ELASTIC REGISTRATION OF THE CORPUS CALLOSUM

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ABSTRACT

Geometric analysis of postmortem normal and autistic human subjects reveal distinctions in deformations in the corpus callosum (CC) that may be used for image analysis-based studies of autism. Preliminary studies showed that the CC of autistic patients is quite distinct from normal controls. We use an implicit vector representation of CC to carry out the registration process which measures the differences between different CC's. This paper introduces a new method for the $2D$ shape registration problem by matching vector distance functions. A variational frame work is proposed for the global and local registration of CC's. A gradient descent optimization is used which can efficiently handle both the rigid and the non-rigid operations together. The registration of real CC extracted from postmortem data sets demonstrates the potential of the proposed approach.

***Index Terms*—** Shape Representation, Shape Registration, Level Sets, Energy Minimization.

1. INTRODUCTION

Autism is a complex developmental disability that typically appears during the first three years of life and is the result of a neurological disorder that affects the normal functioning of the brain, impacting development in the areas of social interaction and communication skills.

During the past two decades, studies of autism's neuropathology have increased dramatically. Most of these studies have reported alterations in some regions of the brain in autistic individuals compared to typically developing ones. Gurin et al. [1] have reported a thin corpus callosum (CC) in his autism study. It was also reported in many MRI based studies that the corpus callosum, which is the largest commisure in the brain that allows neural communications between the two hemispheres, has reduced size in autistic subjects. However, findings are inconsistent as to which segment of the CC is abnormal. Most studies have reported a reduced posterior CC, whereas other studies have found that the reduction was limited to the anterior segment. A more recently conducted MRI study [2], has shown aberrant connections between cortical regions. This study has also revealed reductions in the total colossal area as well as in the anterior third of the CC in autistic sufferers.

So, our target is to measure the differences between normal and autistic CC's by means of registration. The process includes both global and elastic deformation to measure and quantify the deformation at each point of the CC contour; That will require a reasonable shape representation to handle the operation.

Shapes registration is an important complex problem in computer vision, computer graphics and medical imaging. It has been handled in different manners in many applications such as shape-based segmentation, shape recognition, and tracking.

The shapes registration problem is formulated such that a transformation that moves a point from a given shape to a target one according to some dissimilarity measure [3], needs to be estimated. The dissimilarity measure can be defined according to either the curve or by the entire region enclosed by the curve.

Different shapes registration approaches were proposed in numerous literature for example [4, 5, 6]. These approaches suffer from various problems. Scale variations and local deformations can not be covered in many cases. Also their dependency on the initialization represents one of the hardships.

Vector distance functions ($VDF's$) are used in [7] to evolve smooth manifolds. This representation defines a vector that connects any point in space to the nearest point on the curve or surface. This representation can deal with shapes of different dimensions. We proposed shape representation by vector components in a different manner in our shape-based segmentation framework [8]. This representation serves the segmentation and shape registration processes.

In this paper, we focus only on the registration problem by proposing a novel and robust $2D$ shape registration approach. We use VDF representation to handle the $2D$ shape registration process. The use of the VDF results in adequate energy function which is optimized to get the transformation parameters both in the global and local registration schemes. Matching these vector functions formulates a variational framework for the registration process of $2D$ shapes. The optimization criterion employed can handle the global and local pixel-wise

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deformations like in [3]. Promising results for real shapes in $2D$ will be discussed.

This paper is organized as follows; Data collection and protocol are demonstrated in Sec. 2, Section 3 presents the shape representation formalism using VDF, Global registration and alignment technique will be presented in Sec. 4, Section 5 is dedicated for the local registration while results will be shown in Sec. 6. The paper ends with a discussion and future research aspects in Sec. 7.

