Surface coil intensity inhomogeneity correction by entropy minimization

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Introduction: Surface arrays coils are often used to increase signal-to-noise ratio (SNR) in many imaging application such as neck imaging to diagnose atherosclerosis in carotid arteries. In general, signal sensitivity is greatly increased to the detriment of intensity inhomogeneity: signal intensity decreases sharply in the direction away from the coil. Many methods have been designed to reduce this general problem of "shading" artifact when data are intended to be processed by a computer, but they almost always fail in the face of specific challenges. For example with carotid surface coils, issues include: (1) a steep bias field with signal attenuation up to 80%; (2) presence of homogeneous areas lacking high frequency information necessary to distinguish bias from anatomical features; (3) many confounding zero-valued voxels subject to fat suppression, blood flow cancellation, or air, which are not subject to coil sensitivity; and (4) substantial noise. We propose a method that addresses these problems and that relies on local entropy minimization while modeling a smooth bias field with a bicubic spline.

Methods: We first segment all tissue voxels and filter the image as described in [1]. Voxels identified as background are excluded from the optimization since they are void of signal and are not subject to intensity inhomogeneity. We then fit a third order polynomial function to the tissue voxels (Y) to initialize a multiplicative bias field. This initial estimate is next used to initialize a cubic spline model of the bias field (*B*), which is iteratively modified so as to minimize the entropy of Intensity-corrected image. Knots are evenly spaced across the image, and to improve speed and robustness, optimization proceeds on a regional basis. We first consider knot k1, which is located in the area of highest SNR, and an area Ω_{k1} around this knot delimited by its neighboring knots (i.e. k1-1 and k1+1 in the 1-Dimensional case). We optimize the value of the knot k1 to minimize the entropy of the corrected image X=Y/B within Ω_{k1}: $H = -\sum_{l\in\{\text{gray levels}\}} PDF_X(l)\log\left[PDF_X(l)\right]$ where $PDF_X(l)$ is the probability density function of X, approximated by the histogram of the voxels of X in the area Ω_{k1}. We use an algorithm based on the golden section search and parabolic interpolation. We next take the knot in the next highest SNR area, let's say k2, along with its area of interest Ω_{k2}. The entropy of X in $\Omega_{k1}\cup\Omega_{k2}$ is then optimized by adjusting the knot k2. This process is repeated until all the knots have been optimized. At the last knot, the entire image is used in the entropy calculation. Optionally, this entire process can be repeated.

Results: We conducted experiment on synthetic phantom, as well as T1W, T2W and PDW acquisitions of physical phantom and actual patients (Fig. 1). We compared our method to common techniques based on linear filtering (LINF) [2], and adaptative fuzzy c-means (mAFCM) [1] by measuring errors in area of interest (carotid artery). Results in Fig. 2 show that the new method gives a much flatter response in synthetic phantom tests in simulated carotid areas. A physical phantom constructed of different solutions to simulate different T2 values was imaged and corrected. The new method also better corrected intensitities as compared to the other schemes (not shown). Finally, several experiments on patient data allowed to us to show the robustness and the accuracy of the method to correct MRI data subject to strong intensity inhomogeneity and significant noise, by measuring the deviation of skeletal muscle signal intensity across the data which is much reduced with our proposed method.

Discussion: As compared to the conventional schemes listed above, the new method has advantages of robustness, accuracy, and xx for the carotid artery images having challenges not present in brain images. The method also has advantages for carotid artery images as compared to some recent reports of entropy-based methods. Likar et al. [3] optimize entropy over the entire image at once. To keep the implementation tractable they model the bias field with a polynomial function. A high order polynomial function (>4) is necessary to fit the complex shape of the intensity inhomogeneity generated by phased array coils for carotid artery imaging. A cubic spline model seems more appropriate, and a region-by-region optimization approach reduces the computational demand. Furthermore, optimizing the bias field on the whole image introduces errors from low-signal areas. Suckling et al. [4] proposed a method to locally optimize the bias field, but they use a fuzzy c-means technique to model X whose parameters are estimated on the entire image data. With the proposed method we keep the advantages of minimizing the entropy of X instead of a segmentation technique, avoiding specifying a number of class and keeping the optimization local. We use the power of cubic spline modeling to describe the bias field. Our solution to keep the problem tractable is to define first the area with high SNR where the bias field is locally optimized. We proceed further by merging low SNR areas so as to keep bias field estimate in high SNR areas minimally affected by the noise in areas where the signal is much attenuated.

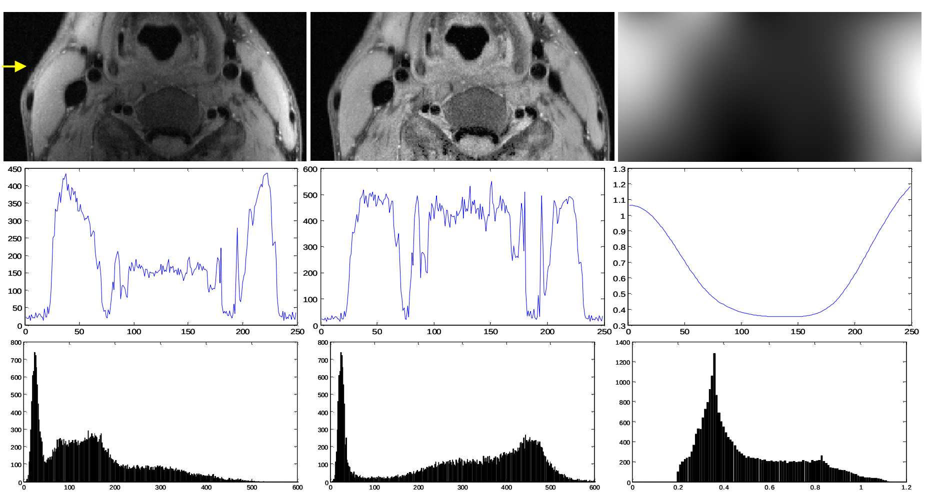

Figure 1: Correction of an actual patient PDW scan with the proposed method. Top panels show the images, middle panels the corresponding row profiles at the location shown by the arrow in the upper left panel. The bottom panels show the corresponding histograms. From left to right are shown: the original image, the corrected image and the estimated bias. As expected, after correction the skeletal muscles are isointense across the image. The profile has been chosen to cross the carotid arteries on both sides.

References:

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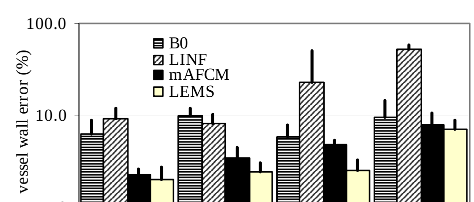

	N/A	15.36	7.73	5.35
B0	6.3	9.9	5.8	9.8
LINF	9.4	8.4	23.3	51.7
mAFCM	2.3	3.5	4.8	7.9
LEMS	2.1	2.5	2.6	7.2

Figure 2: Comparison of bias correction methods applied to the synthetic phantom simulation. Vessel wall error is plotted on a logarithm scale for the three different bias correction methods, as well as for the initial bias *B0*. Values are obtained as a function of decreasing SNR for class 150. The left most value, labeled N/A is the noise free case.