Patch Analysis Based Sparse Coding System for Alzheimer's Disease Diagnosis and Prognosis

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Introduction

Accurate diagnosis of MCI and identification of some MCI patients who later convert to AD are crucial for adequate individual patient care and the design of clinical trial targeting early interventions. Patches Analysis based Sparse-coding System (PASS) is based on multivariate tensor-based morphometry to extract patch based multivariate morphometry statistics (MMS). With the use of dictionary learning and sparse coding for initial feature dimension reductions, max-pooling was adopted to extract final used features. Finally, an AdaBoost classifier was employed for binary group classification. PASS was evaluated on ADNI baseline MRI dataset. With MMS of the hippocampal structure, PASS outperformed several standard image measures in classifying the different stages of AD. The new system may boost classification performance of diagnoses ranging from healthy control to AD.

Methods

From each MRI scan (**Fig. 1 (a)**), we used the FIRST software and marching cube method to automatically segment and reconstruct hippocampal surfaces. With our prior surface fluid registration work, we registered hippocampal surfaces to a common template and computed surface multivariate morphometry statistics (MMS), consisting of surface multivariate tensor-based morphometry (mTBM) and radial distance (RD). The intuition is that mTBM describes the surface deformation along the surface tangent plane while RD reflects surface differences along the surface normal directions. This combines complementary information from mTBM, which measures deformation within surfaces, and RD, which measures hippocampal size in terms of the surface normal direction. We formed the new surface multivariate morphometry statistic (MMS) as a 4×1 vector consisting of the mTBM and radial distance (**Fig. 1 (b)**).

We constructed overlapped patches on hippocampal surface features (**Fig. 1 (c)**) and built an initial sparse coding dictionary. After that, Stochastic Coordinate Coding (SCC) was applied to learn a dictionary and sparse codes on the selected patches (**Fig. 1 (d) (e)**) . Finally, we used the max-pooling algorithm on the newly learned high-dimensional features to obtain a final set of low-dimensional features (**Fig. 1 (f)**). An AdaBoost classifier was then applied some classification tasks: (1) AD vs. CTL, (2) MCI-converters vs. MCI-stable and (3) CTL-converters vs. CTL-stable and 10-fold leave-one-out cross validation protocol was adopted to estimate classification accuracy (**Fig. 1 (g)**). Standard performance measures were computed, including Accuracy, Sensitivity, Specificity, and Negative predictive values (Npv) and the area-under-the-curve (AUC) of the receiver operating characteristic (ROC) curves. Other image measures were also studied for comparison.

