REDUCING PARTIAL VOLUME ARTIFACTS IN MRI SEGMENTATION USING A PARAMETRIC GRADIENT WEIGHTED HISTOGRAM

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Abstract: Nowadays, quantitative MRI measurements play a major role in clinical decisions, as when monitoring subtle variations in some diseases such as MS. Many efforts have been done during the last years in the field of MRI segmentation in order to obtain robust and accurate methods to measure tissue properties. MR images are affected with some characteristic artifacts like non-uniformity and partial volume effect (PVE). Many methods have been developed which try to solve the PVE that happens when more than one tissue is present in a voxel. All these methods try to model the PV voxels (also called *mixels*) using either uniform or Gaussian distributions. Our objective is to present a different approach based on a modified histogram (PGWH) for dealing with mixels in order to obtain an accurate segmentation. Quantitative validation of the method has been done with simulated data and qualitative results on real data are provided.

Introduction

Since data acquired on MR scanners is affected with a variety of image artefacts, proper image pre-processing is needed to asses the quality of data which is necessary to assure an accurate diagnostic. Concretely, MRI brain tissue volumes is a valuable measure for clinical purposes and many efforts has been employed in the last years to measure them properly [1].

Brain tissue classification is a complex task because many reasons such us similar intensities in brain and non-brain pixels, low special resolution, noise, etc. A large number of methods have been developed to solve the brain extraction problem. Some of them use thresholding and morphological operators to separate brain to non-brain tissues while others use deformable meshes or brain templates to incorporate a priori information. There is a good comparison of these methods in [2].

Even when outer tissues have been extracted MRI images are affected with MRI inhomogeneities, random noise and partial volume.

The problem of partial volume has been also addressed, especially on those statistical methods that try to find the parameters of tissues distribution using any kind of EM algorithm to estimate them. Basically, these methods use additional classes for modelling partial volume voxels, as well called *mixels* [8,9].

In this paper we address the problem of partial volume using a non parametric approach. We propose a new kind of histogram similar to the approach of Nagel and Rosenfeld [10] which minimizes partial volume voxels contribution making easier to classify MRI data. We describe some experiments with both real and simulated data to demonstrate its excellent behaviour.

Material and Methods

Most of PV methods try to model partial volume using some kind of basis function. Santago and Cage use an uniform distribution while Ruan et al [13] and others use Gaussian distributions. We think that PV voxels can´t have a known model function as they are an unexpected combination of Gaussian distributed tissues wich is dependent to the concret image geometry and should be different from one image to another.

Instead of modeling PV voxels we propose to erase them in order to estimate properly the mean value of the different tissues.

A MR brain image is commonly modelled as follow:

$$y_i = \mu_j \beta_i + n_i \qquad j \in [1,k] \quad i \in [0,M] \tag{1}$$

Where y_i is the measured pixel at location i, μ_j is the mean of jth tissue at which this pixel belongs, β_i is the multiplicative and positive field at the same location and n_i is a gaussian distributed noise with zero mean and given variance.

This is pure tissue model that does not take into account the partial volume effect. This model assumes that if there is no inhomogeneity noise all tissues share the same variance (noise variance). However, this not true, because the partial volume and tissue heterogeneity. we can reformulate the model as follow to take into account PVE:

$$y_i = \Phi(\mu,\alpha_i)\beta_i + n_i \tag{2}$$

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$$\Phi(\mu,\alpha_i)=\sum_{j=1}^{k}\alpha_{ij}\mu_j \qquad \sum_{j=1}^{k}\alpha_{ij}=1 \tag{3}$$

Where $\Phi(\mu,\alpha_i)$ is a linear mixing function that gives us the intensity in one pixel at location i as the combination of the different tissue proportions.

