Outlier Detection for Diffusion Tensor Imaging by testing for ADC Consistency

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Introduction: Diffusion tensor imaging (DTI) and DTI-based axonal mapping are widely used to study the white matter anatomy. However, diffusion weighted images (DWIs) are often affected by various sources of signal uncertainty, such as thermal noise, eddy currents, physiological motions, and susceptibility artifacts. Among these, image corruption due to motion could lead to substantial errors in tensor estimation. It is, therefore, an important effort to detect and remove corrupted images. Besides the typical least square mean error (LSME) fitting method, several approaches have been proposed to address this issue by identifying outliers (or bad images) manually or automatically during tensor calculation [1-3]. In this work, we proposed a novel approach to improve the robustness of the tensor estimation through automatic outlier rejection. Our approach is unique from the following two points. First, the detection criteria use the smoothness of the fitted surface of the peanut-shaped ADC (apparent diffusion coefficient) directional profile. Second, error-maps are created based on this criterion and a cluster analysis is performed in the error maps because typical signal abnormalities in motion-corrupted images involve multiple pixels. The potential outliers are then excluded from subsequent tensor fitting process.

Outlier Recognition Approach: The measured ADC depends on the applied gradient direction. For the noise-free diffusion images, plotting the ADC profile in each direction generally results in a peanut shaped profile as shown in Fig.1 (a). Fig. 1 (b) depicts an extreme outlier example, in which one of the signal intensities drops substantially, leading to an erroneously high ADC value compared to those of neighboring gradient directions. This sudden change with respect to nearby gradient orientation can be quantified as shown in Fig. 1 (c). The error profiles between the measured ADC and the fitted ADC demonstrate a Mexican-hat shape. The outlier is therefore distinguishable from others by this error profile.

Processing Pipeline: Our algorithm decomposes into the following steps:

1. Image registration of the DWIs on to the b0-image.
2. Noise filtering of the images to reduce the false outlier report caused by isolated random noise pointes.
3. Compute ADCs from DWIs:

$$ADC_{org}(k) = \ln\left[S_0 / S(k)\right] / b \quad (k\text{=1...}K;\ K \text{ is the number of DWIs})$$

S_0 and $S(k)$ are signal intensities of b0 and DWIs respectively;
b is the b-value.

4. For every single slice of the DWIs, do tensor fitting and image quality checking iteratively with following steps:
   - 4.1. Tensor estimation using LSME fitting approach with validated original ADCs;
   - 4.2. Theoretical ADC calculation with the estimated tensor by:

$$ADC_{theory}(k) = g^t(k)\mathbf{D}g(k) \qquad (k\text{=1...}K)$$

Where, D is the tensor matrix, $g(k)$ is normalized gradient vector;

   - 4.3. Obtain the error-maps between original and theoretical ADCs by:

$$ADC_{error}(k) = ADC_{org}(k) - ADC_{theory}(k)$$

   - 4.4. Outlier detection by the error maps and the profile described above;
   - 4.5. Binary clustering of the outliers to detect corrupted images; exclude the outliers and back to step 4.1, otherwise advance to next slice for this iteration until all image slices are processed.

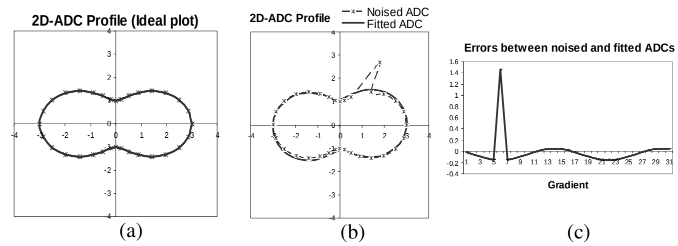

Figure 1. Demonstration of outlier detection based on a simulation data. (a) shows the noise-free peanut-shaped ADC spatial profile obtained from a 2D tensor. (b) depicts results with an extreme outlier. The dotted line represents the measurement data, while the solid line is the fitted *ADC* profile. (c) shows the error map between the measured *ADC* and the fitted *ADC* signals. It clearly demonstrates that the error-curve of the outlier and its neighbors forms a Mexican–hat profile.

Results and Discussion: The algorithm was implemented into DtiStudio [1], for routine processing of diffusion weighted image data. The computation time is typically few minutes using a 1.8 GHz Pentium processor. Fig. 2 shows an example of the results with the proposed approach. This 160x160x52 dataset was acquired with 12 gradient directions. Significant signal drops (dark area) are noticeable in the image of gradient 9. Its close neighbors are gradient 8, 10, 2 and 5 (not all images are shown here). Within the area of interest the error intensity is significantly higher than those with nearby gradient orientations. The profile between the original and theoretical ADC maps shows a typical outlier pattern. The outlier cluster can be removed from subsequent tensor calculation or the entire image can be discarded depending on the size of the clustered outlier pixels. Ideally, this approach can be combined with real-time re-acquisition of the corrupted image. It is important to emphasize that this method relies on having an over-determined dataset and problems may arise if there are many corrupted images within one slice..

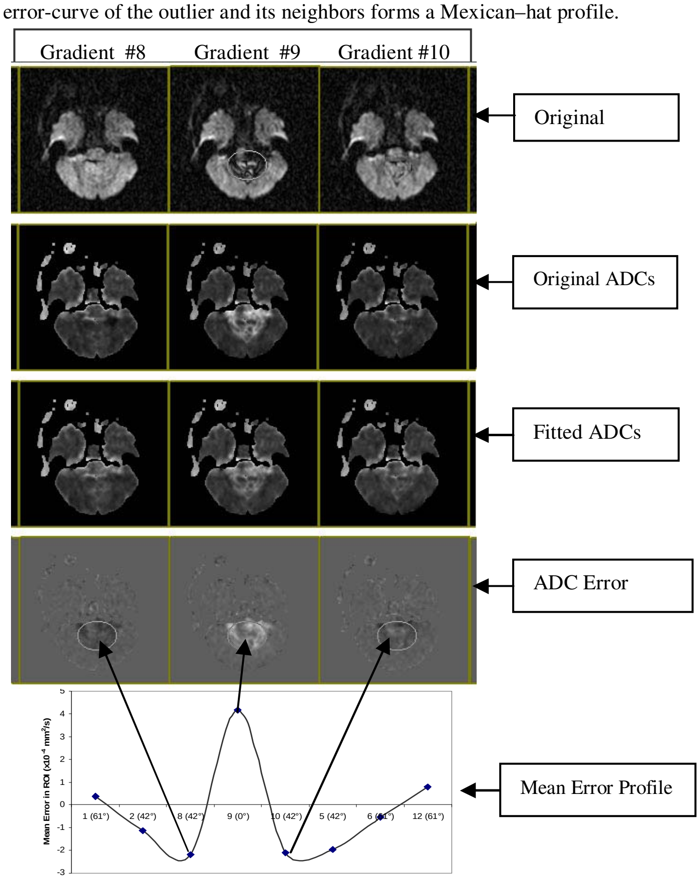

Figure 2. An example of outlier detection. Row 1 is the original DWIs. Noticeable signal drop area can be seen in image of gradient 9 indicated by a white circle. Row 2 is ADC maps derived from the original DWIss. The signal drop appears brighter intensities. Row 3 is the fitted ADCs obtained from the estimated tensor. Row 4 is the error map between the original and fitted ADCs. The bottom row shows the mean error profile within the area of the interest, demonstrating a typical outlier error pattern which is easily recognizable.

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