Studying Ventricular Abnormalities in Mild Cognitive Impairment with Sparse Coding on Hyperbolic Spaces

Jie Zhang[1], Cynthia M. Stonnington[2], Jie Shi[1], Qingyang Li[1], Boris A. Gutman[3], Kewei Chen[4], Eric M. Reiman[4], Richard J. Caselli[2], Paul M. Thompson[3], Jieping Ye[5], Yalin Wang[1]

1. Arizona State University 2. Mayo Clinic Arizona 3. University of Southern California 4. Banner Alzheimer's Institute and Banner Good Samaritan PET Center 5. University of Michigan

ylwang@asu.edu

Introduction

Mild cognitive impairment (MCI) is a transitional stage between normal aging and Alzheimer's disease (AD). This work introduces a hyperbolic space sparse coding method to predict impending decline of MCI patients to dementia using surface measures of ventricular enlargement. The proposed method was tested on a group of MCI subjects (*N* = 133) from the Alzheimer's Disease Neuroimaging Initiative (ADNI) baseline dataset and achieved an accuracy rate of 96.7%, which outperformed some other ventricular morphometry measures.

Methods

- The major steps in the proposed method are illustrated in Fig. 1.
- Given a 3D MR image, as shown in Fig. 1 (a), we segment the lateral ventricle structure and reconstruct the ventricular surfaces with the segmented images.
- With topology optimization [1], we model each ventricular surface as a genus-0 surface with 3 open boundaries, as shown in Fig. 2 (a) with the blue lines $\gamma_1, \gamma_2, \gamma_3$. The resulting surface admits hyperbolic geometry [2].
- We compute the conformal parameterization of the ventricular surface with the hyperbolic Ricci flow algorithm [1,2] and embed it onto the Poincaré disk, as shown in Fig. 2 (b).
- With geodesic curve lifting [1], we introduce consistent geodesics in the parameter space to connect existing boundaries, as shown in Fig. 2 (b) with $\tau_1, \tau_1^-, \tau_2, \tau_2^-$. The resulting parameter domain is consistent across subjects.
- We convert the Poincaré disk to Klein model, as shown in Fig. 2 (c). Then the Klein disk is used as the canonical parameter space to match each ventricular surface to a common template [1].
- After surface registration, we compute the tensor-based morphometry (TBM) [3] to measure the deformations of each ventricular surface. We then smooth the TBM features with a heat kernel smoothing algorithm [4] to increase their SNR.

