# Sulcal Pattern Mathching with the Wasserstein Distance

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We present the unified computational framework for modeling the sulcal patterns of human brain obtained from MRI. These patterns are topologically different across subjects making the pattern matching a challenge. We use the Wasserstein distance in aligning align the sulcal patterns nonlinearly. The codes are provided in https://github.com/laplcebeltrami/sulcaltree.

## Sulcal pattern projection

# Matching via Wasserstein distance

Let  $f_1$  and  $f_2$  be the two probability density defined on  $\Omega_p$  and  $\Omega_q$ . The Kantorovich's formulation for Wasserstein distance is defined as

 $D_W(f_1, f_2) = \inf_{\pi} \left( \int \|p - q\|^2 \pi(p, q) \mathrm{d}p \, \mathrm{d}q \right)^{\frac{1}{2}}$ 

over all possible joint density  $\pi$  with marginals f<sub>1</sub> and  $f_2$  [1]. In the dual formulation, we solve

males. The registration pipeline is summarized in Figure 4. Our pipeline significantly reduces the sulcal pattern variability compared to FreeSurfer's folding-based surface registration method. The intersubject variability of the smoothed original sulcal patterns (left) and deformed patterns (right). The statistical variability after registration is reduced by 96.29%.

We used T1-weighted MRI of 456 subjects (agematched 274 females and 182 males) in the Human Connectome Project [2]. The TRACE algorithm is used for automatic sulcal curve extraction from surface meshes and project them onto a plane [4]. The sulcal pattern f(x, y) is generated by assigning value 1 to sulcal curves and 0 otherwise.



Figure 1: Schematic of the sulcal curve extraction

 $\inf_{\phi+\psi\geq \langle p,q\rangle} \left\{ \int_{\Omega_p} \phi(p) f_1(p) \mathrm{d}p + \int_{\Omega_q} \psi(q) f_2(q) \mathrm{d}q \right\}.$  subject 1 The unique solution is given by

$$\boldsymbol{\psi} = \max_{\boldsymbol{p}} \left( \boldsymbol{p}^{\top} \boldsymbol{q} - \boldsymbol{\varphi}(\boldsymbol{p}) \right)$$

The corresponding objective function is written as  $L(\phi)$  given by [1]

 $L'(\varphi) = f_1 - (f_2 \circ \nabla \varphi) \det (H_{\varphi})$ 

with deformation  $\nabla \varphi$ . The gradient descent is performed in solving for  $\varphi$ :

 $\varphi_{n+1} = \varphi_n - L'(\varphi_n).$ 





registered patterns

Figure 4: Schematic of the Wasserstein-based registration.

The two sample t-statistics (female-male) were constructed and thresholded that correspond to the pvalue of 0.05 after multiple comparisons correction through the permutation test (half millions). The negative t-statistics in most of the brain regions indicates the presence of less sulci for females, which is related to the previous finding [3].

and projection.

# Heat Kernel Smoothing

Heat kernel smoothing was performed on the projected sulcal pattern by solving

 $\frac{\partial}{\partial \sigma} \mathfrak{u}(x, y, \sigma) = \frac{\partial^2}{\partial^2 x} \mathfrak{u}(x, y, \sigma) + \frac{\partial^2}{\partial^2 y} \mathfrak{u}(x, y, \sigma)$ with the initial condition  $u(x, y, \sigma = 0) = f(x, y)$ and the periodic boundary conditions in Figure 2. The solution is given as the weighted Fourier series  $\widehat{\mu}(x,y) = \sum_{j=0}^{n} \sum_{k=0}^{n} e^{-\lambda_{jk}\sigma} [A_{jk}\phi_{jk}^{1} + B_{jk}\phi_{jk}^{2}].$ 

The eigenvalues  $\lambda_{jk} = j^2 + k^2$  and the eigenfunctions corresponding to Laplacian  $\frac{\partial^2}{\partial^2 x} + \frac{\partial^2}{\partial^2 y}$  are

 $\phi_{jk}^{1} = \frac{2\cos(jx)\sin(ky)}{\pi^{2}(1+\delta_{j0})}, \quad \phi_{jk}^{2} = \frac{2\sin(jx)\sin(ky)}{\pi^{2}}$ with  $\delta_{j0} = 1$  if j = 0 and 0 otherwise.  $A_{jk}$  and  $B_{jk}$  Figure 3: Subject 1 (lower transparency) superimposed on top of subject 2 (higher transparency). The arrows are the displacement field of matching subject 1 to subject 2.

# Wasserstein distance after diffusion

Suppose  $f_1$  and  $f_2$  are two empirical distributions on points  $p_i$  and  $q_i$  that define sulcal curves  $f_{1}(p) = \frac{1}{n} \sum_{i=1}^{n} \delta(p - p_{i}), f_{2}(q) = \frac{1}{n} \sum_{i=1}^{n} \delta(q - q_{i}).$  References The heat kernel smoothing of  $f_1$  and  $f_2$  is given by  $\tilde{f}_1(p) = \frac{1}{n} \sum_{i=1}^n K_\sigma(p, p_i), \quad \tilde{f}_2(q) = \frac{1}{n} \sum_{i=1}^n K_\sigma(q, q_i).$ 



Figure 5: t-statistics map of the localized sulcal pattern differences. Values are thresholded in [-2.84, 4.12] corresponding to the corrected pvalue of 0.05.

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[1] Chartrand, R., Wohlberg, B., Vixie, K., Bollt, E.: A gradient descent solution to the monge-kantorovich problem. Applied Mathematical Sciences **3**, 1071–1080  $(01\ 2009)$ 

are estimated in the least square fashion [2].





**Theorem** For restricted Wasserstein distance D<sub>W'</sub> on Gaussian distributions, we have

 $D_{W'}(\widetilde{f}_1, \widetilde{f}_2) = D_W(f_1, f_2).$ 

Thus, the Wasserstein distance is reduced after heat kernel smoothing

 $D_W(\tilde{f}_1, \tilde{f}_2) \le D_W(f_1, f_2).$ 

## Sexual dimorphism

The method is subsequently used to determine the sulcal pattern differences between females and

[2] Huang, S.G., Lyu, I., Qiu, A., Chung, M.: Fast polynomial approximation of heat kernel convolution on manifolds and its application to brain sulcal and gyral graph pattern analysis. IEEE Transactions on Medical Imaging **39**, 2201–2212 (2020) [3] Luders, E., Gaser, C., Narr, K., Toga, A.: Why sex matters: brain size independent differences in gray matter distributions between men and women. Journal of Neuroscience **29**, 14265–14270 (2009) [4] Lyu, I., Kim, S., Woodward, N., Styner, M., Landman,

B.: TRACE: A topological graph representation for automatic sulcal curve extraction. IEEE Trans. Med.

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## Figure 2: Heat kernel smoothing of projected pattern with $\sigma = 0.001$ .