RF Inhomogeneity Correction Algorithm in Magnetic Resonance Imaging

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Abstract. MR images usually present grey level inhomogeneities which are a problem of significant importance. Eliminating these inhomogeneities is not an easy problem and has been studied and discussed in several previous publications. Most of those approaches are based on segmentation processes. The algorithm presented in this paper has the advantage that it does not involve any segmentation step. Instead, a interpolating polynomial model based on a Gabor transform was used to construct a filter that can be used in order to correct these inhomogeneities. The results obtained are really good and show that the grey-level inhomogeneities can be corrected without segmentation.

1 Introduction

Magnetic Resonance Imaging (MRI) is a powerful technique in diagnostic medicine. In the last years the radiological sciences have highly expanded in different modalities, such as X-Ray Mammography, X-Ray Computed Tomography (CT), Single Photon Computed Tomography (SPECT), Positron Emission Tomography (PET) and functional Magnetic Resonance Imaging fMRI)[1]. The appearance of new scanners of Magnetic Resonance Imaging (MRI) with a high field (3 Tesla) and faster and more intense gradients, has given rise to the acquisition of new images of the brain that shows its physiology with a greater degree of detail and amplitude.

Additionally to structural type anatomical images, brain functional activity images are now arising, such as water molecules diffusion tensor imaging, perfusion imaging and blood oxygenation level dependent imaging (BOLD)[2].

Reconstruction techniques, processing and data analysis are development of radiological digital imaging. These techniques require a complex mathematical analysis which can be traced back to the theory of partial differential equations (PDE) and to linear and non linear diffusion processes.

The main difficulty in the analysis the MR[1] images is to locate and correct their inhomogeneities, it is to say, the regions with different levels of grey known as intensity artifacts in MR images. To correct them, it is necessary to employ complex algorithms.

[1] Magnetic Resonance

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Many different approaches to correct low-frequency grey level inhomogeneity in MR images have been published and described. All of them use a segmentation step of MR image. DeCarli [3] compares local correction of MRI[2] spatially dependent image pixel intensity specific tissue classes. Tincher [4] approach used a polynomial model of the RF[3] coil in order to decrease the inhomogeneity in MR images. Cohen [5] described a method for compensating purely intensity-based effects, using simple and rapid correction algorithms. Arnold [6] Qualitative and quantitative evaluation of six algorithms for correcting intensity non-uniformity effects. Gispert [7] Inhomogeneity images by minimization of intensity overlapping. Gispert [8] method for bias field correction of brain TI - Weighted Magnetic Resonance images minimizing segmentation error.

Our approach is simple and effective whereas we have developed a correction method that avoids the problems of intensity artifacts in MR images. This method is based on the theory of PDE and uses a multiscale low-pass filter based on a Gaussian kernel to extract the artifact (or a smoothed version of it) from the initial image which can be considered as a function $u_0 : \Omega \subset I\!R^2 \to I\!R$, being $u_0(x, y)$ the pixel (nodal) intensity values[4]. This allows us to study the fundamental structure of the artifact and to deduce a model for the grey level distribution. This has been calculated in the filtered, smoothed image, say $u_s(x, y)$, fitting the nodal values by using interpolating polynomial functions. The initial image u_0 can be then corrected with a low pass filter in the image domain using a (linear) diffusion attenuation model.

This paper is organized as follows. In Section 2 the algorithm is presented, explaining the details of the development. Section 3 shows the results obtained with real images. At last, in Section 4 conclusion and future works to improve the algorithm are presented.

2 Materials and Methods

The goal of the work presented in this paper is to determine a grey level attenuation correction algorithm. The MR image of the scanned brain is made up with a set of N slices and each slice is extracted from a three dimensional (3D) gradient echo (SPGR) acquisition (using $\alpha = 30^o$, $TR = 20$, $TE = 5$). Each image is represented, in a computational grid which discretize the image domain $\Omega \subset I\!R^2$, by a $n \times m$ matrix, where n is the number of nodes along the width and m is the number of nodes along the height of the slices. The matrix coefficients represents the grey level intensity at each pixel $(x_i, y_j) \in \Omega \subset I\!R^2, \forall i = 1 \dots n, j = 1 \dots m$.

