

# BIRN and Computational Anatomy: A TeraGrid Technology

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## Introduction

The Biomedical Informatics Research Network (BIRN) is building an infrastructure of networked high-performance computers, data integration standards, and other emerging technologies, to pave the way for medical researchers to transform the treatment of disease.

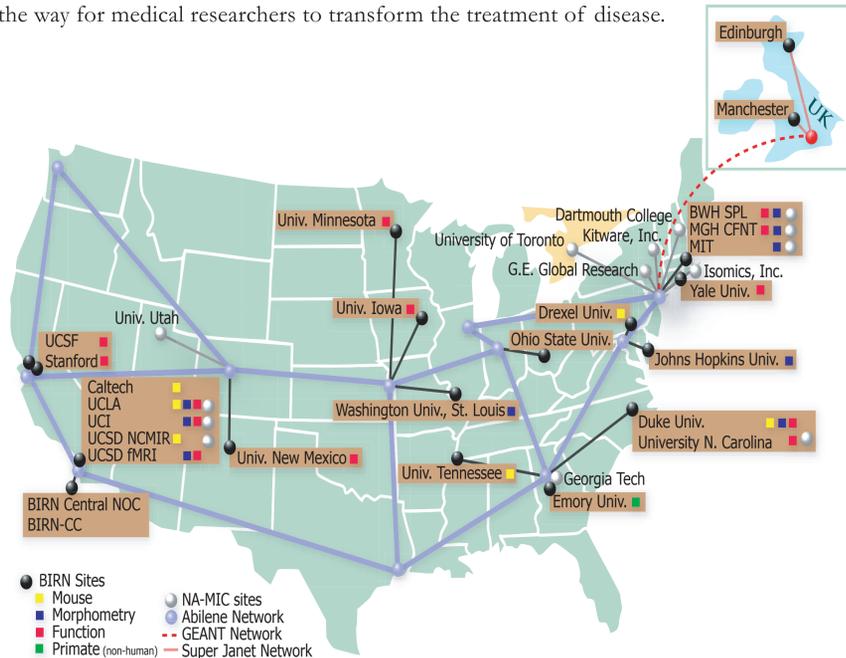


Figure-1

## Computational Anatomy

Computational Anatomy is the mathematical and computational analysis of Human shape and form. Computational anatomy has three parts:

- i. Anatomical manifold generation via segmentation of known structures
- ii. anatomical manifold quantification via morphometric comparison
- iii. disease detection and diagnosis.

This poster presents results from investigators across the country participating in the BIRN projected working together in these three areas.

The BIRN project utilizes computational anatomy techniques in the Semi-Automated Shape Analysis (SASHA) processing. SASHA is a collaborative application aimed at developing a morphometry pipeline that integrates subcortical and shape analyses using tools developed at different sites. Clinical imaging data acquired at one site (WashU) is being analyzed by morphometry tools from two other different sites: Freesurfer subcortical segmentation at MGH followed by shape analysis (Large Deformation Diffeomorphic Metric Mapping, LDDMM) at JHU. A visualization tool from a fourth site (BWH) has been extended to enable the viewing of all the derived results on a single platform. To drive the integration of the pipeline preliminary data from R. Buckner (WashU) were analyzed (45 subjects: 21 nondemented controls, 18 very mild Alzheimer's Disease and 6 semantic dementia).

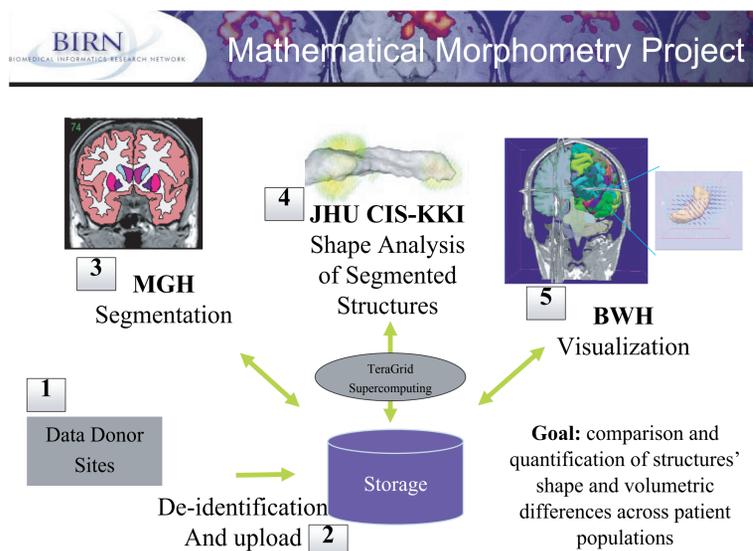


Figure-2

### References:

- [1] Grenander, U., and M.I. Miller. "Computational Anatomy: An Emerging Discipline". Statistical Computing and Graphics 7. 3 (1996):1-8
  - [2] Miller, M.I., A. Trounev, and L. Younes. "On the Metrics and Euler-Lagrange Equations of Computational Anatomy". Annual Review of Biomedical Engineering 4 (2002):375-405
  - [3] M. F. Beg, M. Miller, A. Trounev, and L. Younes. Computing Large Deformation Metric Mappings via Geodesic Flows of Diffeomorphisms. International Journal of Computer Vision, Volume 61, Issue 2; February 2005.
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## Metrics for Homogenous Image Space

