

Performance Evaluation of Two Label Fusion Methods for Segmenting Subcortical Brain Structures using Pre-Labeled Images

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Available online at: www.ijcseonline.org

Accepted: 19/Jun/2018, Published: 30/Jun/2018

Abstract— Multi atlas based image segmentation is a successful method in recent days in segmenting and labeling MRI images and is mainly based on registration and label fusion. In atlas-based label propagation, a pre labeled image is registered to the target image using image registration methods which produces a segmentation based on the labels in the atlas image. The segmentation of the unknown input image is then achieved by warping the atlas label to the target image space. A single atlas will produce a single segmentation which may prone to errors whereas use of N atlases gives N segmentations; then all N segmentations will be merged to get a final target segmentation. Use of N atlas gives more accurate result than use of single atlas. Many label fusion methods have been proposed. In this paper, the performance of two label fusion methods for segmenting three crucial subcortical brain structures using atlases is evaluated and compared. The result shows that joint label fusion outperforms majority voting method.

Keywords— MR Images, atlas based segmentation, multiple atlases, brain structures, label fusion

I. INTRODUCTION

The medical images obtained from various modalities such as X-Ray, CT, MRI, fMRI, PET and SPECT play an important step in the diagnosis and treatment of various diseases. Segmentation of brain magnetic resonance imaging (MRI) volumes is the process of classifying each volume element (or voxel) into various structures. Brain MRI tissue segmentation has several applications, including building population atlases of brain tissue types, guiding surgeons in the operating room, and monitoring anatomical changes in the brain produced by medical treatments. The accurate image segmentation and labeling of such images is a crucial step. Although several image segmentation algorithms have been developed, a lot of research is still going on in this topic. Recently atlas based image segmentation is one of the popular techniques used in medical image analysis. The advantage of the atlas based segmentation is the ability to segment the image with no well defined relation between regions and pixel's intensities.

An atlas is a set of two images: an intensity image and its segmentation. In atlas based segmentation, we can label the target image by wrapping an atlas (expert labeled sample images) to the target image using registration technique. Rather than using a single atlas, a group of atlases (multiple atlases) are used to do efficient segmentation. Various studies have shown that the label fusion outperforms all the alternative strategies of atlas-based segmentations when the

anatomical structure variability is too large to be represented by mean statistics. [2]

In multi atlas method, a group of atlas is used to label the target image using label fusion. Many label fusion methods have been proposed. There are two steps in atlas based segmentation: Registration and Label fusion. The transformation from the atlas to the target image is called registration. The task of combining information from various segmentations is called as label fusion. Various techniques for atlas construction are developed for different human organs, like the heart [3], [4] and especially the brain [5], [6], [7], [8].

Two label fusion methods, majority voting and joint label fusion are evaluated in this paper. The results for these two methods are compared.

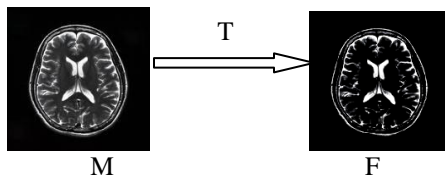
Section I contains the introduction of the multi atlas segmentation. Section II discusses two multiatlas segmentation methods. Section III gives the performance of these methods. Section IV gives the conclusion and further research directions.

II. LABEL FUSION METHODS

Atlas based segmentation requires accurate registrations between the atlas and the target image. Image registration is the task of aligning two images into a common coordinate system. One image, called moving image M, is transformed

into the coordinate system of the other image, called fixed image F. Registration is the problem of finding a transformation T which can spatially align the moving image M with the fixed image F. For the best quality of alignment various metrics have been used such as sum of squared differences (SSD), normalized correlation coefficient (NCC), mutual information (MI), and normalized mutual information (NMI). Atlas based segmentation has two steps.

1. The moving image M is registered to the fixed image ie Transformation (T) from M to F.
2. Transform T is applied on the segmentation S of the moving image M.



In single atlas based segmentations, instead of using single atlas, multiple atlases can be used and results of these can be combined into one atlas. There are so many ways to combine all atlases into one atlas such as finding average atlas, finding probabilistic atlas and finding best atlas. All the above single atlas based segmentations outperforms multi-atlas based segmentations. In multi-atlas based segmentations, each moving image, M is registered to the fixed image, F and compute individual segmentations. Finally, combine all the segmentations to obtain the final segmentation for the fixed image, F. This step is called label fusion.

A MAJORITY VOTING METHOD

Majority voting method is the most widely used label fusion method for multiple atlas-based segmentation techniques. This method considers each candidate segmentation equally and assigns the label to each voxel on which most segmentations agree[2]. This may not appropriate when the size, shape and appearance has larger variation. So weighted majority voting method is used. Larger weights are assigned to the atlases that show larger similarity to the test image. In the majority voting method[9] a patch-based analysis for automatic segmentation of brain MR images is proposed. The proposed approach, by comparing the similarity between patches, avoids the over-segmentation problem of the majority fusion. Local search technique can be used to improve the performance of similarity searching. Summed Squared Distance is used to measure the similarities between the patches. The label from the center of the patch is selected during label fusion. A candidate voxel is selected for each patch. Majority voting is performed twice for selection of label in the final label fusion.

B. JOINT LABEL FUSION

Wang. et.al., [10] proposed a method for label fusion problem, in which weighted voting is formulated in terms of

minimizing the total expectation of labeling error, and pairwise dependency between atlases is explicitly modeled as the joint probability of two atlases making a segmentation error at a voxel. This probability is approximated using intensity similarity between a pair of atlases and the target image in the neighborhood of each voxel[10]. This method reduces the bias produced by the atlases. This uses the joint label distribution of errors produced by any pair of atlases in the neighbourhood of each voxel to be known. This is estimated using intensity similarity between test and each pair of atlases.

III. RESULTS AND DISCUSSION

The choice of the metric is based on the nature of the segmentation task and the properties of the structure to be segmented. To measure the segmentation performance of a small structure, distance based metrics are most suitable. When the volume of the segmentation is measured, the volume similarity metric is found more suitable than the other metrics. The target overlap, dice overlap and jaccard co-efficient indicates the similarities between the automatic segmented using proposed methods and manual segmentation images, which indicates greater accuracy when closer to 1.

The false negative and false positive are the dissimilarities between the automatic segmented using proposed methods and manual segmentation images, which indicates greater accuracy when closer to 0.

The table 1 gives the results for the segmentation of three structures from a single image downloaded from the MIDAS website using majority voting method.

Measures	Amygdala	Basal Ganglia	Hippo campus
TO	0.6431	0.9873	0.51539
JC	0.91812	0.67102	0.59127
DSC	0.52341	0.58914	0.72640
FN	0.65273	0.34321	0.43410
FP	0.34391	0.76293	0.35238

Table 1: Majority Voting

The table 2 table gives the results for the segmentation of three structures from a single image downloaded from the MIDAS website using joint label fusion.

Measures	Amygdala	Basal Ganglia	Hippo campus
TO	0.8123	0.99367	0.84821
JC	0.5123	0.538043	0.41132
DSC	0.79077	0.699647	0.64732
FN	0.4123	0.081637	0.23253
FP	0.0984	0.541932	0.21086

Table 2: Joint Label Fusion

IV. CONCLUSION AND FUTURE SCOPE

When comparing the results of majority voting and joint label fusion, joint label fusion gives better result. Further research in this area moves towards formulating new techniques in label fusion.

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