Real-time MR Diffusion Tensor and Q-ball imaging using Kalman filtering

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Introduction

Magnetic resonance diffusion imaging has become an established technique for inferring structural anisotropy of tissues and mapping the white matter connectivity of human brain [1]. We developed a method to process diffusion tensor and Q-ball imaging in real-time. The basic idea is to use a Kalman filtering framework to fit either the linear tensor or Q-ball model incrementally, thus updating the model estimate after the acquisition of any new diffusion-weighted volume during ongoing scans.

Material and Methods

Several mathematical tools have been designed to model diffusion weighted data. We focus on both the DTI [2] and Q-ball (QBI) [3] models and addressed the feasibility of real-time DTI and QBI processing for displaying reconstructed associated maps during an ongoing scan. Both models can be expressed in the light of the general linear model framework (GLM) assuming a white noise model. Among available techniques for solving least-squares linear regression models, the Kalman filter [4] provides an appropriate answer to the real-time requirement since it is an incremental solver, as previously shown for BOLD imaging [5].

DTI and QBI models can be written using the general linear model $\boldsymbol{y}=\boldsymbol{A}\boldsymbol{d}+\boldsymbol{\varepsilon}$. For the diffusion tensor model, $\boldsymbol{A}$ is a matrix which rows are $\boldsymbol{a}_i=b_i[o_{x,i}^2, 2o_{x,i}o_{y,i}, 2o_{x,i}o_{z,i}, o_{y,i}^2, 2o_{y,i}o_{z,i}, o_{z,i}^2]$, and $\boldsymbol{d}=[D_{xx},D_{xy},D_{xz},D_{yy},D_{yz},D_{zz}]^T$., and for the QBI model, $\boldsymbol{A}=(P(B^TB+\lambda L)^{-1}B^T)^+$ as describes in [6], where $()^+$ stands for the Moore-Penrose pseudo-inverse, P is a Funk-Hecke matrix, B is a matrix corresponding to a modified spherical harmonics (SH) basis, L is a Laplace-Beltrami regularization matrix, and $\boldsymbol{d}$ is the vector corresponding to the decomposition of the orientation distribution function (ODF) onto the SH basis. The Kalman filter exploits any new measure $\boldsymbol{y}$ for updating the unknown parameters $\boldsymbol{d}$. Given the new MR measurement of rank i, $y(i)$, and the vector $\boldsymbol{a}(i)=[A_{i1},\ldots,A_{iP}]^T$ corresponding to the i^{th} row of $\boldsymbol{A}$, the innovation $v(i)=y(i)-\boldsymbol{a}(i)^T\boldsymbol{d}(i-1)$ is computed, where $\boldsymbol{d}(i-1)$ is the current estimate. The Kalman filter then updates the parameters using the recursion:

$$\begin{cases} \boldsymbol{k}(i)=(1+\boldsymbol{a}(i)^T\boldsymbol{C}(i-1)\boldsymbol{a}(i))^{-1}\boldsymbol{C}(i-1)\boldsymbol{a}(i), \\ \boldsymbol{d}(i)=\boldsymbol{d}(i-1)+v(i)\boldsymbol{k}(i), \\ \boldsymbol{C}(i)=\boldsymbol{C}(i-1)-\boldsymbol{k}(i)\boldsymbol{a}(i)^T\boldsymbol{C}(i-1), \end{cases}$$

where the vector $\boldsymbol{k}(i)$ is usually called the Kalman gain. $\boldsymbol{C}(i)$ represents an estimate of the normalized covariance matrix of $\boldsymbol{d}$ given the information at time i. The initial guesses $\boldsymbol{d}(0)$ and $\boldsymbol{C}(0)$ were respectively set to the null vector and zero.

In order to reduce the risk of failure, we optimized the spatial distribution of orientations, implementing the sequence of orientations proposed in [7].

