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SVM Based Multi-Atlas Segmentation with Joint Label Fusion for Alzheimer Disease

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Abstract: Multi atlas segmentations are combined using label fusion. . Multi atlas segmentation is based on the observation that segmentation strongly correlates with image appearance especially for biomedical image. A test FMRI image can be segmented by referring to atlases, which uses expert-labeled sample images. For segmentation Chan vese model is used to segment many types of images, including some that would be quite difficult to segment in means of "classical" segmentation – i.e., using thresholding or gradient based methods. After warping the atlas to the test image via deformable registration, one can directly transfer labels from the atlas to the test image. Multi-atlas label fusion (MALF) is becoming more accessible to the medical image analysis. This 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 test image. Support vector machine for non linear data is used for identification of different segment. For labeling test image Anatomical Automated Labeling (AAL) is used. Label fusion strategies, weighted voting with spatially varying weight distributions derived from atlas-target intensity.

Keywords— Multi-atlas label fusion (MALF), Anatomical Automated Labeling (AAL), Functional Magnetic Resonance Image (FMRI)

I. 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. 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 o 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. [1] For experimental setup FMRI brain images are used. Segmentation of image is done by Chan vese model and for 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.[1][2][7]. Support Vector Machine (SVM) classifier is used to train the dataset. Target image to be segmented in n atlases are labeled by majority voting which reduces errors also.[3][12]

A. Multiatlas-Based Segmentation

Chan-Vese model for active contours [2] is a powerful and flexible method which is able to segment many types of images, including some that would be quite difficult to segment in means of "classical" segmentation – i.e., using thresholding or gradient based methods. This model is based on the Mumford-Shah functional [2] for segmentation, and is used widely in the medical imaging field, especially for the segmentation of the brain, heart and trachea [2].Start with a brief overview of MALF. Let FT be a target image to be segmented and $A_1 = (F_1, S_1), \ldots, A_n = (F_n, S_n)$ be n atlases. Fi and Si denote the ith warped atlas image and the corresponding warped manual segmentation of this atlas, obtained by performing deformable image registration to the target image.[1] Now the segmented atlases are labeled by majority voting algorithm in equation (1)

$$\hat{S}_T(x) = \underset{l\in\{1...L\}}{\operatorname{argmax}} \sum_{i=1}^{n} S_i^l(x), \quad (1)$$

$$S_i^l(x) = \begin{cases} 1 & \text{if } S_i(x) = l; \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

If label is assigned then Si(x) is set to 1 else to 0 as shown in eq (2). Each of the candidate segmentations may contain some errors in segmentation. Label fusion is the process of integrating the candidate segmentations produced by all atlases to improve the segmentation accuracy in the final solution. [8] To improve label fusion accuracy, recent work focuses 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

$$\hat{S}_T^l(x) = \sum_{i=1}^{n} w_i(x) S_i^l(x) \quad (3)$$

Weight wi (x) is calculated by using following formula :

$$w_i(x) = \frac{1}{Z(x)} e^{-\sum_{y\in\mathcal{N}(x)} [F_T(y)-F_i(y)]^2/\sigma}, \quad (4)$$

$$w_i(x) = \frac{1}{Z(x)} \left[\sum_{y\in\mathcal{N}(x)} (F_T(y) - F_i(y))^2 \right]^{-\beta}, \quad (5)$$

B. Joint Label Fusion

For simplicity, in the theoretical exposition that follows consider binary segmentation, i.e., segmentation into foreground and background labels. Assume that each voxel in the target image is labeled 0 or 1. Similarly, a segmentation problem with more than two labels can be decomposed into multiple binary segmentation problems, i.e., segmenting each label from the remaining labels. The method can be applied to multilabel 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.[1][4]

Segmentation errors produced in atlas-based segmentation as follows:

$$S_T(x) = S_i(x) + \delta^i(x), \quad (6)$$

If $S_i(x)$ is 1 then δ^i is {-1,0} and if $S_i(x)$ is 0 then δ^i is {1,0} .

