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Topology of Surface Displacement Shape Feature in Subcortical Structures

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Parkinson's disease

Background

- In 2015, PD affected *6.2 million people*, causing 117,400 deaths globally. GDB, Lancet, Oct 2016.
- 2017 marks 200 years since the publication of James Parkinson's "*An essay on the shaking palsy*".
- Common motor symptoms include tremors, rigidity & bradykinesia.

Neuroimaging findings

- Brain morphology change in PD. Jubault et al. 2009, Ibarretxe-Bilbao et al. 2011.
- Volume loss in subcortical structures in PD. Burton et al 2004, Junque et al. 2005.
- Cortical matter loss in PD. Jubault et al. 2011, Zerei et al. 2013.

PPMI

- PD – 115M/74F, Age: 68 (4.7) yrs.
- NC – 75M/62F, Age: 63.8 (7.4) yrs.

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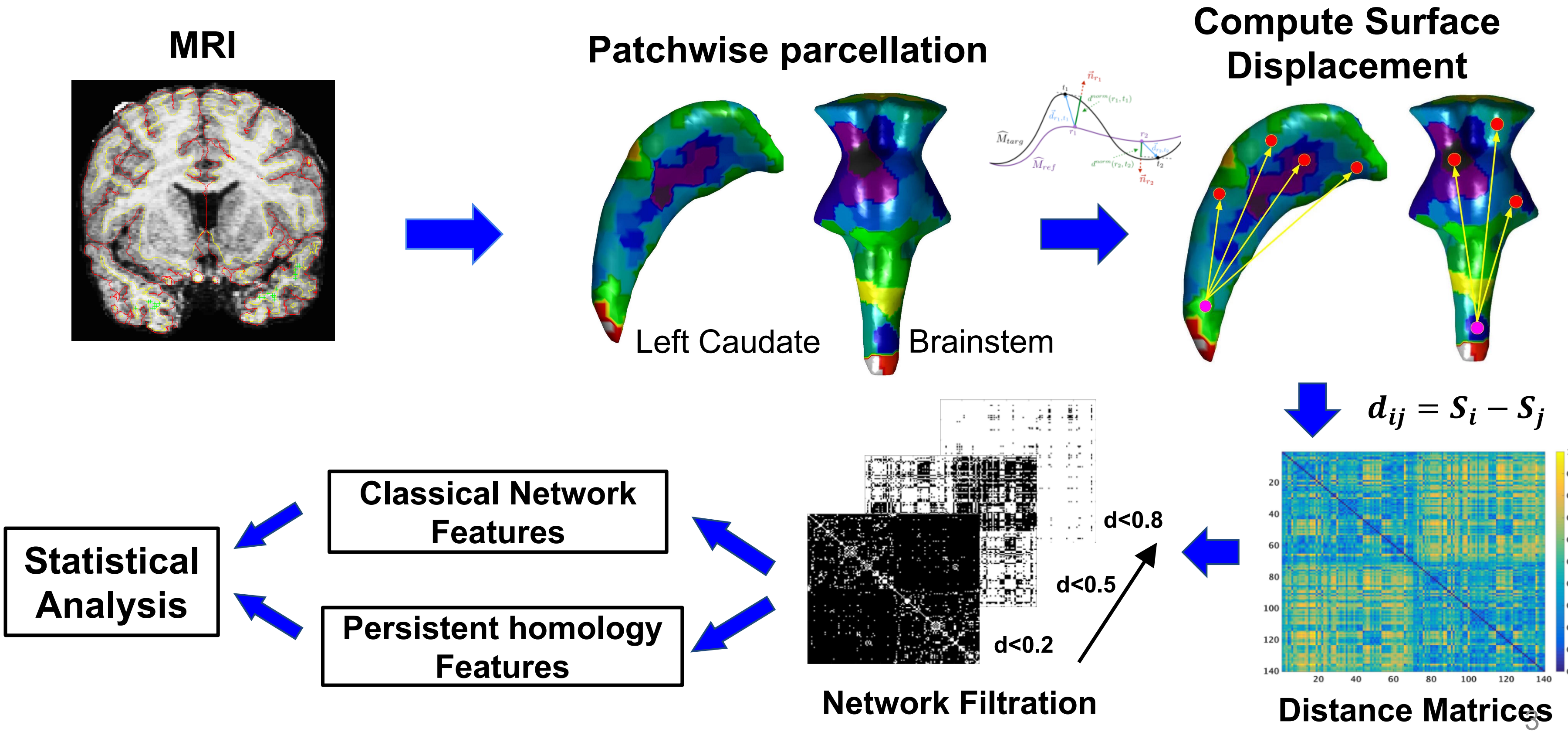
Pipeline workflow



