Automated Judgment of Image Quality for Diffusion Tensor Imaging

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Introduction: Diffusion tensor imaging (DTI) and DTI-based axonal mapping are used increasingly as important tools in clinical research for their ability to study brain white matter anatomy and abnormalities. Diffusion tensor maps are typically calculated by the least square mean error (LSME) fitting of signal intensities from diffusion weighted images as a function of the corresponding b-matrices derived for the diffusion orientation vectors [1]. In practice, diffusion weighted images (DWIs) are usually influenced by both thermal acquisition noise and varying artifacts. The LSME fitting takes into account the thermal noise which is assumed additive and is modeled approximately by a zero-mean Gaussian distribution. However, the signal variability is influenced not only by thermal noise but also by varying artifacts such as temporally and spatially subject motions and cardiac pulsations which do not follow Gaussian distributions. Noisy DWIs can cause the estimated diffusion tensor to be erroneous. Several approaches have been proposed to address this issue by identify the outliers (or bad images) manually or automatically [2,3]. In this work, we introduced the feedback theory into tensor fitting procedure and proposed a novel approach to improve the robustness of the tensor estimation by automatic outlier rejection.

Methods: The algorithm can be described as following steps. First, the b-matrix was computed from known diffusion orientation vectors. Second, the LSME method was implemented on the over-determined linear equations for the diffusion tensor estimation. Next, the DWI-fitting procedure was performed using the estimated tensor and b-matrix. The results of this fitting step were then subtracted against the original DWIs over all pixels of each slice, resulting in so called error-maps. Afterwards, the goodness-of-fitting was evaluated based on the statistic measurements of the error-maps. Auto-correlation coefficients were used as the measurements for this evaluation. The outlier was supposed to have higher coefficient values due to the residuals error caused by varying artifacts. If the goodness of fitting criterion was not satisfied, the outliers were identified and the iterative tensor estimating process was launched again after the outliers were excluded. The whole procedure continues iteratively until it satisfies the goodness criterion or reaches a pre-defined maximum iteration number. The algorithm was implemented on a windows platform with a user-friendly interface and had been incorporated into our in-house program DTI-Studio.

Results and Discussion: A screen shot of the program in action is shown in Fig. 1. The outlier being diagnosed in the first iteration is crossed out with red X in this example.

Artifacts are common in clinical DWIs due to the intrinsic low resolution and related imaged distortions of the image acquisition techniques. Of these, the subject motion when scanning uncooperative patients and residual error from cardiac pulsation are the dominant sources of the observed motion-related artifacts. These artifacts do not follow Gaussian distributions. When no corrupted data were included, all fitting methods showed similar results. In the presence of outliers, especially those orienting from non-Gaussian temporally varying artifacts, our proposed algorithm proved to be a good approach to improve the accuracy of the estimated tensor with respect to the commonly used fitting methods. And the computation time is not increased significantly compared with the linear LS methods we used before.

Despite the good performance of our algorithm, its limitations should be discussed. A potential weakness of this approach is that the method relies on data redundancy. Problems may arise if the original dataset does not have enough orientations or repetitions to correctly identify and exclude the outliers. The number of good data can be also an influence factor on the performance of the algorithm.

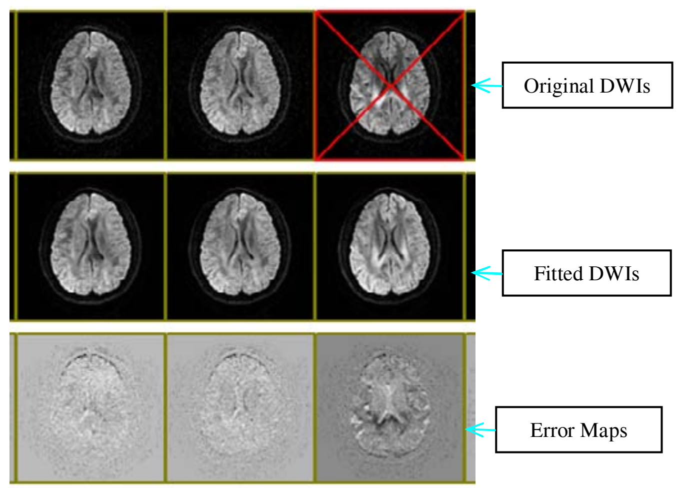

Figure 1: Demonstration of the program in action. The first row shows the original DWIs in different orientations. The second row shows the re-calculated DWIs after the first iteration of the tensor estimation. The third row shows the error-maps between the original and the "ideal" DWIs. The outlier was identified, marked with a red X, and will be excluded in the second iteration.

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References

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