An MLE Based Segmentation Method for Quantitation in MR Images


¹Indian Institute of Technology Kanpur, Department of Mathematics, IIT Kanpur - 208016 INDIA, KANPUR, U.P. INDIA; ²Indian Institute of Technology, Kanpur, Department of Mathematics, KANPUR, U.P. INDIA; ³SGPGIMS, Lucknow, MR Section, Department of Radiology, SGPGIMS, Raebareli Road, Lucknow, India, LUCKNOW, U.P. INDIA; ⁴IT Kanpur, Department of Mathematics, IIT Kanpur, KANPUR, U.P. INDIA;

Introduction
The success of MR Images in soft-tissue differentiation goes hand in hand with their complexity, resulting in problems in their segmentation so crucially needed in current quantitation studies. Since the supervision of a clinician in the segmentation is to be a minimum, the robustness of segmentation methods can not be over emphasized. Due to the high signal variation in MR images, the experience of classical image segmentation methods applied to them has been quite frustrating. Going by the fact that modelling of pathological and normal tissue signals using binomial or poisson processes in the large leads to normal distributions and further that a contribution of many independent causes also gives rise to normal distributions, it seemed natural to try modelling the totality of pixel intensities as a mixture of a number of normal populations of different size ratios [1]:

![Equations 1](image)

Encouraged by the resulting excellent frequency fits the idea was extended to base the present method of segmentation on the same. The results of the segmentation procedure applied on a set of images from a typical brain study on epilepsy follow.

Methods
MRI of a patient with seizures having a frontal lobe cystic cavity with perilesional gliosis was performed on a 1.5 T superconducting system using circularly polarized head coil. Conventional PD, T2 (TR/TE/1,2/n=2200/12,80/1) and T1 (1000/14/2) weighted SE images were acquired in axial plane using 256x256 matrix size, 0.1mm interslice gap and 5mm slice thickness. MT SE T1 weighted MR imaging was also performed with exactly the same parameters as for T1 weighted case except for the off-resonance pulse. In proton density and MT images the appearance of gliosis is hyperintense as compared with cystic cavity while both the cystic cavity and the gliosis are equally hyperintense in T2 weighted image. The gliosis is isointense in T1 weighted image with the surrounding tissues. The mixture density allows easy derivation of the ML equations consistent with following proposed iterative scheme:

![Equations 2](image)

Following determination of ratio, mean and variance parameters of the m-populations the simple applied segmentation procedure is to classify a given pixel to the k-th population if the pixel intensity ‘x’ maximizes the k-th density function (cf. [2]).

In the illustrations below each of the PD, T1, T2, MT images were segmented around the ROI of gliosis and the cystic cavity for examining their relative suitability for quantitative studies.

Results
The first row in Fig. 1 (L to R) shows proton density, T2 and MT T1-weighted images. The corresponding segmented images are shown in the second row (L to R). The first two images in the third row are the T1-weighted and its corresponding segmented image. The last image of the third row shows the excess of the gliosis visible in MT image as compared to the PD image. The respective segments were obtained by using the MLE technique and the two regions were superimposed after coloring the PD segmented part by checkered pattern. The areas estimated from the segments show that the segmented part of the gliosis as seen on MT image is in excess of about 60% of that on the PD image. The cystic cavity and the gliosis separation is not clear on the T2 weighted image where the gliosis merges with the cystic cavity. On the other hand, in the T1 weighted image, the gliosis seems to merge with the white matter.

![Fig. 1](image)

A plot of the constituents of the mixed normal fit, with m=14, for the PD weighted image is shown in Fig. 2. The goodness of the fit and the resulting applicability of it as expected.

![Fig. 2](image)

Discussions
The segmentation based on mixed normal MLE seems quite robust with relatively fewer misclassifications and provides an attractive methodology towards automated segmentation. The possibilities of misclassifications could be minimized by restricting the analysis as close to ROI as possible. The connectivity in the segmentations, i.e., avoiding the perforations, could be improved by a smoothing of the image and/or by going to the heigher resolutions utilizing zero padding. A look at the table appended shows that the standard deviations in the gliosis segments of PD and MT images are respectively 2.54 and 2.19, which are reasonably small indicating the success of the present MLE technique. However, the associated gray level differences could be quite large explaining why method based on thresholds may not provide satisfactory segmentations.

References

<table>
<thead>
<tr>
<th>Table 1</th>
<th>mean</th>
<th>s.d.</th>
<th>no. of pixels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gliosis on PD</td>
<td>145.11</td>
<td>2.54</td>
<td>331</td>
</tr>
<tr>
<td>Gliosis on MT</td>
<td>81.80</td>
<td>2.19</td>
<td>528</td>
</tr>
</tbody>
</table>