Noise-compensated bias correction of MRI via a stochastically fully-connected conditional random field model

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Introduction The bias field inhomogeneity in Magnetic Resonance Imaging (MRI) can lead to challenges in the interpretation of MR images due to difficulties in observing different features and details of the imaged structure especially at locations farther from the MRI coil. Therefore, bias field correction is an important step for improving the visualization of MR images in the clinical setting. Many MR scanners perform a pre-calibration step on the image acquisitions [1] or use post-processing methods such as Surface Coil Intensity Correction (SCIC) algorithm [2] to compensate for the bias field. One important challenge in most bias field correction methods is the noise amplification. In this work, we propose a unified Bayesian-based image reconstruction algorithm which simultaneously corrects for the bias field and suppresses the MRI noise.

Materials and Methods We model the effect of bias field and noise as [3]: $M(y) = B(y)M_C(y) + N(y)$, where $M(.)$ and $M_C(.)$ are the measured and bias-free MR images, respectively, B is the bias field and N represents the MRI noise. In the proposed reconstruction framework, we obtain an estimate of Noise Free Bias Corrected MR (NFBC-MR) image by solving the inverse model of: $M_C = B^{-1}(M)$. To this aim, we design an optimization problem of the form: $\widehat{M_C} = \text{argmax}_B \, \text{P}(M_C|\text{M})$ in a Maximum A Posteriori (MAP) framework which jointly works with a Stochastically Fully Connected Conditional Random Field (SFC-CRF) model [4]. The aim of utilized SFC-CRF model is to use the long spatial interactions that usually exist among the different sets of the image pixels when it effort to model the reconstructed NFBC-MR image. Using the SFC-CRF model helps to better preserve the anatomical features and details of the image structures while suppressing MRI noise.

Results and Discussion The proposed method was tested on two real T2-weighted MR data (Fig. 1(a,d)) that are provided by Brigham and Women's Hospital, the National Center for Image-guided Therapy and Harvard Medical School [6]. Furthermore, a multi-modality prostate training MRI phantom (Fig. 2(a)) from Computerized Imaging Reference Systems Inc (CIRCS Model 053) was imaged using a 3T GE Discovery MR750 MRI system and used to test the proposed method. Visual assessment of the results demonstrates that the proposed method provides a better visualization and preservation of details within the prostate gland in both the Peripheral Zone (PZ) and Transition Zone (TZ) when compared to the tested SCIC algorithm (indicated with the red arrows in Fig. 1). Furthermore, the effectiveness of the proposed reconstruction method for the noise suppression can also be seen (indicated with the green arrows in Fig. 1). For the aim of quantitative analysis, the Coefficient of Variation ($CV = \frac{\sigma}{\mu}$) was calculated for the two different homogeneous regions of the phantom image (red squares in Fig. 2), where σ and μ are the standard deviation and mean intensity values within those regions, respectively. The calculated CV values show the minimum amount of intensity variation for the proposed method (0.02 in R1 and 0.03 in R2) compared to the uncorrected image (0.08 in R1 and 0.1 in R2) as well as the tested SCIC algorithm (0.03 in R1 and 0.06 in R2). The fact that the proposed bias field correction framework suppresses the inherent noise of MR image while preserving the sharpness of the image could significantly improve its usefulness compared to the tested SCIC method.

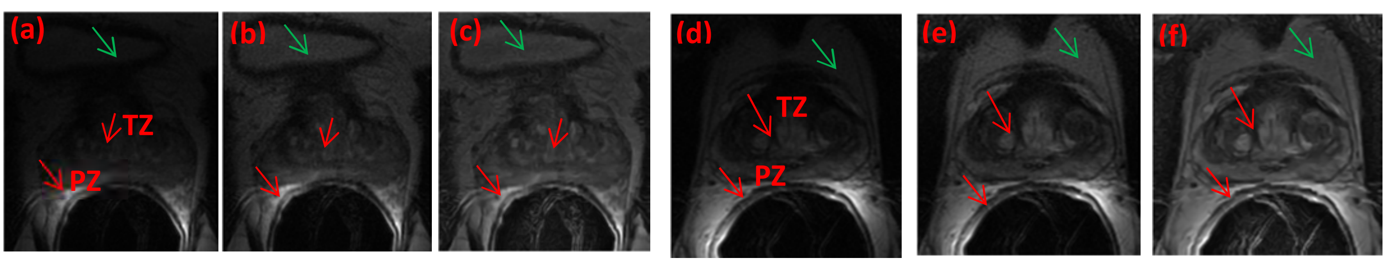

Fig. 1: (a,d) Uncorrected MR images. Reconstructed MR images using (b,e) SCIC method and (c,f) proposed method.

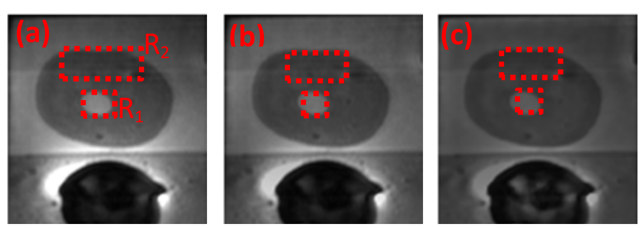

Fig. 2: (a) Uncorrected MR phantom image. Reconstructed MR phantom images using (b) SCIC method and (c) proposed method.

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