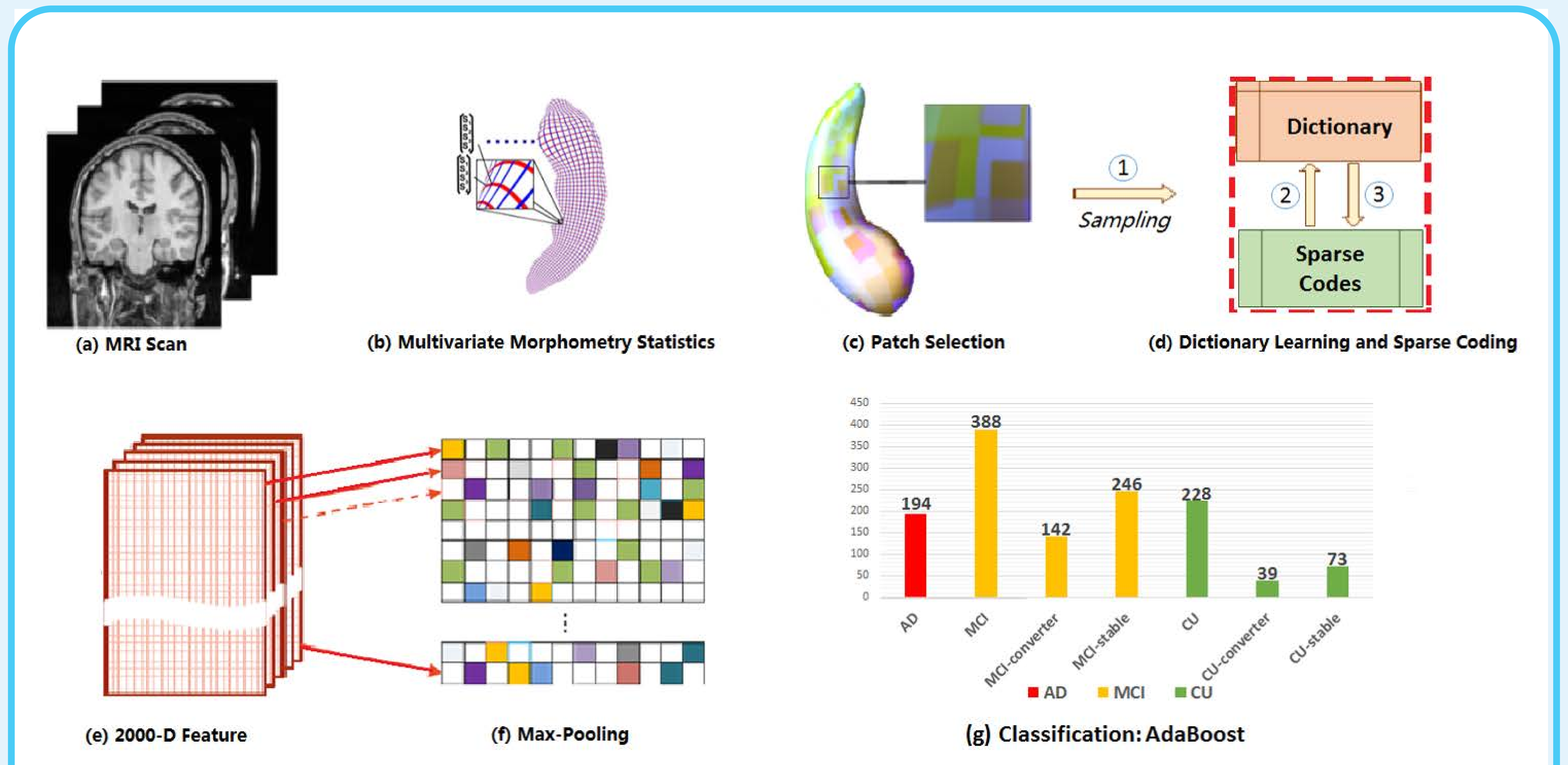


Figure 1. Overall Processing Sequence. A chart showing the key steps in the Patch Analysis based Sparse-coding System (PASS).

ADNI Baseline Dataset

We studied a total of 810 subjects in the ADNI baseline dataset. 3D T1-weighted images were used. The demographic information of studied subjects within groups in ADNI are shown on the right table.

	Gender (M/F)	*Age*	*MMSE*
AD (194)	108/86	75.25±7.50	23.29±2.09
CTL (228)	116/108	76.10±4.92	29.10±1.00
MCI Converter (142)	89/53	74.62±6.88	26.71±1.72
MCI Stable (246)	166/80	74.93±7.46	27.18±1.79
CTL Converter (39)	23/16	76.90±3.85	29.31±0.76
CTL Stable (73)	35/38	76.20±5.39	29.05±1.10

Experimental Results

Hippocampi were segmented with FIRST. Hippocampal surfaces were constructed by marching cube method. The multivariate morphometry statistics were processed with our surface multivariate tensor-based morphometry software. Results are compared with hippocampal volume (Vol), hippocampal area (Area), radial distance (RD), and multivariate TBM (mTBM).