2. DATA COLLECTION

The postmortem MRI data used in this study is described in detail in [9]. In order to optimize white-gray matter substance contrast in formalin-fixed brains, a proton density weighted imaging sequence was used. The method employed a 1.5 Tesla GE MRI system to scan brains that have been placed within a special device that avoids dehydration during the scanning procedure. The images were collected in a 192x256 acquisition matrix and were 0-filled in k space to yield an image of 256x256 pixels, resulting in an effective voxel resolution of approximately 1.0 x 1.0 x 1.5 mm. Eight whole brains and six hemisphere coronal volumes of size 512x512x114. Each slice is 1.6mm thick with an in-plane resolution of 0.625x0.3125mm, on which the WM appears dark, the GM appears light, and the fluid appears brighter. Due to different factors including the removal of the brain from the skull and fixation problems, distortions such as large deep cuts, commonly occur and are revealed in the MRI scans.

3. SHAPE REPRESENTATION AND THE VECTOR DISTANCE FUNCTION

An emerging way to represent shapes boundaries can be derived using level sets. These functions are invariant to rotation and translation and also can handle complex topologies. Using the conventional signed distance function (level set function) will result in handling only homogenous scales. Hence the registration process fails when the scales are different. That is why, we are going to use the VDF to handle this problem as follows [10];

The function $\Phi : R^2 \rightarrow R^2$ is defined for a given smooth curve V that represents boundaries of a certain shape:

$$\Phi(\mathbf{X}) = \mathbf{X}_0 - \mathbf{X}, \forall\, \mathbf{X} \in \Omega, \tag{1}$$

and $\mathbf{X}_0$ is the point on V that has the minimum Euclidean distance to $\mathbf{X}$. We have now Φ set in a vector form:$\Phi(\mathbf{X}) = [\phi_1(\mathbf{X}),\ \phi_2(\mathbf{X})]^T$ where $\phi_1\ and\ \phi_2$ are the components of the vector function in the coordinates directions.

Applying a global transformation with different scales in different directions to a given shape represented by the designed vector map, one can predict the map of the transformed shape. The following relation can be established between two shapes' boundaries ($\alpha\ and\ \beta$) representation:

$$\Phi_\beta(\mathbf{A}) = \mathbf{SR}\Phi_\alpha(\mathbf{X}) \tag{2}$$

The second contour results from scaling, rotating, and translating the first shape by the parameters $\mathbf{S}, \mathbf{R},\ and\ \mathbf{T}$ respectively where $\mathbf{A}$ is defined as the transformation function.

4. GLOBAL REGISTRATION OF SHAPES

The VDF shape representation changes the problem from the $2D$ shape to the higher dimensional vector representation. Looking for a transformation $\mathbf{A}$ that gives a pixel-wise vector correspondence between the two shapes representations Φ_α and Φ_β, is our target. The problem now is considered as a global optimization that includes all points in the image domain. Sum of squared differences will be used to show the performance of the proposed approach.

4.1. Energy Formulation

The vector shape representation is invariant to translation only, so the following vector dissimilarity measure is used to measure the difference between the current vector (rotated and then scaled) and the target one (note that the magnitude of the vector representation is invariant to rotation and translation):

$$\mathbf{r} = \mathbf{SR}\Phi_\alpha(\mathbf{X}) - \Phi_\beta(\mathbf{A}) \tag{3}$$

and the optimization objective function is given by summing up the vectors differences over the domain:

$$E(\mathbf{S}, \mathbf{R}, \mathbf{T}) = \int_\Omega \mathbf{r}^T \mathbf{r} d\Omega \tag{4}$$

The complexity of the problem is reduced by taking only points around the zero level of the vector function since far away points mapping can be neglected. The matching space is limited to a small band around the surface that can be selected by introducing the following energy function:

$$E(\mathbf{S}, \mathbf{R}, \mathbf{T}) = \int_\Omega \delta_\epsilon(\Phi_\alpha, \Phi_\beta) \mathbf{r}^T \mathbf{r} d\Omega \tag{5}$$

where δ_ϵ is an indicator function [10]. The transformation parameters are estimated using the gradient descent optimization.