Subcortical segmentation

- Multi-template registration based segmentation
- FreeSurfer + Large deformation diffeomorphic metric mapping (FS+LDDMM).

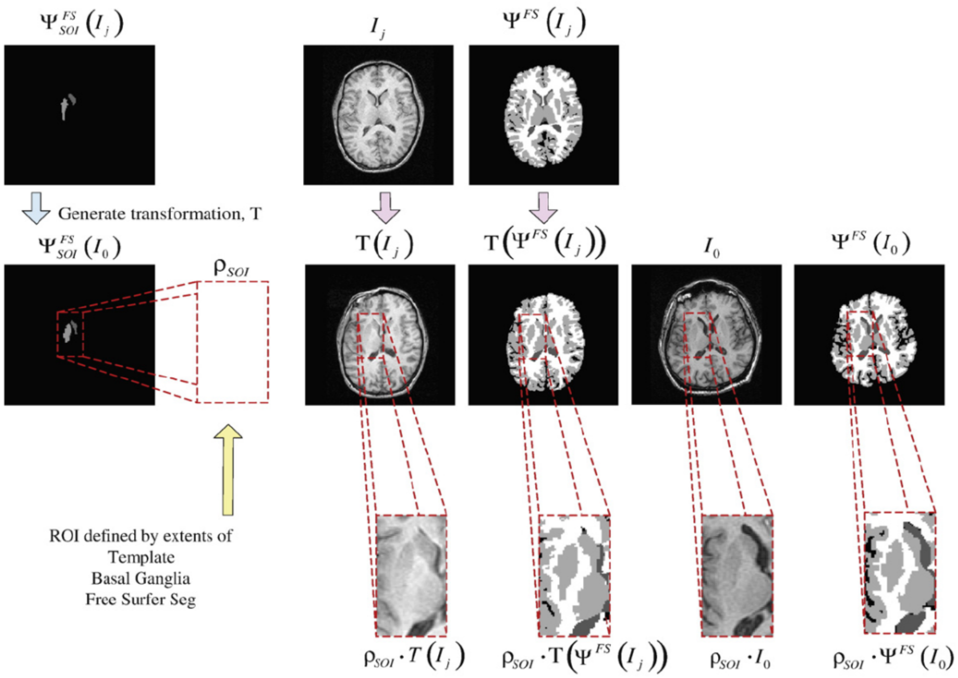
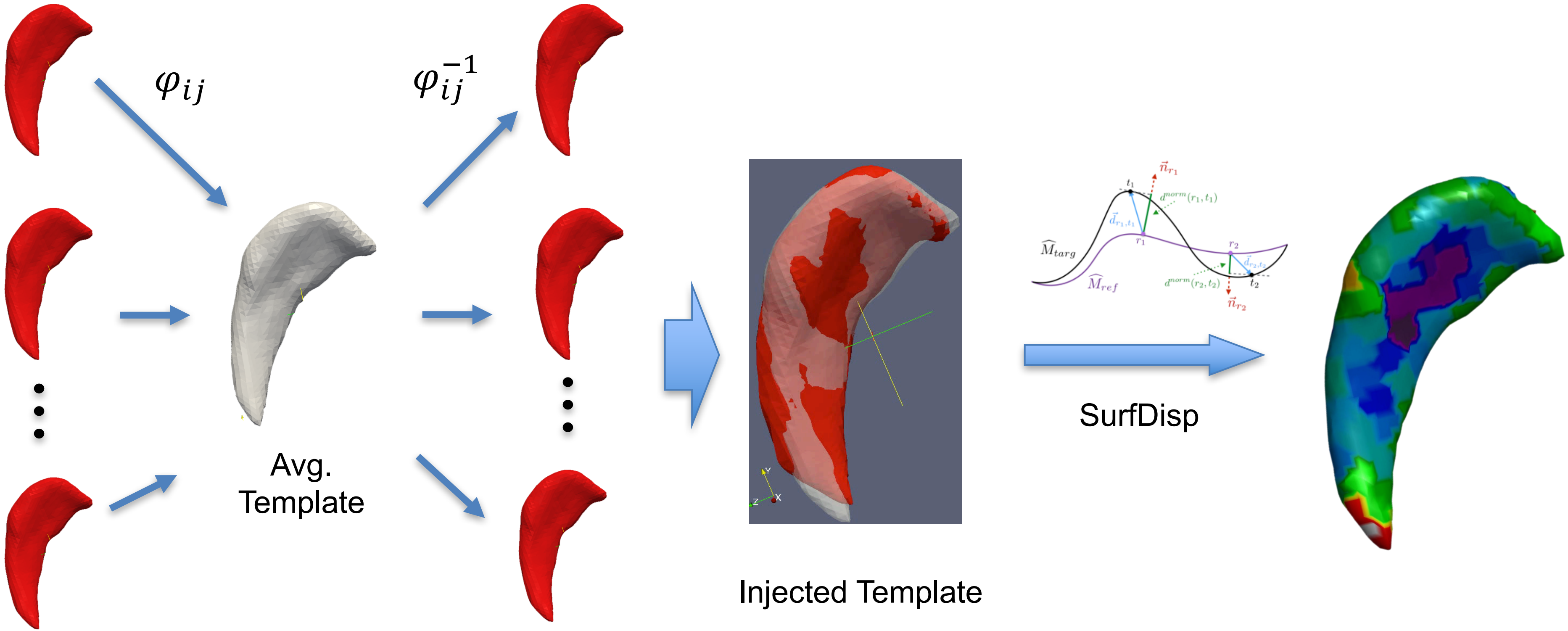


