Non-rigid Cerebral Surface Registration for Neonates Using ICP Algorithm

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Magnetic resonance (MR) images are widely used to diagnose cerebral diseases. MR image registration based brain shape evaluation is effective to diagnose brain diseases because the diseases may deform the brain shape, and the deformed region differs among types of diseases. This paper focuses on neonatal brain MR images, and introduces a non-rigid image registration method using sulcal-distribution index (SDI), which is calculated from MR signal on the cerebral surface. The method is based on an iterative closest point (ICP) algorithm. The proposed method will be effective for the neonatal brain because the method evaluates the correspondence of cerebral sulci distribution. Results in seven neonates (modified age was between 3 weeks and 2 years) showed that the method registered the cerebral shapes successfully.

1. Introduction

The early treatment of developmental brain disorders is effective to suppress the severity of symptoms. Current medical treatment for brain disorders patients begin in school period because there are no methods to predict childhood onset of the development disorders in neonatal period.

Some cerebral diseases deform brain shape, and the deformation site and the amount are different among kinds of diseases[1]. We are considering a possibility to predict onset of childhood developmental disorders from cerebral deformation in neonates. There are few computer-aided diagnosis (CAD) systems, which evaluate the brain shape deformation. Voxel-based-morphometry (VBM) [2,3] is a method of investigating regional brain deformation based on non-rigid image registration (IR) of brain magnetic resonance (MR) images. Also, non-rigid IR has been used for functional MRI analysis such as statistical parametric mapping (SPM)[4]. It evaluates brain activity and investigates statistical differences of activation by means of group analysis using non-rigid IR among evaluating subjects.

There are some conventional non-rigid IR methods for brain MR images; HAMMER[5] and DARTEL[6]. HAMMER registers different brain MR images by using image features such as edge type, image intensity, and geometric moment invariants. DARTEL has been used in VBM, SPM, etc. It registers images by computing a flow field, which generates both forward and backward deformations. These conventional methods mainly use MR signal based likelihood. Thus, they do not evaluate cerebral surface anatomy such as sulci and gyri. In addition, they focus on the adult brain, which has a high intensity contrast between the gray matter (GM) and the white matter (WM) tissues. Therefore, it is difficult to apply their methods to neonatal brain because the neonatal brain has a low intensity contrast between tissues and narrow sulci.

Iterative closest point (ICP) [7,8] has been widely used for registering different 3-D shapes. ICP is a method to minimize distances between two point clouds. Ref.[9] proposed an ICP based non-rigid point matching algorithm and applied it to sulcal points. It shows that the registration accuracy was improved in comparison with the MR signal based approaches. However, we cannot apply the method to neonatal brain because it is difficult to extract sulci from neonatal brain.

Flattening [10,11] has been used to recognize cerebral sulci on a hyperplane. It maps the 3-D shape of the brain surface onto a parametric surface. The feature values mapped are distances from the parametric surface to the brain surface. The method works well for the adult brain, although, it is difficult to analyze the neonatal brain because of narrow and concaved sulci.

In order to extract the cerebral surface shape of

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neonates, we proposed a new feature called sulcal-distribution index (SDI)[12], which is calculated from MR signal on the cerebral surface. The results showed that SDI was available to characterize the spatial distribution of sulci on the cerebral surface of the neonatal brain.

This paper proposes a non-rigid IR method for registering neonatal cerebral surface. The method applies ICP algorithm to sulci extracted from SDI using hessian matrix. Thus, the method evaluates the corresponding of cerebral sulci to register the cerebral shape.

This paper organized as follows. Section 2 introduces subjects and materials used in this study, and describes edge detection algorithm using hessian matrix. Section 3 describes the proposed method. In Section 4, the proposed method is evaluated by applying it to seven neonatal subjects. Finally, Section 5 concluded this paper with a discussion on future works.

2. Preliminaries

2.1 Subjects and Materials

This study used T2-weighted MR images of seven neonates whose revised age was between 3 weeks and 2 years. The revised age is defined as an age of preterm babies that is adjusted by normal fatal periods. We had obtained parental informed consent from all subjects according to local ethics committees at Hyogo College of Medicine, JAPAN.

