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Comparison of 3D OS-EM and 4D MAP-RBI-EM reconstruction algorithms for cardiac motion abnormality classification using a motion observer

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Abstract

Using a heart motion observer, we compared the performance of two image reconstruction techniques, a 3D OS-EM algorithm with post Butterworth spatial filtering and a 4D MAP-RBI-EM algorithm. The task was to classify gated myocardial perfusion (GMP) SPECT images of beating hearts with or without regional motion abnormalities. Noise-free simulated GMP SPECT projection data was generated from two 4D NCAT beating heart phantom models, one with normal motion and the other with a 50% motion defect in a pie-shaped wedge region-of-interest (ROI) in the anterior-lateral left ventricular wall. The projection data were scaled to clinical GMP SPECT count level before Poisson noise was simulated to generate 40 noise realizations. The noise-free and noisy projection data were reconstructed using the two reconstruction algorithms, parameters chosen to optimize the tradeoff between image bias and noise. As a motion observer, a 3D motion estimation method previously developed was applied to estimate the radial motion on the ROI from two adjacent gates. The receiver operating characteristic (ROC) curves were computed for radial motion magnitudes corresponding to each reconstruction technique. The area under the ROC curve (AUC) was calculated as an index for classification of regional motion. The reconstructed images with better bias and noise tradeoff were found to offer better classification for hearts with or without regional motion defects. The 3D cardiac motion estimation algorithm, serving as a heart motion observer, was better able to distinguish the abnormal from the normal regional motion in GMP SPECT images obtained from the 4D MAP-RBI-EM algorithm than from the 3D OS-EM algorithm with post Butterworth spatial filtering.

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Keywords

Cardiac motion observer; myocardial perfusion SPECT

I. Introduction

In gated myocardial perfusion (GMP) single-photon emission computed tomography (SPECT), regional analysis of wall motion provides information to identify stunned and hibernated revascularization [1]. It also helps in differentiating scar tissue from artifacts, and thereby reduces the number of equivocal studies and improves specificity of GMP SPECT [2], [3]. Quantitative evaluation of the cardiac motion is more valuable for the cases when a motion defect is present without the coexistence of a perfusion defect (e.g., myocardial stunning) [4]. Cardiac motion estimation techniques for CT images [5], PET images [6], and SPECT images [7], [8] have been developed. These techniques were visually evaluated and mainly applied for cardiac motion compensation in the reconstruction process. In [9], with the realistic 4D NCAT beating heart phantom, the performance of a 3D cardiac motion estimation method was studied quantitatively and optimized in terms of detecting regional motion abnormalities. The purpose of this study is to use the optimized cardiac motion estimation technique as a heart motion observer to compare the performance of a 4D MAP-RBI-EM reconstruction algorithm [10] with that of a standard 3D OS-EM algorithm with post Butterworth filtering. It was shown that the 4D MAP-RBI-EM reconstruction algorithm with optimized parameters [11] provided better perfusion defect contrast than the EM reconstruction algorithm with post-reconstruction filtering. The 4D MAP-RBI-EM algorithm was also shown to suppress noise level while improving image resolution [11]. In this study, the task for the performance comparison of the two image reconstruction algorithms is to classify normal hearts and abnormal hearts with regional myocardial motion defects.

II. Methods

In this section, we first describe the generation of noisy GMP SPECT projection data corresponding to a normally beating heart and an abnormally beating heart from the 4D NCAT phantom. Two image reconstruction techniques, the 3D OS-EM reconstruction algorithm with post-filtering and the 4D MAP-RBI-EM reconstruction algorithm, are then described. The 3D cardiac motion estimation technique, which serves as a heart motion observer, is briefly presented afterwards. At the end of this section, we provide the mathematical criterion and motion-classification task-based criterion for evaluating the two reconstruction methods.

