DEVELOPMENT OF A MATLAB GRAPHICAL USER INTERFACE FOR THE MULTI-TENSOR ANALYSIS OF DIFFUSION MAGNETIC RESONANCE IMAGING

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***Abstract*-The estimation of diffusion tensors in diffusion tensor imaging (DTI) is based on the assumption that each voxel is homogeneous and can be represented by a single or multi tensor. As a result, estimation errors arise particularly in voxels with partial voluming of white matter or gray matter with cerebrospinal fluid (CSF) and voxels where fibers cross. This paper presents a tool for analysis of DTI called MultiTensor which was developed in Matlab language in order to help DTI researchers by making the analysis more easier and faster. The user enters the number of slices, bvalues, the gradient directions , the number of excitations. Then the program begin by preparing the Dicom file, estimates both single and two tensor, the anisotropy indices and the error in estimation.**

Keywords–**Diffusion Imaging, GUI, multi-tensor , magnetic resonance Imaging.**

I. INTRODUCTION

This paper presents a tool for the multi-tensor analysis of the diffusion tensor magnetic resonance imaging (DTI) called MultiTensor, which was developed using Matlab 7.01. This software was designed to help the DTI researchers by making easy to find accurate estimation of single and two-tensor, their anisotropy indices (Fractional anisotropy, Relative Anisotropy and Partial volume) and find the error in estimation.

This tool was developed in Matlab language provided by the Math works Inc. software, which help in implementing the more complex algorithms as huge matrix operations and analysis. It is also a powerful system for Image viewing and its open source nature allows one to adapt the software needs. The graphical user interface (GUI) is not as easy as C^{++} Builders or .net programming, but the availability of matrix analysis and graphic functions turned Matlab into the software of choice as the development environment for MultiTensor.

The Diffusion tensor imaging (DTI) is a non-invasive method of characterizing tissue micro-structure. Diffusion imaging attempts to characterize the manner by which the water molecules within a particular location move within a given amount of time. Using a simple pulse gradient spin echo (PGSE) imaging sequence, it is possible to obtain a change of the MR signal that is related to the diffusivity of water in a certain direction.[1] The advantage of this modality lies in the fact that the changes in water diffusion, produced by alterations in brain biochemistry, can be observed on diffusion weighted (DW) images long before the effects of ischemic injury can be seen on conventional T1, or T2 weighted images.[2] Measurement of the diffusion tensor (D) within a voxel enables the mobility of water to be characterized along orthotropic axes, allows a macroscopic voxel-averaged description of fiber structure, orientation[3] and fully quantitative evaluation of the microstructural features of healthy and diseased tissue.[2]

II. DATASET PREPARING

The user must enters the parameters identifying the dataset as the number of slices, the bvalues, the gradient directions and the number of Excitations (NEX), shown in Fig. 1, which will lead him to browse for the directories containing the dataset. The program must check the founding of the typical number of DICOM figures in each folder then begin to calculate the averages of corresponding slices with same bvalues and directions defined in the NEX folders. As the number of NEX increases the signal to noise ratio (SNR) decreases. The dataset is ready now to begin the tensors estimation. Fig. 2 shows a slice viewing after been averaged

III. ADDING NEW DATASET PARAMETERS

When loading the program for the first time, the most known gradient combinations 6, 12 and 30 directions are added to the program, and the same for the b-value sets. Adding new sets for both the gradient directions and the b-value is available as shown in fig.3.

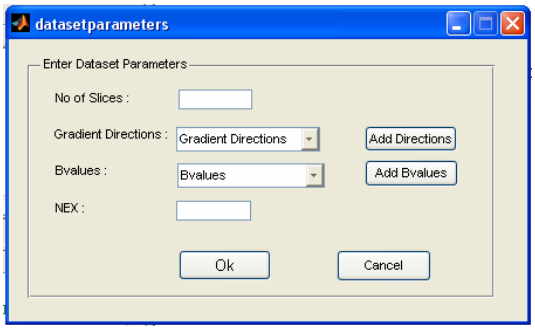


Fig.1: The parameters needed for the dataset.

