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Partial Volume Tissue Segmentation using Grey-Level Gradient

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Abstract

A Bayesian probability based tissue segmentation method is presented, which makes use of the grey level information in the images and also the local grey level slope. The grey level distributions are modelled as a combination of Gaussian distributions and triangle-Gaussian convolutions. The local grey level slope distribution is modelled as a linear combination of Rician distributions. The parameters are fitted and used to provide the information required to constructed a Bayesian tissue classifier. Results presented for a synthetic data set illustrate that the model distributions describe well the distribution of grey levels and local grey level slope in a 2D image. Application of the method to an MR image of a human brain demonstrate how the segmentation method removes commonly occuring artifacts in partial volume probability maps.

Summary

This work addresses the problem of partial volume estimation, where a mixture of two or more tissues combine to produce the image intensity value for a particular voxel. Bayes theory is used to generate probability maps for each segmented tissue which estimates the most likely *tissue volume fraction* within each voxel as opposed to previous approaches which attempt to compute how likely it is that a certain grey level would be generated by a particular tissue class. Overall, the importance of this method lies in improved image segmentation based on a probabilistic approach, thanks to inclusion of a partial volume model and availablity of more clearly defined tissue separation through use of image derivatives.

The requirements for partial volume analysis have previously been indentified by Laidlaw [1] with suggestions for a less general framework. A method for combined multi-image segmentation and field inhomogeneities correction within an EM framework have been suggested by Wells [8]. In previous work we have demonstrated the value of partial volume approaches using single images for longitudinal development of tumours.

In addition some of this work has attempted to modify the essentialy Bayesian formalism to account for local structure, such as boundaries, by using local prior estimates based upon a local resampling of data. In the work presented here we take an alternative view that local information regarding image structure can be included directly. The Bayesian modelling can be modified to include local image derivatives as well as grey levels using only the same assumptions underlying the standard approaches. The method makes use of results from analysis of noise processes in magnitude MR images where the noise distribution and computation are directly analogous.

Our new approach makes use of the grey level information in the images and also the local grey level slope. The grey level distributions are modelled as a combination of Gaussian distributions and triangle-gaussian convolutions. The local grey level slope distribution is modelled as a linear combination of Rician distributions. The parameters are fitted and used to provide the information required to constructed a Bayesian tissue classifier. Results are presented for a synthetic data set illustrate the ability of the model distributions to describe the distribution of grey levels and local grey level slope in an image. Further results obtained from an actual MR image of a human brain demonstrate how the segmentation method can remove commonly occuring artifacts in partial volume probability maps. In low contrast situations, this approach effectively doubles the information avalable for partial volume estimation and improves the accuracy.

The devised algorithm has been implemented and tested on simulated image data (a fraction of which is presented here to illustrate the calibration processes. We then demonstrate the effects on the new partial volume estimation process on an inversion recovery turbo spin-echo image of the brain.

Introduction

For an image containing only a few tissues, resonable segmentation (forced choice) can be achieved from a knowledge of the distribution of the grey levels [1]. Such segmentations however can be quite inaccurate and are often supplemented by local smoothness assumptions or noise filtering. These methods are not based upon justifiable assumptions regarding the image formation process and bias partial volume estimates towards pure tissue classes. A major motivation for this work is the need for a reliable method to determine a volumetric value for the contents of each voxel in MR data. Such measurement is necessary to accurately determine the structural volume and is also useful to correct the metabolite concentration maps produced from chemical shift imaging. In the latter, partial volume effects can lead to apparent anomolous values in what should be normal grey matter and white matter. In previous work we have found that the contrast to noise separation between tissues is quite poor. If more than three tissues are present it is necessary to examine the distribution of the grey levels in two or more co-registered images in order to achieve 10 % or better volumetric estimation accuracy [2]. In much work regarding probabilistic analysis of voxels contents, the assumption that there is a negligible occurence of pixels with partial volume mixtures is often made and only pure tissues are modelled. In fact, Laidlaw, [1], Noe [3] and our own work [4], [5] have all demonstrated that this is inadequate, especially with respect to MR images of the brain. In addition some of this work has attempted to modify the essentially Bayesian formalism to account for local structure, such as boundaries, by using local prior estimates based upon a local resampling of data. The freedom to take such a step is linked to the classic problem of identifcation of prior probabilites in Bayesian methods. However, in the work presented here we take an alternative view that local information regarding image structure can be included directly. The Bayesian modelling can be modified to include local image derivatives as well as grey levels using only the same assumptions underlying the standard approaches. This leaves the prior probabilities to be determined separately (according to the task). In low contrast situations, this approach effectively doubles the information available for partial volume estimation and improves the accuracy.