A. Data Generation

The 4D NCAT phantom [15] with a realistic beating heart model [16] was used to simulate normal and abnormal cardiac motion. The abnormal cardiac motion is achieved by altering the normal motion in a specified pie-shaped wedge region on the left ventricle (LV). Two models of the beating heart phantom were used, one with normal motion and the other with a transmural motion defect (with no coexisting perfusion defect) in the region-of-interest (ROI) on the anterior-lateral wall of the LV. The ROI is illustrated in Fig. 1 with parameters specified as: $\theta_{\text{center}} = 45^\circ$, $\Delta\theta = 60^\circ$, and $\Delta Z = 3$ cm. For the abnormally beating heart, the magnitudes of motion for voxels in the center of ROI are reduced to 50% of the normal motion. The reduced motion magnitudes gradually diffuse back to normal with specified transition regions across the edges of the ROI in both short-axis (7.5°) and long-axis (0.3 cm) directions. Fig. 2 shows the quiver plots of the in-plane components of the normal and

abnormal motion vector fields (MVF) on the short-axis and long-axis slices of the LV at the end-diastole phase. Both the plots are zoomed to the ROI to show the reduced magnitudes of the abnormal MVF compared to those of the normal MVF. Note that the two MVFs are the same on areas other than the defect region, so we only see the abnormal MVF which is plotted on top the normal MVF.

From the normally and abnormally beating heart models in the NCAT phantom, GMP SPECT projection data (of 16-gate scheme) were generated. The heart models have 256^3 voxels with each voxel size as 0.156^3 cm^3 . An analytical projector was used to simulate 64 projection views over 180° using a parallel hole low-energy high-resolution (LEHR) collimator. After projection, the data was collapsed to pixel size of 0.312^2 cm^2 . The projector modeled the effects of non-uniform attenuation, collimator-detector response, and scatter. The slab-derived scatter simulation method was used to model the scatter effect [17]. The projection data from each of the two phantom models were scaled to the corresponding count level of a typical $^{99\text{m}}\text{Tc}$ patient GMP SPECT study. Then 40 Poisson noise fluctuations were generated using a Poisson random number generator from the scaled noise-free projection data for both normally and abnormally beating hearts.

B. Image Reconstruction Techniques

The 3D ordered-subset (OS) expectation-maximization (EM) algorithm [18] and the 4D maximum a posteriori rescaled-block iterative (MAP-RBI) EM algorithm [10] were used in the image reconstruction. The reconstruction algorithms were modified to include models of image degradation factors including attenuation, collimator-detector response, and scatter for their compensation. The scatter compensation used the effective source scatter estimation method [19].

In emission tomography, where the projection data follows Poisson distribution, the 3D ML-EM algorithm was developed to seek the maximum likelihood (ML) solution of the reconstruction problem through the expectation maximization (EM) steps [20] [21]. While the quality of the iterative EM reconstruction is better than the analytical reconstruction, the application is computer-intensive and convergence-slow. The OS-EM algorithm [18] accelerates the convergence of the ML-EM algorithm using the ordered subsets technique:

$$x_i^{\text{new}} = \frac{x_i^{\text{old}}}{\sum_{j \in S_n} C_{ij}} \sum_{j \in S_n} C_{ij} \frac{p_j}{\sum_k C_{kj} x_k^{\text{old}}}, \quad (1)$$

where x_i is the reconstructed image estimate at voxel i and p_j represents the measured projection data at bin j . The updated estimate and the previous iteration's estimate for spatial voxel i are represented by x_i^{new} and x_i^{old} , respectively, and C_{ij} represents an element of the projection matrix that models the contribution of voxel i to projection bin j . In the OS-EM algorithm, the projection bins are grouped into mutually exclusive subsets $\{S_n\}$. During each iteration, the image vector $\{x_i\}$ is updated once using each subset, resulting in an acceleration of the reconstruction by a factor that approximately equals the number of subsets. The images reconstructed using OS-EM (or ML-EM) algorithm are usually post-filtered to suppress noise. We originally applied 4D low-pass Butterworth filters (8th order in 3D spatial and 1D temporal domain, separately with varying cutoff frequencies) to the 3D OS-EM algorithm reconstructed image frames. It was found that post-reconstruction temporal filtering on all gates (after the 3D spatial filtering) with cutoff frequency at the Nyquist frequency did not change the image quality much (in terms of both evaluation criteria presented later in this section). But cutoff frequencies smaller than the Nyquist frequency provided smoothing that reduced the magnitudes of the estimated motion vectors;

the smaller the cutoff frequency, the more significant reduction in the magnitudes of the estimated motion vectors. As a result, the reconstructed images were only filtered by 3D spatial filters with different cutoff frequencies.

