Title	Inhomogeneity correction of magnetic resonance brain images
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NANYANG TECHNOLOGICAL UNIVERSITY

URECA *Undergraduate Research Experience on CAmpus*

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Abstract

Magnetic resonance imaging (MRI) is a widely used noninvasive visualization technique in medical field. The images acquired often suffer from intensity nonuniformity, or inhomogeneity, which hampers automated analysis of the images. This artifact is mainly caused by the radio frequency (RF) coil design, gradient-driven eddy currents, and acquisition pulse sequences. In this research, we are focusing on techniques to correct the intensity inhomogeneity by performing a coarse preliminary segmentation on the MR images and then use the segmentation result to estimate the bias field.

I. Problem Statement

The intensity inhomogeneity is the variation of image intensity in a region of homogeneous tissue. Figure 1 shows a brain image acquired by a MRI scanner, which exhibits this artifact.

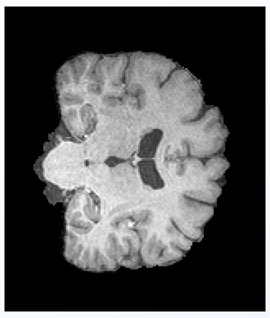

Figure 1 A brain image acquired by a MRI scanner, which exhibits intensity nonuniformity. The center left part appears to be brighter than the rest of the image.

The problem of intensity inhomogeneity is often modeled as a smooth multiplicative bias field and an additive noise corrupting the true image. By taking the logarithm of the image intensities, the multiplicative bias field becomes additive [1-2] as below:

$$V(\mathbf{x}) = U(\mathbf{x}) + B(\mathbf{x}) + N(\mathbf{x}) \qquad (1)$$

where ***x*** is a pixel, *V(**x**)*, *U(**x**)*, *B(**x**)* and *N(**x**)* are the logarithms of the acquired image, artifact free image, bias field, and noise, respectively. We capture the smooth-varying bias field using linear combination of *P* Legendre polynomials [3].

$$b(\mathbf{s}) = \sum_{k=1}^{P} a_k \varphi_k(\mathbf{s}) \qquad (2)$$

Where ***s*** is a pixel, a_k is the coefficient of the *k*-th basis function and φ_k is the *k*-th degree Legendre polynomial.

II. Bias Field Estimation

By representing the bias field using linear combination of basis functions, equation (1) can be written in matrix form as:

$$v = Am + n \qquad (3)$$

where *v* is a row matrix of logarithmic pixel intensities, *m* is the unknown parameters to be estimated, *n* is the noise, which is ignored in the estimation, matrix *A* has the following form:

$$A = \begin{bmatrix} \varphi_1(v_1) & \cdots & \varphi_P(v_1) & 1 & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \varphi_1(v_{N_1}) & \cdots & \varphi_P(v_{N_1}) & 1 & 0 & \cdots & 0 \\ \varphi_1(v_{N_1+1}) & \cdots & \varphi_P(v_{N_1+1}) & 0 & 1 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \varphi_1(v_{N_1+N_2}) & \cdots & \varphi_P(v_{N_1+N_2}) & 0 & 1 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \varphi_1(v_N) & \cdots & \varphi_P(v_N) & 0 & 0 & \cdots & 1 \end{bmatrix}$$

where v_i is the Cartesian coordinate of the pixel s_i. N_i is the number of pixels for region *i*. The least-squares error (LSE) estimation of *m* is given in [4] as:

$$m = (A^T A)^{-1} A^T v \qquad (4)$$

III. Performance Evaluation

The variance of the estimated bias field is obtained from the covariance matrix below, which is part of equation (4).

$$\Sigma = (A^T A)^{-1} \qquad (5)$$

The averaged over all pixels estimation error variance is given by the sum of the main diagonal of Σ divided by the total number of pixels, *N*. For a 2D square image with 1 square segmented region of size N_1, the average error variance, v_1^2, is found to be:

$$v_1^2 = \frac{2(\sqrt{N})}{(\sqrt{N_1})^3} \qquad (6)$$

To achieve an error variance of less than 0.1, the size of the segmented region N_1 should be at least 35% of *N*.

IV. Implementation

A GUI-based application program for implementing the algorithm has been developed using Matlab®.

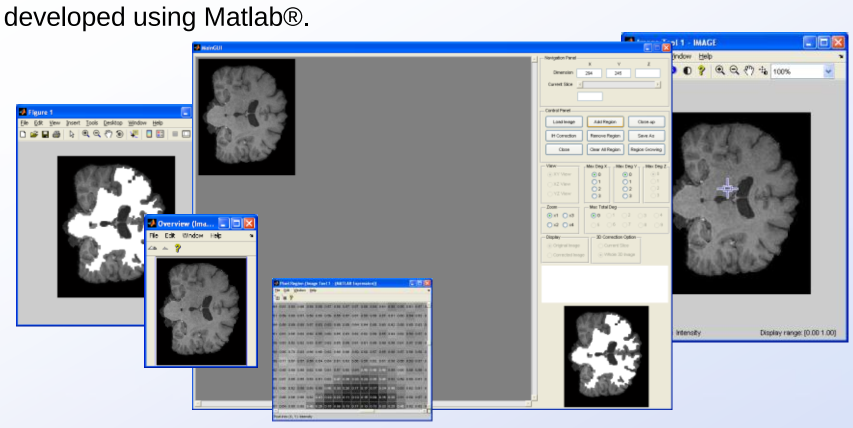

Figure 2 A GUI-based application developed using Matlab®.

V. Practical Results

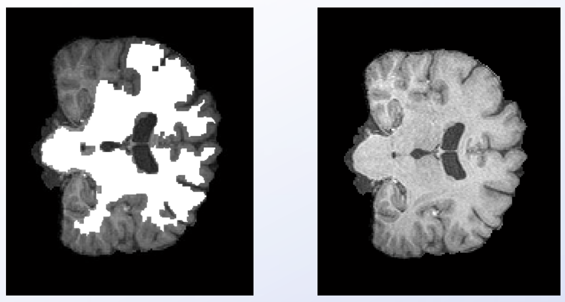

Figure 3 Result of inhomogeneity correction. The region in white of the left MR image shows the segmentation result of Figure 1 using region growing method. The MR image on the right shows the corrected image of Figure 1, where the intensity variation among its white matter has been reduced.

VI. Future Work

For theoretical part, we would like to extend the performance estimation to non-linear bias field. In the practical part, we would like to develop methods to perform the selection of seed and segmentation automatically.

References

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