Image Source : Khan et al 2008.

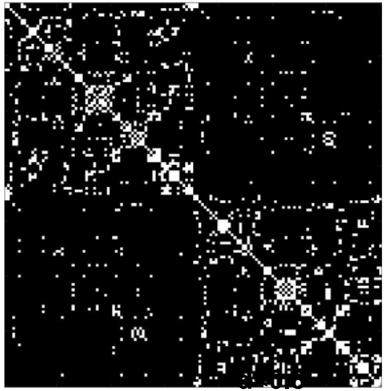
SurfDisp Computation



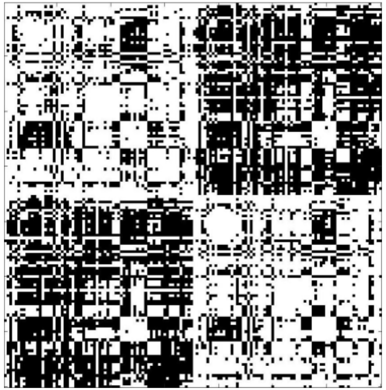
Original Surfs

*Garg, A., Appel-Cresswell, S., Popuri, K., McKeown, M.J., Beg, M.F.: Morphological alterations in the caudate, putamen, pallidum, and thalamus in Parkinson's disease. Frontiers in Neuroscience 9(March), 1{14 (2015)