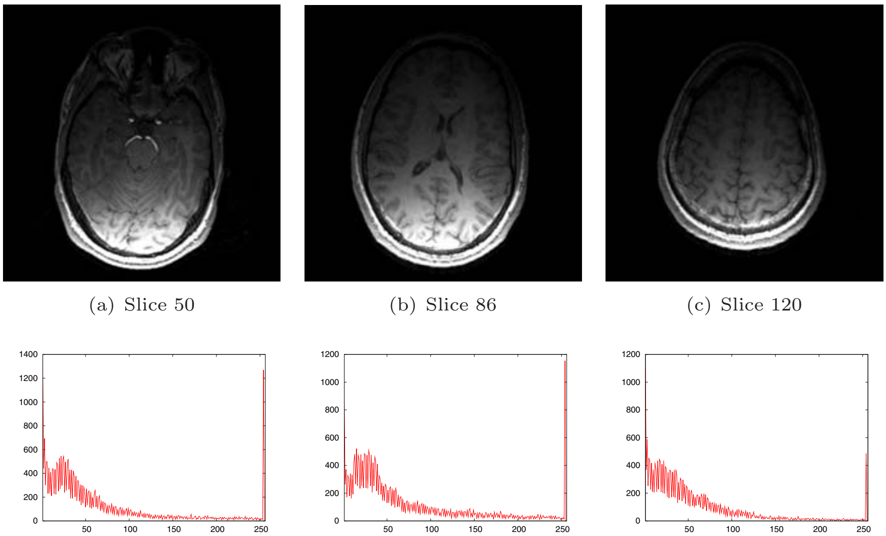
Grey-scale attenuation in our images is caused by a coil smaller than usual head coil in the occipital area in order to obtain a good signal-noise ratio in visual areas of the brain but losing signal from frontal areas. It is usually used in Brain activity studies.

[2] Magnetic Resonance Imaging

[3] Ratiofrequency

[4] In this communication we are not interested in the mathematical details of the analysis. Nevertheless it is well known ([9]) that a grey-scale image u can be represented by a real-valued mapping $u \in L^1(I\!R^2)$

In Fig. 1 an example of three different slices from the same brain is shown. As can be noticed the three of them are affected by the inhomogeneity artifact. Below each image its histogram is depicted.



(a) Slice 50 (b) Slice 86 (c) Slice 120

(d) Slice 50 histogram (e) Slice 86 histogram (f) Slice 120 histogram

Fig. 1. Three different slices from the same brain acquisition

The implemented algorithm involve 3 different steps, as can be seen in Fig. 2. In the following, each step is described.

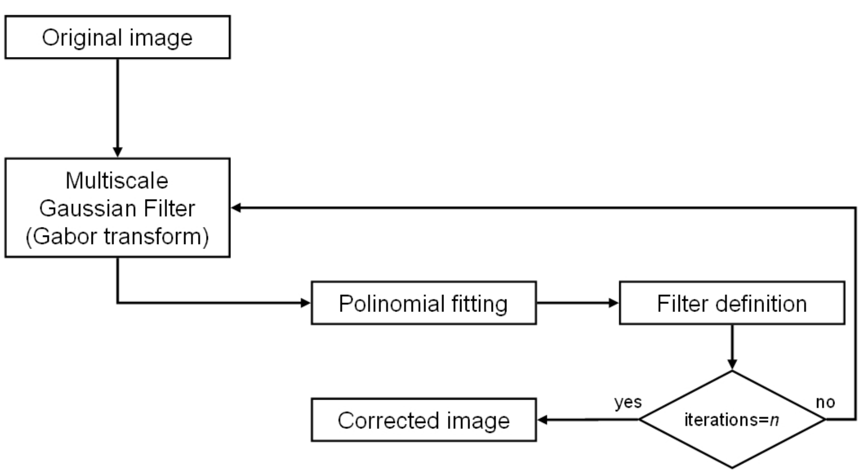


Fig. 2. Blocks diagram describing the algorithm

2.1 Multiscale Gaussian Filter

The first step is done in order to get a new, smoothed image u_s. Indeed, according to Shannon's theory, an image can be correctly represented by a discrete set of values, the samples, only if it has been previously smoothed. This simple remark, that smoothing is a necessary part of image formation, leads us to the theory of PDE [10] and linear diffusion.

The new image represents how is the illumination artifact, i.e., the distribution of the grey level inhomogeneity. This smoothing process is done using a low-pass filter based on a Gaussian kernel of the form:

$$K(x,y) = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{|(x,y)|}{2\sigma^2}\right) \tag{1}$$

where $\sigma > 0$ is the width (standard deviation). This filter attenuates high frequencies in a monotone way. It is well known, [9], that this is equivalent to linear diffusion filtering where smoothing structures of order σ requires to stop the diffusion process at time $T = \sigma^2/2$.

