META: Multiple Entangled denoising and Thresholding Algorithms for suppression of MR image reconstruction artifacts

Johannes F. M. Schmidt[1] and Sebastian Kozerke[1,2]

[1]Institute for Biomedical Engineering, University and ETH Zurich, Zurich, Switzerland, [2]Division of Imaging Sciences and Biomedical Engineering, King's College London, United Kingdom

Introduction: Incoherent image artifacts from random undersampling can be suppressed with a large variety of algorithms proposed in recent years [1-5]. If the image representation in a given transform domain is sufficiently sparse [6] for a given undersampling factor, each algorithm can reconstruct an image within bounds given by the measurement noise. However, in practical applications the undersampling factor is often pushed beyond the limits of each individual method and, accordingly, image artifacts remain. The various denoising methods introduce characteristic artifacts including Wavelet blocking artifacts, steps from total variation constraints or smoothing and blurring when using the temporal Fourier transform.

In this work, a statistical approach is proposed to combine multiple reconstruction and denoising techniques for suppressing reconstruction artifacts of individual algorithms. In each iteration step, different denoising algorithms generate a set of temporary images from the current image estimate. These images are then combined by extracting image features, which are present in the majority of the denoised data.

Methods: Fully sampled 2D cardiac images were acquired after written consent on a 1.5T system (Philips Healthcare, Best, The Netherlands). The k-space data was compressed to 4 virtual coils [7]. Retrospective undersampling with a factor of 5 in phase encode direction was performed as in [1]. For an acquisition matrix of 192x192, this resulted in 38 k-space profiles used for reconstruction. An iterative thresholding algorithm [8] was implemented in Matlab (Mathworks, Natick, USA) with various denoising and thresholding techniques including Wavelet transform, gradient transform, second gradient transform, bilateral filter [9] and non-local means filter [4,10]. Images were reconstructed with each of the denoising filters.

The proposed algorithm was implemented as in Figure 1. The initial image was set to 0. Three steps were performed in each iteration: (1) the image was updated using the acquired k-space data by adding the gradient of the data consistency constraint; (2) temporary images in every iteration were generated using the 5 denoising algorithms (Wavelet, gradient, second gradient, bilateral, non-local means). Automatic parameter adaption was achieved by performing each algorithm three times using the initial parameters as well as the initial parameters multiplied by 2 and divided by 2. Outliers due to wrong parameter settings were identified based on large Euclidean distance to the majority of the temporary images and were removed by k-means clustering; (3) the temporary images were combined using Gaussian weighting with a kernel width based on the mean of the Euclidean distances to the center of the cluster. Each reconstruction algorithm was run on a standard PC for 300 iterations. Wavelet, gradient domain and a non-local means filter coded in C had reconstruction times less than a minute. The Matlab bilateral filter and, hence, the proposed algorithm including the bilateral filter took a few minutes.

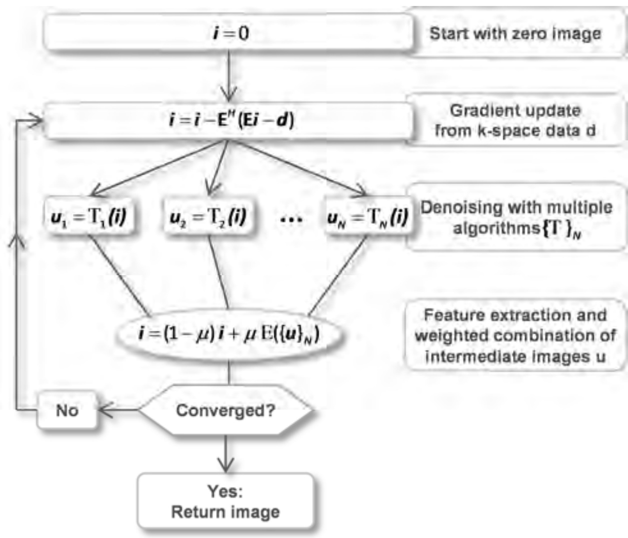

Figure 1: Flowchart for the proposed iterative reconstruction algorithm: Every iteration consists of three steps: (1) Gradient update using the acquired k-space data. (2) A set of denoised images is generated using different denoising techniques. (3) The denoised images are combined to the new image estimate as follows: A k-means clustering is used to remove outlier images which are very different from the majority of the images. The remaining images are combined using Gaussian weights. An optional step length μ can improve stability.