The MR image acquisition was performed using 3.0 Tesla MRI Scanner. Acquisition parameters were as follows; image matrix was 320 × 320 voxels, resolution was 0.75 × 0.75 × 0.75 mm³, echo time (TE) was 160-165 ms, repetition time (TR) was 2000 ms. Table 1 shows subjects’ gender and revised age. The number of slices was adjusted so that the volume covers the whole brain.

![Fig. 1 Raw MR images](image)

| # | Sex | Revised age | Number of slices |
|---|-----|-------------|-----------------|
| 1 | M   | 3m3w        | 200             |
| 2 | M   | 3w          | 130             |
| 3 | M   | 4w          | 200             |
| 4 | F   | 3m3w        | 220             |
| 5 | M   | 2y          | 220             |
| 6 | M   | 5w          | 180             |
| 7 | F   | 10m3w       | 190             |

Fig. 1 shows raw MR images. The brain region consists of two tissues; the GM and the WM. The GM tissue mainly locate on the cerebral surface. And, the cerebrospinal fluid (CSF) region fulfills the intracranial region and covers the brain. In T2-weighted MR images, the CSF region has the highest MR signal, and the pre-myelinated WM has higher MR signal than the GM.

2.2 2-D Edge Detection Using Hessian Matrix

Hessian matrix in 2-D space is defined by:

$$\mathbf{H}(x,y) = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix}$$

$(1)$

$D_{xx}$, $D_{yy}$, and $D_{xy}$ at a pixel $(x,y)$ are defined by:

$$D_{xx} = M_{(-2,0)}(x,y) + M_{(+2,0)}(x,y) - 2M_{(0,0)}(x,y)$$

$$D_{yy} = M_{(0,-2)}(x,y) + M_{(0,+2)}(x,y) - 2M_{(0,0)}(x,y)$$

$$D_{xy} = M_{(-1,-1)}(x,y) + M_{(+1,+1)}(x,y) - M_{(-1,+1)}(x,y) - M_{(+1,-1)}(x,y)$$

$(2)$

where $M_{(i,j)}$ is a coefficient at $i$th row and $j$th column of relative position from $(x,y)$. Eigen values of hessian matrix $\mathbf{H}$ are calculated by:

$$\lambda_1, \lambda_2 = \frac{D_{xx} + D_{yy} \pm \sqrt{(D_{xx} - D_{yy})^2 + 4D_{xy}^2}}{2}$$

$(3)$

where $\lambda_1 < \lambda_2$. When both of $\lambda_1$ and $\lambda_2$ are small, pixel of interest is “Flat”, when both of $\lambda_1$ and $\lambda_2$ are large, pixel of interest is “Corner”, and when $\lambda_1 \ll \lambda_2$ pixel of interest is “Edge”.

3. Proposed Method

Fig. 2 illustrates a flowchart of the proposed method. First, the brain region is segmented manually. Next, it extracts sulci using hessian matrix with SDI values on the sphere surface. The ICP based registration method estimates transfer vectors by iterative calculation.

The proposed method is performed on the sphere surface represented by uniformly distributed points. The regular icosahedron is used as the initial polyhedron, and is divided $N_t$ times ($7$ was used in this experiment) on the sphere surface by connecting middle points of the triangle sides constituting the polyhedron. The radius of the sphere is experimentally determined and is enough large to contain all subject’s brain region. The origin $O$ of the sphere is the inferior end of genu corporis callosi given manually.
3.1 Segmentation

The brain region is extracted manually from the MR images and MR signal of the background region is set to 0. Fig. 3 shows volume-rendering images of the segmented region.

3.2 Definition of SDI

In preliminary, it dilates the segmented brain region to obtain a rough smoothed brain surface. The dilated region is treated as a pseudo CSF region whose MR signal is 0.

The proposed method performs a flattening by calculating SDI of all points on the sphere. SDI of point \( q \) on the sphere surface is defined by:

\[
SDI(q) = \frac{\sum_{s \in LS(q)} f(s)}{\text{card}(LS(q))}
\]

where \( LS(q) \) is a set of voxels on a line segment which starts from the outer boundary voxel of the dilated region, the direction is from point \( q \) to origin \( O \), and the length is \( d \) mm (16mm was chosen through our experiment), \( \text{card}(t) \) is the number of voxels belonging to \( t \), and \( f(s) \) is MR signal of voxel \( s \).