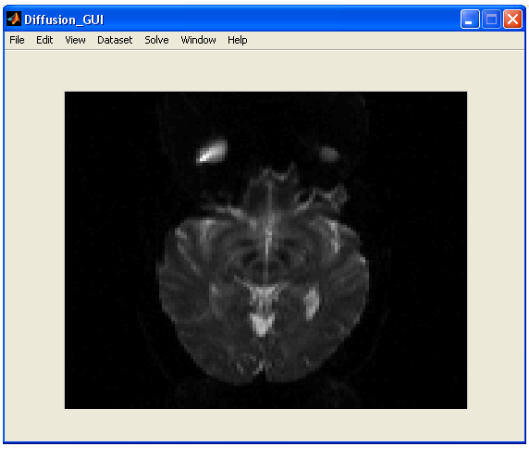
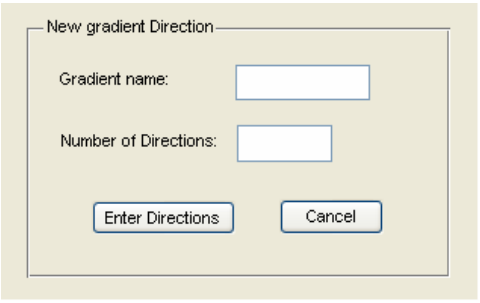
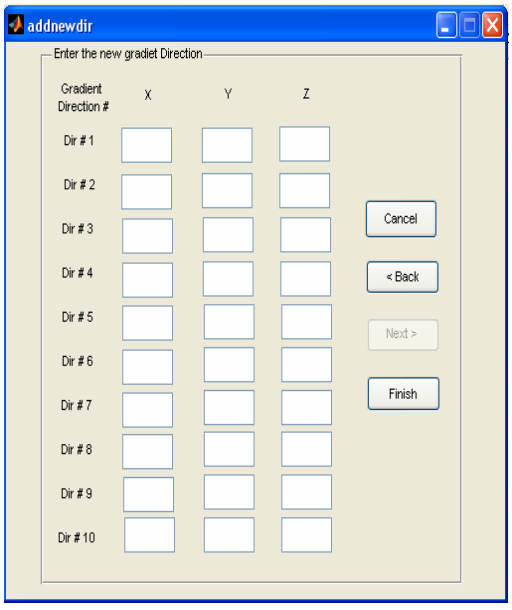


Fig. 2: Slice viewing after been averaged.



(a)



(b)

Fig.3: The entry of new gradient directions parameters

IV. TENSOR ANALYSIS

A- Single Tensor Estimation

The diffusion signal from a single diffusion compartment is given by:

$$E(q_k) = \exp(-q_k^T D q_k \tau). \quad (1)$$

where $E(\mathbf{q}_k)$ is the normalized diffusion signal magnitude for the diffusion gradient wave-vector $\mathbf{q_k}=\gamma\boldsymbol{\delta}\mathbf{g_k}$, $\boldsymbol{\gamma}$ is the gyromagnetic ratio, $\boldsymbol{\delta}$ is the diffusion gradient duration, $\mathbf{g_k}$ is the k^{th} diffusion gradient, τ is the effective diffusion time, and $\mathbf{D}$ is the apparent diffusion tensor.[4],[5] The output of this module is shown in Fig. 4(b).

B- Two Tensors Estimation

Assuming a two-component model without loss of generality, the projection along any given direction can be given as,

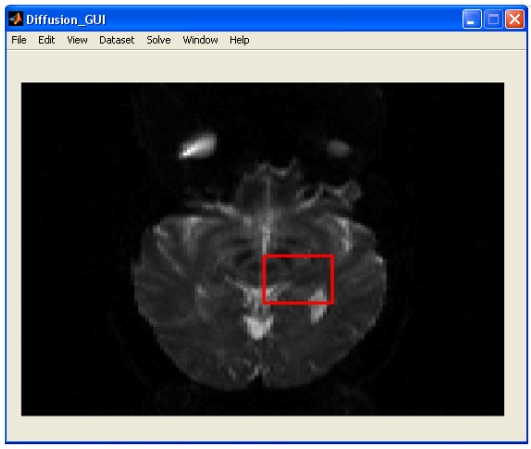
$$E(q_k) = \alpha_1 \exp(-q_k^T D_1 q_k \tau) + \alpha_2 \exp(-q_k^T D_2 q_k \tau). \quad (2)$$

