Intra-Voxel Linear Spectral Mixture Analysis Method for Tissues Quantification in Brain MRI

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Background and Purpose:

Quantification of brain volume is important for understanding brain structure and diagnosis of subtle anatomical changes in variant brain diseases. Magnetic resonance imaging (MRI) provides a stack of high quality images with different tissue contrast, based on the local tissue parameters of T1, T2 relaxation times and proton density, makes more reliably characterization of each voxel than single-contrast techniques [1]. Brain tissue segmentation from MR scans is often complicated by the existence of partial volume voxels that contain a mixture of two or more tissue types [2]. Currently MR image analysis is generally performed by spatial domain-based inter-voxel techniques which take advantage of inter-voxel spatial correlation among data samples but do not provide quantification results of tissue substances. Linear spectral mixing analysis (LSMA) has recently applied to MR image classification and shown potential in MR image classification [3]. Unlike the traditional classification which is mainly focused on inter-voxel correlation among data samples, the LSMA explores intra-voxel correlation to characterize spectral properties for classification. As a result, a major strength of the LSMA is to perform mixed voxel classification by estimating abundance fraction of each tissue substance present in a voxel to provide the likelihood of each tissue substance to be classified in one particular class. In order for the LSMA to be able to do so, this paper aims to designing a technique, called fully constrained least squares (FCLS)[4], which allows users to estimate the abundance fraction of each of tissue substances so as to compute their partial volumes in a complete MR image slice cube. To demonstrate the performance of our proposed approach, experiments are conducted for performance analysis and evaluation.

Materials and Methods:

The synthetic brain images available from McGill University, Montreal, Canada (available at www.bic.mni.mcgill.ca/brainweb/) were used allowing reproduce our experiments. Multispectral data of axial T1, T2, and proton density MR brain images [with 5-mm section thickness, and the noise is simulated with its intensity varying from 0-20%.] were analyzed to test the performance of our proposed methods.

Linear spectral mixture analysis (LSMA)

Linear spectral mixture analysis (LSMA) is a widely used technique to unmix multi-component composition in remote sensing imagery. More specifically, let $\mathbf{m}_1, \mathbf{m}_2, \cdots \mathbf{m}_p$ be p image endmembers assumed to be the data and $\mathbf{M} = [\mathbf{m}_1 \mathbf{m}_2 \cdots \mathbf{m}_p]$ be the signature matrix formed by these p image endmembers to be used to model an L-dimensional image voxel vector r as a linear mixture given by $\mathbf{r} = \mathbf{M}\boldsymbol{\alpha} + \mathbf{n}$ (equation 1), where n is a noise vector which can be used to describe a model or measurement error and $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \ldots, \alpha_p)^T$ is an unknown p-dimensional abundance vector associated with $\mathbf{m}_1, \mathbf{m}_2, \cdots \mathbf{m}_p$ with α_j representing the abundance fraction of the j^{th} endmmeber m_j present in the voxel vector $\mathbf{r}$. Due to physical constraints two abundance constraints are generally imposed on (equation 1), which are Abundance Sum-to-One Constraint (ASC) specified by $\sum_{j=1}^{p} \alpha_j = 1$ and Abundance Non-negativity Constraint (ANC) specified by $\alpha_j \geq 0$ for all $1 \leq j \leq p$. In other words, linear spectral unmixing takes advantage of $\mathbf{r} = \mathbf{M}\boldsymbol{\alpha} + \mathbf{n}$ to unmix p image endmembers, $\mathbf{m}_1, \mathbf{m}_2, \cdots \mathbf{m}_p$ by finding their respective abundance fractions $\alpha_1, \alpha_2, \cdots, \alpha_p$ with/out the abundance constraints, ASC and ANC. In this paper the LSMA is implemented by a fully abundance constrained method, called Fully Constrained Least Squares (FCLS) developed by Heinz and Chang in [4].

Three dimensional (3D) Receiver Operating Characteristic (3D ROC)

One of most widely used evaluation tools in medical diagnosis is so-called receiver operating characteristic (ROC) which evaluates a given detector based on a curve, referred to as ROC curve plotted as a function of detection probability versus false alarm probability [5]. The detection probability (P_D) and the probability of false alarm (P_F) can be expressed as follows.

$\mathbf{P_D} = \int_{\Lambda(\mathbf{r})>\tau} p_1(\mathbf{r})d\mathbf{r} + \gamma P(\{\mathbf{r} \mid \Lambda(\mathbf{r}) = \tau\})$ and $\mathbf{P_F} = \int_{\Lambda(\mathbf{r})>\tau} p_0(\mathbf{r})d\mathbf{r} + (1-\gamma) P(\{\mathbf{r} \mid \Lambda(\mathbf{r}) = \tau\})$ with the τ determined by the prescribed P_F.

In order to evaluate the detection performance, a Receiver Operating Characteristic (ROC) analysis is commonly used as an evaluation tool to assess the effectiveness of a detector based on an ROC curve plotted as a function of P_D versus P_F for analysis as shown in Fig. 1. As an alternative to the use of ROC curves, the area under curve (AUC), A_z which has been widely used in medical diagnosis [5] is also calculated by the area under the ROC curve.

Results:

Fig. 2 present one set classification results of FCLS via 0% noise corrupted synthetic brain MR image. The experimental results demonstrate the utility of the intra-voxel multispectral techniques to compute partial volumes of each of tissue substances via their estimated abundance fractions. The 3D ROC analysis is also developed for performance evaluation where a third dimension is introduced to threshold abundance fractions so as to detection rates. To further quantify the 3D ROC plots, we calculated their related area under curves, denoted by (A_z) correspond to overall detection, true positive detection and false positive detection performance measures. These values were further tabulated in the following tables where Table 1 shows the A_z for FCLS with different noise levels.

Conclusion:

The intra-voxel multispectral techniques provide a means of computing partial volumes of tissue substances, a task which generally cannot be accomplished by many existing inter-voxel based techniques. It offers better and more accurate partial volume estimates than inter-voxel spatial-based techniques by interpolation.

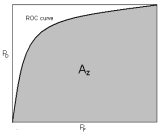
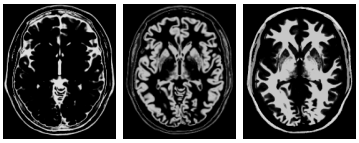


Fig. 1. An example of AUC, A_z calculated by an ROC curve



CSF GM WM

Fig. 2. The classifying tissues of interest (CSF, GM, and WM) were used the FCLS method.

Table 1. A_z of 3D ROC analysis for mean classification rates of CSF, GM and WM for 3-tissue (GM, WM, CSF) classification of FCLS.

Noise level	FCLS ($A_z(P_D,P_F)$, $A_z(P_D, \tau)$, $A_z(P_F, \tau)$)
0% noise	(0.9259, 0.6706, 0.0934)
5% noise	(0.9272, 0.6697, 0.0925)
10% noise	(0.9287, 0.6685, 0.0918)
20% noise	(0.9270, 0.6602, 0.0911)

Reference:

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