

# Overview on Partial Volume Estimation in Brain MRI: Models and Methods

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## I. INTRODUCTION

Quantitative analysis of magnetic resonance (MR) images to gain knowledge about anatomy of human brain is increasingly important. For example, disorders or healthy aging can cause structural changes in the brain. These changes can be quantified by measuring properties of the anatomical structures of interest. However, it is not straight-forward to extract these structures of interest from images for quantification. For example, a single voxel may consist of several brain structures. This phenomenon, termed partial volume effect (PVE), is caused by the finite spatial resolution of imaging devices. Due to the complexity of human anatomy, the PVE is an important factor when an accurate structure extraction is needed. A standard segmentation problem within MRI is the task of labeling voxels according to their tissue type that are white matter (WM), gray matter (GM), and cerebro spinal fluid (CSF). An extension of this classification task is partial volume (PV) estimation, the estimation of the amount of each tissue type within each voxel. In this abstract, we present a concise overview of statistically-based PV estimation.

## II. MIXEL MODEL

The mixel model [1] is a simplified model for formation of image intensities in MRI. In the mixel model, each intensity value in the image is a realization of a random variable (RV) which is a weighted sum of RVs describing individual tissue types and white measurement noise. In symbols, if  $\mathbf{x}_i$  is the RV corresponding the voxel  $i$

$$\mathbf{x}_i = \sum_{j=1}^3 w_{i_j} \mathbf{l}_j + \mathbf{a}, \quad (1)$$

where  $\mathbf{l}_j$ s are RVs representing the tissue types and  $\mathbf{a}$  is RV related to measurement noise. The tissue type weights  $w_{i_j}$ , called here partial volume coefficients (PVC)s, model the amount of that particular tissue type within a voxel. PVCs receive values from 0 to 1 and sum to one for each voxel. All RVs are assumed to be multivariate Gaussian. The problem is to estimate the true values of PVCs based on image data.

In practise, the mixel model has to be simplified because it is impossible to distinguish between measurement noise and variability within tissue types. The *sampling noise model* assumes that randomness in the model is due to measurement noise only [2]. This leads to a model, where tissue types are described by intensity values instead of RVs. The *material dependent noise model* is obtained by embedding the measurement noise into material noise components  $\mathbf{l}_j$ , i.e.  $\mathbf{a}$  is dropped from Eq. (1) [2]. This model is more complex than the sampling noise model, but it is probably more realistic.

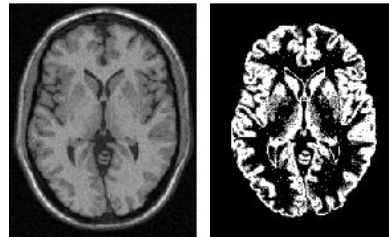


Fig. 1. A T1-weighted MR image and gray matter PVCs estimated from it.

## III. METHODS FOR PV ESTIMATION

The basic problem is to maximize the likelihood of PVCs given the image data. Because PVCs for a voxel must be estimated given only a single intensity value (or a vector in the multi-spectral case), modeling spatial dependence between PVCs is advantageous. This leads to MAP (maximum a posteriori) estimation where the prior term is modeled as a Markov random field.

Procedures for solving the estimation problem can be divided into two main categories. *Direct procedures* aim to solve the problem directly, leading to a large scale constrained optimization task. Multi-spectral images are needed and the sampling noise model must be assumed. *Two-stage procedures* first detect voxels that contain more than one type of tissue. Thereafter, PVCs are estimated for these voxels. It is assumed that there are at most two types of tissue present in a single voxel.

The parameter values for the densities describing tissue types need still to be learned. Expectation maximization (EM) schemes learn parameter values simultaneously with the PV estimation. However, the spatial dependence between PVCs makes the (standard) EM algorithm intractable. Well-grounded approximate EM algorithms exist, but they are typically computationally expensive. Another approach is to identify the parameters before the PV estimation using, for example, histogram analysis or heuristics [3]. The downside of histogram analysis is that it often leads to challenging global optimization problems.

## REFERENCES

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