PATCHING CARDIAC AND HEAD MOTION ARTEFACTS IN DIFFUSION IMAGING

M. P. Zwiers[1]

[1]Donders Institute for Brain, Cognition and Behaviour, Radboud University Nijmegen, Nijmegen, -, Netherlands

Introduction

Diffusion weighted (DW) images are highly sensitive for bulk motion artefacts. Methods for compensating these artefacts during acquisition have been suggested, but are generally not very robust and/or time-efficient. Alternatively, the artefacts can be taken into account during post-processing, but this field is poorly explored. Two methods, GMM[1] and RESTORE[2], have estimated the diffusion tensor model using robust estimation techniques that assign low weights to outliers (artefacts). This study improves the accuracy, sensitivity and robustness of the approach by targeting the most common artefacts, namely head and cardiac motion artefacts, and using their spatio-temporal structure. The method is named Patching ArTefacts from Cardiac and Head motion (PATCH) and is tested with simulated and acquired DW data.

PATCH algorithm

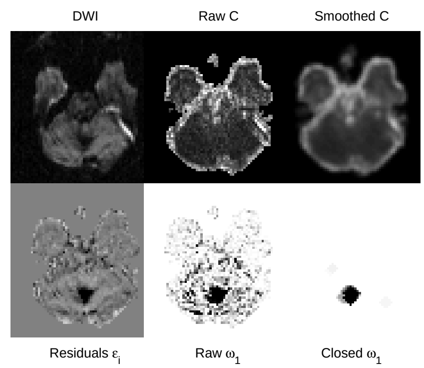

Figure 1. Intermediate processing steps

Ordinary least squares (OLS) regression is commonly used to compute the diffusion tensor[3] and minimizes the sum of squared residuals ε_i^2 in: $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, with $\mathbf{y}$ the logarithmic DW data, $\mathbf{X}$ the diffusion gradient directions and $\boldsymbol{\beta}$ the diffusion tensor coefficients. It is, however, very sensitive to non-Gaussian outliers. Weighted least squares (WLS) regression is more robust against such outliers and minimizes the sum of squared weighted residuals $(\omega_i\varepsilon_i)^2$ in: $\boldsymbol{\Omega}\mathbf{y} = \boldsymbol{\Omega}\mathbf{X}\boldsymbol{\beta} + \boldsymbol{\Omega}\boldsymbol{\varepsilon}$, with $\boldsymbol{\Omega}$ the diagonal matrix of the weights ω_i. Previous studies[1,2] used weights that hyperbolically decay with the size of the residuals: $\omega_i = (\varepsilon_i^2 + C^2)^{-1/2}$ with C a robust estimate of the standard deviation (SD): $C = 1.4826\times\text{median}\{|\varepsilon_i|\}$. The PATCH method introduced here uses linear WLS regression but with some important modifications. The prime change is that ω_i is split into three factors: $\omega_i = \omega_{1i}\,\omega_{2i}\,\omega_{3i}$, where ω_1 weights the cardiac effect, ω_2 the head motion effect and ω_3 the normal distribution distortion that results from taking the logarithm[3].

- **ω_1** The weights ω_1 decay exponentially with the size of the residuals: $\omega_{1i} = \exp(-[0.3\varepsilon_i / C_1]^2)$. Simulations show that this gives more robust and accurate results (not shown). Further, ω_1 is spatially processed to take the patchy structure of cardiac artefacts into account (Fig. 1). First, C_1 is mildly smoothed to reduce noise. Then, ω_{1i} is computed and processed with a 2D image closure operation (disc-shaped kernel with 12.5mm diagonal), which very effectively removes noise and which is equivalent to low-pass filtering in morphological space.
- **ω_2** Head motion artefacts have a slicewise structure and are accounted for by the residual weighting function $\omega_{2j} = \exp(-[0.1E_i / C_2]^2)$, where $E_i = \Sigma_{ik}\varepsilon_{ik}/\sqrt{n}$, n the number of in-plane brain voxels (k) and $C_2 = 1.4826\times\text{median}\{|E_i|\}$. The computation of E_i is equivalent to estimation of the mean residual over the acquisition plane and correcting for the reliability of this estimate (NB not all slices have the same number of brain voxels).
- **ω_3** The logarithmic deformation of the data is corrected according to[3]: $\omega_3 = S_i/\sigma_i$, with S_i being the image intensity and σ_i the estimated noise.

Outliers were defined (detected) by $\varepsilon_i > 3$ SD (RESTORE) or by ω_{1i} and/or $\omega_{2i} < 0.5$ (PATCH). Here, the final step consisted of OLS estimation with discarded outliers.

