Classification of brain disease from magnetic resonance images based on multi-level brain partitions

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***Abstract*— In this paper, we present a classification method based on the multi-level brain partitions. Bag-of-visual-words model is used. Firstly, the representative SIFT features are extracted from brain template as the basic visual words. Secondly, individual MR images are described using the basic visual words and support vector machine classifiers are trained for different brain partitions respectively. Thirdly, the final classification is derived from the combination of multiple classifiers. We apply this method to MR images of Alzheimer's disease and Parkinson's disease. The results demonstrate that the multi-level partitions favors the classification accuracy of brain disease from MR images.**

I. INTRODUCTION

Magnetic resonance imaging (MRI) is a powerful, non-invasive medical imaging technique widely used in neuroscience and brain disease research [1]. Detecting brain structural changes from MRI can facilitate early diagnosis and treatment of neurological and psychiatric disease [2]. In recent years, there has been growing interest within the objective assessment of disease status using MRI.

Traditional methods for analyzing MRI brain images such as voxel-based morphometry (VBM) [3] and deformation-based morphometry (DBM) [4] always require nonlinear alignments to a template, in order to achieve voxelwise inter-subject correspondence [5]. However, the differences caused by disease may be removed in the registration process and cause an over-alignment problem [6]. Toews et al. [6] first proposed feature-based morphometry (FBM), which represent brain using localized image features. In FBM, the comparison of brain images is based on image features, instead of voxels, and therefore voxel-level alignments are not required [2].

After FBM, research on how to represent MRI using local features are increasing. Bag-of-visual-words (BOVW), a method for image representation, is invariant to location changes and affine transformations. The basic idea of this method is to represent the image visual content as a probability distribution (histogram) of local features (visual words) and collect a knowledge based from a set of images, previously labeled [7].

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BOVW is widely used in target classification and target recognition, and in recent years it is used to analyze MRI gradually. Daliri [8] used the scale-invariant feature transforms (SIFT) to extract features from different slices in MR images, and proposed a classification method based on BOVW and support vector machines (SVM). Rueda et al. [7] proposed a BOVW image representation scheme for brain MR images using gray pixel intensities as features, which combined with a SVM. Mizotin et al. [9] proposed a method which uses the Laguerre Circular Harmonic Functions coefficients as feature vectors instead of SIFT features. Ahmed et al. [10] propose a BOVW method which extracts the hippocampus region of interest (ROI) and uses circilar Harmonic Function as features.

The above methods extract features from the whole brain or some fixed regions for every subject, and these features are then clustered into groups of visual words which they can be used to transform a full 3-dimensional image from a subject to a histogram of these features. However, the location information of these features are ignored.

Based on FBM and BOVW, in this paper, we take features' location into consideration and propose a BOVW based on multi-level partitions to utilize the probability distribution in different brain partitions.

II. METHODS

In this paper, we propose a method for classification of brain disease from MR images based on multi-level brain partitions. Figure 1 illustrates the overall flow of our method. This method consists of six steps, which is summarized as following: (1) preprocess, (2) feature extraction, (3) multi-level partition, (4) BOVW construction, (5) BOVW histogram, (6) Classification.

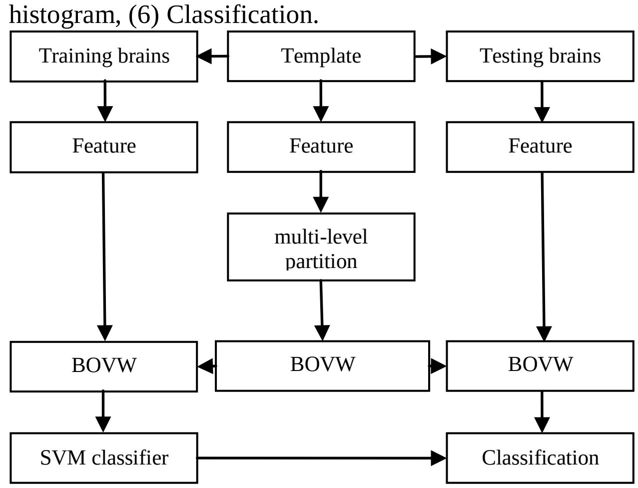

Figure 1. Flow chart of the overall method

A. Preprocessing

The proposed method is evaluated on public datasets in Open Access Series of Imaging Studies (OASIS) [11] for Alzheimer's disease (AD).

