A MHT-BASED ALGORITHM FOR PERFORMANCE ESTIMATION IN DT-MRI BAYESIAN TRACKING METHODS

L. M. San José Revuelta
ETSI Telecommunication, University of Valladolid, Campus Miguel Delibes, Valladolid, Spain

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Abstract: This paper deals with the development of a recursive fuzzy inference system that can be applied to estimate the error probability of several tracking algorithms used in medical image processing systems. Specifically, we are interested in the fiber bundles estimation process (*fiber tracking*) in diffusion tensor (DT) fields acquired via magnetic resonance imaging (MRI). As tracking algorithm we have considered a variation of the Bayesian tracking scheme proposed by Friman and Westin. This paper studies the analogies between this tracking approach and a typical Multiple Hypotheses Tracing (MHT) system, for which fuzzy systems are closely related. This comparison leads to the development of a SAM (Standard Additive Model) fuzzy system that on-line estimates the certainty of the estimated fiber tracts. Its low computational load as well as its efficiency in very isotropic volumes are its main advantages.

1 INTRODUCTION

The technique of Diffusion Tensor Magnetic Resonance Imaging (DT-MRI) measures the diffusion of hydrogen atoms within water molecules in 3D space. Since in cerebral white matter most random motion of water molecules are restricted by axonal membranes and myelin sheets, diffusion anisotropy allows depiction of directional anisotropy within neural fiber structures (Ehricke, 2006).

There exist many important applications for white matter tractography: brain surgery, white matter visualization using fiber traces and inference of connectivity between different parts of the brain, to name a few.

The great majority of DTI visualization techniques focuses on the integration of sample points along fiber trajectories and their three-dimensional representation (Mori, 2002). These streamline-based approaches are called *fiber tracking* and they usually make use only of the principal eigenvector of the diffusion ellipsoid as an estimate of the predominant direction of water diffusion in a voxel (Ehricke, 2006). Nevertheless, and due to some deficiencies in these tracking algorithms and several shortcomings inherent in datasets (noise, partial voluming), they may depict fiber tracts which do not exist in reality or miss to visualize important branching structures. In order to avoid misinterpretations, the viewer of the visualizations must be provided with some information on the uncertainty of a depicted fiber and of its presence in a certain location. This task can be efficiently tackled if a Bayesian approach is used.

In this paper, we have considered a Neural network-based simplified implementation of a well-known Bayesian tracking algorithm (Friman, 2005). Specifically, this algorithm has been implemented with a simplification method based on those used in (San José, 2005) in the context of a Bayesian detector for digital multiuser communications.

Our goal is to establish a parallelism between a standard Bayesian tracking scheme and another procedure, the Multiple Hypotheses Tracking (MHT) strategy (Alberola, 1999; Reid, 1979), which is directly related to fuzzy logic and, to our knowledge, has not been directly applied to fiber estimation. The thus developed fuzzy system will calculate more reliable estimates of the depicted tracts certainty.

2 BAYESIAN TRACKING ALGORITHM

Bayesian modelling has already been applied to fiber tracking. However, its main drawback is the large computational load involved. In this paper we propose to use the Bayesian algorithm of Friman and

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Westin (Friman, 2005) with the *Stochastic Drawing Sampling Selection* (SDSS) scheme developed in (San José, 2005) for complexity limitation. This Bayesian algorithm is next described.

The goal of the Bayesian modelling is to find a pdf of the local fiber orientation[1] $p(\hat{\mathbf{v}}_k|\hat{\mathbf{v}}_{k-1}, D)$, where vectors $\hat{\mathbf{v}}_k$ and $\hat{\mathbf{v}}_{k-1}$ contain the path samples up to time k or $k-1$, respectively, and D denotes the measured diffusion data. If a model that relates the diffusion measurements D with the underlying tissue properties and architecture is assumed, then it must contain at least one fiber direction $\hat{\mathbf{v}}_k$ and a set of nuisance parameters denoted by θ. Thus, applying the Bayes theorem,

