Gaussian Process Modeling for EPI Distortion Correction

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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 encode direction.
- We present a computational method of minimizing reference scan time while correcting EPI artefacts by applying an iterative data selection tool and Bayesian learning algorithm to standard and reduced field of view point spread imaging techniques [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 which can be deduced from the third coordinate 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 Δw(x,y) which link the distorted and undistorted coordinate systems

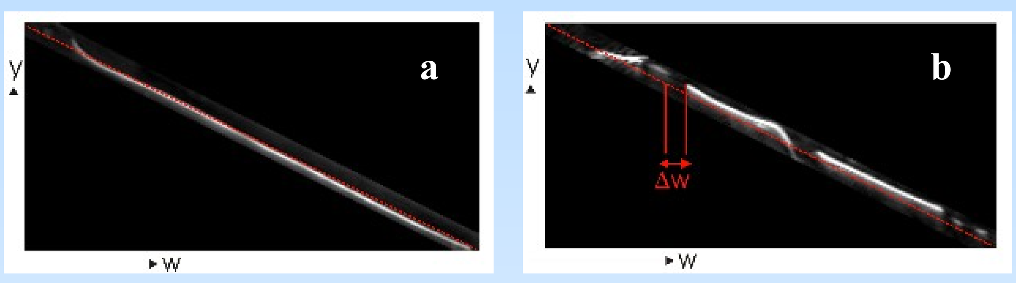


Fig 1. When the imaged region is free of intense susceptibility artifacts, a smooth set of shifted peak values is readily acquired (a). However, as can be seen in (b), intensely fluctuating PSF shifts occur along boundaries between tissue and air filled regions of the brain; air filled regions which provide no NMR signal at all. A complete shiftmap requires compensation for these areas of no support.

- Phase shift maps have been modeled and extended using straightforward methods [2,3], which provide smooth and complete coverage of the image space.
- Our algorithm attempts to improve the accuracy of predicted field inhomogeneities in regions of no support by using a Bayesian statistical regression model.

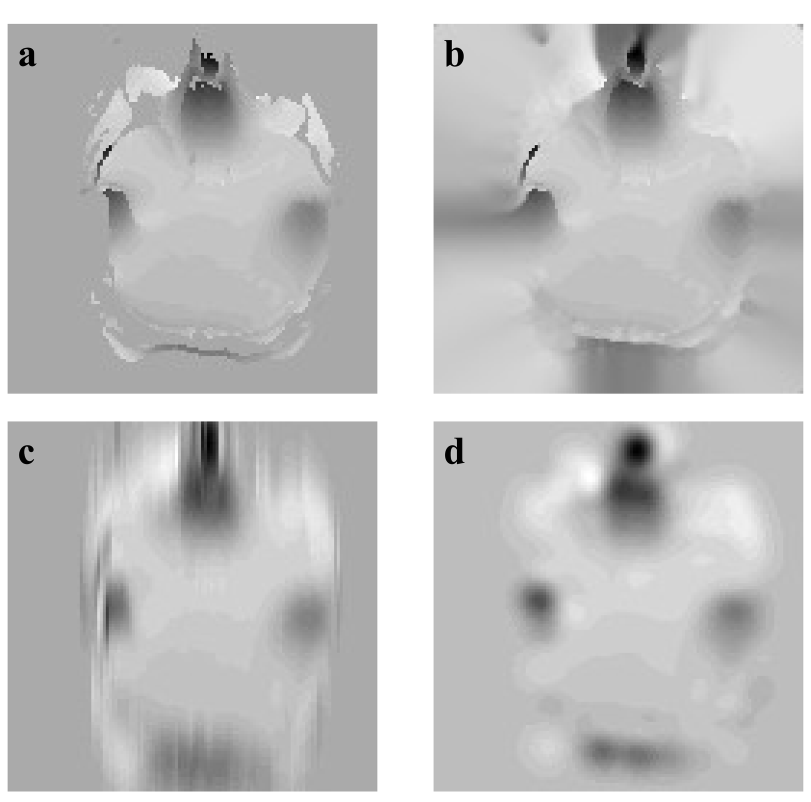


Fig 2. Extending the phase shift map to areas of no support. a) measured shift values, b) weighted average of neighboring voxels [2] c) 1D Gaussian process model, and d) 2D Sparse Gaussian process model.

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 for each column of shifts in the phase encode direction are then passed to our learning algorithm as a set of input vectors. For flexibility, smoothness, and realistic behaviour, we have chosen to use a Gaussian Process model [4] which assumes that the off-resonance effects on voxel shift likelihoods can follow a Gaussian distribution. The customizable covariance matrix C_N with elements

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

determines the strength of correlation between each of the locations r_n and $r_{n'}$ 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, given the collection of observed signals using Bayesian statistics:

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

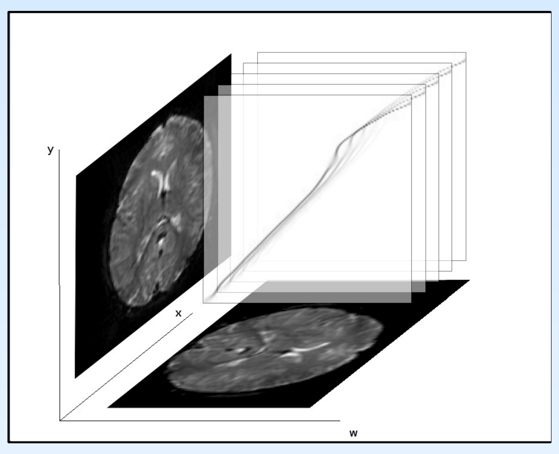


Fig 3. An illustration of the re-mapping from distorted (x,y) to undistorted (x,w) coordinates. The diagonally distributed point spread function peaks provide a link between the coordinate systems that can be intelligently modeled and applied to future acquisitions.

