

The Effects of Magnetic Resonance Image Inhomogeneities on Automated Tissue Classification

Stephen Aylward and James Coggins
Department of Computer Science
University of North Carolina at Chapel Hill

Ted Cizadlo and Nancy Andreasen
Department of Psychiatry
University of Iowa Hospitals and Clinics

Introduction

A magnetic resonance (MR) imaging system measures the magnitude and relaxation rate of the inductive field generated by a sample when the axis of the proton spin of a portion of its atoms become partially aligned by a strong magnetic field [6]. Image quality is highly sensitive to slight variations in the consistency of either field. Field inhomogeneities may result from variations in the densities and magnetic properties of the sample. They create intensity gradients across the image [3, 6]. These gradients are barely visible, but they prevent the automated labeling of the tissues based on point operations on the multiecho data. Advances in MR systems have reduced these effects, but they are still present in modern MR systems [3]. An automated tissue classification algorithm robust in the presence of these distortions will extend the useful lifetime of older equipment and potentially reduce the cost of purchasing and maintaining newer equipment.

Consider the registered proton density (PD) and T₂-weighted multiecho images shown in Figures 1 and 2. There exists a visible darkening of these images in the inferior cerebellum. The scattergram of these images in Figure 3 shows a poor separation of the gray and white matter tissues. This effect is further illustrated in Figure

4, which shows histograms of the PD values from hand-labeled gray and white matter pixels from several training images. The histograms of both classes are skewed, suggesting that a gaussian fit is not ideal for these observed distributions. The intensity distortions are reflected in a negative correlation between the PD values of pixels in each tissue class and the row number of those pixels.

MR Methods and Data Processing

For all experiments presented in this paper, the training data consists of hand labeled pixels from three coronal slice images. Figures 1 and 2 are one of the 57 slices used for testing. This data was collected during a single scanning run on a 1.5 Tesla GE MRI system at the University of Iowa. MR parameters were chosen to provide the best visual separation of the classes (echo time = 32 and 96 msec with repetition time = 3,000 msec). The slices are 3 mm thick and contiguous. The gray matter in Figures 1 and 2 has also been hand segmented. These labeled testing pixels are used to quantify the performance of the classifiers discussed.

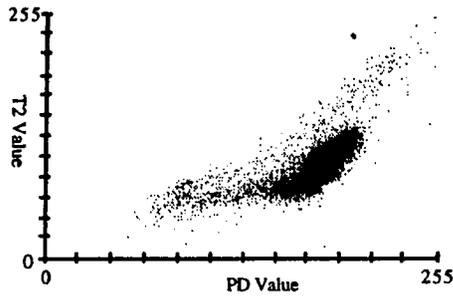
In order to suppress the high-frequency noise in the images while maintaining sharp edges, variable conductance diffusion is applied [9]. This algorithm uses gradient information from both the



Test PD MR Image
Figure 1



Test T₂ MR Image
Figure 2



Scattergram of Figures 1 and 2
Figure 3

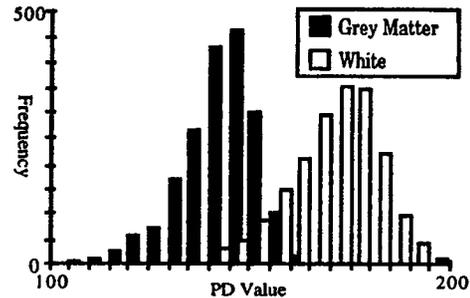
PD and T₂ images to control the diffusion process. Twenty iterations were run with conductance = 3 and $\sigma = 0.6$ so that small image structures are preserved. The end result is an improvement in the separation and variance of the tissue classes in feature space. This process provides only minimal compensation for the intensity distortion.

Two Dimensional Feature Space

The PD and T₂ values at each pixel provide the coordinates of that pixel in the two dimensional feature space commonly used by MR classification methods (Figure 3) [1, 3, 4, 5, 6, 8].

To label pixels in test images, a gaussian density can be fitted to the observed distribution of pixels in each class. A maximum likelihood estimator can then be developed using the fitted densities. This is the most common process for MR pixel labeling [1, 3, 4, 5, 6].