Label difference as a discrete random variable, characterized by the following formula

$$q^i(x) = p(|\delta^i(x)| = 1 | F_T, F_1, \ldots, F_n). \quad (7)$$

By weighted voting framework, where at each x, a consensus segmentation $S_i(x)$ is generated as the weighted sum

$$\bar{S}(x) = \sum_{i=1}^{n} w_i(x) S_i(x) \;, \quad (8)$$

$$E_{\delta^1(x),\ldots,\delta^n(x)}[(S_T(x)-\tilde{S}(x))^2 \mid F_T, F_1, \ldots, F_n]$$

$$= E_{\delta^1(x),\ldots,\delta^n(x)}\left[\left(\sum_{i=1}^{n} w_i(x)\delta^i(x)\right)^2 \mid F_T, F_1, \ldots, F_n\right]$$

$$= \sum_{i=1}^{n}\sum_{j=1}^{n} w_i(x)w_j(x)E_{\delta^i(x),\delta^j(x)}[\delta^i(x)\delta^j(x) \mid F_T, F_1, \ldots, F_n]$$

$$= \mathbf{w}_x^t M_x \mathbf{w}_x, \quad (9)$$

Where $w_{x} = [w_1(x) ; \ldots\ldots; w_n(x)]$ and t stands for transpose. M_x is pairwise dependency matrix with

$$M_x(i,j) = E_{\delta^i(x)\delta^j(x)}[\delta^i(x)\delta^j(x) \mid F_T, F_1, \ldots, F_n]$$

$$= p(\delta^i(x)\delta^j(x) = 1 \mid F_T, F_1, \ldots, F_n) . \quad (10)$$

II. EXPERIMENTAL SETUP

For implementation of this MALF used the data in the Alzheimer's Disease Neuroimaging Initiative (ADNI).[1] FMRI images depict details of the internal structure of the hippocampus with high in-slice resolution and good contrast between subfields[10], but these images also have a limited field of view and large slice spacing. The test images is loaded for multi atlas segmentation and label fusion. The 3D fMRI T1-weighted image with 7 degree flip angle, 1.0 x1.0 x1.0 mm^3 resolution, with FOV 256 x 256 x176. The 17 .nii fMRI images with their respective label map are used to train the dataset where 21 ,nii images are tested. Labels are assigned using AAL(Automated Anatomical Labeling) labeling.

Multi atlas segmentation and joint label fusion is done in MATLAB 2012a on single core i3 processor and 2.53GHz CPU. For segmentation of 3d brain image it takes 18 to 21 minutes.

2.1 Segmentation using Chan Vese Model:

Introduction Segmentation is the process of partitioning a digital image into multiple segments (sets of pixels). Such common segmentation tasks including segmenting written text or segmenting tumors from healthy brain tissue in an MRI image, etc. Chan-Vese model for active contours is a powerful and flexible method which is able to segment many types of images, including some that would be quite difficult to segment in means of "classical" segmentation – i.e., using thresholding or gradient based methods.[11] This model is based on the Mumford-Shah functional for segmentation, and is used widely in the medical imaging field, especially for the segmentation of the brain, heart and trachea. The model is based on an energy minimization problem, which can be reformulated in the level set formulation, leading to an easier way to solve the problem. In this project, the model will be presented (there is an extension to color (vectorvalued) images [2], but it will not be considered here), and MATLAB code that implements it will be introduced.

2.2. Joint Label Fusion:

As a result, the Dice scores produced by LWInverse and LWGaussian similarity-based weighted voting without local search. Again, LWGaussian and LWInverse produced similar performance, which is significantly better than majority voting and STAPLE. LWJoint method produced the best average Dice similarity for all subfields. Improvements made by LWJoint for most subfields are statistically significant. Classification tasks based on drawing separating lines to distinguish between objects of different class memberships are known as hyperplane classifiers. Support Vector Machines are particularly suited to handle such tasks.The illustration below shows the basic idea behind Support Vector Machines. Here we see the original objects (left side of the schematic) mapped, i.e., rearranged, using a set of mathematical functions, known as kernels. The process of rearranging the objects is known as mapping (transformation). Labels are assigned to test image from warped images using majority voting.

