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REDUCED ATLAS DATABASE AND ITS APPLICATION IN MULTI-ATLAS SEGMENTATION

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ABSTRACT

To simplify the problem of atlas selection in multi-atlas segmentation, we define Minimum Reduced Atlas Database (MinRAD), and give an algorithm of selecting MinRAD. Furthermore, nine types of MinRAD model are proposed based different similarity measures and input images, and their performances on multi-atlas segmentation are compared in two databases. Finally, we give some advice on how to select similarity measure and its threshold.

Keywords: *Reduced Atlas Database; Medical Image Processing; Multi-atlas Segmentation; Brain MRI Segmentation; Structural Similarity*

1. INTRODUCTION

An atlas, in medical image processing, is a couple of a structural MR scan and corresponding manual segmentation, namely label image. In atlas based segmentation, the atlas image can be registered to the query image, yielding a transformation which allows the atlas segmentation to be transformed and treated as a segmentation result. If a database of atlas is available, multiple segmentations from different atlas can be combined to a final result. This is called multi-atlas segmentation. For its high accuracy, it has been extensively applied for medical image segmentation, especially for brain MR images segmentation.

Atlas selection is one of the most critical factors affecting the segmentation accuracy in atlas segmentation. [1] For example, Rohlfing et al. [2] and Wu et al. [3] investigated the optimal template selection during single-atlas segmentation. Aljabar et al. explored multi-atlas selection, proved similarity- and age-based selection produce a similar result, and give the optimal selection of size of atlas subset is between 15 and 25. [4] In the classical methods of atlas selection, all atlases in the atlas database are compared with the query image to select a best similar atlas or several best similar atlases. In a practical level, the most important problem of atlas selection is its large computational cost, linearly increasing with the size of the database. On the other hand, it is possible that selecting the best similar atlases from the whole database results in redundancy bias. For a simple example, if a atlas is duplicated multiple times in the atlas set, the label result will bias towards the repeated atlases in the similarity based voting model. [5]

To simplify atlas selection and reduce redundancy bias, we define Minimum Reduced Atlas Database (MinRAD), and give two evaluation indices of MinRAD in the next section. In Section 3, nine MinRAD models are compared on two brain databases. Furthermore, based on experiment result and analysis, Section 3 also gives some advices on the selection of similarity measure and threshold. Finally, conclusions and future work are summarized.

2. MINIMUM REDUCED ATLAS DATABASE

In this section, we give the definition of Minimum Reduced Atlas Database, propose a method of constructing MinRAD, and give two evaluation indices of MinRAD.

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2.1 Definition of MinRAD

Definition 1: For a given threshold θ and similarity measure function *SM*, a subset *R* of atlas database *D* is defined RAD, if it satisfies the following condition:

$\forall$ $atlas_i \in R$, there is at least a $atlas_j \in D$, and $SM(atlas_i, atlas_j) \geq \theta$

Definition 2: For a given threshold θ and similarity measure function S*M*, a subset *R* of atlas database *D* is defined MinRAD, if it satisfies the following condition:

$\forall$ $atlas_i \in R$, there is only a $atlas_j \in D$, and $SM(atlas_i, atlas_j) \geq \theta$

MinRAD is the special RAD which has least size.

2.2 Construction of MinRAD

It is obvious that a database maybe has more than one MinRAD for a given threshold and similarity measure. How to select the optimal one? We adopt the maximum entropy principle. The aim is to maintain more information of original database. The algorithm of the selection of constructing MinRAD is described as follows.

Algorithm of constructing MinRAD*:*

Step1: Give a threshold value θ of similarity measure *SM*, and initialize MinRAD as null

Step2: Calculate the similarity measure between $atlas_i$ and $atlas_j$, denote $SM(atlas_i, atlas_j)$, $i \neq j$

Step3: Put these atlas satisfied $SM(atlas_i, atlas_j) \geq \theta$ into a same Group *k*, $k=1,2,\ldots,K$

Step4: *if length*(Group *k*)>1

Put the atlas with max entropy in Group *k* into MinRAD

else

Directly put the atlas in Group *k* into MinRAD

Step5: Repeat *Step4* until all Group are carried out, the final result of RD is the desiring database.

