Impact of the noise model on intra-voxel incoherent motion (IVIM) parameter estimates in abdominal DW-MRI

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Introduction: Diffusion-weighted MRI (DW-MRI) is a non-invasive imaging technique sensitive to the thermally-driven, random motion of water molecules modified in living tissue by the interaction with cell membranes and macromolecules. This microscopic motion is most commonly characterized through a decay of water signal with b-factor represented as a mono-exponential function associated with the so-called, apparent diffusion coefficient (ADC) as the decay rate parameter, expressed conveniently in units of $\mu m^2/ms$. (1) Depending on the acquisition parameters, in-vivo measurements of the ADC are known to reflect a combination of both diffusive and perfusive motions. (2) The intra-voxel incoherent motion bi-exponential model (IVIM), as initially proposed by Le-Bihan et al. (3), attempts to separate intra- and extracellular water diffusion from the incoherent motion of water molecules within randomly oriented capillaries. Several studies have utilized IVIM DW-MRI parameters for various clinical applications in the abdomen including the differential analysis of tumors and the assessment of liver cirrhosis.

Commonly IVIM model-fitting methods, including least-squares (LS) (4), segmented least-squares (SLS) (5), and Bayesian model fitting (2), assume the measured signal is altered from the ideal signal by additive Gaussian noise with zero mean and some variance. However, the MR signal from magnitude reconstructions is known to be altered by additive Rician noise (6) as opposed to Gaussian noise. As the raw signal becomes attenuated in DW-MRI, it yields a relatively low signal-to-noise ratio in which Rician noise has a very different form from Gaussian noise. As previously shown, the maximum likelihood estimator for the Stejskal-Tanner mono-exponential model that accounts for Rician noise is the least biased for ADC estimation, with higher sensitivity to heterogeneity in the ADC values found in both simulations and in vivo mice experiments.(7) However, the influence of the assumed noise model on the IVIM model parameters has not, to our knowledge, been fully explored. The purposes of this study were to 1) develop a maximum-likelihood estimator for the bi-exponential IVIM model parameters that accounts for Rician noise (ML_R); and 2) assess the differences in estimated IVIM model parameters due to the assumed noise model through in-vivo imaging studies of human abdominal organs.

Materials and Methods: We obtained images from 15 subjects; 9 males and 6 females with a mean age of 14.13 (range 7-24, std 4.09) that underwent MRI studies between Sep. 2010 and Mar. 2011. We carried out MR imaging studies of the abdominal organs using a 1.5-T unit (Magnetom Avanto, Siemens Medical Solutions, Erlangen, Germany) and a body-matrix coil and spine array coil for excitation and receiving. We performed free-breathing single-shot echo-planar imaging using the following parameters: repetition time/echo time (TR/TE) = 6800/59 ms, SPAIR fat suppression, matrix size = 192×156, field of view = 300×260 mm, number of excitations = 1, slice thickness/gap = 5 mm/0.5 mm, 40 axial slices, 8 b-values = 5,50,100,200,270,400,600,800 s/mm^2. A tetrahedral gradient scheme, first proposed in Conturo et al. (8), was used to acquire 4 repeated images at each b-value with an overall scan acquisition time of 4 min. Using the ITK-SNAP software tool , we completely segmented the abdominal organs (i.e., the liver, spleen, kidneys, and pancreas), and were thus able to define the ROIs for parameter estimates. However, as the cortex and medulla of the kidney have different diffusivity properties, we analyzed each of these sub-structures separately.

The IVIM model was fitted to the data for each voxel in the ROI assuming Rician noise model with our proposed ML_R estimator:

$$[s_0, D^*, D, f] = \arg\max_{s_0, D^*, D, f} \sum_{i=1}^{N} \ln I_0\left(\frac{s_i m_i}{\sigma_R^2}\right) - \sum_{i=1}^{N}\left(\frac{m_i^2}{2\sigma_R^2}\right)$$

In addition, the IVIM model was fitted to the data assuming Gaussian noise model with the LS (4) and the SLS (5) estimators.

We examined the in-vivo measurements of the IVIM model parameters values according to organ, subject, and estimation method. We used the "repeated measures one-way analysis of variance" (ANOVA) method to test the statistical significance of the differences among the various estimation methods. For all analyses, $P < .05$ was accepted as indicating a significant difference.