In a similar way we generate a pyramidal decomposition in a multiscale approach named Gabor Transform [11, 12]. The *evolution* of the image under this Gaussian scale–space like–process allows a *deep structure analysis* (see [9]) which provides useful information for extracting semantic information from an image, i.e, finding the most relevant scales (scales-section, focus-of-attention) of the artifact.

This method is justified from the nature of the artifact, because it is a low-frequency effect. The goodness of Gabor transform comes from the fact of having the best resolution in terms of frequency and spatial localization.

2.2 Artifact Polynomial Modelling

Once the artifact distribution is obtained it is necessary to infer a mathematical model of it. Several models can be used (exponential, Rayleigh, etc.) but in order to get the best approximation of the artifact behaviour a polynomial interpolation was used was used to exploit the spatial distribution of u_s and the discrete nature of the data.

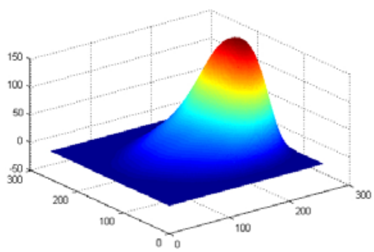
For each image column an interpolation is computed, so that the whole artifact model for each slice is composed of n interpolating polynomials. Fig. 3(b) shows the n polynomials as a unique interpolating surface.

2.3 Filter Definition

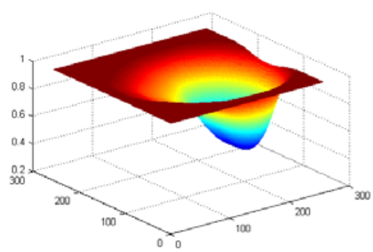
The mathematical model that we used to solve our restoration problem is based on Gaussian distribution of phases and produces an exponential attenuation of the signal (cutting-off the high frequencies). The result is that additional attenuation can be writen using a diffusion model of the form [13]:

$$A(D) = e^{-bD} \tag{2}$$

(a) Illumination artifact



(b) Artifact model



(c) Filter

Fig. 3. (a) Illumination artifact extracted from the Gabor tranform, (b) 3D representation of the artifact and (c) the 3D representation of the built filter

This expression describes the signal attenuation, where D represents the local tissue diffusion coefficient and b-factor depends on the amplitude and timing parameters of the gradient pulses used in the acquisition step of the initial data.

Empiric observations have proven that the diffusion coefficient can be replaced with the polynomial artifact model, while the b-factor has been replaced by a constant we called k. Using this notation Equation 2 can be written as follows:

$$A(P_i) = e^{-kP_i(y)}, \quad i = 1 \dots n \tag{3}$$

This means that the mathematical model used in molecular diffusion MRI can be also used to correct the grey level inhomogeneity. Based on this idea we defined the image filter (in the image domain) $e^{-kP_i(y_j)}$ to obtain the basic formula:

$$u_f(x_i, y_j) = u_s(x_i, y_j)e^{-kP_i(y_j)} \tag{4}$$

where u_f is the final, corrected image, u_0 is the original image with the inhomogeneity, P_i is the interpolating polynomial the i column and k is the constant previously mentioned.

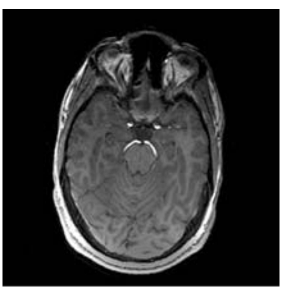
In Fig. 3(c) a 3D representation of a filter example can be seen.

3 Results and Discussion

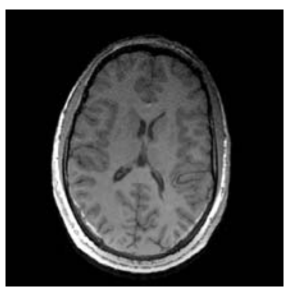
As said previously, the problem discussed within this paper is the correction of grey scale inhomogeneities in MR images. The original images affected with this intensity artifact can be seen in Fig. 1 while corresponding corrected images are depicted in Fig. 4. Comparing both figures it can be observed that the intensity artifact has been corrected, giving rise to homogeneous images.

