The relation between color spaces and compositional data analysis demonstrated with magnetic resonance image processing applications

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Abstract

Images of living human brains can be acquired non-invasively by using magnetic resonance imaging (MRI). Different scanning parameters weight the image contrast to different tissue properties. A few examples of these differently weighted images are: T1 weighted (T1w) images to maximize the contrast between white matter and gray matter tissues, proton density weighted (PDw) for measuring concentration of hydrogen atoms and T2* weighted (T2*w) for creating a contrast highlighting the iron content. These images are commonly combined pairwise (using e.g. simple ratio images) to mitigate intensity inhomogeneities or to reveal specific tissue properties such as gray matter myelination. A principled way to combine more than two images at once is to consider multi-modal MRI data as compositions. The present study relates color space based image fusion to compositional data analysis and applies this concept to multi-modal MRI data in order to simultaneously reduce artefactual intensity inhomogeneities, enhance color balance and highlight specific tissue characteristics. To this end, brain images with three different contrasts (T1w, PD, T2*w) were acquired in-vivo at ultra high field (7 Tesla) MRI scanner and compositional data analysis methods were used to create virtual MR contrasts similar to conventional ratio images. In addition, simplicial centering was used to improve color balance and isometric logratio transformed coordinates of the tissue compositions were explored with two-dimensional transfer functions to probe meaningful compositional characteristics of brain tissues.

Key words: compositional data analysis, magnetic resonance imaging, MRI, image fusion, color space
1 Introduction

Compositional data analysis can be applied to images with multiple values for every picture element such as color images. Color images are commonly stored as triplets of non-negative integers representing the additive primary colors; red, green, blue (RGB). The creation of color images by assigning different sources of information to RGB channels to enhance the interpretation of multi-modal data is the simplest image fusion method (Pohl and Genderen, 2016, p. 96). Once the color image is formed in RGB format, the color space transformation from RGB to hue, saturation and lightness (HSL) is commonly used as the first step to improve image visualization. This transformation can be depicted as the projection of a cube representing the possible combinations of RGB values (also called as the RGB color cube) to a bi-hexcone model (Smith, 1978; Levkowitz and Herman, 1993). In the bi-hexcone model the height of the cones represents the lightness (averaged minimum and maximum of RGB components at every element) and the hexagonal slices represents the scale invariant saturation and hue components (spectral components). An alternative way to think about saturation and hue in the RGB to HSL transformation is to consider the isometric logratio (ilr) transformation after applying closure to the RGB color cube (the ilr transformation and closure operator are standard operations in compositional data analysis; Pawlowsky-Glahn et al., 2016). The ilr coordinates can be used in the conventional way to derive hue and saturation since ilr transformation of the closed RGB color cube also forms a hexagon (Figure 1, panels A and B) and multiplying ilr coordinates of each element with lightness (averaged minimum and maximum components of each element in $R^3$) creates an approximate bi-hexcone (Figure 1 panel C).

![Figure 1: (A) A cubic lattice in three dimensional euclidean space. (B) After closure ($C(R^3)$) and ilr transformation, the cubic lattice transforms into a lattice with hexagonal edges in two dimensional euclidean space. (C) Multiplying ilr coordinates of each element with lightness (averaged minimum and maximum components of each element in $R^3$) results in a lattice contained in an approximate bi-hexcone.](image)

Although useful, the representation of multi-modal data by means of RGB or HSL channels limits this application to cases with up to three values per picture elements (i.e. pixels). In contrast, the compositional data analysis interpretation of the RGB to HSL color space transformation provides a principled framework to operate on images with more than three information channels, and thereby overcomes this limitation of the color space based methods. For instance, the saturation and hue of an image with four values in every pixel can be derived from the ilr transformed coordinates of the channel compositions, while the lightness can still be calculated as the average of the minimum and maximum of channel magnitudes.

Magnetic resonance imaging (MRI) data is suitable to illustrate the compositional data analysis on multi-modal images because (I) different scanning parameters weight the image contrast to different
tissue properties thus providing multitude of informative images; (II) although the MRI data is of complex type, the magnitude images are often analyzed which means that the images are bound to have non-negative values. A few of these images with different contrast weightings are: T1 weighted (T1w) images to maximize the contrast between white matter and gray matter tissues, proton density weighted (PDw) for measuring concentration of hydrogen atoms and T2* weighted (T2*w) for creating a contrast highlighting the iron content. It should be noted that the combination of information coming from different medical imaging modalities (e.g. MRI, computed tomography, positron emission tomography) has been widely explored (for a review see: James and Dasarathy, 2014) but not under the compositional data framework. When considering MRI information alone, multi-modal MRI data have been used for tissue segmentation purposes (for a review see: Helms, 2016) and ratio images between pairs of modalities have been used to enhance/improve contrast visualization. For instance the ratio between T1w and PD images is used to mitigate artefactual image intensity inhomogeneities due to variations in sensitivity of the measurement method across brain areas (Van de Moortele et al. 2009) and the ratio between T1w and T2w or T2*w images is used to reveal relevant tissue properties such as myelination in the cortex (Glasser and Van Essen 2011; De Martino et al., 2014).

