

Direct and Indirect Surface Coil Correction for Cardiac Perfusion MRI

H. Xue¹, S. Zuehlsdorff², and J. Guehring¹

¹Corporate Research, Siemens Corporation, Princeton, NJ, United States, ²CMR Research and Development, Siemens Healthcare, Chicago, IL, United States

Introduction Although the first-pass myocardial perfusion MRI has proven its effectiveness in the diagnosis of ischemic heart disease, this technique is still not routinely used. Certain technical difficulties prevent perfusion MRI from being added into the clinical workflow, including complex cardiac motion, limited imaging time, and B1-field inhomogeneity caused by non-uniform characteristics of the receiver coils. While the perfusion imaging sequences and motion correction has been thoroughly investigated by many researchers [1], the B1-field inhomogeneity correction still lacks intensive studies. Even as qualitative visual reading is often not compromised by the inhomogeneity [2], it causes the drifting of signal intensities and leads to errors of quantitative or semi-quantitative perfusion analysis [1]. We therefore propose algorithms to perform surface coil inhomogeneity correction (SCC) using proton density (PD) weighted images and B-Spline Free-Form Deformation (FFD) [3]. Two strategies were developed: one was to directly approximating the inhomogeneity field and the other interleaved the FFD approximation and PD image tissue classification using the Expectation-Maximization (EM) algorithm. The feasibility of the proposed techniques was verified on patient datasets.

Material and Methods Sequence Design: A MR perfusion pulse sequence was implemented and tested on two clinical 1.5T scanners (MAGNETOM Avanto and MAGNETOM Espree, Siemens Healthcare). The sequence supports the commonly used readout modules, TurboFLASH, TrueFISP, and GRE-EPI, respectively. The pulse sequence was modified to first acquire a small number (e.g. 2) of PD images prior the start of the first pass perfusion data acquisition. **Direct SCC:** This approach assumes that the proton density across the myocardial anatomy is constant [1] and that the intensity changes of PD images are positively related to local surface coil sensitivity. Therefore, an approximation of the B-Spline FFD is computed to extract the low-frequency (LF) component of PD images. This LF image is directly applied to correct the B1 inhomogeneity of the entire perfusion series. To eliminate the influences of background pixels, the Otsu method [4] was performed iteratively to find an optimal threshold. **Indirect SCC(Fig. 1):** Unlike the direct approximation of the inhomogeneity field, the indirect method interleaves the tissue classification and bias correction. We assume a multiplicative bias field. Therefore, using the notation $\tilde{x}_i = \log(x_i)$, the image formation model can become additive $\tilde{x}_i = \tilde{r}_i + \tilde{b}_i$, where x_i is measured intensity at pixel i and corresponding bias field is b_i . The unbiased signal \tilde{r}_i is estimated using the EM algorithm. The dense 2D bias field is parameterized at a sparse control point lattice using a 2D FFD. To find the optimal control point value of this FFD, we estimate a ‘bias-free’ image: $\tilde{r}_i^{(m)} = \sum p^{(m)}(k|x_i) \cdot \tilde{\mu}_k^{(m)} / \sum p^{(m)}(k|x_i)$ where $\tilde{r}_i^{(m)}$ denotes the estimated real signal at pixel location i for iteration m and $\tilde{\mu}_k^{(m)}$ is the EM mean and $p^{(m)}(k|x_i)$ is the posterior probability for tissue class k . The bias for this iteration can be estimated as $\tilde{b}_i^{(m)} = \text{approx}(\tilde{x}_i^{(m)} - \tilde{r}_i^{(m)})$. $\text{approx}(\cdot)$ is the FFD approximation step. Given the estimated bias field, the corrected signal can be updated as $\tilde{x}_i^{(m+1)} = \tilde{x}_i^{(m)} - \tilde{b}_i^{(m)}$. Once the iteration converges or a maximum number of iterations is reached, the final bias field and corrected PD image are calculated by an exponential operator. Based on experimental evidence, we decided to classify PD images into three classes: background (BG), tissue with low intensity (TL) and tissue with high intensity (TH) because the contrast level in PD images is not sufficient to delineate specific tissue classes and the purpose here is not to get a detailed segmentation. We found this three-class assumption is robust for separating the regions of background and lung from organ tissues. To improve the accuracy of the inhomogeneity estimation, all background pixels are then excluded from further computations. Furthermore, for both direct and indirect SCC, a multi-level extension of FFD is employed (2 levels, 3 and 5 control points respectively) because it offers lower approximation errors [5].