For example, consider two points \( q_1 \) and \( q_2 \) shown in Fig. 4. \( LS(q_1) \) and \( LS(q_2) \) are line segments evaluated. When a point of interest locates on the gyrus (\( q_2 \)), \( SDI(q_2) \) takes a high value because almost voxels of \( LS(q_2) \) are GM or WM voxels. While, \( LS(q_1) \) takes a low value. SDI represents a degree how the point of interest locates on the sulci. The higher value shows the higher degrees of locating on the gyri.

3.3 Sulci Extraction Using Hessian Matrix

It classifies the points into sulcal point or not using hessian matrix of SDIs which is mapped onto the sphere surface. As shown in Fig. 5, hessian matrix is calculated on the sphere surface. To calculate hessian matrix at a point \( q \), eq. (2) is modified into:

\[
D_{xx} = M_{(-2,0)}(q) + M_{(+2,0)}(q) - 2M_{(0,0)}(q)
\]

\[
D_{yy} = M_{(0,-2)}(q) + M_{(0,+2)}(q) - 2M_{(0,0)}(q)
\]

\[
D_{xy} = M_{(-1,+1)}(q) + M_{(+1,+1)}(q) - M_{(-1,-1)}(q) - M_{(+1,-1)}(q)
\]

\[
M_{(i,j)}(q) \text{ is defined by; }
\]

\[
M_{(i,j)}(q) = SDI(q_{(i,j)}(\theta))
\]

where \( \theta \) is an adjacent rotation angle to determine the adjacent point. \( q_{(i,j)}(\theta) \) is a point where \( q \) is rotated by \( i\theta \) along axis \( u \) and \( j\theta \) along axis \( v \). \( u \) and \( v \) axes are orthogonal to each other, and \( u \) axis is determined as a direction of outer product of \( q \) and an arbitrary vector because eigen values of hessian matrix are invariant under rotation.

Sulci extraction is performed with two steps. First, it calculates Eigen values of Hessian matrix at each point. When eq. (7) holds at a point, the point is extracted as edge point.

\[
\frac{|\lambda_1(p) - \lambda_2(p)|}{\lambda_{max} - \lambda_{min}} > TH
\]

where \( \lambda_1(p) \) and \( \lambda_2(p) \) are the first and the second eigen values of hessian matrix at point \( p \), respectively. \( \lambda_{max} \) and \( \lambda_{min} \) are the maximum and minimum eigen values in \( \lambda_1 \) and \( \lambda_2 \) of all points, respectively. \( TH \) is a threshold, which takes between 0 and 1 (0.3 was used in this experiment).

As shown in Fig. 5, the method can extract various width edge by changing the adjacent rotation angle, \( \theta \). Thus, this step is repeated with changing the adjacent rotation angle from 0.01 to 0.3 rad with an interval.
The resultant edge extraction contains both of concave region (i.e., sulci) and convex region (i.e., gyri). The second step of sulci extraction is to classify them into sulci or gyri. Fig. 6 shows a histogram of SDIs on the detected edge points. The lower SDIs are SDI values of points on the sulci, and the higher SDIs are those of points on the gyri. Discriminant analysis determines a threshold value between the sulci and the gyri from the histogram. Sulcal points are edge points whose SDI is lower than the threshold.

3.4 ICP for Non-rigid Cerebral Surface Registration

The proposed method registers two sets of sulcal points extracted from two neonates. One is called a base model and the other is called a float model. The float model is deformed so that the deformed model is registered to the base model.

First, the deformation process is applied to the initial polyhedron (called 1st scale), which is synthesized by a regular icosahedron. After convergence, the polyhedron is divided, and then the deformation process is applied to the divided polyhedron (called 2nd scale). It is repeated until the number of dividing exceeds \( N_s \) which was defined as the number of polyhedron division. In each scale, when the number of updated point is less than 10% of the total number or the number of repetition exceeds maximum repetition number (100 was used in this experiment), the deformation process is converged.

In each scale, the float model is deformed by moving their points sequentially on the sphere based on ICP algorithm. A point can move in a half-length distance area to the adjacent points. The area is called candidate area in the following. Consider a point, \( C_p \), in the float model. The destination point, \( C_p' \), is a point which maximizes a local likelihood between the base model and the float model.

