 Improved Myocardial Perfusion PET Imaging with MRI Learned Dictionaries

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Abstract—The purpose of this study is to form PET image reconstruction sparse priors based on MR image learned dictionaries in Bayesian PET image reconstruction and to evaluate the performance in myocardial perfusion (MP) defect detection. A set of time activity curves representing the typical patient Rb-82 bio-distribution was applied in the analytical simulation with 2.5-min and 4.5-min cumulated activities. For each count levels, we used the 4D XCAT phantom to simulate two MP imaging datasets, one with normal MP and the other with a reduced activity region on the left ventricle. Using the SIMRI simulator, MR images were simulated with sequence specified to be 3D T1-weighted as in a clinical PET/MRI protocol. The maximum a posterior (MAP) PET image reconstruction that took dictionary-based sparse approximation of PET images as the prior was applied. Assuming that the PET and MR images can be sparsified under the same dictionary, the K-SVD algorithm was used in the dictionary learning (DL) process from the MR images. The receiver operating characteristic (ROC) analysis on the reconstructed images for perfusion defect detection was performed using a channelized Hotelling observer (CHO). The DL MAP algorithm demonstrated improved noise versus bias tradeoff compared to that from the ML algorithm and also provided better performance in the MP defect detection task.

I. INTRODUCTION

PET imaging has limited resolution due to physical degradation factors and the images are inherently noisy as of limited counting statistics. Incorporation of anatomical information measured from higher resolution MR or CT has been studied with the potential to improve quantitative accuracy of PET images [1]. The recent advent of integrated whole-body PET/MRI provides new opportunities and challenges to fully take advantage of the simultaneously acquired anatomical and functional information [2]. Anatomical information has been applied as different forms of priors in the Bayesian PET image reconstruction framework (e.g. [3-5]).

Sparsity representation has been proven to reduce the amount of data needed to acquire and to successfully accelerate MR imaging [6]. We developed a PET image reconstruction technique to incorporate a sparse prior based on the dictionary learned from MR images. The technique was applied and evaluated in brain imaging [7]. In this study, we propose to use the dictionary-based sparse prior for myocardial perfusion (MP) PET image reconstruction. Using realistically simulated cardiac PET data and MR images, our goal is to evaluate the performance of the proposed dictionary learning (DL) based maximum a posteriori (MAP) technique in MP perfusion defect detection.

II. MATERIALS AND METHODS

In this study, we simulated realistic MP PET imaging data and MR images. We performed MAP reconstruction using the prior based on sparse approximation of the PET images over the learned dictionary from the corresponding MR image. To evaluate the proposed technique, we compared the DL MAP reconstructed images with the conventional maximum likelihood (ML) method reconstructed images in the tradeoff between noise and bias on the left ventricle (LV) region and also in the task of MP abnormality detection.

A. PET Data Simulation

We simulated PET imaging data corresponding to two count levels, using the set of time activity curves representing the typical Rb-82 biodistribution [8]. This set of TACs was acquired by smoothing and averaging the TACs of blood pool, myocardium, and other organs extracted from the Rb-82 PET images of 5 patients with normal cardiac function. Analytical simulations were performed to simulate noise-free PET data. The noise-free sinograms were scaled to 2.5-min and 4.5-min cumulated activity after pre-scan delay of ~30 sec to avoid high blood pool activity. Using the 4D XCAT phantom, we simulated two MP imaging datasets, one with normal perfusion and the other with regionally reduced perfusion, for each count level. The perfusion defect was a nontransmural (endocardial) defect spanning 40° over the anterior-lateral region and 1.5 cm over the long-axis direction. Its activity was 10% less than the normal activity. Two-hundred Poisson noise fluctuations were created for both normal and abnormal perfusion cases at each count level.

B. Sparse Prior Incorporated Image Reconstruction

We developed a closed-form PET image reconstruction algorithm incorporating dictionary based sparse representation prior within the one-step-late (OSL) MAP expectation maximization (EM) approach. The iterative procedure is derived as [9]:

Manuscript received November 30, 2014. This work was supported in part by the U.S. National Science Foundation under grants ECCS-1228091 and CBET-1265612.
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\[ f_{\text{new}}^i = \frac{f_{\text{old}}^i}{\sum_j c_{ij} + \beta \frac{\partial V(f)}{\partial f^i}} \sum_j c_{ij} g_j, \]

where the new estimate of voxel \( i \) in the image vector \( f \) is updated from the old estimate. A single bin \( j \) of the measured emission data is represented by \( g_j \), and \( c_{ij} \) represents an element of the projection matrix \( C \), modeling the contribution of voxel \( i \) to projection bin \( j \).

