Constrained Self-organizing Map for the Reconstruction of the Brain Lateral Ventricle

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Abstract—**This paper presents a constrained self-organizing map (SOM) model for the visualization and reconstruction of the human brain lateral ventricle. The SOM model is a widely used method to approximate large and complex high dimensional data and reduce the data dimension for advanced applications. In our applications, the SOM model is used to deform a spherical network field to a 3D crooked brain lateral ventricular surface. The main disadvantages of the formal SOM algorithm are its difficulties in stretching the network inside the concave parts of the lateral ventricular surface. Hence, a constrained SOM model is proposed to first obtain an elementary model of lateral ventricle which can be easily mapped to the lateral ventricle later by the SOM model. Based on this method, the SOM network field can successively and precisely map to the brain lateral ventricular surface. The simulations on T1-weighted MR images show that the proposed algorithm is robust to reconstruct 3D meshed brain lateral ventricular structures and its application to 3D morphometry is practicable.**

I. INTRODUCTION

In clinical medicine, it is important to diagnose hydrocephalus and atrophy from the ventricular dilatation by physicians. Among various symptoms, the lateral ventricle of a human brain contains some significant features that can be estimated to differentiate between hydrocephalus and atrophy. These features measured from CT or MR scans include ventricular index, ventricular angle, frontal horn radius, and so on [1, 2]. However, these features are estimated and observed only in 2D CT or MR images. No stereo structures can help to visualize or observe the shape or volume change of the lateral ventricle. Therefore, it is essential to reconstruct the 3D brain lateral ventricle to assist physicians in diagnosing normal or abnormal, hydrocephalus or atrophy.

Due to the advanced MR techniques, MR scans are often used in the analysis of cognitive neuroscience, diseases (e.g., epilepsy, schizophrenia and Alzheimer's disease), cerebration, and so on. In the diagnosis of hydrocephalus, MR provides its ability to visualize small obstructing lesions and to clearly delineate anatomic changes resulted in the mass effect of the distended ventricles [3]. Accordingly, in our simulations, we use T1-weighted MR images to reconstruct the brain lateral ventricle.

The preprocessing of MR images including intensity normalization and correction, registration and resample, and tissue classification or segmentation is important to make comparisons across different subjects feasible. There are various tools or software that can help to complete the preprocessing, e.g., SPM (http://www.fil.ion.ucl.ac.uk/spm/), AIR (http://bishopw.loni.ucla.edu/AIR3/index.html), etc. In our previously developed adaptive mixture models [4], brain MR image voxels can be partitioned into cerebral spinal fluid (CSF), gray matter, and white matter, which can help to segment the lateral ventricle. However, in this paper, we do not focus on these techniques. The spotlight is how to reconstruct the brain lateral ventricle by a mesh structure.

The self-organizing map (SOM) model [5, 6, 7] is a well-known algorithm which is designed to topologically map an input space to a network field. This model provides not only a geometrical surface mapping but also a dimensionality reduction from the input space to the network field. In our applications, it is applied to map a spherical surface to boundary voxel data for obtaining the meshed surface of the brain lateral ventricular structures. We attempt to construct a meshed lateral ventricular surface which has the intrinsic property of the SOM for advanced applications. However, the lateral ventricle has some concave shapes that is not easy to be mapped by the SOM model. The main reason is that the approximation between the network and data is accomplished only by the Euclidean distance evaluation, i.e., the nearest data is regarded as the best match with a network node. Although the SOM model has an iterative and progressive mechanism, it is difficult to adjust the parameters that are needed for the SOM model to adapt the network to the lateral ventricular structure. Therefore, a constrained SOM model is proposed and applied first to get an elementary model of lateral ventricle. This strategy uses a progressive distance criterion to conditionally map the network to the target and obtain the elementary model which is topologically and roughly similar to the target. Then this elementary model is fine tuned to successively and precisely map to the brain lateral ventricle by the formal SOM model.

In the simulations, mapping a 3D meshed sphere to the brain lateral ventricle is experimented to show the differences between the formal SOM algorithm and the proposed method. Our studies on T1-weighted MR images show that the proposed method gains more precise results to reconstruct 3D meshed brain lateral ventricular structures. Afterward a manual modification of lateral ventricle is employed to display the change on the ventricular shape.

This reconstruction method can also be applied to other organs or brain tissues, e.g., a cortical surface. The meshed cortical surface can be used to support an estimation of neural dipoles of EEG signals [8] and the measurement of cortical thickness in human brains [9, 10].

