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A Hybrid Technique for the Automated Segmentation of Corpus Callosum in Midsagittal Brain Mri

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Abstract
The corpus callosum (CC) is the largest white-matter structure in human brain. In this paper, we take two techniques to observe the results of segmentation of Corpus Callosum. The first one is mean shift algorithm and morphological operation. The second one is k-means clustering. In this paper, it is performed in three steps. The first step is finding the corpus callosum area using adaptive mean shift algorithm or k-means clustering . In second step, the boundary of detected CC area is then used as the initial contour in the Geometric Active Contour (GAC) mode and final step to remove unknown noise using morphological operation and evolved to get the final segmentation result. The experimental results demonstrate that the mean shift algorithm and k-means clustering has provided a reliable segmentation performance.
Index term: corpus callosum, mean shift, geometric active contour and morphological techniques

I. INTRODUCTION

The corpus callosum is the largest neural pathway that connects the two cerebral hemispheres in mammals. Consisting of between 200 and 800 million axon fibers (Banich, 1995a), the primary function of the corpus callosum is to provide a connection between homologous cortical areas. Exactly how that connection is functionally manifested is the topic of this review. Although most researchers believe that the corpus callosum plays an important role in the development of hemispheric asymmetry, the question remains as to whether the corpus callosum exerts an inhibitory or excitatory influence on interhemispheric communication.

Previous studies have mainly investigated effects of various pathologies on the corpus callosum [1-2]. However, a fully automated, fast, and accurate method for segmenting corpus callosum without penetrating into irrelevant neighboring structures, using data acquired in routine clinical protocols, is still lacking.

Previously, image processing methods have been proposed for segmenting corpus callosum in anatomical magnetic resonance images (MRI) [3-5]. These methods rely on intensity information of two-dimensional images and their results may need pruning. Recently, attention has been oriented towards diffusion tensor imaging (DTI) to segment white matter tracts of the brain [6,7].

In the proposed technique, using the adaptive mean shift clustering technique, the image is first clustered into various homogeneous areas, representing various brain tissues. The CC area is then detected based on area analysis, template matching, in conjunction with shape and location analysis.

The boundary of obtained CC area is extracted and evolved under the mechanism of GAC model, for final segmentation of CC structure. The major contribution of the proposed technique is to provide an accurate initialization of the CC region, which results in better performance in terms of the segmentation accuracy.

The rest of this paper is organized as follows. In section II, we describe the proposed system. Section III explain the k-means clustering. Section III gives some experimental results. Finally, a conclusion will be presented in section VII.

II. PROPOSED METHOD

We implemented the proposed algorithm in MATLB R2008a using a PC with Intel ® Core™ 2Duo CPU (E8400@ 3.00 GHz, 3.00 GHz) and 4 GByte RAM and 64 bit VISTA operating system. The proposed method contains three steps. They are 1) Adaptive Mean Shift Clustering 2) Geometric Active Contour based Segmentation 3) morphological operation.

The block diagram of proposed method as shown in figure 1.

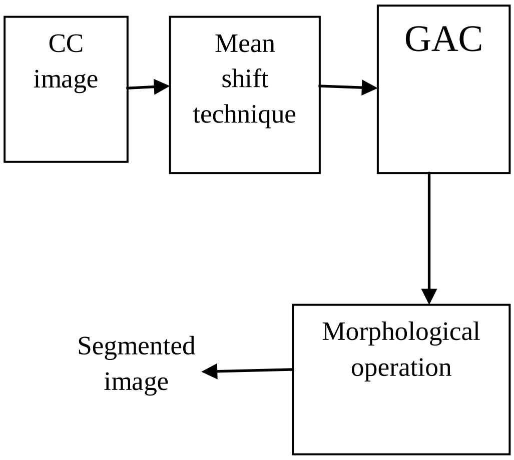

Fig1. Schematic of the proposed technique

III. mean shift algorithm

In most MRIs, CC area is an area with homogeneous intensity. In this work, we use an adaptive mean shift (AMS) technique to cluster homogenous areas. The AMS is a useful tool for finding modes (stationary points of the density of image intensity) of an image.

The mean shift algorithm is a nonparametric clustering technique which does not require prior knowledge of the number of clusters, and does not constrain the shape of the clusters.

Given n data points xi, I = 1, ..., n on a d-dimensional space Rd, the multivariate kernel density estimate obtained with kernel K(x) and window radius h is

$$f(\mathrm{X}) = \frac{1}{nh^d}\sum_{i=1}^{n} K\left(\frac{X - X_i}{h}\right)$$

For radially symmetric kernels, it suffices to define the profile of the kernel k(x) satisfyin

$$K(X) = C_{k,d}\, k\left(\|X\|^2\right)$$

Where c is a normalization constant that makes the integral of K(x) equals to one.

Shift the center of window xi by f(x), and repeat till the norm of f(x) is less than 1, and store the convergence points as modes, which are centers of different homogeneous regions in the image.

B. Geometric Active Contour based Segmentation

Geometric active contours attempt to segment an object based on its edges, in a level-set framework.The initial contour is chosen to include the object. The contour evolves according to

$$C_t = g(l)\,\mathrm{kN}$$

Where g(· · ·) is a function which should drop to zero at edges. The contour evolution tends to smooth the contour, if no other information is available. The contour according to this evolution will shrink to a point. Hence, a balloon force (Cohen '91) may be added

$$C_t = (g(l)k - \beta)N$$

However the choice of a balloon force is arbitrary. It is not clear if we actually minimize some functional, and the global 2 inimize is not clear either. The geodesic active contour tries to remedy this by minimizing the following weighted length functional:

$$\int_0^{L(c)} g(l)ds$$

g(I) constitutes an (inverse) edge indicator. For example,

$$g(I) = \frac{1}{\sqrt{|\nabla I|^2 + \epsilon}}$$

The resulting curve evolution is given by

$$C_t = \left(\underbrace{g(l)k}_{GeometricAC} - \underbrace{\langle \nabla g, N\rangle}_{Edge-Seeking}\right)N$$

C. Morphological operation

Removing the unknown noises from cc images using morphological operation. The basic morphological operators are erosion, dilation, opening and closing.

