Application of Aitchison metrics on magnetic resonance imaging data with multiple contrasts at ultra high field (7 Tesla) to investigate compositional characteristics of brain tissues in living humans

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Introduction

The compositional data framework is suited for the analysis and visualization of multimodal MRI data as it provides a principled way to combine multiple images (similar to color space based image fusion methods). The present study applies the concepts of compositional data analysis to multi-modal MRI data in order to reduce artefactual intensity inhomogeneities and highlight specific tissue characteristics. To this end, brain images of a healthy volunteer were acquired with three different contrasts (T1 weighted, Proton Density, T2* weighted) at ultra-high field 7 Tesla MRI scanner and Aitchison metrics were used to create virtual MR contrasts. In addition, the ilr transformed coordinates of the tissue compositions were explored with 2D transfer functions to probe meaningful compositional characteristics of brain tissues (see the extended abtract for further details: https://arxiv.org/abs/1705.03457).

Methods

Data Acquisition

- A male participant (age 26) completed one MRI scanning session.
- 7 Tesla whole body MRI scanner (Siemens) with 32 channel head coil (Nova Medical).
- T1 weighted (T1w), Proton density (PD), T2* weighted (T2*w) images were acquired using magnetization-prepared rapid acquisition gradient-echo (MPRAGE) sequence.
- 0.7 mm isotropic voxel resolution

Data Processing

- Brain extraction using FSL-BET.
- Closure, centering, standardizing, aitchison distance, ilr transformation are used as implemented in: https://github.com/ofgulban/tetrahydra, version 0.1.1.
- Interactive probing was performerd with 2D transfer function widgets on a 2D histogram of ilr transformed coordinates and brain images as implemented in: https://github.com/ofgulban/segmentator, version 1.1.1.
- Clustering was performed using normalized graph cuts as implemented a modified fork of in scikit-image (https://github.com/ofgulban/scikit-image)

Aitchison distance images derived from three different image contrast to create virtual contrasts:

