Validation of mean apparent propagator MRI

Alan Seth Barnett[1,2], Elizabeth Hutchinson[1,2], Ferenc Horkay[1], Michal Komlosh[1,2], Evren Ozarslan[3], Carlo Pierpaoli[1], and Peter Basser[1]
[1]NICHD, NIH, Bethesda, MD, United States, [2]CNRM, USUHS, Bethesda, MD, United States, [3]Department of Radiology, Harvard Medical School, Boston, MA, United States

Introduction

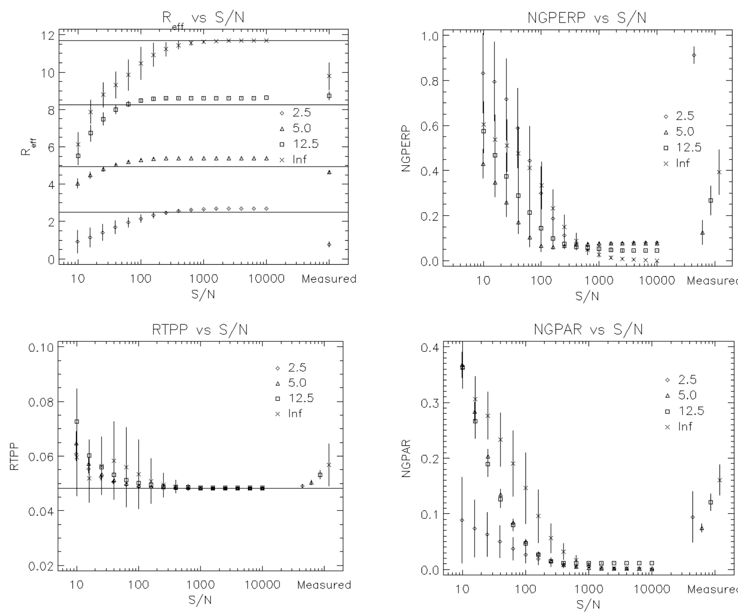
Mean apparent propagator (MAP)-MRI uses diffusion MRI data to estimate the diffusion propagator[1]. The method employs simple harmonic oscillator wave functions as the basis functions in which to expand the propagator. The coefficients of the expansion are determined by fitting diffusion MRI data. The fit results can be used to compute the diffusion orientation distribution function (dODF) in addition to several parameters that characterize the propagator. In this work we use numerical simulations and diffusion data acquired on a special calibrated phantom to assess the accuracy and precision, as a function of signal-to-noise ratio (S/N), of the determination of four of the parameters: Return To Axis Probability (RTAP), Return To Plane Probability (RTPP), parallel Non-Gaussianity (NGpar), and perpendicular Non-Gaussianity (NGperp).

METHODS

To assess the performance of MAP-MRI we use a model system consisting of a glass capillary array (GCA). Our GCA phantom comprises multiple layers. Each layer is between 0.5mm and 2.0 mm thick and contains parallel cylindrical pores with uniform radius; the pore radii are 2.5μm, 5μm, and 12.5μm. In addition, there is layer of free water. We acquired a dataset consisting of 432 diffusion weighted images with b-values between 180 and 10600 s/mm^2. To analyze the data we wrote an IDL program that implemented, the method described in Reference 2In addition to the phantom data we also analyzed a synthetic dataset. We wrote a Matlab program that uses the multiple correlation functions (MCF) method[2] to simulate the phantom experiment..(The simulations assumed ideal (delta-function) diffusion pulses and did not include imaging gradients).We then added various amounts of Gaussian noise to the computed values, permitting us to examine the noise sensitivity of the parameter estimates.

RESULTS

The figures show the computed values of the effective radius (R_{eff} =1/sqrt(π*RTAP^2)), RTPP, NGpar and NGperp plotted vs S/N for the simulated data, as well as the values calculated form the cylinder phantom data. S/N is defined as the ratio of the anattenuated signal to the amplitude of the Gaussian noise introduced in each quadrature channel. For the phantom data, the noise level was estimated from the pixel values in the background. The horizontal lines in the figures show the "correct" value of the parameters. Calculated values of all parameters show a bias at low S/N; R_{eff} decreases while RTPP, NG_{perp} and NG_{par} increase as S/N decreases. The decrease in R_{eff} is larger for large diameter cylinders and free water than for small diameter cylinders. Furthermore, the non-Gaussianity parameters are more strongly affected than are R_{eff} and RTPP. S/N greater than 500 is required for unbiased determination of NG_{perp} and NG_{par}, while 100 would suffice for R_{eff} and RTPP. The S/N of the phantom data was about 140. At that S/N, the biases in the calculated NG_{perp} and NG_{par} values are not negligible. On the other hand, the measured RTPP in all compartments is close to the free water value, and the measured R_{eff} reflect the pore sizes. The anomalously small value for R_{eff} in the 2.5 μm array is probably due to the finite width of the diffusion pulses.



Discussion

Our results, while preliminary, imply that MAP-MRI parameters acquired at moderate S/N can be biased. A probable source of the bias is the signal floor imposed by the rectified noise. Using PIESNO[3] to reduce the effect of the noise floor should reduce the bias.

Our results have important implications for other methods of modeling non-Gaussian diffusion, such as Diffusion Kurtosis Imaging. Analogous biases probably affect all methods that involve fitting data that include magnitude images near the noise floor.

REFERENCES

[1]Ozarslan, E., et al., Neuroimage. **78**: p. 16-32.,
[2]Grebenkov, D.S., J Chem Phys, 2008. **128**(13): p. 134702.
[3]Koay, C.G., E. Ozarslan, and P.J. Basser, Journal of Magnetic Resonance, 2009. **197**(2): p. 108-119.