# An Efficient MR Inhomogeneity Corrector Using Regularized Entropy Minimization

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## Introduction

MR images usually exhibit intensity inhomogeneity (aka bias field or shading) due to imperfections of image acquisition process, such as magnetic field non-uniformity and radiation-patient interactions[1]. Manifesting itself as spatially slow varying intensities, the inhomogeneity reduces the image quality and is unfavorable for image perception and diagnosis. In the literature, both prospective and retrospective bias-field reduction has been proposed[1]. Retrospective approaches have more flexibility of being data-driven compared to prospective correction which usually requires a specific protocol prior to patient scans. In this work, we propose a nonparametric 3-dimensional retrospective bias corrector by minimizing a regularized-entropy criterion. Numerically, the proposed solver is particularly efficient, scalable and parallelizable compared to existing entropy-based approaches. The effectiveness and the robustness of the corrector have been confirmed by vast clinical evaluations on breast and brain applications.

## Method

We consider the bias field as a point-wise multiplicative artifact. Applying the logarithmic scale, the bias $H$ is converted to an additive component: $y(\vec{x}) = H(\vec{x}) + y_0(\vec{x})$. Here $y$ and $y_0$ are respectively the observed and the bias-free images, both in logarithmic scale, and $\vec{x} = (x; y; z)$ the location of any voxel. We estimate $H$ by minimizing the following constrained energy: $\text{argmin}_{H \in C}\, J(H) \coloneqq \mathcal{E}(H) + R(H)$. The term $\mathcal{E}(H)$ quantifies the Shannon entropy of the image $y_0$, which can be approximated by the image log-likelihood: $\mathcal{E}(H) = -\sum_n W(\vec{x}_n) \log \Pr\big(y(\vec{x}_n) - H(\vec{x}_n)\big)$. Here, $\Pr(l)$ represents the probability of intensity level $l$; $W(\vec{x}_n)$ denotes a binary mask with zero value for background and unity for the object of interest; the subscript $n$ indexes the voxels. Next, the term $R(H)$ applies a regularity prior on the bias field using fractional Laplacian operator: $R(H) = \left\| D_\lambda^\beta H \right\|^2$ with $D_\lambda^\beta H(\vec{x}) = \left( -\lambda_x^2 \frac{\partial^2}{\partial \vec{x}^2} - \lambda_y^2 \frac{\partial^2}{\partial \vec{y}^2} - \lambda_z^2 \frac{\partial^2}{\partial \vec{z}^2} \right)^\beta H(\vec{x})$ and $\beta, \lambda_x, \lambda_y, \lambda_z > 0$. Finally, the constraints $C$ impose field bounds $H_{min} \le H(\vec{x}) \le H_{max}$ as well as an average-preservation condition $\sum_n H(\vec{x}_n) = 0$. In order to numerically estimate $H$, we propose to apply the Alternating Direction Method of Multipliers[2] which alternatively relaxes and minimizes the constrained entropy and the regularization terms. It turns out that the minimizations only involve point-wise operations in the image and in the discrete cosine transform domains. This makes the entire algorithm highly efficient, scalable and parallelizable.

## Results

Our method was clinically evaluated on a range of breast and brain datasets acquired by Philips Ingenia and Achieva 1.5T and 3T scanners. For breast application, 43 volumes of T1, T2 and DCE scans from 21 patients were tested, where the shading mainly degenerated the LR breast uniformity. Visual assessment from radiologists confirmed bias reduction on all three protocols, with most effect observed on T2 scans. Fig 1 shows a correction example where we also compare the histograms of left and right breasts manually segmented. A better LR uniformity is shown as a closer matching of histogram peaks. Regarding the brain application, 50 patients containing 242 volumes of T1, post-contrast T1, T2, and FLAIR scans were evaluated. One example is shown in Fig. 2. In about 90% of the scans the corrected images were preferred by radiologists over uncorrected ones. In both breast and brain tests, no loss of diagnostic information was reported. The algorithm also ran fast: satisfactory corrections were generated with no more than 15 iterations typically. This requires about 100 evaluations of the entropy term per image, an order of magnitude less than previously reported[3]. In time, the correction typically lasted several seconds, in contrast to order of minutes in previous frameworks[4,5].

## Conclusion

The corrector shows good effectiveness and robustness on both breast and brain applications. Its high numerical efficiency makes the approach suitable for many practical correction situations in daily clinical practice.

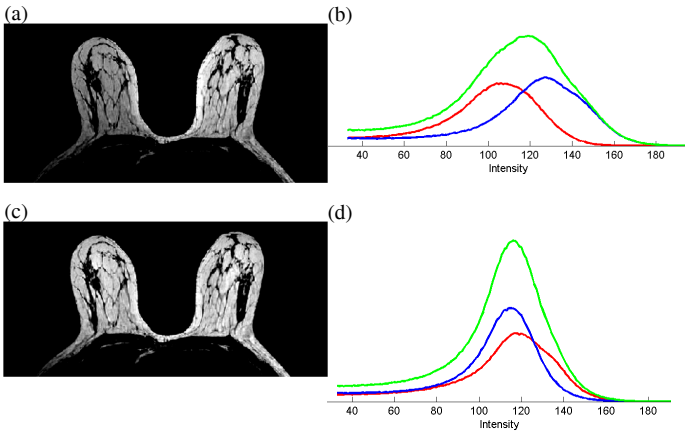


Fig. 1 T2-weighted breast scan. (a) and (c) are respectively uncorrected scan (with LR breast shading) and the correction shown at central slice. (b) and (d) are histograms computed from volumes of (a) and (c) respectively. Green: histogram of both breasts; Blue: histogram of left breast; Red: histogram of right breast.

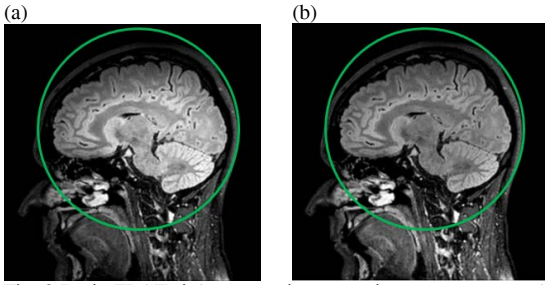


Fig. 2 Brain FLAIR inhomogeneity correction. (a) uncorrected; (b) correction shown at central slice. Green markers highlight the inhomogeneous areas of interest.

## References

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