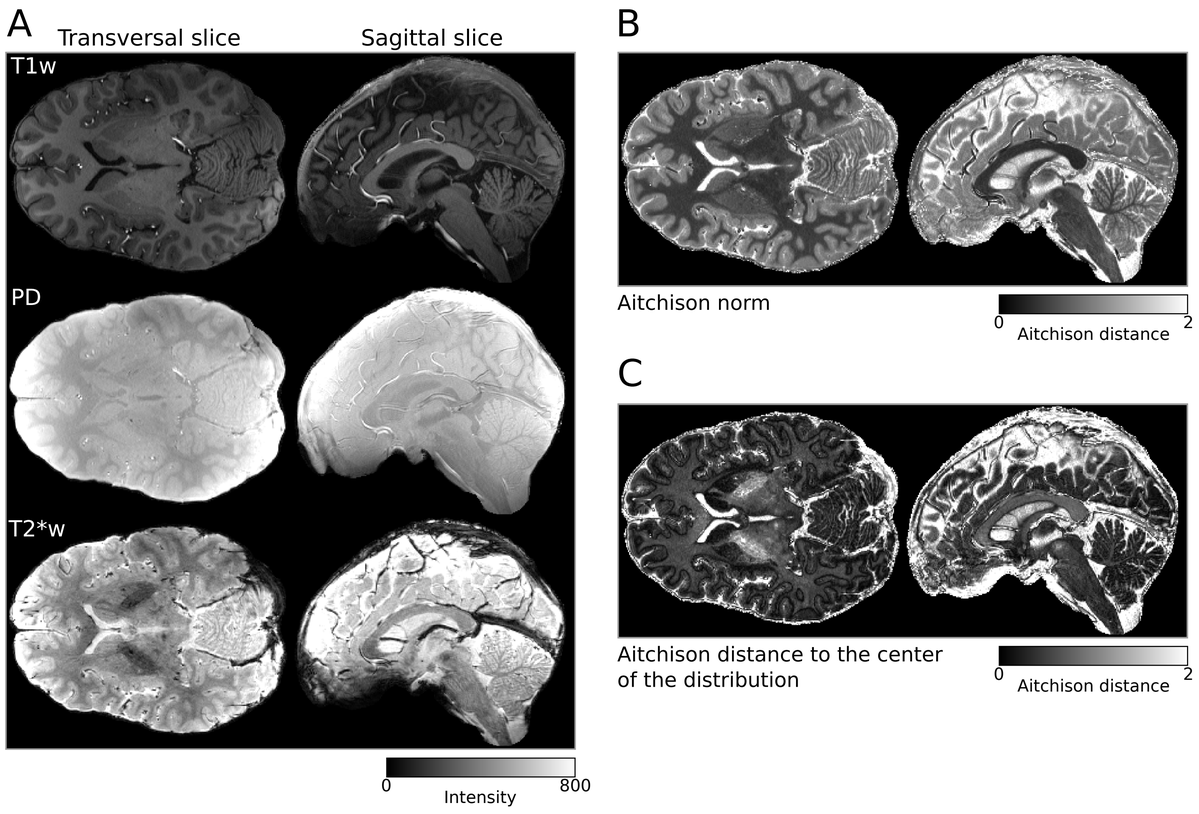

Figure 1: (A) Magnitude images of the T1w, PD and T2*w MRI data. (B) Voxel-wise Aitchison norm (aitchison distance to the center of the simplex) image of the brain extracted MRI data composition. (C) Aitchison distance to the center of the compositional distribution. Two slices of the brain extracted MRI data are visible in all panels, transversal slice (left hand side) and sagittal(right hand side) relative to the panels.

2D transfer function widgets are used to probe ilr transformed coordinates for revealing compositional tissue characteristics:

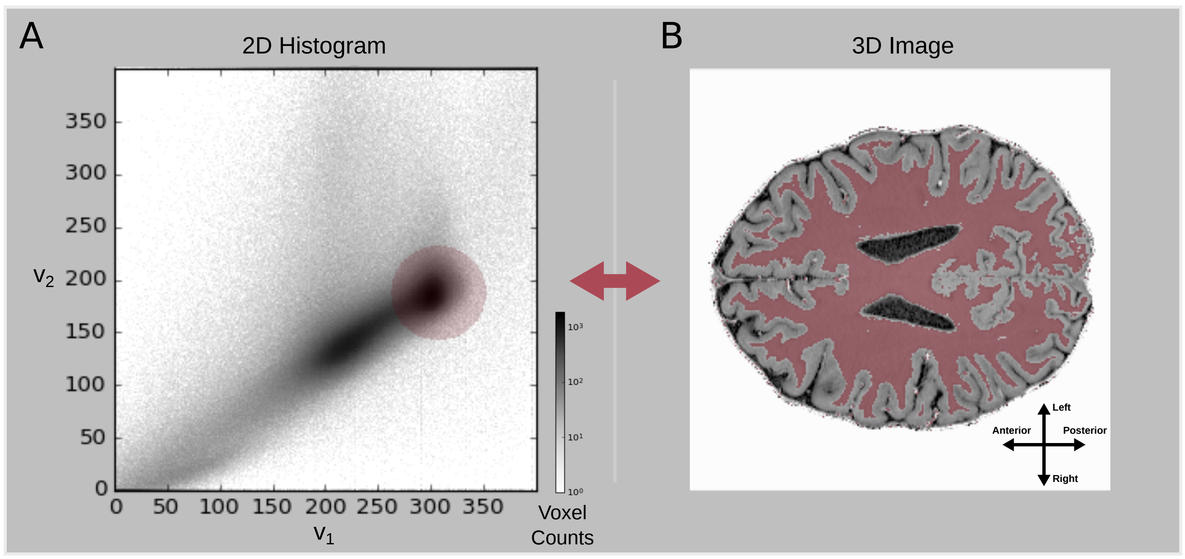

Figure 2: (A) 2D histogram is used to represent ilr-transformed coordinates of the 3D brain image. The red circle (probe) is a simple transform function widget. (B) A transversal slice of the 3D brain image. The probe in panel A can be freely moved around by the user to update the corresponding voxels (with transparent red overlay) in panel B.

