Computer modelling of iterative technique application for tissue thermal imaging

Konstantin M. Bograchev¹ and William M. D. Wright²
Department of Electrical and Electronic Engineering, University College Cork, Cork, Ireland
Email: ¹konstantinb@rennes.ucc.ie, ²bill.wright@ucc.ie

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-beam 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 the sound speed 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 x 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:

\[ t = A^w, \]  

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where $t = [t_1, ..., t_R]$ is a vector of all the measured propagation times, $w = [f(x_1, y_1), ..., f(x_N, y_N)]$ is an unknown vector of contrast function values in the nodes, $A = (a_{nm})$ is the matrix mapping $w$ to $t$, and $a_{nm}$ 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 $T_{\text{max}}$. For this reason, the reconstructed temperature value ($T_{\text{rec}}^{\text{max}}$) at the focus is a criterion for assessing the reconstruction quality. Another criterion is the mean square error of reconstruction over all the nodes:

$$d T^{\text{rec}} = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (T_n - T_{\text{rec}}^{\text{max}})^2}.$$  

(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:

$$w_n^{(t+1)} = \frac{\sum_{r=1}^{R} a_{mn} (t_r / \bar{T}_r)}{\sum_{r=1}^{R} a_{mn}}$$  

(4)

where the initial estimate was a vector $w = [0.01, ..., 0.01]$, $n = 1, ..., N$, and:

$$\bar{T}_r = \sum_{n=1}^{N} a_{rn} w_n^{(t)}$$

(5)

B. Algebraic Reconstruction Technique

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

$$w_r = w_{r-1} + \frac{\beta}{\lambda} (t_r - a_r w_{r-1}) a_r$$

(6)

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

C. Simultaneous Algebraic Reconstruction Technique

The SART method is formulated [9] as follows:

$$w_n^{(k+1)} = w_n^{(k)} + \beta \left( \frac{\sum_{r=1}^{R} a_{mn} (t_r - \bar{T}_r)}{\sum_{r=1}^{R} a_{mn}} \right)$$

(7)

where $\bar{T}_r$ is the same as in equation 5, $n = 1, ..., N$, and the relaxation coefficient $\beta$ 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 $\beta$ 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 $\sim 0.5^\circ\text{C}$ and for the mean square temperature reconstruction error is $\sim 0.3^\circ\text{C}$.

(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 $T_{10}(x,y)$. 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


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).