The 4D MAP-EM image reconstruction algorithm utilizes a 4D space-time smoothing prior (3D prior in the spatial domain and 1D prior in the temporal domain), which defines the relationship between a given image voxel and its neighbor voxels [22]. This algorithm reconstructs all the time frames simultaneously and the iterative process is given by

$$x_{i,t}^{\text{new}} = \frac{x_{i,t}^{\text{old}}}{\sum_j C_{ij} + \frac{\partial U(\mathbf{x})}{\partial x_{i,t}} \Big|_{\mathbf{x}=\mathbf{x}^{\text{old}}}} \sum_j C_{ij} \frac{p_{j,t}}{\sum_k C_{kj} x_{k,t}^{\text{old}}}, \quad (2)$$

where $x_{i,t}$ is the reconstructed image estimate for spatial voxel i in time t , $p_{j,t}$ represents measured projection data at bin j in time t , and C_{ij} represents the corresponding projection matrix element. The function $U(\mathbf{x})$ is the total potential function of the neighborhood (NH) and it is defined as the weighted sum of potentials of individual “cliques” (or pairs, in this study) of voxels. The derivative of $U(\mathbf{x})$ is computed with respect to the previous iteration’s estimate. In 4D image reconstruction, the function $U(\mathbf{x})$ covering both the spatial and temporal domains is defined as

$$U(\mathbf{x}) = \beta \left(\sum_{i,k \in \text{NH}_s} w_{ik} V_{\text{space}}(x_{i,t} - x_{k,t}) + \sum_{(i,t)(k,t+1) \in \text{NH}_t} w_{(i,t)(k,t+1)} V_{\text{time}}(x_{i,t} - x_{k,t+1}) \right), \quad (3)$$

where $\mathbf{x}$ represents the set of voxels in the neighborhood of voxel $x_{i,t}$. The first summation covers the cliques within a single time frame, and the second summation covers the cliques crossing time frames. The parameter and function definition in temporal domain is similar to that in spatial domain so we will only describe those in spatial domain here. For the spatial domain, the summation is taken over all pairs of voxels $x_{i,t}$ and $x_{k,t}$ that belong to the spatial neighborhood NH_s , and w_{ik} is the relative weighting factor associated with the designated pair. We used the so-called generalized potential function [22] for $V(d)$. Its derivative that more clearly shows the action is given by

$$\frac{\partial V(d)}{\partial d} = \frac{d}{|d|} \left(1 - \frac{\gamma}{2} \right) \left[1 + \alpha^2 \left(\frac{d}{\delta} - \frac{\delta}{d} \right)^2 \right]^{-\frac{1}{2}} + \gamma \left(\frac{d/\delta}{1 + |d/\delta|} \right), \quad (4)$$

where $d = x_{i,t} - x_{k,t}$. The parameters δ , α , and γ define the smoothing constraints in terms of difference between voxels within the specified clique. The neighborhood in the spatial domain consists of 18 nearest neighboring voxels which share at least a common edge with the current voxel. In the temporal domain, the neighborhood of the current voxel contains 6 voxels, which are located in the next frame sharing a common face with the voxel of the same spatial position as the current voxel. The MAP-EM algorithm was extended into the MAP-RBI-EM algorithm, in which an update was performed using a subset of the projection bins, for decreasing the reconstruction time [10]. The optimization of prior parameters in the generalized potential function in terms of trade-off between reconstructed image resolution and noise was studied in [11]. Eight subsets with eight projections per subset and 20 iterations¹ were applied to both the 4D MAP-RBI-EM and the 3D OS-EM reconstruction methods.

