Estimation of Partial Volume Effect Using Spatial Context. Application to Morphometry in Cerebral Imaging

Thierry Géraud, Lars Aurdal, Henri Maître, Isabelle Bloch,
Département Images, Ecole Nationale Supérieure des Télécommunications,
46 rue Barrault, 75634 Paris CEDEX 13, France
and
Catherine Adamsbaum,
Hôpital St. Vincent de Paul, Service de Radiologie (Pr. Kalifa),
82 avenue Denfert Rocherau, 75014 Paris, France

Abstract

The purpose of the work presented in this article is the estimation of the partial volume effect very often observed in medical image processing. Our working hypothesis is that such partial volume effects will occur in tissue interfaces, the proposed method uses a tissue-labeled distance map to detect tissue interfaces as being those pixels closer to two particular tissues than to any others. The tissue labeled distance map is also used to detect pure tissue means as being the gray-level means of pixels far from tissue interfaces. Knowing the positions of the different interfaces as well as the pure tissue means, we are able to compute the proportion of the two tissues mixed in each pixel of the interface.

I. INTRODUCTION

A problem with virtually all medical imaging devices is the partial volume effect: if the support of an image voxel overlays the boundary between two or more tissues, then the measured intensity value for that voxel will consist of a mixture of partial contributions from all the involved tissue types. Most of the work on segmentation of medical images has been done using algorithms that make 'hard decisions' concerning tissue type i.e. that label a voxel as being of the most predominant tissue type in the voxel. This will inherently reduce precision of morphometric measurements especially in thick-slice 3D scanner acquisition. We overcome this problem by estimating the composition of a mixed voxel using a new approach where contextual information is used to detect tissue interfaces, a tissue interface being defined as the region in the image in which two tissues may interact to produce partial volume voxels. Having located these interfaces and calculated the pure tissue means we compute the proportion of the two tissues mixed in each pixel of the interface.

* This work was supported in part by the French Ministry of Research and by the Royal Norwegian Council for Industrial and Scientific Research.

A. Related Works

Numerous methods aiming at solving these problems have been proposed. Soltanian-Zadeh et. al. [1] use eigenimage filtering. Choi et. al. [2] and Santago et. al. [3] introduce statistical modeling based on Markov random fields (MRF); Johnston et. al. extend this to 3D. Fessler [4] has recently presented a new statistical model for reducing the large computational burdens associated with earlier methods. Finally, Vincken et. al. [5] propose a multi-scale approach in which partial volume voxels are analyzed at a sub-voxel resolution. Unfortunately, existing methods do not take large scale spatial context into consideration.

B. Image Material

The images used during this study were made using an 0.5T MR scanner (General Electric) installed at the Cochin hospital in Paris. The patients under study suffer from adrenoleukodystrophy (ALD) [6], a serious genetic disorder characterized by multi-focal demyelinisation of the central nervous system along with adrenal insufficiency. It is associated with an impairment of the degradation of saturated very-long-chain fatty acids. ALD has a wide phenotypic variation, but most cases appear in childhood or adolescence as devastating degenerative neurological disorders leading to major neurological deterioration and death within a few years [7].

A typical MR examination of a patient suffering from this disease lasts about 30 minutes, allowing for the acquisition of images of twelve axial and frontal slices of the brain. The thickness of each slice is 7 mm, a gap of 1 mm is left between each slice. Figure 1a) shows one of the axial slices with key anatomical features indicated. Due to the thickness of the slice, numerous partial volumes are to be found. As can be seen in 1a), gray-level values varies strongly in the pathological region.

II. PROPOSED ALGORITHM

Estimating the partial volume voxel tissue content requires knowledge of the spatial interaction between the classes

0-7803-3180-X/96$5.00©1996

that gave rise to the partial volumes. We propose an algorithm in which such contextual information is taken into account in order to obtain reliable estimations. Having calculated a class-labeled distance map (CLDM), we deduce the pure-tissue gray-level means as well as what classes might have interfered to produce the partial volume voxels. This permits estimation of tissue fractions in each voxel.

A. *Calculating the CLDM*

Starting from an initial crisp and rough classification of the image to be processed, a map of distances to all class borders is calculated using the chamfer transform [8]. In addition to propagating distances, we also propagate the class defining the border from which the distance is measured. Thus we know, for each voxel in the image, its a priori class label (as given by the original classification) and we have found the distance from its class boundary as well as a label indicating to which neighboring class this voxel is closest.