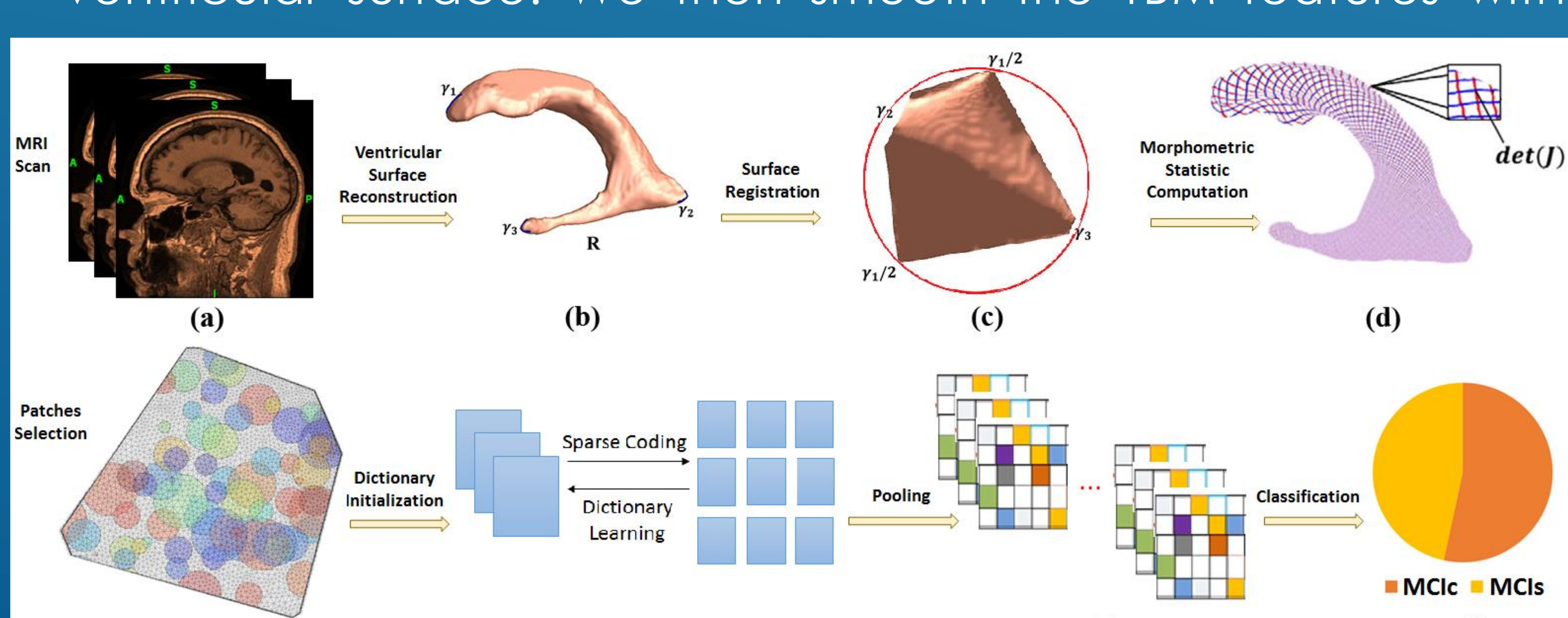

Figure 1. The major processing steps in the proposed method.

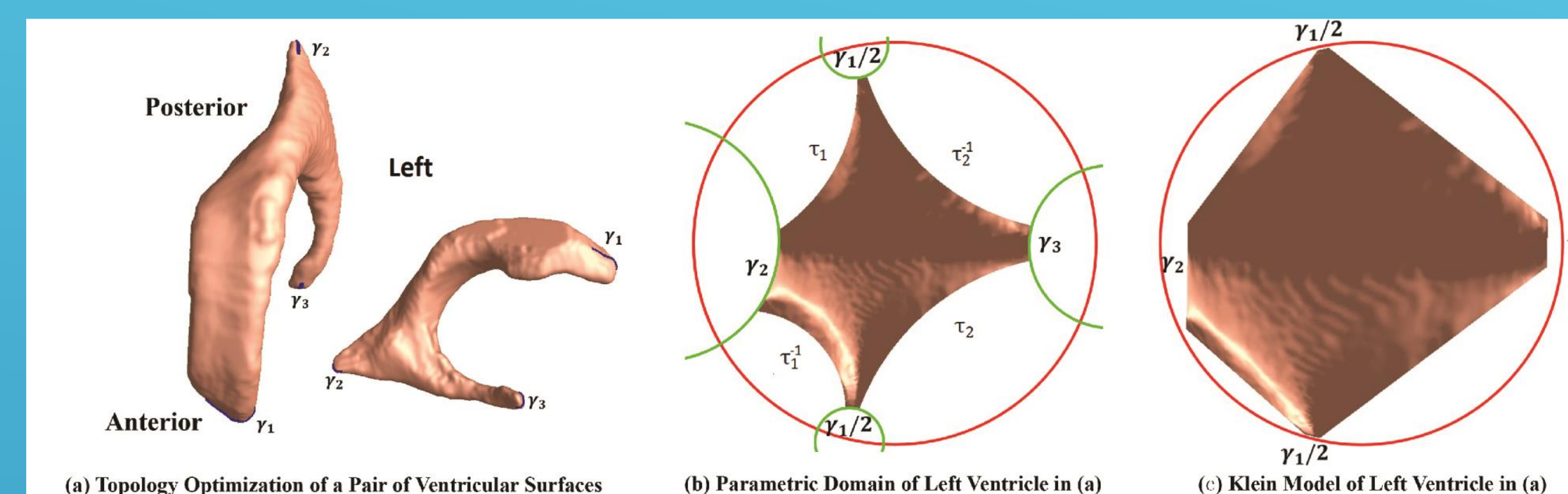

Figure 2. Ventricular surface conformal parameterization with hyperbolic Ricci flow.

- In the Klein disk, we propose a Farthest point sampling method with Breadth-first Search (FBS) to select patches in the hyperbolic space, which are used to initialize the original dictionary for sparse coding, as shown in Fig. 3 (b). Fig. 3 (a) shows that when projected back to the 3D surface, the selected patches maintain the same topological structures as in the parameter domain.
- We use dictionary learning [5] with pooling to reduce the TBM feature dimension before prediction and build the sparse codes for each patch.