We adopted dictionary-based signal representation framework to construct \( V(f) \) in this paper. Mathematically, let \( x \in \mathbb{R}^M \) and \( D \in \mathbb{R}^{M \times L} \) be the given signal and dictionary, respectively, sparse coding (SC) aims to solve the following problem:

\[ \alpha = \arg \min_{\alpha} \| x - D\alpha \|_2^2 \quad \text{s.t.} \quad \| \alpha \|_0 \leq K, \]

where \( \| \cdot \|_0 \) counts the number of non-zero entries in the vector, \( \alpha \in \mathbb{R}^L \) is called the sparse representation of \( x \) over \( D \), and \( K \) is the sparsity constraint. This \( l_0 \) problem can be efficiently solved by the orthogonal matching pursuits (OMP) algorithm [10]. When such a sparse representation is incorporated as a prior into the MAP reconstruction framework, we have the potential function \( V(f) \) as:

\[ V(f) = \sum_{i,j,k} \| R_{ijk} f - D\alpha_{ijk} \|_2^2. \]

The dictionary \( D \) is given a priori and has a size of \( M \times L \), with \( M = n_x \times n_y \times n_z \) and \( L \) being the number of element signals called atoms. The indexes \( (i, j, k) \) should cover all the available patches. The potential function \( V(f) \) also depends on \( \alpha_{ijk} \). In each reconstruction iteration, \( \alpha_{ijk} \) is first computed by the OMP algorithm based on current estimation of \( f \), and then \( f \) is updated according to (1). The derivative of \( V(f) \) with respect to \( f \) is:

\[ \frac{\partial V(f)}{\partial f} = 2 \sum_{i,j,k} \left( R^T_{ijk} R_{ijk} \right) f - 2 \sum_{i,j,k} R^T_{ijk} D\alpha_{ijk}. \]

C. MR Image Simulation and Dictionary Learning

The MR image simulation was performed using the open source MRI simulator SIMRI [11], which we modified to take the T1, T2, and proton density maps created using the XCAT phantom with known tissue values. To simulate a protocol used in the clinical PET/MRI, we specified the sequence to be 3D T1-weighted (turbo spin echo, echo time/repetition time: \( 2.3\text{ms/4ms} \)) with low flip angle of \( 2^\circ \).

In the proposed method, the dictionary \( D \) was learned from the anatomical images, and the process is called dictionary learning (DL). We used the well-known K-SVD (singular value decomposition) algorithm for DL due to its efficiency [12]. The K-SVD algorithm applies OMP (orthogonal matching pursuit) [10] for the SC sub-problem. As for the dictionary update stage, \( D \) was updated atom-by-atom by using the SVD operation. In the DL stage, the size of an atom \( (M) \) is \( n_x \times n_y \times n_z = 4 \times 4 \times 4 = 64 \). The number of atoms \( (L) \) is set to 256. The sparsity constraint \( K \) were set to two different values as 10 and 20. The sparsity values are used when computing \( \alpha_{ijk} \). An initial guess of \( D \) was needed in the K-SVD algorithm, and the 3D over-complete discrete cosine transform (DCT) dictionary was used for the initialization. The simulated MR image (center slice) and the corresponding learned dictionary are shown in Fig. 1.

D. Quantitative Image Evaluation Criteria

To quantitatively evaluate the performance of the DL MAP algorithm and compare it with the ML algorithm, we used the tradeoff between the noise and bias on the left ventricle (LV) region of the reconstructed normal MP images. Using the PET reconstructed images with 200 noise realizations, we calculated the normalized mean square error (NMSE) as a measure of bias:

\[ \text{NMSE} = \frac{\sum_{i=1}^{m} \left( \frac{\bar{f}_i - \bar{\mu}}{\bar{\mu}} \right)^2}{\sum_{i=1}^{m} \left( \frac{\bar{f}_i}{\bar{\mu}} \right)^2}, \]

where \( \bar{f}_i = \frac{1}{n} \sum_{i=1}^{n} f_i \) and \( \bar{\mu} = \frac{1}{n} \sum_{i=1}^{n} \mu_i \); \( f_i \) denotes the \( i \)th reconstructed voxel intensity from the \( i \)th noise realization and \( \mu_i \) denotes the reference true activity value; \( n \) is the number of voxels in the LV region and \( m \) is the number of noise realizations.

The normalized standard deviation (NSD) was calculated to measure noise

\[ \text{NSD} = \frac{1}{n} \sum_{i=1}^{n} \sqrt{\frac{1}{m-1} \sum_{j=1}^{m} (f_{i,j} - \bar{f}_i)^2}, \]

where \( f_{i,j} \), \( n \) and \( m \) were defined as those in (5); \( \bar{f}_i = \frac{1}{m} \sum_{j=1}^{m} f_{i,j} \) representing the ensemble mean value of voxel \( i \).
E. Receiver Operating Characteristic Analysis

To evaluate the ability of defect classification, we performed receiver operating characteristic (ROC) analysis for the perfusion defect detection task. We used a channelized Hotelling observer (CHO) with four octave-wide rotationally symmetric frequency channels to generate ratings for the defect-present and defect-absent images [13]. Each of the reconstructed images was reoriented and the short-axis slice covering the centroid voxel of the perfusion defect region was cropped to the channel template size, with the centroid voxel at the center of the cropped image. The leave-one-out strategy was applied in training and testing the observer for each combination of reconstruction method, iteration, and post-reconstruction filters. The resulted ratings acquired from the CHO were used to estimate ROC curves with the LABROC4 program [14]. This program estimates the parameters of the ROC curve, the area-under-curve (AUC) value and the standard deviations of these parameters. We compared the AUC values estimated from images from the proposed DL MAP algorithm at different sparsity levels and the conventional ML algorithm. The CLABROC program were used to test the significance of the difference between two ROC curves [15].