Figure 1b) shows the result of an MRF-based segmentation [9] of the original image in figure 1a) which provides the a priori class labels in the following process. Part c) shows the labeling of voxels obtained with the extended chamfer transform explained above. Consider for instance point 1 in part b); this point clearly belongs to the brain matter class. In part c) we see that this point has been labeled so as to indicate that its closest neighboring class is disease. Points 2 and 3 can be seen to fall within the disease class but have different closest neighboring classes, brain matter and ventricles respectively, as indicated by their label in part c). Finally, point 4, being in the ventricles, has disease as closest neighboring class.

B. *Calculating Pure Tissue Means*

As explained above, generation of the quantization tables to be applied to each interface depends on estimates of the pure tissue means. Assuming that the interior regions of each tissue are pure (in the sense that only the tissue type in question occurs), such estimates are easily obtained using the CLDM. We base our estimates on the gray-level values of voxels that are in the interior of each class, that is, voxels that are at a certain distance from all tissue interfaces. Figure 2 shows the evolution of gray-level means as a function of the distance from the interface of *brain matter* with *disease*. Starting at a certain negative distance from this interface (that is, in the interior of the brain matter tissue) we observe that the gray-level mean is stable until we are at a distance of about -5. At this point we are sufficiently close to the interface to observe the onset of a mixture with disease tissue and gray levels will gradually change from that of pure brain matter to that of pure disease. As is evident from this figure, the pure tissue means can be obtained from the interiors of the different tissues, i.e. in regions where the gray-level mean is stable.

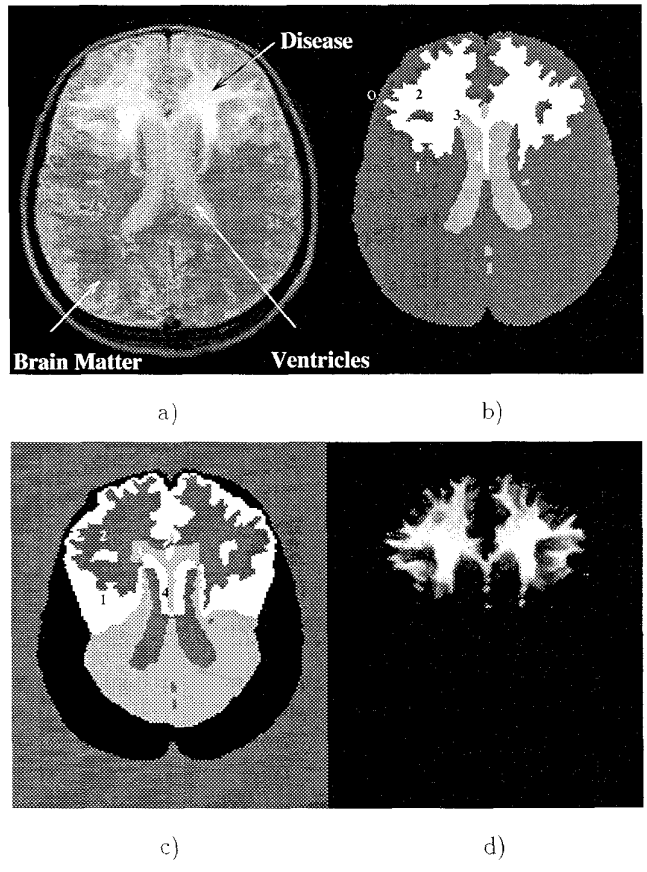

Figure 1: Illustration of the algorithm.

C. *Estimating Disease Content*

Now consider searching for all voxels that may contain disease tissue. These voxels are to be found in the two interfaces *disease/brain matter* and *disease/ventricles*; these interfaces are easily identified using the label images shown in parts b) and c): for instance, points 1 and 2 belong to the interface *disease/brain matter* and points 3 and 4 to the interface *disease/ventricles*. Using estimates of the pure tissue means (see below), we calculate for each interface quantization tables indicating the link between voxel gray levels in the original image and the corresponding disease tissue content.

Part d) shows the fractional content of disease tissue for each voxel in the original image limited to the two interfaces previously defined. A measure of the pathological region volume is finally obtained by summing these fractions.