Also, the following observations can be pointed out:

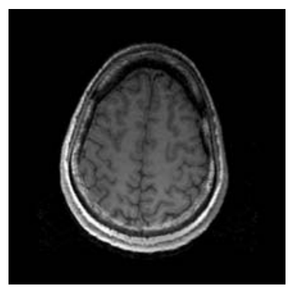
- In the corrected images new structures not clearly evident in the original images appear, such as the fat in the frontal and lateral-front parts.
- A good tissue texture definition can be seen in the rear or occipital part and a worse definition in the frontal of the brain. This can be explained taking into consideration that the original images have more information around occipital part than around the frontal part.



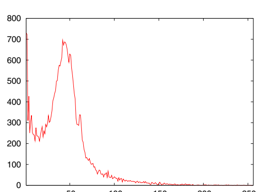
(a) Corrected slice 50



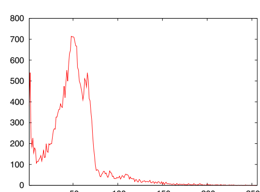
(b) Corrected slice 86



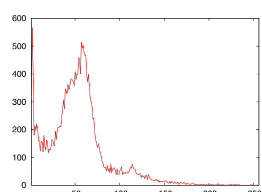
(c) Corrected slice 120



(d) Corrected slice 50 histogram



(e) Corrected slice 86 histogram



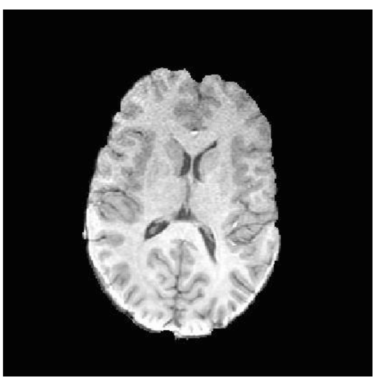
(f) Corrected slice 120 histogram

Fig. 4. Images from Fig. 1 after running the correction algorithm

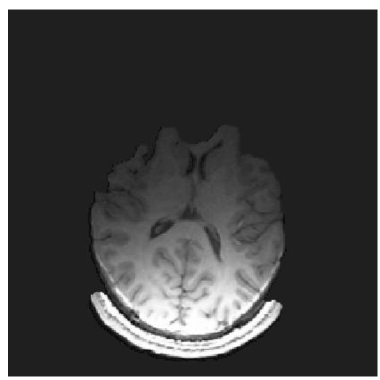
In the other hand, looking at the original histograms (see Figure 1) it can be pointed out the presence of a great concentration of pixels in highest intensity values. Those pixels represent the intensity artifact. Comparing it with the corrected histograms can be observed that this concentration has dispersed. While the original histograms have two peaks (corresponding to background and artifact) and a distribution of quite dark pixels (representing the rest of the structure) the corrected ones only present two distributions corresponding to the background and the structure.

The correction of the inhomogeneity artifact in MR images has a lot of utilities in different fields. The most important are:

1. **Visualization:** the image quality improvement will enable the physician to study the brain information not only on the RF affected part but the whole brain information.
2. **Segmentation:** the correction algorithm presented in this papers can be used as a previous step to brain segmentation algorithms, not being necessary to include an artifact modelling step in its process.
3. **Brain activity:** as a result of the better visualization of the whole brain and the homogeneous textures, brain activity can be detected in a more accurate way.
4. **3D rendering:** artifact images are not suitable for 3D rendering processes while corrected images can be used as a good input for this kind of techniques. In next figure (Fig. 5) we can observe one axial slice after 3D rendering with the artifact (Fig. 5(a)) and without the artifact (Fig. 5(b)).



(a) 3D corrected



(b) 3D non corrected

Fig. 5. One axial slice after 3D rendering with the artifact (a) and without the artifact (b)

4 Conclusions and Further Work

In this paper a method to correct the inhomogeneity in MRI has been presented. The main advantage of our method is that we don not need any segmentation step for restoration. As a result of this, our algorithm is simpler than the rest and our results are less affected by numerical errors.

A remarkable feature of the presented technique is the analogy with diffusion molecular model, where the diffusion coefficient has been replaced by a polynomial artifact model.

In future work we aim to exploit this analogy. Specifically we are interested in a non linear diffusion model where diffusion coefficient depends on the intensity of the illumination artifact. This can lead to a new approach where the RF artifact inhomogeneity is more realistic modelled.

Acknowledgments

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