Probabilistic reconstruction of undistorted EPI images using a Rician noise model

J. L. Andersson[1], and M. Jenkinson[1]
[1]fMRIB, Oxford University, Oxford, Oxfordshire, United Kingdom

Introduction:

The reverse-blip method [1] has been used successfully to estimate and correct for distortions in EPI data. However, all implementations of it hinge implicitly on a Gaussian noise model, attempting to match the images in a least-squares sense. This is a problem for poor SNR data when the method attempts to "compress" intensity that has been "stretched" by the distortions. In these cases the Rician noise floor will be compressed too, resulting in an overestimation of signal. Hence it will be difficult both to estimate the field and to properly correct the data once/if the field is known. In this abstract we present a method that uses a forward model to predict what the images "should" look like and a Rician noise model that allows us to calculate the probability of the observed images. We can then use Bayesian inversion to find the parameters (undistorted image) that maximizes that probability.

Theory:

A model is used that is parameterized by one intensity value (v) and one field value (d) for every voxel. In addition there is a Rician noise parameter σ^2. With knowledge of v and d, and of the sequence used, one can make predictions about what an acquired image would look like. The model used to make the predictions is similar to the one used by Munger *et al.* [2] and is separable into columns along the phase-encode direction. Hence there is a model $f(\mathbf{v},\mathbf{d})$, where **v** and **d** are vectors containing the intensities and the values of the field along one column respectively, that predict what the observed intensities along that column should be. This can be used together with a Rician noise model to estimate the probability $p(\mathbf{y}|\mathbf{v},\mathbf{d},\sigma^2)$ of actual observed intensities (column **y**). This model has twice as many free parameters as there are observations and cannot be used directly to estimate **v** (which is the "true" undistorted image). However, if one extends **y** to consist of two distinct acquisitions where the mapping **d**→distortions is different and introduce priors on the parameters one can obtain a MAP estimate as the set of **v**, **d** and σ^2 that maximizes $p(\mathbf{v},\mathbf{d},\sigma^2|\mathbf{y}) \propto p(\mathbf{y}|\mathbf{v},\mathbf{d},\sigma^2)p(\mathbf{v})p(\mathbf{d})p(\sigma^2)$. Separating the problem into columns has the advantage that it converts a difficult problem of simultaneous estimation of a very large number of parameters (the values of **v** and **d** everywhere in the FOV) to a set of consecutive small problems. However, we wanted to use a 2D smoothness prior (based on bending energy) on **d** which means that the estimation was performed "per slice" rather than "per column", at the cost of a more difficult estimation. The estimation was performed using Fisher-scoring.

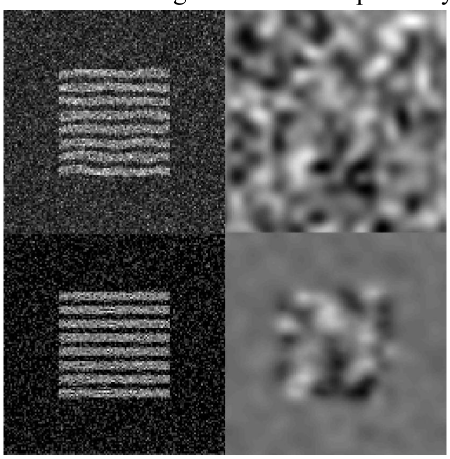

Fig 1: Top row: Distorted image and field used to distort it. Bottom row: Estimated undistorted image and field. Note how the noise floor has been reduced in the estimated image.

Methods:

The method described above was implemented in Matlab. Synthetic data was generated for a variety of geometries, fields, acquisition schemes and SNR. The method was used to estimate the field (**d**) and in particular the "true image" (**v**) from the simulated data. It was also tested on real data with high-resolution, and poor SNR, on Macaques where our previous method for correcting distortions [3] had failed because of the problems with the Rician noise floor described above.

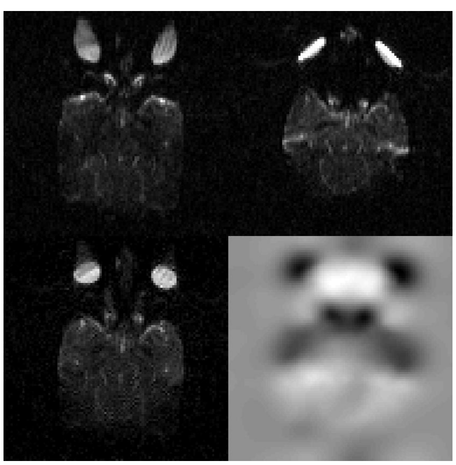

Fig. 2: Top row: Images acquired with positive and negative phase-encode blips respectively. Bottom row: Estimated image and field.

Results:

Examples of distorted images and estimated undistorted images and fields are shown in figures 1 (simulated data) and 2 (Macaque data). In general the method has performed very robustly even with very low SNR data, though the noise is of course reflected in the estimated **v**.

Discussion:

The suggested method has been able to estimate fields and images from low SNR data where our previous method [3] has failed or performed poorly. The main "output" is the corrected image **v**, but it also supplies a field **d** that can be applied to other images (*e.g.* to dwis if **d** was estimated from a pair of b=0 images). An additional effect is that the resulting image is "corrected" for the Rician noise floor, something which may be useful in the further processing of e.g. diffusion data. It will also be useful for correcting distorted images with poor SNR when the field is "known". The Rician noise floor becomes a problem when acquiring high b-value data as part of a diffusion protocol. The problem is exacerbated by the compression of Rician noise when correcting for distortions. The suggested method solves that by using a realistic noise model.

References: 1. IEEE TMI, 1992, 319-29. **2**. IEEE TMI, 2000, 681-89. **3**. NeuroImage, 2003, 870-88.