The dilation process is performed by laying the structuring element B on the image A and sliding it across the image in a manner similar to convolution as shown

$A\phi B$

The erosion process is similar to dilation, but we turn pixels to 'white', not 'black'. As before, slide the structuring element across the image and then follow these steps:

1. If the origin of the structuring element coincides with a 'white' pixel in the image, there is no change; move to the next pixel.
2. If the origin of the structuring element coincides with a 'black' pixel in the image, and at least one of the 'black' pixels in the structuring element falls over a white pixel in the image, then change the 'black' pixel in the image (corresponding to the position on which the center of the structuring element falls) from 'black' to a 'white'.

$$A\theta B$$

The most useful of these for morphological filtering are called opening and closing . Opening consists of an erosion followed by a dilation and can be used to eliminate all pixels in regions that are too small to contain the structuring element. In this case the structuring element is often called a probe, because it is probing the image looking for small objects to filter out of the image. See Fig. 7.6 for the illustration of the opening process.

$$A \circ B = (A \Theta B) \oplus B$$

IV. K-MEANS CLUSTERING

This technique has provided a reliable segmentation performance and less computation complexity. k-means is used to solve the well known clustering problem. Given a set of observations (x1, x2, …, xn), where each observation is a d-dimensional real vector, k-means clustering aims to partition the n observations into k sets (k ≤ n) S = {S1, S2, …, Sk} so as to minimize the within-cluster sum of squares (WCSS):

$$\underset{\mathbf{S}}{\arg\min} \sum_{i=1}^{k} \sum_{\mathbf{x}_j \in S_i} \|\mathbf{x}_j - \boldsymbol{\mu}_i\|^2$$

Where µ is the mean of s. in this equation use to estimate the distance between the pixels
'||xi - µj||' is the Euclidean distance
between xi and µj.
'k' is the number of data points in ith cluster.
The algorithm of k-means clustering is given by
Let Xi is the set of data points and Vi is the set of centers.

1) Randomly select cluster centers of c.
2) Calculate the eludian distance between each data point and cluster centers.
3) Assign the data point to the cluster center whose distance from the cluster center is minimum of all the cluster centers.
4) Recalculate the new cluster center vi
5) Recalculate the distance between each data point and new obtained cluster centers.
6) If no data point was reassigned then stop, otherwise repeat from step 3).

IV. EXPERIMENTAL RESULTS

Fig. 3 and 5 presents the results based on the Geometric Active Contour (GAC) technique. The proposed technique has provides a reliable segmentation performance.

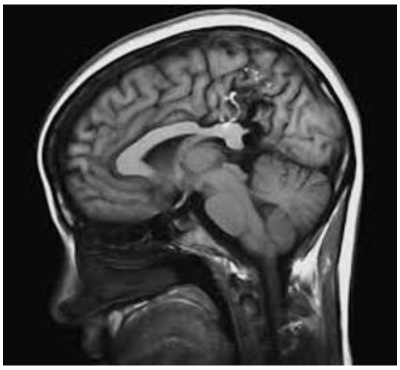

Fig.2. An input midsagittal T1-weighted brain MRI

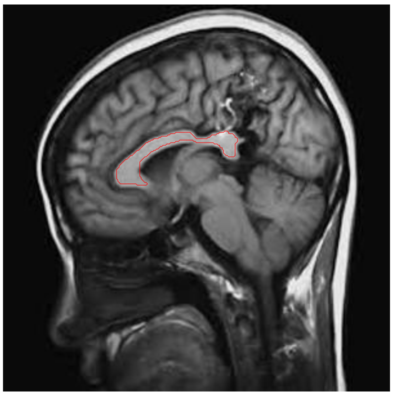

Fig.3. Detection result based on the GAC technique

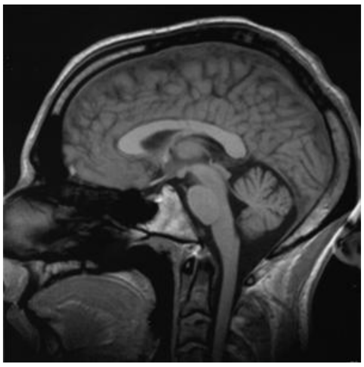

Fig.4. An input midsagittal T1-weighted brain MRI

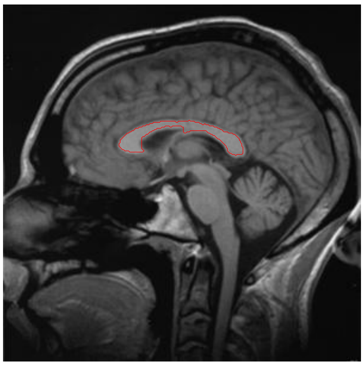

Fig.5. Detection result based on the k-mean algorithm

V. CONCLUSION

This paper presents a simple and novel technique for the automated segmentation of CC using GAC technique and k-means algorithm. It is simple, fast and does not require parameter settings; the proposed method is well suited for clinical applications. The choice of the markers in watershed technique and the use of different weighted maps can be further explored in future work, so that the method can be modified to improve its performance in the corpus callosum segmentation.

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