Multi-channel Diffusion Tensor Image Registration via Adaptive Chaotic PSO

Yudong Zhang, Shuihua Wang, Lenan Wu, Yuankai Huo
School of Information Science and Engineering, Southeast University, Nanjing, China
yuzhang@childpsych.columbia.edu

***Abstract*—Registration or spatial normalization of diffusion tensor images plays an important role in many areas of human brain white matter research, such as analysis of Fraction Anisotropy (FA) or whiter matter tracts. More difficult than registration of scalar images, spatial normalization of tensor images requires two important parts: one is tensor interpolation, and the other is tensor reorientation. Current tensor reorientation strategy possessed many defects during tensor registration. To overcome the shortcomings, we first presented a multi-channel model with one FA and six log-Euclidean tensors, and then proposed an adaptive chaotic particle swarm optimization to find the global minima of the objective function of the multi-channel model. The results on 42 slices inter-subject registration indicate that our proposed method can produce accurate and optimized parameters of tensor registration with fastest speed relative to Genetic Algorithm and Particle Swarm Optimization**

***Index Terms*—multi-channel registration; genetic algorithm; particle swarm optimization**

I. INTRODUCTION

Diffusion MRI is a magnetic resonance imaging (MRI) method that produces in vivo images of biological tissues weighted with the local micro-structural characteristics of water diffusion, especially in brain [1]. An important diffusion MRI modeling and analysis method is diffusion tensor imaging (DTI), which is a MRI technique that enables the measurement of the restricted diffusion of water in tissue in order to produce neural tract images [2].

With diffusion tensor image, the motion of water molecules in human brain can be well formulated by a Brownian motion in each voxel of the image as 3×3 symmetric positive-definite matrices. Diffusion tensor can be reconstructed from a sequence of diffusion weighted imaging (DWI) dataset. The processing and analysis of DTI data are much more difficult than the processing and analysis of DWI. To make DTI data more computationally tractable, investigators have developed a family of so-called diffusion anisotropy indices (DAIs). Most analysis of DTI is constrained on DAIs, which are scalar images. For population study of specific diseases, it's important to do statistical analysis directly on tensor itself. Therefore, registration of different tensor images from different subjects is a fundamental procedure.

Registration is a key step in many areas of white matter research, such as analysis of Fraction Anisotropy (FA) [3] or mapping white matter tracts in different applications, including white matter disorders, demyelination and dysmyelination, brain tumor, and surgical interventions. Image registration can be formulated as a general optimization problem including four major parts: a metric that defines the difference measure between images; a transformation that defines the spatial transformation applied to the moving image, (e. g., affine transform, B-Spline deformable transform, demon deformable transform); an optimized function (e.g, Powell method) that searches the parameter space of the transformation; and an interpolation method that interpolates image intensities in the transformed moving image. Unlike scalar images, spatial normalization of tensor images requires two important parts, one is tensor interpolation, and the other is tensor reorientation. Current tensor reorientation strategy possessed many defects during tensor registration without consideration of full tensor information.

To overcome the weakness, we proposed a novel model and a new optimization method to solve our model. The structure of this paper is organized as follows. Section II introduces in the background of DWI, DTI, and diffusion tensor. Section III gives our proposed multi-channel model. Section IV presents an improved adaptive chaotic particle swarm optimization (ACPSO) to solve the proposed model. Experiments in section V compared the ACPSO with the standard genetic algorithm and particle swarm optimization. Final section VI is devoted to discussion.

II. BACKGROUND

A. DWI and DTI

Diffusion MRI is a MRI method that produces in vivo images of biological tissues weighted with the local micro-structural characteristics of water diffusion. The field of diffusion MRI can be understood in terms of two distinct classes of application—DWI and DTI. Traditionally, in DWI, three gradient-directions are applied, sufficient to estimate the trace of the diffusion tensor or 'average diffusivity', a putative measure of edema. Clinically, trace-weighted images have proven to be very useful to diagnose vascular strokes in the brain, by early detection (within a couple of minutes) of the hypoxic edema. More extended DTI scans derive neural tract directional information from the data using 3D or multidimensional vector algorithms based on three, six, or more gradient directions, sufficient to compute the diffusion tensor. The diffusion model is a simple model that can characterize the diffusion process in human brain, assuming homogeneity and linearity of the diffusion within each image voxel [4].

