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Review on Multi Atlas Based Segmentation Using Joint Label Fusion for Alzheimer Disease

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Abstract: ***Basically this paper states about multi atlas segmentation and joint label fusion is better than any other methods for biomedical images. In this paper the images of brain are segmented in multi atlases and then joint label fusion is used. A target image is segmented by referring to atlases, i.e., expert-labeled sample images. As an extension, multi-atlas-based segmentation makes use of more than one atlas to compensate for potential bias associated with using a single atlas and applies label fusion to produce the final segmentation. This method requires higher computational costs but, as extensive empirical studies have verified in the recent literature. It is more accurate than single atlas-based segmentation. Enabled by the availability and low cost of multicore processors, multi-atlas label fusion (MALF) is becoming more accessible to the medical image analysis community. Recently, the concept has also been applied in computer vision for segmenting natural images. Errors produced by atlas-based segmentation can be attributed to dissimilarity in the structure (e.g., anatomy) and appearance between the atlas and the target image.***

Keywords: Multi-atlas label fusion segmentation, dependence, hippocampal segmentation

1. Introduction

Atlas based segmentation is motivated by the observation that segmentation strongly correlates with image appearance. A target image can be segmented by referring to atlases, i.e., expert-labeled sample images. After warping the atlas to the target image via deformable registration, one can directly transfer labels from the atlas to the target image. Multi-atlas-based segmentation makes use of more than one atlas to compensate for potential bias associated with using a single atlas and applies label fusion to produce the final segmentation [1]. Single Atlas segmentation requires higher computational costs but, as extensive empirical studies have verified in the recent literature, e.g.,[16],[3], [22], it is more accurate than single atlas- based segmentation. Enabled by the availability and low cost of multicore processors, multi-atlas label fusion (MALF) is becoming more accessible to the medical image analysis community. Recently, the concept has also been applied in computer vision for segmenting natural images [1], [21].Errors produced by atlas-based segmentation can be attributed to dissimilarity in the structure and appearance between the atlas and the target image.

Recently for research researcher are focusing on addressing this problem. For instance, such errors can be reduced by optimally constructing a single atlas that is the most representative of the population using training data [12], [11], [18]. Constructing multiple representative atlases from training data has been considered and usually works better than single-atlas-based approaches. Multi-atlas construction is done either by constructing one representative atlas for each mode obtained from clustering training images [5], [2], [32] or by simply selecting the most relevant atlases for the unknown image on-the-fly [30], [1]. Either way, one needs to combine the segmentation results obtained by referring to different atlases to produce the final solution. Most existing label fusion methods are based on weighted voting[30],[16],[3],[17], [33], where each atlas contributes to the final solution according to a nonnegative weight, with atlases more similar to the target image receiving larger weights. Among weighted voting methods, those that derive weights from local similarity between the atlas and target, and thus allow the weights to vary spatially, have been most successful in practice [3], [17], [33]. One common property of these spatially variable weighted voting MALF methods is that the weights for each atlas are computed independently. It is taking into consideration the similarity between the warped atlas and the target image. These methods are less effective when the label errors produced by the atlases are not independent, e.g., most atlases produce similar errors. As a simple example, suppose that a single atlas is duplicated multiple times in the atlas set. If weights are derived only from atlas-target similarity, the total contribution of the repeated atlas to the consensus segmentation will increase in proportion to the number of times the atlas is repeated, making it more difficult to correct the label error produced by the duplicated atlas.[1],[4].Likewise, if the atlas set is dominated by a certain kind of anatomical feature or configuration, there will be an inherent bias toward that feature, even when segmenting target images which do not share that feature. As a result, the quality of the segmentation for the less frequent anatomical features/configurations may be reduced. Another class of label fusion methods performs majority voting (MV) among a small subset of atlases that globally or locally best match the target image, discarding the information from poor matching atlases [3], [7]. This paper derives a novel label fusion strategy that aims to reduce the bias due to the fact that atlases may produce correlated segmentation errors, without sacrificing the attractive properties of voting. The strategy is derived from formulating the weighted voting problem as an optimization problem over unknown voting weights, with the expected total error of the consensus segmentation relative to the unknown true segmentation being minimized. This formulation requires the joint distribution of label errors produced by any pair of atlases in the neighborhood of each

voxel to be known. In practice, this distribution is unknown, and we estimate it using image intensity similarity. However, unlike previous methods, similarity with the target image is not measured independently at each atlas. The similarity between the target and each pair of images is considered, which leads to an ability to explicitly estimate the probability that a pair of atlases produce the same segmentation error. They hypothesized that this strategy improves segmentation accuracy over existing techniques that consider atlas-target similarity independently [3], [33].

They used the dataset of the Alzheimer's Disease Neuroimaging Initiative (ADNI).[3] ADNI MRI data include 1.5 T structural MRI from all 800 subjects and 3 T structural MRI from 200 subjects. Our study is conducted using only 3 T MRI and only includes data from mild cognitive impairment (MCI) patients and controls. Overall, the dataset contains 139 images (57 controls and 82 MCI patients). The images were acquired sagittally, with 1 mm 1 mm in-plane resolution and 1.2 mm slice thickness[1].