Method

The probability that a pixel may be assigned a specific tissue class i can be written as $P(i|g,s)$. This is the conditional probability that the data were generated by process i given the grey level g and the local grey-level slope (square-root of the sum squared derivatives) s. From Bayes theory the conditional probability can be written as

$$P(i|g,s) = \frac{P(i)P(g,s|i)}{\sum_i P(i)P(g,s|i)}. \tag{1}$$

In this expression $P(i)$ are the prior probabilities of the tissue class, $P(g,s|i)$ is the likelihood of the grey level g and the derivative s given a tissue class i and $P(g,s)$ is the joint likelihood of the instance of data g,s. Taking into account the non-independence of the grey level and slope probabilities it is possible to write

$$P(g,s|i) = P(g|i)P(s|g,i). \tag{2}$$

where $P(g|i)$ is the expected distribution of grey levels for each class and $P(s|g,i)$ is the expected distribution of slope values as a function of grey level for each class. We show below how it is possible to construct appropriate models for these terms for poth pure and partial volume tissue classes, based upon the standard noise distribution (uniform independent Gaussian) assumed for MR data.

In common with a number of other pieces of work regarding tissue segmentation [1], [3], [6], [7], [8], the grey level distributions are considered to be Gaussian with a mean μ and a variance σ^2.

$$P_G^i(g) = \frac{1}{\sqrt{2\pi}\sigma} \exp^{-\frac{(g-\mu)^2}{2\sigma^2}} \tag{3}$$

Here the superscript i identifies the tissue class and g is the the grey level at a given pixel. To model the distribution of the grey levels associated with the partial volume regions the convolution of a right angled triangular distribution and a Gaussian are used. The distribution is normalised to $\frac{1}{2}$ because it represents the contribution of one tissue component to a tissue mixture. It is therefore complemented by a second triangular distribution with equal size but a negative gradient. The total distribution is equivalent to a rectangular distribution as used by other authors but the relative components of tissue in the mixture are more readily determined. The convolution takes the form

$$P_{GT}^i(g) = -\frac{Mg+C}{2}\{erf(\frac{g-b}{2\sigma^2}) - erf(\frac{g-a}{2\sigma^2})\} - \frac{M\sigma}{\sqrt{2\pi}}\{\exp^{-\frac{(g-b)^2}{2\sigma^2}} - \exp^{-\frac{(g-a)^2}{2\sigma^2}}\} \tag{4}$$

Where erf is the single sided error function, M and C are the slope and intercept of the triangle and a and b are the limits of the triangular distribtion. The full grey level distribution of a tissue ($P(g|i)$ above) is modeled as a linear combination of Gaussian distributions for the pure tissue and the appropriate Gaussian-triangle convolution for each possible partial volume mixture.

To model the distribution of the grey-level slope ($P(s|g,i)$) it is necessary to consider the method of determining the slope. Firstly the square of the difference of the grey-level values of the two pixels adjacent to the pixel of interest in the x-direction is determined and likewise in the y-direction. The grey-level slope is then taken to be the positive square root of the sum of the g and s square gradient values. An analogous situation (with equivalent noise distributions) is encountered in formation of magnitude MR images from the square of the real and imaginary images. In this case it has been shown that the noise in these images is distributed according to the Rician distribution [9], [10]

$$P_{Rice}(z) = \frac{z}{\sigma^2} \exp^{-\frac{(z^2-A^2)}{2\sigma^2}} I_0(\frac{A \cdot z}{\sigma^2}) \tag{5}$$