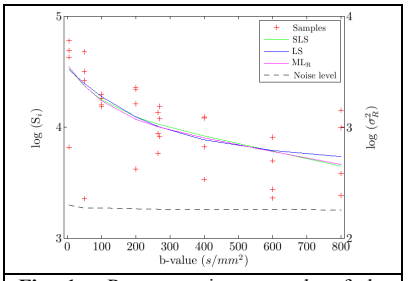

Fig. 1: Representative example of the fitted curves using the SLS, LS, and ML_R estimators for one voxel in the liver.

Results: Fig. 1 presents representative examples of the fitted curves using the different estimators with the acquired DW-MRI data. Table 1 depicts average IVIM model parameters values for the following abdominal organs: liver, kidney, spleen, and pancreas, estimated respectively with the SLS, LS and ML_R estimators. For all organs, the SLS method estimates higher D values compared to the LS and ML_R methods. For all organs except the spleen, the SLS method estimates lower D* and f values as compared to the LS and MLR methods. The medulla of the kidney and the liver, which have higher perfusion compartments as compared to the other organs, showed the greatest discrepancies between the SLS and ML_R estimators; specifically, ~30% in the f values; ~20% in the D* values; and ~12% in the D values. Between the LS and the ML_R estimators, however, we observed much smaller discrepancies in the range of ~2%-3% of the ML_R. The differences among the estimated IVIM model parameters values using the different estimation methods were significant (one way ANOVA with repeated measures, $p < 0.05$). The spleen was the one notable exception because of its lower perfusivity as compared to other abdominal organs.

Table 1	***f***			***D**** **(μm²/ms)**			***D*** **(μm²/ms)**		
	SLS	**NLLS**	**ML_R**	**SLS**	**NLLS**	**ML_R**	**SLS**	**NLLS**	**ML_R**
Liver	0.19(0.04)	0.24(0.04)	0.24(0.04)	21.44(3.92)	25.38(3.25)	25.42(3.68)	1.12(0.12)	1.06(0.12)	1.09(0.11)
Kidney Cortex	0.10(0.02)	0.14(0.02)	0.13(0.02)	17.87(2.92)	20.77(3.67)	20.62(3.52)	1.93(0.06)	1.93(0.06)	1.94(0.06)
Kidney Medulla	0.24(0.05)	0.32(0.06)	0.31(0.07)	16.98(5.12)	20.33(7.35)	20.35(7.13)	1.51(0.05)	1.41(0.08)	1.44(0.08)
Kidney (entire)	0.16(0.04)	0.21(0.05)	0.21(0.05)	17.74(3.39)	20.96(4.70)	20.81(4.56)	1.76(0.06)	1.71(0.08)	1.73(0.08)
Spleen	0.10(0.04)	0.13(0.05)	0.13(0.05)	16.80(4.99)	17.83(4.32)	17.87(3.99)	0.94(0.07)	0.90(0.07)	0.91(0.07)
Pancreas	0.30(0.12)	0.36(0.12)	0.36(0.12)	19.84(6.51)	24.41(9.16)	24.00(9.03)	1.04(0.22)	0.96(0.22)	0.99(0.22)

Discussion: Our in-vivo measurements show that the SLS method may yield discrepancies of up to 30% in the f values; 20% in the D* values; and 12% in the D values as compared to the LS and MLR estimates. These results suggest that simultaneous optimization of the entire set of IVIM model parameters rather than separate optimization of each parameter (as done in the SLS approach) is warranted.

The differences between the LS and MLR estimators were relatively small (~2%-3%), but statistically significant, reflecting the effect of the assumed noise model on the parameter estimates. In conclusion, we have demonstrated that the choice of the assumed noise model and estimation method have a substantial impact on the calculated IVIM model parameters. In addition, we show that the SLS method is sensitive to actual perfusion parameters; hence, its impact on the IVIM parameter values differs among the several abdominal organs included in this study.

Bibliography:

1. Stejskal EO, Tanner JE. J Chem Phys 1965;42:288–292.
2. Koh DM, Collins DJ, Orton MR. Am J Roentgeno 2011;196(6):1351-1361.
3. Le Bihan D, et al. Radiology 1988;168(2):497-505.
4. Yamada I, et al. Radiology 1999;210(3):617-623.
5. Sigmund EE, et al. Magn Reson Med 2011;65(5):1437-1447.
6. Gudbjartsson H, Patz S. Magn Reson Med 1995;34(6):910-914.
7. Walker-Samuel S, et al. Magn Reson Med 2009;62(2):420-429.
8. Conturo TE, et al. Magn Reson Med 1996;35(3):399-412.