Volumetric Bias Correction

Edoardo Ardizzone, Roberto Pirrone, Salvatore La Bua and Orazio Gambino

Universita’ degli Studi di Palermo
DINFO - Dipartimento di Ingegneria Informatica
viale delle Scienze - Edificio 6 - Terzo piano
90128 Palermo
ardizzon,pirrone@unipa.it slabua@gmail.com gambino@csai.unipa.it

Abstract. This paper presents a method to suppress the bias artifact, also known as RF-inhomogeneity, in Magnetic Resonance Imaging (MRI). This artifact produces illumination variations due to magnetic field fluctuations of the device. In the latest years many works have been devoted to face this problem. In this work we present the 3D version of a new approach to bias correction, which is called Exponential Entropy Driven Homomorphic Unsharp Masking ($E^2D - HUM$)). This technique has been already presented by some of the authors for the 2D case only. The description of the whole method is detailed, and some experimental results are reported.

1 Introduction

The RF-inhomogeneity, also called bias artifact, is an interesting research topic in Magnetic Resonance Imaging (MRI). Bias corrupted MR images exhibit strong brightness variations so that voxel’s grey levels change spatially also inside the same tissue. Statistical estimations of the corruption to restore the images have been proposed in [8][4][19]. Some methods[11][13] need of a special probe inserted into the device to capture the image representing the artifact so that the image is restored using this estimation with a homomorphic-like method. These techniques move from [12] which applies the Homomorphic Unsharp Masking (HUM) method and continued by [14], but they don’t perform a volumetric approach. Some of the methods cited above have been compared in [18]. We propose a fully 3D approach to bias correction in a MR volume, and we called it Exponential Entropy Driven Homomorphic Unsharp Masking ($E^2D - HUM$). Our technique is an evolution of the HUM method proposed by Guillemaud [10]. In our work, an accurate region segmentation is performed to avoid some typical artifacts introduced by the homomorphic filter. Moreover, we obtain automatically the cutoff frequency ($cf$) of the filter; this is a typical drawback when using the homomorphic approach. $E^2D - HUM$ doesn’t require any a priori hypothesis about the tissues under investigation, and it performs well regardless the MR spectrum (T1, T2, PD, FLAIR ...). The experimentation of this article is focused on some T1-weighted image volume of the knee because it is the most common MR modality used, but it is not a limitation. Moreover, the hardware configuration of low magnetic field MR devices specialized in lower limbs particularly
affected by this artifact is prone to generate a considerable bias artifact, due to the use of surface coils. The paper is arranged as follows: Section 2 describes the 3D version of $E^2D - HUM$ and the related theoretical background, Section 3 shows the improvement of the presented method with regards to the inter-slice brightness variations arising when a bias correction technique is applied separately to each slice and not to the entire volume, Sections 4 describes the measures employed to validate the effectiveness of the method and shows some experimental results that have been compared with the well known SPM technique. This can be considered a state-of-the-art approach to the bias correction. Section 5 reports some conclusions.

2 3D $E^2D - HUM$

The presented method moves from $E^2D - HUM$ algorithm [1] for MR images. Here this algorithm is extended to volumes. The degradation model of a volume affected by RF-inhomogeneity shows that the artifact is multiplicative:

$$I(x, y, z) = I_{corrected}(x, y, z) \cdot B(x, y, z)$$  \hspace{1cm} (1)$$

where $I(x, y, z)$ is the voxel intensity of the corrupted volume whose coordinates are $x, y, z$; $I_{corrected}(x, y, z)$ is the intensity of the uncorrupted volume and $B(x, y, z)$ is the intensity of the artifact. For all the following formulas, the $x, y, z$ coordinates will be omitted. A natural logarithm function $ln$ can be applied to both members of 1 to transform the multiplicative model into an addictive one:

$$I_{log} = \ln(I) = \ln(I_{corrected}) + \ln(B)$$  \hspace{1cm} (2)$$

In this way a linear filtering can be applied. The bias artifact $B$ corrupts the illumination signal located at low frequencies of the Fourier spectrum, while the high frequencies aren’t altered. This is a classical luminance/reflectance model suited to the application of the homomorphic filter. To separate low frequencies from high ones, a high pass filtering can be performed on the $I_{log}$ and an exponential function is computed on the result, achieving the classic homomorphic filter. But if a strong edge is present in the image, like the one between foreground and background of a medical volume, luminance peaks arise on the boundaries between the two zones. The Guillemaud ($Gf$) filter prevent this problem. A toy problem has been prepared to compare the $Gf$ with a homomorphic one. A 32x32x32 volume has been filled with values 120 and 128 for each part and has been padded by zero voxels obtaining a 63x63x63 volume. A bias artifact has been simulated multiplying the closest harmonics to the DC component by 4. Fig.1 shows a slice taken from the original and corrupted volume along with the 2D 1/2 representation of their grey levels. The figure also shows the effect of the homomorphic filter and Guillemaud one. The luminance peaks effect can be seen very well on both images while they are absent in the Guillemaud result.
Fig. 1. The first row shows a slice taken respectively from the following volumes: original, corrupted, after homomorphic filtering, after Guillemaud filtering. The experiments are performed with $D_0 = 0.1$. The second row shows their 2D $1/2$ representation.

