# Correction of Intensity Inhomogeneities Utilizing Histogram-based Regularization

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**Abstract.** Magnetic resonance imaging is one of the most important imaging modalities. However, local magnetic inhomogeneities of the coils system and susceptibility effects can cause severe problems for post-processing of the data sets and medical diagnostics. In literature, these artifacts are called signal inhomogeneities caused by a bias field. The approach proposed in this article presents a new regularizer for an entropy based method to correct these signal intensity artifacts. In contrast to most state-of-the-art methods, our approach introduces a-priori knowledge about the used data sets. The additional knowledge about the images is stored in histograms. It can be computed from either an atlas or previously acquired images. Furthermore, it can be automatically approximated from the histogram of the given image. The bias field is modeled by bi-cubic splines. In order to estimate a bias field approximation, each node defining the bias field model, is iteratively optimized. As distance measure a combination of the entropy within the images and to regularize the computation of the bias fields, the Kullback Leibler distance to the reference histogram is used. First, the proposed approach was evaluated using simulated brain images. Furthermore, the algorithm was tested on real T1 weighted data sets acquired in clinical routine; thus, the volumes included lesions and other pathologies. The results show, that using a-priori knowledge as additional regularization can enhance the robustness of bias field correction algorithms. Compared to Homomorphic Unsharp Masking, our approach increased the SNR by up to 3.7 db.

## 1 Introduction

MRI is the preferred imaging modality of the brain due its excellent soft tissue contrast. Susceptibility effects and local inhomogeneities of the coils system on the other hand can influence signal intensity values. This means, that a single tissue class might have different intensities within a single volume. In general, intensity inhomogeneities have no significant influence on medical diagnostics, but automatic segmentation and quantification methods will fail as these heavily depend on the observed image intensities. In the last decade several algorithms to correct these inhomogeneities (bias field, gain field) in MRI images have been developed [1]. In the following the most widely used approaches are summarized. Basically there are two types of methods: classifying and non-classifying approaches. For each pixel all methods assume a multiplicative bias

field $y_i = x_i \cdot b_i + n_i$, where $y_i$ is the observed image intensity, $x_i$ is the ideal image intensity and $b_i$ is the bias field value. The additive noise $n_i$ is neglected in general.

The quality of the correction of classifying methods is highly related to the segmentation results they provide. If a reliable segmentation was possible, the resulting bias fields are estimated very accurately. A drawback of these methods is, that they cannot be generalized to other body regions or sometimes even to different pulse sequences. Ahmed et al. [2] present a bias field correction method based on a segmentation using a modified fuzzy c-means approach. In [3] the bias field is estimated by modeling the brain intensities by a mixture of Gaussians. The mixing parameters as well as the bias field are approximated using the expectation maximization algorithm.

Non-classifying methods are more general and usually faster. However, the resulting bias field is not as precise as the estimated bias field of classifying approaches. In general non-classifying bias field correction methods require additional assumptions about the shape of the bias field, like smoothly varying intensity inhomogeneities. Furthermore, most approaches rely on the assumption that all tissue classes are homogeneously distributed in the MRI image. Simple methods for intensity correction are fitting a polynomial surface to the image intensities and frequency domain filtering. These approaches are directly derived from the mentioned assumptions. Based on this Axel et al. propose a method called Homomorphic Unsharp Masking (HUM)[4]. Sled et al. propose a nonparametric method for automatic bias field correction (N3) that relies on image statistics [5] only. The histograms of images affected by bias fields are smoothed, as intensities of a single tissue class are spread. Consequently, the entropy of the images is increased. In [6] Salvado et al. a method is introduced that relies on the minimization of the entropy of the images. In this article we introduce an extension to Salvado's method [6] that utilizes prior knowledge about the shape of the probability density functions of the data sets to increase the robustness of the algorithm.

## 2 Methods

### 2.1 Entropy Minimization

Salvado's method [6] bases on the assumption that the observed images are composed by an ideal image corrupted by signal inhomogeneities, that can be approximated using a bi-cubic spline model. As the observed image contains information of both signal components, the entropy of the corrected image has to be smaller than that of the observed image. The correction approach iteratively estimates a bi-cubic spline model that minimizes the entropy in the corrected image. A regularizer has to be introduced into the optimization process, as otherwise a trivial solution will be found.

The initial bias field estimation is based on a least-squares approximation with a two-dimensional polynomial. A fourth order polynomial was used. After that a bi-cubic spline interpolator is set up with a node spacing of $d$. The initial

bias field is used to initialize the nodes of the interpolator by evaluating the polynomial $B$ at the node locations of the interpolator.

The optimization itself is performed by a golden section search and parabolic interpolation. The entropy is computed using

$$E_\Omega = -\sum_{l=g_{\min}}^{g_{\max}} h_\Omega[l] \log\left(h_\Omega[l]\right), \tag{1}$$

where $h_\Omega$ is the histogram of the active region $\Omega$ of the image $Y$. The histogram has a binning resolution of half a gray level value and serves as an estimate of the real probability density function (pdf). $g_{\min}$ and $g_{\max}$ are the minimal/maximal possible gray values of the image. The bias field is obtained by evaluating the estimated bi-cubic spline at each image position.

### 2.2 Histogram-based Regularization

In order to increase the robustness a histogram-based distance measure that rates the similarity of the corrected histogram to a previously computed reference histogram is introduced. We chose the Symmetric KL-Divergence

$$\hat{D}_{\mathrm{KL}}(p_Y, p_R) = \int_t p_R(t) \log \frac{p_R(t)}{p_{\tilde{X}}(t) p_R(t)} dt + \int_t p_{\tilde{X}}(t) \log \frac{p_{\tilde{X}}(t)}{p_R(t) p_{\tilde{X}}(t)} dt \tag{2}$$

as similarity measure with $p_R(x)$ being the reference pdf and $p_{\tilde{X}}(x)$ being the pdf of the corrected image.