One of the Holy Grails of Image Analysis is the construction of metric space structure for families of images. In the emerging discipline of Computational Anatomy, this amounts to the placement of all the observed anatomical images in metric spaces, akin to the metric space structure which forms the basis of modern communications engineering. Unlike the  $L^2$  spaces of modern communications, this metric space is a curved Riemannian manifold, with the metric length between elements computed via the shortest path variational formulation. The metric space structure allows the precise quantification of the shape and size of objects represented in the images.

The anatomical imaging model is the deformable template model, where the set of images  $\mathcal{I}$  is an orbit under the group of diffeomorphisms  $\mathcal{G}$  of the underlying coordinate space. The set  $\mathcal{I}$  is a homogenous space, with all images in the set being topologically equivalent. Given any two images  $\mathbf{I}_0, \mathbf{I}_1$  in the orbit, there exists a diffeomorphism between them. The group of diffeomorphisms  $\mathcal{G}$  is an infinite-dimensional Riemannian manifold with the choice of a Riemannian metric in the tangent space of the manifold. It is a metric space with the metric distance between points as the length of the shortest path joining the points i.e. a geodesic on the manifold. The metric distance on the space of images is inherited from the metric structure on the space of diffeomorphisms. Given any two images, and the diffeomorphism  $\phi^1$  matching the images  $\mathbf{I}_1 = \mathbf{I}_0(\phi^{-1})$ , the metric distance between the images is:

$$\rho(\mathbf{I}_0, \mathbf{I}_1) = \inf_{\substack{\phi(\cdot, t) = v(\phi(\cdot, t), t) \\ \phi(\cdot, 0) = id, \mathbf{I}_1 = \phi(\cdot, 1)^{-1} \mathbf{I}_0}} \sqrt{\int_0^1 \|\dot{v}(\cdot, t)\|_L^2 dt}$$

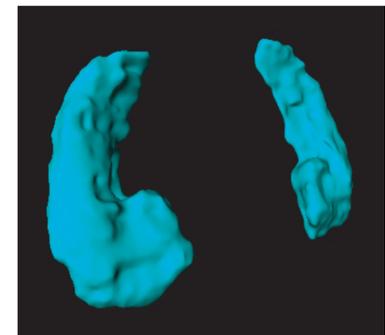


Figure-3: BIRN segmented hippocampus data

## Pattern Classification of Hippocampal Shape Analysis in a Study of Alzheimer's Disease

Through the statistical analysis of the metric distance, we were able to identify grouping of subjects. The approach is a three step classification process involving extraction of interpoint distance via large deformation metric mapping (LDDMM), subsequent mapping to Euclidean space via multidimensional scaling (MDS) and ultimate classification via linear discriminant analysis (LDA). Figure 4 represents the grouping of subjects.

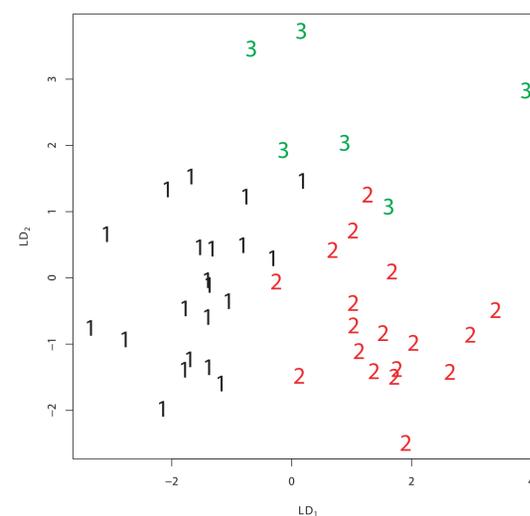


Figure-4: A scatter plot. The legends are 1: controls, 2: Alzheimer's patients, and 3: semantic dementia.

## Conclusion

Initial findings for using the LDDMM metric distance as a medical imaging classifier look promising. A larger subject population study is underway. The new study will require 30 cpu/years of processing and 40TB of storage. This research could not be accomplished without a cyberinfrastructure such as the TeraGrid.