Results: Images from fully sampled and 5-fold undersampling are given in Figure 2. Reconstruction results of the 5 denoising algorithms and the combined result are shown in Figure 3. Each of the standard thresholding techniques show characteristic artifacts. In the reconstruction results of the proposed algorithm, the artifacts of the individual algorithms are suppressed.

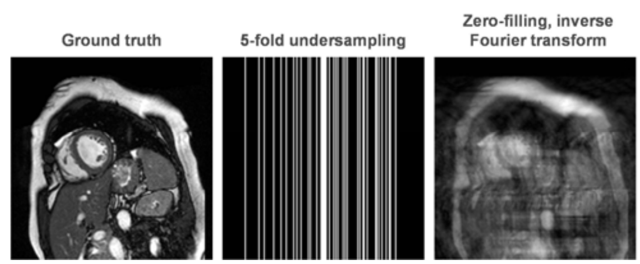

Figure 2: Exemplary ground truth image, the 5-fold undersampling pattern and the inverse Fourier transform image after zero-filling.

Discussion: A statistical approach for suppression of reconstruction artifacts has been proposed. Characteristic artifacts of an individual reconstruction method can be suppressed by incorporation of multiple algorithms and recombination of individual intermediate results into a single image estimate for each iteration.

References: [1] Lustig M, MRM (58), 2007; [2] Adluru G, ISBI, 2007; [3] Jung H,MRM (61) 2009; [4] Adluru G,JMRI (32),2010; [5] Ravishankar S, TMI 30(5), 2011; [6] Candès EJ, Comptes Rendus Math. (356), 2008; [7] Buehrer M, MRM (57), 2008; [8] Daubechies I, Comm. Pure Appl. Math. (LVII), 2004; [9] Tomasi C, IEEE Computer Vision, 1998; [10] Buades A, Multiscale Modeling & Simulation, 4(2), 2005.

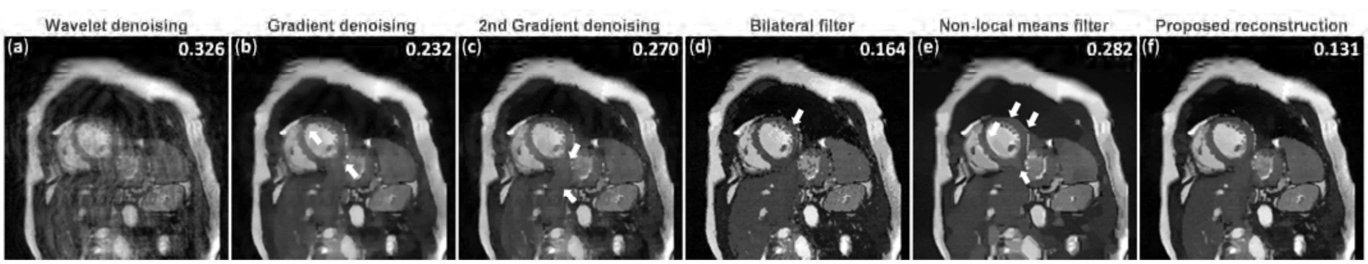

Figure 3: Reconstruction results for iterative thresholding using 5 different denoising techniques (a-e). Image (f) shows the results using the proposed algorithm with the combination of each denoising technique. Root mean squared differences are indicated in the upper-right corner of each image.