2.1 The 3D Guillemaud filter

Guillemaud [10] proposed a method to avoid the problem mentioned before in MRI for the 2D case and here the 3D extension is presented for a complete volume. According to the Guillemaud approach, a 3D Region of Interest (ROI) is a binary volume which identifies only the foreground voxels, so that the $\ln$ function in 2 is applied only on the foreground:

$$I^*_{\log} = \{ \ln I : ROI = 1 \}$$

Here the high pass filter is accomplished subtracting the result of the low pass filtering, which estimates the artifact. The result of the low pass filtering will be used also in the next section. The low pass filtering is performed using the 3D version of the Butterworth filter whose Frequency Impulsive Response is:

$$H = \frac{1}{1 + \left( \frac{D(u,v,w)}{D_0} \right)^{2n}}$$

where $D(u,v,w)$ is the euclidian distance from the origin of the frequency domain, $n$ is the filter order and $D_0$ is the $cf$. The order of the filter must be set to 1, so that the well known ringing artifact can’t appear. The filter is applied to $I^*_{\log}$ obtaining $\hat{I}$:

$$\hat{I} = FFT^{-1} \left[ H \cdot FFT \left( I^*_{\log} \right) \right]$$

The same filtering is applied to the 3D ROI:

$$\hat{ROI} = FFT^{-1} \left[ H \cdot FFT \left( ROI \right) \right]$$

The ln-transformed version of the Bias image is obtained dividing pixel-by-pixel the magnitude of $\hat{I}$ and $\hat{ROI}$:
\[
\ln(Bias) = \frac{\|j\|}{\|ROI\|} \tag{3}
\]

The image is obtained performing the following step:

\[
I^* = \exp(I_{\log}^* - \ln(Bias)) \tag{4}
\]

Due to the non-linearities introduced during the process, the dynamics of \(I^*\) is different from the one of the original volume. A contrast stretching can be performed obtaining the restored volume with the original dynamic:

\[
I_{\text{corrected}} = \frac{I^* - \min(I^*)}{\max(I^*) - \min(I^*)} \cdot \max(I) \tag{5}
\]

The \(Bias\) volume is obtained applying an exponential function to 3 and performing the same contrast stretching showed in 5. Even if the ROI selection prevents the luminance peaks on the external volume boundary, it cannot avoid some overshoots along the boundaries between those sub-volumes corresponding to tissues with very different brightness. This is the case of muscles surrounded by fat. We propose a more careful procedure to obtain the ROI. Once a restored volume has been obtained using the Guillemaud ROI, a fuzzy c-means [2] segmentation is performed using three clusters. We choose three clusters to distinguish between dark, medium and bright grey levels. The new ROI is obtained merging the voxels pertaining to the medium and bright class. Fig.2 reports a comparison of the behavior of the filter with the Guillemaud ROI and using our selection. White arrows indicate the presence of luminance peaks that are completely corrected in our approach.

**Fig. 2.** Results using ROI (first row) and MASK (second row). From left-to-right: original image, selected region, estimated bias and restored image. The black arrows show the luminance peaks introduced by the filter using a ROI instead of a MASK.
2.2 The volumetric cutoff frequency $D_0$

It’s hard to find the right value of this parameter to prevent a certain amount of luminance to be removed from the restored image. There are no approaches dealing with an automatic estimation of the $cf$ in the literature devoted to MRI. The core of $E^2D – HUM$ is the $Gf$ and an entropy based method automatically computes the $cf$. Here the 3D version of this method is also given. The corrupted volume contains more information than an uncorrupted one; the useful information and the one of the artifact. The $Gf$ attenuates the low frequencies of the corrupted volume while the ones of the Bias image are enhanced of the same amount, so that this process can be considered an information transfer between the volumes. The amount of information moved from the corrupted volume to the Bias one becomes bigger and bigger while increasing the $cf$. The problem consists in finding a criterion for placing the $cf$ to move a sufficient information away from the corrupted volume. A classical information measure is the Shannon Entropy [15] computed on the grey value of each voxel. The plot of the Bias volume entropy versus an increasing value of the $cf$ shows an increasing of this function, according to the considerations said before. In correspondence of the low frequencies the most part of the information moved away from the corrupted volume is made by the artifact so the slope of the curve is steep, as shown in fig3. After this transient phase, the curve appears flat because all the information placed at the high frequencies is related to the tissues luminance. We can choose to place $D_0$ at the end of the transient phase. Due to its shape the curve can be modelled using an exponential function:

