Mitigating the Effects of Motion in EPI Time Series

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Introduction Motion corrupts EPI time-series data through both voluntary and involuntary movements. The standard deviation of the motion typically varies over a range of .2 to 1.1 mm [1,2] in healthy adult subjects. Motion of this magnitude perturbs the steady-state magnetization thereby increasing the temporal variance. This variance can be reduced using restraint methods, image realignment, and exclusion of subjects with excessive motion but it is nevertheless a major source of variance. We propose a model that can be used to optimize sequence parameters, validate it using phantoms, and draw conclusions about optimal parameters.

Methods. For sufficiently small motions, the effect on the steady state magnetization can be approximated by the first two terms of its Taylor series expansion to yield the result that $\mathrm{SNR} = 1\Big/\sqrt{\sigma_T^2/s^2 + \sigma_{\mathrm{phys}}^2/s^2 + g^2(\sigma_p^2+\sigma_z^2)}$ where g is a gain that quantifies the sensitivity to motion, s is the signal, σ_T^2 is variance to due to thermal noise, σ^2_{phys} is the variance due to noise that modulates T_2^*, σ_p^2 is the variance of the pulsatile motion, σ_z^2 is the variance of the motion orthogonal to the slice plane, and w is the range of integration. The gain is given by

$$g^2 = \sum_{i=0}^{N-1}\left\| \int_{-w/2}^{w/2} b^{N-i-1}(z) f(z) \frac{\partial M_{ss}(z)}{\partial z} dz \right\|^2 \Bigg/ \left\| \int_{-w/2}^{w/2} f(z) M_{ss}(z) dz \right\|^2 \qquad (1)$$

where $b(z)=\cos\theta(z)\exp(-\Delta t/T_1)$, Δt is the TR, M_{ss} is the steady state magnetization, and $f(z)$ is a complex-valued function describing the mapping of M_{ss} into the transverse plane. If the pulsatile motion is small and the physiological noise constant, the model can be simplified to $\sigma^2 = \mathrm{SNR}^{-2} = \sigma_0^2 + g^2\sigma_z^2$. The motion variance, σ_z^2 was estimated from motion covariates computed with AFNI as the variance of the motion of a point at coordinates (5,5,5) cm relative to the center of rotation. This variance overestimates the through-slice component of motion by including all three axes but underestimates sub-pixel and sub-TR motions due to insensitivity of the correction to small movements. The model in Eq (1) was computed using the Stanford Bloch equation simulator [3] for a spectral-spatial excitation pulse (GE software version ESE12M4). The simplified model was fit to data from an autism study averaged over central white matter regions in 63 juvenile subjects aged 14.7+/-4.5 years (GE 3T Signa, TR/TE=2000/30, flip=90, 4/1mm). (This population samples large σ_z well). White matter regions were used to minimize the effects of CSF and pulsatile motion. A similar analysis was applied to 175 EPI runs in 41 normal 18 year-old subjects to characterize the effect of noise in low-motion subjects. The model was validated by acquiring data from a silicone oil phantom (TR=990ms) using an EPI sequence modified to randomly translate the slice prescription at each frame. This enables repeated runs with the same motion variance but different sequence parameters. Phantom data were acquired on a GE MR750 3T scanner with the same parameters.

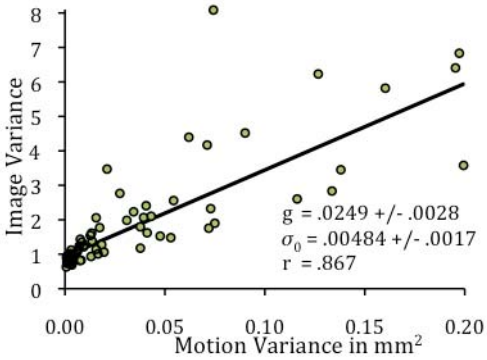

Figure 1. Fit of simplified model to measured variance in human subjects.

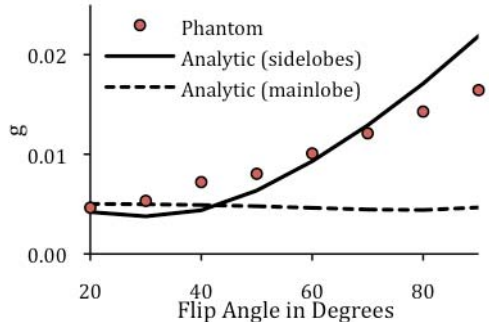

Figure 2. Comparison of g measured in a phantom and values predicted with two value of w in Eq (1).

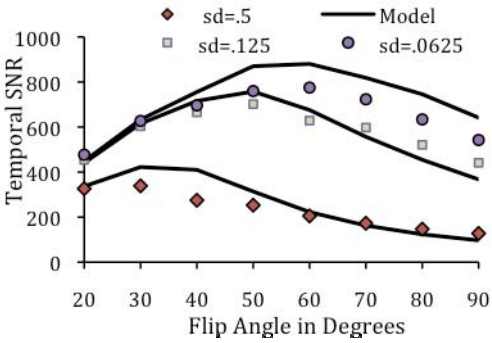

Figure 3. Comparison of predicted TSNR and TSNR measured in a phantom.

Results. The analysis of data in normal 18 year-olds shows that small increases in σ_z from .05mm to .1mm results in a 30% reduction in observed temporal SNR (TSNR) and that $\sigma_z >$ .1mm for 40% of subjects. Figure 1 shows that the simplified model fits well in white matter regions. The estimated value of g is .0249 +/- .0028 (r=.87) compared to an analytical value of .0180. This suggests that the motion variance is underestimated by 28%. The motion sensitivity computed for two ranges of integration in Equation (1) is compared to phantom results in Figure 2. The predicted motion sensitivity is nearly constant if Equation (1) is integrated only over the central lobe of the slice profile (w=7mm) but increases with flip angle when integrated over the sidelobes (w=60mm). The phantom data support the latter result, suggesting that a significant fraction of the noise due to motion comes from the sidelobes for high flip angles. Comparison of phantom results and analytical results for the effect of flip angle on TSNR for three levels of subject motion show that the model accurately predicts the optimum flip angle. For typical noise levels (σ_z=.125) a ten degree deviation from the optimum flip angle yields an 11% decrease in TSNR. Computing Eq (1) over a range of inter-slice gaps predicts that motion sensitivity increases with decreasing slice thickness and increasing inter-slice gaps.

Conclusions. i) Motion significantly increases time-series variance even in low-motion subject populations. ii) The variance component due to motion is proportional to the spatial derivative of the steady-state magnetization; iii) The sidelobes of the slice profile contribute disproportionately to this variance at high flip angles; iv) The optimum flip angle can be computed if the variance of the underlying motion is known; v) This variance can be approximated from motion parameters estimated during image realignment; vi) Gaps between slices increase sensitivity to motion while simultaneously reducing signal and should be zero. The methodology presented here can be used to optimize protocol parameters for specific scanners, RF pulses, and subject populations.

References: 1. Green et al., J Nucl Med, 35(9):1538-46. 2. Seto et al., Neuroimage, 14(2):284-97. 3. Hargreaves, Bloch Equation Simulator, mrsrl.stanford.edu/~brian/mritools.html