DWI test data

Synthetic DWI datasets were created using Monte Carlo simulations (n=100) of 100×50×5 imaging volumes. Half of the volume had voxels with an isotropic (grey matter) diffusion tensor and the other half voxels with an anisotropic (white matter) tensor ($\lambda_1=5\lambda_2=5\lambda_3$; MD=$7\cdot10^{-4}$ mm^2/s). Multiplicative noise was added to small circular patches (diameter 7 voxels) or entire slices to simulate cardiac and head motion artefacts, respectively. The magnitude of this noise was varied from 0–0.5, and the incidence frequency from 0–50%. Thermal acquisition (Rician) noise was also added, such that unweighted images had a realistic SNR=25. The DW sampling scheme consisted of 30 uniformly oriented DW acquisitions with b=1000 s/mm² and 5 unweighted acquisitions. Furthermore, a representative DWI data set was taken from a typical 1.5T clinical MR study (TRSE-EPI sequence; TR 10100 ms, TE 93 ms, 2.5x2.5x2.5 mm, 30 uniform DWI with b=900 s/mm², 4 unweighted images).

Results

Simulated DWI data were analyzed using OLS, GMM, LRESTORE (a linear RESTORE implementation) and PATCH for various artefact magnitudes at 13% incidence frequency. The results (Fig. 2, left) for the artefact-free condition are all close to true value. For larger magnitudes, OLS results rapidly deteriorate and GMM, LRESTORE and PATCH remain very robust, but with PATCH always closest to truth. Furthermore, PATCH is most robust for increasing incidence frequency (Fig. 2, right; magnitude 0.4). In sum, the PATCH algorithm assigns more consistent and appropriate weightings, as indicated by its better (steeply rising) true-positive and near perfect (zero) false-positive outlier detection scores.

The benefits of PATCH become even more apparent for head motion artefacts, as these artefacts are simply more extended (slice vs patch) and hence provide more statistical power. Indeed, for all magnitudes, the artefacts are perfectly detected and the tensor estimates optimal, while for increasing incidence frequency the estimates are similarly robust as for cardiac artefacts (not shown).

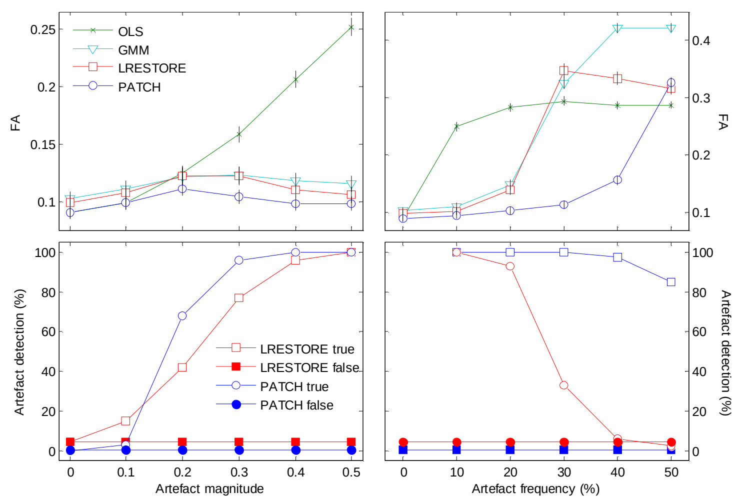

Figure 2. Cardiac artefacts in grey matter voxels. Fractional anisotropy (FA) estimates (top row) and corresponding artefact detection scores (bottom row) for different artefact magnitude (left) and frequency (right). Note the overall small performance drop of GMM and LRESTORE, which is due to the early hyperbolic decay of the weighting function, resulting in non-zero false-positive detection percentages (lower panels). The small performance drop for intermediate artefact magnitudes can be attributed to true-positive scores that have not yet reached 100%. Akin results were found for white matter voxels, MD and PDD (not shown).

Discussion

Simulations of cardiac and head motion artefacts have clearly demonstrated the benefit of the PATCH method in using the spatial structure of the artefacts. The method is more robust and accurate than previous methods and, moreover, improves results significantly using real DWI data (not shown) – particularly for motion-prone clinical patients. Finally, it should be noted that the accurate PATCH weights can well be used for subsequent processing (e.g. to discard data), such as higher-order diffusion modelling (in which outliers are harder to detect).

References

1. Mangin et al. (2002), Med Image Anal. 6:191-8.
2. Chang et al. (2005), Magn Reson Med. 53:1088-95.
3. Basser et al. (1994), J Magn Reson B. 103:247-54.