Region Based Joint Bi-exponential T2 Fitting for Small Lesions

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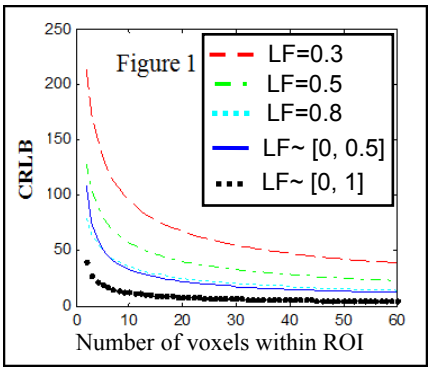
Introduction: T2 estimation has proven to be a valuable quantitative tool for assessing pathologies. It plays a particularly important role in the characterization of liver lesions (1). Partial volume is generally a factor in lesion T2 estimation, particularly for lesions with diameters < 15 mm. In order to obtain accurate T2 estimates for lesions with partial volume, bi-exponential fitting is required. However, bi-exponential model fitting suffers from large uncertainty of the fitted parameters when noise is present (2). To reduce this uncertainty one approach, known as region fitting (RF), is to combine the signals of voxels within a region-of-interest (ROI) to increase the SNR of the individual time points and improve estimation (3).

In this work, we propose a novel ROI-based joint bi-exponential fitting (JBF) algorithm to estimate T2 of lesions affected by partial volume. This approach takes advantage of the lesion fraction (*LF*) variation among voxels within an ROI, a factor that is neglected in the conventional RF approach.



Theory: The signal from a voxel containing a mixture of lesion and background tissue can be modeled by a bi-exponential decay:

$$s(TE) = I_l\, e^{-TE/T2_l} + I_b\, e^{-TE/T2_b} + \varepsilon(TE), \quad [1]$$

where I_l, I_b are the equilibrium signal intensity of the lesion and background tissue, $T2_l$, $T2_b$ are the corresponding T2 values, $\varepsilon(TE)$ are independent and identically distributed (complex) Gaussian noise at echo time (*TE*). Under the assumption that the lesion and background are homogeneous for small lesions, we can constrain $T2_l$, $T2_b$ on each voxel inside the lesion's ROI to two global quantities $\overline{T}2_l$, $\overline{T}2_b$. The proposed JBF algorithm is expressed as:

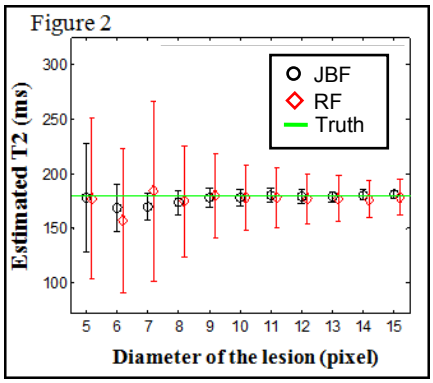
$$\underset{I_l^1,\cdots,I_l^M,I_b^1,\cdots,I_b^M,\overline{T}2_l,\overline{T}2_b}{\arg\min} \{\sum_{n=1}^{N}\sum_{m=1}^{M} \| I_l^m e^{-TE_n/\overline{T}2_l} + I_b^m e^{-TE_n/\overline{T}2_b} - s_m(TE_n)\|^2\}, \quad [2]$$

where I_l^m, I_b^m are the signal intensity of the m^{th} voxel inside the lesion's ROI, and $s_m(TE_n)$ is the signal from the m^{th} voxel at TE_n.

Methods: Cramer-Rao Lower Bound (CRLB) analysis, which estimates the lower bound for the standard deviation of any unbiased estimator, was used to evaluate the effects of *LF* on the uncertainty of T2 estimation. In this analysis, we chose $T2_l$=180 ms and $T2_b$=40 ms to represent a lesion within the liver (background) that is near the cutoff between benign and malignant neoplasms (4). In the CRLB analysis we compare the effects of a constant *LF* (fixed to 0.3, 0.5, 0.8) within the lesion's ROI to a uniformly distributed *LF* with intervals of [0, 0.5] and [0, 1].