C. Cardiac Motion Estimation Method

A 3D cardiac motion estimation technique was used as the heart motion observer. It determines the 3D MVF $\mathbf{m}$ from two images through minimizing the cost function consisting of an image matching error term and a weighted regularization term:

$$E_I(\mathbf{m}) + \alpha E_s(\mathbf{m}). \quad (5)$$

The image matching error is defined as the intensity difference between the normalized first frame and the warped correspondence of the normalized second frame with an assumed MVF:

$$E_I(\mathbf{m}) \triangleq \sum_{\mathbf{r}} [f_1(\mathbf{r}) - f_2(\mathbf{r} + \mathbf{m}(\mathbf{r}))]^2, \quad (6)$$

where $\mathbf{r}$ is the spatial coordinate of a voxel, f_1 and f_2 are the normalized intensity images from which an MVF is to be estimated. For cardiac motion estimation, the images cover the heart region separated from the rest of the body with a predetermined mask. The strain energy function for a linear isotropic elastic material [23] is chosen to serve as the regularizing constraint:

$$E_s(\mathbf{m}) \triangleq \frac{1}{2} \sum_{\mathbf{r}} \left(\lambda (u_x + v_y + w_z)^2 \right) + \sum_{\mathbf{r}} \left(\mu (u_x^2 + v_y^2 + w_z^2) \right) + \frac{1}{2} \sum_{\mathbf{r}} \left(\mu \left[(u_y + v_x)^2 + (u_z + w_x)^2 + (v_z + w_y)^2 \right] \right), \quad (7)$$

where u , v , and w are the components of $\mathbf{m}$ in the x , y , and z directions of the Cartesian

coordinate, and u_x is the notation for partial derivative $\frac{\partial u}{\partial x}$. The parameters λ and μ are the 1st and 2nd Lamé constants, which arise in strain-stress relationships. One set of the Lamé constants uniquely defines the elasticity property of the modeled myocardium and the choice of λ and μ affects the performance of the motion estimation technique. In this study, the shear modulus μ was determined from the cross-fiber equibiaxial data and λ was calculated from the μ value and the bulk modulus determined from an LV finite element model developed by Veress *et al.* [24].

The MVF $\mathbf{m}$ is estimated using an iterative method that updates the current estimate $\mathbf{m}$ by minimizing the quadratic approximation of the cost function. $\tilde{\mathbf{m}}$ The conjugate gradient algorithm is applied to find the estimate that minimizes the convex function

$$Q(\mathbf{m}) + \alpha E_s(\mathbf{m}), \quad (8)$$

where

$$Q(\mathbf{m}) = \sum_{\mathbf{r}} \left[f_1(\mathbf{r}) - f_2(\mathbf{r} + \tilde{\mathbf{m}}(\mathbf{r})) - (\mathbf{m}(\mathbf{r}) - \tilde{\mathbf{m}}(\mathbf{r})) \cdot \nabla f_2(\mathbf{r} + \tilde{\mathbf{m}}(\mathbf{r})) \right]^2, \quad (9)$$

¹The iteration number was chosen based on similar studies on 3D and 4D cardiac SPECT imaging, performed in our research group [12], [13], [14]. These studies indicated that the 20th iteration was an optimal choice while the span of optimal iteration numbers was also fairly broad for the optimized filtering parameter.

is the quadratic approximation of $E_I(\mathbf{m})$.

In [9], we extensively studied the performance of this motion estimation technique in terms of detecting regional motion defects. We optimized parameter α for a better separability of normally beating hearts and hearts with regional motion defects. The signal-to-noise ratio, which reflected the statistical separability of the estimated normal and abnormal radial motion, was maximized [9].

D. Image Quality Evaluation

In evaluating the quality of reconstructed images, we used both the mathematical criterion and the task-based criterion, which are described in this subsection. The mathematical criterion is the tradeoff between the normalized mean-squared error (NMSE) and the normalized standard deviation (NSD), which are indices representing image bias and noise [11]. The task for judging the reconstructed image quality is classification of regional motion estimated from the heart motion observer.