$$p(\hat{\mathbf{v}}_k, \theta|\hat{\mathbf{v}}_{k-1}, D) = \frac{p(D|\hat{\mathbf{v}}_k, \theta)p(\hat{\mathbf{v}}_k|\hat{\mathbf{v}}_{k-1})p(\theta)}{p(D)} \quad (1)$$

where we have assumed that the prior distribution can be factorized $p(\hat{\mathbf{v}}_k, \theta|\hat{\mathbf{v}}_{k-1}) = p(\hat{\mathbf{v}}_k|\hat{\mathbf{v}}_{k-1})p(\theta)$. The main problems found are (Friman, 2005): (i) the calculation of $p(\hat{\mathbf{v}}_k|\hat{\mathbf{v}}_{k-1}, D)$ needs to marginalize Eq. (1) over θ, and (ii) the normalizing factor

$$p(D) = \int_{\hat{\mathbf{v}}_k, \theta} p(D|\hat{\mathbf{v}}_k, \theta)p(\hat{\mathbf{v}}_k|\hat{\mathbf{v}}_{k-1})p(\theta) \quad (2)$$

is difficult to evaluate due to the high-dimensional integral and the intractable integrand. Eq. (1) has to be calculated in every step in the sequential sampling of the fiber paths and, unless an approximation for the integral in Eq. (2) is found, the cost is prohibitive.

Some attempts have been made to approach this problem. In (Friman, 2005), a solution based on drawing samples from a pdf defined on the unit sphere is proposed. This is accomplished by evaluating the pdf at a sufficiently large number of points evenly spaced over the unit sphere, effectively approximating the continuous pdf with a discrete pdf, from which it is straightforward to draw the random samples. However, the continuous pdf must be densely enough sampled, specifically, Friman proposes to use 2,562 predefined points thus involving an important computational burden. At this point, we propose to use a sampling strategy where those points (*hypotheses*, in the Bayesian terminology of (San José, 2005)) with the largest probabilities have more chances to be selected. However, notice that some randomness is introduced in the selection procedure. This way, those directions with the highest probability to prolong the current fiber path will *probably* be selected. Specifically, we have implemented the Stochastic Drawing Sampling Selection (SDSS) algorithm in order to reduce the number of sampled points in the above-mentioned unit sphere.

[1] Using the notation found in (Friman, 2005).

3 COMPARISON BETWEEN BAYESIAN AND MHT

A fuzzy version of Reid's classical Multiple Hypotheses Tracking (MHT) algorithm (Reid, 1979) was proposed in (Alberola, 1999). This system is based on the likelihood discrimination and it was applied to the tracking of natural language text-based messages. It shows the possibility of handling information about any time-varying phenomenon, as long as the phenomenon can be described by means of a few keywords, and the phenomenon itself is statistically causal in the sense that the distribution of future states is statistically dependent on the past observed states.

It is not difficult to see the following parallelism that leads to the possibility of a tract probability estimation based on text-messages (fuzzy-messages): (i) the natural-language messages in (Alberola, 1999) and the noisy DT-MR image constitute, in both cases, the source of *noisy* or *ambiguous* information, (ii) the *tracks* used in the MHT algorithm, which are defined as *sequences of associated symbols*, can be clearly associated to the possible sequences of points in the 3D space, in the tracking context, (iii) the MHT system associates multiple messages generated along time by using a specific stochastic model for the applications' dynamics. In our case, this model can be the information provided by the measured anisotropy, (iv) the term *target* denotes some condition that generates observable phenomena. In our context, these targets are the sequences of points that define a tract.

As a consequence, the MHT system can be viewed as a Bayesian approach for multiple targets tracking. Theoretically, this algorithm conserves *all* the hypotheses that explain the observation until certain time, together with an estimation of the probability of each hypothesis. At the end, the hypothesis with the highest likelihood is taken as the solution. On the other hand, the Bayesian tracking algorithm maintains a finite set of hypotheses (section 2) with their associated probabilities, and a tract is coloured and visualized based on these data.