If we restrict the possible tissue combination to two classes as proposed in [13] then we have the next expression for the mixing function:

$$\Phi(\mu,\alpha_i)=\alpha_{ij}\mu_j+(1-\alpha_{jj})\mu_{j+1} \qquad \sum_{j=1}^{k}\alpha_j=1 \tag{4}$$

Where α_i is the proportion of tissue i in a voxel and (1-α_i) is the proportion of tissue i+1.Other tissues than i and i+1 has zero proportion of tissue. CSF y WM is despreciable.

If eliminate bias noise using available methods [x] our resulting model is:

$$y_i=\Phi(\mu,\alpha_i)+n_i/\beta_i \tag{5}$$

where random noise is now bias related and is not longer gaussian.

If we apply a low pass filter to the bias corrected image which does not affect tissue means then we obtain the next model:

$$y_i=\Phi^*(\mu,\alpha_i)+n_i^* \tag{6}$$

where n* is gaussian due to central limit theorem and Φ^* is a modified mixing function due to filtering.

If no random noise were present at image tissue content of each voxel can be obtained from the tissue means using the follow expression:

$$\alpha_{ij}=\begin{cases}(y_i-\mu_{j+1})/(\mu_j-\mu_{j+1}) & if\ (\mu_j<y_i<\mu_{j+1})\\ 1 \quad if\ (y_i<\mu_1) \quad or \quad if\ (y_i>\mu_k)\\ 0 \quad Otherwise\end{cases} \tag{7}$$

Then the problem resides on finding the means of the tissues.

Many authors model the image histogram using mixture of Gaussians using either uniform or Gaussian distributions for PV voxels [11-13]. However, the real distribution of these *mixels* can not be known in a general framework because this is an unexpected mixing function which can vary highly from one image to another and has high relation with image noise and level of the PV. Instead of modeling the PV voxels, we will consider them as outliers of the pure tissue distribution. As the PV voxels mainly appear on the interfaces between tissues (edges), a simple way to avoid them could be to delete all the voxels that have a high gradient using a cost function-based thresholding as done in [xx]. However, this approach introduces a truncation in data which is not desirable making the mean estimation hard to reach.

We propose to solve this problem to use a parametric histogram which is almost insensitive to the contribution of PV voxels.

Parametric Gradient Weighted Histogram (PGWH)

Let be *y* an image of M pixels and *L* grey levels and y^* is the image resulting from the application of an average lowpass filter.

$$y^*=y\otimes H \tag{8}$$

We define the Parametric Gradient Weighted Histogram (GWH) of the image y as follows:

$$H(l)=\sum_{i=0}^{M}w_i\delta\{y_i^*-l\} \qquad l\in L \tag{9}$$

$$w_i=\left(1+\left|\nabla(y_i^*)\right|^d\right)^{-1} \tag{10}$$

The histogram is normalized to use it as a pdf:

$$H(l)=\frac{H(l)}{\sum_{\forall l\in L}H(l)}$$

Where ∇ is the local gradient of image y* in a neighborhood window of radius 1 (3x3 size) centered at position i. δ is the Dirac-delta function. H integrates to 1, which is important for its interpretation as a probability density function (pdf).

The basic idea is that those pixels that have a high gradient will have a lower contribution to the histogram than pure tissue voxels which are mainly in homogeneous regions with a low gradient. The only parameter d modulates the degree of cancellation of PV voxels. The histogram is calculated over the smoothed image because it gives a better estimation of pure tissue intensities at homogeneous regions.

The optimum factor d that eliminates PV voxels contribution is reached when variance of tissues is minimal and can be obtained using a Gauss-Newton optimization scheme.

The PGWH not only erases partial volume voxels but also reduces noise contribution. This is possible because we estimate a better histogram by applying a low-pass filter on histogram calculation which reduces random noise (but increase partial volume) combined with a PV

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cancellation scheme. The only parameter of this histogram is the d factor which plays a main role on PV cancellation.

