A Fast Method to Estimate SAR Distribution from Temperature Images Highly Affected by Noise

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Target audience: Anyone interested in the relationship between SAR and temperature.

Introduction: several methods to estimate SAR-induced temperature increase with simulations[1-3] and measurements [4] have been recently published because temperature has a more direct relationship to risk than does SAR. Specifically, MR thermometry [4] techniques are becoming popular and are used in various applications because they allow measurement of the distribution of temperature increase through a cross-section of the sample. However, 10g average SAR is still the quantity most used to assess safety with reference to existing guidelines, even though it is troublesome to measure since it is complicated to have an accurate estimate of the electric fields and electric conductivity maps of the tissues. Recently, a method to estimate SAR distributions from MR thermometry maps has been presented [5]. In this work we propose a fast and simple alternative method to obtain SAR distributions from temperature increase maps based on the inversion of a recently-published digital filter approach to rapidly calculating temperature from SAR [2].

Methods: The method is here applied to the simulated temperature distribution of a cylindrical phantom after 10 minutes of heating. Strong background noise was added to simulate a more realistic scenario, since MR thermometry images can be highly affected by noise. The bioheat equation governing the relationship between the SAR distribution and temperature increase T for the phantom is: $\rho c \frac{\partial T}{\partial t} = \nabla \cdot (k \nabla T) + \rho SAR$ (1), where c is the heat capacity, k the thermal conductivity and ρ the material density. Eq. 1 can be solved by approximating the effect of the thermal conductivity with intermittent application of a digital filter to the solution of the differential equation $\rho c \frac{\partial T}{\partial t} = \rho SAR$ (2), where the thermal conductivity is neglected during short time intervals of duration t_{int}. The digital filter operates in the Fourier domain and filter design has been described thoroughly [2]:

$$P(\lambda_x, \lambda_y, \lambda_z) = \frac{1}{\left(1+\frac{i\lambda_x}{p_{x1}}\right)^{\alpha_{x1}}\left(1+\frac{i\lambda_x}{p_{x2}}\right)^{\alpha_{x2}}\left(1+\frac{i\lambda_y}{p_{y1}}\right)^{\alpha_{y1}}\left(1+\frac{i\lambda_y}{p_{y2}}\right)^{\alpha_{y2}}\left(1+\frac{i\lambda_z}{p_{z1}}\right)^{\alpha_{z1}}\left(1+\frac{i\lambda_z}{p_{z2}}\right)^{\alpha_{z2}}} \qquad (3)$$

where λ_x, λ_y and λ_z are the spatial frequencies in the Fourier domain corresponding to x, y, and z directions in space, respectively; p_{x1}, p_{y1}, and p_{z1} are the first cutoff frequencies and p_{x2}, p_{y2}, and p_{z2} the second cutoff frequencies in the Fourier domain. In addition, α_{x1}, α_{y1}, and α_{z1} are the orders of the first cutoff frequencies, and α_{x2}, α_{y2}, and α_{z2} the orders of the second cutoff frequencies. The optimum parameters for three different time intervals t_{int} as a function of object size and resolution are reported in [2]. In the inversion process, a first preprocessing step, 3D variational denoising, was performed using the TGV^2 functional [6]. Due to its ability to preserve both sharp image boundaries as well as smooth signal changes, this image model is particularly well suited for temperature maps.

It can be shown that the temperature increase after n time intervals can be written as $T_n = \sum_n F^{-1}\left\{P^n\, F\left\{t_{int} \frac{SAR}{c}\right\}\right\}$ (4) where F and F^{-1} represent respectively the Fourier and the inverse Fourier transform operator [2]. Given a temperature distribution, it is possible to obtain the unaveraged SAR distribution by inverting this process: $SAR = \frac{c}{t_{int}}\, F^{-1}\left\{\frac{1}{\sum_n P^n}\, F\{T_n\}\right\}$ (5) . Since the inversion of the filter P in Eq. 5 acts as a perfect high-pass filter, an additional gentle low-pass filter has been added to avoid enhancement of discontinuities at the edges. Finally, the 10g SAR distribution has been computed with a method published previously [2].

Results and Discussion: Even though the noise dominates the initial temperature image, its effects are strongly reduced in the final reconstructed average 10g SAR distribution, mainly due to the denoising function. The noise is also not amplified for a digital filter P designed to use time intervals t_{int} larger than those allowed by direct Finite Difference methods. The method presented estimates a maximum value of 10g SAR average with a difference of less than 4.5% respect to the original value (Figure 1). The process is also very fast: for the examined case the computation time was less than 5 minutes.

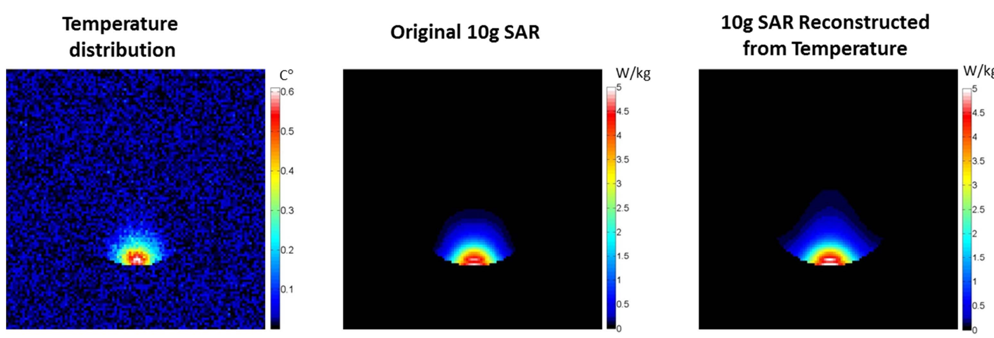

Figure 1: Spatial distributions of temperature increase affected by noise (left), 10g SAR average which generated the temperature distribution (center), reconstructed 10g SAR from the noisy temperature distribution (right).

Conclusion: The speed and the accuracy of this new method, and its ability to be unaffected by strong noise that may be present in temperature images can be considered a useful tool to estimate SAR from noisy temperature images.

Refernces: [1] Collins CM *et al*., JMRI, 19:650-656, 2004. [2] Carluccio G *et al*., IEEE TBME, 60:6:1735-1741, 2013. [3] D Shrivastava, JT Vaughan, 2009, J Biomech Eng., Jul;131(7):074506. [4] Cao Z *et al*., Proc. 21st ISMRM 2012, p. 312. [5] Alon L. *et al*. Proc. Bioelectromagnetics, Greece, 2013, PA-77. [6] Knoll, F. *et al*., MRM, 65, 480-491, 2011.