Physics and Imaging in Radiation Oncology 4 (2017) 32–38

Contents lists available at ScienceDirect

Physics and Imaging in Radiation Oncology

journal homepage: www.elsevier.com/locate/phro

Original Research Article

Physical correction model for automatic correction of intensity non-uniformity in magnetic resonance imaging

Stefan Leger[a,*], Steffen Löck[a], Volker Hietschold[b], Robert Haase[c], Hans Joachim Böhme[d], Nasreddin Abolmaali[a,e]

[a] OncoRay – National Center for Radiation Research in Oncology, Faculty of Medicine and University Hospital Carl Gustav Carus, Technische Universität Dresden, Helmholtz-Zentrum Dresden – Rossendorf, Dresden, Germany
[b] Institute and Policlinic for Radiology, Faculty of Medicine and University Hospital Carl Gustav Carus, Technische Universität Dresden, Dresden, Germany
[c] Scientific Computing Facility, Max Planck Institute for Cell Biology and Genetics, Dresden, Germany
[d] Department of Artificial Intelligence, Faculty of Computer Science/Mathematics, University of Applied Science Dresden, Dresden, Germany
[e] Clinic for Radiology, Teaching Hospital Dresden – Friedrichstadt, Technische Universität Dresden, Dresden, Germany

ARTICLE INFO

Keywords:
Intensity non-uniformity
Magnetic resonance imaging
Bias correction
Quantitative image analysis

ABSTRACT

Background and purpose: Magnetic resonance imaging (MRI) plays an important role in the field of MR-guided radiotherapy or personalised radiation oncology. The application of quantitative image analyses like radiomics as well as automated tissue characterisation is frequently disturbed by the effect of intensity non-uniformity. We present a novel fully automated physical correction model (PCM) for the reduction of intensity non-uniformity.
Materials and methods: The proposed algorithm is based on a 3D physically motivated correction model, which maximises the image information expressed by the Shannon entropy. The PCM was evaluated using the coefficient of variation (cv) on 176 MRI datasets of the human brain and abdomen acquired on 1.5 Tesla and 3 Tesla MR scanners. The resulting cv was compared to the cv of the original images and to the results of the established N4 algorithm.
Results: The PCM algorithm significantly improved the image quality of all considered 1.5 and 3.0 Tesla MR scans compared to the original images ($p < .01$). Furthermore, the PCM outperformed or competed with the N4 algorithm in terms of image quality. Additionally, the PCM approach preserved the tissue signal of different tissue types due to smooth correction gradients.
Conclusion: The proposed PCM algorithm led to a significantly improved image quality compared to the originally acquired images, suggesting that it is applicable to the correction of MRI data. Thus it may help to reduce intensity non-uniformity which is an important step for advanced image analysis.

1. Introduction

Magnetic resonance imaging (MRI) is an established non-invasive imaging technique for clinical diagnostic and treatment [1]. Due to its high soft-tissue contrast MRI received increasing attention in radiation oncology over the last years [2–5]. For instance, MRI plays an important role in the field of MR-guided radiotherapy or personalised radiation oncology which aims to characterise the tumour phenotype based on imaging data (radiomics) [6,7].

Typical MR images are influenced by artefacts caused by different sources. One of the most frequent artefacts is intensity non-uniformity (bias) [8,9]. It occurs as a smooth intensity variation across the image, such that the intensity of the same tissue changes within the image region. It may be caused by a number of factors, such as magnetic field or radio frequency (RF) inhomogeneity of the MRI scanner and patient anatomy [10]. Intensity non-uniformity is usually hardly perceived by the human observer. However, automatic image segmentation or registration algorithms are very sensitive to such variations of image intensities [11]. Also, the performance of radiomics risk models may be negatively influenced, *e.g.*, due to a high variation in the expression of imaging biomarkers. Therefore, a reduction of intensity non-uniformity prior to automated quantitative image analyses is required.

During the last years, several correction methods have been proposed to correct bias in MRI by numerous authors [12,13]. For instance, George et al. [14] proposed a 2D non-iterative multi-scale approach using Log-Gabor filter bank. However, this approach used only 2D

* Corresponding author at: OncoRay - National Center for Radiation Research in Oncology, Faculty of Medicine and University Hospital Carl Gustav Carus, Technische Universität Dresden, Fetscherstraße 74, PF 41, 01307 Dresden, Germany.
E-mail address: Stefan.Leger@oncoray.de (S. Leger).

https://doi.org/10.1016/j.phro.2017.11.003
Received 28 June 2017; Received in revised form 23 November 2017; Accepted 23 November 2017

instead of the entire 3D image information to estimate the bias correction field which may reduce the correction performance. In contrast, Chang et al. [15] proposed a higher-order variational model for bias correction for brain MR scans. Furthermore, Ivanovska et al. [16] presented a level-set based approach for simultaneous intensity non-uniformity correction and segmentation of MR images. Segmentation-based bias correction methods usually depend on the accuracy of the segmentation. This may lead to good correction results in the case of images with a homogenous tissue structure, such as brain MR scans. However, for the correction of more heterogeneous parts, *e.g.*, abdomen scans, the correction may lead to poor results caused by imprecise segmentation. A further class of correction algorithms are histogram based methods. They estimate the correction function directly from the image intensity histograms. A typical strategy is based on an iterative deconvolution approach which attempts to maximise the high frequency content of the tissue intensity distribution in terms of an optimisation process [17]. A well-known and widely used correction approach of this category is the N4 algorithm [18]. While the N4 generally performs well in the case of simple tissue structures, a strong intensity correction can occur when the tissue structures are more complex.