Network filtration



d<0.2



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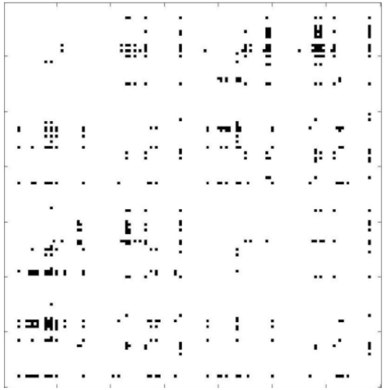

d<0.8

Classical Network Features

- Nodal degree $$k_i = \sum_{j \in N} a_{ij}$$
- Clustering Coefficient $$C_i = \frac{1}{n} \sum_{j \in N} \frac{2t_i}{k_i(k_i - 1)}$$
- Local efficiency $$E_{loc,i} = \frac{\sum_{h,j \in N, j \neq i} a_{ij} a_{ih} [d_{jh}(N_i)]^{-1}}{k_i(k_i - 1)}$$

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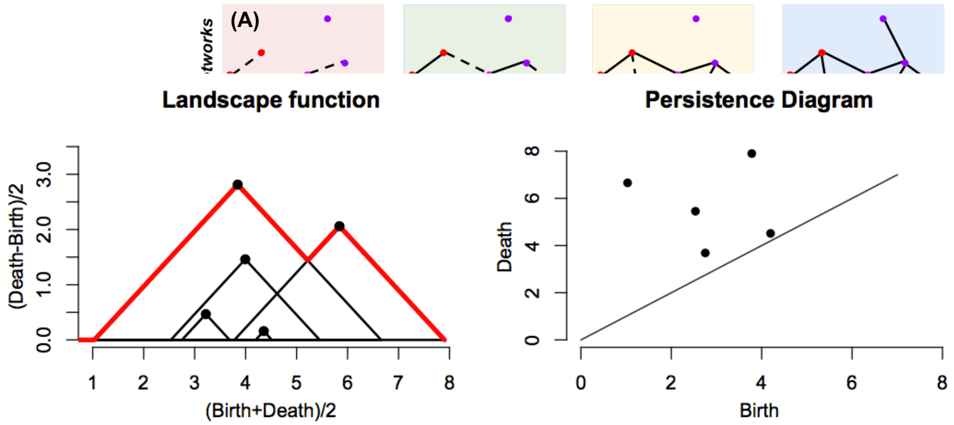
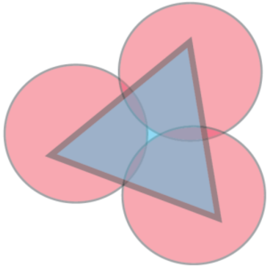
Why persistence homology ?

- Classical network feature is based on the simplified assumption of a pairwise interaction.
- Human brain interacts between many regions.
- Persistence Homology enables us to model the polyadic(many-to-many) interactions between nodes of a network.

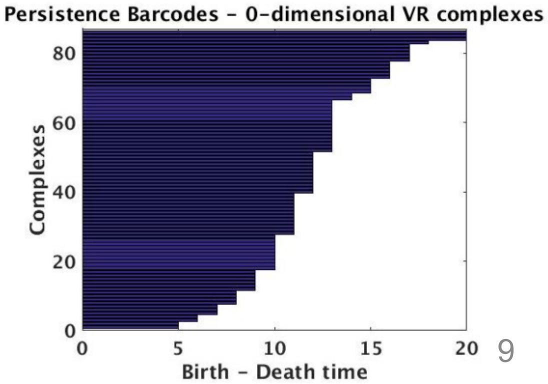
Persistence Homology Features



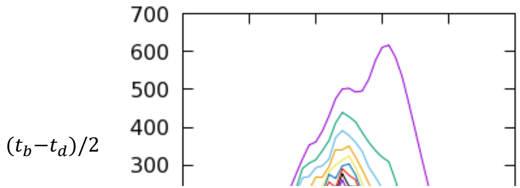
Persistent homology
Vietoris-Rips Complex



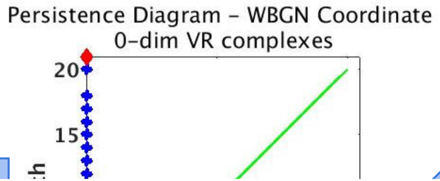
Persistence barcodes



Persistence Landscapes



Persistence Diagrams



Bubenik, Peter. "Statistical topological data analysis using persistence landscapes." *The Journal of Machine Learning Research* 16.1 (2015): 77-102.