A numerical phantom where TE images were generated for a spherical lesion embedded in a background (with the lesion centered at the edge of the background slice) was used in the evaluation. Parameters were chosen to mimic clinical liver imaging: ETL (ie, number of TE points)=16, echo spacing=8 ms, in-plane resolution=1.4 mm/pixel, slice thickness=8 mm, SNR at TE_0 was 60, $T2_l$=180 ms, $T2_b$=40 ms. The lesion diameter was varied from 6-12 pixels. Independent Gaussian noise was added to the complex Fourier data. Ten noise realizations were used for statistical evaluation.

Physical phantom data were acquired on a 1.5T MRI scanner. The phantom consisted of 5-mm vials (filled with gels of different concentrations to yield different T2s) embedded in a background with T2=34 ms. As shown in Figure 3 (bottom is a close up of the top), an oblique slice was used to create ROIs containing voxels with a mixture of vial and background. Data were acquired with a Fast Spin Echo sequence yielding data for 16 TEs (with 256 k-space lines per TE), echo spacing=8.29ms, TR=1s, slice thickness = 8mm. The FOV was set to 20 cm to yield roughly a 6-pixel diameter object for the 5 mm diameter tubes.



Results: Figure 1 shows the CRLB of the standard deviation for the lesion T2 estimator for ROIs of different sizes. When the *LF* for all voxels in the ROI is constant, the CRLB analysis indicates that the lower bound of the T2 standard deviation is dependent on *LF*; the higher the *LF* the lower the CRLB. When *LF* is uniformly distributed within the ROI, the CRLB is significantly lower than when *LF* is constant, with the uniform distribution in the interval [0,1] yielding the lower CRLB.

Figure 2 shows a plot of T2 estimated with the RF and JBF algorithms for a numerical phantom where the lesion diameter is varied. Note that the standard deviations of the JBF estimation are considerably smaller than for the RF algorithm which is consistent with the CRLB analysis.

To evaluate results using real MRI data we used the physical phantom shown in Figure 3. We estimated T2s within the two ROIs indicated by the yellow squares. The gold standard T2 of the vial crossing ROI #1 is 76 ms and the estimated T2 using the JBF algorithm was 77 ms. The RF estimated both background T2 and lesion T2 to be 63 ms. For vial crossing ROI #2, the gold standard T2 is 204 ms and the T2 estimated by JBF was 202 ms. RF yielded T2=356 ms. Thus the results on the physical phantom also indicate the JBF algorithm is superior to the RF approach.

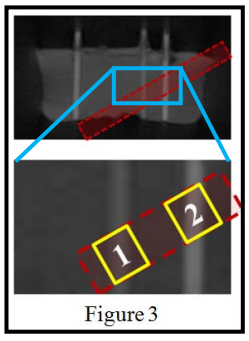


Figure 3

Conclusions: In this work we proposed a novel algorithm to correct partial volume effects in lesion T2 estimation. The algorithm reduces the uncertainty of the fitted parameter by exploiting the variation of *LF* (which is naturally present in ROIs containing small lesions). We demonstrated that with the proposed JBF algorithm the T2 estimation of small structures was considerably better than with the conventional region fitting approach. Unlike the conventional RF algorithm, JBF also provides estimates of the signal intensities for each tissue and for each voxel (I_l^m, I_b^m) which can be useful for other applications such as brain volume calculation. This study can be easily expanded to multi-channel coil data by including joint estimation from different channels (5) to Eq. [2].

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References: (1) Cieszanowski A, et al. Euro. Radiol, 2002:12, pp2273 (2) Bretthorst GL. Concepts Magn. Reson., 2005; 27A, pp73 (3) Graham SJ, et al. MRM, 1996:35, pp370 (4) Altbach MI, et al. JMRI, 2002:16, pp179 (5) Quirk JD, et al. JMR 2009:198, pp49