRODUCTION

Ultrasonic tomography is a convenient method for imaging the internal acoustic properties of an object. This technique is often used in medicine and non-destructive testing, and can also image other properties, which may be correlated with the acoustic properties of an object.

One potential medical application of ultrasonic tomography is temperature imaging during the process of thermal cancer treatment. This is an emerging method of treatment that has been somewhat restricted in its clinical application due to a lack of non-invasive temperature monitoring. In this work, the comparative effectiveness of iterative reconstruction methods was investigated by simulation of *in-situ* non-invasive imaging of internal temperature distribution.

The techniques investigated were used to produce internal cross-sectional images of acoustic properties from measurements of the time propagation delays of ultrasonic waves passing directly through the region of interest. It was assumed that sound speed increases linearly with temperature, which is correct for non-fatty liver tissue [1,2]. The straight ray approximation was also assumed.

II. GEOMETRY OF TOMOGRAPHIC SET-UP

The geometry of the modelled fan-beam tomographic set-up is shown in Figure 1. The region of interest is filled with water and contains an object (tissue). The area is scanned with an ultrasonic array of 60 sensors with a 2mm lateral spacing, rotating within the range 0° - 350° with a 10° step, so that the total number of rays R in all projections is 2160. The propagation time measured for each rays is

$$t_r = \int_l \frac{dl}{c(x,y)} = \int_l f(x,y)dl, \qquad (1)$$

where the integration takes place along the ray and $c(x,y)$ is the speed of sound distribution. The electronic noise level for measuring the propagation time is 1.4 ns.

The ultrasonically heated region is situated somewhere within the inner 60mm x 60mm square, in which the sound speed $c(x,y)$ and temperature field $T(x,y)$ should be reconstructed. The value of $c(x,y)$ outside the inner square is assumed to be known from preliminary measurements. The inner square was covered by a mesh (which contains $N = 46 \times 46 = 2116$ nodes); in between the nodes bilinear interpolation was assumed. The temperature rise in the heated region is ~ 43°C, while the general tissue temperature is 37°C.

For temperature reconstruction the matrix equation has to be solved:

$$\mathbf{t} = \mathbf{A}*\mathbf{w}, \qquad (2)$$

where $\mathbf{t} = [t_1,\ldots,t_R]$ is a vector of all the measured propagation times, $\mathbf{w} = [f(x_1,y_1),\ldots,f(x_n,y_n),\ldots,f(x_N,y_N)]$ is an unknown vector of contrast function values in the nodes, $\mathbf{A} = (a_{rn})$ is the matrix mapping $\mathbf{w}$ to $\mathbf{t}$, and a_{rn} measures the contribution of w_n to t_r. Equation (2) can be effectively solved using iterative methods. In this work, expectation maximization (EM), algebraic reconstruction technique (ART), simultaneous algebraic reconstruction technique (SART) and its combinations were investigated. For monitoring thermal cancer treatment it is necessary to accurately measure the maximum temperature value T_{max}. For this reason, the reconstructed temperature value ($T_{\max}^{rec}$) at the focus is a criterion for assessing the reconstruction quality. Another criterion is the mean square error of reconstruction over all the nodes:

$$dT^{rec} = \sqrt{\sum_{n=1}^{N} (T_n - T_n^{rec})^2 / N}. \quad (3)$$

A. Expectation Maximization (EM) technique

The EM technique [3-6], which produces the maximum likelihood estimates in the Poisson environment, is formulated [7] as follows:

$$w_n^{(k+1)} = w_n^{(k)} \left(\frac{\sum_{r=1}^{R} a_{rn} (t_r / \overline{t_r})}{\sum_{r=1}^{R} a_{rn}} \right), \quad (4)$$

where the initial estimate was a vector $\mathbf{w} = [0.01,\ldots, 0.01]$, $n = 1,\ldots,N$ and:

$$\overline{t_r} = \sum_{n=1}^{N} a_{rn} w_n^{(k)} \quad (5)$$

B. Algebraic Reconstruction Technique

The version of ART is formulated [8] as follows:

$$\mathbf{w}_r = \mathbf{w}_{r-1} + \frac{\beta}{|a_r|^2}(t_r - a_r^T \mathbf{w}_{r-1}) a_r \quad (6)$$

where $r = 1,\ldots, R$, and the relaxation coefficient β is in the range $0 < \beta < 2$. This is one iteration step, after which it passes from approximation $\mathbf{w}^{(k)}$ to approximation $\mathbf{w}^{(k+1)}$.

