

# Retrospective Correction of Physiological Noise in DTI Using Peripheral Measurements in an Extended Tensor Model Framework

Siawoosh Mohammadi<sup>1</sup>, Chloe Hutton<sup>1</sup>, Zoltan Nagy<sup>1</sup>, Oliver Josephs<sup>1</sup>, and Nikolaus Weiskopf<sup>1</sup>  
<sup>1</sup>Wellcome Trust Centre for Neuroimaging at UCL, ION UCL, UCL, London, London, United Kingdom

**Target Audience:** DTI users and researchers investigating physiological noise.

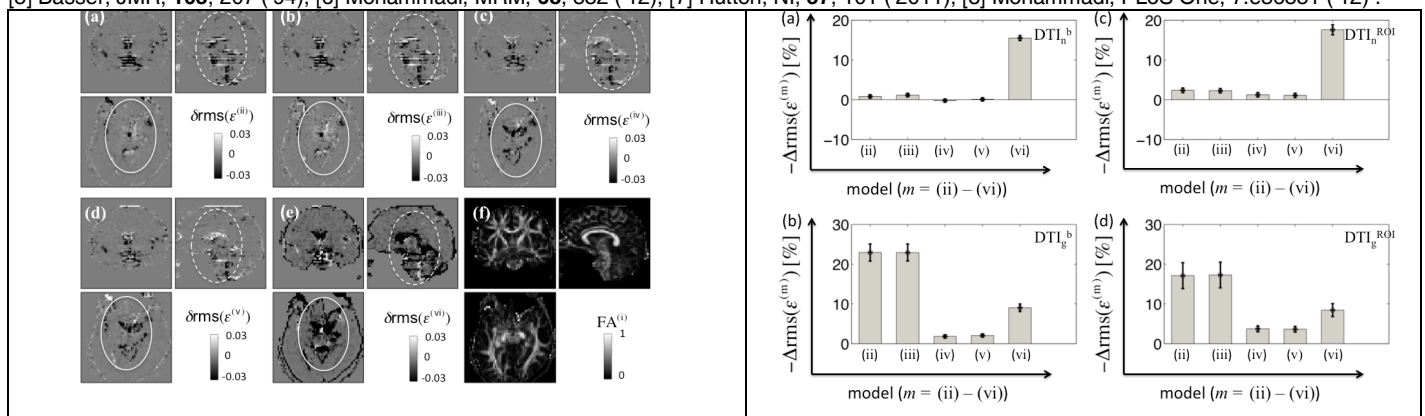
**Purpose:** One important and still unresolved artefact in diffusion MRI is due to physiological movement (e.g. cardiac pulsation), which can lead to severe bias in the diffusion signal [1,2]. To better understand and model physiological noise in diffusion tensor imaging (DTI), we developed an easy-to-implement extension of the original diffusion tensor model using measures of peripheral physiology (pulse and respiration), the so-called **extended tensor model**. We tested the performance of four different instances of extended tensor models with different physiological noise regressors on non-gated and gated DTI data, and compared it to an established robust fitting method [3,4].

**Methods:** The diffusion tensor can be estimated from the apparent diffusion coefficient (ADC) using a linear model with a tensor-design matrix  $\mathbf{X}$  that describes the diffusion-gradient scheme (via the components of the  $\mathbf{B}$  matrix [5,6]). Assuming that the physiological noise can be modelled as a linear, time-dependent additive term on the diffusion-weighted signal, the perturbed ADCs can be linearised. To calculate the corrected diffusion tensor,  $\mathbf{D}^{\text{cor}}$ , from the perturbed ADCs, the tensor design matrix  $\mathbf{X}$  is extended by additional physiological noise regressors (summarised in the  $\mathbf{Q}$  matrix)  $\mathbf{X}' = [\mathbf{X} \mathbf{Q}]$ . Six healthy volunteers (1 female) were scanned on a Siemens TIM Trio 3T scanner: 60 DW images, 6 non-DW images, 2.7mm isotropic resolution, whole brain coverage. For each subject two sets of data were acquired, using a pulse-gated ( $\text{DTI}_g$ ) and non-gated ( $\text{DTI}_n$ ) diffusion sequence (volume repetition time was 8.5s and  $\approx 17$ s, respectively). During scanning peripheral measurements of subject pulse and breathing were recorded and regressors describing the physiological noise were constructed similar to [7]. Within the framework of the extended tensor model two types of regressors, which respectively modelled small (linear models (ii) and (iii)) and strong (nonlinear models (vi) and (v)) variations in the diffusion signal, were derived from peripheral measures. Model (ii) and (vi) were based only on the cardiac pulse regressors, model (iii) and (v) on the pulse and respiratory regressors. To investigate the spatial characteristics of the physiological noise models, the fractional anisotropy (FA) and the map of the root-mean-square of the residual error of the tensor fit ( $\text{rms}(\epsilon)$ ) were calculated using the standard tensor model ( $\mathbf{Q}=0$ , method (i)), the extended tensor models, and robust tensor fitting [4]. The individual images were registered to a group template using the FA-VBS toolbox [8]. Two region of interests (ROI) were defined (lower basal brain area and whole brain ROI).