The compositional data framework is ideally suited for the analysis and visualization of multi-modal MRI data as it provides a principled way to combine multiple images (i.e. more than a pair as in ratio type of approaches). The present study applies the concepts of compositional data analysis to multi-modal MRI data in order to simultaneously reduce artefactual intensity inhomogeneities and highlight specific tissue characteristics. To this end, brain images of a healthy volunteer were acquired with three different contrasts (T1w, PD, T2*w) at ultra-high field 7 Tesla MRI scanner (for a review see: Ugurbil, 2014) and compositional data analysis methods (Pawlowsky-Glahn et al., 2015) were used to create virtual MR contrasts. In addition, simplicial centering and standardization is used to improve color balance and the ilr transformed coordinates of the tissue compositions were explored with 2D transfer functions to probe meaningful compositional characteristics of brain tissues.

2 Methods

2.1 Data acquisition

Whole head T1 weighted, PD and T2* weighted images at 0.7 mm isotropic voxel (3D picture elements are referred to as voxels in the context of MRI data) resolution were acquired in one male participant using a 3D magnetization-prepared rapid acquisition gradient-echo (MPRAGE) sequence with a 32-channel head-coil (Nova Medical) on a 7 Tesla whole-body scanner (Siemens; for details regarding the acquisition parameters see De Martino et al., 2014).

2.2 Preprocessing

Brain extraction was performed based on the PD image using FSL-BET (version 2.1; Smith, 2002). The resulting volumetric mask was applied to the T1w, PD and T2*w images in order to discard compositions in the non-brain regions (e.g. air, bones) from further analyses.

2.3 Analysis

The three three-dimensional images (T1w, PD, and T2*w) were concatenated, obtaining a four-dimensional image. Voxel-wise closure was performed to obtain the barycentric coordinates of every composition. The dataset consisting of ~4.5 million compositions was centered and standardized inside of the simplex. The ilr transformation was performed to acquire real space coordinates (ilr
coordinates) of the compositions. The operations in analysis pipeline are implemented in a free and open source Python package (available at https://github.com/ofgulban/tetrahydra; version 0.2.0).

In order to reveal the correspondence of compositional data clusters and brain tissues, slices of the multi-modal brain images were rendered in color together with a 2D histogram of the ilr coordinates of all compositions. The clusters were interactively explored with two-dimensional transfer function widgets implemented as a part of the free and open source Python package Segmentator (available at: https://github.com/ofgulban/segmentator; version 1.3.0).

3 Results

Figure 2: (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 simplicial center of compositions. Two slices of the MRI data (brain extracted) are visible in all panels, transversal slice (left hand side) and sagittal (right hand side) relative to the panels.

Figure 2A depicts one transversal and one sagittal slice of the brain extracted MRI data in image space. Due to the different image contrasts, each image reflects different properties of the tissues. For instance, the cerebrospinal fluid in the 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. It can also be noted that the smooth, artefactual intensity inhomogeneity field is similar across images (note the overall intensity differences that covary across the three images). Figure 2B shows the Aitchison norm image computed by considering the T1w, PD and T2*w values of each voxel as a composition after mapping these values from the real space ($R^3$) to the simplex space ($S^3$) with closure operator. This image is similar to a conventional ratio images, however different because it can be computed.
from more than two images. The Aitchison distance to the center of all compositions inside the simplex is depicted in Figure 2C. 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 tissues. The Aitchison distance image illustrates that the compositional data analysis framework can be used to create virtual contrasts, which can be used to create tissue membership maps. For instance, the hypo-intense white matter/gray matter interface might aid the common task of segmenting these two tissue types in functional brain imaging studies by highlighting the contrast at the interface of these tissues.

Figure 3: (A) MRI measurements rendered as a color image. Red channel is assigned to T1w, blue to PD and green to T2* values. (B) 2D histogram of the ilr coordinates of the same data. The projection of primary axes of RGB color cube (in $R^3$) to ilr coordinates are embedded to provide an intuitive reference for the characteristics of the compositions. (C) The effect of simplicial centering and standardization is visible as color balance improvement in the rendered brain slice. (D) 2D histogram of centered and standardized compositions, note that the embedded RGB color cube primary axes were not centered. Exemplary tissue labels are overlaid in addition in C and D. The overlaid circles on panel D are the edges of the 2D transfer functions used to probe the tissues.