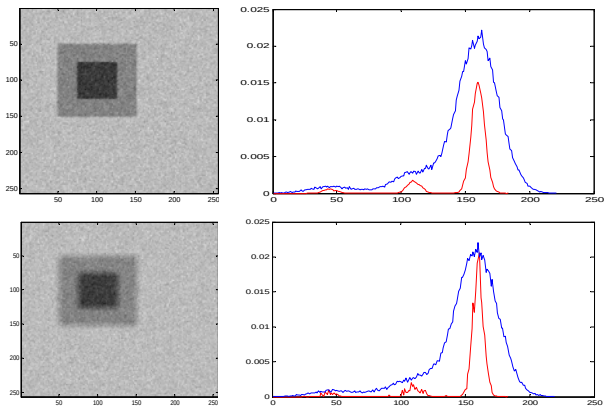

Figure 1: Left-up: Test image with no PV and Gaussian noise(10%). Right-up: Normal histogram and Average Gradient Weighted Histogram. Left-down: Test image with PV and Gaussian noise(10%). Right-down: Normal histogram and Average Gradient Weighted Histogram.

Adjusting d factor

The factor d regulates the degree of PV cancellation on the histogram and has to be set to obtain optimum results. To adjust this factor we can remember eq.1 where we see an idealistic situation with no PV at all. If there is no partial volume (and no bias noise) the variance of each class should be equal between their selves and equal to noise variance. Then, the optimum d factor can be seen as the one that minimizes the common varianceof all the classes .

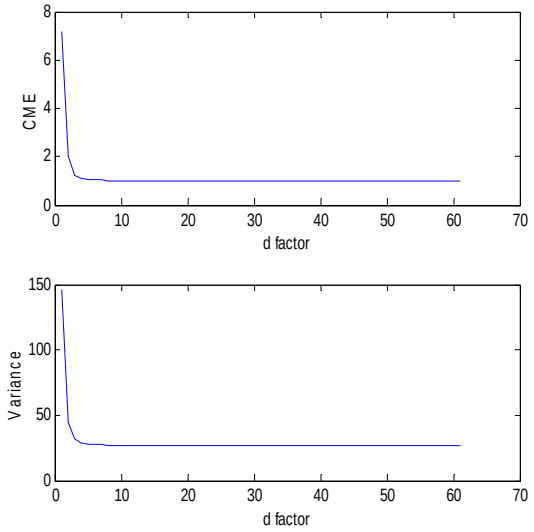

Figure 2: Class Mean Error and Tissue Variance vs d factor.

However, this situation is never reached cause there is some amount of anatomical tissue variance but and some differences between variances can present. Then the optimum d value can be obtained from the value that minimizes the variances of the classes. To estimate the common this variance we have to classify the tissues using a clustering algorithm. We have used the Expectation Maximization algorithm (EM) [dempster et al,1974] which provides an estimation of class means and variances. EM were used over the PGWH. We have used an EM reformulation of Jones and McLachlan [12] fro working with grouped data assuming that all tissues have the same variance.

To measure the error in class mean estimation we define the class mean error (CME) as:

$$CME = \sum_{i=1}^{k} \left| \mu_{ei} - \mu_i \right| /\mathrm{k} \qquad (11)$$

Where μ_{ei} is estimated mean of the class i μ_i is the real mean.

After mean estimation we will apply Eq. 4 for image segmentation. Although a soft segmentation is prefered a hard segmentation will be used to easy to comparison with other methods. According with Eq. 4 each pixel will be assigned to the tissue class that has a higher contribution in that pixel.

To measure the segmentation accuracy will use the DICE metric also know as kappa index.

$$k = \frac{A \cap M}{A \cup M} \qquad (12)$$

Where A is the automatic segmentation and M is the manual.