**Results and Discussion:** Figure 1 shows that the spatial noise pattern differs between the linear-regressor [(ii), (iii)] and the nonlinear-regressor [(iv), (v)] extended tensor models (solid circles). The non-linear-regressor models [(iv), (v)] showed greater similarities to the robust-tensor-fitting model (vi). Similar to the robust fitting model (vi), the nonlinear-regressor extended tensor models [(vi), (v)] explained less noise in the whole brain (Fig. 2c,d) than in the brainstem ROI (Fig. 2a,b), which is probably more affected by physiological-noise-induced outliers. However, opposite to the robust fitting model, the extended tensor models explained more noise for gated (2b,d) than for non-gated (2a,c) data.

**Conclusion:** The suggested extended tensor models address both large-amplitude outliers and small-amplitude signal changes. The framework of the extended tensor model allows for a more comprehensive investigation into physiological noise in DTI, and it can be readily combined with other artefact correction methods such as robust fitting and eddy current correction.

**Acknowledgement:** This study was supported by the Wellcome Trust and Deutsche Forschungsgemeinschaft (DFG, MO 2397/1-1). **References:** [1] Skare et al., MRI, 19, 1125 ('01), [2] Nunes et al., JMR, 177, 102 ('05), [3] Zwiers, NI, 53, 565 ('00), [4] Mohammadi et al., MRM, *in press* ('12), [5] Basser, JMR, 103, 207 ('94), [6] Mohammadi, MRM, 68, 882 ('12), [7] Hutton, NI, 57, 101 ('2011), [8] Mohammadi, PLoS One, 7:e36851 ('12).



**Fig. 1:** The spatial noise characteristics of the non-gated ( $\text{DTI}_n$ ) data explained by the extended tensor models (a and b) with linear regressors [(ii) and (iii)], (c and d) with non-linear regressors [(iv) and (v)], and (e) the robust fitting model (vi). To determine how much noise can be explained by each model, the difference map of the adjusted rms of the tensor-fit errors before and after correction [ $\delta \text{rms}(\epsilon^{(m)})$ ,  $m = (\text{ii})-(\text{vi})$ ] is depicted for one representative subject. For easier anatomical localization the corresponding FA image is depicted in (f). The effect of the noise correction was most pronounced in the basal brain regions and the brainstem (dashed circle). The robust fitting correction performs best [(v)].

**Fig. 2:** Quantitative comparison of the physiological noise correction within the whole brain (a and b) and the brainstem ROI (c and d) using the extended tensor with linear regressors [(ii) and (iii)], with nonlinear regressors [(iv) and (v)], and the robust fitting model (vi). The relative improvement of the adjusted rms of the tensor-fit error [ $\Delta \text{rms}(\epsilon^{(m)})$ ,  $m = (\text{ii})-(\text{vi})$ ] with respect to the standard tensor model (i) is depicted. For the non-gated data ( $\text{DTI}_n$ , top row), the reduction in the tensor-fit error was maximal when the robust fitting model (vi) was used (about 18%). For the gated data ( $\text{DTI}_g$ , bottom row), it was maximal for the extended models (ii) and (iii) (about 23%).