$$y(x) = k_1 + k_2 e^{-\frac{x}{\tau}}$$

Eq.6 is the capacitance charge function where the end of transient phase is obtained at $5\tau$, so that $D_0$ can be obtained using this approximation. The model is fitted on the curve using a Nelder-Mead algorithm [3]which minimizes the following objective function:

$$E = \frac{1}{2} \sum_{i=1}^{n} \left[ k_1 + k_2 \cdot e^{-\frac{x(i)}{\tau}} - H [x(i)] \right]^2$$

![Fig. 3. The local entropy diagram and the superimposed exponential model, original image and the restored ones obtained with the $cfs$ corresponding to the point on the diagram. The point 2 is selected by $E^2D – HUM$.](image)
here $H[x(i)]$ are the entropy values computed for each $cf$ sample $x(i)$. The initial conditions can be set as follows: $k_1$ is the final value of the model in the flat region and can be set to mean of the last ten entropy values; due to the profile of the function, $k_2$ can be set to -1; $\tau$ can be set to the minimum of the frequency range, because has to increase. Three points on the curve are sampled in fig.3 shows the filtering obtained using the respective $cf$s, justifying the proposed approach.

3 Inter-slice variations

When a multi-slice acquisition is performed, the excitation of the slices must be carefully applied. In fact, adjacent slices produce inter-slice variations caused by cross-talk between them, even if the excitation is interleaved. To avoid this undesirable phenomenon, the time between excitation of adjacent slices can be increased or special slice-selective acquisition sequences can be employed [6]. Of course, these particular treatments can be implemented by the radiologist only during the medical examination. Once the images are acquired, only a software solution can be implemented. Some techniques reported in the literature for bias correction are not able to suppress the inter-slice variations. Rapid variations are badly corrected by N3 [4] while FMI [9] isn’t able to remove the smooth ones, as shown in the paper of Likar et al. [15]. If the 2D version of $E^2D - HUM$ were applied on each slice of a volume, the average luminance would be different from a slice to another. This happens for two reasons: a different $cf$ is found for each slice and the $cf$ along the 3rd dimension isn’t defined. Our approach uses a 3D filtering kernel that processes the bias along all the directions. Fig.4 shows this result. Here two slices are shown that have been reconstructed respectively on the transversal and the coronal plane. In other words the slices are both orthogonal to the plane of acquisition (the sagittal one). The figure shows the inter-slice brightness variations that are enhanced by the application of the 2D $E^2D - HUM$, while the 3D version of the filter significantly reduces this artifact.

4 Experimental Setup

The method has been applied on several volumes decoded from DICOM files format, to avoid the presence of other artifacts that can be introduced by an

![Fig. 4. For each group of images, from left to right: original, 2D correction of each slice, 3D $E^2D - HUM$ restored image. Left group shows a transversal plane reconstruction, the other one the coronal plane.](image-url)
optical scanner acquisition. The device is an ESAOTE ARTOSCAN C with a magnetic field intensity of 0.18 Tesla. The dataset consists in multi-slice acquisitions of knees on sagittal plane each composed by 87 T1-weighted images. The volumes have been acquired with the following parameters: Spin Echo sequence, Repetition time (980 ms), Echo time (26 ms), Slice thickness (1mm), Flip Angle (90). The useful resolution of FOV is 512x512 pixels with 12 bit of pixel depth. In order to validate the choice of $D_0$, we introduce two measures. The former is the coefficient of variation $cv$ that is used to measures the non-uniformity intensity of a region, the latter is the coefficient of contrast and it measures the contrast between two adjacent tissues. They are defined as follows:

\[
\text{cv}(\text{zone}) = \frac{\sigma(\text{zone})}{\mu(\text{zone})} \quad \text{cc}(\text{zone}_1, \text{zone}_2) = \frac{\mu(\text{zone}_1)}{\mu(\text{zone}_2)}
\]

where $\sigma$ and $\mu$ are, respectively, the standard deviation and the mean of gray values in the region under examination. A region affected by bias artifact exhibits a higher $cv$ than a normal one. Table 1 reports that in general 3D $E^2D-HUM$ has lowest $cv$ both the original value and the one obtained using SPM2. The coefficient of contrast ($cc$), which consists in the ratio between the mean values $\mu$ of two adjacent zones, has been introduced to check the loss of contrast in the restored volume. In fact, a normal consequence of the bias reducing is a loss of contrast among the tissues; this fact compromises the tissue identification during a visual inspection. Both the measures require homogenous regions, so a handmade segmentation has been performed on a volume by an orthopedic physician to identify the tissues for each slice. Even though the Table 2 shows that $cc$ is in general lower than SPM2, but the values are around of 150%, which