Therefore, we propose a novel fully automated approach for the correction of intensity non-uniformity for retrospective evaluation of MR images, which we call physical correction model (PCM). The PCM is based on the assumption that the image signal emitted by the tissue is slowly decreasing to the image centre caused by the physical construction of an MRI surface coil array (*e.g.*, head coil). The estimation of the correction function is performed during an optimisation process with the aim to maximise the image information expressed by the Shannon entropy [19]. We applied the PCM to simulated and clinical data of the human brain and abdomen to evaluate its correction performance. Furthermore, we compared the achieved results with the established N4 correction algorithm. In addition, the tissue signal was assessed between different tissue types for the abdomen dataset.

2. Material and methods

2.1. Physical correction model

Intensity non-uniformity in MRI is induced by a number of factors, such as magnetic field inhomogeneity, radio frequency or patient anatomy [9,10,20,21]. The proposed PCM is based on the assumption that the effect of intensity non-uniformity in MRI occurs because the image signal emitted by the tissue is slowly decreasing to the coil array centre. We hypothesised that this decrease is basically caused by damping of the RF intensity emitted by the coil and the tissue response. To confirm this hypothesis we performed an experiment using a cylindrical water phantom, which should have a uniform intensity in the image region. The image volume was acquired with a 1.5 Tesla MR scanner using a typical MRI receiver head coil array with eight single coil segments. Further details about the experiment are described in Supplement A. Based on these experimental results we defined the physical correction model f depending on the image coordinates (x, y, z) by

$$f(x,y,z) = f_z(z)\cdot\sum_{i=1}^{n} e^{-a_i\sqrt{(f_{ix}(z)+x)^2+(f_{iy}(z)+y)^2}}, \tag{1}$$

$$f_z(z) = \frac{q_1}{\sqrt{2\pi\sigma^2}}e^{-\frac{(z-v_z)^2}{2\sigma^2}}, \tag{2}$$

$$f_{ix}(z) = \cos(i\alpha+\omega)\cdot d_i - x_m - S_x(z), \tag{3}$$

$$f_{iy}(z) = \sin(i\alpha+\omega)\cdot d_i - y_m - S_y(z), \tag{4}$$

$$S_x(z) = s_x\cdot z + v_x, \tag{5}$$

$$S_y(z) = s_y\cdot z + v_y. \tag{6}$$

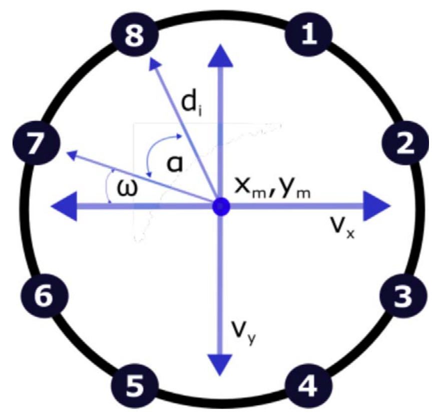

Fig. 1. Illustration of the geometric parameters of the physical correction model (PCM) for a typical MRI head coil consisting of eight coil segments.

The gradually decreasing image signal to the coil centre (x_m, y_m) was modelled by an exponential base function for each coil segment $i = 1...n$ and the exponential decay rate of coil segment i is described by a_i. The functions f_{ix} and f_{iy} describe the geometric location of coil i, where d_i is the distance from image centre to coil i, α is a constant angle between the coil segments and ω is the angular shift. Furthermore, the MRI image signal in longitudinal direction was described by a Gaussian base function f_z, in which v_z describes the shift in z-direction and σ the standard deviation of the Gaussian function. In addition, we included the linear shifts S_x and S_y in z-direction for each horizontal and vertical position of the patient on the scanner table. The parameter q_1 is a global pre-factor to scale the whole correction function. Fig. 1 shows a schematic 2D-view of a typical MRI head coil as well as the geometric parameters of the introduced model. For a typical head coil array, which consists for example of eight single coil segments ($n = 8$), the proposed correction model has in total 27 free parameters. Three of these parameters, x_m, y_m and $\alpha = 360\,n^{-1}$ are given by the geometry of the coils which can be extracted, *e.g.*, from the meta information of the image file.

To correct intensity non-uniformity in MRI images, an established formation model is a simplified multiplicative approach [22,23]. According to this approach, the acquired image
I(x, y, z) was obtained by

$$I(x,y,z) = t(x,y,z)\cdot f(x,y,z) + \xi(x,y,z), \tag{7}$$

where (x, y, z) is the spatial position, t is the wanted uniform signal emitted by the tissue, f is an unknown non-uniformity function and ξ describes independent additive noise. The noise will be neglected in the following considerations. The multiplicative model (7) can be used to obtain the uniform image t which is emitted by the tissue,

$$t(x,y,z) = \frac{I(x,y,z)}{f(x,y,z)}. \tag{8}$$

To compensate intensity non-uniformity according to (8) we estimated the function f by (1). The optimal parameters of this model are determined by maximisation of the image information, which was expressed by the fitness function F,

$$F(I) = E(I) + e, \tag{9}$$

where $E(I)$ is the Shannon entropy and e is an additional penalty term. The Shannon entropy $E(I)$ is defined as

$$E(I) = -\frac{1}{X}\cdot\sum_{b=1}^{B} p_b\cdot log_2(p_b). \tag{10}$$

It is based on the intensity distribution of the MRI image I computed by a grey value histogram. Furthermore, it contains the volume X of the spatial domain as normalisation factor, the number of bins B of the