A renormalization method for inhomogeneity correction of MR images

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ABSTRACT

A correction method for inhomogeneity of magnetic resonance (MR) images was developed based on renormalization transformation. It is a post-processing algorithm on images. Unlike previous post-processing methods, which need to determine either a filter size or a free adjustable parameter for different applications, this presented method is fully automated. Tests on physical phantom data, patients' brain and neck MR images were presented.

Keywords: renormalization transformation, bias field, inhomogeneity correction, MRI.

1. INTRODUCTION

Correction for the intensity inhomogeneities in inter- and intra- slices is essential to automated quantitative analysis of MR (magnetic resonance) images. The inhomogeneities locally alter image intensity mean, median, and variance. It is known that they vary over time and with different acquisition parameters and subjects [1]. The intensity inhomogeneities can be caused by radio frequency (RF) pulse attenuation in tissues, non-uniform RF coil transmission, non-uniformity sensitivity in the scanner's magnetic field, gradient-induced eddy current, RF standing waves, magnetic susceptibility of tissues, and inter-slice cross talks [2].

Previously reported correction methods can be classified into two categories. One takes pre-processing correction approach that considers only the RF (radio frequency) effects and ignores the tissue-specific susceptibility and related factors. This correction is based on phantom measurements [3]. The other category takes post-processing correction approach that models the inhomogeneities as a bias field [4, 5]. The bias field is characterized by the lowest frequency component of the image data, where an assumption is made that anatomical information has much higher spatial frequencies than that of the inhomogeneity variation. The presented correction method in this study belongs to the latter category.

The popular intuitive idea is to develop a theoretically-based filtering scheme to estimate the bias field by the lowest frequency component of the MR image and to correct for the inhomogeneity of the image based on the estimated bias field [6, 7]. Most of the previously reported filtering methods must appropriately choose a size for their filter kernel. Usually, the size of the filter kernel is chosen based on empirical experience and varies for different types of MR images and different anatomies. This free-adjustable factor limits the robustness and adaptation of those methods.

The renormalization group (RG) theory had been successfully used to study the scale-invariant characteristics in phase transition and critical phenomena [8]. The similar counterpart of the scale-invariant component for a band limit signal is its lowest frequency component in time domain. If the bias field of spatial intensity inhomogeneities can be modeled as the lowest frequency component of the MR image, the RG theory is a theoretically-founded choice for determining the bias field.

In this study, a renormalization transformation (RT) for band limited two-dimensional (2D) images was presented. The RT-based algorithm [9] for estimating the bias field was extended to study both multiplicative and additive correction models. The algorithm was evaluated on a physical phantom and tested on patient brain and neck spinal MR images. The two models of the correction approach for the bias field were discussed.

2. METHODS

2.1) Renormalization transformation. The RT was originally defined on an infinite dimensional space [8]. By iteratively applying the RT, the state of a physical system would converge to an equilibrium state. This equilibrium state is a fixed point of the RT. In the language of physics theory, the RT is a linear scaling transformation. The fixed point means that the state is scale-invariant, which is one of the important characteristics of the equilibrium state.

When a 2D image is scaled down to a small size, the higher frequency information will disappear, while the lower frequency information will remain. Thus the counterpart of the scale-invariant component of an infinite system should be the lowest frequency component in a band limited 2D image. In the theory of signal processing, there are a lot of filtering methods to extract the component of a specific frequency. It is often necessary to choose the kernel size for a filter. However, the MR images vary greatly in local features due to spatial resolution, anatomy size, and range of partial volume effect. This means that it is difficult to choose a fixed filter size to obtain satisfactory results for different applications. The RG theory does not suffer from this problem. No matter how large or small of the local RT size, by iteratively applying it to a state, the process should converge to a scale-invariant state of that system. If we could define a similar RT for band-limited 2D images, we can obtain a general tool for extracting the component of the lowest frequency.

We modified the RT (renormalization transformation) [8] to allow it being applicable to band-limited 2D images. Before giving the mathematical definition, we need to introduce some notations. Let *S* be a single-connected, finite subset of the 2D integer lattice. One can consider *S* as the pixel locations of a region of interest (ROI) in a 2D image. Let $X = \{x_i : i \in S\}$ be an image, where x_i is the intensity value of pixel *i* and it takes value within a finite set. Denote ∂_i and $|\partial_i|$ as the first order neighborhood of the pixel *i* and the number of pixels inside this neighborhood (pixel *i* itself is also a member of this neighbor). The RT is defined as:

$$T(X) = \{y_i : y_i \equiv \frac{\sum_{k \in \partial_i \cap S} x_k}{|\partial_i \cap S|}, i \in S\}. \qquad 2.1$$

Actually, *T(X)* is a new image with the same pixel location and its intensity value of each voxel is the average intensity of those of pixels in its neighborhood. The RT is a linear transformation and can be calculated locally. This makes it possible for a fast parallel implementation.