2.3 Evaluation Indices

For easy to compare the performance among different MinRADs derived from the same database, we define two evaluation indices: size of MinRAD and difference of percentage accuracy between segmentation result based the whole atlas database segmentation result based MinRAD. The percentage accuracy is calculated by overlap radio between manual segmentation and automatic segmentation.

$$N = |\text{MinRAD}| \quad (1)$$

$$PA = OR(R_m, R_a) = \frac{2|R_m \cap R_a|}{|R_m| + |R_a|} \quad (2)$$

$$DPA = PA_R - PA_W \quad (3)$$

where $|\cdot|$ represents pixel counts, R_m is manual segmentation, R_a is automatic segmentation, PA_w and PA_R respectively denotes the percentage accuracy based whole database and MinRAD. *DPA* ranges from -1 to 1. If *DPA* is less than 0, the segmentation result based on MinRDA is inferior to that based on whole database. If *DPA* is greater than 0, the segmentation result based on MinRDA is superior to that based on whole database. If *DPA* is equal to 0, the segmentation result based on MinRDA is as good as the result based on whole database, but the two result maybe are different.

3. EXPERIMENTAL RESULTS AND ANALYSIS

3.1 Selection of Similarity Measure

To compare the sensitivity of MinRAD to similarity measure, we select three different similarity measures between two atlases: Dice coefficient, NMI and SSIM, typically reflecting the similarity in intensity, quantity of information, and spatial structure.

- Dice Similarity Coefficient

Dice coefficient is given by [6]

$$DSC(A,B) = \frac{2|A \cap B|}{|A| + |B|} \quad (4)$$

where $|\cdot|$ represents pixel counts.

- Normalized Mutual Information (NMI)

NMI is the normalization of Mutual Information (MI). MI is given by

$$MI(A,B) = H(A) + H(B) - H(A,B) \quad (5)$$

Where $H(\cdot)$ is entropy, $H(A,B)$ is joint entropy between *A* and *B*.

There are many normalized variants of MI. Here we adopt the symmetrical NMI proposed by Witten& Frank in 2005. [7] It is defined as

$$NMI(A,B) = \frac{2MI(A,B)}{H(A) + H(B)} \quad (6)$$

- Structural SIMilarity (SSIM)

The SSIM metric is calculated on various windows of an image. [8][9] The measure between two windows *x* and *y* of common size N×N is:

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$$SSIM(x,y)=\frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (7)$$

where μ_x is the average of x, μ_y is the average of y, σ_x^2 is the variance of x, σ_y^2 is the variance of y, σ_{xy} is the covariance of x and y , $c_1=(k_1L)^2$, $c_2=(k_2L)^2$, L is the dynamic range of the pixel-values. In this paper, we set N=8, $k_1=0.01$, $k_2=0.03$.

3.2 Design of Experiment

Since an atlas is a couple of scan image and label image, there are in fact three groups of input for any similarity measure: scan image, label image, and scan and label image. Therefore, we need to compare 3*3 kinds of MinRAD based different similarity measures. The similarity between scan and label image can be calculated by the average of the scan similarity and label similarity. We carry out the same multi-atlas segmentation method on two brain database and their MinRAD. The two databases both have 20 images. One is adult brain image, and another is adolescent brain image.

In our work, the cross validation leave-one-out approach was employed, and the query image is selected in the whole database, not in MinRAD. Note that all similarity measures must be normalized to [0,1], for they should be compared in a uniform scale. Here we adopt min-max normalization.

