MR image intensity inhomogeneity correction

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Abstract. MR technology is one of the best and most reliable ways of studying the brain. Its main drawback is the so-called intensity inhomogeneity or bias field which impairs the visual inspection and the medical proceedings for diagnosis and strongly affects the quantitative image analysis. Noise is yet another artifact in medical images. In order to accurately and effectively restore the original signal, reference is hereof made to filtering, bias correction and quantitative analysis of correction. In this report, two denoising algorithms are used; (i) Basis rotation fields of experts (BRFoE) and (ii) Anisotropic Diffusion (when Gaussian noise, the Perona-Malik and Tukey’s biweight functions and the standard deviation of the noise of the input image are considered).

Keywords: MR images; Basis rotation fields of experts; Anisotropic Diffusion; bias field correction; image quality assessment

1. Introduction

Generally, pertaining to neurological research, MR technology is one of the best and most reliable ways of studying the brain. Various methods and procedures for the quantitative study of different brain pathologies were developed since the MRI technique has been elaborated [1-16]. In spite of the huge progress recorded by the means of this technique, different artifacts such as noise, poor homogeneity in the radiofrequency, and intensity inhomogeneity or bias field may be present in the images. These artifacts are corrected by using various mathematical algorithms which mainly focus on noise removal, inhomogeneity correction, contrast enhancement or edge emphasizing [1-7].

The aim of this paper is that of providing an accurate insight into the effective restoration methods of the original signal. Statistical method, diffusion method and intensity inhomogeneity or bias field correction method are used. In addition, the quality of the processed images is also an important factor that is being taken into consideration. This work particularly focuses on brain MR images, although such artifacts appear in all MRI techniques.

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2. Methodology

2.1. Experimental dataset
The data sets used in this study are freely available for download from ‘The whole brain atlas’ database of the Harvard Medical School's Whole Brain Atlas. The MR images measure (256 × 256). The total number of the images selected in our database was 42. The following diseases were investigated: cerebrovascular diseases/fatal stroke; carcinoma; Creutzfeld-Jacob disease and Alzheimer disease (figure 1). (http://www.med.harvard.edu/AANLIB/home.html)

![Brain MR images in axial views](image)

**Figure 1.** Examples of brain MR images in axial views. (a) Normal cognitive in axial view (NCAx); (b) normal cognitive in sagittal view (NCSag); (c) carcinoma (Car); (d) acute stroke (ASK); (e) Creutzfeld-Jacob disease (CJ); (f) fatal stroke (FSk); (g) Alzheimer's disease (AzD).

The experimental methodology was developed by using the Matlab ver. R2010a software (The Mathworks Inc., Natick, MA).

2.2 Anisotropic diffusion
The concept of anisotropic diffusion (AD) has been introduced by Perona and Malik [8] and it refers to the restoration of the images against the destruction of the features of the images due to noise artifacts. The AD model uses the image intensity as a ‘concentration’ and noise as a ‘little concentration inhomogeneity’. The conductance function, the gradient threshold parameter and the stopping time of the iterative process are the parameters that govern the anisotropic diffusion process and they were presented in [8]. The following conductance functions are used: the Gaussian filter and the results of the filtration operation are referred to as AD1; \( g_1 = \exp \left[ -\left( \frac{x}{K \sqrt{2}} \right)^2 \right] \) denotes the Perona and Malik conductance function [9]. \( K \) is the gradient magnitude threshold parameter that controls the rate of the diffusion. The results of this filter algorithm are referred to as AD2. The second conductance function used in our study is Tukey’s biweight function [10]

\[
g_2(x) = \begin{cases} 
0.67 \left[ 1 - \left( \frac{x}{S} \right)^2 \right]^2, & x \leq S \\
0, & \text{otherwise}
\end{cases}
\]

defines the threshold between the image gradients corresponding to the noise and those attributed to the true edges. The experimental results of this filter are referred to as AD3. In [9], an estimation of the standard deviation \( \sigma \) of the Gaussian noise of the original image as a stopping time parameter was used. Two cases were analyzed: the standard deviation of the noise of the input image is known a-priori (referred to here as AD4) and the standard deviation of the noise is estimated automatically (referred to here as AD5).

2.3 Basis rotation fields of experts
The Basis Rotation algorithm is part of Field of Experts models (BRFoE) was set up in [11] in order to improve the maximum likelihood filters performance in denoising task. They claimed that BRFoF filter shows a very good denoising performance. The optimization of the filters is done by using the
principle of maximum likelihood. The main improvement brought by the BRFoE is broader in frequency.

2.4. Bias field correction

The intensity inhomogeneity or bias field in MR images represents a smooth variation of signal intensity across the image. In [12] the intensity inhomogeneities are derived and estimated by using the local intensity clustering property. It allows an energy functional to be defined, which is integrated in a level set formulation. In a two-phase level set formulation, intended for the reading of brain MR images, the intensities within each brain tissue become quite homogeneous in the bias corrected images. For a precise evaluation and comparison of the algorithms the following objective quality metrics are used: the mean squared error (MSE), the peak signal to noise ratio (PSNR), the average difference (Av Diff) and normalized absolute error (NAE). As correlation-based measurements the normalized correlation (NC) and the structural content (SC) are considered [13-15].

3. Results and discussions

![Graphs showing objective quality measures](image)

**Figure 3. Objective Quality Measures for different algorithms and various brain MR images**

Figures 1 to 6 comparatively show the computed quality metrics. It can be observed that, the BRFoE algorithm operates better in the case of noise removal for all MR analyzed images. In the case
of the anisotropic diffusion algorithm, Tukey’s biweight function (or AD3) and the standard deviation of the noise automatically estimated as $\sigma = 0.002$ (or AD5) are the best de-noising methods. The metrics that were most sensitive to the bias field and to image set variation were NC and SC.

Regarding the image type, the Alzheimer disease is the most responsive to the current analysis as it strongly correlates these metrics but in a negative way. These images are strongly affected by noise and their structural content is affected by de-noising and bias field correction operations.

The case of bias correction is a special one. The bias field is quite smooth and most parts cover the anatomical structure. The bias removal was conducted under the regularization of the level set formulation. This algorithm performs well in the case of for normal cognitive in axial view, carcinoma and acute stroke MR images. During the bias field correction a part of the pixels were removed from the bias corrected images. The pixel distribution value was checked and it was found that the range of the intensity of the gray level became narrower because some pixels, especially in the range from 190 to 255 were removed. This clearly affects the objective quality measures. Thus, NAE is ranging from 0.3606 for the acute stroke to 6.977 for Alzheimer disease. Similar data has been also found for NC (as a global measure, which compares the total weight of the corrected image and original image) and SC (that provides the closeness between the original and decoded image) measurements.

4. Conclusions
The experimental results indicate that the objective quality measurements such as MSE, PSNR and NC are close to the optimum values. Special attention was paid to the bias correction technique that shows a very high variation due to the number of pixels variation performed by the algorithm.

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