The tradeoff between the NMSE and NSD as a function of iteration number provides information on the variation of image bias and noise in the reconstruction process. The NMSE was calculated from the entire heart region (a cubic volume encompassing the myocardium, blood pool, and background) of reconstructed noise-free images with respect to the phantom images:

$$\text{NMSE} = \frac{1}{n} \sum_{i=1}^n \left(\frac{x_i}{\bar{x}} - \frac{\lambda_i}{\bar{\lambda}} \right)^2, \quad (10)$$

where x_i is the i th heart voxel value of the noise-free reconstructed image, $\bar{x}$ is the mean of x_i , λ_i is the i th heart voxel value of the corresponding phantom image, $\bar{\lambda}$ is the mean of λ_i , and n is the number of voxels in the heart region. Note that the reconstructed or phantom images were normalized individually so that images of different scales could be compared. The NSD was calculated from the noisy reconstructed images, on an operator-selected region covering voxels along the central portion of the LV wall with relatively uniform intensities:

$$\text{NSD} = \frac{1}{n} \sum_{i=1}^n \frac{\sqrt{\frac{1}{m-1} \sum_{j=1}^m (x_i^j - \bar{x}_i)^2}}{\bar{x}_i}, \quad (11)$$

where x_i^j is the i th voxel value of the j th noise realization, $\bar{x}_i$ is the i th ensemble mean value of voxel i , n is the number of voxels in the region and m is the number of noise realizations. The NMSE and NSD were calculated for each frame and then averaged over the frames.

We propose to use the estimated regional radial motion magnitude as a decision variable in motion defect detection, i.e., the classification of the simulated normally and abnormally beating heart model images. The 3D motion estimation algorithm described in the last section was applied to the reconstructed normal and abnormal beating heart images at the end-diastole and its adjacent gates for each noise realization. The end-diastole and its adjacent gates contain motion of the largest magnitudes in the cardiac contraction cycle. It is better to detect motion defects from these two gates than from the other gates. The estimated end-diastole motion vectors were decomposed in radial, circumferential, and longitudinal

directions (as demonstrated in Fig. 1). The radial motion magnitudes on voxels within the ROI were averaged to represent the regional radial motion of the ROI. In this process, the 3D motion estimation algorithm serves as a mathematical observer which provides the regional radial motion magnitude as the rating values for the detection of cardiac motion defect.

The performance of the motion observer on images reconstructed by the 3D OS-EM algorithm with post Butterworth filtering and the 4D MAP-RBI-EM algorithm was characterized by receiver operating characteristic (ROC) curves. The PROPROC program [25] was applied, which fits an ROC curve by maximum-likelihood estimation and always provides convex fitted curves. The corresponding area-under-the-curve (AUC) values were also calculated as an index for classification of regional motion. The CLABROC program [26] was then applied to test the statistical significance of the differences between the ROC estimates obtained from images reconstructed by the two reconstruction algorithms.

III. Results

As mentioned in the II.B, the images reconstructed using the 3D OS-EM algorithm were post-filtered using low-pass Butterworth filters with different cutoff frequencies. When data were reconstructed with the 4D MAP-RBI-EM algorithm, different overall smoothing were applied by varying parameter β in the potential function (3). Note that the optimization of parameters within the individual potential function $V(d)$ in (4) was performed as described in [11] before studying the effect of parameter β . The parameter values chosen (for both spatial and temporal domains) were $\delta = 2$, $\alpha = 2$, and $\gamma = 0.5$.

A. NMSE-NSD Tradeoff

We calculated the NMSE and NSD for the reconstructed images corresponding to both the normally and the abnormally beating hearts. Since there was only motion defect but no coexisting perfusion defect on the LV, the NMSE or NSD from normal and abnormal heart images were very similar. Therefore, we only present NMSE and NSD results calculated from the normally beating heart images here.

The effect of the cutoff frequency of 3D spatial Butterworth filtering on the bias-noise tradeoff in the 3D OS-EM reconstructed images was plotted in Fig. 3. As shown, lower cutoff frequencies resulted in more bias (NMSE) in the noise-free reconstructed images but less noise (NSD) in the noisy reconstructed images. Among the cutoff frequencies tested, 0.5 cycle/cm generates result of the optimized NMSE-NSD tradeoff, as it lies more toward the origin, i.e., the lower-left corner of the plot.