Feature space is optimized by computing eigenvectors of the Hotelling matrix, $H = S_b S_w^{-1}$. This matrix is a multivariate signal-to-noise ratio that has been shown to correlate with discrimination in human perception. Eigenvectors of this matrix define a new basis for the feature space based on how well the features separate the classes defined by the training data. The



Histograms of Gray and White
Matter PD Values in Training Data
Figure 4

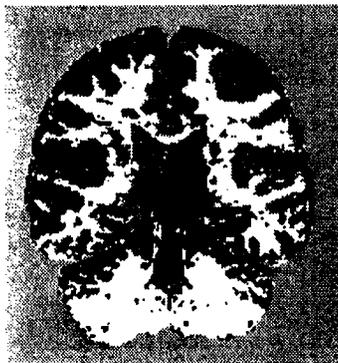
minimum Mahalanobis distance of test pixels from the class-conditional densities provides the maximum likelihood assignment of pixels to classes [2, 4, 9].

Classification of Figures 1 and 2 using a gaussian classifier based on the optimized basis defined by the eigenvectors of the Hotelling matrix yields the labeling shown in Figure 5. While the classification is accurate in the upper portion of the image, poor labeling occurs in the lower part. This classifier misclassified 29.1% of the hand labeled gray matter test pixels.

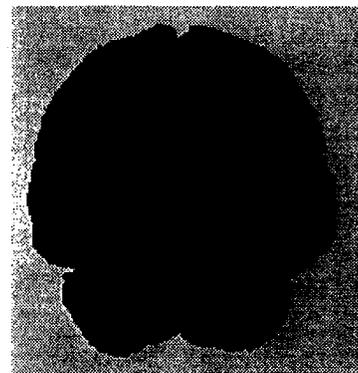
Augmenting Feature Space

A map of the intensity distortion is obtained by calculating the mean of the gray matter class as a function of the row and column number. Figure 6 shows the map generated from the training data. The correlation visible in the figure suggests that improved classification might result if the row number and perhaps also the column number are added as features.

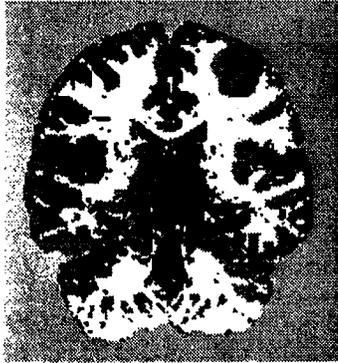
Using the four dimensional feature space (PD, T₂, row, and column) a gaussian classifier does yield improved results (Figure 7). Gray matter misclassification is reduced to 16.8%. However, overlaying the approximated class



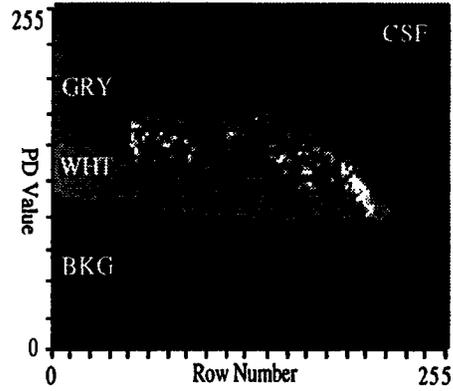
Gaussian Classification
Using PD and T₂ Values
Figure 5



Map of the Intensity
Deformations Affecting Classification
Figure 6



Gaussian Classification Using PD, T₂, Row, and Column Information
Figure 7



Location of Classes in Row Versus PD Feature Space with T₂ = 175
Figure 8

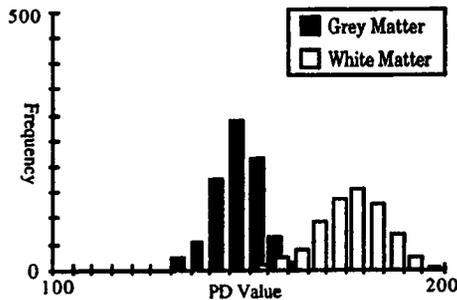
distributions onto the distribution of the PD values for the hand labeled gray matter test pixels indicates that a single gaussian does not capture all of the deformation (Figure 8).

Improving the Classifier

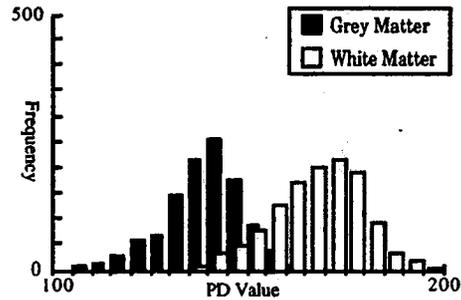
A more accurate model of the distribution of the classes in feature space can be obtained by

using a gaussian mixture model. The classifier uses multiple gaussians to represent each class. For this study, the training data for each class was manually separated into two subclasses using a hyperplane at the point of highest curvature in the feature space. This point corresponds roughly with the top of the cerebellum, row number 175.