1. The ADNI (www.loni.ucla.edu/ADNI) was launched in 2003 by the National Institute on Aging (NIA), the National Institute of Biomedical Imaging and Bioengineering (NIBIB), the Food and Drug Administration (FDA), private pharmaceutical companies, and nonprofit organizations as a $60 million, 5-year public and private partnership. The primary goal of ADNI has been to test whether serial magnetic resonance imaging,

positron emission tomography (PET), other biological markers, and clinical and neuropsychological assessment can be combined to measure the progression of MCI and early Alzheimer's disease (AD).

III. OUTPUT

The result of MALF using Matlab 2012a incorporated with SPM8 toolbox. The result is improved with joint label fusion. All labels are assigned with AAL selection.

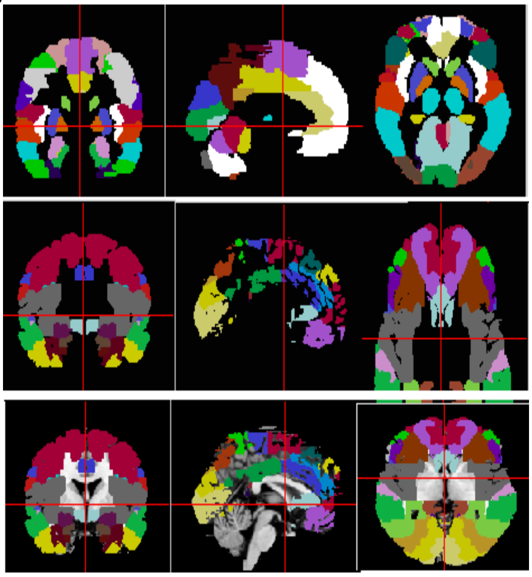

Fig 1. Multi-atlas segmentation using joint label fusion
LWGaussian ,LWInvesre and LWJoint method.(First row shows LWGaussian,Second row shows LWInvesre and third row shows LWJoint method)

IV. RESULT

Comparing to independently assigning voting weights to each atlas, our method requires an additional step of solving the inverse of the pairwise dependency matrix. Since the number of atlases applied in practice is often small, solving the matrix inverse does not substantially increase the computational burden for label fusion. In fact, the most time consuming step is the local searching algorithm. Without the local searching algorithm, for brain segmentation experiment on ADNI data MALF algorithm segments one hippocampus in a few minutes on a single core 2G HZ CPU using current Matlab 2012a.

Anatomical region	**LWGaussian**	**LWInverse**	**LWJoint**
All labels	0.782± 0.061	0.787 ± 0.160	0.791 ± 0.055
Cortical labels	0.882 ± 0.024	0.878± .025	0.885± 0.023
Subcortical labels	0.647± 0.128	0.648± 0.129	0.652± 0.126

Table 1 : Average performance of Different label Fusion strategies for Brain images

Table 1 reports the average segmentation accuracy, relative to LWInverse, LWGaussian, and LWJoint. Again, LWGaussian and LWInverse produced similar performance, which is significantly better than majority voting and STAPLE. This method produced the best average Dice similarity for all subfields. On average, we outperformed similarity-based label fusion methods by 1 percent Dice Similarity. Improvements made by LWJoint for most subfields are statistically significant. Table 1 also reports the optimal results produced by each local weighted voting methods without applying local search; LW joint method outperformed the competing methods in most subfields as well.

V. CONCLUSIONS AND DISCUSSION

Previous label fusion techniques that independently assign voting weights to each atlas, this 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 this experiments, estimated the pairwise dependency terms from local image intensities and compared LWjoint method with previous label fusion methods in whole hippocampus segmentation and whole brain image using FMRI images.

Computational Complexity

Comparing to independently assigning voting weights to each atlas, our method requires an additional step of solving the inverse of the pairwise dependence matrix.Since the number of atlases applied in practice is often small, solving the matrix inverse does not substantially increase the computational burden for label fusion. In fact, the most time consuming step is the local searching algorithm. Without the local searching algorithm, for this hippocampus segmentation experiment on ADNI data this algorithm segments one brain 3D image in a 18 to 21minutes on a dual core 2.53G HZ CPU using Matlab 2012a. Regardless, the few seconds of the computational time is spent performing deformable registration between the atlases and the target image, and the cost of label fusion is negligible in comparison.

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