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Knowledge-based self-organization network for visualization and reconstruction of the brain

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Abstract

This research presents a precise knowledge-based self-organization network for visualization and reconstruction of the human brain. The self-organizing map (SOM) model is a widely used method to approximate a network field to a 3D irregular surface and reduce the data dimension for advanced applications. The main disadvantage of the formal SOM algorithm is its difficulty in stretching the network inside the depth of a narrow sulci. Hence, a prior index is defined and calculated to get a smoothed surface which can be easily mapped by the SOM model. Based on this prior knowledge, the SOM neural network can successively and precisely map to the complex brain surface. The simulations using T1-weighted MR images show that the proposed algorithm is robust to reconstruct 3D meshed brain structures. This knowledge-based mesh can be used to support an estimation of neural generators of EEG signals and deformation measurement of brains.

I. The Proposed Methodology and Experiments

In our previously developed adaptive mixture models [1], brain MR image voxels can be partitioned into cerebral spinal fluid (CSF), gray matter, and white matter. The detected boundary voxels between CSF and gray matter are identified as the margin of the cerebral cortex. Since boundary voxels are integrated from boundary pixels in each 2D scan image, we take the spatial connections among neighboring image pixels as the prior knowledge. Then a curve smoothing algorithm is applied to smooth image pixels at different levels, i.e., image pixels are convoluted with a Gaussian function at different scales. The convolution takes the following form: $X'(i) = X(i) * g(i,\sigma)$, where $X(i) = (x(i), y(i))$ and $X'(i) = (x'(i), y'(i))$ denote the boundary pixels with index i before and after the convolution, $g(i,\sigma)$ is the Gaussian function with standard deviation σ, and $*$ marks convolution.

The SOM model is defined as an optimal match function in the following: $F(X)=\|X-W_c\|=\arg\min_i\|X-W_i\|,\ W_i\in W$, where $X=(x(i),y(i))$ is the input data, W is the synapse vector set, Wc is the nearest synapse vector corresponding to data X. Its update function denotes: $W_i^{new}=W_i^{old}+\alpha H(D(c,i))(X-W_i^{old})$, where $\alpha\in[0,1)$ is the learning rate, H is the neighborhood function with a distance metric D. According to this update function, the SOM model can form an optimal approximate structure corresponding to input data.

We experimentally use a 2D SOM to show the differences between the formal SOM algorithm and the proposed method. Figure 1 shows the initial detected boundary pixels (red points) on the T1-weighted image. Figures 2 and 3 show the result pixels after the convolution of the Gaussian function at σ =10 and σ =20, respectively. Some concave parts of the contour pixels disappear or become smoother in Fig. 3. The red points shown in Fig. 1 are the input data in the formal SOM model. Figure 4 shows the initial SOM which is a circle. The boundary pixels in the largest smooth scale, that is, those red points in Fig. 3, are taken as the input data in the first level. The converged SOM of the first level is shown in Fig. 5, which is precisely mapped to the data in Fig. 3. After the first level of SOM converged, the second level starts and its input data is changed to those red points shown in Fig. 2. Finally, the SOM is precisely mapped to the original data shown in Fig. 6. Figure 7 shows the defects of a converged SOM using the formal SOM model. The initial SOM is also the same as that in the multi-scale SOM model shown in Fig. 4. In Fig. 7, some of the SOM nodes pass through the white matter. These nodes fail to catch the part of narrow and deeper sulcus. This experiment shows the superior results of our knowledge-based self-organization network in a 2D manner.

In the 3D SOM experiment, the T1-weighted images which contain 133 scans in the whole brain are used for simulations. The prior knowledge is taken only the 2D spatial connections among neighboring image pixels in each scan and five levels of different smooth scales are used. Then all data in each scan is integrated to form 3D data. Each level has 200 iterations in SOM processing. The initial SOM is a 3D spherical mesh with 40,962 nodes that enclose the brain. Some sample figures of multi-scale SOM processing are shown in Part III. The deformation error mapping on the sphere is also shown. We can see that the region of the longitudinal fissure maps to a red exclamation-mark-like on the sphere. Therefore, we can observe the change on the mesh surface. It is important for the application of brain deformation measurement.