II. THE PROPOSED METHOD

The SOM model is an effective algorithm for the mapping between the model and data sets. It is a nonlinear, ordered, smooth function that can map a high-dimensional data set onto a low-dimensional model set. For example, 3D space data maps to a 2D array of grid nodes. The visualization of high-dimensional data, therefore, can be easily achieved by a low-dimensional display. In our applications, it is desired to map the brain lateral ventricle onto a simple graph, e.g., a sphere. The boundary voxels of brain lateral ventricle are defined to be the data set. Then a spherical mesh structure consisting of nodes is established to be the model set. The SOM model is applied to construct the mapping between the boundary voxels and the mesh nodes.

The SOM model is mathematically described in the following. First, a best matching function is defined as

$$F(X) = \|X - m_c\| = \min_j \|X - m_j\|,\ m_j \in M, \tag{1}$$

where $X = (x(i), y(i), z(i))$ is the input data, M is the model set or reference network, and m_c is the nearest model node corresponding to data X. The smallest of the Euclidean distances $\|X - m_j\|$ can be made to define the best matching node. Its update function denotes

$$m_j(t+1) = m_j(t) + \alpha(t)H(D(c,j),t)[X - m_j(t)], \tag{2}$$

where t=0, 1, 2…is the iteration number, $\alpha(t) \in [0,1)$ is the learning rate, and H is the neighborhood function which decreases iteratively with the distance metric $D(c,j)$. The Gaussian function is usually applied to be the smoothing kernel, i.e.

$$H(D(c,j),t) = \exp\left(-\frac{D(c,j)}{2\sigma^2(t)}\right), \tag{3}$$

where $\sigma(t)$ is the standard deviation, i.e. the width of the smoothing kernel. In our algorithm, the function $D(c,j)$ is defined as the angle with endpoints $m_c(0)$ and $m_j(0)$ located on the initial sphere and the vertex located on the spherical center, that is

$$D(c,j) = \cos^{-1}\left(\frac{m_c(0) \cdot m_j(0)}{\|m_c(0)\|\|m_j(0)\|}\right), \tag{4}$$

where $\cdot$ represents the inner product operation and t=0 indicates the initial sphere model state. The neighborhood function H and the learning rate can be monotonically decreasing functions in iterations.

The constrained SOM model is similar to the formal model but with a conditional update function that denotes as

$$m_j(t+1) = m_j(t) + \alpha(t)H(D(c,j),t)[X - m_j(t)],\ \text{if}\ F(X) > \tau(t), \tag{5}$$

where $\tau(t)$ represents a threshold distance which decreases iteratively. This conditional update procedure means that the model node m_c and its neighbor nodes involved with the neighborhood function H are updated when the Euclidean distance $\|X - m_c\|$ is larger than the threshold distance $\tau(t)$. According to this update function, the SOM model can form an elementary model, i.e., an approximate structure roughly similar to input data. Finally, the elementary model is updated without the limitation by the formal SOM algorithm.

III. SIMULATION AND EXPERIEMNT

In our simulations, the T1-weighted MR images in which the dimensions are 181x217x181 and the slice thickness is 1 mm are used for experiments. The boundary voxels of the lateral ventricle in T1-weighted images are first manually extracted to be the data set. The data set contains 7619 three-dimensional coordinate points. Figure 1 shows some sample 2D slices with the location of lateral ventricle in transverse, sagittal, and coronal views and its spatial position. The initial reference network is a 3D spherical mesh with 4002 nodes that enclose the lateral ventricle. The spherical center is moved to the geometric centroid of data set. The total iteration of SOM model is set to 2000.