Results of AD vs. CTL Group (N=194 vs. N=228)

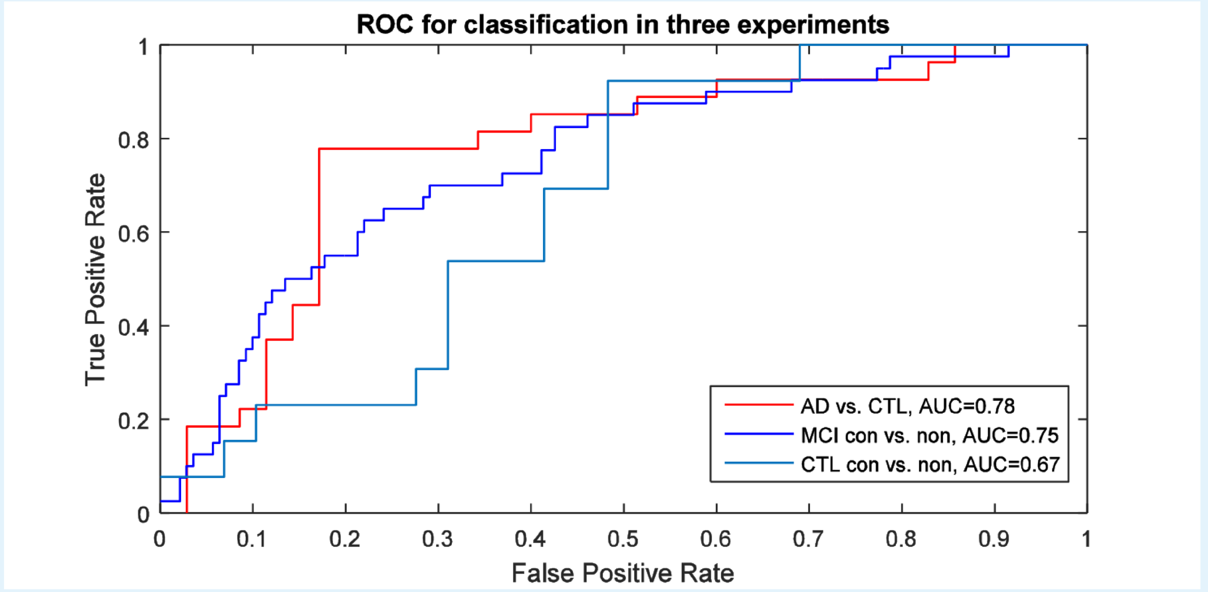
	Vol.	Area	RD	mTBM	RD+mTBM
Accuracy	0.70	0.58	0.65	0.66	**0.81**
Sensitivity	0.63	0.5	0	**0.83**	**0.83**
Specificity	**0.80**	0.58	0.65	0.61	0.78
Npv	0.72	**0.97**	1	**0.97**	0.83
AUC	0.69	0.57	0.53	0.74	**0.78**

Results of MCI-Converters vs. MCI-stable (N=194 vs. N=228)

	Vol.	Area	RD	mTBM	RD+mTBM
Accuracy	0.72	0.53	0.68	0.74	**0.77**
Sensitivity	0.70	0.57	0	0.67	**0.82**
Specificity	0.73	0.52	0.67	0.69	**0.76**
Npv	0.84	0.82	1	**0.99**	0.95
AUC	0.61	0.56	0.55	0.61	**0.75**

Results of CTL-Converters vs. CTL-stable (N=39 vs. N=73)

	Vol.	Area	RD	mTBM	RD+mTBM
Accuracy	0.64	0.39	0.67	0.67	**0.71**
Sensitivity	0.62	0.22	0	0	**0.71**
Specificity	0.69	0.42	0.67	0.67	**1**
Npv	0.77	0.64	**1**	**1**	**1**
AUC	0.57	0.38	0.62	0.62	**0.67**



Acknowledgement

This research was supported by the National Institute on Aging (R21AG043760, R21AG049216, R01AG031581, P30AG19610 and U54EB020403), the National Science Foundation (DMS-1413417 and IIS-1421165).