[1] Lee, J.-D., Cheng, P.E., & Liou, M. (2002). MR brain image segmentation by adaptive mixture distribution. Proceedings ICONIP, 216-218.

II. The 2D SOM Experiment

Boundary data (e.g., pixels between CSF and gray matter) extraction and spatial connection

Curve smoothing with a Gaussian function at different scales

Create initial SOM

Multi-scale SOM process
1st level (large scale),
2nd level (small scale), …

Final multi-scale SOM results

Segmented pixels

Fig. 1　Fig. 2　Fig. 3

Gaussian smoothing at σ =10

Gaussian smoothing at σ =20

Initial 2D circle

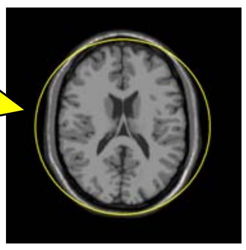


Fig. 4

Fig. 5

1st level 2D SOM result

Final multi-scale 2D SOM result

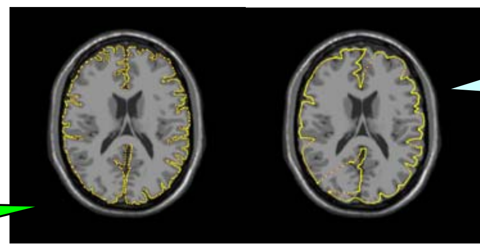
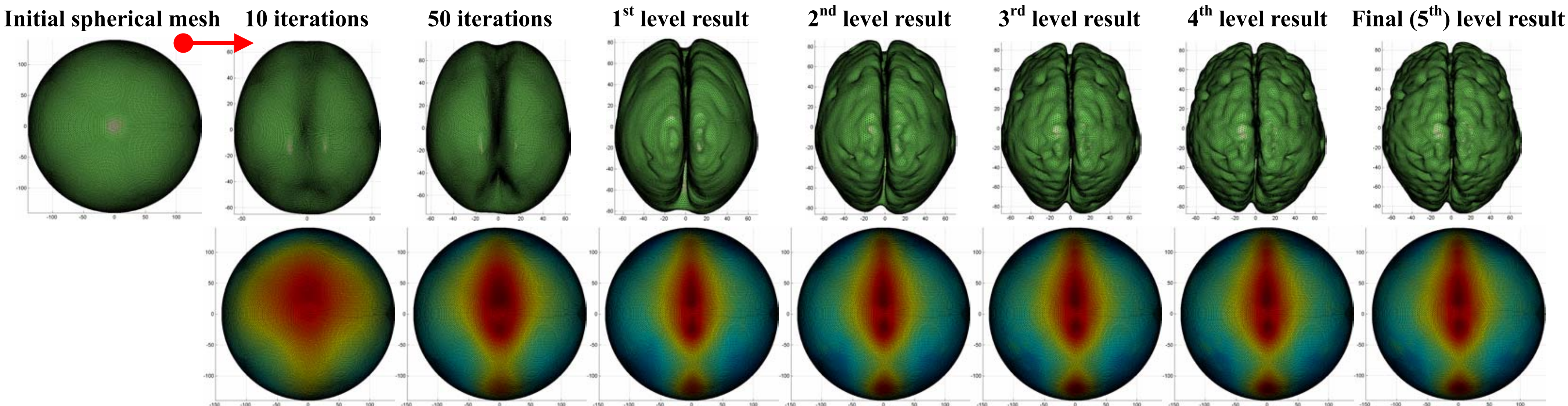


Fig. 6　Fig. 7

Formal 2D SOM result

III. The 3D SOM Experiment



Deformation error mapping on the sphere