A comprehensive Gaussian Process framework for correcting distortions and movements in diffusion images

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Introduction

Diffusion weighted EP images suffer from off-resonance related distortions due to the low bandwidth in the phase encode (PE) direction. The off-resonance field is caused by the subject itself perturbing the field and by eddy currents (EC) from switching the diffusion gradients. In addition the subject is liable to move during the acquisition. If uncorrected these artifacts will lead to bias and loss of precision of tractography. Registration based methods are difficult because of the varying contrast in images acquired with different direction diffusion gradients. This is particularly problematic for high *b*-values. We present a new method that solves this by registering Gaussian Process (GP) based predictions [1] to the observed data.

Theory

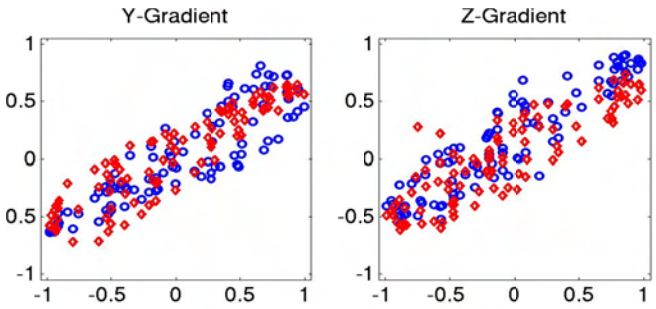
At the heart of the method is a GP based prediction maker which is able to predict what a diffusion weighted image should look like given a set of observed images. We denote this by $\mathbf{y}=\mathcal{G}_{\mathbf{Y}}$, where $\mathbf{y}$ is the prediction made by $\mathcal{G}$ given the training data $\mathbf{Y}$. The eddy current-induced off-resonance fields and movements are parameterized by $\boldsymbol{\Theta}$. In addition there may be a susceptibility-induced field parameterized by $\boldsymbol{\Phi}$, which is considered as a constant in this context. Each scan in $\mathbf{Y}$ is associated with a set of acquisition parameters that determine how a given off-resonance field translates to distortions and we denote the set of all such parameters by $\boldsymbol{\Psi}$. Given the current estimates of $\boldsymbol{\Theta}$ there are functions $f(\mathbf{Y},\boldsymbol{\Theta};\boldsymbol{\Phi},\boldsymbol{\Psi})$ and $g(\mathbf{y},\boldsymbol{\Theta};\boldsymbol{\Phi},\boldsymbol{\Psi})$ that spatially transform data from observation space into prediction (ideal) space and from prediction to observation space respectively. The algorithm starts by using, possibly, supplied values for $\boldsymbol{\Phi}$ and by assuming that $\boldsymbol{\Theta}=\mathbf{0}$ and by using f to transform the observed data $\mathbf{Y}$ to $\mathbf{Y}^*$. $\mathbf{Y}^*$ is then loaded into the prediction maker that allows us to make predictions $\mathbf{y}=\mathcal{G}_{\mathbf{Y}^*}$ that are transformed back into observation space using g and compared to the observed images. $\boldsymbol{\Theta}$ is updated by modeling the observed difference as a linear combination of the derivatives of the predictions w.r.t. $\boldsymbol{\Theta}$. $\boldsymbol{\Theta}$ is then further updated by modeling them as a GP combined with a linear model. The updated values of $\boldsymbol{\Theta}$ are used to reload the prediction maker for the next iteration.

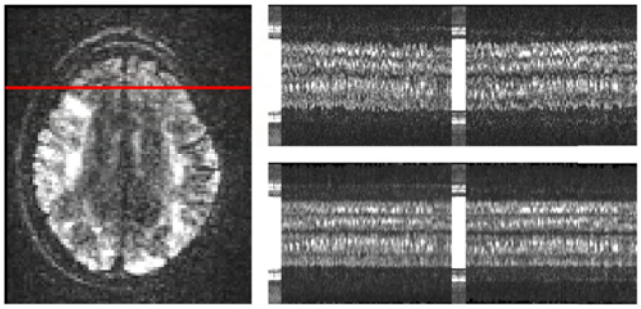
Experiments

Diffusion data was collected on a 3T Siemens Skyra (SC72 gradient operating at G_{max}=84 mT/m) with a 32-channel head coil, 512 isotropic directions with a *b*-value of 3000. Mono-polar diffusion scheme was used in order to reduce echo-time and hence improve SNR. Multi-band excitation (MB3) and in-plane GRAPPA (iPAT2) were used to reduce volume acquisition time [2] and reduce in-plane distortions respectively. PE direction was left-right to allow for a reduction of FOV in the PE direction. This protocol is part of the piloting for the Human Connectome Project (HCP) where the aim is to acquire high *b*-value, high angular resolution data with short acquisition times.

Results

The acquisition protocol resulted in diffusion weighted images with highly variable contrast (due to the high *b*-values), severe EC distortions (due to the mono-polar diffusion gradient) and a high, non-central χ-distributed noise floor (due to the 32 channels). The combined effect of these issues makes it difficult to estimate and correct for EC distortions and subject movements using registration based approaches. Despite this our method was able to estimate and correct for both. Figure 1 shows the estimated EC gradient (Hz/mm) in the y- and z-directions versus y- and z-component of the diffusion gradient for the 98 first directions. Blue indicates PE left->right and red right->left. Figure 2 shows a profile through a single slice across the 106 first acquisitions (8 *b*=0 and 98 *b*=3000, 106 PE left->right + 106 PE right->left) before (top) and after (bottom) correction. The original profile exhibits both EC induced scan-scan variations as well as movement induced drift, both of which are corrected.





Discussion

Previous registration based methods have suggested using model based predictions [3], data acquired with opposite polarity diffusion gradients [4] or data acquired with opposite polarity PE [5]. The present method combines the information from all three of those sources, and does so without the disadvantages associated with the earlier methods. By using a GP instead of the diffusion tensor model we are able to make more accurate predictions and make predictions across shells. The second level model for the EC fields utilizes the same information as [4], but without having to acquire images with opposite polarity diffusion gradients, which would be wasteful from an angular resolution perspective, and without a strong assumption of linearity (thanks to the second level GP). Using data acquired with opposite polarity phase-encoding for EC correction is difficult because the observed differences are due to a combination of EC and susceptibility-induced distortions, but by including both sources in the model we have removed that ambiguity. The method is designed to work even if one or two of these sources are missing, so if for example diffusion directions are sampled on the half sphere (removing the information in [4]) and using a single PE polarity (removing the information in [5]) it will still use the remaining information (GP based predictions) to perform the correction.

References

[1] Abstract 507 [2] MRM 63:1144-53, 2010. [3] NeuroImage 16:177-99, 2002. [4] MRM 51:188-93, 2004. [5] NeuroImage 20:870-88, 2003.

Acknowledgements

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