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B. Diffusion Tensor

The tensor can sufficiently describe the molecular mobility along each direction and correlation between these directions. A typical tensor is described as follows

$$D = \begin{Bmatrix} D_{xx} & D_{xy} & D_{xz} \\ D_{yz} & D_{yy} & D_{yz} \\ D_{zx} & D_{zy} & D_{zz} \end{Bmatrix} \qquad (1)$$

The tensor is symmetric, viz., $D_{ij}=D_{ji}$ with $i, j= x, y, z$.

III. MODEL

A. Log-Euclidean Vectorization of tensors

Tensors are always analyzed on Euclidean metrics, which has many defects, such as swelling effects. Recently, some researchers have introduced Log-Euclidean metrics based on affine-invariant Riemannian metrics for tensor analysis. Log-Euclidean metrics have excellent theoretical properties and provide powerful processing tools, also with simpler and faster computations. Under the matrix logarithm and exponentiation operation which are the theoretical basics of Log-Euclidean, one can combine tensor space and vector space together smoothly [5]. The Log-Euclidean vectorization is calculated in following three steps:

Step 1 Perform a diagonalization of $\boldsymbol{D}=R^TER$, which provides a eigenvector matrix R and a eigenvalue matrix E;
Step 2 Transform each eigenvalue of E into its natural logarithm in order to obtain a new diagonal matrix $\log(E)$;
Step 3 Recompose $\log(D)=R^T\log(E)R$ to obtain the logarithm of D;
Step 4 Since $\log(D)$ has only 6 degrees of freedom, it can be represented by 6D vectors in the following way

$$\begin{aligned}\log(D) = [&\log(D)_{xx}, \log(D)_{yy}, \log(D)_{zz}, \\ &\sqrt{2}\log(D)_{xy}, \sqrt{2}\log(D)_{xz}, \sqrt{2}\log(D)_{yz}]^T\end{aligned} \qquad (2)$$

Here $\log(D)_{i,j}$ denote the ith row and jth column of the matrix $\log(D)$.

B. Tensor reorientation

During scalar image registration, the intensity of each voxel is transferred, via the spatial transformation, to the reference image with an interpolation method. Spatial normalization of tensor images which requires two important parts, one is tensor interpolation, and the other is tensor reorientation, is more complex than scale images. In the case of registration of scalar images, transformation T only change the position of voxel i, while keep the value of intensity. In the case of registration of tensor images, the transformation T can't correct the wrong topology of whiter matters after registration. Reorientation needs to be procedured after tensor registration to keep the topology of whiter matter [6]. Given moving image *Mov* and reference image *Ref*, the spatial transformation T are composed of local affine transformations. In order to test our method in a simple way, we only considered a global affine transformation in this paper.

According to Polar Decomposition Theorem, the affine transformation can be represented by Jacobian matrix Jaco and translation Trans:

$$T = Jaco + Trans \qquad (3)$$

$$Jaco = Rot * Def \qquad (4)$$

here *Rot* denotes the orthogonal rotation matrix, *Def* denotes the deformation matrix. The final affine transformation can be represented by:

$$T = Rot * Def + Trans \qquad (5)$$

Therefore, each tensor S is reoriented by Finite Strain strategy as follows

$$\mathrm{Reo}[T(S)] = Rot^T \cdot T(S) \cdot Rot \qquad (6)$$

C. Multi Channel Mutual Information

Mutual information is an effective method for multimodality image registration. Mutual information is derived from Shannon's entropy, which is a quantity that measures the mutual dependence of the two variables [7]. Mutual information is an intensity-based image registration method. Given a reference image and a moving image, image registration involves spatially transforming the moving image to align with the reference image. Intensity-based methods compare intensity patterns in images via correlation metrics, such as mutual information. Knowing the correspondence between a number of points between moving image and the reference image, a transformation, rigid, affine or no-rigid, is then determined to map the moving image to the reference images, thereby establishing point-by-point correspondence between the reference and target images. For single-channel images, the final spatial transformation of registration is determined by maxim value of MI between the reference image *Ref* and the moving image *Mov*:

$$T^* = \arg\max_T MI\{\mathrm{Reo}[T(Mov)], Ref\} \qquad (7)$$

where T denotes the spatial transformation. Here, we used multi-channel to increase the registration accuracy, where the first 6 channels represent the 6 components of log tensor mentioned in section A, and the last channel represents the FA value. Fig. 1 gave a detailed example.

Afterwards, we intend to find the best affine parameters of each channel

$$T_k^* = \arg\max_T MI\left\{\mathrm{Reo}\left[T(Mov_k)\right], Ref_k\right\} \qquad (8)$$

The final transformation T was calculated as a weighted function of the transformations T_k^* with the corresponding MI values as weighting factors,

$$T^* = \frac{1}{\Omega}\sum_{k=1}^{7}\omega_k T_k^* \qquad (9)$$

where $\omega_k = MI[T_k^*(Mov_k), Ref_k]$, and $\Omega = \sum_{k=1}^{7}\omega_k$.

IV. ALGORITHM

Traditional methods to solve the image coregistration problem focus on the BFGS methods [8], However, BFGS is easy to be trapped into local minima, namely, the registered image does not match the reference image. In this study, we proposed an adaptive chaotic algorithm to minimize formula (8).

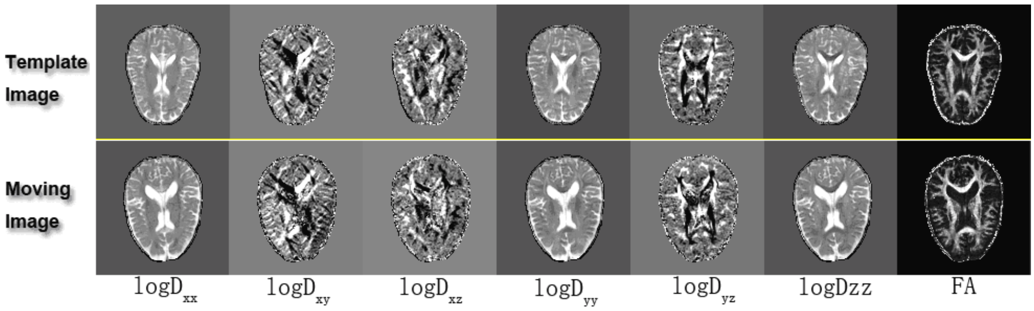

Fig. 1 An example of seven channel registration

A. Particle Swarm Optimization

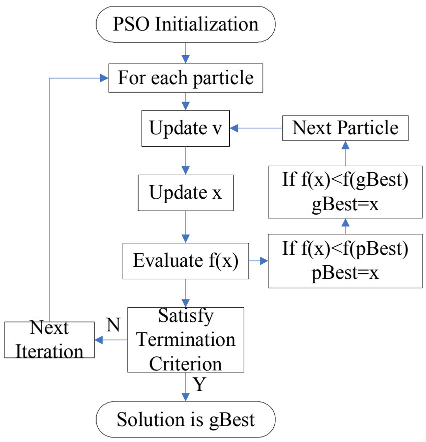

Fig. 2 Flow chart of the PSO algorithm

PSO is a population based stochastic optimization technique, which simulates the social behavior of a swarm of bird, flocking bees, and fish schooling. By randomly initializing the algorithm with candidate solutions, the PSO successfully leads to a global optimum. This is achieved by an iterative procedure based on the processes of movement and intelligence in an evolutionary system. Fig. 2 shows the flow chart of a PSO algorithm.