Here, the relative amplitudes are given by α_1 and α_2 and the variances are generally different for both components and vary with projection direction. The x value is known and can be computed given the b-value and the direction of diffusion gradients. The 1D component estimation problem amounts to the estimation of α_1, α_2, D_1 and D_2 given $E(q_k)$. Notice that the component amplitudes are the same between projections. This property will be used to aid in the labeling of components among different projections. This estimation problem is nonlinear and therefore only iterative estimation methods have been proposed [6],[7],[8]. Given the convergence issues associated with such methods and their generally high computational burden, another more stable strategy is needed to solve this problem in practice. Note that for any given parameter estimation accuracy, there exists a finite number of possible solution that are determined by the *a priori* information about parameter ranges and the desired accuracy. Hence, the problem of finding the solution to this problem amounts to a combinatorial optimization problem. This means that a globally optimal solution can be found by exhaustive search or one of the more efficient random search strategies such as simulated annealing or genetic algorithms. Nevertheless, the computational effort involved in such techniques is prohibitive. Here, we combine exhaustive search and least squares estimation to obtain a more efficient implementation while maintaining the robustness and global optimality. In particular, instead of attempting to find all parameters by exhaustive search, we limit this strategy to those parameters of more importance in terms of accuracy and compute the remaining ones using least-squares estimation. This is implemented as follows:

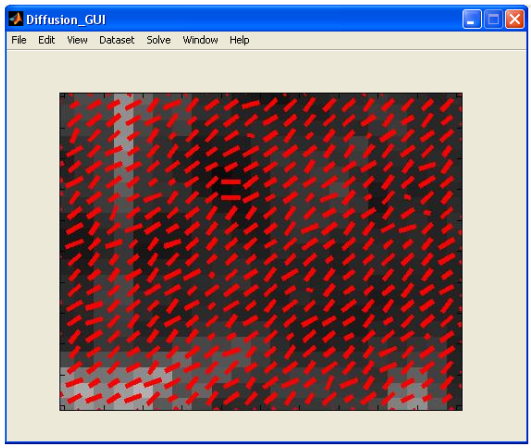
Step 1. Take the variances to be the parameters estimated by exhaustive search while the partial volume ratios are estimated from them by least squares.

Step 2. Generate a list of possible values for the variances within the range from 0 to the maximum eigenvalue of the diffusion tensors of interest with the desired accuracy as the step.

Step 3. Plug in values for the variances in the equation from the list and compute the least-squares solution to the



(a)



(b)

(c)

Fig. 4: (a) Selecting the area to be calculated. (b) Single Tensor Estimation. (c) Two Tensor Estimation.

partial volume ratios for such values and compute the value of the residual error with such values plugged in.

Step 4. Loop on all possible variance values in the list and repeat step c and find the combination of values that generate the lowest error. Consider such combination to be the solution.

Step 5. This method allows an order of magnitude saving in computation time while providing a solution with sufficient accuracy.

Once the individual component estimates from projections are computed, the projections of each component are used to estimate the component tensor in very much the same way as the single tensor estimation is performed. One problem arises in this part because of component labeling. The basic assumption of the model that the partial volume ratios remain the same in projections may not be practical given the superimposed noise and other sources of error in DTI. In other words, partial volume ratios from different projections are different in practice. To solve this problem, an initial labeling is obtained whereby the first component is calculated from the projection components having the larger partial volume ratio, while the second component is calculated from the components with the smaller one. Once the two tensors are computed using this strategy, a least squares estimate for the partial volume ratios is computed while imposing the constraint of unit summation upon their values. Then, the calculated values are used in a second iteration of the procedure above to update the projection variances while imposing the same partial volume ratios obtained from the first iteration. A second estimate of the partial volume ratios is computed at the end of the second iteration and this process is repeated until estimates from two successive iterations come out within a predetermined tolerance. In this case, the estimates represent the global solution that is not be biased by error within individual projections.