Results

Figure 1A depicts transversal and sagittal slices of MRI data in image space. Due to different contrast weightings, each image reflects different properties of the tissues. For instance, the cerebrospinal fluid in ventricles is very dark in the T1w image, but bright in the T2*w image. On the other hand, the sagittal sinus (visible in the sagittal slice) is bright in the T1w and PD images and very dark in the T2*w image. Figure 1B shows the Aitchison norm image computed by considering every voxel in the T1w, PD and T2*w images as compositions. The Aitchison distance to the center of the distribution inside the simplex is depicted in Figure 1C. In this image, the interface between white matter and gray matter is very dark, which demonstrates that the center of the distribution falls within the transition of white and gray matter. The Aitchison distance image illustrates that the compositional data analysis can be used to create virtual contrast, which can be used to create tissue membership maps.

The 2D histogram of the ilr transformed coordinates of the MRI brain image compositions (Figure 2) contains 3 heavy clusters. Probing the real coordinates of the compositional data points using interactive 2D transform function widget reveals that these clusters represent the white matter, gray matter and cerebrospinal fluid (Figure 3A). At more peripheral coordinates, the arteries and sinuses can be seen. Although both of these are blood vessels, the difference between arteries and sinuses is meaningful because sinuses contain mostly deoxygenated hemoglobin, leading to a rapid decay of the MRI signal. In contrast, arteries contain oxygenated blood with slower MR signal decay. The color brain image (in Figure 3B) created by assigning T1w, PD, T2*w images to red,green, blue color display channels depicts the fused picture of the MRI data. The labels in Figure 3 shows the correspondence between compositional characteristics and the coloration of tissues in the fused image.

Figure 4 shows that normalized graph cuts can be used to cluster and label meaningul tissues, replacing the more manual interaction represented in Figure 2 with simple transfer function widgets.

Color brain images are used together with ilr transformed coordinates to describe different tissue types:

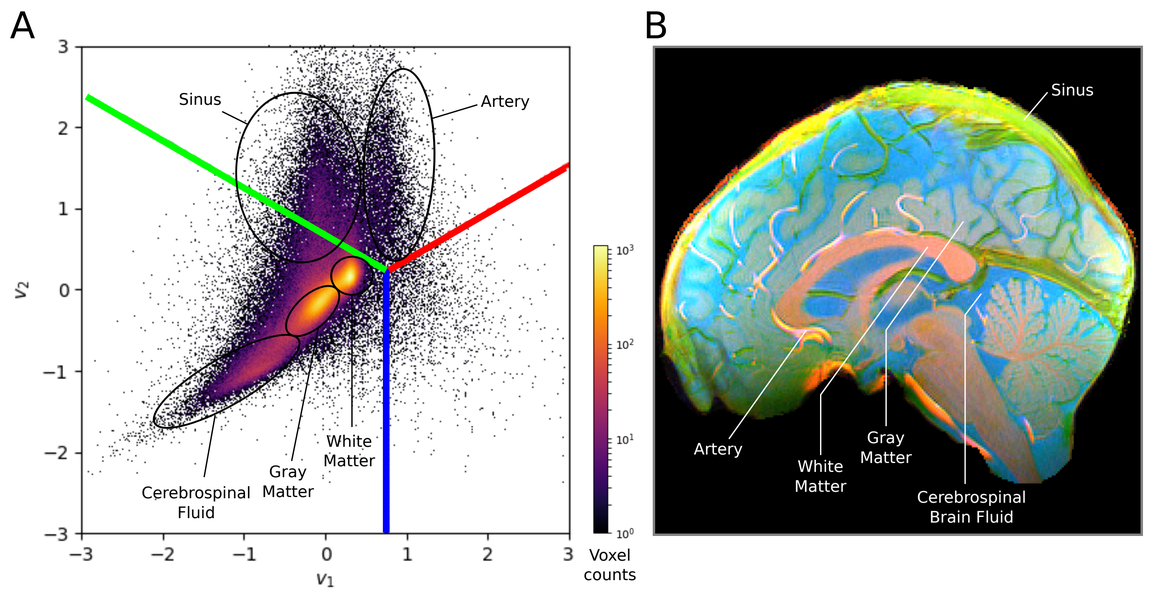

Figure 3: (A) A sagittal slice of the brain extracted MRI data in false color. T1w image is assigned to the red channel, PD to the green, T2* to blue channels. (B) 2D histogram of the ilr transformed coordinates of the MRI brain data compositions. Projections of the primary axes of RGB color cube are embedded (red line for T1w, green line for PD, blue line for T2*w) to provide an intuitive reference for the characteristics of the compositions. The tissue labels are overlaid on top in both panels.

Normalized graph cuts are used to parcellate brain tissues:

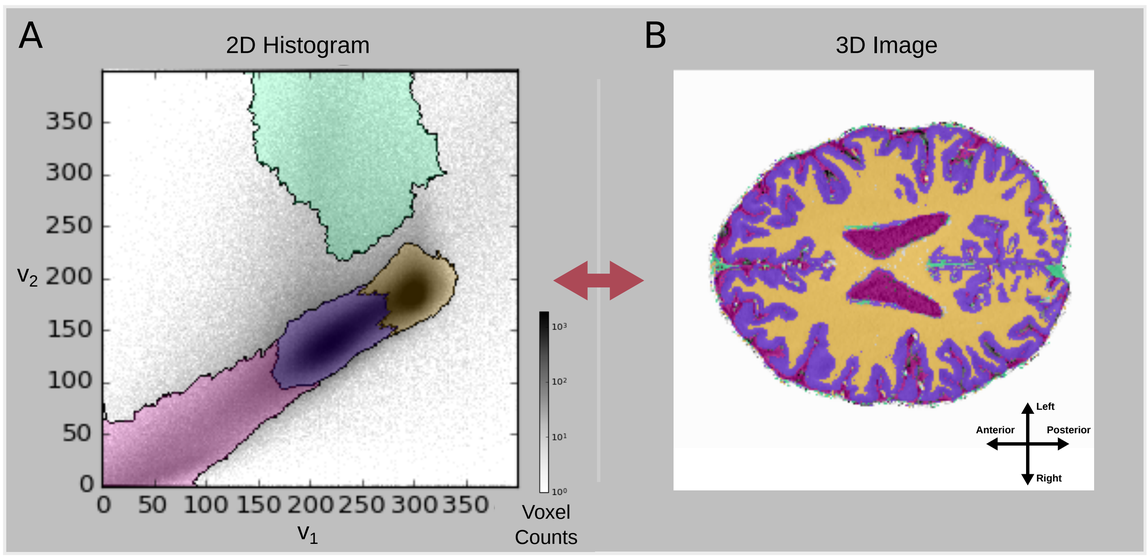

Figure 4: (A) Same as in Figure 2 but the colored regions represent clusters detected by interactive hierarchical exploration of the normalized graph cuts. (B) Regions delineated in panel A are mapped to the 3D brain image to show biologically meaningful parcellation of tissues. The voxels fall in unlabeled areas in Panel A mostly belong to the sub-cortical structures, pial surface, arteries and low signal-to-noise ratio areas.

Discussion & future directions

Compositional data analysis applied to multi-modal MR images provides a promising framework which can be seen as an extension to color space based image fusion methods. Although the present study only considered MRI data with three contrasts, compositional data analysis provides a principled way to analyze arbitrary number of image modalities, overcoming a major limitation of color space based image fusion methods. Addition of other types of magnetic resonance image conrasts such as short-inversion time T1 weighted images or cerebral blood flow measurements can be considered in the future. Quantification of compositional tissue classification performance (cortical and sub-cortical) together with time series analysis on multi-echo echo planar imaging data to detect blood oxygenation level dependent responses are two future applications remains to be studied.

References

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