Persistence Landscape Kernel: The distance between two persistence landscapes $\mathbb{L} = \{\mathbb{L}_k\}$ and $\mathbb{L}' = \{\mathbb{L}'_k\}$ can be obtained as the L^p norms for $1 < p < \infty$ which is defined as,

$$\|\mathbb{L}_k - \mathbb{L}'_k\|_p = \left[\sum_{k=1}^{K} \int \|\mathbb{L}_k - \mathbb{L}'_k\|_p^p\right]^{\frac{1}{p}} \tag{1}$$

and for $p = 2$, the L_2 distance between two persistence landscapes acts as a kernel metric between them named as a Persistence Landscape (PL) kernel [1].

Persistence Scale Space Kernel: The persistence scale space kernel (PSSK) [6] represents the multiset of points in a persistence diagram as a sum of dirac delta functions centered at each point. This enables the representation of points in persistence diagrams in a Hilbert space thereby supporting computation of a kernel between two point. Briefly, for two persistence diagrams F and G we compute the PSSK kernel ($k_\sigma(F,G)$) as:

$$k_\sigma(F,G) = \frac{1}{8\pi\sigma} \sum_{p\in F, q\in G} \exp^{-\frac{\|p-q\|^2}{8\sigma}} - \exp^{-\frac{\|p-\bar{q}\|^2}{8\sigma}} \tag{2}$$

where each $p = (b_i, d_i)$, $q = (b_j, d_j)$ and $\bar{q} = (d_j, b_j)$. For two persistence timelines represented as persistence diagrams we can compute the kernel matrix between all data groups.

Experiments

- Statistical group difference:
  - Permutation Test (significance at $p<0.05$)
- Classification:
  - Support Vector Machine Classifier

Results : Parkinson’s disease

1.Statistical group difference:

Feature	Caudate L	Caudate R	Putamen L	Putamen R
Persistence Landscape	0	0	0	0
Local efficiency	0.03	0.333	0.0064	0.482
Clustering Coefficient	0.8	0.028	0.121	0.261
Nodal degree	0.231	0.003	0.049	0.5829

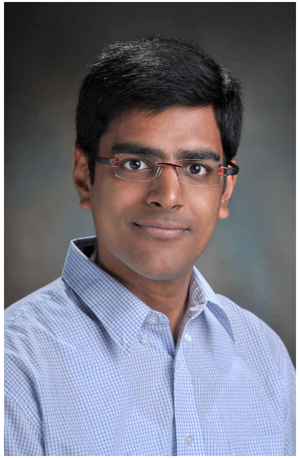
2.Classification:

ROI	Feature	Accuracy	Sensitivity	Specificity	F1
Left Pallidum	Persistence diagram	74.91%	0.883	0.145	0.847
	Nodal degree	59.11%	0.686	0.331	0.675
Right Pallidum	Persistence diagram	75.01%	0.886	0.141	0.852
	Local efficiency	52.52%	0.530	0.514	0.619

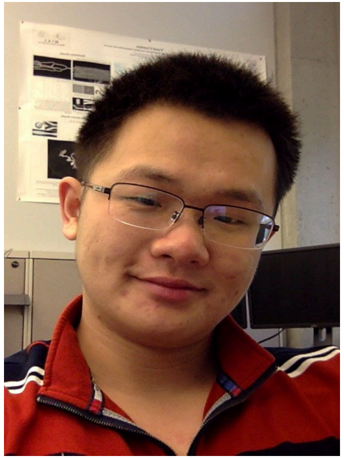
Conclusion

- Persistence homology features show superior performance to network features in differentiating between disease and control brain.
- Polyadic interactions between brain regions are important differentiators for PD and show a potential for clinical application

Dr. Mirza Faisal Beg



Dr. Amanmeet Garg



Donghuan Lu

Dr. Karteek Popuri

NSERC
CRSNG

CIHR IRSC

PARKINSON'S
PROGRESSION
MARKERS
INITIATIVE
Play a Part in Parkinson's Research

Mitacs

Thank You !

