Automatic Segmentation of the Human Hippocampus Using Superquadric Surface Model

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Introduction

The human hippocampus is the essential portion of the limbic system. It has been shown that changes of volume and shape of the hippocampi is often an indication of existence of memory-loss related diseases such as Alzheimer's disease [1], mild cognitive impairment [2], and others. There are also many other clinical pathologies that involve the hippocampus. Hippocampus segmentation is a necessary step toward accurate hippocampal volumetric quantification and shape analysis. Currently, manual segmentation by trained experts remains the gold standard for hippocampus segmentation. Not only it is time consuming, it also suffers from low inter-rater and intra-rater reproducibility. In this work, we present an automatic method for the segmentation of the hippocampus.

Methods

a. Difficulties: The hippocampus consists of Cornu Ammonis (CA) and Gyrus Dentatus (GD). Both are grey matter structures (CA has a very thin layer of white matter, alvenus. However, its volume is negligible [4]). The difficulties in the segmentation of hippocampus lie in the fact that there are other grey matter structures adjacent to the hippocampus, and the imaging contrasts between these tissues are very similar. For example, the boundary between the amygdale (a grey matter) and the hippocampus head is very blurry and even invisible in some cases. And the boundary between the hippocampus and the pulvinar, which is also a grey matter structure and that lies superiorly to the hippocampus tail, can become very blur as well. There is no visible boundary between the subiculum and the entorhinal cortex. To deal with these almost undistinguishable boundaries is the most challenging task. In this work, we present a model-based approach to overcome these difficulties.

b. Surface Modeling Approach: This approach consists of two parts: the construction of the statistical hippocampal surface model through training data and the segmentation of the hippocampus using the learned model for new data. The segmentation of the hippocampus consists of three main steps: 1) Defining the region of interest that includes the hippocampus; 2) Classifying grey matters (GM) within the region of interest as the GM initial condition; 3) Applying the parametric surface model to the GM initial condition and segmenting out the hippocampus. This approach is based on the observation that the hippocampus has a rather smooth surface and a common shape. Variations of this surface can be approximated by parametric surface models. The surface model used the superquadric equation, which is capable of modeling the smooth surface with relatively complicated shapes. This model is built through training data sets with the hippocampus of one data set being segmented manually by human experts. The model also includes the statistical parameters of the superquadric equation to better represent the variation of hippocampal surface. To classify all GMs within the region of interest, the method proposed by *Peng et al.* [3] is used. This method is based on Maximum a posterior – Markov random field (MAP – MRF) framework and spatially varying Gaussian Mixture Model (SGMM), and it provides a good starting point, the GM initial condition. The segmentation of the hippocampus is achieved by fitting the superquadric surface model to the GM initial condition. A local adjusting measure that is based on single voxel and its neighborhood statistics is also applied to further fine-tune the segmentation result.

b. imaging data: 1.5 Tesla T1-weighted brain volume data from McGill University [5] were used to test our approach. Imaging data selected had a matrix size of 181x271x181, an 8-bit imaging resolution, a voxel size of 1x1x1 mm^3, a noise level of 0% and an inhomogenity level of 0%.

Results

Figure 1 shows segmentation results from this new approach (right panel) as compared to those from Peng's method (left panel). The bottom volume of the left panel was the right hippocampus that was manually segmented and was agreed by two neuroradiologists. The top volume was a 3D segmentation result using the MAP-MRF automated segmentation approach, which was the initial condition of this new approach. It shows that Peng's method does a pretty good job in the segmentation of the hippocampus except regions in the boundary between the hippocampus and the amygdala, and that between the hippocampus and the pulvinar and the entorhinal cortex (indicated by circles). After using the surface model-based approach, the segmentation results improved significantly and results are shown in the right panel of Fig. 1. The hippocampus segmentation between expert manual drawing (bottom, right) and computer automatic segmentation (top, right) agree very well.

Figure 1: Results from export-guided manually (left panel) and computer-guided automatically (right panel) segmented hippocampus.

Discussion

We have presented an automatic method to segment the human hippocampus. The method is based on the statistical superquadric surface model, which is constructed through training sets. This approach is superior to the approach proposed by Peng et al [3]. However, Peng's approach can provide a very good starting point for our approach. Finally, local adjusting measures based on the neighborhood statistic information can assist in fine-tuning the result. We have demonstrated that the model-based approach worked well for a simulated volume data. Future work will focus on improving statistical representation of the hippocampus surface information, the computational speed on parametric fitting, and the application of the approach to high-field MRI data.

Reference

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