MR Image Reconstruction with Optimized Gaussian Mixture Model for Structured Sparsity

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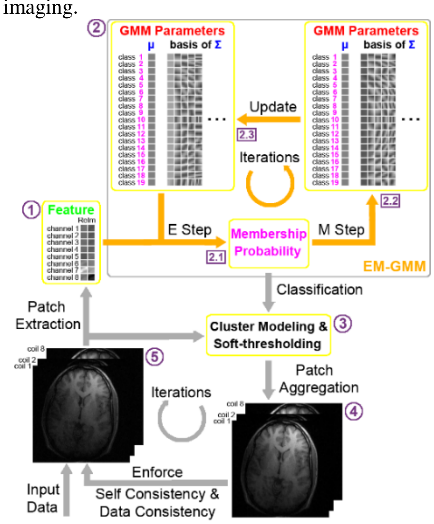
Introduction: Parallel Imaging (PI)[1,2] and Compressed Sensing (CS)[3,4] can be jointly used to restore undersampled data by exploiting k-space data correlations across different coils and data sparsity in transform domains respectively. However, the actual reconstruction performance is limited by noise amplification and image boundary/structure blurring especially at high reduction factor. With learned sparsifying transform adapted to image representation, the dictionary learning method[5] can outperform conventional CS techniques using analytical transforms in both noise suppression and detail preservation. But nonlinear sparse estimation such as L1 or matching pursuits may be unstable and imprecise with a full degree of freedom in selecting dictionary atoms[6]. Recently, LOST[7] attempted to overcome this problem by combining k-nearest neighbor (kNN) based clustering with low rank approximation to retain structured sparsity. However, it is computationally intensive to apply kNN procedure for each image patch even searching within a local region. Moreover, it is risky to assume that those nearest neighbors found in a local region can carry truly similar information. In this work, a Gaussian Mixture Model (GMM) was optimized to promote structured sparsity for the entire image patches and it was further merged into SPIRiT[3] framework to evaluate its performance for reconstruction of accelerated 3D high resolution brain imaging.

Theory and Methods: *GMM optimization:* Instead of finding similar patches within a local region for every image patch, GMM was used to generate a global similarity based clustering and classify the entire multichannel complex valued image patches in terms of their structural information. This structural similarity was primarily measured by the covariance matrices of GMM. As shown in Figure 1, the major basis of each covariance matrix was designed to represent one particular directional structure. Therefore, 18 groups of Gaussian models were established to characterize the potential directional boundary information (every 10 degree) in an image and their directional basis can be simply obtained by a numerical simulation[6]. In order to capture more complex structural patterns, another Gaussian model was initialized with the Discrete Cosine Transform (DCT) basis. *Image reconstruction:* The proposed method was implemented in an iterative Projection-Onto-Convex-Sets (POCS) fashion and its main steps (Figure 1) include: *1)* reshape multichannel complex valued MR image datasets into a matrix whose columns are vectorized patches extracted by sliding a multichannel window across the entire image data. *2)* classify image patches into different classes by Expectation Maximization (EM) GMM algorithm[8]. *3)* apply soft thresholding method[9] to enhance structural similarity within each class. *4)* aggregate overlapping patches to form multichannel image datasets. *5)* enforce parallel imaging self consistency[3] and data consistency. *Data acquisition:* To evaluate algorithm performance, one 8 channel T1 weighted brain dataset was downloaded from author's webpage[3,4] and another 3D isotropic 0.6mm Proton Density (PD) weighted brain dataset was acquired on a Philips 3T scanner (Philips Healthcare, Best, Netherland) with a 32 channel head coil.



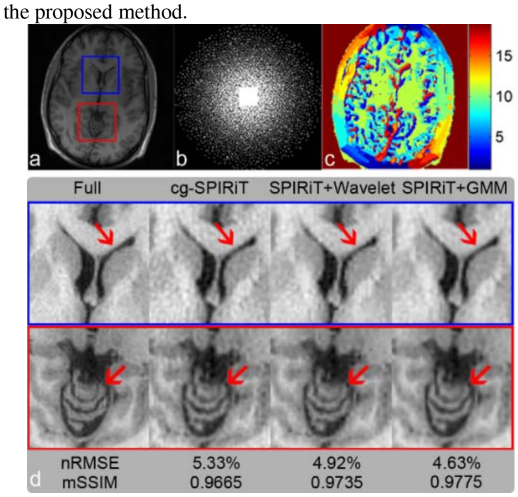
(↑)**Figure 1.** Flowchart of the proposed POCS algorithm. Within each outer (gray) iteration, Gaussian Mixture Model (GMM) was updated using inner (orange) iterative Expectation Maximization (EM) algorithm.