where, $I_0(\frac{A \cdot z}{\sigma^2})$ is the modified zeroth order Bessel function of the first kind, σ is the standard deviation of the Gaussian noise in the original image and A is the pixel value in the absence of noise. The probabilities corresponding to pure tissue contributions can be calculated from

$$P(s|i) = P_{Ray}(s; \frac{\sigma_{noise}}{\sqrt{2}}) \tag{6}$$

as expression (5) reduces to the Rayleigh distribution, a Rician distribution with $A = 0$. For partial volume data there is not one single mean slope value A, but a range of possible values depending upon proximity to the boundary. We must therefore write down the partial volume slope distribution with the mean as a function of g, $A(g)$.

$$P(s|g,i) = P_{Rice}(s; g, A(g), \sigma) \tag{7}$$

for the partial volume distribution between tissues i and j. We can now write equation 2 as;

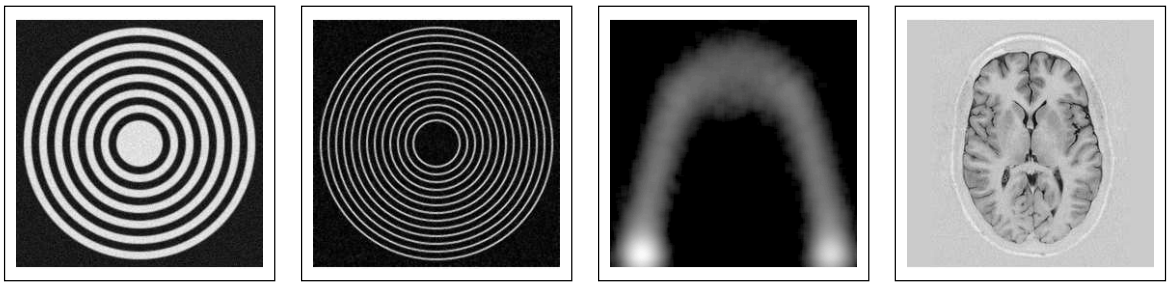
$$P(g,s|i) \propto P(i)P^i_G(g;\mu_i,\sigma)P_{Ray}(s;\frac{\sigma_{noise}}{\sqrt{2}}) + \sum_{j \neq i} P(i,j)P^{i,j}_{GT}(g;\mu_i,\mu_j,\sigma)P^{ij}_{Rice}(s;g,A(g),\sigma) \tag{8}$$

The global likelihood for a given g and s is simply the sum of such probabilities for each tissue class. The only additional component for this model which does not follow directly from standard assumptions is $A(g)$ which must be determined empirically.

Results

In order to test the proposed segmentation method it was necessary to generate synthetic images. Contrast to noise ratios (CNR) were chosen which were in the same range as clinical data. The synthetic image is shown in Figure 1 (a) together with its slope image (figure 1(b)). Figure 1(c) shows the scatter plot of the dependency of slope (y-axis) on grey-level (x-axis). The slope distribution was found to be consistent with the model suggested above. Results for fits to the grey level marginal distribution of this data (circles) are shown as the solid line in Figure 2 (a). Also shown are the separate components of the partial volume and the pure tissue distributions (dashed lines). Figure 2(b) shows a typical result for a full fit (solid line) of the slope distribution (circles) for a limited range of g, which were used to determine $A(g)$ together with the theoretical distribution for the central g value. In general this distribution can be accounted for as a linear combination of a Rayleigh and a Rician distribtuion (shown as dotted lines). We have found that for the image formation process modelled here the slope/greylevel distribution $A(g)$ (in equation 5) is effectively a circular arc joining the mean grey level values (Figure 2 (c)). This distribution can change slightly depending upon the degree of local smoothness but can always be calibrated by the process presented here.