The color brain images in Figure 3A and C depict the fused picture of the multi-modal MRI data. The difference between Figure 3A-C and Figure 3B-D demonstrates the color balance effect of simplicial centering and standardization. In figure 3B and C it can be seen that the 2D histogram of the ilr transformed coordinates of the brain image compositions contain three heavy clusters. Probing ilr transformed coordinates of the compositions using interactive 2D transform function
widgets reveals that these clusters represent the white matter, gray matter and cerebrospinal fluid. At more peripheral coordinates, the arteries and sinuses can be found. 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 labels pointing to the tissues indicated in Figure 3 Panel B shows the relation of the compositional characteristics with the coloration. To illustrate this point, it should be noted that the arteries have mostly reddish-white colors and the sinuses appear in green, which corresponds to the areas delineated for these tissues in Figure 3B when the positions of clusters are considered relative to the embedded RGB color cube axes. Similarly the compositional change from white matter to gray matter to cerebrospinal fluid can be seen as an approximately straight line in Figure 3C which corresponds to the change from red heavy color of white matter to cyan of cerebrospinal fluid in Figure 3D.

4 Discussion

The application of compositional data analysis methods to the multi-modal MR images provides a promising extension to color space based image fusion methods. The scale invariance principle of compositional data can be leveraged to mitigate intensity inhomogeneities. This is particularly beneficial in case of state of the art ultra high field MRI data, where intensity inhomogeneities are much more pronounced than at lower field strengths. However, proposed method assumes approximately the same intensity inhomogeneity fields across images. If this assumption is not fulfilled, intensity inhomogeneity correction algorithms may be employed as a preprocessing step, and the proposed method may still be used for data exploration and tissue classification. Moreover, image regions with very low signal to noise ratio (e.g. air), or locations affected by strong artifacts, such as signal drop-outs, should be discarded from the compositional analysis.

Although the present study only considered MRI data with three types of measurements (T1w, PD, T2*w), compositional data analysis provides a framework to analyze an arbitrary number of image modalities, overcoming a major limitation of color space based image fusion methods. Thus, combining multi-modal images using compositional data analysis methods opens the possibility to create a generalization of conventional ratio images with an arbitrary number of image components. In addition, compositional data analysis is also suitable to investigate the compositional characteristics of temporal processes such as the blood oxygenation level dependent signal in multi-echo functional MRI data (in which multiple images of the brain are acquired in two temporal scales; one in milliseconds the other in seconds). Another potential use is the application of clustering methods to the compositional coordinates of multi-contrast MRI data for creating binary segmentations of various cortical or sub-cortical tissues with a possibility of application to detect diseased tissues. Further investigation will be necessary to establish the relevance of the proposed applications of compositional data analysis specifically to MRI data and generally to multi-modal medical image processing.

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References

De Martino, F., Moerel, M., Xu, J., van de Moortele, P.-F., Ugurbil, K., Goebel, R., Yacoub, E., Formisano, E. (2014). High-Resolution Mapping of Myeloarchitecture In Vivo: Localization of Auditory Areas in the Human Brain. Cerebral Cortex, 25 (10), 3394-405.

Glasser, M. F., Van Essen, D. C. (2011). Mapping human cortical areas in vivo based on myelin
content as revealed by T1- and T2-weighted MRI. *Journal of Neuroscience, 31* (32), 11597-616.

Helms, G. (2016). Segmentation of human brain using structural MRI. *Magnetic Resonance Materials in Physics, Biology and Medicine, 29* (2), 111-124.

James, A. P., Dasarathy, B. V. (2014). Medical image fusion: A survey of the state of the art. *Information Fusion, 19* (1), 4-19.

Levkowitz, H., Herman, G.T. (1993). GLHS: A Generalized Lightness, Hue, and Saturation Color Model. *CVGIP: Graphical Models and Image Processing, 55* (4), 271-285.

Pawlowsky-Glahn, V., Egozcue, J. J., Tolosana-Delgado, R. (2015). *Modelling and Analysis of Compositional Data*. Chichester, UK: John Wiley & Sons, Ltd.

Pohl, C., van Genderen, J. (2016). *Remote Sensing Image Fusion*. Taylor & Francis Group, 6000 Broken Sound Parkway NW, Suite 300, Boca Raton, FL 33487-2742: CRC Press.

Smith, A. R. (1978). Color gamut transform pairs. *ACM SIGGRAPH Computer Graphics, 12*(3), 12-19.

Smith, S. M. (2002). Fast robust automated brain extraction. *Human Brain Mapping, 17* (3), 143-155.

Ugurbil, K. (2014). Magnetic Resonance Imaging at Ultrahigh Fields. *IEEE Transactions on Biomedical Engineering, 61* (5), 1364-1379.

Van de Moortele, P.-F., Auerbach, E. J., Olman, C., Yacoub, E., Ugurbil, K., Moeller, S. (2009). T1 weighted brain images at 7 Tesla unbiased for Proton Density, T2* contrast and RF coil receive B1 sensitivity with simultaneous vessel visualization. *NeuroImage, 46* (2), 432-46.