T2 estimation for small lesions using a Model-Based reconstruction with sparsifying penalty functions and highly under-sampled radial FSE data

C. Huang[1], A. Bilgin[2], C. Graff[3], and M. I. Altbach[4]

[1]Dept of Mathematics, University of Arizona, Tucson, Arizona, United States, [2]Department of Electrical and Computer Engineering, University of Arizona, [3]Program in Applied Mathematics, University of Arizona, [4]Dept of Radiology, University of Arizona

Introduction: T2 weighted MRI is used clinically for characterization of various pathologies. Currently, radiologists use visual methods to evaluate the T2 characteristics of a lesion based on signal intensity changes. It has been demonstrated that quantitative methods for measuring T2 values are superior to visual evaluation [1, 2]. For body imaging, however, many of the proposed methods to measure T2 values suffer from long acquisition times, motion-induced errors, misregistration of images acquired in different breath holds, low spatial resolution and/or low number of measured points on the T2 relaxation curve. A radial fast spin-echo (FSE) method was developed for fast T2 mapping of the body[3]. The method uses data from undersampled TE data sets which are mixed appropriately to produce images with different TE contrast from a single k-space data set. As pointed out in [3], the mixing of TE's, however, introduces artifacts in the image and the accuracy of T2 is compromised when lesions or structures are very small.

To overcome this problem we proposed a model-based approach with sparsifying penalty functions for estimating T2's from radial FSE data. Sparse reconstructions have received considerable attention recently since Compressed Sensing theory illustrated that signals with sparse representations can be reconstructed from a small number of measurements.

Theory: An iterative reconstruction for T2 mapping from radial FSE data can be formulated as [4]:

$$\arg\min_{\boldsymbol{\rho},\mathbf{T_2}} \sum_j \| F(\boldsymbol{\rho},\mathbf{T_2},TE_j) - \mathbf{K}_j \|^2 + \sum_i \lambda_i P_i(\boldsymbol{\rho},\mathbf{T_2}) \qquad (1)$$

In this formulation the goal is to minimize the inconsistency between the acquired data and the T2 decay model (data consistency term) subject to penalty functions $\boldsymbol{P_i}$. In Eq. 1, $\boldsymbol{\rho}$ and $\mathbf{T_2}$ are the proton-density and T2 maps, respectively. $\mathbf{K}_j$ is the measured k-space data at echo time $\mathbf{TE}_j$. $\boldsymbol{F}$ denotes the single exponential T2 decay model which depends on $\boldsymbol{\rho}$, $\mathbf{T_2}$, and $\boldsymbol{TE_j}$. $\boldsymbol{F}$ can be computed as

$$F(\boldsymbol{\rho},\mathbf{T_2},TE_j) = FT(\boldsymbol{\rho}\cdot e^{-TE_j/\mathbf{T_2}}) \qquad (2)$$

where $\boldsymbol{FT}$ is the forward Fourier transform operator.

Methods: In order to have the "truth" for T2 evaluations we used a computer generated phantom of an axial cut through the abdomen [5]. In the phantom the different organs have been generated using T2 and T1 and ρ distributions compatible with in vivo values as well as imaging conditions that are typical for breath hold T2-weighted imaging with a radial FSE pulse sequence (ETL=16, echo spacing = 10 ms, TR=1.5 s, acquisition matrix =256 (readouts) x 256 (views) yielding a total of 16 views for each of the 16 TE data sets). Six lesions (sizes listed in Table 1) with T2 values representing typical liver lesions were added to the phantom as shown by the bright circular regions in Fig. 1. K-space measurements were generated from the phantom using a Fast Fourier Transform (FFT) operation and keeping the samples along approximately radial lines as was done in [6]. Gaussian noise was added independently to the real and imaginary components of k-space to give an SNR comparable to in vivo images. In our experiment five noise realizations were used.