The effect on the bias-noise tradeoff of the prior weighting parameter β of the 4D MAP-RBI-EM algorithm was plotted in Fig. 4. When more smoothing weight was applied, less noise (NSD) but more bias (NMSE) were found in the reconstructed images. The $\beta = 0.001$ and $\beta = 0.005$ were comparably better than the other two values in terms of balancing the NMSE-NSD tradeoff, one favoring the NMSE and the other favoring the NSD.

To compare the image quality reconstructed from the two reconstruction algorithms, we selected images at which their performance was optimized in terms of the resulting NMSE-NSD tradeoff. The NMSE-NSD tradeoff curve from 3D OS-EM reconstructed images with 0.5 cycle/cm cutoff frequency filtering and the one from 4D MAP-RBI-EM reconstructed images with $\beta = 0.005$ were plotted in Fig. 5. With comparable NMSE values, the 4D MAP-RBI-EM reconstructed images appeared to present lower NSD values than the post-filtered 3D OS-EM reconstructed images. For direct impression of the reconstructed images, we

show four noise realizations of a short-axis slice from each reconstruction algorithm (20th iteration) in Fig. 6.

B. ROC Analysis

The ROC curves fitted from the estimated abnormal and normal regional radial motion magnitudes were plotted in Fig. 7. Fig. 7(a) shows the ROC curves corresponding to different cutoff frequencies of the Butterworth filtered images reconstructed by the 3D OS-EM algorithm. The ROC curves corresponding to the 4D MAP-RBI-EM algorithm reconstructed images with different prior weights (β values) are shown in Fig. 7(b).

For the 3D OS-EM algorithm reconstructed images filtered with different cutoff frequencies, the AUC values corresponding to the ROC curves in 7(a) are shown in Table I. The cutoff frequency of 0.5 cycle/cm resulted in the largest AUC value of 0.75 among AUC values from the tested cutoff frequencies. Corresponding to the ROC curves presented in Fig. 7(b), the AUC values for regional radial motion estimated from the 4D MAP-RBI-EM algorithm reconstructed images with different prior weighting are listed in Table II. The β values of 0.001 and 0.005 resulted in better AUC values than the other two β values tested.

Showing classification of the regional radial motion, the AUC values estimated from the 4D MAP-RBI-EM algorithm reconstructed images were generally larger than the AUC values estimated from the 3D OS-EM algorithm reconstructed images. Comparing the ROC curve resulting in the largest AUC value from the 3D OS-EM with post-filtering algorithm (Fig. 7(a)) and the one from the 4D MAP-RBI-EM algorithm (Fig. 7(b)), the CLABROC test indicated that the difference between the two fitted ROC curves (Fig. 7(c)) was statistically significant with the two-tailed P level as 0.01. Therefore, the heart motion observer detects motion abnormality from the image reconstructed by the 4D MAP-RBI-EM algorithm better than from those reconstructed by the 3D OS-EM algorithm with post-filtering.

IV. Discussion

The tradeoff between NMSE calculated from reconstructed noise-free images and NSD from reconstructed noisy images was used to provide information on image bias and noise. It served as a mathematical image quality evaluation index in choosing parameters for an image reconstruction/filtering algorithm [11]. Although the NMSE and NSD are not task-based image quality indices, it was found that the tradeoff between them correlates with the AUC value that serves as the separability indices of the estimated regional radial motion.

Relating the NMSE-NSD tradeoff shown in Fig. 3 (Fig. 4) to the AUC values in Table I (Table II), we noticed that parameters (cutoff frequency in the Butterworth filter after 3D OS-EM reconstruction and weighting of the prior in 4D MAP-RBI-EM algorithm) generating better images in terms of NMSE-NSD tradeoff also resulted in better separability of the motion observer estimated normal and abnormal regional heart motion. More obviously, a better NMSE-NSD tradeoff is shown in the 4D MAP-RBI-EM algorithm with $\beta = 0.005$ reconstructed images than in the 3D OS-EM algorithm with 0.5 cycle/cm cutoff frequency filtered images (Fig. 5). The images from the former algorithm resulted in AUC value of 0.84, which is also better than the images from the latter algorithm resulting in AUC value of 0.75. These analyses demonstrate that, with the proposed heart motion observer, regional radial motion estimated from reconstructed images with better bias-noise quality led to better classification of normally and abnormally beating hearts.