Results: Our proposed method (SPIRiT+GMM) was compared to L2 norm regularized SPIRiT (cg-SPIRiT) and wavelet domain L1 norm regularized SPIRiT (SPIRiT+Wavelet) methods[3]. Both in-vivo brain datasets were retrospectively undersampled with variable density Poisson Disk Sampling (vd-PDS) pattern but with different reduction factors. Figure 2 demonstrates that the proposed method can better preserve the image boundary information while providing improved noise suppression at R = 5 for 8 channel T1 weighted brain dataset. Figure 3 showes that the proposed method can improve delineation of both image boundary and detail structure (e.g. basilar arterial vessel wall as orange arrows indicated) at R = 6 for high resolution PD weighted brain dataset. Figure 2(c) and Figure 3(c) denote that optimized GMM can effectively recognize directional boundary and detail structure features. In addition, quantitative image quality measured by normalized Root Mean Square Error (nRMSE) and mean Structural SIMilarity index[10] (mSSIM) further demonstrated the overall image quality improvement of the proposed method.

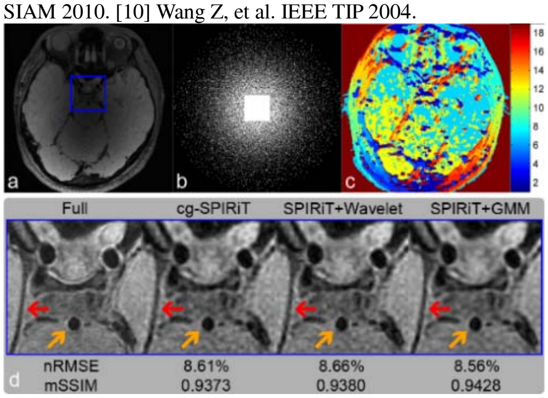
Discussion: The results demonstrated the improved performance of the optimized GMM for structured sparsity. Since the proposed algorithm is a self learning based method, image contrast estimation error can be eliminated compared to other dictionary learning methods using other weighted reference images. Moreover, this GMM *a priori* simplifies the traditional nonlinear sparse estimation into several piecewise linear problems that dramatically reduces the degree of freedom in estimations and are thus more stable. The proposed algorithm is expected to improve clinical applications with 3D high resolution imaging which are limited by long scan time.

Conclusion: In this work, we proposed an optimized GMM based algorithm for structured sparsity promotion to improve undersampled MR image reconstruction in terms of both noise suppression and structural information preservation.

References: [1] Pruessmann KP, et al. MRM 1999. [2] Griswold MA, et al. MRM 2002. [3] Lustig M, et al. MRM 2010. [4] Lustig M, et al. MRM 2007. [5] Ravishankar S, et al. IEEE TMI 2011. [6] Yu G, et al. IEEE TIP 2012. [7] Akcakaya M, et al. MRM 2011. [8] Redner RA, et al. SIAM 1984. [9] Cai JF, et al. SIAM 2010. [10] Wang Z, et al. IEEE TIP 2004.



(↑)**Figure 2.** Demonstration of image boundary preservation using T1 weighted brain image. (a) Fully sampled reference image. (b) vd-PDS pattern with net reduction factor of 5 (R = 5). (c) Final GMM clustering result where 19 categories were labeled with different colors. (d) Two local zoom-in results as indicated by blue and red squares in (a). Note the distinct capabilities for boundary sharpness delineation as illustrated by red arrows. nRMSE and mSSIM values were also measured and provided at bottom.



(←)**Figure 3.** Demonstration of detail structure representation using PD weighted brain dataset. (a) Full data as reference. (b) vd-PDS pattern with R = 6. (c) Final GMM clustering result labeled with 19 different colors. (d) Zoom-in results as indicated by blue square in (a). Note the local detail structure representation difference as illustrated by orange and red arrows. nRMSE and mSSIM values were also evaluated and shown at bottom.