In PSO, each potential solution is represented as a particle. Two properties (position x and velocity v) are associated with each particle. Suppose x and v of the ith particle are given as

$$x = (x_{i1}, x_{i2}, \cdots, x_{iN}) \quad (10)$$

$$v = (v_{i1}, v_{i2}, \cdots, v_{iN}) \quad (11)$$

where N stands for the dimensions of the problem. In each iteration, a fitness function is evaluated for all the particles in the swarm. The velocity of each particle is updated by keeping track of the two best positions. One is the best position a particle has traversed so far and called "*pBest*". The other is the best position that any neighbor of a particle has traversed so far. It is a neighborhood best called "*nBest*". When a particle takes the whole population as its neighborhood, the neighborhood best becomes the global best and is accordingly called "*gBest*". Hence, a particle's velocity and position are updated as follows

$$v = \omega \cdot v + c_1 r_1 (pBest - x) + c_2 r_2 (nBest - x) \quad (12)$$

$$x = x + v\Delta t \quad (13)$$

where ω is called the "*inertia weight*" that controls the impact of the previous velocity of the particle on its current one. The parameters c_1 and c_2 are positive constants, called "*acceleration coefficients*". The parameters r_1 and r_2 are random numbers that are uniformly distributed in the interval [0, 1]. These random numbers are updated every time when they occur. The parameter Δt stands for the given time-step.

The population of particles is then moved according to (12) and (13), and tends to cluster together from different directions. However, a maximum velocity $v_{\max}$, should not be exceeded by any particle to keep the search within a meaningful solution space. The PSO algorithm runs through these processes iteratively until the termination criterion is satisfied.

B. Improved ACPSO

The PSO algorithm has proven to be very effective for solving global optimization. It is a recently invented high-performance optimizer that is very easy to understand and implement, and it also requires little computational bookkeeping and only a few lines of code.

The parameters (r_1, r_2) were generated by pseudo-random number generators (RNG) in classical PSO. The RNG cannot ensure the optimization's ergodicity in solution space because they are absolutely random; therefore, a chaotic operator was employed to generate parameters (r_1, r_2) by the following formula:

$$r_i(t+1) = 4.0 * r_i(t) * [1 - r_i(t)] \quad i = 1,2 \quad (14)$$

Another improvement lies in changing the parameters (ω, c_1, c_2) adaptively. In the search process of PSO, the search space will gradually reduce as the generation increases. Therefore, we hope to search an expansive area with low precision at the prophase stage while search a restricted area with high precision at the anaphase stage as listed in Tab.1.

Tab.1 Parameters variation

	Prophase	Anaphase
Ω	Larger	Smaller
c_1	Larger	Smaller
c_2	Smaller	Larger
Performance	PSO Searches for global optimal in an expansive area with low precision	PSO Searches for local optimal in a limited area with high precision

The detailed formulas of those adaptive parameters are as follows:

$$\omega = \omega_i - \frac{\omega_i - \omega_f}{MaxGeneration} * Generation \quad (\omega_i > \omega_f) \quad (15)$$

$$c_1 = c_{1i} - \frac{c_{1i} - c_{1f}}{MaxGeneration} * Generation \quad (c_{1i} > c_{1f}) \quad (16)$$

$$c_2 = c_{2i} - \frac{c_{2i} - c_{2f}}{MaxGeneration} * Generation \quad (c_{2i} < c_{2f}) \quad (17)$$

Here, the indexes i and f denotes "initial" and "final", respectively.