C. Simultaneous Algebraic Reconstruction Technique

The SART method is formulated [9] as follows:

$$w_n^{(k+1)} = w_n^{(k)} + \beta \left(\frac{\sum_{r=1}^{R} a_{rn} \frac{(t_r - \overline{t_r})}{\sum_{n=1}^{N} a_{rn}}}{\sum_{r=1}^{R} a_{rn}} \right), \quad (7)$$

where $\overline{t_r}$ is the same as in equation 5, $n = 1,\ldots, N$, and the relaxation coefficient β is in the range $0 < \beta < 2$ as before.

III. Results of Temperature Reconstruction

Figure 2 shows an original temperature distribution (a), which has two peaks (one circular and one ellipsoidal), its reconstruction from data without noise (b), from data with noise (c) and cross sections (d). The EM technique with the number of iterations $N_I = 50$ was used for reconstruction. Figure 3 shows the reconstruction of a circular peak from noisy data using two methods for improving the image: filtering (a) and a threshold condition that the sound speed in heated tissue can only be higher than the background value (b). This condition is fulfilled, for example, in non-fatty liver tissue. Figure 4 shows reconstruction quality parameters as a function of N_I for various reconstruction methods, including EMART and EMSART. The research [10] has shown that:

(a) in ultrasonic tomography it is efficient to combine the different reconstruction techniques using one iteration obtained with the EM technique as an initial estimate for another iterative reconstruction method (like ART and SART).

(b) excluding ART (which gives a very large error) all the iterative techniques investigated (EM, EMART, SART, EMSART) gave similar reconstruction qualities if the optimal number of iterations was used, as shown in Figure 4.

(c) the peak value reconstruction accuracy increases with the number of iterations (Figure 4, first row), whereas the mean reconstruction error has a minimum for certain N_I and then increases (Figure 4, second row). This is because the large N_I value provides better reconstruction accuracy in the heated region, but also gives higher general noise in the reconstructed image. The optimal N_I value, which provides both good peak reconstruction accuracy and low noise, can be determined in verification experiments. For some methods, the relaxation parameter β allows the shape of the quality parameter functions from the number of iterations to be controlled to reduce the computation time. For $N_I = 50$, a typical value for the peak reconstruction error is ~0.5°C and for the mean square temperature reconstruction error is ~0.3°C.

(d) applying *a priori* information about physical properties of tissue and of heating process allows the reconstructed image to be significantly improved.

IV. Results of Temperature Reconstruction with Obstacles

In some situations the tissue may contain acoustically non-transparent objects (ANTOs) such as medical devices or implants, which cause missing parts in the projection data. Interpolation of the missing parts introduces very large errors, whereas elimination of the missing parts from the reconstruction process makes the problem under determined.

A special 'subset' method has been developed for temperature reconstruction in tissue with ANTOs (Figure 5). In this method, all the nodes in which the temperature has to be reconstructed are divided into 2 equal subsets, A and B. The EM technique (with the missing parts eliminated) is used to obtain an initial estimate $T_0(x,y)$ for the temperature values in all the nodes. Then the temperature values in the nodes from set A are assumed unknown, while the temperature values in the nodes from set B assumed known $T_0(x,y)$. This allows the number of unknowns to be reduced twice. Then subsets A and B are swapped to obtain $T(x,y)$ in all the nodes. The procedure is then repeated as the next 'subset' iteration, as shown in Figure 5.

The developed method represents, therefore, an improved modification of the EM technique [11]. The accuracy of the developed 'subset' method was investigated by computer modelling and compared with the known EM technique. Figure 6 shows an example of a temperature field with two ANTOs (a), its reconstruction by the 'subset' method from data without noise (b), from data with noise (c) and cross sections (d). It shows that ANTOs cause a reduction in the reconstructed peak temperature value. However, this reduction (~1.65°C) is less than for the EM technique alone (~2.1°C). This new method, therefore, may give a better opportunity to monitor the thermal cancer treatment of those parts of the human body, which contain acoustically non-transparent objects.