V. Conclusions

We applied a 3D motion estimation technique as the heart motion observer to compare the detectability of regional cardiac motion abnormality from simulated noisy GMP SPECT images reconstructed by two image reconstruction methods. These methods are the standard 3D OS-EM algorithm with post Butterworth low-pass spatial filtering and a 4D MAP-RBI-EM algorithm, both with compensation of the major image degradation factors. Two beating heart models in the 4D NCAT phantom, one modeling a normally beating heart and the other modeling a beating heart with regional motion defect, were used to generate noise-free and noisy GMP SPECT data. The ROC analysis was applied to the estimated regional radial motion magnitudes from reconstructed adjacent gates of different noise realizations and AUC values for classification of normal and abnormal hearts were calculated. It was shown that the tradeoff between NMSE and NSD in the reconstructed images served as a practical guide in determining reconstruction/filtering parameters for better classification of estimated normal and abnormal regional motion. The 3D cardiac motion estimation technique detects the regional myocardial motion defect significantly better from the GMP SPECT images reconstructed with the 4D MAP-RBI-EM reconstruction algorithm than those reconstructed with the 3D OS-EM algorithm with post Butterworth spatial filtering.

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Fig. 1. Schematic diagrams showing (a) short-axis and (b) long-axis views of LV with shaded ROI. A motion vector is decomposed into radial (R), circumferential (C), and longitudinal (L) components as demonstrated.

Fig. 2. Quiver plots of the normal and abnormal MVFs superimposed on the beating heart phantom slices at the end-diastole phase: (a) zoomed short-axis slice and (b) zoomed long-axis slice.

Fig. 3. NSD vs. NMSE of images reconstructed from the 3D OS-EM algorithm post-filtered with 3D spatial Butterworth filter at different cutoff frequencies, reconstruction iterations increasing from 2 to 20.

Fig. 4. NSD vs. NMSE of images reconstructed from the 4D MAP-RBI-EM algorithm with different β in the potential function (3), reconstruction iterations increasing from 2 to 20.

Fig. 5. NSD vs. NMSE of reconstructed images, from 3D OS-EM algorithm with 0.5 cycle/cm Butterworth filtering and from 4D MAP-RBI-EM algorithm with $\beta = 0.005$, reconstruction iterations increasing from 2 to 20.

Fig. 6. Four noise realizations of reconstructed images from (a) 3D OS-EM algorithm with 0.5 cycle/cm Butterworth filtering and (b) from 4D MAP-RBI-EM algorithm with $\beta = 0.005$, 20th iteration, short-axis view zoomed to the LV, end-diastole phase.

Fig. 7.

Fitted ROC curves for classification of estimated regional radial motion from normal and abnormal heart images: (a) reconstructed from 3D OS-EM algorithm with post-filtering of different cutoff frequencies; (b) reconstructed from 4D MAP-RBI-EM algorithm with different β values; (c) reconstructed from 3D OS-EM algorithm with plus post-filtering of cutoff frequency as 0.5 cycle/cm and from 4D MAP-RBI-EM algorithm with $\beta = 0.005$.

TABLE I

EFFECT OF CUTOFF FREQUENCY OF 3D POST BUTTERWORTH FILTER FOR OS-EM ALGORITHM ON AUC VALUE FOR CLASSIFYING REGIONAL RADIAL MOTION

Cutoff frequency (cycle/cm)	1.6	1.0	0.5	0.3
AUC Value	0.59 ± 0.06	0.57 ± 0.06	0.75 ± 0.05	0.72 ± 0.06

TABLE IIEFFECT OF PRIOR WEIGHT β IN 4D MAP-RBI-EM ALGORITHM ON AUC VALUE FOR CLASSIFYING REGIONAL RADIAL MOTION

β	0.0005	0.001	0.005	0.01
AUC Value	0.75 ± 0.06	0.83 ± 0.06	0.84 ± 0.04	0.78 ± 0.05