All acquisitions were performed on a Signa 1.5T Excite II MR system (GE Healthcare, Milwaukee) provided with a 40mT/m / 150T/m/s gradient system and an 8-channel head coil. Two different acquisitions were performed using a DW single shot Dual Spin Echo EPI pulse sequence for validating both DTI and QBI solvers. Acquisition parameters were set to b=700s/mm^2, 42 diffusion directions, matrix 128x128, 60 slices, FOV=24cm, slice thickness=2mm, T_E/T_R=66.2ms/12.5s for the DTI scan, and were set to b=3000s/mm^2, 200 diffusion directions, matrix 128x128, 60 slices, FOV=24cm, slice thickness=2mm, T_E/T_R=93.2ms/19s for the QBI scan.

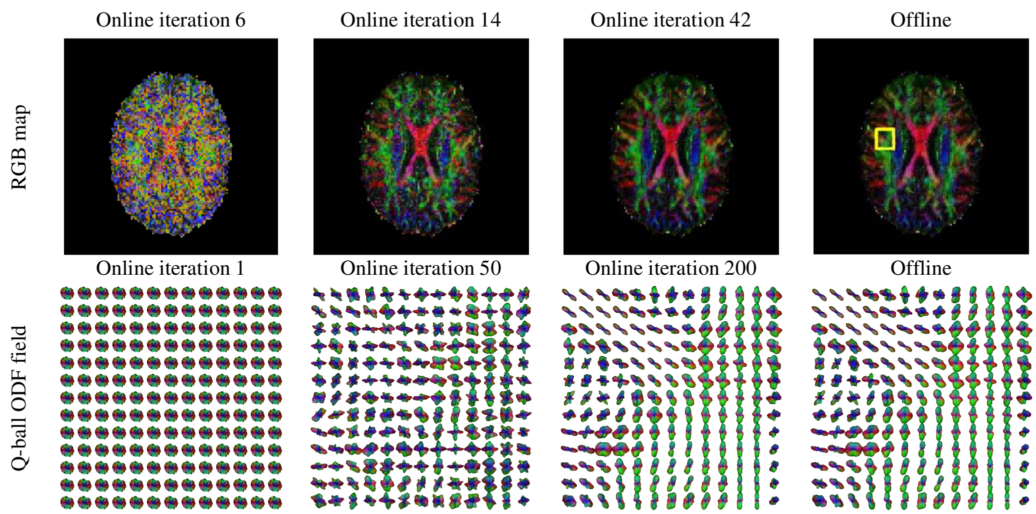
Results and Discussion

At each iteration of the scan, an approximation of the diffusion tensor is available for each voxel of the brain. It is then possible to process its eigen-system online to estimate the ADC / FA / RGB maps. Top columns 1-3 of the figure below depict the refinement of the RGB map during the ongoing scan. There is no qualitative difference between results obtained at the last iteration of the Kalman filtering and the standard offline SVD analysis (4th column). The time required to perform one iteration over the whole brain is less than 8s, which is lower than the used T_R, making this protocol truly real-time.

Similarly, a Kalman filter was implemented to process Q-ball ODFs online. The ODFs were computed on a distribution of 400 normalized uniform orientations from the SH decomposition estimated in real-time, and 3D renderings of the ODFs were built on the fly for each iteration. Bottom columns 1-3 of the figure below depict the refinement of the ODF map on a region of interest located in the subcortical white matter (yellow rectangle). It exhibits some fiber crossings and voxels with homogeneous fiber populations. One iteration on a single slice requires almost 5s which is lower than T_R, and enables up to 4 slice locations to be processed in real-time on a PC workstation. The code can obviously be optimized and parallelized on a grid of processors if the whole brain is to be processed in real-time.

Conclusion

This incremental Kalman-filter based framework dedicated to real-time diffusion MR imaging addresses both diffusion tensor and Q-ball models, and enables processing the standard DTI / QBI maps during ongoing scans. This is very suitable for clinical use when a quick feedback is required during the acquisition or when the cooperation of the subject is not sure.



References

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