Results Validation was performed on anonymized data from 40 subjects, with a total of 260 perfusion series. Three different MR perfusion imaging sequences (74 TurboFLASH, 12 TrueFISP, and 174 GRE-EPI) were used in these scans. All scans were performed with a minimum of three slice positions (basal, mid-ventricular and apical) and 2 PD images were acquired before the perfusion acquisition. The inhomogeneity correction fields estimated from the PD images were applied to the entire perfusion series to correct for the bias introduced by the surface coils. Visual inspection showed the reduction of intensity inhomogeneity that was consistently discernible throughout the whole data cohort. To quantitatively verify the effects of bias correction, we selected the first frame of the perfusion acquisition and measured the intensity profile across the heart. We then fit a straight line to the data and estimated the absolute slope (AS) with and without bias correction. Because saturation recovery or inversion recovery pulses are normally applied to null the pre-contrast blood and tissue in the perfusion imaging, the intensity profile of the first phase often shows bias through the heart. For a group of 20 randomly selected series from the whole data cohort, the mean AS was originally 0.17 ± 0.13 and reduced to 0.06 ± 0.07 for indirect SCC and 0.08 ± 0.04 for direct SCC. An illustration of SCC performance is provided in Fig. 2.

Discussion Both SCC approaches count on the B-Spline FFD to estimate the bias field. While the direct method is more computationally efficient, the indirect method shows higher accuracy. Current algorithm parameters are empirically determined and further work includes studying the optimal FFD parameters and evaluating the performance of the proposed methods on semi-quantitative perfusion parameter maps and absolute myocardial blood flow estimation.

References [1] Kellman P *et al.*, JCMR 10:525-537 (2007) [2] Guillemaud R *et al.*, IEEE TMI 16:238-251 (1997) [3] Lee SY *et al.*, IEEE VCG 3:228-244 (1997) [4] Otsu N, IEEE SMC 2:62-66 (1979) [5] Schnabel JA *et al.*, The 4th MICCAI 573-518 (2001)

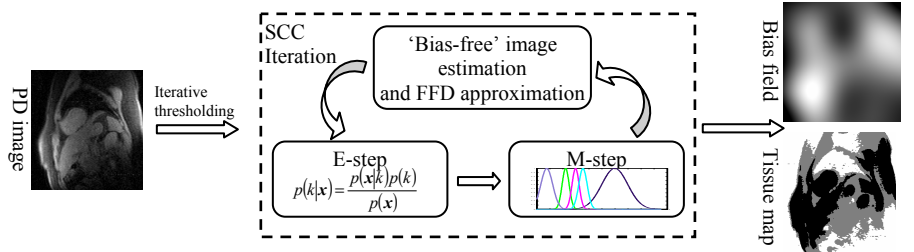


Figure 1. An illustration of indirect surface coil correction using EM algorithm and Free Form deformation.

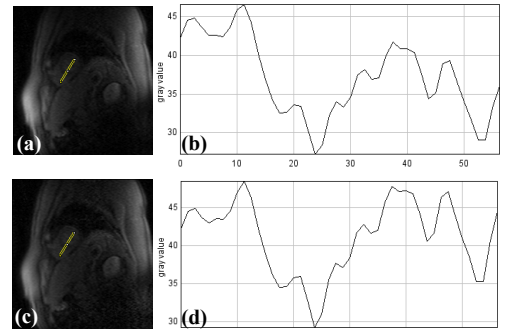


Figure 2. Performance of surface coil correction. (a) First frame of a GRE-EPI perfusion series; (b) Intensity profile shows clear inhomogeneity; (c) Corrected perfusion image; (d) Improved intensity profile. The indirect SCC method is used here.