2.2) Estimation of the bias field. The estimation of the bias field is based on the following observation. Though it has not been proved in mathematical rigorous, our numerical experiments had shown strong positive evidence to support the following statement.

Conjecture: When *n* goes to the infinite, $T^{(n)}(X)$ converges to a limit image M.

The limit image *M* is the bias field. In other words, it is the lowest frequency component in the image *X*. If the conjecture is true, we can designed the estimation algorithm as follows.

Estimation algorithm: If $\max_{i \in S} |T^{(n)}(X)_i - T^{(n+1)}(X)_i| \le t$, then $M \approx T^{(n)}(X)$, where *t* is a pre-set threshold. In our experiment, we set *t* as the average intensity of the image dividing by 3000.

2.3) Correction for the inhomogeneities based on the estimated bias field. Most of previous papers modeled the bias field similar as the following model [6]:

$$Y = X \cdot f + n \qquad 2.2$$

where *Y* is the obtained MR image, *X* is the ideal image without inhomogeneity, f is the bias field, and n is the noise. If we ignore the noise, the image data is the multiplication of the ideal image and the bias field. Following this model, the correction procedure should be performed by dividing the image data by the estimated inhomogeneity bias field.

In our RT model, the RT is a linear transformation rather than a multiplication transformation. In other words, the following model might be more accurate for RT method:

$$Y = X + f + n \qquad 2.3$$

where Y, *X*, *n*, and f were defined above. For correction algorithms ignoring the noise, we could induce the following model:

$$X = Y + \alpha \cdot (f - M_0) \qquad 2.4$$

where $\alpha(f - M_0)$ is a linear transform applied on the estimated bias field f, α is a scaling factor and M_0 is an image calculated from *X*. To use this model, we assumed that all pixels are the same kind of a tissue type. In practical situation, this assumption always failed. Hence, we had to apply model (2.4) in a flexible way to ensure that the assumption was satisfied as much as possible. The determination of α and M_0 should also be adaptive to the practical situation. For phantom data (see Figure 1), since it was a uniform material, we set $\alpha = -1$, and M_0 is the constant image with value equal to the average intensity of the image. For brain images (see Figure 2), we extracted the region of intra-cranial volume as ROI and set $\alpha = -1$ and computed M_0 on the ROI. For sagittal neck spinal image (see Figure 3), since the neck coil was used, the spatial inhomogeneity showed different features along the x and y directions, as compared to other figures. Therefore, a different approach should be taken. Note that almost the same tissues were distributed along the y direction. So we applied the correction by column by column. In other words, we still set $\alpha = -1$, but computed M_0 values, which were different from column to column. For each column, the value for M_0 was the average intensity of that column in the original image.

2.4) Correction of volumetric data. The renormalization transformation could be easily generalized to three-dimensional (3D) situation. However, the inter-slice intensity inhomogeneity usually has different characteristics from that of intra-slice. Therefore, we preferred to correct the intra-slice and inter-slice inhomogenerities separately. One of the practical solution is to correct each slice first, and then to apply a segmentation to each slice. Following that, we can calculated the average intensity of a specific tissue for each slice and obtained a profile of the average intensity. Applying the one-dimensional (1D) RT to this profile image, we got a bias map for the profile associated to all the slices. This bias map provides the information between slices.

3. RESULTS AND CONCLUSION

A physical phantom of water was scanned by a 4 Tesla MR imager (located at the Brookhaven National Laberatory) using a routine protocol. The inhomogeneity effect is commonly seen in all images. For the original image, the average intensity is 3.45 and the standard deviation is 2.4. For the corrected image, the average intensity is 3.41 and the standard deviation is 0.7. Figure 1 shows the results on a T_2-weighted brain image acquired by a 1.5 Tesla GE whole body MR scanner using a routine clinical protocol. The inhomogeneity effect is clearly seen. Figure 1 (a) is a slice of the original image, (b) the estimated bias map, and (c) the corrected image. Figure 2 (a) shows a T_1-weighted sagittal neck spinal image acquired by a 1.5 Tesla GE whole-body scanner with the body coil as the transmitter and a neck coil as the receiver. A routine protocol was employed by a MEMP sequence to acquire the image covering the whole neck with 90^o flip angle, TE/TR = 25 ms/600 ms, 3 mm slice thickness, 20 cm FOV (field-of-view), and 256x256 matrix size. The inhomogeneity effect is also commonly seen in all such images. Figure 2 (b) is the estimated bias map and (c) the corrected image.