The local likelihood of point \( a \) in the float model, \( LL(a) \), is defined by:

\[
LL(a) = \sum_{p \in \Omega(a)} L(p, CP(p)) - \omega \tau(a) \tag{8}
\]

where \( \Omega(a) \) is a set of points in the candidate area in the float model, and \( CP(p) \) is the closest point to point \( p \) in the base model at the finest scale. \( \omega \) is a weight parameter. \( \tau(a) \) is a regularization term employed for the purpose of locally smoothing the deformation vectors, and is defined by:
\[ \tau(a) = \sqrt{\sum_{q \in N P(a)} \frac{((v(a) - v(q)) - \mu(a))^2}{\text{card}(NP(a))}} \]  
\[ \text{where } \mu(a) = \sum_{q \in N P(a)} \frac{\|v(a) - v(q)\|}{\text{card}(NP(a))} \]

\( v(x) \) is coordinate value of point \( x \), \( NP(x) \) is a set of connecting points to point \( a \) in the float model, and \( \text{card}(t) \) is the number of points in \( t \). \( L(s,t) \) is a likelihood between point \( s \) in the float model and \( t \) in the base model, and is defined by:

\[ L(s,t) = 1 - \frac{\|v(s) - v(t)\|^n}{D^n + \|v(s) - v(t)\|^n} \]

where \( D_n \) is a minimum distance between adjacent points in the \( n \)th scale polyhedron.

### 4. Experimental Results

The proposed method was performed on Intel Xeon E5-2630 2.30GHz × 2 with 16GB RAM. The computational time of all procedure was about 137 minutes; of sulci extraction was 49 seconds, of non-rigid registration was 136 minutes.

#### 4.1 Sulci Extraction Results

Fig. 7 shows a result of flattening with SDI, and the SDI value is linearly converted to the range of 0 to 255. The whiter shows the gyri, and the darker shows the sulci. We can recognize the spatial distribution of sulci on the cerebral surface. Fig. 8 shows the edge detection results with edge detection angle. The green color describes the detected edges. It shows that the larger adjacent rotation angle detected the wider edge. Fig. 9 shows the result of sulci extraction. All sulci were extracted by the proposed method.

#### 4.2 Non-rigid Registration Results

The angular differences of anatomical landmarks between the base model and the float model were measured to numerically evaluate the proposed method. The landmarks were the right and the left points of intersection of the superior frontal sulcus, the superior precentral sulcus, and the right and the left points of the temporal lobe anterior extremity. Their landmarks were given by radiologists. Fig. 10 shows angular differences of all combinations and it is defined as the average of angular difference between a base model feature point and its corresponding float model feature point from the inferior end point of genu of corpus callosum. When the proposed method registers the feature points completely, the angular difference becomes 0. T-test was performed to evaluate the effectiveness of the proposed method. A significant difference was not recognized between init and DARTEL (p value was 0.186), but was appeared between init and proposed (p value was 0.002), and between DARTEL and proposed (p value was 0.004).

Fig. 11 shows the average and standard deviation of angular differences. For comparison, the results with a conventional method (DARTEL) were given. This figures show the angular difference was decreased 1.31 degree by the proposed method, and it is about 1.7 mm difference on the sphere surface. The standard deviation was increased from 7.72 degree to 8.88 degree. In many combination, there was about 4 degree of angular difference which is almost same with the adjacent sulci.

Fig. 12 shows the sulci distribution of combination (2,1). That is, the brain shape of subject 1 was registered to that of subject 2. Fig. 12(a) and (b) show the sulci of subject 2 and subject 1, respectively. Fig. 12(c) shows the registered subject 1 brain. In comparison Fig. 12(a) with (c), we can visually recognize that the coincidence of sulci distribution was
improved by the proposed method. Fig. 13 shows the sulci distribution of combination (7,2) which the angular difference was increased by the proposed method. It is considered that the proposed method fell into a local solution because subject 7 contains many small sulci.

5. Conclusion

This paper has proposed an ICP based non-rigid cerebral surface registration method for neonates. The method registers the spatial distribution of cerebral sulci by extracting sulci using SDI. The results showed the proposed sulci extraction method was able to extract the neonatal brain sulci. And, the proposed registration method was superior to the conventional method, but its result depends on the sulci distribution of base model.

In the future, we will evaluate the neonatal brain shape deformation caused by a brain disease using the proposed method.

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