Optimal real-time q-ball imaging with incremental recursive orientation sets

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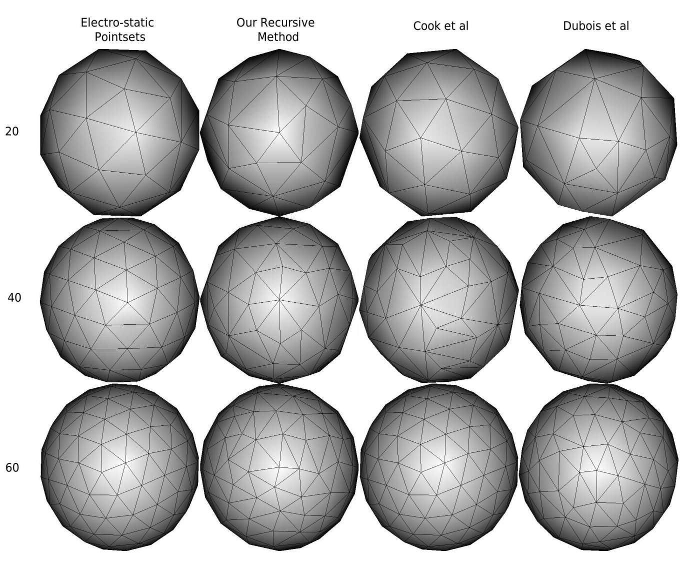
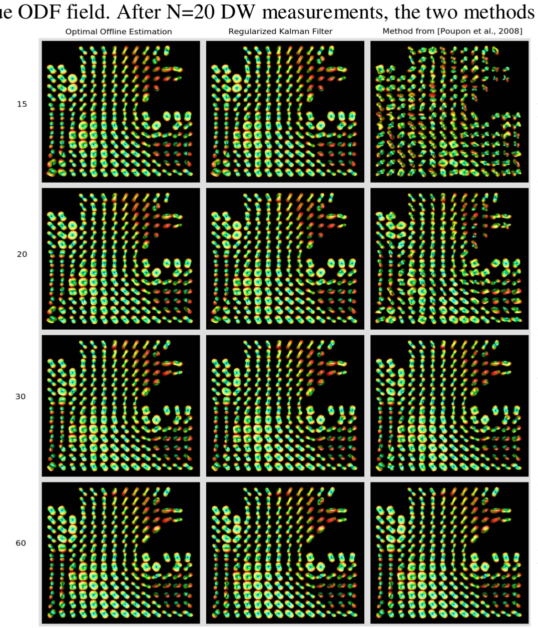
INTRODUCTION: High angular resolution diffusion imaging (HARDI) requires more diffusion-weighted (DW) measurements than traditional diffusion tensor imaging acquisitions, but it can resolve some fibre crossings. This comes at the price of a longer acquisition time, which can be problematic for clinical studies involving children and people inflicted with certain diseases. Excessive motion of the patient during the acquisition process can force an acquisition to be aborted or make the diffusion weighted images useless. Thus, one would like to make only as many acquisitions as is necessary. According to the literature, this number is likely to be somewhere between 50 and 200 DW measurements but this is still an open question. Recently, Poupon et al. [1], addressed this issue and proposed an algorithm for real-time estimation of the diffusion tensor and the orientation distribution function (ODF) from q-ball imaging (QBI) using the Kalman filtering framework. However, this solution is in fact optimal only for the last iteration of the q-ball ODF estimation, and sub-optimal at earlier iterations. This is problematic for the intended real-time QBI system. As we would like to stop the acquisition at any time or as soon as the ODF estimation has converged, a good estimation of the ODF is highly desirable at the beginning of the acquisition and thus, the development of an optimal and incremental solution is important. In this work, we adapt the Kalman filtering solution to correctly incorporate the regularization into the filter parameters without changing the ODF reconstruction model [2]. The basic idea is to go back to the derivation of the Kalman filtering equations and include this regularization term. Moreover, in order for this framework to be fully incremental and take its full power in real-time, we also tackle the problem of the optimal choice of the DW gradient orientation set. Typically, each measurement is acquired along a given orientation extracted from an optimised set of orientations estimated and ordered off-line [3]-[6], before the acquisition is started. Hence, we propose a fast algorithm to recursively compute gradient orientation sets whose partial subsets are almost uniform.