V. References

[1] N. R Miller, J. C. Bamber and P. M. Meaney, "Fundamental limitations of noninvasive temperature imaging by means of ultrasound echo strain estimations", Ultrasound in Medicine and Biology, vol. 28, No. 10, pp. 1319-1333, 2002.

[2] W. L. Straube and R. M. Arthur, "Theoretical estimation of the temperature-dependence of backscattered ultrasonic power for noninvasive thermometry", Ultrasound in Medicine and Biology,. vol 20, No. 9, pp. 915-22, 1994.

[3] G. Wang, D. L. Snyder, J. A. O'Sulivan and M. W. Vannier, "Iterative deblurring for CT metal artifact reduction", IEEE Trans. Med. Imag., vol. 15, pp. 657-664, 1996.

[4] D. L. Snyder, T. J. Schulz and J. A. O'Sullivan, "Deblurring subject to nonnegativity constraints", IEEE Trans. Signal Processing, vol. 40, pp. 1143-1150, 1992.

[5] L. A. Shepp and Y. Vardi, "Maximum likelihood reconstruction for emission tomography", IEEE Trans. Med. Imag., vol. MI-1, pp. 113-122, 1982.

[6] K. Chidlow and T. Möller, "Rapid emission tomography reconstruction", Volume Graphics, 2003.

[7] X. Li, M. Jiang and G. Wang, "A numerical simulator in VC++ on PC for iterative image reconstruction", Journal of X-Ray Science and Technology, vol. 11, No. 1, pp. 61 - 70, 2003.

[8] F. Natterer, The mathematics of computerized tomography. John Wiley & Sons, 1986, p. 137.

[9] M. Jiang and G. Wang, "Convergence of the simultaneous algebraic reconstruction technique (SART)", IEEE Transactions on Image Processing, vol. 12, No. 8, pp. 957 – 961, 2003.

[10] K. M. Bograchev and W. M. D.Wright, "Iterative methods of ultrasonic tomography for temperature imaging during thermal cancer treatments," submitted to IEEE Trans. Ultrason., Ferroelec. Freq Contr., unpublished.

[11] K. M. Bograchev and W. M. D. Wright, "Tomographic reconstruction of temperature distribution in the presence of acoustically non-transparent objects," submitted to J. Acoust. Soc. Am., unpublished.

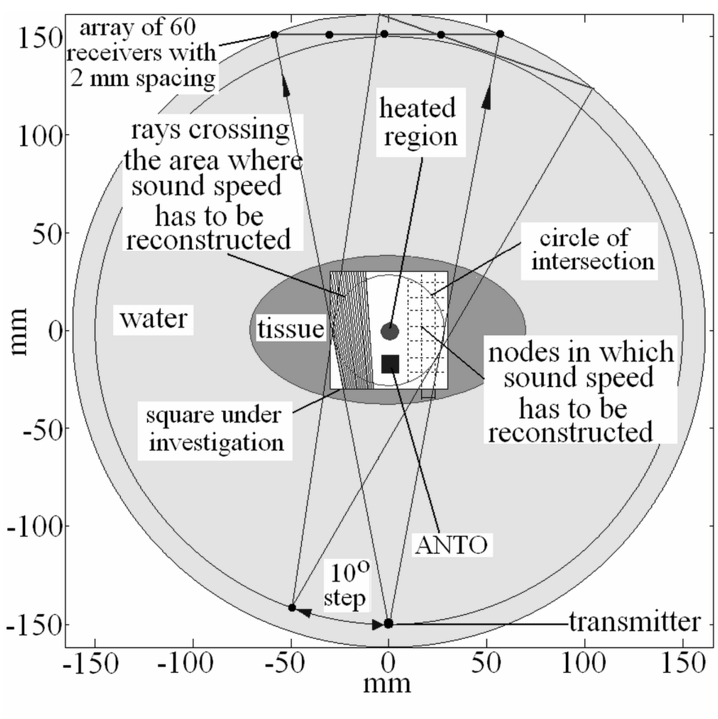

Figure 1. Schematic of the scanning geometry model.