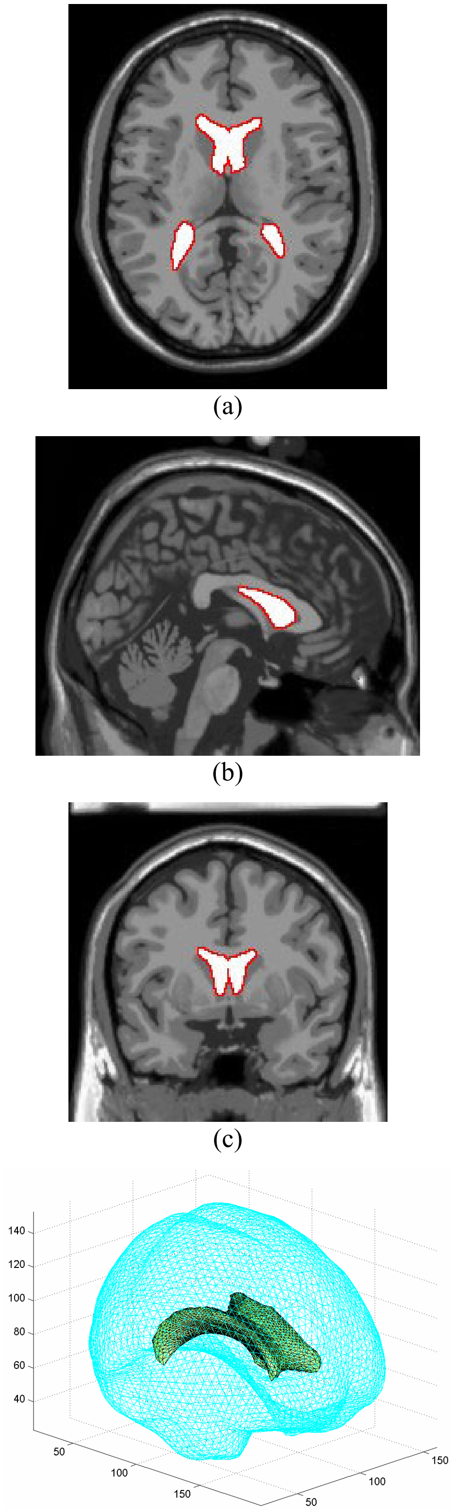

(a) (b) (c) (d)

Fig. 1 The location of brain lateral ventricle in some sample T1-weighted MR images: (a)~(c) the white regions circled with red show the lateral ventricle in the transverse, sagittal, and coronal views, respectively, (d) the 3D spatial location of lateral ventricle inside the brain.

The Euclidean distances between the mesh nodes and the corresponding data are applied to evaluate the quality of the 3D SOM results [6, 11], that is to calculate all the shortest distances between the SOM mesh nodes and the data points. The error function E is defined as

$$E(m_j) = \min_i \left\| X - m_j \right\|,\ m_j \in M, \tag{6}$$

where $X = (x(i), y(i), z(i))$ is the input data and m_j is the jth mesh node in M. Then the maxima and mean of the distance measures in all mesh nodes are calculated to compare two different results of the formal and the proposed SOM models.

The mesh with the minimal value of maximal distance measure is selected to be the final result. Figure 2 shows the result by using the formal SOM model, where the concave parts of the lateral ventricle are not well mapped. Figure 3 shows the elementary model formed by the constrained SOM model. The threshold distance term $\tau(t)$ in the conditional update function is empirically set to the value from 10 to 2 with a decreasing rate 0.9. Figure 4 shows the result by using the proposed SOM model. Although some crooked and concave surfaces exist in the lateral ventricle, the proposed SOM model can properly mesh it.

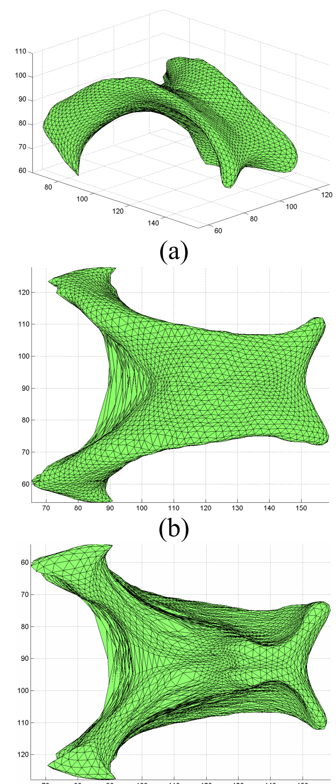

(a) (b) (c)

Fig. 2 The reconstruction of brain lateral ventricle by using the formal SOM model: (a) the result of meshed structure, (b) the top view of (a), (c) the bottom view of (a).

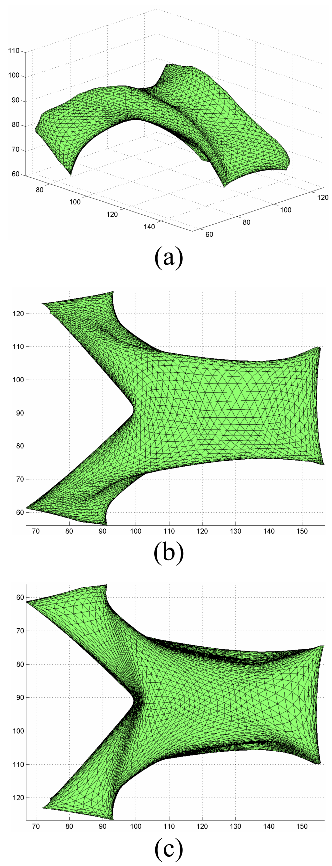


Fig. 3 The elementary model formed by the constrained SOM model: (a) the result of meshed structure, (b) the top view of (a), (c) the bottom view of (a).