5 Conclusions and Future work

An automatic method to suppress RF-inhomogeneity in MR image volumes has been presented. It doesn’t require any hypothesis both on the tissues and on the artifact shape. A semi-automatic version of our filter can be implemented, so that the physician can select the value of $D_0$, according to her visual preferences. Even

![Fig. 5. Slice contours of the Bias artifact.](image)
tough in this paper it is applied on a knee volume, $E^2D - HUM$ can be applied to whatever anatomical region due to its general purpose designing. Most of the cited paper are devoted to brain MRI and they don’t care of other body parts. It’s worth noticing that the 3D nature of the approach allows the filter to reduce also the inter-slice brightness variations. In this way it is possible to obtain a good restoration also when we create a slice by sectioning the volume along an orthogonal plane with respect to the acquisition one. In general the bias artifact has an anisotropic nature due to the non uniform displacement of the magnetic coils with respect to the patient. We are currently working on a 2D anisotropic $E^2D - HUM$, and we plan to derive an anisotropic kernel also in the 3D case.

References

1. Ardizzone, E.; Pirrone, R. and Gambino, O. : Exponential Entropy Driven HUM on Knee MR Images.Proc. OF IEEE XXVII Engineering in Medicine and Biology Conference - 4/7 September 2005 SHANGHAI (CHINA)
2. Bezdek J.C. : Pattern Recognition with Fuzzy Objective Function. Plenum Press 1981.
3. Nelder, J. A. and Mead, R. : A Simplex Method for Function Minimization. Comput. J. 7, 308-313, 1965.
4. J. G. Sled, A. P. Zijdenbos, and A. C. Evans. A nonparametric method for automatic correction of intensity nonuniformity in MRI data. IEEE Trans. Med. Imag., vol. 17, pp. 8797, Feb. 1998. MRI
5. J. Ashburner and K. Friston. MRI sensitivity correction and tissue classification. NeuroImage, 7: S706, 1998.
6. Y De Deene. Fundamentals of MRI measurements for gel dosimetry. Journal of Physics: Conference Series 3 (2004) 87114.
7. Guillemaud, R.: Uniformity Correction with Homomorphic filtering on Region of Interest. IEEE International Conference on Image Processing 2 (1998) 872–875
8. Dawant B.M.; Zijdenbos A.P.; Margolin R.A.: Correction of Intensity Variations in MR Images for Computer-Aided Tissue Classification. IEEE Transactions on Medical Imaging 12 (1993) 770–784
9. Axel L.; Costantini J.; Lutjens J.: Intensity Correction in Surface Coil MR Imaging. American Journal on Roentgenology 148 (1987) 418–420
10. Tincher M.; Meyer C.H.; Gupta R.; Williams D.M.: Polynomial Modelling and Reduction of BF Body Coil Spatial Inhomogeneity in MRI. IEEE Transactions on Medical Imaging 12 (1993) 361-365
11. Brinkmann R. B. ; Maiti A. and Robb B. A. : Optimized Homomorphic Unsharp Masking for MR Greyscale Inhomogeneity Correction. IEEE Transactions on Medical Imaging, 17 (1998) 161-171
12. Liskar B.; Vergeyver M.A.; Permut F.: Retrospective Correction of MR Intensity Inhomogeneity by Information Minimization. IEEE Transactions on Medical Imaging 20 (2001) 1398–1410
13. Kwan R.K.S.; Evans A.C.; Pike G.B.: Extensive MRI Simulations for Post-Processing Evaluation. Visualization in Biomedical Computing (VBC)’96. Lecture Notes in Computer Science, vol. 1311. Springer-Verlag, (1996) 135-140
14. Arnold JB; Liew J-S; Schaper KS; Stern J; Sied JG; Bhatkonde DW; Worth AJ; Cohen MS; Leahy RM; Mazziotta JC; Rottenberg DA: Quantitative and Qualitative Evaluation of Six Algorithms for Correcting Intensity Non-Uniformity Effects. Neuroimage (2003) 13(5) 931-943
15. Christian Brechbuhler, Gudo Gerig, and Gabor Székely. Compensation of spatial inhomogeneity in MRI based on a multi-valued image model and a parametric bias-estimation. Visualization in Biomedical Computing Proc. VBC’96, Lecture Notes in Computer Science, No. 1311, Springer, pp. 141-146, Sept. 1996