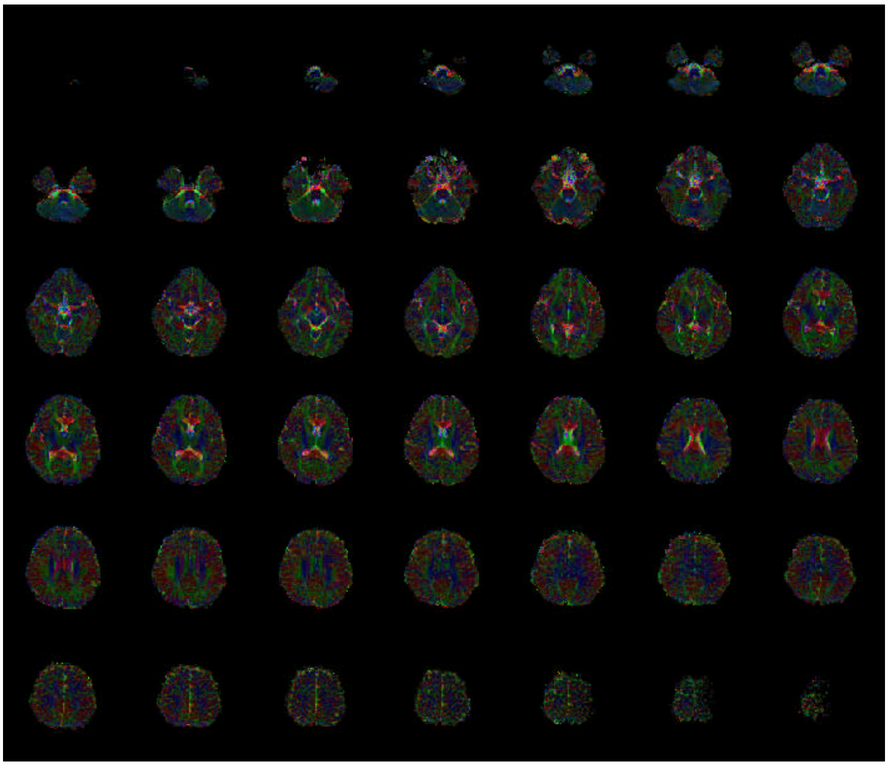

Fig. 3 42 slices images of subject I

V. EXPERIMENTS

In this study, images were acquired on a 1.5 T MRI signal scanner. The parameters of DWIs are: TR=2.4s, TEs are around 65ms, b=1000s/mm^2, FOV=24cm×24cm, slice thickness=2mm, voxel size=2mm×2mm×2mm, diffusion directions=15. For all subjects, a high-resolution T1-weighted structural image contains 128 axial slices (acquisition matrix: 256×256) was also acquired for other usages. The experiment computer has Intel Core2 CPU with 2GHz and 1GB memory.

We used our proposed algorithm to register two adult subjects. Subject I is determined as the reference image while subject II is determined as the moving image. The 42 slices of subject I are shown in Fig. 3, and those of Subject II are omitted.

A. Algorithm Comparison

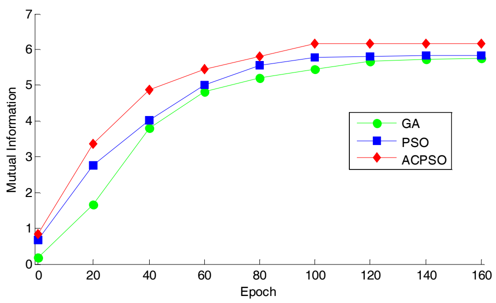

Fig. 4 Comparison of different algorithms

We compared our algorithm with the standard GA method and canonical PSO method. A typical convergence curve is shown in Fig. 4, indicating that GA and PSO are trapped into local minima, however, our proposed method resist from being misled and converges into global minima.

B. Time Comparison

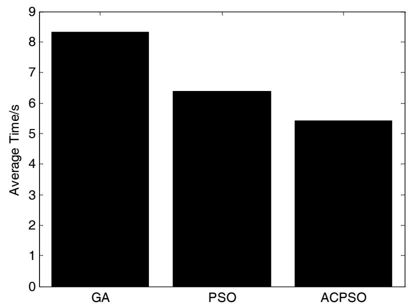

Fig. 5 Time comparison

The average computation time of registering one pair of images was calculated and shown in Fig. 5. It indicates that our method takes about 5.43s to register one pair of images, PSO needs 6.38s, GA is the most time-consuming which needs 8.34s.