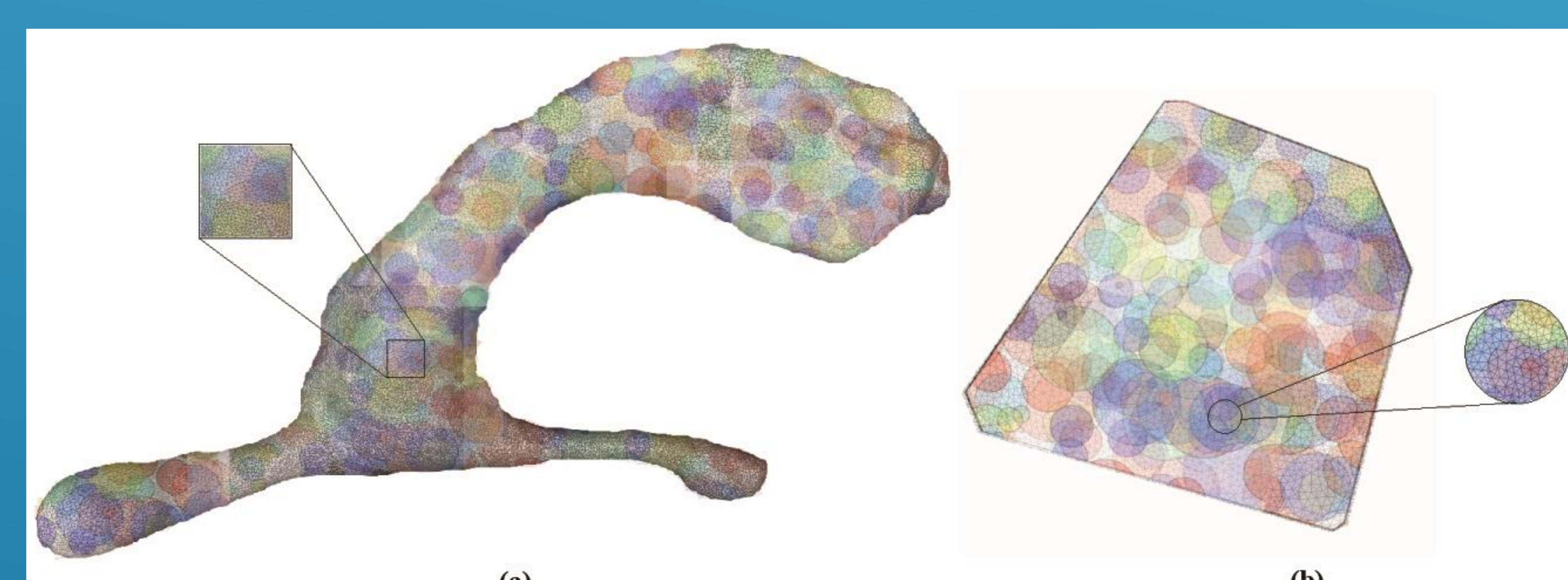
Figure 3. Visualization of computed image patches on a ventricular surface and its hyperbolic space, respectively.

Experiments

- Our dataset consisted of 133 subjects from the MCI group of the ADNI baseline dataset, including 71 subjects who converted to AD 36 months after screening and 62 subjects who did not convert during the same period. The demographic information is in Table 1.
- We applied the Adaboost method [6] to perform the binary classification between the two groups.

	Number	Gender (F/M)	Education	Age	MMSE
MCIc	71	26/45	15.99±2.73	74.77±6.81	26.83±1.60
MCIs	62	18/44	15.87±2.76	75.42±7.83	27.66±1.57

Table 1. Demographic information of the tested data.

- We compared our method with other ventricular morphometry measures, including surface volume, surface area, and a shape based measurement [7].
- The classification result comparisons with left, right, and both ventricles (whole) are in Table 2 and Fig. 4.