Figure 5 plots the maxima (dashed and solid lines) and the mean (dash-dot and dotted lines) of the distance measures. The dashed and dash-dot lines correspond to the error measures of the formal SOM model and others correspond to those of the proposed model. From the result selection rule (the minimal value of the maximal distance measure), their iteration numbers are 2000 and 540 in the formal and proposed SOM models, respectively, and their error distance measures are also plotted in Fig. 5 with the star symbols.

In the error measures, the results of proposed method have less maximal distance errors than those of the formal SOM model. The quality measures of Fig. 2 and Fig. 4 are shown in Fig. 6 where the error range is set from 0 to 6.5949 mm. Figures 6(a) and 6(b) are the error maps corresponding to Figs. 2(b) and 2(c) while Figs. 6(c) and 6(d) are the error maps corresponding to Figs. 4(b) and 4(c). The maximal and minimal errors are 6.5949 and 0.0224 mm in Figs. 6(a)(b), and 2.7125 and 0.0613 mm in Figs. 6(c)(d), respectively.

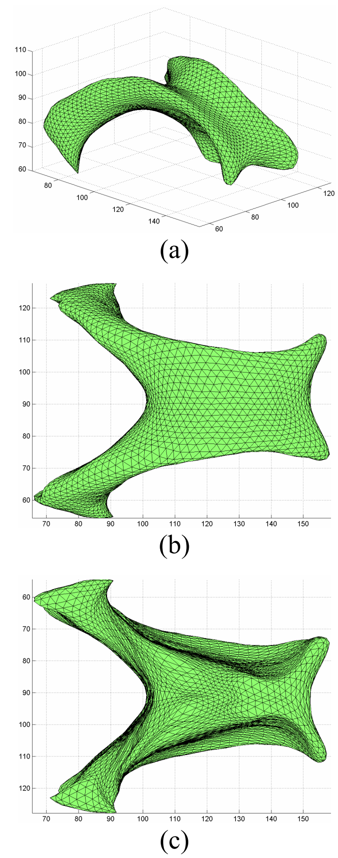


Fig. 4 The reconstruction of brain lateral ventricle by using the proposed method: (a) the result of meshed structure, (b) the top view of (a), (c) the bottom view of (a).

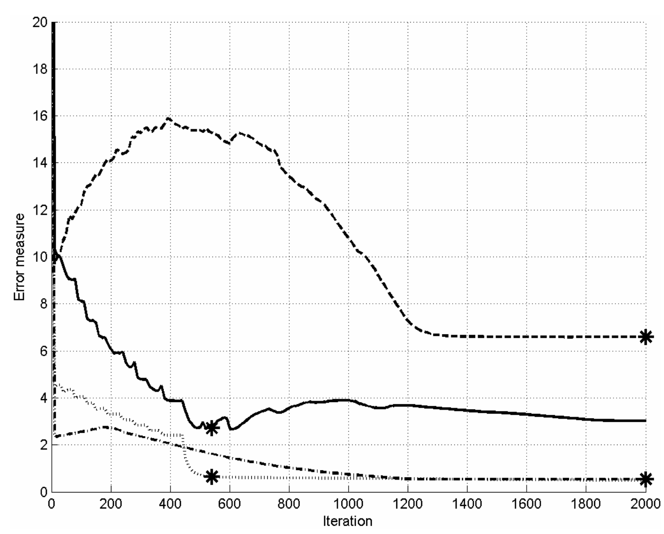
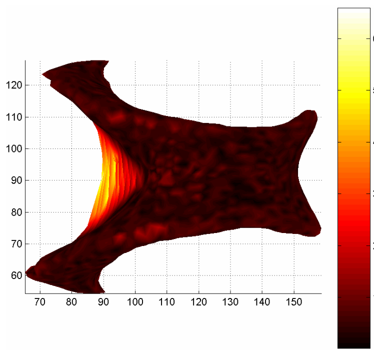
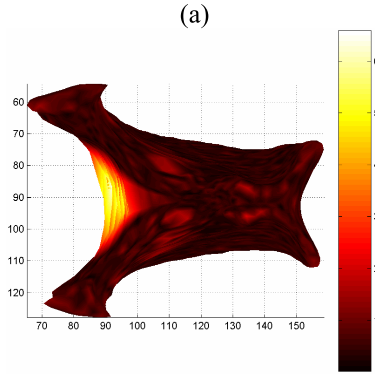