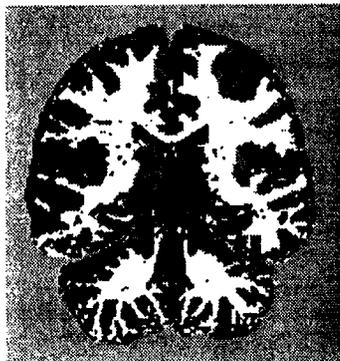
The resulting eight class classifier (gray matter below row 175, gray matter at or above row



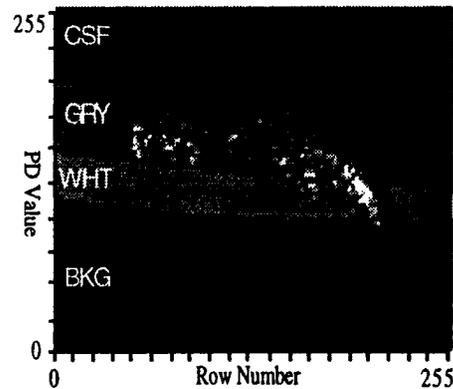
Histogram of PD Values for Gray and White Matter for Training Subclass with Row < 175
Figure 9



Histogram of PD Values for Gray and White Matter for Training Subclass with Row >= 175
Figure 10



Subclass Gaussian Classifier Results
Figure 11



Location of Classes in Row Versus PD Feature Space with T₂ = 175
Figure 12

175, etc.) was created by treating each subclass as a unique class and then applying standard gaussian classification techniques. This produced a much more accurate system.

Figures 9 and 10 show how the partitioning of the training data isolates the skewness to just one of the subclasses. Notice the reduction in class overlap and the increase in distance between the means when compared with Figure 4. Figure 11 shows the accurate labeling of the test data in both the upper and lower portions of the image. Gray matter misclassification is reduced to 7.4%. Figure 12 depicts the modeling of the classes in feature space which is achieved using this technique.

From the labeling of the 57 test slices it is possible to reconstruct the 3D structure of the sample being imaged. Figure 13 shows one view of this data as displayed by a real-time 3D volume visualization tool which is under development at the Department of Radiology in the School of Medicine at the University of North Carolina.



*Real-Time Volume Rendering
of the 3D Structure Reconstructed
from the Classified Slices*
Figure 13

Conclusion

Inhomogeneities in the generated and induced fields of MR systems produce nonlinear intensity distortions in the resulting MR image data. An analysis of feature space clearly shows that these inhomogeneities reduce classification accuracy when standard classifiers and feature spaces are used. Improved labeling of tissues in MR images can be achieved by augmenting feature space with spatial information and increasing the class representation capabilities of the classifier using mixture modeling techniques.

Current work is focusing on implementing an automated mixture model clustering algorithm. This should both simplify and improve the accuracy of the MR classification process. Additional work is being performed on the 3D visualization tool and on the multimodal variable conductance diffusion algorithm.

We would like to thank Terry Yoo, Mike North and Graham Gash from UNC for their assistance with this project. We would also like to thank Victor Swayze from the Veterans Affairs Medical Center in Iowa City for his insight into the issues of MR tissue classification.

References

- [1] Cohen, G. et al, "Segmentation Techniques for the Classification of Brain Tissue Using Magnetic Resonance Imaging", *Psychiatry Research: Neuroimaging*, Elsevier, Vol. 45, 1992. pp. 33-51
- [2] Duda, R. and Hart, P., Pattern Classification and Scene Analysis, John Wiley and Sons, 1973
- [3] Gerig, G. et al, "Automating Segmentation of Dual-Echo MR Head Data" *Information Processing in Medical Imaging*, Springer-Verlag, 1991
- [4] Hanson, K., "Introduction to Bayesian Image Analysis", SPIE Medical Imaging, Vol. 1898, 1993
- [5] Kubler, O. and Gerig G., "Segmentation and Analysis of Multidimensional Data-Sets in Medicine", *3D Imaging in Medicine*, Springer-Verlag, 1990
- [6] Loeffler, W., "Magnetic Resonance Imaging", *3D Imaging in Medicine*, Springer-Verlag, 1990
- [7] McLachlan, G. and Basford, K., Mixture Models: Inference and Applications to Clustering, Marcel Dekker, INC. 1988
- [8] Vandermeulen, D. et al., "Continuous Voxel Classification by Stochastic Relaxation: Theory and Application to MR Imaging and MR Angiography" *Information Processing in Medical Imaging*, Springer-Verlag, 1993
- [9] Yoo, T. and Coggins, J., "Using Statistical Pattern Recognition Techniques to Control Variable Conductance Diffusion", *Information Processing in Medical Imaging*, Springer-Verlag, 1993