5. LOCAL REGISTRATION OF SHAPES

The above registration method can not handle local deformations. It maximizes the overlapping between the given two shapes. The global transformation $\mathbf{A}$ is combined with a local deformation vector $\mathbf{U} = [u_x\ u_y\ u_z]^T$ using the following dissimilarity measure:

$$\mathbf{r}_n = \mathbf{SR}\Phi_\alpha(\mathbf{X}) - \Phi_\beta(\mathbf{A} + \mathbf{U}) \tag{6}$$

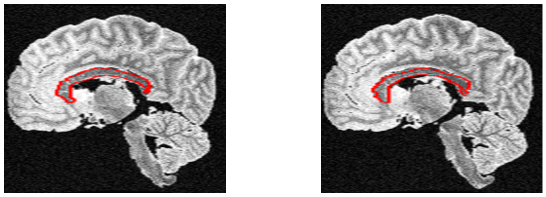


Fig. 1. Two different slices in the sagittal section of a post-mortem data set. The CC is segmented using and marked in red.

Fig. 2. Corpus callosum registration demonstrates the random selection of transformation parameters for the initial positions of shapes. Initial position is given in the left column and final registration is illustrated in the middle. Registration energy is plotted versus iteration number in the last column.

and hence the following objective function is used:

$$E(\mathbf{S},\mathbf{R},\mathbf{T},\mathbf{U}) = C_1 \int_{\Omega} \delta_{\epsilon} \mathbf{r}^T \mathbf{r} d\Omega + C_2 \int_{\Omega} \delta_{\epsilon} \mathbf{r}_n^T \mathbf{r}_n d\Omega \quad (7)$$

The energy contains a term for the global registration and another part for covering the local deformations. Each part is weighted by the corresponding coefficient C. The deformation field is smoothed by adding another term that includes their derivatives as follows:

$$E(\mathbf{S},\mathbf{R},\mathbf{T},\mathbf{U}) = C_1 \int_{\Omega} \delta_{\epsilon} \mathbf{r}^T \mathbf{r} d\Omega + C_2 \int_{\Omega} \delta_{\epsilon} \mathbf{r}_n^T \mathbf{r}_n d\Omega + C_3 \int_{\Omega} (\nabla^2 u_x + \nabla^2 u_y + \nabla^2 u_z) d\Omega \quad (8)$$

These local deformations are handled by the incremental free form deformations as in [11].

6. EXPERIMENTAL RESULTS

We carry out shape registration on different CC's coming from postmortem data sets. The structure is segmented using the shape-based segmentation technique we proposed in [8] (see Fig. 1). Implicit vector representation is calculated for each structure. A global registration is performed first to estimate the scales, rotation, and translations parameters. A demonstration for some registration cases is found in Fig. 2. The energy decreases smoothly to make sure that the parameters are going to the steady state to get the boundaries of the source and target near to each other. The results go with local deformations covering by minimizing sum of differences of the vector representations as well. Two different cases are demonstrated in Fig. 3. The approach is able to cover local deformations as shown in each case and also keep the topology of the shapes (see the grid deformation at the last column). The algorithm is successful because it can give exact meaningful anatomical correspondences (it is clear from the ends of the corpus callosum which correspond to the ends of its target). To quantify the algorithm, 100 registration cases are carried out. In each case, the similarity between the source and target shapes is calculated by measuring the correlation coefficient (between the magnitudes of the vector representations) before and after registration. The results are impressive. The improvement is very big and the coefficient is very close to 1.