III. RESULTS

A. Reconstructed Images

The reconstructed images from the ML and the DL MAP algorithms without post-filtering (4.5-min cumulation data at iteration 2, with perfusion defect) are shown in Fig. 2, the latter of which clearly demonstrates the noise reduction achieved compared to the former. We also present the short-axis view of the corresponding reconstructed images (zoomed to the left ventricle and cropped for the ROC analysis) with and without post-filtering at different cutoff frequencies in Fig. 3 for visual comparison.

Fig. 2. Transaxial slice of reconstructed images (iteration 2, 4.5-min cumulation) from (a) the ML algorithm and (b) the DL MAP algorithm (sparsity at 20, applied to a cuboid covering the heart region), defect present, no post-filtering.

B. Tradeoff between Noise and Bias

In Fig. 4, we show the noise versus bias along with iteration number curves for images reconstructed by the ML and DL MAP algorithms. The effect of the sparsity level of OMP algorithm on the noise versus bias tradeoff in the DL MAP reconstructed images is also displayed in Fig. 4. With the same prior weighting parameter $\beta$ (Eqn. (1)), the lower sparsity level resulted in more bias (NMSE) but less noise (NSD) in the reconstructed images from the DL MAP algorithm. Overall, the DL MAP algorithm results in improved noise versus bias tradeoff, compared to the ML algorithm.

C. ROC Analysis

We first studied the DL MAP algorithm at different sparsity levels and compared the AUC values with those from the ML algorithm. Fig. 5 shows the AUC value plotted as a function of the cut-off frequencies for the perfusion defect detection...
from images reconstructed using the ML algorithm and the DL MAP algorithm. We use iteration 5 for comparing the performance of sparsity levels of the DL MAP algorithm. Between the two sparsity levels tested, sparsity level 10 results in AUC values higher than those from sparsity level 20 in the DL MAP algorithm at all the cut-off frequencies. The same results are observed for images at both the lower (Fig. 5 (a)) and the higher (Fig. 5 (b)) count levels.

After comparing the performance of sparsity levels incorporated in the DL MAP algorithm, we studied the effect of iteration number on the perfusion defect detection for the selected sparsity level. In Fig. 6, plots of the AUC versus the cut-off frequency at the iterations 2 and 5 from the ML algorithm are presented together with those from the DL MAP algorithm at sparsity 10. It is clearly illustrated that the iteration 2 results in better AUC values than the iteration 5, for both the ML and the DL MAP reconstructed images. The same conclusion can be drawn for images at both the lower (Fig. 6 (a)) and the higher count (Fig. 6 (b)) levels as well.

In Figs. 5 and 6, it is shown that the DL MAP algorithm results in improved AUC values compared to the ML algorithm. Specifically, as an example, the CLABROC test indicated that at the iteration 2 of the 4.5-min cumulation activity case the DL MAP algorithm with sparsity level 10 outperformed the ML algorithm statistically significantly with a corresponding two-tailed p-level less than 0.01. In general, the performance of the DL MAP algorithm is also much less influenced by with or without post-reconstruction filtering and the choice of cutoff frequency when filtering is applied.

IV. DISCUSSION

For the proposed DL MAP algorithm applied to the MP PET image reconstruction, we studied the effect of incorporated sparsity level and the iteration number on perfusion defect detection. The comparison of the DL MAP algorithm with different sparsity levels indicates the lower sparsity level, which results in larger bias however lower noise, performs better than the higher sparsity level. It appears that noise plays a more important role than bias in the images for the task of perfusion defect detection. In addition, in terms of optimizing iteration number for the defect detection task, the DL MAP algorithm demonstrates similar trend to that of the ML algorithm. That is, the earlier iteration results in better performance than the later iteration.

To further explore the DL MAP algorithm, we plan to study its performance in quantitative kinetic parameter estimation from MP PET imaging. The effect of sparsity level and iteration number on the estimation could vary from what we analyzed here for the perfusion defect detection task. More understanding of the DL MAP algorithm will be drawn from the coming investigations.
V. CONCLUSIONS

We developed a DL-based MAP algorithm for MP PET image reconstruction to incorporate the sparse representation of the reconstructed images as a prior. Using realistic MP PET imaging simulation studies, we demonstrated quantitative improvement on noise versus bias tradeoff and better performance in the MP defect detection task, achieved by the proposed DL MAP algorithm compared to the ML algorithm.

ACKNOWLEDGMENT

We thank Eric Stevens for the computational support.

REFERENCES