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Contents

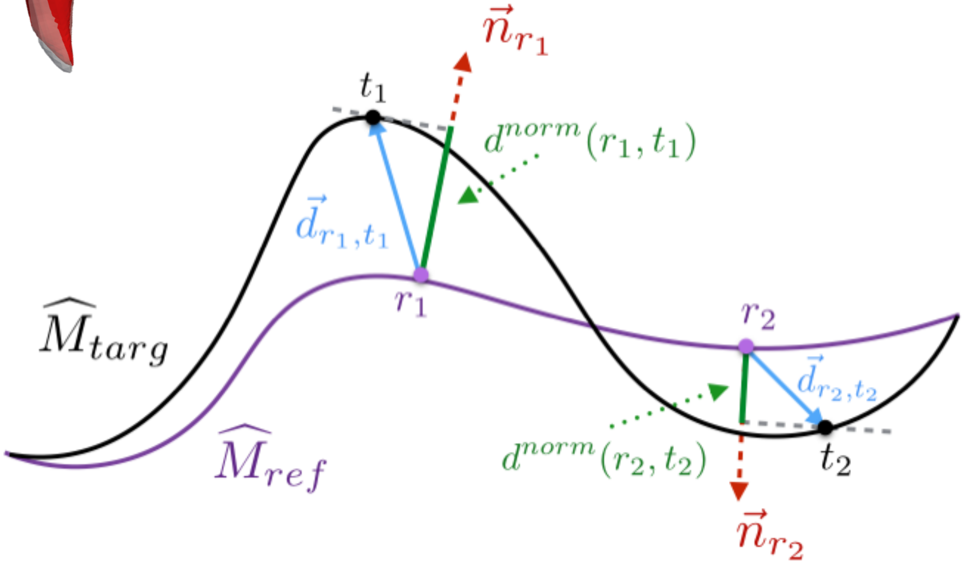
1. Background
2. Surface displacement (SurfDisp) shape feature
3. Shape Topology in Subcortical Structures
4. Experiments
5. Results
6. Conclusions

Why persistence homology ?

- Complex network analysis is based on the simplified assumption of a pairwise interaction.
- Human brain interacts between many regions.
- Model the polyadic (many-to-many) interaction between nodes of a network.
- Simplicial Homology enables modeling of such polyadic interactions.

Surface displacement shape feature

Injected template surface



- M_{ref} : average template
- M_{targ} : target surface
- d^{norm} : surface displacement
- Projected distance along the normal vector on the reference surface.

Why Study Shape Topology ?

- Subcortical structures closely packed in white matter.
- Neurodegeneration related deformation of one surface (e.g. medial) of a structure potentially influences the other surfaces (e.g. lateral, inferior).
- Thus: shape change is not independent.
- Study interaction of shape features across regions in the structure : Shape Topology.

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What is shape ?

- Shape can be understood as the geometrical information of a structure that remains after the removal of position, orientation and scale effects. (Stegmann et al. 2002)

- Shape Features
  - Spectral approach : Laplacian Eigen-functions
  - Set of basis functions : Spherical Harmonics
  - Medial representation : Radial Distance
  - Deformetrics : Surface currents
  - Ng et al., Book chapter LNCVB 14 , 2014

