

# Non-uniform density EPI acquisition improves the SNR of smoothed MR images

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**Introduction** Smoothing MR-images is a common preprocessing step, e.g. in functional MRI, to improve both certain signal and noise characteristics of the image. On the signal side, the advantages are twofold, firstly overcoming inter-subject variability when co-registering corresponding anatomical sites. Secondly, the matched filter theorem states that optimal signal detection in noisy data requires the smoothing with a kernel whose width matches the extent of expected activation sites. Regarding the noise, on the other hand, in particular mass-univariate fMRI analyses such as SPM rely on a smooth spatial structure of the random field of the modeling error.

Here, we show that if the method of smoothing is known before the acquisition, tailoring the k-space trajectory with respect to its density weighting increases the SNR and introduces desired manipulations in the signal and noise structure of the image.

## Methods

**Theory** Smoothing an MR image refers to a convolution of the reconstructed image with a smoothing kernel, typically a Gaussian. This alters the point spread function (PSF) of our measured magnetization. If we consider the MR encoding equation for finite sampling  $\text{data} = \mathcal{F}(\text{magnetization} \cdot \text{sampling pattern})$  with  $\mathcal{F}$  the Fourier transform operator, the convolution theorem yields

$$\text{image} = \text{PSF} * \text{magnetization} = \mathcal{F}^{-1}(\text{data}_{k\text{-space}} \cdot \text{sampling pattern}) \quad (1)$$

with  $\text{sampling pattern} = \mathcal{F}(\text{PSF})$ .

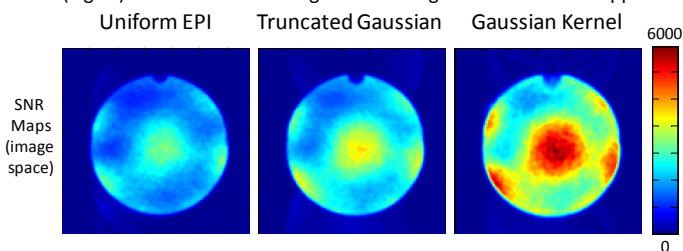
For typical reconstruction schemes, the PSF often resembles an approximation of a Dirac-distribution on our voxel grid [1], thus we can think of the PSF after smoothing as a discrete variant of the applied smoothing kernel.

Because of (1) smoothing introduces a non-uniform weighting of the acquired k-space data. For a Gaussian kernel, for instance, data from the central part of the k-space would get higher weighting (according to a Gaussian with inverse full width at half maximum (FWHM)) and noise acquired concomitantly in these data samples gets more pronounced in the image, too. We can exploit this fact by actually following the dictated sampling pattern of the smoothing during acquisition. Thereby areas of k-space with higher weighting in the reconstruction are also sampled more densely, which decreases these noise contributions in turn.

**Simulation** A uniformly sampled EPI trajectory with a standard resolution of 1.5 mm (6 shots, single slice acquisition, 2 x Nyquist-oversampling in phase-encode direction) was generated in Matlab (The MathWorks, Natick, NA). Fixing the readout length we transformed the spacing of the traverses to match a Gaussian density weighting in phase encoding direction (Fig. 1). We used a Gaussian kernel of 4 mm FWHM in image domain, either spreading over the whole FOV or truncated at  $2.5 \cdot \text{FWHM}$  (as implemented in SPM) and determined the spacing of the EPI traverses by discretizing the cumulative k-space weighting function of the kernel [2].

**Measurements** All scans were performed on a 7T Philips Achieva systems (Philips Healthcare, Best, NL / Cleveland, USA). We used a 3rd-order field camera to measure the trajectories in a separate calibration experiment [3]. A spherical water phantom (doped with CuSO<sub>4</sub> to shorten T<sub>1</sub>) was measured. The data was reconstructed using gridding and Fourier-transform, incorporating a B<sub>0</sub>-map. All images were smoothed after reconstruction using the specified smoothing kernel. SNR maps were derived as ratio of this smoothed signal image and the standard deviation of equally reconstructed images of simulated noise. An identical noise scan without excitation provided the noise statistics for the simulation.

**Results** The SNR increased for the non-uniform sampling in all parts of the smoothed image by a factor of 2 (Fig. 2). Whereas the stronger smoothing with the broad-support Gaussian kernel additionally introduced



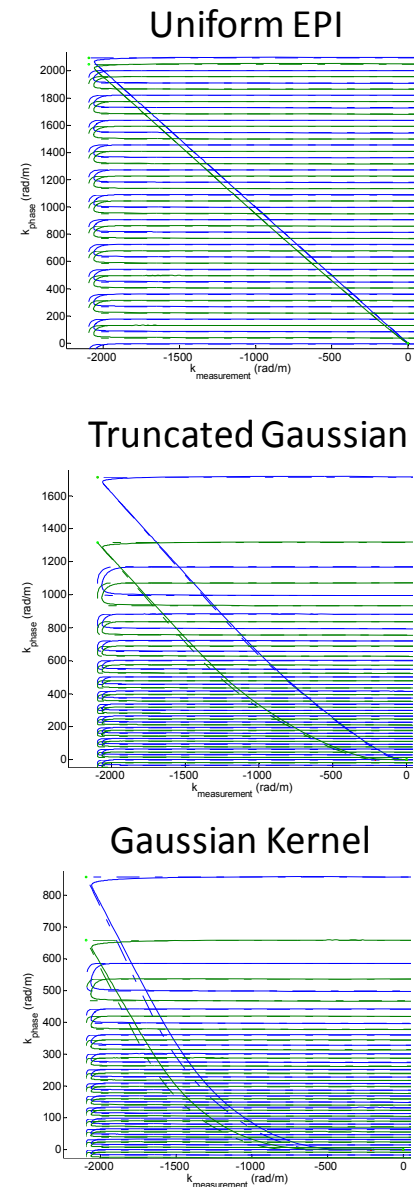
**Figure 2.** The SNR maps show an increase by a factor of 2 of Gaussian-weighted vs uniform EPIs.

smoothing for uniform sampling is counteracted by the corresponding Gaussian weighted trajectories. The deviations of the measured to the nominal trajectory were substantial for the non-uniform EPIs (Fig. 1).

**Conclusion** We showed that the consideration of post-acquisition image processing steps for trajectory optimization leads to considerable SNR-increase in a combination of EPI-acquisition and image smoothing, which is typically used in standard fMRI protocols. Furthermore, the concurrent possibility to alter the spatial noise structure in k-space itself will become relevant for statistical requirements of image analysis. To make full use of this strategy by consistent reconstructions, it is necessary to monitor the trajectory for this kind of cumbersome trajectories, which thus far precluded the usage of these schemes.

## References

- [1] Prüssmann et al., 1999, MRM 42, p952—962
- [2] Greiser, von Kienlin, 2003, MRM 50, p1266—1275
- [3] Barmet, Wilm, Pavan and Pruessmann, 2009 Proceedings of the ISMRM, p780



**Figure 1.** K-space trajectories with different density weighting. (1st & 3rd interleave shown for the 2nd quadrant (dashed: nominal full line: measured trajectory))