The RG-based estimation method for the bias field is not a regular filtering scheme, so it is not necessary to choose the size of the filter kernel. The variance of spatial intensity inhomogeneity was directly calculated from the bias field. This was an important progress, since in most previous work, the variance must be set based on empirical experience rather than be adaptive to the image data. Both the bias field estimation and the correction algorithms were automatic in our approach. Hence, this presented method was a general correction method for all kinds of MR images. The additive correcting model was unique to those multiplicative models presented in most previous work. With modification of our algorithm to multiplicative model, we obtained the similar results.

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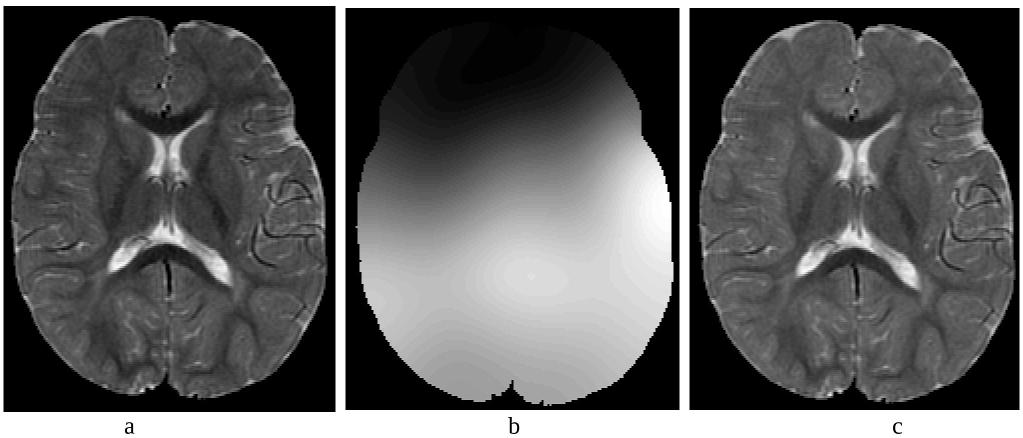

Figure 1 (a) is the T_2-weighted image of brain, (b) is the estimated bias map, and (c) is the corrected image.

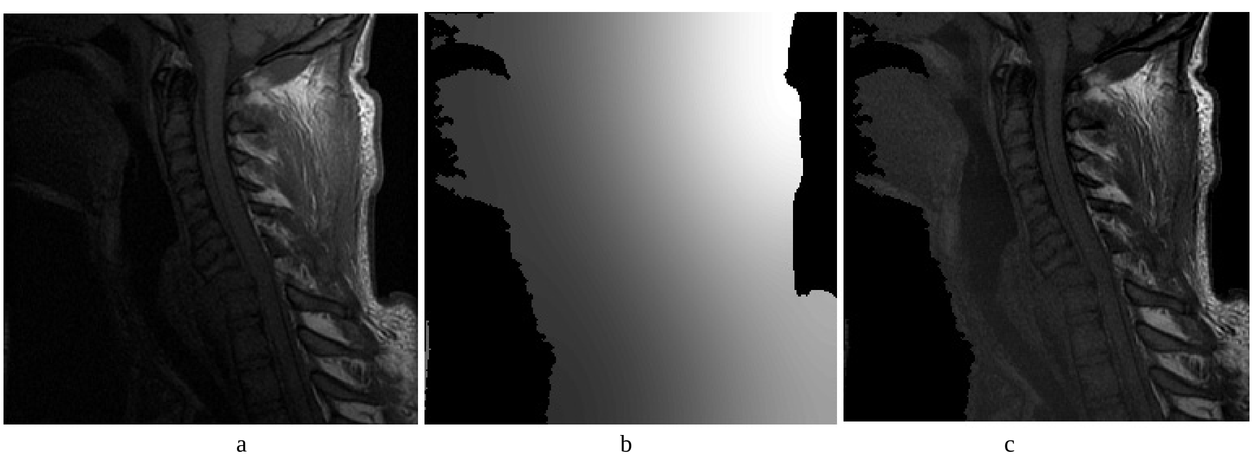

Figure 2 (a) is the T_2-weighted image of neck, (b) is the estimated bias map, and (c) is the corrected image.