OASIS contains 416 subjects aged from 18 to 96, we use the subjects aged 60-80 years, CDR (Clinical Dementia Rating)=1. This subset contains 66 normal control (NC) and 20 AD. OASIS scans are first averaged and gain-field corrected in advance to improve signal/noise ratio, and then registered to Talairach space via affine transform and the skull are masked out. Marcus et al. [11] present the detailed description of the preprocessing steps for this dataset.

B. Feature Extraction

Features generated by SIFT are robust to distortion, noise and resolution [6]. SIFT features are generated in four stages: identify potential interest points that are invariant to scale and orientation using difference-of-Gaussian function; select keypoints based on measures of their stability; assign one or more orientations to each keypoint location based on local image gradient directions; measure the local image gradients at the selected scale in the region around each keypoint.

Here, a SIFT feature is described by 131 numbers: 1 number for slice order of the 2D slice image, 2 numbers for voxel location in the slice image, 128 numbers for appearance matrix, which characterizes the image appearance around the center of the feature in more detail. In this paper, package vlFeat [14] is used to extract SIFT features from the 2D slices of MR images in brain template and every subject.

C. Multi-level Brain Partition

BOVW is invariant to location changes. If the features' spatial distribution are ignored, the lateralization of features may be vague. This paper presents a scheme based on multi-level brain partition.

This paper will analyze features' distribution in terms of four levels of brain partitions. Figure 2 illustrates the multi-level brain partition used in this paper.

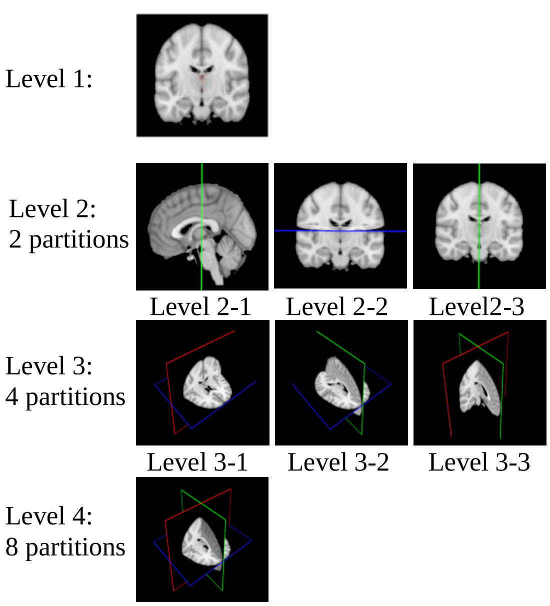

Figure 2. Multi-level partition

Level 1: one whole brain as one partition.

Level 2: two partitions of brain region, namely the whole brain is divided based on one central plane of three orientations (coronal, axial or sagittal). Level 2 can be subdivided into Level 2-1, Level 2-2 and Level 2-3 according to different brain partitions shown in Figure 2.

Level 3: four partitions of brain region, namely the whole brain is divided based on two central planes of three orientations (coronal, axial and sagittal). Level 3 can be subdivided into Level 3-1, Level 3-2 and Level 3-3 according to different brain partitions shown in Figure 2.

Level 4: eight partitions of brain region, namely the whole brain is divided based on coronal, axial and sagittal central planes.

D. BOVW construction

Bag-of-words is a popular representation for document within information retrieval [15]. In this method, the document is regarded as a set of words, in which word's sequence, grammar and syntax are negligible. The BOVW image representation is analogous to the bag-of-words representation of text documents in terms of form and semantics [16]. An image can be represented by a set of keypoint descriptors, but this set varies in cardinality and lacks meaningful ordering [16]. In this paper, the visual words are extracted from SIFT features.

