

## An Image Searching Engine to Utilize Past Clinical Data for the Future Diagnosis

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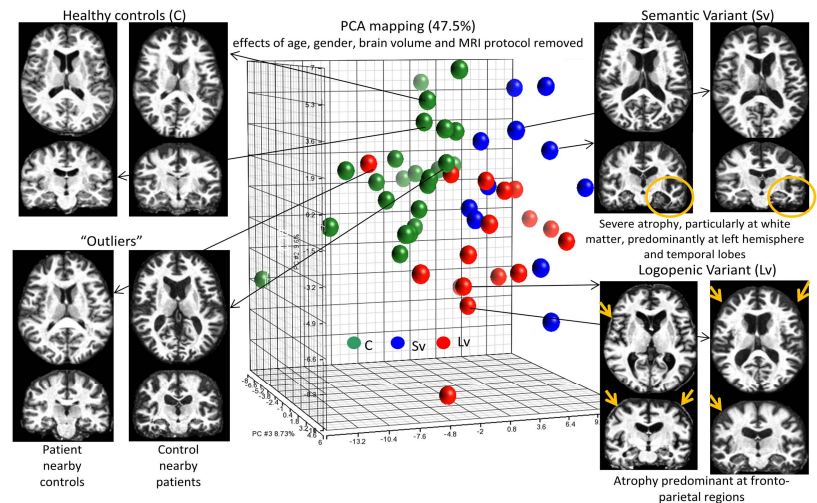
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**Target Audience:** Researchers and clinicians, particularly radiologists, interested in automated tools for diagnostic aid.

**Purpose:** Currently, radiological diagnosis is based on primarily subjective judgment by radiologists, in which image-based findings and text-based clinical information are integrated to reach a decision. The ability to make a diagnosis is acquired by experience and it is difficult to document and share. This is a major obstacle to adopt the evidence-based medicine in radiology, which calls for a systematic integration of past evidences for medical decision making. Herein we report our initial attempt to develop a technology to structurize image features and facilitate direct image searching. Among other applications, this technology would allow clinicians to search for similar image phenotypes in a database, what would be crucial for educational and diagnostic purposes.

**Methods:** The structurization was based on automated parcellation of the entire brain into 211 pre-defined anatomical structures (anatomy-vector conversion)<sup>1,2</sup> using T1-weighted MR images and voxel-to-voxel high-dimensional image transformation method by LDDMM (Large Deformation Diffeomorphic Metric Mapping)<sup>3</sup>. Then images with similar anatomical features were searched using these vectors. We tested this approach using a patient population (n=30) with primary progressive aphasia (PPA) and age-matched controls. This is an ideal model because: a) the atrophy is prominent and visible and the results can be compared with human judgment; and b) the atrophy extension and location vary. **1)** We first tested if the structurized anatomical data actually captured the anatomical features that can be perceived by trained clinicians. The clinicians were asked to rate the degree of atrophy (0 to 3) in various anatomic regions and their scores were compared with the volumetric z-score obtained by the automated quantitative analysis. **2)** Second, the anatomical variability within the PPA population was characterized using the principal component analysis (PCA) of the structured data and examined if such analyses could provide individual vs. population evaluation of the anatomical phenotypes. **3)** Third, we performed integrative analysis of anatomical (image data) and clinical phenotype (diagnosis based on clinical symptoms) using discriminant analyses and tested how informative it was to discriminate two PPA variants: logopenic (Lv) and semantic (Sv).

**Results and Discussion:** **1)** The agreement between the automated z-score and the averaged visual scores ( $r=0.81$ ) was virtually the same as the inter-evaluator agreement, showing that the automated method can be considered as good as one of the raters. **2)** This figure is the PCA plot based on 211 regional volumes. Two "neighboring" cases in the PCA space have visually similar anatomical features while the cases distant to each other have markedly different anatomical features. Although there is a natural segregation of these three groups, it is not perfect. For example, there a patient diagnosed as Lv based on clinical information is closer to the controls (c). This is understandable if we examine the MRI, which seems to have normal appearance. On the other hand, a control nearby the PPA patients have enlarged ventricles and parenchyma atrophy. This



indicates that the anatomic vectors extracted capture the gross anatomical features. **3)** The PLS-DA resulted in a model with accuracy of 0.875 on distinguish Lv from Sv. In the first component, that has greatest power in separate the groups, the loading (absolute) weights are higher in frontal and parietal areas in Lv and left temporal areas in Sv, which agrees with the pattern of atrophy described before<sup>4</sup>. The second component revealed a common pattern of atrophy in this population, with high loading weights in frontal areas, deep gray and white matter, some temporal, parietal, and occipital left areas, and frontal horn of left ventricle.

**Conclusion:** We demonstrated structurization of image data through image-vector conversion, which provides new opportunities to mine existing clinical database for medical decision support.

**References:** <sup>1</sup>Mori S, Oishi K, Jiang H, et al. Stereotaxic white matter atlas based on diffusion tensor imaging in an ICBM template. *Neuroimage*. 2008;40: 570-82; <sup>2</sup>Oishi, K, Zilles K, Amunts K, et al. Human brain white matter atlas: identification and assignment of common anatomical structures in superficial white matter. *Neuroimage*. 2008;43: 447-57; <sup>3</sup>Miller M I, Beg MF, Ceritoglu C, et al. Increasing the power of functional maps of the medial temporal lobe by using large deformation diffeomorphic metric mapping. *PNAS*. 102:9685-90; <sup>4</sup>Mesulam M, Weineke C, Thompson C, et al. Quantitative classification of primary progressive aphasia at early and mild impairment stages. *Brain*. 2009;135:1537-53.

**Support:** NIH grants P41RR15241, RO1AG20012, and RO1NS058299 (SM), RO1HD065955 (KO), RO3EB014357 (AVF), R01 DC011317 and R01 DC 03681 (AH).