4 PROPOSED FUZZY SYSTEM

In this section we propose a recursive SAM (Standard Additive Model) fuzzy subsystem that allows to monitor the performance of a DT-MRI tracking system. The SAM model allows to work with linguistic descriptions and ambiguities. This kind of description allows to fuzzy-quantify the errors in the tractography problem. On the other hand, the uncertainty in the prediction of the future positions found in the MHT of

(Alberola, 1999), resembles the creation of new fiber tracts based on the previous ones.

The system here proposed consists in three connected fuzzy inference engines (FIEs) –see Fig. 1. It is necessary to develop an algorithm where the inputs to the MHT system have some correlation in time.

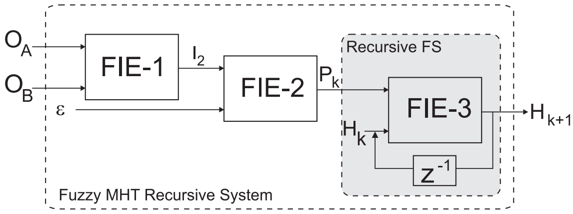

Figure 1: Recursive SAM fuzzy system for estimation of the error probability of the estimated error tracts.

The inputs O_A and O_B to the FIE-1 are two different tracts (hypotheses) estimated by the algorithm sharing in common the first and the last points (in practice, both tracts must start and finish in near voxels). These tracts are prolonged on one side with a new sample every time a new point is considered (at every iteration of the tracking algorithm), while the last point of the tracts is lost. This way, compared tracts have always the same length.

In order to evaluate the similarity between two tract hypotheses O_A and O_B, it is necessary to quantify their proximity using a 3D distance. As a consequence, a *similarity coefficient* that depends on the distance between these two considered tracts can be assigned.

In order to implement a fuzzy system, we must establish a relation between this *crisp* value (defined in $[0-K]$) and the fuzzy sets where a linguistic variable is defined, i.e.,

$$\begin{bmatrix} K \\ K-1 \\ \vdots \\ 1 \\ 0 \end{bmatrix} \longrightarrow \begin{bmatrix} \textit{Very Unlikely} \\ \textit{Unlikely} \\ \vdots \\ \textit{Likely} \\ \textit{Very Likely} \end{bmatrix} \tag{3}$$

This allows to obtain the possible fuzzy values of I_2 (output of the first FIE and input to the second).

Next, we relate the *prediction error* ε used as input in the FIE-2 with the anisotropy observed in the last (currently processed) point of the tract. This way, if a large anisotropy is obtained, the tract would be rather smooth in the proximity of the current voxel and ε will take a small value for those hypotheses (future points to expand the current tract) that involve a small change in the fiber direction. On the other hand, when the anisotropy is small (isotropic area), parameter ε would be the same for every direction (hypotheses). The value of ε must, also, be fuzzified.

This way, FIE-1 estimates the likelihood of two close tracts while FIE-2 weights this estimate with respect to the prediction error (that is inversely proportional to the anisotropy) and obtains a second likelihood. This value is used to update the *global likelihood* (or *global reliability*), which is a measure of the tracking estimation error probability. This third process is performed by FIE-3. Thus, this third block updates, with a feedback system, the previous system knowledge every time a new point is processed.

5 NUMERICAL RESULTS

5.1 Synthetic Images

First, four different synthetic DT-MRI data in a $50 \times 50 \times 50$ grid have been generated (three of them –*cross*, *earth* and *log*– can be seen in Fig. 3 of (San-José, 2006) while the fourth one, named *star*, –the most complex one– is new. To make the simulated field more realistic, Rician noise was added in the diffusion weighted images which were calculated from the Stejskal-Tanner equation using the gradient sequence in (Westin, 2002) and a *b*-value of 1000.

The desired noisy synthetic diffusion tensor data was obtained using an analytic solution to the Stejskal-Tanner equation. The eigenvectors in the isotropic areas were $\lambda_1 = \lambda_2 = \lambda_3$, while in the remaining voxels of the image $\lambda_1 = 7$, $\lambda_2 = 2$, $\lambda_3 = 1$. In our study, the SNR varies from 13 to 29 dB.