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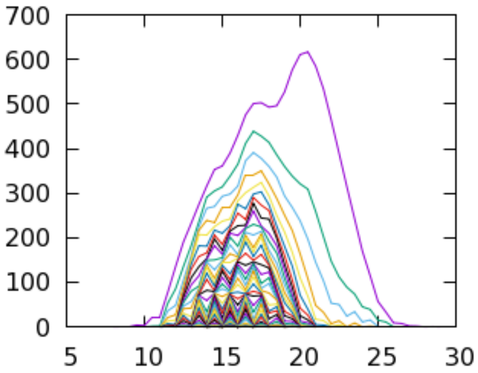
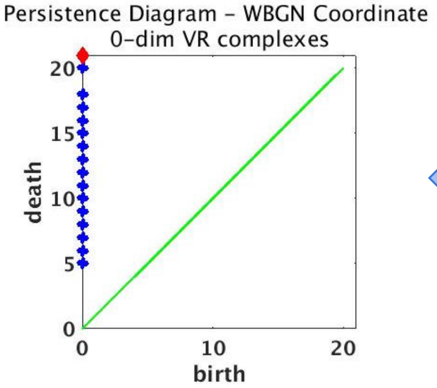
Analysis of PH Features

Persistence Landscapes (PLs)



Persistence Diagrams (PDia)



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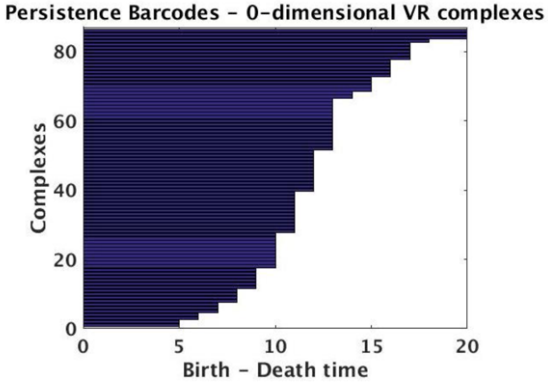

Features ?

Persistence Landscapes Kernel

Persistence Scale Space Kernel

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Experiments

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- Classification:
  - Kernel Support Vector Machine classifier.
  - Repeated Hold out Stratified Training (RHST).

Betti Numbers	RBF kernel
Persistence Landscapes	PL kernel
Persistence Diagrams	PSSK kernel
Network Features	RBF kernel

PL: Persistence Landscapes Kernel, PSSK: Persistence Scale Space Kernel, RBF: Radial basis function kernel

Demographics

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Why ?

- Morphometry studies on neurodegenrative disorders have shown local and global volume loss in the brain.
- Brain volume loss leads to asymmetric deformation of the brain surface.
- Geometrical arrangement of brain regions changes with shrinkage.
- Potential signature to diagnose brain abnormalities.

Healthy

Disease

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Conclusion

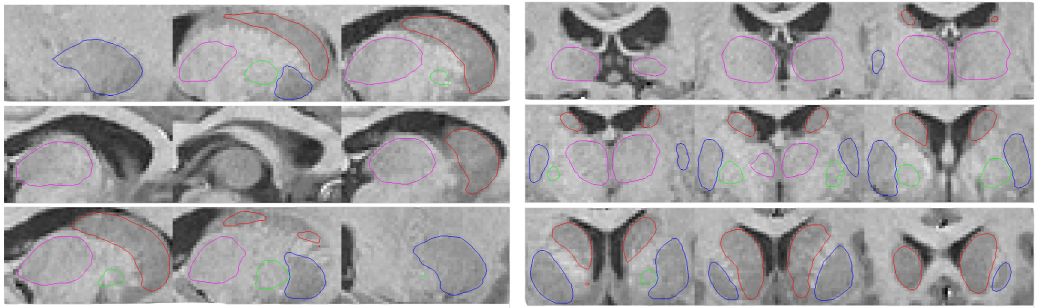
- Geometry Networks have a potential to capture the change in brain geometrical arrangement.
- Persistence homology timeline features show superior performance to complex network features in differentiating between disease and control brain.
- Polyadic (many-to-many) interactions between brain regions are important differentiators between disease and control brains.

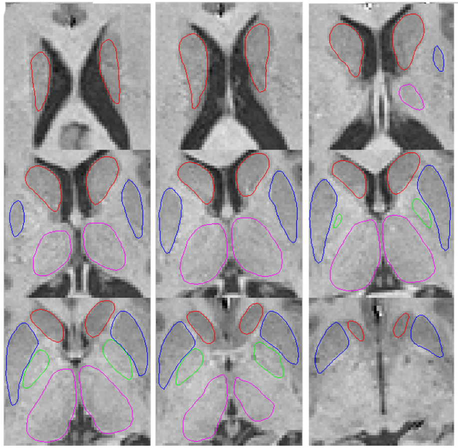
Topology of Brain Geometry

- First work to study the brain geometry networks.
- A method to model the polyadic interactions in brain geometry networks.
- Potential utility in clinical application.