2. Multiatlas Based Segmentation

Let FT be a target image to is segmented and A1 = (F1,S1),……,An=(Fn,Sn) be n atlases. Fi and Si denote the i^{th} warped atlas image and the corresponding warped manual segmentation of this atlas, obtained by performing deformable image registration to the target image. Each of the candidate segmentations may contain some segmentation errors. Label fusion is the process of integrating the candidate segmentations produced by all atlases to improve the segmentation accuracy in the final solution. Errors produced in atlas-based segmentation are mainly due to registration errors, i.e., registration associates wrong regions from an atlas to the target image. To test this hypothesis, they performed cross-validation segmentation experiments in manually labeled MRI datasets, and report significant improvements over earlier methods. Preliminary versions of this work appeared in [1], effectively reduce label errors. For example, the majority voting method [13], [19] simply counts the votes for each label from each warped atlas and chooses the label receiving the most votes to produce the final segmentation ST:

$$\wedge \quad S_T(x) = \text{argmax} \sum S_i^{\,l}(x) \qquad (1)$$

where l indexes through labels and L is the number of all possible labels, x indexes through image pixels. S(x) is the vote for label l produced by the i^{th} atlas, defined by

$$S_i^{\,l}(x) = \begin{cases} 1 \text{ if } si(x) = l \\ 0 \text{ otherwise} \end{cases} \qquad (2)$$

The recent work focused on developing segmentation quality estimations based on local appearance similarity and assigning greater weights to more accurate segmentations. For instance, the votes received by label l can be estimated by

$$\wedge \quad S_T(x) = \sum w_i(x)\, S_i^{\,l}(x) \qquad (3)$$

where $w_i(x)$ is a local weight assigned to the i^{th} atlas, with $\sum_{i=1}^{n} wi(x) = 1$

They estimated the weight is based on local image similarity under the assumption that images with similar appearance are more likely to have similar segmentations. When the summed squared distance (SSD) and a Gaussian weighting model are used [33], 1 the weights can be estimated by

$$w_i(x) = \frac{1}{z(x)}\, e^{-\sum y \varepsilon N(X) [FT(Y) - Fi(y)]^2 / \sigma} \qquad (4)$$

where N (x) defines a neighborhood around x and Z(x) is a normalization constant.

3. Joint Label Fusion

It is applied to multi label segmentation problems by producing weight maps as described below, using weighted voting to compute a consensus segmentation for each label, and selecting at each voxel the label with the highest value of the consensus segmentation. In binary segmentation, they are modeling segmentation errors produced in atlas-based segmentation as follows:

$$S_T(x) = S_i(x) + \delta^i(x) \qquad (5)$$

where $\delta^i(x)$ is the label difference between the ith atlas and the target image at x.

The weighted voting framework, where at each x, consensus segmentation $S^i(x)$ is generated as the weighted sum

$$S_T(x) = \sum w_i(x)\, S_i^{\,l}(x) \qquad (6)$$

4. Hippocampal Subfield Segmentation

To illustrate the performance of LWJoint on a segmentation problem with multiple labels, they apply it to the problem of automatic segmentation of the subfields of the hippocampal formation from oblique coronal T2-weighted MRI. The Coronal views of some subfield segmentation results produced by MV, LWGaussian, and thier method. Segmentation performance is evaluated using cross

validation. Note that cross validation is performed twice,once to separate the dataset into an atlas subset and a test subset, and the second time to search for the optimal value of the label fusion parameters among the atlas subset. For outer cross validation, we randomly select 20 images to be the atlases and another 20 images for testing. Image-guided registration is performed between all pairs of atlases, and between all atlases and the target image. Global registration was performed using the FSL FLIRT tool [35] with six degrees of freedom and using the default parameters (normalized mutual information similarity metric; search range from -5 to 5 in x, y, and z). Deformable registration was performed using the ANTS Symmetric Normalization (SyN) algorithm [4] with the cross-correlation similarity metric (with radius 2) and a Gaussian regularizer with _ ¼ 3. After registration, reference segmentations from each of the atlases were warped into the target image space.

Fig. 1 illustrates optimal label fusion parameter selection for the three methods in the first cross-validation experiment. The figure plots the number of voxels mislabeled by the

automatic segmentation, averaged over 20 inner cross-validation experiments, against the value of each parameter. Note that although the figure plots each parameter separately, the actual search for optimal parameters considers all possible combinations of parameter values. Note that using the appearance window with r ¼ 1, all methods performed significantly worse than using larger appearance windows. This indicates that estimation of joint atlas error probabilities in (18) is inaccurate for very small appearance windows. For this cross-validation experiment, the optimal parameters for LWGaussian, LWInverse, and LWJoint are (_ ¼ 0:05, r ¼ 2, rs ¼ 2), (_ ¼ 6, r ¼ 2, rs ¼ 2), and (_ ¼ 0:5, r ¼ 2, rs ¼ 3), respectively. LWJoint gives better result rather than any other method.