The "star" image consists of six orthogonal sine half-waves, each of them with arbitrary radius. Notice that this scenario constitutes the most complicated situation since the diffusion field experiments variations with the three coordinate axes and there exists a crossing region.

The reliability of four approaches for estimating the tracts certainty is first studied. These methods are: (i) the tracking algorithm described in (San-José, 2006), ("ALG"), (ii) the Bayesian algorithm described in section 2 ("BAY"), (iii) ALG with the fuzzy engine for probability of error estimation ("ALG+Fuzzy"), and (iv) BAY with the fuzzy procedure ("BAY+Fuzzy"). Figure 2 shows the mean probability of wrong estimation (average value in 25 executions) and Table 1 presents the mean variance of these estimators, for five different signal qualities ranging from 13 to 29 dB.

Analyzing the results it can be seen that: (i) the probability of error increases as the SNR of the original image improves; more complex images have

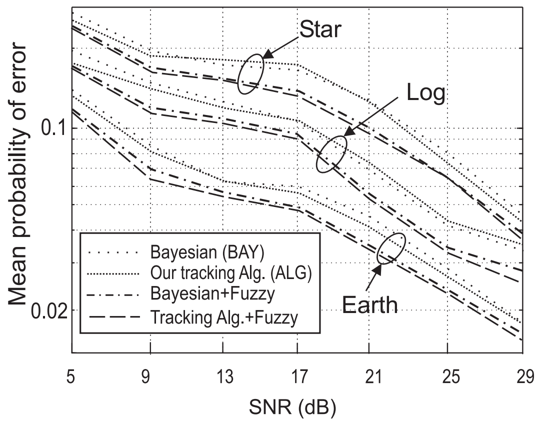

Figure 2: Mean probability of error for the tracking methods studied, with and without the fuzzy procedure for estimation of the probability of error. Three synthetic images were used: earth, log and star.

Table 1: Variance of the tracking error estimation method. Each cell represents the values for: BAY/**ALG**/Fuzzy-estimation.

	SNR (dB)		
	13	21	29
Earth	4.2/**3.7**/1.6	2.3/**1.9**/0.7	1.4/**0.9**/0.2
Log	4.5/**4.1**/2.0	2.8/**2.3**/0.9	1.5/**0.9**/0.3
Star	6.4/**5.1**/2.8	3.2/**2.7**/1.5	2.2/**1.7**/0.7

larger tracking error estimates, (ii) in general, the accuracy of the ALG method is slightly better than the BAY approach, and (iii) the tracking error of both methods (BAY and ALG) improves notably when the fuzzy engine is used for estimation. These figures are closer to the real probability of error when a human expert manually evaluates the tracts obtained.

Table 1 shows how the fuzzy procedure greatly decreases the variance of the estimator, leading to more robust and accurate estimations, specially for low quality images. The values shown in each cell represent the variance of the different estimation approaches: BAY, ALG and the fuzzy-based estimation using the strategy proposed in section 4. The fuzzy method obtained very similar results when combined to both BAY and ALG. Thus, only one value is included in each cell.

It can be observed that the fuzzy approach gets estimates with much smaller variances. This estimation procedure is scarcely influenced by both the SNR of the image and image complexity (in terms of anisotropy). This implies that the estimation convergence will not depend on the presence of branching or crossing areas of the MR figure –as it would be the case in real DT-MR images.

5.2 Real Images

Finally, we have applied the proposed tracking algorithm to a real DT-MR image. Specifically, we have selected the *corpus callosum* of the brain.

The variance of the same four estimation methods has been evaluated. Results are shown in Table 3. Once again the improvement on the estimates reliability can be observed for both BAY and ALG.

Table 2: Variance of different probability of error estimation methods.

BAY:	8.4	BAY+fuzzy:	3.8
ALG:	7.4	ALG+fuzzy:	3.2

If noisy voxels are present along the paths of interest it is worth noting that the MHT-based fuzzy method is less sensitive to these variations. The reason is that the MHT performs a kind of *smoothing* or data *filtering*, which decreases the disturbing effects of the occasionally high noisy samples (this is addressed using the FIE-3 in Fig. 1).

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