Results

To evaluate the proposed method we used a simulated test image over different conditions of PV and random noise. Our test image consisted on a 256x256 image with 3 classes (see Fig.1). Partial volume was simulated by applying a low pass-filter with different radios of average window. Different amplitude gaussian noise was added. In order to know the goodness of the method we compared with an existing well known method for Partial Volume modelling, the method proposed by Ruan et al in [13]. We applied PV window from 0 (no PV) to 5(11x11 window) and we added from 0 to 10% gaussian noise. In table 1 and in figure 3 we summarize the results.

PV	CME (1)	CME (2)
0	1.8498	0.0727
1	1.4258	0.0920
2	1.4275	0.0845
3	1.5328	0.1105
4	2.1232	0.1555
5	4.2318	0.1992

Table 1: Comparison between Ruan method(1) and PGWH(2).

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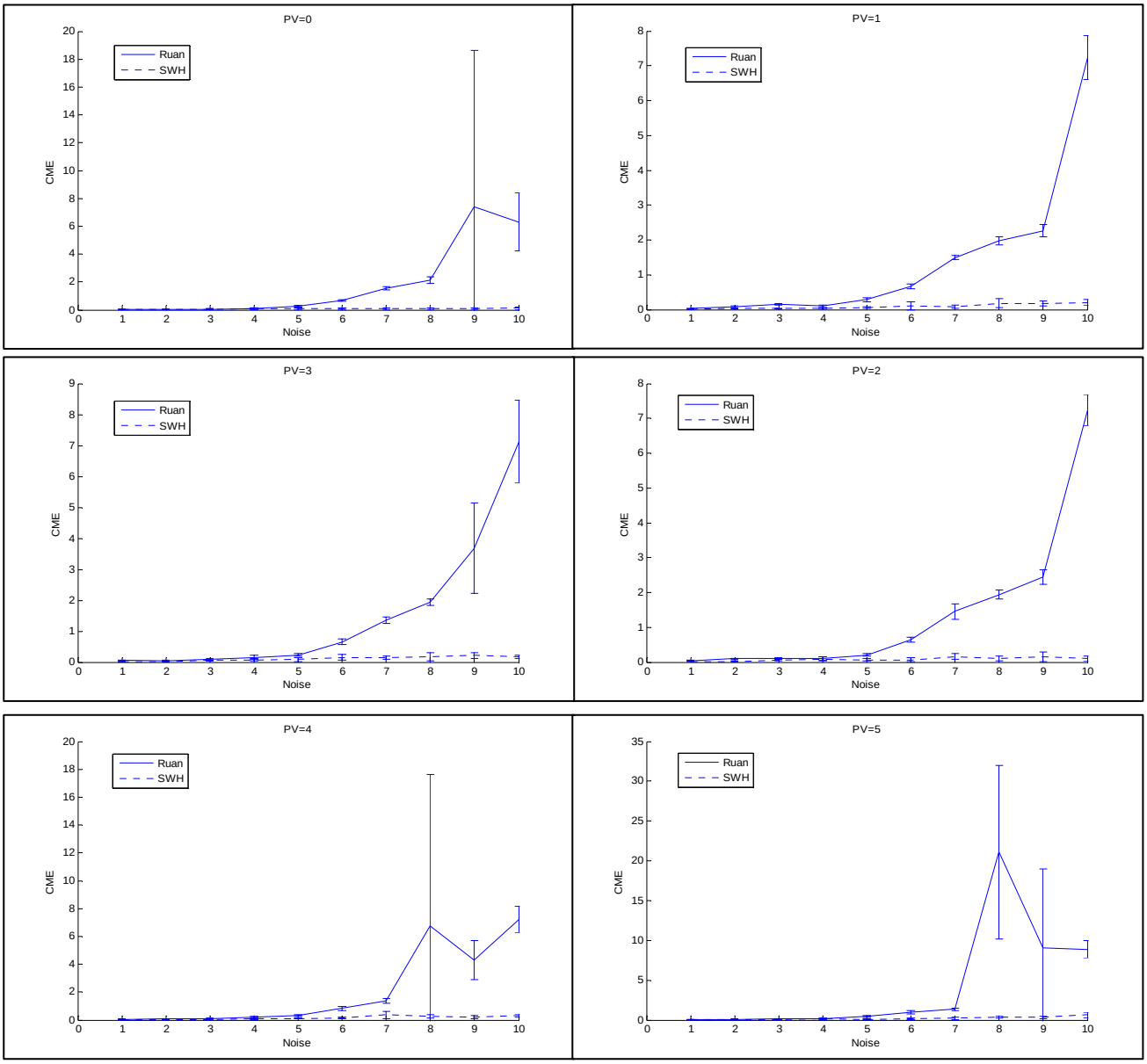