3.2 Results and Analysis

The experiment results achieved by different similarity measures and thresholds are listed in Tab. 1and Tab.2. SM_i in Tab.1 and Tab.2 represent the following similarity measures:

$$SM_1=DSC(S_i,S_j) \quad (8)$$

$$SM_2=NMI(S_i,S_j) \quad (9)$$

$$SM_3=SSIM(S_i,S_j) \quad (10)$$

$$SM_4=DSC(L_i,L_j) \quad (11)$$

$$SM_5=NMI(L_i,L_j) \quad (12)$$

$$SM_6=SSIM(L_i,L_j) \quad (13)$$

$$SM_7=\frac{DSC(S_i,S_j)+DSC(L_i,L_j)}{2} \quad (14)$$

$$SM_8=\frac{NMI(S_i,S_j)+NMI(L_i,L_j)}{2} \quad (15)$$

$$SM_9=\frac{SSIM(S_i,S_j)+SSIM(L_i,L_j)}{2} \quad (16)$$

where S is scan image , L is label image.

From comparing the results in Tab.1 and Tab.2, we can draw the following conclusions:

(1) MinRAD not only get the same percentage accuracy as whole database (the region of gray background in Tab. 1), but also get a more percentage than whole database (the region of black background in Tab. 1).

(2) With the increasing of threshold, the percentage accuracy of segmentation firstly becomes large, but when threshold reaches a certain value, it stop rise, even begin to descend (the area marked by rectangular).

(3) For a given threshold, different similarity measures produce different sizes of MinRAD.

(4) SSIM is very suitable to select the optimal MinRAD, while NMI is not suitable.

(5) Similarity of label images is more important than similarity of scan image.

(6) The size of MinRAD of adolescent brain database is smaller than that of adult brain database. The reason is that the individual differences of human brain become large with the growth of age.

The first two conclusions demonstrate the best performance of MinRAD on reducing the redundancy bias. The latter conclusions imply the choosing method of similarity measure and threshold:

(1) Structural feature based similarity measure is a better choice than other similarity measures.

(2) The input of similarity measure should contain label images.

(3) The choice of threshold depends on the individual differences of atlases and type of similarity measure. The individual differences of atlases rely on medical an biochemical character, e.g. age. The feature-based similarity measures choose a bigger threshold, while intensity-based similarity measures choose a smaller threshold.

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4. CONCLUSIONS

In this paper, we proposed a novel strategy of simplifying the atlas selection in multi-atlas segmentation by constructing a MinRAD for the atlas database, which can effectively reduce the redundancy bias and the computational cost of atlas selection. By comparing the difference of segmentation results based whole database and nine types of MinRAD, we demonstrated the validity of our method and give some advice on the selection of similarity measure and its threshold. In future work, we will analyze the sensitivity of performance of MinRAD to threshold and similarity measure, and further extend our work on 3D atlas datasets.

Table 1: D_{OR} Of Adult Brain Atlas Database With Different Similarity Measures And Thresholds

θ	$SM(S_i,S_j)$			$SM(L_i,L_j)$			*average of* $SM(S_i,S_j)$ *and* $SM(Li,Lj)$		
	SM_1	SM_2	SM_3	SM_4	SM_5	SM_6	SM_7	SM_8	SM_9
0	-0.0314	-0.0426	-0.0314	-0.0426	-0.4971	-0.0426	-0.0426	-0.0497	-0.0426
0.1	-0.0239	-0.0426	-0.028	-0.0502	-0.4971	-0.0502	-0.0228	-0.0497	-0.0502
0.2	-0.0239	-0.0426	-0.028	-0.0187	-0.4971	-0.0502	-0.0228	-0.0497	-0.0265
0.3	-0.0168	-0.0426	-0.028	-0.0187	-0.4971	-0.0502	-0.0187	-0.0497	-0.0265
0.4	-0.0168	-0.0426	-0.0243	-0.0187	-0.4971	-0.0265	-0.014	-0.0497	-0.0187
0.5	-0.0098	-0.0401	-0.0243	-0.0131	-0.4971	-0.0187	-0.0117	-0.0497	-0.0187
0.6	-0.0098	-0.0401	-0.0134	-0.0065	-0.4976	-0.0033	-0.0065	-0.0418	-0.0131
0.7	-0.0063	-0.0359	-0.0029	-0.0072	-0.4976	**0.0003**	-0.0065	-0.0064	-0.0024
0.8	-0.0063	-0.0351	0	0	-0.4965	0	0	-0.0064	-0.0024
0.9	0	-0.0351	0	0	-0.4869	0	0	-0.0064	0
1	0	-0.0351	0	0	-0.0061	0	0	-0.0064	0