The objective function is a combination of both measures with a parameter $\alpha$ that defines the influence of the measures:

$$O_{\mathrm{EH}} = (1-\alpha) E_\Omega + \alpha D_{\mathrm{KL}}, \tag{3}$$

where $E_\Omega$ is the entropy, $D_{\mathrm{KL}}$ the approximated KL-Distance.

Note that these two measures still have to be computed on their own histograms: The entropy is calculated on the local histogram of region $\Omega$ whereas $D_{\mathrm{KL}}$ is always based on the global histogram.

The parameter $\alpha$ has to be chosen carefully, as the two measures cover different ranges which depend on parameters like the binning resolution for the histograms or the input image size. In general the KL-Divergence yields larger values than the entropy.

Combining both measures allows us to get rid of the regularizer proposed by Salvado [6] and replaces it with a robust histogram-based distance measure. However, an additional parameter $\alpha$ is introduced which has to be chosen carefully. Since the measures work on different histograms, there are little synergies that can be used for optimization. This makes the computation time considerably worse compared to the "single-measure" approaches. A further problem of this approach is how to acquire a reference histogram. There are three possibilities:

1. From reference data (e. g. an atlas)
2. From an image with a similar tissue distribution which is known to be bias field free
3. Generated from the histogram of the disturbed image

## 3 Results

### 3.1 Simulated MR Brain data sets

*Data:* First, the proposed method was evaluated using simulated MR brain images provided by the McConnell Brain Imaging Centre (BIC) of the Montreal Neurological Institute, McGill University [7]. All used volumes had a slice thickness of 1mm and a resolution of $181 \times 217$ pixels. The reference images are taken from undisturbed data without noise and bias field but inheriting partial volume effects. The distorted T1 and T2 images show 3% noise and signal intensity inhomogeneities of 40%. The PD images have 3% noise and a linear bias field with a strength of 50%.

*Evaluation Method:* As a quality measure we use the *signal-to-noise ratio (SNR)* and *peak signal-to-noise ratio (PSNR)* between the true bias field and the approximated bias field. The measures are defined as

$$\mathrm{SNR} = 10 \log_{10} \left( \frac{\sum_{i=1}^{N} b_i^2}{\sum_{i=1}^{N} (b_i - \hat{b}_i)^2} \right) \quad \text{and} \quad \mathrm{PSNR} = 10 \log_{10} \left( \frac{N b_{\max}^2}{\sum_{i=1}^{N} (b_i - \hat{b}_i)^2} \right).$$

The signal to noise ratio is based on the ratio between noise energy and signal energy. The values $b_i$ denote the reference bias field intensities and $\hat{b}_i$ are the values of the approximated bias field. Negative values indicate that the noise power exceeds the signal power. PSNR is based on the ratio between the maximal image power $b_{\max}^2$ and the *mean square error (MSE)*. For evaluation all bias fields were scaled, such that the mean intensity value of the estimated fields corresponds to the mean value of the true bias field.

*Results:* The correction results of the proposed method were compared to Homomorphic Unsharp Masking (HUM). As only one image was available for each acquisition protocol, the reference histogram had to be estimated from the observed image. Using HUM a SNR value of $s_{\mathrm{HUM,T1}} = 14.88$ db, $s_{\mathrm{HUM,T2}} = 17.27$ db and $s_{\mathrm{HUM,PD}} = 19.07$ db and a PSNR value of $p_{\mathrm{HUM,T1}} = 17.42$ db, $p_{\mathrm{HUM,T2}} = 19.70$ db and $p_{\mathrm{HUM,PD}} = 22.78$ db. The results for the proposed histogram-based entropy optimization are $s_{\mathrm{HR,T1}} = 17.79$ db, $s_{\mathrm{HR,T2}} = 19.63$ db and $s_{\mathrm{HR,PD}} = 19.29$ db and a PSNR value of $p_{\mathrm{HR,T1}} = 20.34$ db, $p_{\mathrm{HR,T2}} = 22.06$ db and $p_{\mathrm{HR,PD}} = 23.01$ db.

### 3.2 MR data sets from clinical routine

*Data:* The T1-weighted volume had a resolution of $208 \times 256 \times 19$ with an isotropic in-plane resolution of 0.86 mm$^2$, 7.2 mm slice thickness and TE = 14 and TR = 510 ms. The images were acquired during clinical routine on a Siemens Symphony 1.5 T MR scanner at the clinics for diagnostic radiology at the University of Erlangen.

*Evaluation Method:* As the bias fields of the data sets were not known, the results were presented to several experts in order to judge the quality of the correction result. This was done by presenting the images pairwise. The expert had to evaluate which of the presented image he prefers. At this the evaluator

did not know which image was the original and which was corrected by HUM, the entropy optimization approach introduced by Salvado [6] and the proposed extension.

*Results:* In total all methods for bias correction increased the image quality. However, the difference between the different evaluated algorithms was not as big as for the artificial images. There a several reasons for this. First, many physicians are used to the intensity distorted images; thus, they prefer images with slight intensity inhomogeneities. Moreover, only clearly visible differences can be judged by the experts. Using the SNR and PSNR measures, small differences, that can affect segmentation algorithms for instance, can be measured as well.

## 4 Summary

In this article we presented an extension to Salvado's method [6] for bias correction basing on entropy optimization. The new regularizer increases the robustness and the applicability of the method. Hence, it is possible to use the method on a broad variety of problems. The experiments on simulated MR brain images show, that the proposed method outperforms other state-of-the-art methods like HUM. How to compute the reference images is still an open research topic. In this article we used filtering techniques to generate the references from the histograms of the disturbed images.

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