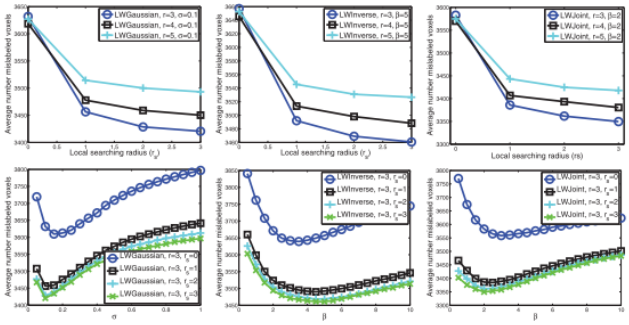

Fig. 1 illustrates optimal label fusion parameter selection for the three methods LWGaussian, LWInverse, and LWJoint respectively.

Table 1: Hippocampus Segmentation Performance for Each Label Fusion Method, in Terms of Dice Similarity Between MALF Results and Reference Segmentation

Label Fusion Strategy	Dice similarity(Left Hippocampus)	Dice Similarity
Majority Voting	0.836±0.084	0.829±0.069
STAPLE	0.846±0.086	0.841±0.086
LWGaussian	(0.885±0.025)0.886±0.027	(0.873±0.030)0.875±0.030
LWInverse	(0.884±0.026)0.886±0.027	(0.872±0.030)0.873±0.030
LWJoint	(0.893±0.025)0.897±0.024	(0.884±0.027)0.888±0.026

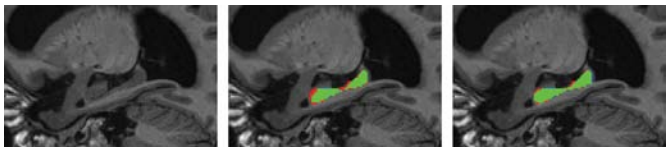

Image L W Gaussian LWJoint

Figure 2: Sagittal views of a segmentation produced by LWGaussian and our method. Red: reference segmentation; blue: automatic segmentation;green: overlap between manual and automatic seg.

Table 2: Hippocampal Volume (MM3) (Left/Right) Measured by Different Label Fusion Methods for Control and MCI Cohorts

	Left Hippocampus		
Label Fusion Method	Volume (CTL)	Volume (MCI)	Cohen's d
LWGaussian	2026±277	1642±334	1.726
LWInverse	2014±274	1635±326	1.7266
LWJoint	2156±285	1755±353	1.7468
Reference Seg.	2285±325	1841±368	1.5747
	Right Hippocampus		
Label Fusion Method	Volume (CTL)	Volume MCI)	Cohen's d
LWGaussian	1947±311	1553±346	1.5576
LWInverse	1930±309	1544±338	1.5504
LWJoint	2083±322	1668±373	1.57
Reference Seg.	2201±378	1785±408	1.3643

Table 2 presents the average hippocampal volume in control and MCI cohort obtained using different label fusion techniques. The corresponding Cohen's d effect size [14] is also shown (computed as the difference of the sample means of the two cohort, divided by the pooled sample standard deviation). To account for differences in head size, the effect size is computed after normalizing the hippocampal volumes by the subject's intracranial volume. Larger values of Cohen's d indicate greater effect, i.e., greater ability to tell cohorts apart based on hippocampal volume. This method produced more accurate volume measurements than LWGaussian and LWInverse, compared to the reference segmentations.

All results are produced with local searching using the optimal parameter for each method. Label description: red—CA1; green—CA2; yellow—CA3; blue—DG; light brown—miscellaneous label; brown—SUB; cyan—ERC; pink—PHG.

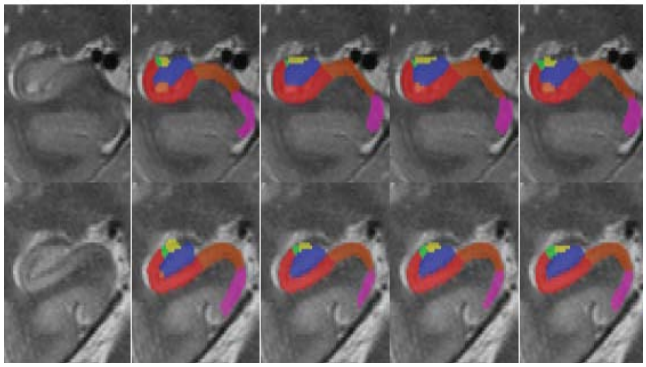

Figure 3: The MALF result and corresponding manual segmentation for each subfield, also averaging over left and right hemispheres and over 10 cross-validation experiments Label description: red—CA1; green—CA2; yellow—CA3; blue—DG; light brown—miscellaneous label; brown—SUB; cyan—ERC; pink—PHG

5. Conclusions

Label fusion techniques that independently assign voting weights to each atlas, MALF method takes the dependencies among the atlases into consideration and attempts to directly reduces the expected label error in the combined solution. Provided estimated pairwise dependencies among the atlases, the voting weights can be efficiently solved in a closed form. In their experiments, they estimated the pairwise dependency terms from local image intensities and compared our method with previous label fusion methods in whole hippocampus segmentation and hippocampus subfield segmentation using MR images.

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