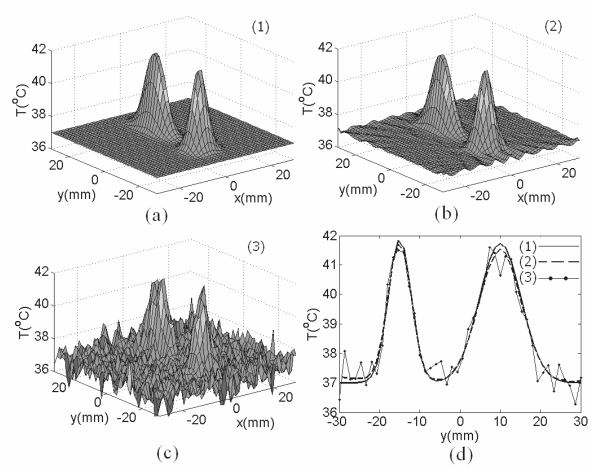

Figure 2. Reconstruction of circular and ellipsoidal temperature peaks.

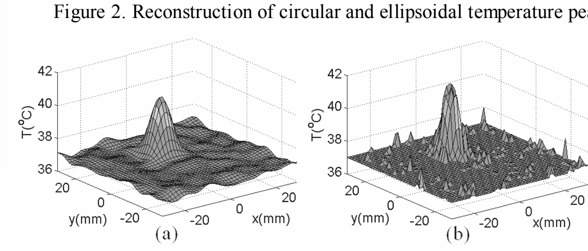

Figure 3. Improving the reconstructed image from noisy data.

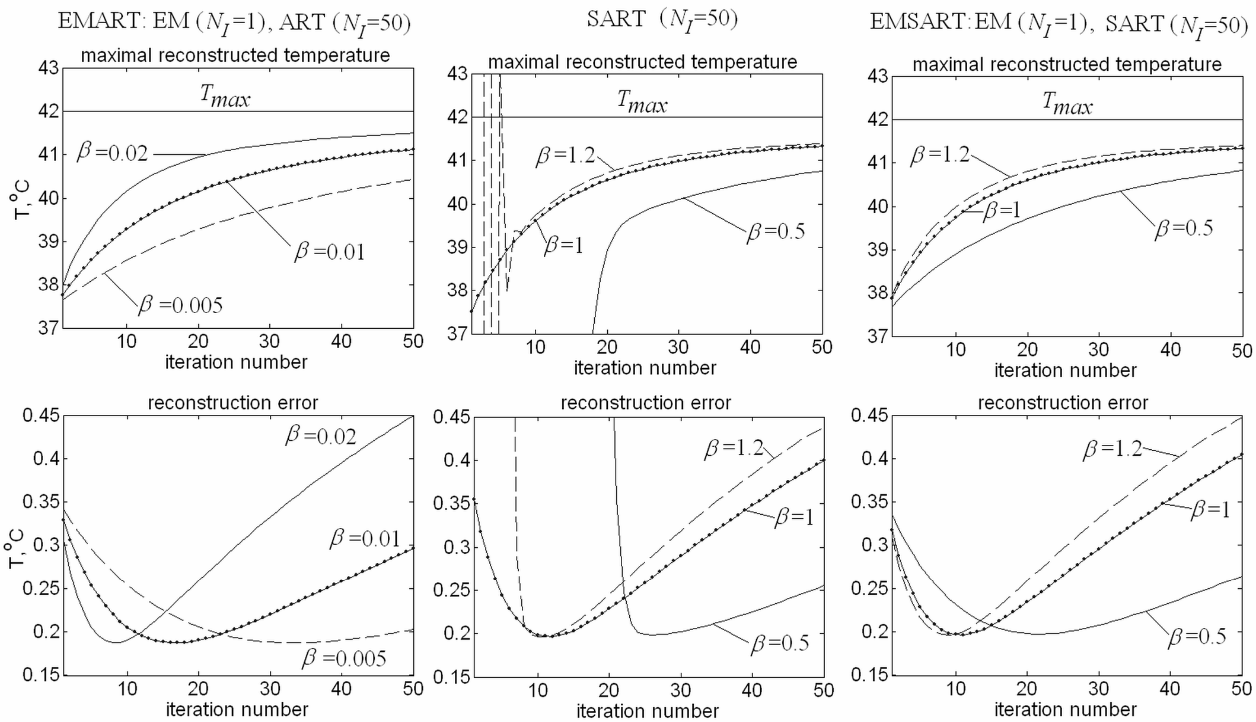

Figure 4. Reconstruction quality parameters as a function of the number of iterations for various reconstruction techniques.