- Using our standard stationary covariance function, we have applied this 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.
- Additionally, we have implemented a 2D GP model which is parameterized by a sparse set of pseudo-input vectors in order to perform training and prediction calculations with an order of magnitude reduction in computation time.

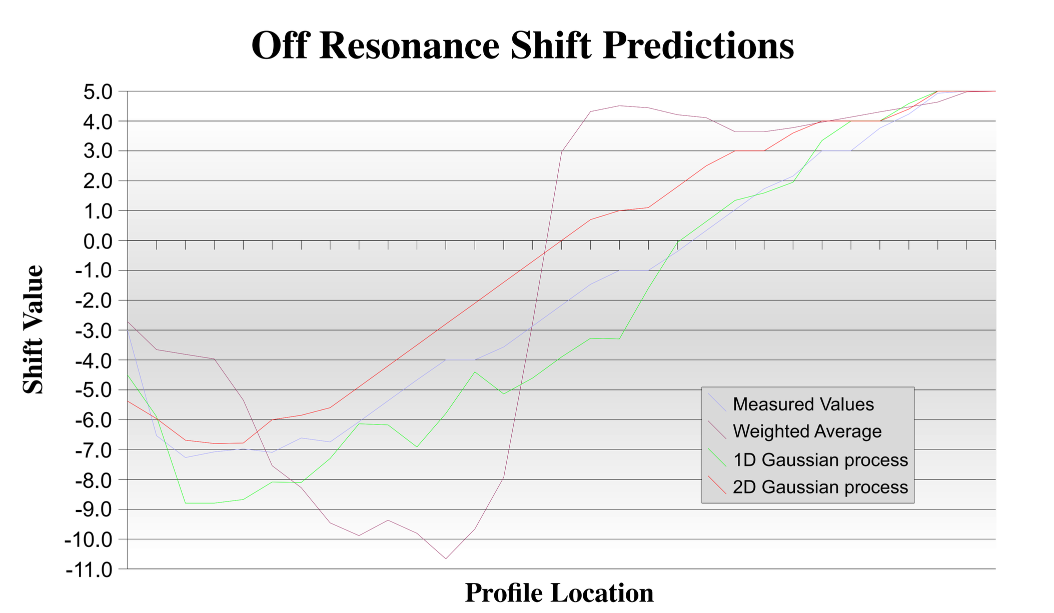
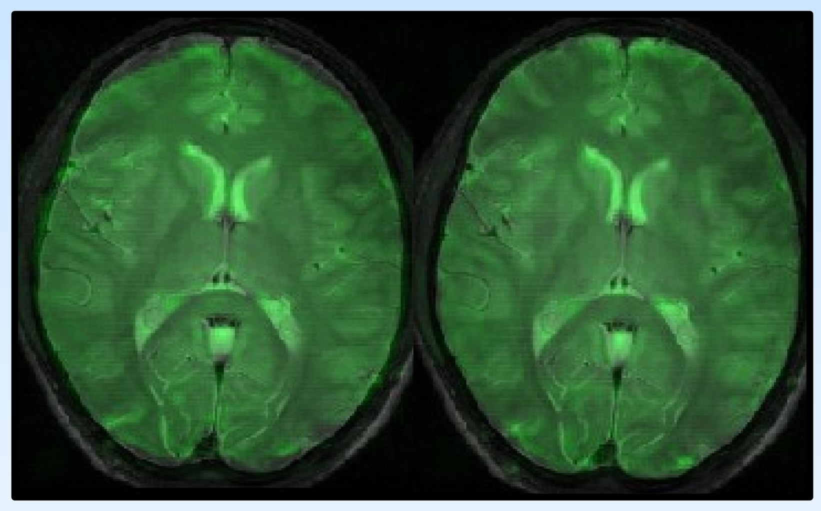


Fig 4. Measured voxel shift values are compared with predicted values using three different algorithms: weighted average of neighboring voxels [2] (purple), 1D GP inference (green), and 2D GP inference (red).

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 shown below, the maximized mutual information shows a better correlation between the corrected EPI and a higher bandwidth acquisition, scaled between 1.0 (no mutual information), and 2.0 (identical images).
- Fig 4. compares the accuracy of predicted shift values across a 20x20 voxel region of no support for three different extrapolation techniques. Both GP prediction algorithms produce more realistic maps, with the 2D GP being smoother.

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



- Each of the three hyperparameters was found to play a valuable role 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.

Conclusions

- 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 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.

References

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