It should be noted that the extension of this method to multiple exponential is straight-forward. The computational complexity of the developed method can be shown to depend linearly on the number of components. This allows the possibility of addressing more challenging tasks. We still gain the separation between the problems of estimating the variances and the magnitudes. Moreover, the same direct magnitude estimation method can still be applied in this case once the roots are calculated. This can, at least in principle, reduce the require complexity dramatically. [9], [10] The output of this module is shown in Fig. 4(c).

V. ANISOTROPY INDICES

Several scalar indices have been proposed to characterize diffusion anisotropy. Initially, simple indices, calculated from diffusion weighted images or apparent diffusion coefficients (ADCs) obtained in perpendicular directions were used [8]. They are clearly dependent on the choice of directions made for the measurements. The degree of anisotropy would then vary according to the respective orientation of the gradient hardware and the tissue frames of reference and would generally be underestimated. Here again, invariant indices must be found to avoid such biases and provide an objective, intrinsic structural information [11].

Invariant indices are thus made of combinations of the terms of the diagonalized diffusion tensor, i.e., the eigenvalues λ_1, λ_2 and λ_3. The most commonly used invariant indices are the relative anisotropy (RA), the fractional anisotropy (FA), and the volume ratio (VR) indices, defined respectively as:

$$FA = \frac{\sqrt{3[(\lambda_1-\bar{\lambda})^2+(\lambda_2-\bar{\lambda})^2+(\lambda_3-\bar{\lambda})^2]}}{\sqrt{2(\lambda_1^2+\lambda_2^2+\lambda_3^2)}} \quad (3)$$

$$RA = \frac{\sqrt{[(\lambda_1-\bar{\lambda})^2+(\lambda_2-\bar{\lambda})^2+(\lambda_3-\bar{\lambda})^2]}}{\sqrt{3}\bar{\lambda}} \quad (4)$$

$$VR = \frac{\lambda_1 \lambda_2 \lambda_3}{\bar{\lambda}^3} \quad (5)$$

The FA measures the fraction of the magnitude of D that can be ascribed to anisotropic diffusion. The RA, a normalized standard deviation, also represents the ratio of the anisotropic part of D to its isotropic part. FA and RA vary between 0 (isotropic diffusion) and 1(=2 for RA) (infinite anisotropy). As to the VR, it represents the ratio of the ellipsoid volume to the volume of a sphere of radius equal to the average eigenvalue and its range is from 1 (isotropic diffusion) to 0 [12].

VI. ERROR IN ESTIMATION

The error in Estimation was then calculated from the following Equation:

$$Error = \frac{1}{nj}\sqrt{\sum_{i=1}^{n}\sum_{k=1}^{j}(S(b_i,q_k)-\hat{S}(b_i,q_k))^2}. \quad (6)$$

where $S(b_i,q_k)$ is the original signal used in Estimation and $\hat{S}(b_i,q_k)$ is the predicted diffusion signal based on the single/multi tensor model. The output of Error in estimation is shown in Fig. 5.

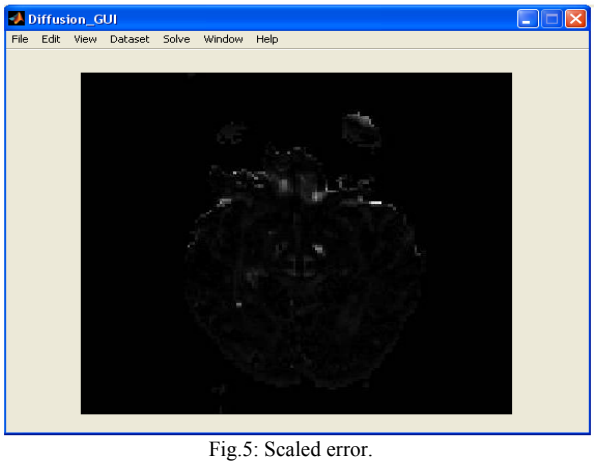


Fig.5: Scaled error.

VII. CONCLUSION

This paper presented a powerful tool for analysis of Diffusion tensor images called MultiTensor. This software, which was developed using Matlab 7.01, helps the Diffusion tensor researchers as providing the estimation of the tensors that can be used next in any other application as the fiber tracking. The choice of using Matlab will also allow others to modify and improve MultiTensor, making it even more versatile.

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