III. Discussion and Conclusion

We have introduced the CLDM as a contextual approach to partial volume estimation. Using the distance map we are capable of selecting voxels in each class that are far from any border in order to calculate accurate class gray-level

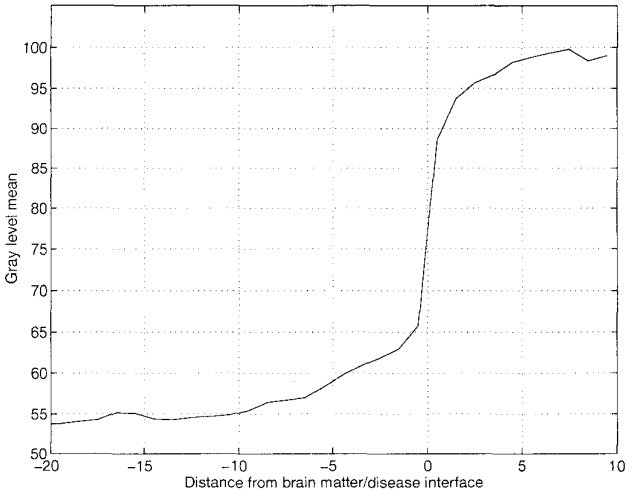

Figure 2: Change in gray level means as a function of distance from the interface between brain matter and disease.

means. Due to this, our estimations are not influenced by partial volume effects and are not sensitive to the shape of the initial segmentation. The second advantage of the CLDM is that it will identify the different types of tissue interfaces. This allows us to treat each interface separately (by applying different quantization tables) instead of globally as with classical methods; this guarantees more precise measurements of tissue fractions. Compared with hard decision based morphometric approaches, we are no longer as dependent on the shape of the region in which the volume is estimated due to the fact that the voxel volumes are weighted using their tissue fractions. It should be pointed out that all algorithms used in this study have been extended to 3D and that the proposed methods are applicable also in 3D . Note that the calculations of tissue mixture assume linear variation of gray levels with respect to tissue fraction.

REFERENCES

[1] H. Soltanian-Zadeh, J. Windham and A. Yagle, "Optimal Transformations for Correcting Partial Volume Averaging Effects in Magnetic Resonance Imaging", *IEEE Transactions on Nuclear Science*, 40(4):1204–1212, August 1993.

[2] H. Choi, D. Haynor and Y. Kim, "Partial Volume Tissue Classification of Multichannel Magnetic Resonance Images- A Mixel Model", *IEEE Transactions on Medical Imaging*, 10(3):395–407,September 1991.

[3] P. Santago and H. Gage, "Quantification of MR Brain Images by Mixture Density and Partial Volume Modeling", *IEEE Transactions on Medical Imaging*, 12(3):566–574, September 1993.

[4] J. Fessler, "A Mixture Model for Edge Preserving Image Restoration", in *Proceedings ICIP-94*, 3:162-166, November 1994.

[5] K. Vincken, A. Koster and M. Viergever, "Probabilistic Segmentation of Partial Volume Voxels", *Pattern Recognition Letters*, 477-484, May 1994.

[6] H. Moser, S. Naidu, A. Kumar and A. Rosenbaum, "The Adrenoleukodystrophies", *Critical Reviews in Neurobiology*, 3(1):29–88, 1987.

[7] P. Aubourg, S. Blanche, I. Jambaqué, F. Rocchiccioli, G. Kalifa, C. Naud-Saudreau, M. Rolland, M. Debré, J. Chaussian, C. Griscelli, A. Fischer and P. Bougnères, "Reversal of Early Neurologic and Neuroradiologic Manifestations of X-Linked Adrenoleukodystrophy by Bone Marrow Transplantation", *The New England Journal of Medicine*, 322(26):1860-1866, June 1990.

[8] G. Borgefoss, "Distance Transformations in Digital Images", *Computer Vision, Graphics, and Image Processing*, 34:344-371, 1986.

[9] L. Aurdal, X. Descombes, H. Maître, I. Bloch, C. Adamsbaum and G. Kalifa, "Fully Automated Analysis of Adrenoleukodystrophy from Dual-Echo MR Images", in *Proceedings CAR-95*, Berlin, 35-40, June 1995.