Gaussian Process Modeling for EPI Distortion Correction

J. W. Stevick[1], S. G. Harding[2], U. Paquet[3], R. Ansorge[4], A. Carpenter[2], and G. Williams[2]

[1]WBIC, University of Cambridge, Cambridge, United Kingdom, [2]WBIC, University of Cambridge, United Kingdom, [3]Machine Learning, University of Cambridge, United Kingdom, [4]Physics, University of Cambridge, United Kingdom

Introduction

Echo planar imaging (EPI) protocols are used in a wide range of clinical and research applications such as diffusion weighted, BOLD, blood perfusion, and cardiac imaging. Unfortunately, EPI images are also subject to distortion as a result of low bandwidth in the phase direction. We present a computational method of minimizing reference scan time while correcting EPI artifacts by applying an iterative data selection tool and Bayesian learning algorithm to a reduced field of view point spread imaging technique [1,2].

Theory

Point spread function (PSF) imaging acquires multiple k-space profiles of an image slice with an additional independent phase encoding gradient, thus creating a three dimensional block of data which contains both distorted EPI information and 'undistorted' geometry information in the new direction of the conventional imaging loop. Once Fourier transformed in all three coordinates and treated for field of view reduction, the off-resonance effects in each voxel's PSF location are perceived as a warping of the 3D data set, with measurable deviations $\Delta w(x,y)$ measured by fitting each PSF peak.

Methods

In our implementation, the shift values are calculated from the maxima in the dataset, filtered and thresholded to exclude data from regions of low signal-to-noise, and then passed to our learning algorithm as a set of input vectors. To compensate for the reduced field of view phase wrapping, we have included an iterative method of selecting the correct data based on the standard error between each set and a zero order phase shifted line of slope 1.0. The correct input vectors are then passed to our learning algorithm as a set of input vectors. To model the entire EPI distorted space, we have chosen to use a Gaussian Process model [3] which assumes that the likelihood of a voxel shift follows a Gaussian distribution. The customizable covariance matrix $\mathbf{C}_N$ with elements

$$C_{nn'} = \partial_{nn'}\sigma_\upsilon^2 + \theta \exp[-\frac{|\mathbf{r}_n - \mathbf{r}_{n'}|^2}{2\xi^2}]$$

determines the strength of correlation between each of the locations $\mathbf{r}_n$ and $\mathbf{r}_{n'}$ in distorted space based on the influence of hyperparameters σ_υ^2, θ and ξ^2. The matrix is then used to compute the conditional probability of new locations Δw_{N+1}, given the collection of observed signals using Bayesian statistics.

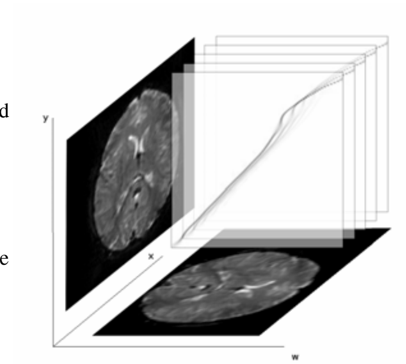

Fig. 1 An illustration of the re-mapping fr distorted (x,y) to undistorted (x,w) coordinates. The diagonally distributed po spread functions provide a link between th two coordinate systems that can be intelligently modeled and applied to future acquisitions.

$$P(\Delta w_{N+1} \mid \Delta \mathbf{w}_N) = \frac{P(\Delta w_{N+1}, \Delta \mathbf{w}_N)}{P(\Delta \mathbf{w}_N)} \propto \exp[-\frac{1}{2}\begin{pmatrix}\Delta \mathbf{w}_N \\ \Delta w_{N+1}\end{pmatrix}^T \mathbf{C}_{N+1}^{-1}\begin{pmatrix}\Delta \mathbf{w}_N \\ \Delta w_{N+1}\end{pmatrix}]$$

Using a standard stationary covariance function, we have applied our learning algorithm to gradient echo planar imaging PSF, and successfully applied the modeled phase-shift maps to subsequent standard EPI with the same protocols. All scans were performed on a Bruker MedSpec S300 3T imaging system at the Wolfson Brain Imaging Centre, Cambridge.

Results

Corrected images show improvement in general structure, especially along the frontal lobe and sinus cavities where maximum distortions typically appear in the brain. As an indirect assessment of structural improvement, both the original and corrected images were affine registered to a RARE scan of the same geometry. The maximized mutual information shows a better correlation between the corrected scan and the original geometry, scaled between 1.0 (no mutual information), and 2.0 (identical images). Each of the three hyperparameters was found to play a valuable roll in tuning the model to behave appropriately in the absence of data. The expected noise σ_υ^2 modifies the response to outlying input vectors, the scale parameter θ governs the distribution of sampled functions, and ξ^2 influences the spatial frequencies.

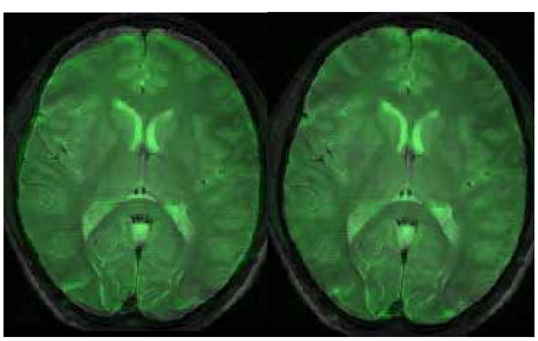

Fig. 2 Original (left) and phase corrected EPI (right) in green, overlaid with RARE acquisition for comparison of structural accuracy.

Image	**Normalized Mutual Information with RARE**
Original EPI	1.10665
Corrected EPI	1.11152

Discussion

It is possible to extend the usefulness of PSF mapping as a multi-slice distortion removal technique to regions of low signal and large inhomogeneities through the use of learning algorithms such as Gaussian process modeling. Combined with field of view reduction and a clever data selection tool, this technique has the potential for providing reasonably undistorted images at very little cost to the overall scanning session time by pre-acquisition of a PSF-image. Using this technique we have eliminated significant distortions effectively while implementing rFOV acceleration factors as large as 8, and recovered convincing geometry in sparse regions such as the frontal nasal cavity. The major advantage of this method over existing algorithms is that it is able to infer shift patterns from sparse datasets, without the need for basis functions. The additional confidence measures inferred from the modeling further allow a categorization of the degree of success of the correction process.

[1] H. Zeng and R. T. Constable. *MRM*. 2002 48 (1):137–146,

[2] M. Zaitsev, J. Hennig, and O. Speck. *MRM* 2004 52:1156–1166,

[3] D. J. C. MacKay. *Information Theory, Inference, and Learning Algorithms*. Cambridge University Press, 2003.