Having confirmed that this model was also sensible on real MR data (Figure 1(d)), we have constructed a three tissue classifier (grey matter (GM), white matter (WM) and cerebrospinal fluid (CSF)) for brain data and compared its performance to partial volume estimation based upon only the grey level. The main differences between volumetric estimates were found in the grey level volumetric probability map (Figure 3 (a) and (b), where the simple technique demonstrates a thin line running close to the edge of the brain and around the edges of ventricles. Since the difference in the grey levels of CSF and of bone is large the gradient segmentation method is be able to distinguish this from pure grey matter. For grey matter white matter segmentation, when working solely with the grey level distribution partial volume effects are almost indistinguishable from noise. As a consequence, the Bayesian volumetric estimate is always biased towards partial volume tissue estimates. By comparison, the



(a) A synthetic two tissue model.

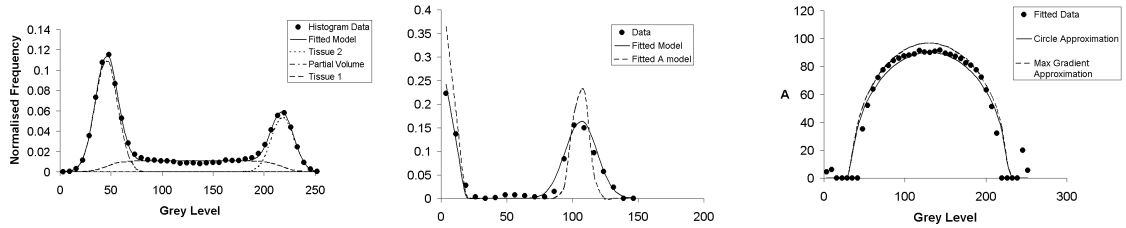
(b) Slope for a two tissue model.

(c) Scatter plot of slope (y) against grey level (x) for the two tissue model.

(d) Inversion Recovery MR Image.

Figure 1: Images for a two tissue model and MR brain.

additional information provided by the gradient based technique allows better separation of true partial volume and pure tissue voxels. Figures 3 (a) and (b) illustrate the elimination of false pure tissues, particularly around the margins of the skull. Figures 3 (c) and (d) illustrate the improvement in partial volume estimation, where a much clearer distinction has been obtained between true pure tissue and partial volume (particularly in white matter). Figure 3 (d) also provides a good illustration of the new techniques ability to extract the grey-matter white matter interface.

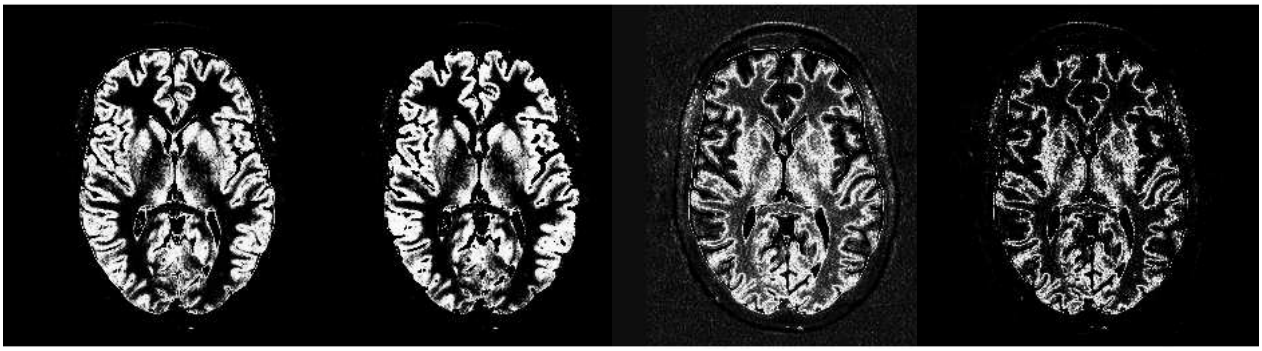


(a) Grey Level Marginal Distribution

(b) Rayleigh plus Rician Model for Slope Distribution at Fixed g.

(c) Mean Value Dependency for Parial Volume Voxels

Figure 2: Marginal Distribution fits.



(a) GM volumes from grey level technique.

(b) GM volumes from gradient technique.

(c) Partial GM/ WM from grey level technique.

(d) Partial GM/ WM from gradient technique.

Figure 3: Typical inversion recovery MR brain image and volume estimation.