METHODS: QBI can be solved analytically using a regularized spherical harmonic (SH) estimation of the diffusion signal [2]. Firstly, we propose a new Kalman filtering method that correctly incorporates the regularization term of [2] in the initial condition of the system. Surprisingly, one can show (mathematical details not shown here) that only the initial covariance matrix needs to be modified to correctly implement the regularization term. The general linear model does not have to and should not be modified as done in [1]. Secondly, we propose a fast recursive algorithm to incrementally generate orientation sets whose ordered subsets are approximately uniform. The algorithms proposed in [5] and [6] perform their respective minimizations over all the points in the orientation set. Thus, the algorithms are very slow and the global minima are difficult to find as there are many local minima present. We note that this optimization problem naturally leads to a recursive solution; instead of minimizing over all the orientations at once, we propose to minimize incrementally over each ordered subset. That is, our method is defined recursively: given a set of k orientations, we choose direction k + 1 so as to minimize the incremental electrostatic energy [3]. To validate and test our proposed method, we compare our recursive orientation sets with algorithms from [3], [5] and [6] for sampling schemes N = 20, 40, and 60. Then, we compare our proposed optimal q-ball ODF estimation with the offline ODF reconstructions from [2] and from [1]. The q-ball ODF reconstructions were computed from a data obtained on a 3T system, with 60 encoding directions, averaged three times per direction, seven b = 0 images, b = 1000 s/mm^2, 72 slices with isotropic 1.7 mm resolution, 128x128 image matrix, TE = 100 ms, and TR = 12s.

RESULTS: First Fig.1 shows that we can generate comparable uniform point-sets with a fast algorithm whose complexity is linear with respect to the number of points in the orientation set. Second, Fig 2 shows that our proposed algorithm yields optimal ODF estimation at each iteration (from the beginning to the end of the acquisition). Visual difference between the optimal estimation using 15 versus 60 acquisitions is very small. Quantitatively, this is found (not shown here), where the difference between our method and the optimal estimation is seen to be negligible for each iteration. This example also visually shows that the Kalman filtering method from [1] is sub-optimal. After N=15 acquisitions, our optimal estimation is very good and close to the true offline ODF, but the method of from [1] is clearly quite far from the optimal solution. In fact, it has very little in common visually with the true ODF field. After N=20 DW measurements, the two methods are visually more similar, and we see that after the complete 60 directions, both kalman methods converge to the optimal solution. In total, the ODF estimation took approximately 6.23 seconds for both methods. As this is less than the repetition time of 12 seconds, our method is also possible in real-time settings. Hence, one can now imagine that as new directions incrementally arrive in the Kalman system, one can stop the process if the added value of the new directions is small.





DISCUSSION: Two important contributions were shown in this work. 1) Real-time QBI can be done optimally with a regularized Kalman filtering framework. 2) Incremental orientation sets that are approximately uniform can be generated on the fly with a recursive method. Hence, this can potentially allow one to start the diffusion acquisition just with the minimum number of gradient directions and an initial estimate of the ODF so that all other processing steps, including next gradient direction generation and ODF reconstruction, are recursively, incrementally and optimally determined. This will truly allow the acquisition to be stopped at any time with the optimal ODF estimate. Visualization is still a very computationally intensive process and on a single workstation cannot be done in real-time. Further work is aimed at implementing this algorithm on a cluster of workstations so visualization can also be performed in real-time.

References: [1] Poupon et al, Med Imag Anal 2008. [2] Descoteaux et al, MRM 2007. [3] Jones et al, MRM 1999. [4] Papadakis et al, Magn Reson Imaging 2000. [5] Dubois et al, MAGMA 2006. [6] Cook et al, J Magn Reson Imaging 2007. [7] Anwander et al, Cerbral Cortex 2007.