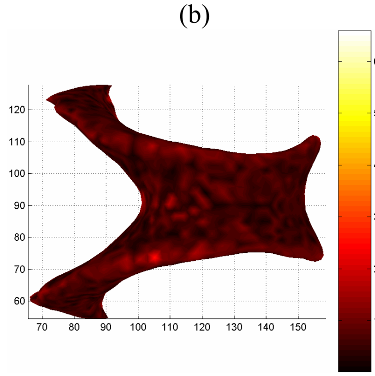
Fig. 5 The plot of error measures $E(m_j)$: dashed and dash-dot lines are the maximal and mean errors by using formal SOM model; solid and dotted lines are the maximal and mean errors by using the proposed method.



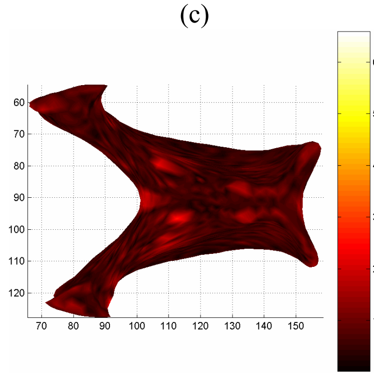
(a)



(b)



(c)



(d)

Fig. 6 The quality measures of the experiments: (a)(b) the top and bottom views of the error map corresponding to Fig. 2(b)(c), where the maximal and minimal errors are 6.5949 and 0.0224 mm, respectively, (c)(d) the top and bottom views of the error map corresponding to Fig. 4(b)(c), where the maximal and minimal errors are 2.7125 and 0.0613 mm, respectively.

In another experiment, a manual modification of lateral ventricle is employed to show the preliminary shape change on the ventricle. The modification is only focused on the frontal horns of lateral ventricle that usually dilate when a hydrocephalus happened. The lateral ventricle before the modification is considered to be the normal or standard case while the one after the modification is regarded as the abnormal case. It is feasible to show the differences between the normal and abnormal cases in a stereo view. Figure 7 shows the normalized error map in the meshed lateral ventricular structure. This application by using the lateral ventricular surface reconstruction technique can be established and embedded in a hospital PACS (Picture Archiving and Communication System) system for helping physicians to diagnose hydrocephalus and atrophy.

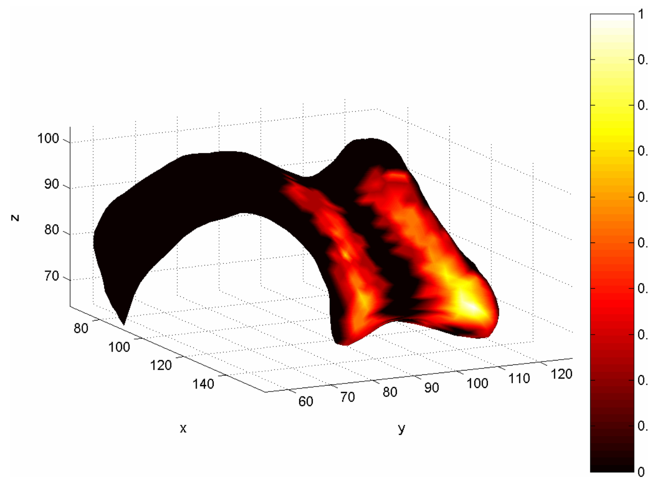


Fig. 7 Normalized error map in the meshed lateral ventricular structure to show the change on the frontal horns.

IV. CONCLUSIONS

In this paper, a constrained SOM model is proposed for the reconstruction of the human brain lateral ventricle. The method provides a good capability to construct an elementary model which can be easily mapped to the crooked and concave surfaces of the lateral ventricle by the SOM algorithm. Based on this method, the 3D mesh structure can successively and precisely map to the surface of the lateral ventricle. This 3D meshed structure can be used to support the visualization and morphometry of brain lateral ventricle which is sensitive to brain abnormal phenomena, e.g. hydrocephalus. The future work of our research is to apply more real MR images to establish an assistant diagnosis system. Moreover, some critical techniques, e.g. segmentation or data acquisition, can be embedded into our system for automation.

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