Figure 3: CME evolution over different conditions of PV and Gaussian noise with Ruan´s Method and PGWH method.

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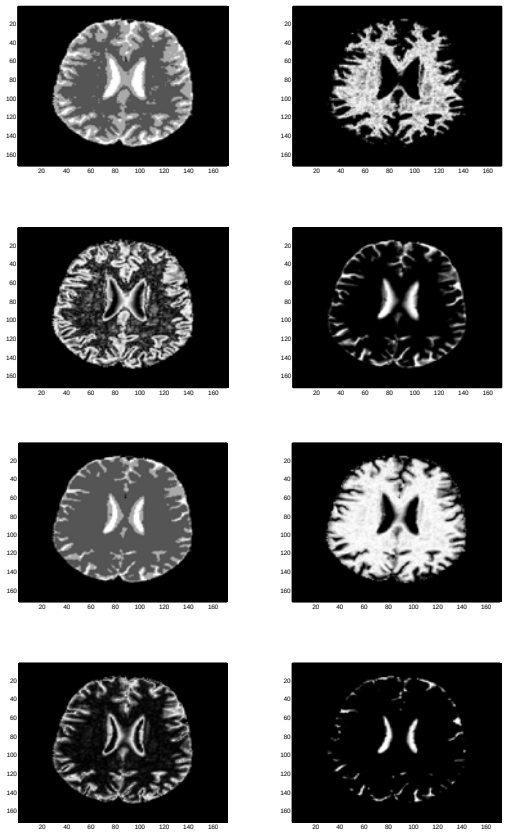
Experiments with phantoms

We tested our method over the BrainWeb phantom (http://www.bic.mni. mcgill.ca/ brainweb/). All experiments were developed using MATLAB 7.0 (Mathworks Inc). The noiseless volume was firstly segmented by software developed in our laboratory to obtain the brain mask in which there are only three brain tissues(GM,WM and CSF). The tissue classification was carried out within this mask using eq 5 using class means (45,111,158).

In the next table we show the results.

Real Data (Koen´s data)



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References

[1] ANDREW J. WORTH, NIKOS MAKRIS, VERNE S. CAVINESS, JR., AND DAVID N. KENNED. Neuroanatomical Segmentation in MRI: Technological Objectives. International Journal of Pattern Recognition and Artificial Intelligence, Vol. 11, No. 8 (1997).

[2] DAVID E. REX,et all. A meta-algorithm for brain extraction in MRI. NeuroImage 23 (2004) 625–637.

[3] E. VOKURKA, N. THACKER AND A. JACKSON. A Fast Model Independant Method for Automatic Correction of Intensity Non-Uniformity in MRI Data. JMRI, 10, 4, 550-562, 1999.

[4] JOHN G. SLED,* ALEX P. ZIJDENBOS. A Nonparametric Method for Automatic Correction of Intensity Nonuniformity in MRI Data. IEEE TRANSACTIONS ON MEDICAL IMAGING, Vol. 17, No. 1, FEBRUARY 1998.

[5] W.M. WELLS, L. GRIMSON. Adaptative Segmentation of MRI Data. IEEE TRANSACTIONS ON MEDICAL IMAGING, Vol. 15, No. 4, AUGUST 1996.