(1) ICBM-152 template

BOVW construction is comprised by a clustering algorithm on the extracted SIFT features, allowing to construct a visual bag by finding the most representative features. Each cluster centroid is considered as a visual word in the bag.

When it comes to MR images, spatial normalization is an important preprocessing step used to reduce intersubject anatomical variability in human brain mapping studies [17]. The most basic form of spatial normalization adjusts position, orientation and size of an individual brain to match a reference brain [18]. In this paper, we assume that brain template has contained most basic visual words. In this paper, we construct BOVW using ICBM-152 brain template. This scheme can reduce the computation load in clustering greatly. Besides, for the rarity of MR images, algorithm evaluation is often performed by leave-one-out cross-validation. This scheme can also avoid double counting of BOVW.

(2) AP clustering

K-means method is most used to find the representative features, namely basic visual word. Before clustering, the number of clusters and initial clustering centers must be given. From the work of Daliri [8], we can summarize that the accuracy of classification depends on the number of clusters largely. In this paper, we adopt Affinity Propagation (AP) clustering algorithm, which considers all data points as potential exemplars [19]. By viewing each data point as a node in a network, this algorithm recursively transmits real-valued messages along edges of the network until a good set of exemplars and corresponding clusters emerges [19].

AP clustering is able to avoid many of the poor solutions caused by unlucky initializations and hard decisions. And the number of clusters is not required in this clustering.

(3) BOVW based on brain partitions

After extracting SIFT features from ICBM-152 brain template, we regroup features based on their location. The feature in the same brain partition are gathered and AP clustering is performed to find cluster centers in this brain partition. These centers will be considered as basic visual words in the bag of this brain partition. For example, for every brain partition in Level 4 shown in Figure 3, we cluster SIFT features in this partition and extract centers as basic visual words in the bag of this partition. From Level 4, we can obtain 8 bags. Similarly, for every brain partition in Level 1, Level 2, Level 3, we cluster SIFT features in every partition respectively and obtain corresponding bag.

E. BOVW histogram

The idea of BOVW model is to represent an image using the basic visual words in the bag. The image will be represented as a histogram with as many elements as basic visual words. We have 8 different kinds of partitions (Level 1, Level 2-1, Level 2-2, Level 2-3, Level 3-1, Level 3-2, Level 3-3, Level 4). For every brain partition of every level, we have obtain its bag. The following work is representing an image using words in these bags and calculating histogram respectively for every level.

(1) Searching substitution

In this step, features extracted from training subjects are substituted with the basic visual words in the bags of brain partitions which is most similar with the features. In this paper, the similarity is measured by Euclidean distance. The nearest distance means the most similar, and vice versa.

(2) Histogram based on brain partitions

After searching substitution for every SIFT feature, we get the frequency of every visual word in the bags of brain partitions. The histogram for every brain partition is a vector of words' frequency in order.

(3) Level histogram

For every partition of every level, we calculate its histograms. The level histogram for one level is a histogram which combines histograms from different partitions of same level in order. The level histogram is used to represent the content of brain image for corresponding level.

F. Classification

(1) SVM classifier

SVM was proposed by Vapnik [20] which is widely used in classifying the data especially in high dimensional feature spaces [8]. For every level, we have got a histogram and this histogram is used as the feature vector for this subject in this level. The label of feature vector is in according with the group this subject belong to (-1 for patient subject and +1 for healthy control subject). We train a SVM classifier for every partition Level respectively, namely we train 8 classifier. In this paper, LIBSVM [21] is used to implement the classification.

(2) Classifying new subject

We classify new subject using 8 SVM classifiers we have already trained. The final classification result is decided by a majority voting of 7 classifiers except the one in Level 1. The result in Level 1 is used for comparison.

