Multivariate cortical shape modeling based on sparse representation

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Introduction:
A shape representation is an important problem to understand brain morphological changes related to illness or disease. We represent a new shape representation method using the eigenfunctions of Laplace-Beltrami (LB) operator. Since the LB-eigenfunctions reflect the intrinsic geometry of the surfaces, cortical surfaces can be intrinsically represented as a Fourier series expansion using the LB-eigenfunctions [4]. However, some coefficients may not necessarily contribute significantly in reconstructing the surfaces. Thus, we aim to find an optimal sparse solution for the Fourier expansion using an l_1-penalty. By doing so, we can avoid surface smoothing [1,2,5] that reduces statistical power. We applied this sparse representation in detecting abnormal local shape variations in autism via multivariate general linear modeling [2].

Methods:
Data:
We obtained 3-T brain MRI data for 16 high functioning autistic and 11 control right-handed males, with average ages of 17.18 ± 2.89 and 16.13 ± 4.51 respectively. After a sequence of image processing steps, outer cortical surfaces are extracted as triangular mesh with n=40,962 vertices via deformable surface modeling [1] which establishes a surface correspondence across all the surfaces.

Fourier Analysis:
The eigenfunctions Ψ_j of the LB operator Δ on a cortical manifold, i.e.

$$\Delta\Psi_j = - \lambda_j\Psi_j,$$

form an orthonormal basis for the space of square integrable functions on the manifold. Taking surface coordinates as functions to be estimated, the coordinates can be represented as a linear combination of the LB-eigenfunctions. Firstly, we construct a template cortical surface by averaging coordinates of corresponding mesh vertices. Then, the LB-eigenfunctions are computed on the template mesh using the Cotan formulation [4,5]; Fig. 1 shows few representative eigenfunctions. The MATLAB code is given at http://brainimaging.waisman.wisc.edu/~chung/lb. The Fourier coefficients can be obtained from the least squares estimation (LSE) by solving the system of linear equations

$$p_i = \Psi\beta,$$

where p_i is the i-th coordinate vector, Ψ is a matrix having LB-eigenfunctions as columns, and β is the Fourier coefficient vector. Fig. 2 blue line shows absolute value of the coefficients estimated by the LSE with first 7396 eigenfunctions for one particular coordinate.

Sparse representation:
We can get a more compact and sparse representation than LSE by assuming some of coefficients are not contributing significantly. This is achieved by solving the following l_1-norm regularization problem [3]:

$$\min \left(\| p_i - \Psi\beta \|_2 \right)^2 + \lambda \| \beta \|_1.$$

The parameter λ controls the sparsity, and we empirically selected λ=10 leading to sufficient sparsity (Fig. 2 red line); in average, 1100 nonzero elements out of 7396 remain.

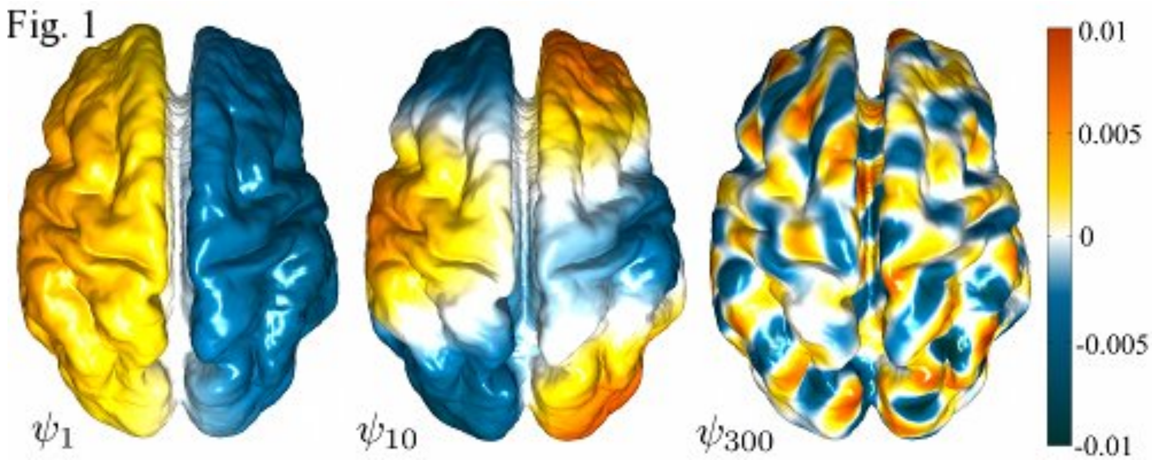
Multivariate general linear model:
To localize shape difference between the groups, we used a multivariate linear model [2]:

$$[\, p_1 \;\; p_2 \;\; p_3 \,] = B_0 + \text{age}\, B_1 + \text{group}\, B_2 + \text{age} \cdot \text{group}\, B_3.$$

Results:
We have tested the group effect (B_2) while accounting for age effect, but could not detect any shape difference between autistic and control groups at α =0.1 level (corrected). However, for an interaction between age and group (B_3), we detected the regions where the rate of local shape variation is different (Fig. 3a). Fig. 4 shows regression plots at the most significant vertex (maxF = 67.31, corrected p= 0.006, Fig. 3a arrow) in the left prefrontal cortical region. With the LSE (Fig. 3b), we have observed similar results but with less smoothing (maxF = 79.38, p= 0.005).

Conclusions:
The proposed sparse shape representation demonstrates its potential for

modeling cortical shape variations without using surface-based smoothing that reduces statistical power unnecessarily.



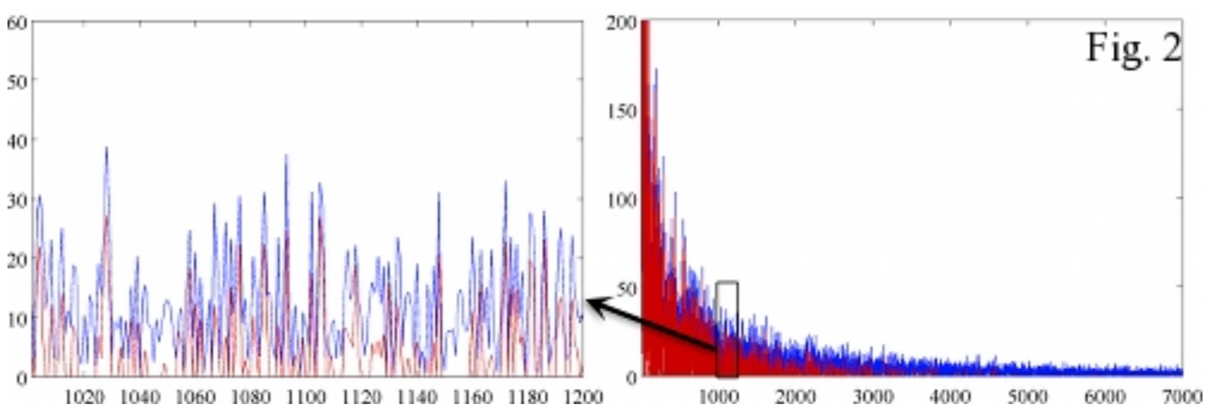


Fig. 3a

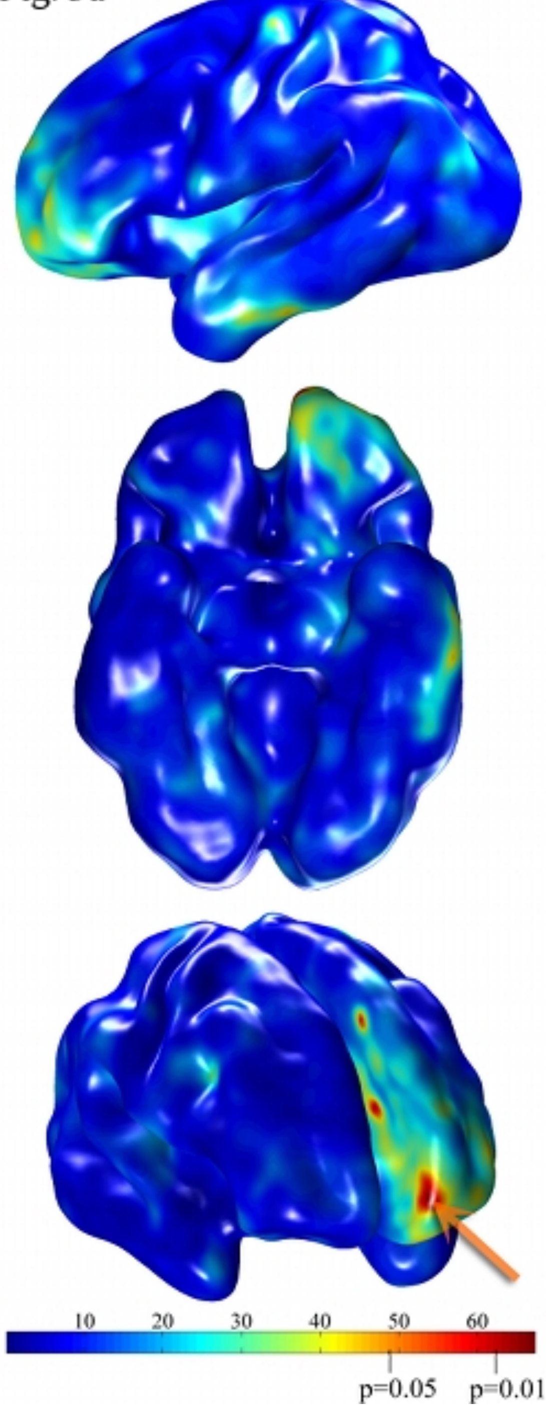


Fig. 3b

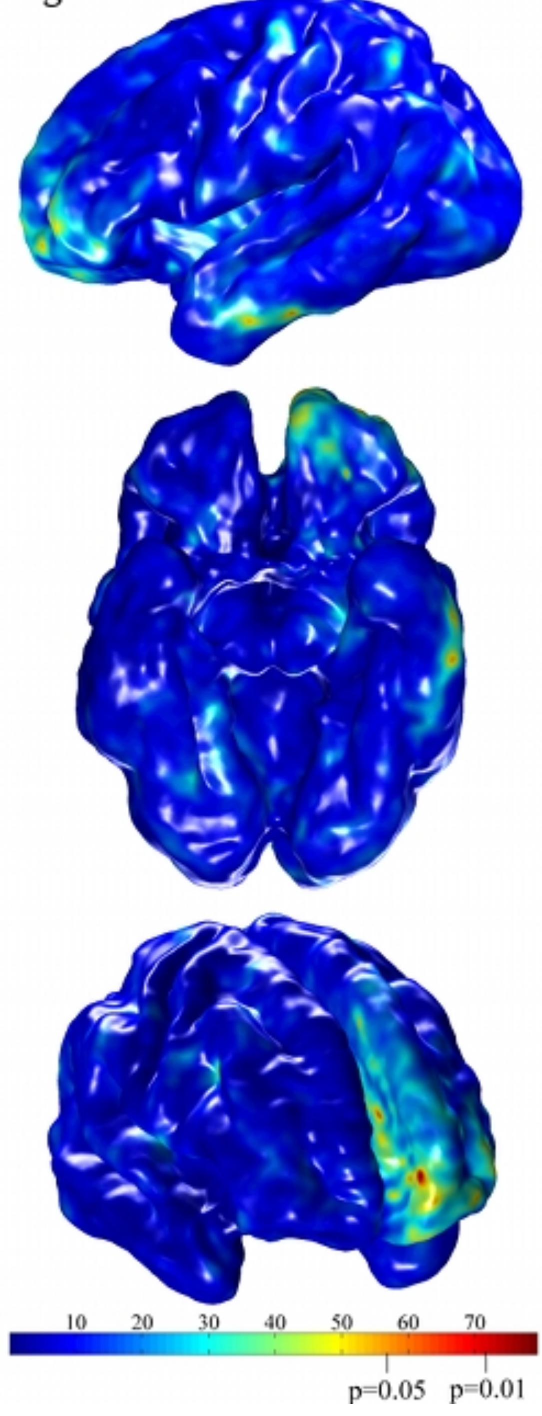
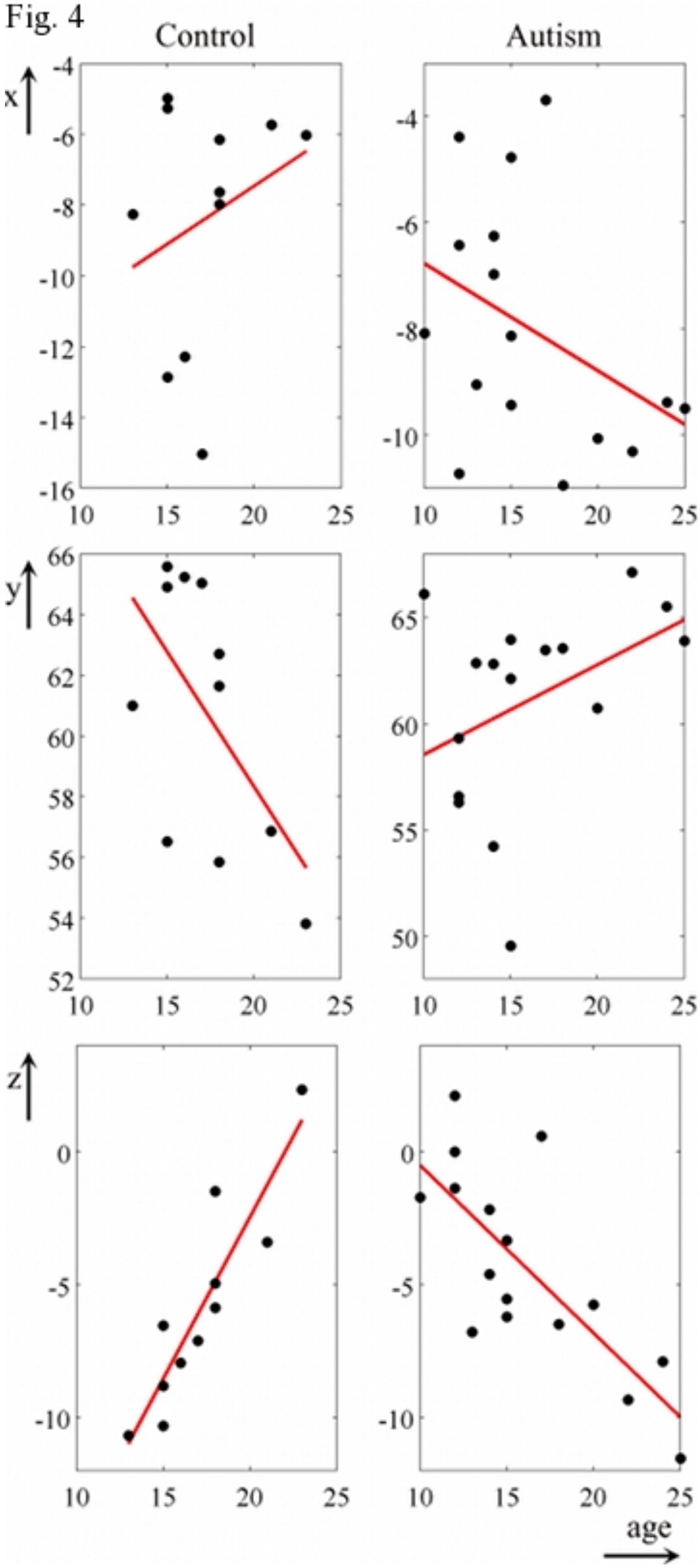


Fig. 4



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