Conclusions

In this work a method to utilise not only the grey level information but also the local grey level slope information in a MR image was proposed. The method can be considered as an alternative to both the assumption of local regional smoothness or local resampling of the prior probabilities, which have previously been suggested by other authours [3, 1]. Unlike these methods, local information is used directly in a manner which is quantitatively related to the image formation process. The new gradient technique was found to be applicable to images with CNR that were far below the levels at which the grey level segmentation is unable to unambiguously classify tissue

mixtures. It should be noted however, in images where the CNR is high and there is little partial voluming the two methods provide almost identical results. Also the method presented here is strictly only accurate for 2D data and modifications may be required to the slope distribution for 3D. In previous work we have extended standard volumetric estimation techniques to multiple images. The inclusion of the local grey-level gradient segmentation method into a multi-spectral algorithm offers a promising application for the method. The inclusion of the gradient method adds one extra measurement per image, which in theory could halve the number of required data sets for an accurate segmentation.

It is intended that this new technique will be used to extend our previous method for the analysis of the distribution of cerebral atrophy, to include grey matter volumes [11]. We are also using the technique to impove graphical rendering of 3D MR datasets when using projection techniques such as marching cubes [12]. In addition we intend to use the technique to improve interpretation of metabolite maps returned from chemical shift imaging.

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References

[1] K. W. Fleischer D. H. Laidlaw and A. H. Barr. Partial-volume bayesian classification of material mixtures in mr volume data using voxel histograms. *IEEE Transactions on Medical Imaging.*, 17(1):74–86, 1998.

[2] N. A. Thacker and A. Jackson. Mathematical segmentation of grey matter, white matter and cerebral spinal fluid from mr image pairs. *British Journal of Radiology*, 74:234–242, 2001.

[3] A. Noe and J. C. Gee. Partial volume segmentation of cerebral mri scans with mixture model; clustering. *IPMI*, pages 423–430, 2001.

[4] M. Pokric N. A. Thacker M. L. J. Scott and A. Jackson. Multi-dimensional medical segmentation with partial volumes. *MIUA*, pages 77–80, 2001.

[5] M. Pokric N. A. Thacker M. L. J. Scott and A. Jackson. The importance of partial voluming in multi-dimensional medical image segmentation. *MICCAI*, pages 1293–1294, 2001.

[6] M. W. Vannier R. L. Butterworth D. Jordan W. A. Murphy R. G. Levitt and M. Gado. Multispectral analysis of magnetic resonance images. *Radiology*, 154:221–224, 1985.

[7] L. P. Clarke R. P. Velthuizen M. A. Camacho J. J. Neine M. Vaidyanathan L. O. Hall R. W. Thatcher and M. L. Silbiger. Mri segementation:methods and applications. *Magnetic Resonance Imaging*, 13(3):343–368, 1995.

[8] W. M. Wells W. E. L. Grimson R. Kikinis and F. A. Jolesz. Adaptive segmentation of mri data. *IEEE Transactions on Medical Imaging.*, 15(4):429–442, 1996.

[9] H. Gudbjartsson and S. Patz. The rician distribution of noisy mri data. *Magnetic Resonance in Medicine*, 34:910–914, 1995.

[10] R. Verhagen O. T. Karlsen and W. M. M. J. Bovée. Parameter estimation from rician-distributed data sets using a maximaum likelihood estimator: Application to t_1 and perfusion measurements. *Magnetic Resonance in Medicine*, 41:614–623, 1999.

[11] N. A. Thacker and A. Jackson. Quantification of the severity and distribution of cerebral atrophy provides diagnostic information in dementing diseases. *Radiology*, 2002. in press.

[12] A. Jackson N. W. John N. A. Thacker R. T. Ramsden J. E. Gillespie E. Gobbetti G. Zanetti R. Stone A. D. Linney G . H. Linney G. H. Alushi S. S. Franceshini A Schwerdtner and A. Emmen. Developing a virtual reality enviroment for petrous bone surgery: "a state-of-the-art" review. *Journal of Otology and Neurotology*, 2002. in press.