Introduction:

This tool uses the simple linear tensor approach to estimate the diffusion tensor. The methods available to estimate the tensor are: ordinary least squares, weighted least squares, and robust tensor fitting (that basically used the method of Zwiers (2010) with a couple of modifications). The robust tensor fitting approach down-weights outliers in the diffusion signal and thus is recommended if your data suffers from outliers, e.g. due to physiological noise or subject motion. It works well if your outliers are sparsely distributed along different diffusion directions (Zwiers (2010)) and you acquired enough data (N>30, where "N" is the number of images in the DTI sequence, Chang et al. (2005)). *Note that for data with low SNR (SNR $\approx$ 4) the Gaussian noise distribution might be violated and the methods in this toolbox might not be valid anymore.*

Fit Diffusion tensor pre-processing

- Use EC and Motion Correction to correct for EC and motion artefacts. The EC and motion corrected images will have a prefix "r".
- Define two variables in matlab, which cover the diffusion directions (3xN matrix) and b-values (1xN vector), before running the Fit Diffusion tensor toolbox. The "i-th" column (component) must correspond to the vector of the diffusion gradient (and the b-value) of the "i-th" image in the DTI dataset. If the b-value for the low-b-value images is unknown, type b=1, and if its diffusion gradient direction is unknown, type a random direction, which is normalised to 1.
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Use Fit Diffusion tensor:

1. Load pre-processed DTI images.
2. Load the diffusion directions (3xN vector).
3. Load the b-values (1xN vector).
4. Methods to estimate the diffusion tensor:
   - ordinary least squares,
   - weighted least squares,
   - robust fitting (Note that this methods assumes that you acquired 2D EPI data with: z = slice encoding).

Settings:

5. Choose whether you want to write out the estimated DTI data (i.e. low-b-value and high-b-value images).
6. "The confidence interval" changes the threshold above which outlier will be down-weighted. By increase C you became more sensitive to outliers but also increase the noise level in your tensor estimates. The used value for C has been recommended by previous studies (see e.g. Zwiers (2010) or Meer et al. (1991)). Don't change this value, if you don't know what you are doing.
7. "Smoothing the residuals": This measure determines the width of a two-dimensional in-plane smoothing kernel which is applied on your residual map (i.e. root-mean-square of your tensor-fit error).
8. Option to write all eigenvectors (by default the eigenvector with greatest eigenvalue as well as all eigenvalues are also written as an output).

9. Option to write the diffusion tensor and the diffusion-weighted in a format that can be read by the Freiburg DTI&Fiber tools (Freiburg DTI tools).
10. Standard deviation of logarithm of the signal outside the brain. This measure is used if the noise cannot be estimated from outside the brain (see brain mask option).
11. Option: write brain mask. Note this brain mask is not optimised to cover the brain shape but to separate brain-tissue from voxels outside the brain. This option is only there to check your settings. To construct a useful brain mask see “Pre-processing/Make brain mask”.

Referencing

Please cite the following paper when using this toolbox:

Mohammadi S, Hutton C, Nagy Z, Josephs O, Weiskopf N (2012), Retrospective correction of physiological noise in DTI using an extended tensor model and peripheral measurements. Magnetic Resonance in Medicine, (in press); doi: 10.1002/mrm.24467.

Other literature:

Chang LC, Jones DK and Pierpaoli C (2005), RESTORE: robust estimation of tensors by outlier rejection. *Magnetic Resonance in Medicine* 53: 1088-1095.

Meer P, Mintz D, Rosenfeld A, Kim DY (1991), Robust regression methods for computer vision: a review. Int J Comput Vis 6: 59–70.

Zwiers M (2010), Patching cardiac and head motion artefacts in diffusion-weighted images. *NeuroImage* 53: 565-575.