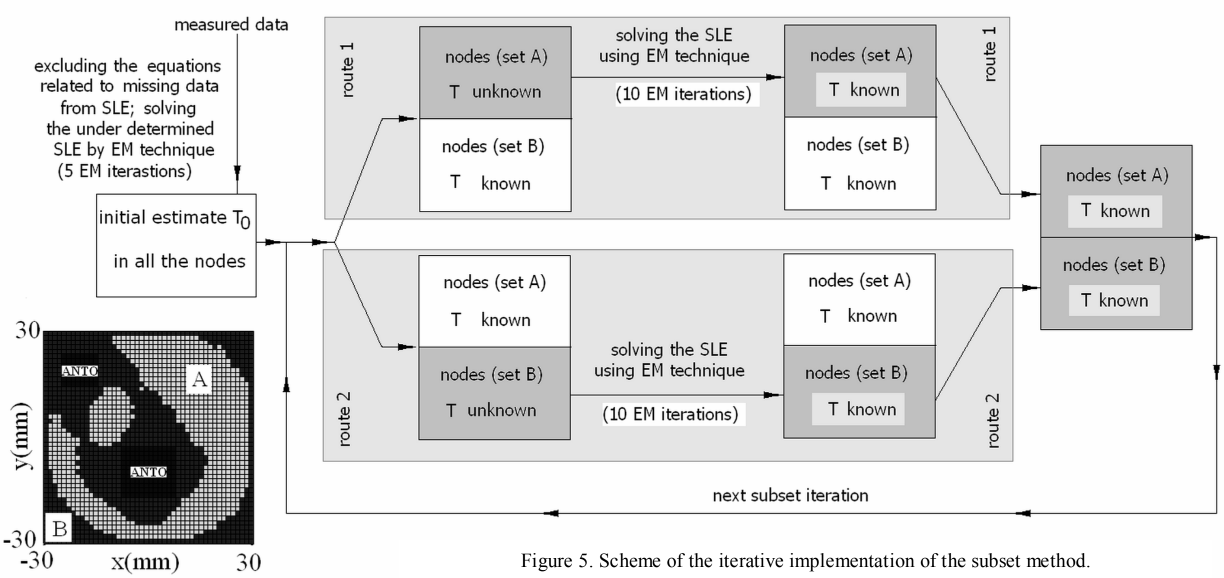

Figure 5. Scheme of the iterative implementation of the subset method.

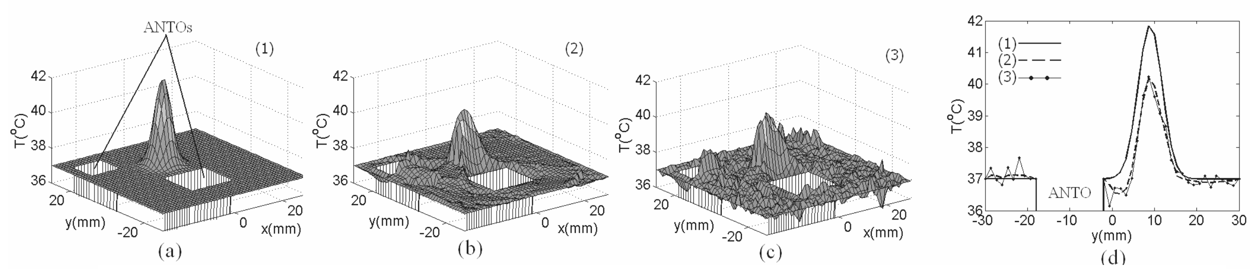

Figure 6. Reconstruction of a circular temperature peak in the presence of obstacles (ANTOs).