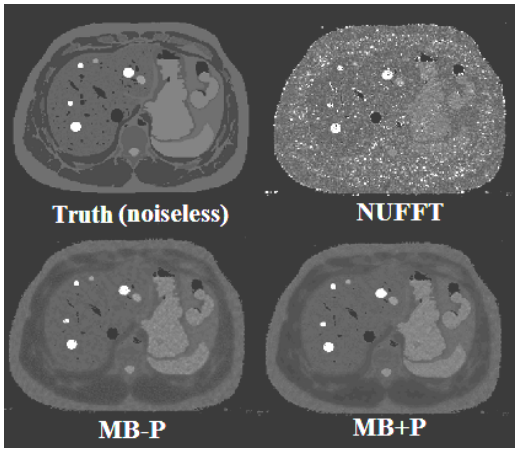

Figure 1. T2 map generated by different methods

Table 1. Comparison among the T2 estimation methods

	Small Lesions (diameter about 5 pixels)						Large Lesions (diameter about 10 pixels)					
	Lesion 1 True T2=232 ms		Lesion 2 True T2=200 ms		Lesion 3 True T2=100ms		Lesion 4 True T2=250 ms		Lesion 5 True T2=200 ms		Lesion 6 True T2=100 ms	
	Mean T2 bias	σ	Mean T2 bias	σ	Mean T2 bias	σ	Mean T2 bias	σ	Mean T2 bias	σ	Mean T2 bias	σ
NUFFT	33.8%	44.0%	66.6%	10.3%	33.7%	2.74%	33.7%	30.9%	20.0%	16.6%	15.3%	2.56%
MB-P	3.70%	4.87%	6.12%	1.36%	4.25%	2.29%	5.80%	4.13%	2.85%	3.69%	5.10%	2.96%
MB+P	3.46%	2.11%	4.3%	1.32%	2.2%	1.01%	1.3%	1.00%	2.8%	0.74%	4.66%	0.85%

T2 maps were generated using Eq. 1. The values of the weights λ_i were determined empirically. Alternatively an L-curve analysis can be used for selection of the weights. A steepest descent algorithm was used for minimizing the cost function. The initial value of T2 for all the pixels was set to 20 ms. For comparison, T2 maps were also generated from TE images (total of 16 images) reconstructed using non-uniform fast Fourier transform (NUFFT).

Results: Results for the T2 estimation using the NUFFT reconstruction and model-based reconstruction with and without sparse penalty functions (MB+P and MB-P, respectively) are shown in Fig. 1 and Table 1. Note that in Fig. 1 the NUFFT T2 map has significant undersampling artifacts whereas the maps obtained with MB+P and MB-P are comparable to the "Truth". Also, note that the T2 biases reported in Table 1 are much larger for the NUFFT than for the MB+P and MB-P for most lesions. Differences between the MB+P and MB-P methods can be assessed by comparing the σ in Table 1 which is the standard deviation of the %T2 bias among the 5 noise realizations. In general the σ's are larger for MB-P. Note that the ratio $\sigma_{MB\text{-}P}/\sigma_{MB+P}$ yields values: 2.31, 1.04, 2.26, 4.10, 4.98, 3.48, which indicates that in general the MB+P method is more stable than the MB-P method.

Conclusions: In this work we showed that a model-based reconstruction yields accurate T2 estimates of small lesions from highly undersampled data. We also showed that adding sparsifying transforms as prior constraints improves the specificity of the reconstruction process. This novel method has great potential for characterization of small neoplasms in the body, where the acquisition time is restricted to a breath hold.

Acknowledgement: NIH grants: CA099074 and HL085385.

References: [1] Cieszanowski A et al *Eur Radiol.* 12:2273, 2002. [2] Kim YH et al *J Comput Assist Tomogr*. 29:571, 2005. [3] Altbach MI, *MRM* 54:549, 2005. [4] Block KT et al ISMRM 16, 1432, 2008. [5] Graff C et al ISMRM 16, 492, 2008. [6] Candes E et al *IEEE IT* 52:2, 2006