Table 2: N Of Adult Brain Atlas Database With Different Similarity Measures And Thresholds

θ	$SM(S_i,S_j)$			$SM(L_i,L_j)$			*average of* $SM(S_i,S_j)$ *and* $SM(Li,Lj)$		
	SM_1	SM_2	SM_3	SM_4	SM_5	SM_6	SM_7	SM_8	SM_9
0	1	1	1	1	1	1	1	1	1
0.1	3	1	2	2	1	2	4	1	2
0.2	3	1	2	4	1	2	4	1	3
0.3	5	3	5	4	1	3	6	1	3
0.4	5	3	6	4	1	4	7	1	4
0.5	7	5	9	5	1	7	9	1	5
0.6	7	5	11	7	2	9	10	2	7
0.7	8	8	12	8	2	**12**	11	10	7
0.8	8	12	15	10	5	14	13	10	9
0.9	16	12	16	10	8	15	15	10	12
1	20	12	16	15	9	15	20	10	10

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Table 3: D_{OR} Of Adolescent Brain Atlas Database With Different Similarity Measures And Thresholds

θ	$SM(S_i,S_j)$			$SM(L_i,L_j)$			average of $SM(S_i,S_j)$ and $SM(Li,Lj)$		
	SM_1	SM_2	SM_3	SM_4	SM_5	SM_6	SM_7	SM_8	SM_9
0	-0.0422	-0.0929	-0.0422	-0.054	-0.0054	-0.054	-0.054	-0.0577	-0.054
0.1	-0.029	-0.0929	-0.029	-0.0331	-0.0565	-0.0371	-0.0371	-0.0577	-0.0371
0.2	-0.0239	-0.0861	-0.029	-0.0331	-0.0565	-0.0371	-0.0371	-0.0577	-0.0408
0.3	-0.0239	-0.0861	-0.029	-0.0331	-0.0565	-0.0331	-0.0331	-0.0577	-0.0407
0.4	-0.0193	-0.0787	-0.019	-0.0408	-0.0565	-0.0408	-0.0199	-0.0577	-0.0308
0.5	-0.0145	-0.0729	-0.0145	-0.0408	-0.0565	-0.0256	-0.0256	-0.0573	-0.0206
0.6	-0.0145	-0.0729	-0.0145	-0.0123	-0.0563	-0.0256	-0.0123	-0.0547	-0.0006
0.7	-0.0049	-0.0729	-0.0099	-0.0123	-0.0556	-0.0123	-0.0017	-0.022	**0.0256**
0.8	-0.0036	-0.0729	-0.0099	-0.0017	-0.0556	**0.0031**	0	-0.022	0
0.9	0	-0.0729	-0.0049	0	-0.0544	0	0	-0.022	0
1	0	-0.0729	0	0	-0.0217	0	0	-0.022	0

Table 4: N Of Adolescent Brain Atlas Database With Different Similarity Measures And Thresholds

θ	$SM(S_i,S_j)$			$SM(L_i,L_j)$			average of $SM(S_i,S_j)$ and $SM(Li,Lj)$		
	SM_1	SM_2	SM_3	SM_4	SM_5	SM_6	SM_7	SM_8	SM_9
0	1	1	1	1	1	1	1	1	1
0.1	4	1	4	5	2	4	4	1	4
0.2	5	2	4	5	2	4	4	1	6
0.3	5	2	4	5	2	5	5	1	6
0.4	7	4	6	6	3	6	6	1	6
0.5	9	5	7	6	3	7	7	3	7
0.6	10	5	7	8	3	7	8	9	7
0.7	10	5	8	8	6	8	9	10	**7**
0.8	13	5	8	9	6	**8**	10	10	7
0.9	13	5	9	10	9	9	10	10	7
1	20	5	10	20	10	10	20	10	8

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