[6] JOHN ASHBURNER. Another MRI Bias Correction Approach. Neuroimage Human Brain Mapping 2002.

[7] MARTIN STYNER, CHRISTIAN BRECHBUHLER , GABOR SZEKELY, GUIDO GERIG. Parametric estimate of intensity inhomogeneities applied to MRI. IEEE TRANSACTIONS ON MEDICAL IMAGING, Vol. 19, No. 3, March 2000.

[8] DAVID H. LAIDLAW, KURT W. FLESCHER, AND ALAN H. BARR. Partial-volume Bayesian classification of material mixtures in MR volume data using voxel histograms. In *IEEE Transactions on Medical Imaging*, volume 17, pages 74–86, February 1998.

[9] D.C. WILLIAMSON, N.A. THACKER, S. R. WILLIAMS ,M. POKRIC. Partial Volume tissue Segmentation using Grey Level Gradient. MIUA 2002.

[10] NAGEL, R., ROSENFELD, A. Steps toward handwritten signature verification. In: Proceedings of the First International Joint Conference on Pattern Recognition. 1973.

[11] HARTIGAN J. AND WONG M. Algorithm AS136: A k-means clustering algorithm. *Applied Statistics.* 1979;28:100-108.

[12] JONES, P.N. AND MCLACHLAN, G.J. (1990). Algorithm AS 254. Maximum likelihood estimation from grouped and truncated data with finite normal mixture models. *Journal of the Royal Statistical Society Series C (Applied Statistics)* **39**, 273-282.

[13] SU RUAN*, CYRIL JAGGI, JINGHAO XUE, JALAL FADILI, AND DANIEL BLOYET. Brain Tissue Classification of Magnetic Resonance Images Using Partial Volume Modeling. IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 19, NO. 12, DECEMBER 2000

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		CME		DICE similarity	
Noise	**PV**	**Ruan**	**GWH**	**Ruan**	**GWH**
0%	1mm	0.2186	0.3736	0.9975	1.0000
1%		0.3584	0.3878	0.9893	0.9901
3%		0.6992	0.5096	0.9685	0.9690
5%		1.0504	0.5936	0.9429	0.9433
7%		1.6939	0.4761	0.9074	0.9078
9%		1.8776	0.6288	0.8659	0.8656
0%	3mm	3.8583	0.4444	0.9441	1.0000
1%		0.4756	0.4673	0.9860	0.9876
3%		1.1770	0.5420	0.9600	0.9607
5%		2.2239	0.6229	0.9294	0.9305
7%		2.1298	0.9445	0.8910	0.8915
9%		2.0754	1.4116	0.8502	0.8495
0%	5mm	4.7415	0.9250	0.9241	0.9961
1%		1.0012	0.9463	0.9841	0.9843
3%		2.7064	1.0587	0.9485	0.9528
5%		2.9155	1.1870	0.9151	0.9176
7%		2.7012	1.7310	0.8755	0.8763
9%		2.6151	2.2793	0.8336	0.8331
0%	7mm	5.4348	1.1804	0.9118	0.9957
1%		3.1790	1.1649	0.9693	0.9822
3%		3.0662	1.2780	0.9403	0.9464
5%		3.0228	1.9144	0.9043	0.9082
7%		3.2744	2.0060	0.8643	0.8658
9%		3.7677	3.0228	0.8197	0.8197
0%	9mm	5.3770	2.4824	0.9544	0.9745
1%		5.4840	2.6180	0.9449	0.9692
3%		5.3045	2.9288	0.9210	0.9390
5%		5.0459	3.3792	0.8888	0.8981
7%		4.6060	3.9609	0.8505	0.8538
9%		6.0482	4.3357	0.8007	0.8076
Average		2.9377	1.5267	0.8577	0.9272

Table 2: (GWH) Comparison of 2different classification methods over BrainWeb Phantom.

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