Name	Region	ACC	SEN	SPE	PPV	NPV	AUC
FBS	Left	0.727	0.786	0.684	0.647	0.813	0.754
	Right	0.652	0.652	0.000	1.000	0.000	0.567
	Whole	**0.967**	**0.933**	**1.000**	**1.000**	**0.889**	**0.976**
Shape	Left	0.535	0.615	0.412	0.615	0.412	0.572
	Right	0.512	0.515	0.500	0.773	0.238	0.526
	Whole	0.605	0.656	0.500	0.731	0.412	0.656
Volume	Left	0.558	0.571	0.552	0.381	0.727	0.532
	Right	0.517	0.536	0.467	0.652	0.350	0.430
	Whole	0.535	0.607	0.400	0.654	0.353	0.452
Area	Left	0.558	0.552	0.571	0.727	0.381	0.626
	Right	0.465	0.625	0.370	0.370	0.625	0.493
	Whole	0.512	0.482	0.563	0.650	0.391	0.517

Table 2. Classification results compared with other measures.

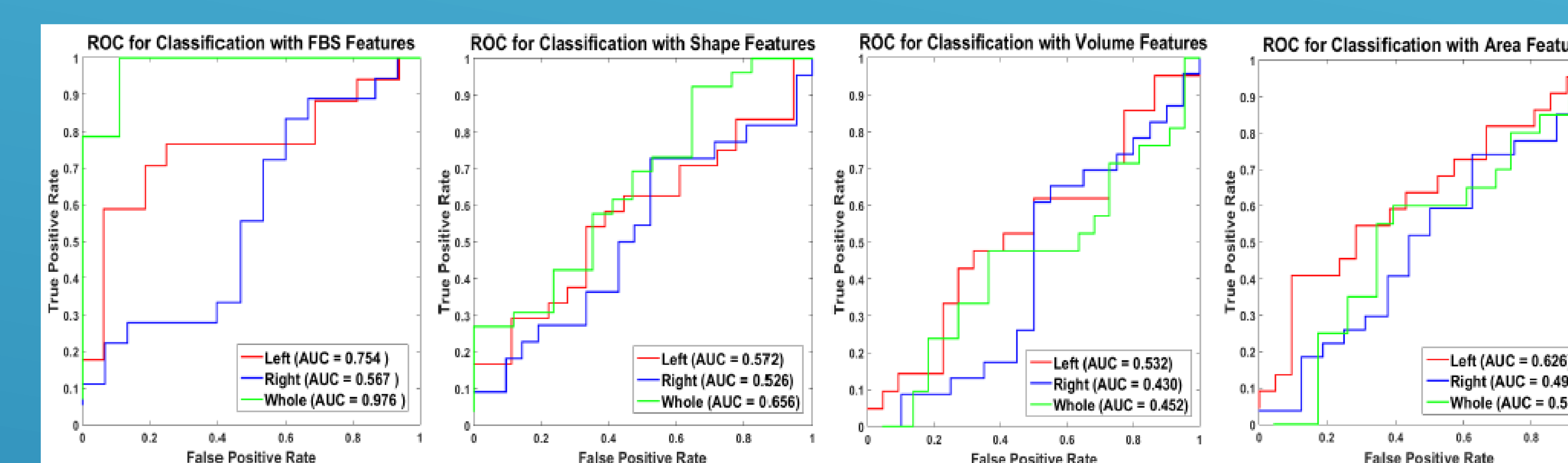

Figure 4. Classification performance comparison with ROC curves and AUC measures.

Citations

[1] J. Shi, et al., 2015. "Studying Ventricular Abnormalities in Mild Cognitive Impairment with Hyperbolic Ricci Flow and Tensor-based Morphometry", *NeuroImage*, 104(1): 1-20.

[2] W. Zeng, D. Samaras, et al., 2010. "Ricci Flow for 3D Shape Analysis," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32(4): 662-677.

[3] M. K. Chung, et al., 2008. "Tensor-based Cortical Surface Morphometry via Weighted Spherical Harmonic Representation", *IEEE Trans. Med. Imaging*, 27: 1143–1151.

[4] M. K. Chung, et al., 2005. "Cortical Thickness Analysis in Autism with Heat Kernel Smoothing", *Neuroimage*, 25: 1256–1265.

[5] J. Mairal, et al., 2009. "Online Dictionary Learning for Sparse Coding", in *Proceedings of the 26th Annual International Conference on Machine Learning*, 689-696.

[6] R. Rojas, 2009. "Adaboost and the Super Bowl of Classifiers a Tutorial Introduction to Adaptive Boosting", Freie University, Berlin.

[7] L. Ferrarini, et al., 2008. "Ventricular Shape Biomarkers for Alzheimer's Disease in Clinical MR Images", *Magnetic Resonance in Medicine*, 59(2): 260-267.