Noise Estimation in Spiral Imaging

Sudarshan Ragunathan[1], Dinghui Wang[1], Zhiqiang Li[1], and James G Pipe[1]
[1]*Neuroimaging Research, Barrow Neurological Institute, Phoenix, Arizona, United States*

Introduction: Quantifying noise contribution during non-Cartesian data acquisition and reconstruction[1,2] can be useful in certain applications. Existing methods for noise estimation focus primarily in the image domain with help of statistical models[3,4,5], or using the background of the image as a region of interest[6]. This work estimates the standard deviation of noise by eliminating signal content from a single set of acquired data when using spiral or similar center-out trajectories. Image reconstruction from a single coil is considered here, although extension to multiple coils is straightforward.

Theory: The standard deviation of noise in the image domain is:

$$\sigma_{image} = C.\sigma_{kspace}.\sqrt{\Sigma W^2} \qquad (1)$$

where σ_{image} and σ_{kspace} are the standard deviations in image and k-space respectively, W denotes the sampling density coefficient (SDC) weights and C is a constant reflecting scaling during the reconstruction process. The oversampling of k-space data along a spiral trajectory at lower spatial frequencies is shown in Fig. 1(A). Image reconstruction, satisfying Nyquist criteria, is achieved by selecting either the odd or even samples from a data subset (N samples) with a sampling density greater than 2. The odd and even k space datasets are then subtracted from each other to obtain noise. The estimate of the noise standard deviation is obtained as:

$$\sigma_{image} = \sigma_{diff}.\frac{\sqrt{\Sigma W_T^2}}{\sqrt{\Sigma W_N^2}}, \qquad (2)$$

where σ_{diff} is the standard deviation of the difference dataset, W_N denotes the SDC weights for the first N samples, and W_T denotes the weights for all the samples.

Methods: Modified SDC weights (W_M) were calculated according to:

$$\begin{aligned} W_M(i) &= -a_M W_T(i), i \in odd, i \le N \\ &= a_M W_T(i), i \in even, i \ge N \\ &= 0, i > N \end{aligned} \qquad (3)$$

where a_M is a scaling factor that enables the RMS values of W_M and W_T to be equal (Fig. 1(B)). The modified weights were input to a gridding reconstruction algorithm to obtain the noise image represented in Fig. 1(D).

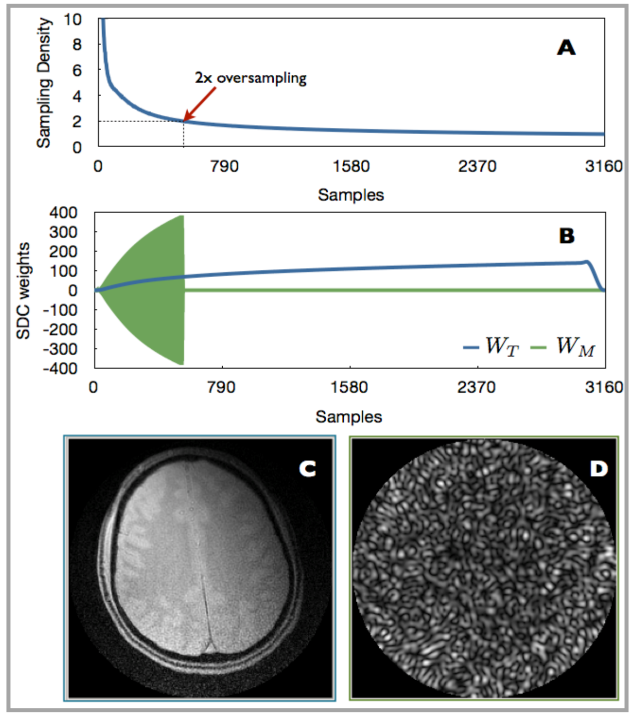

Figure 1: (A) Sampling density monotonically decreases with increasing data acquisition (B) SDC weights (W_T) used in spiral reconstruction and Modified SDC weights (W_M) to generate noise (C) The single coil reconstructed image containing signal and noise (D) Reconstructed noise images

Table 1: Standard Deviation Estimates (σ_{image})

Phantom		Volunteer	
RF=0, G=0	T1W FFE	RF=0, G=0	T1W FFE
0.950	0.952	1.272	1.253

The standard deviation of the reconstructed noise image provided an estimate of the noise. Phantom and volunteer T1-FFE data were obtained using a Philips 3T Ingenia scanner. A reference noise dataset was also obtained from the scanner by turning off the RF waveform and gradients.

Results: Table 1 shows the estimate of the noise standard deviation for the phantom and volunteer data. In each case, the noise estimate was found comparable to the standard deviation of noise obtained from the reference scan.

Conclusion: The method described eliminates signal content to provide an estimate of noise content of a spiral based MR image. This method does not require multiple acquisitions, and does not require appropriate selection of background region for noise quantification.

References: [1] A. Macovski, MRM 36: 494-497, 1996. [2] C. Mosquera, P. Irarrázabal, D. G. Nishimura, ICASSP-95 4: 2281-2284, 1995. [3] P. Coupé, et al., Medical Image Analysis 14: 483-493, 2010. [4] J. Sijbers et al., Physics in Medicine and Biology, 52: 1335-1348, 2007. [5] S. A. Fernández, A. T. Vega, C. A. López, Magnetic Resonance Imaging, 27: 1397-1409, 2009. [6] B. W. Murphy et al., Magnetic Resonance Imaging 11(3): 425-428, 1993.

Acknowledgement: This work was funded in part by Philips Healthcare.