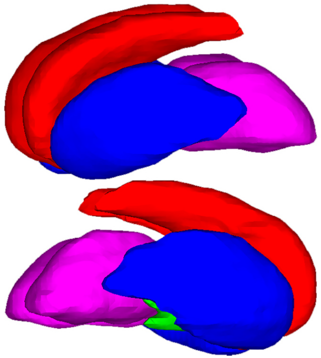
1.Garg A., Poskitt K., Fitzpatrick K., Bjornson B., Miller S., Grunau R., (**2017**) Persistence homology of brain geometry: a marker for preterm birth. OHBM conference 2017.
2.Garg A. Lu D., Popuri K., Beg M.F., (**2017**) *Brain geometry persistent homology marker for Parkinson's disease* , ISBI 2017, Melbourne, Australia.
3.Garg A., Lu D., Popuri K.,Beg M.F., (**2016**) *Cortical Geometry Network and Topology Markers for Parkinson's Disease Diagnosis*, MICCAI, Brain Connectivity workshop.

Subcortical Segmentation





Caudate Pallidum Putamen Thalamus



Freesurfer initiated Large Deformation Diffeomorphic Metric Mapping (FSLDDMM) segmentation with adult templates.

Subcortical segmentation

- Multi-template registration based segmentation
- FreeSurfer + Large deformation diffeomorphic metric mapping (FS+LDDMM).

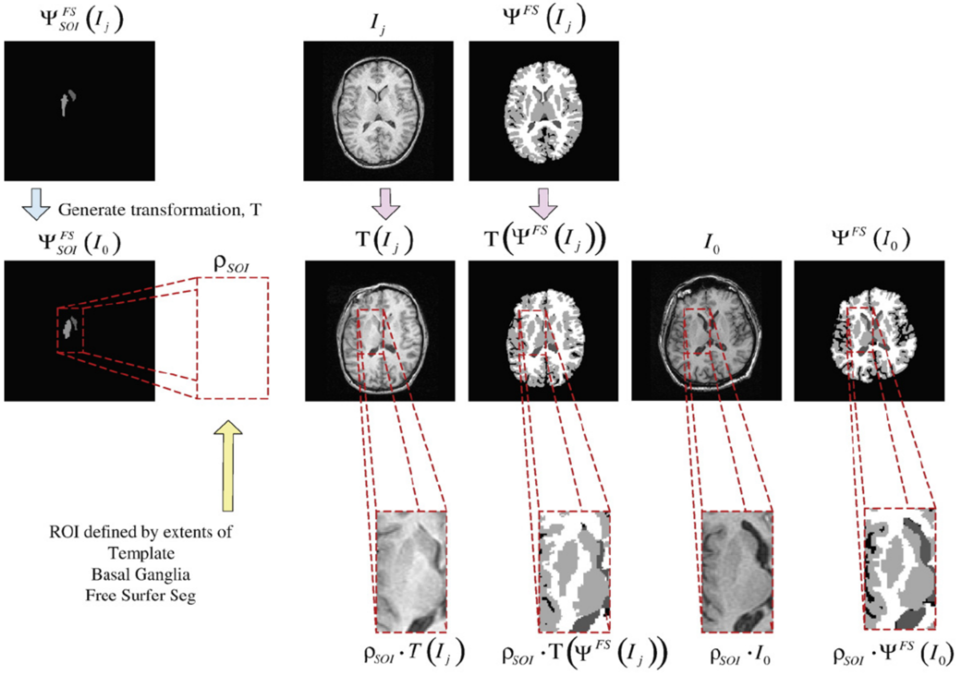


Image Source : Khan et al 2008.