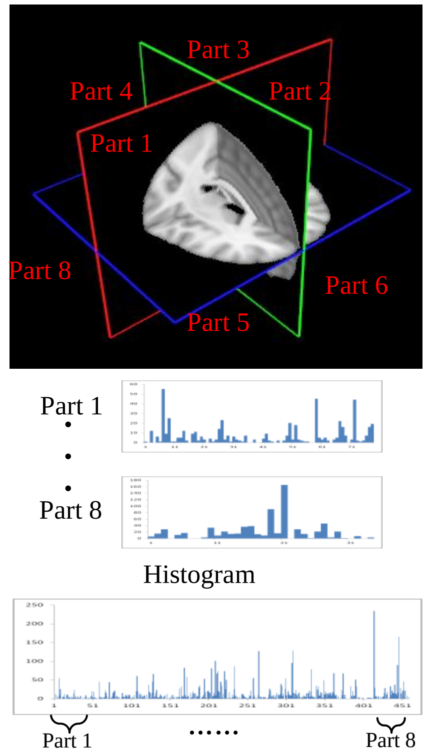

Figure 3. Typical histogram

III. RESULTS

(1) Performance measures

To exhibit the advantage of classification based on multi-level partitions, we evaluate the performance in terms of accuracy, precision, sensitivity and specificity [22].

(2) Evaluation

To evaluate the validity of our method, we apply this method to 10 subsets which contain 20 NC subjects randomly chosen from OASIS and 20 AD subjects. For every subset, leave-one-out cross-validation is performed. That is, one individual MR images are chosen as the testing images and the remaining individual MR images are used for training. The result is given in Table 1.

The measures in 3 Level Union (one of Level 2, one of Level 3, Level 4) is the average performance of 9 kinds of union. The measures in 5 Level Union (two of Level 2, two of Level 3, Level 4) is the average performance of 9 kinds of union.

To demonstrate the effectiveness of multi-level partitions, t-test is also performed for two samples (Level1 and 7 Level Union) in AD20-NC20. The p-value associated with the t-test is 0.0143 for AD20-NC20 group, confirming that better performance from multi-level partitions is not obtained by coincidence.

TABLE I. PERFORMANCE IN OASIS

AD20-NC20		Average Accuracy	Average Precision	Average Sensitivity	Average Specificity
Reference	Level 1	69.25%	69.88%	68.00%	70.50%
Multi Partitions	Level 2-1	74.00%	75.20%	71.50%	76.50%
	Level 2-2	74.75%	76.14%	72.00%	77.50%
	Level 2-3	73.50%	74.10%	72.50%	74.50%
	Level 3-1	71.00%	72.73%	67.50%	74.50%
	Level 3-2	73.00%	73.34%	72.50%	73.50%
	Level 3-3	73.25%	75.51%	69.00%	77.50%
	Level 4	74.25%	74.92%	73.00%	75.50%
	3 Level Union	75.25%	76.13%	73.78%	76.72%
	5 Level Union	75.31%	76.43%	73.56%	77.06%
	7 Level Union	75.75%	77.26%	73.50%	78.00%

IV. CONCLUSION AND DISCUSSION

This paper, we propose a method for classification of brain disease from MR images based on multi-level brain partitions. Compared with BOVW model based on the whole brain, BOVW model based on multi-level brain partitions obtains better accuracy in dataset OASIS. In this paper, we construct BOVW using the brain template, which can reduce the computation load in clustering. AP clustering is used and avoids the possible poor solutions caused by the unlucky initializations or hard decisions. We evaluate our method using leave-one-out cross-validation in OASIS, and the result proves better classification performance based on multi-level brain partitions than no partition. In general, more levels lead to better performance. However the improvement is small, and this may due to that classification results in Level 2 and Level 3 are stable. Besides, from the results, it seems that a BOVW model based on one kind of suitable brain partitions may also get better result than no brain partition. It may be that the BOVW based on brain partitions utilize more spatial information of different brain regions. This study demonstrates that combination of multi-level partitions favors the classification of brain disease from MR images. To be noted, in this paper, we use a 2D SIFT algorithm mainly due to its robustness and feasibility, as many 3D SIFT implementations couldn't achieve the full orientation invariance respect to 3 degrees of rotational freedom [23]. Besides, for the limitation of computing capability in our lab, the serial images are down-sampled once to reduce computation load.

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