C. Registration Evaluation

In order to evaluate the registration results, we calculated the average overlap of eigenvalue-eigenvector pairs (AOE) [9] of the resulting images. The AOE measures, on average, the extent to which two tensors at each voxel are aligned, are defined as:

$$\frac{1}{N}\sum_{i=1}^{N}\frac{\sum_{j=1}^{3}\lambda_j^i\lambda_j^{'i}\left(\varepsilon_j^i\varepsilon_j^{'i}\right)^2}{\sum_{j=1}^{3}\lambda_j^i\lambda_j^{'i}} \tag{18}$$

Where λ_j^i, ε_j^i and λ'^i_j ε'^i_j are the jth eigenvalue-eigenvector pair at the ith voxel location in the pair of images, and N is the total number of voxel locations for comparison. Fig. 6 shows the AOEs from different algorithms, demonstrating that our proposed algorithm has the highest AOE on every slice and is the most approximate to the ideal line.

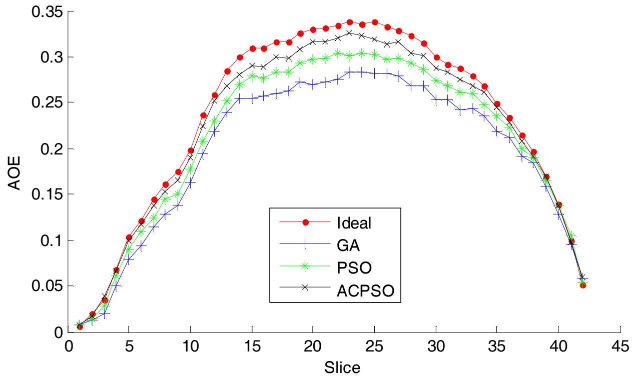

Fig. 6 The registration evaluation

VI. DISCUSSION

A new registration method for DTI was presented in this study. We first proposed a seven-channel (FA plus 6 Log-Euclidean tensor vectors) model based on maximum mutation information, afterwards, we proposed an ACPSO to solve the problem. The experiments on 42 slices of intra-subject brain images of demonstrate that our proposed method performs satisfying, takes the least convergence steps, consumes the least time, and gets the highest AOE value. The future work focuses on the application of this method to other fields such as fiber clustering.

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Yudong Zhang was born in Suzhou, China. He received a B.S. degree in 2004 and M.S. in 2007 in electronic engineering from Nanjing University of Aeronautics and Astronautics, Nanjing. He received a Ph.D. degree in 2010 in communication and signal processing from Southeast University, Nanjing.

Now he researches as a postdoctor in Columbia University and a research fellow in New York State Psychology Institute. His research interests in computer science are in the areas of data mining for artificial neural network, decision tree, expert system, artificial intelligence, genetic algorithm, and particle swarm optimization. He is the first-author of over 10 papers published on SCI-index journals and is an active consultant for industry in these areas.

Mr Zhang is the editor of “International Journal of Intelligent Information Processing”, “Journal of Convergence Information Technology”. He is a member of IEEE, New York Academy of Science, Chinese Computer Federation (CCF), and China Institute of Electronics (CIE). Besides, he is a Council Member of Audio/Video Technician Association and Multimedia Institute in Nanjing.

Lenan Wu was born in Fujian, China, in July 1952. He received the B.S. degree in radar engineering and M.S. degree in communication & electronic systems in 1982 and 1987, respectively, both from the Nanjing Aeronautical Institute, China, and the Ph.D. degree in signal & information processing in 1997 from the Southeast University, Nanjing, China. In 1987 he joined the Department of Radio Engineering (now, the Institute of Information Scien & Engineering), Southeast University, where he is presently a Professor of Signal & Information Processing.

He has been the Deputy Chairman of the Department during 1992 to 2000 and the Director of the Multimedia Technical Research Institute (MTRI) since 1992. He is presently a Fellow of China Institute of Electronics (CIE), a Senior Member both of China Institute of Communications (CIC) and of China Computer Federation (CCF), a Vice Chairman of the Microcomputer Application Association of China Institute of Instruments, and a Council Member of the Multimedia Technology Committee of National Standardization Commission of Information..

He has published over 200 journal papers and is the author or co-author of nine books, including Data Compression, and Principles and Applications of Multimedia and Associated Techniques. He holds eleven Chinese patents.As a doctorial advisor, he has graduated 7 Postdoctors, 27 Doctors, and 83 Masters since 1995.