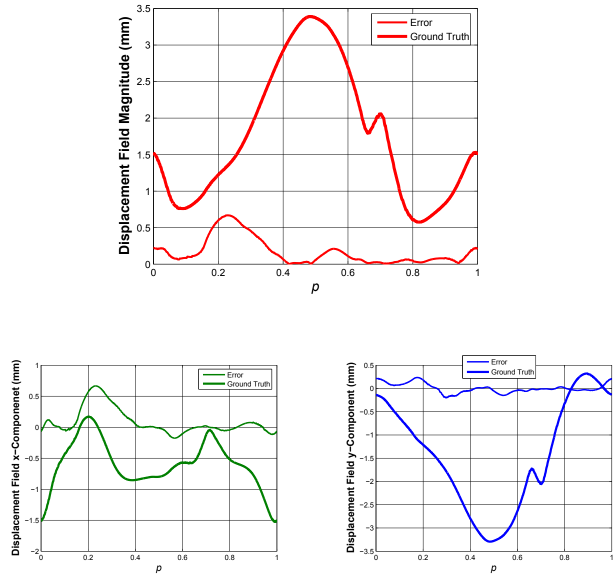
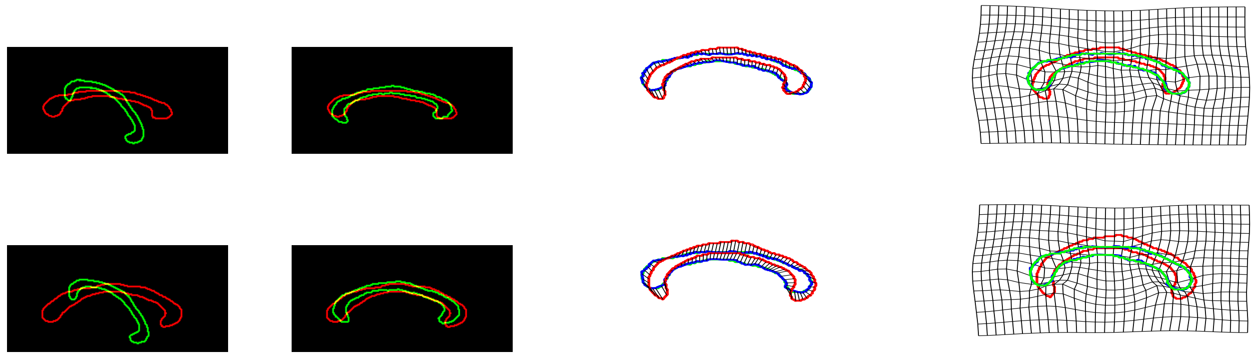


Fig. 4. Validation example of a local registration case with displacement field measurements: (Top) Displacement field magnitude plot over the shape contour, (Bottom Left) x-Component of the displacement field error, and (Bottom Right) y-Component of the displacement field error.

Figure 4 shows a validation experiment for the proposed approach. Two boundaries are used with known point correspondences. The approach is applied by increasing the resolution of the control lattice one step in each direction at a time starting from a grid of 5×5. The contours come closer to each other iteratively until the steady state is reached. The displacement field is achieved with an average error of $0.1677mm$. Errors of the displacement fields are plotted versus the curve parameterization allowing a follow up of the error distribution over the whole shape boundary.



(a) (b) (c) (d)

Fig. 3. Global and local registration of two different CC's: (a) Initial position, (b) Results after global alignment, (c) Anatomical correspondences between the source and target shapes, and (d) Grid deformation after elastic registration.

7. CONCLUSION AND FUTURE RESEARCH

We have proposed an implicit $2D$ shape registration problem. The shapes are implicitly represented by higher dimensional vector distance functions. The vector distance function is used within an energy formulation that measures the dissimilarity between the two given contours and a variational scheme is derived to calculate the registration parameters both for the global and local cases. The results are promising and do not need any point correspondences. The accuracy of the elastic registration is measured against a ground truth model. This process is the main test to quantify the changes between normal and autistic structures. In the future, many data sets will be enrolled to get a conclusion about the main differences and morphological changes. Also, implementation in 3D will be taken into consideration.

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