Deformable left-ventricle mesh model for motion-compensated filtering in cardiac gated SPECT

Thibault Marin and Jovan G. Brankov^{a)}

Department of Electrical and Computer Engineering, Medical Imaging Research Center, Illinois Institute of Technology, 3440 S. Dearborn St., Chicago, Illinois, 60616

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Purpose: In this article, the authors present a motion-compensated spatiotemporal processing algorithm to reduce noise in cardiac gated SPECT. Cardiac gated SPECT data are particularly noisy because the acquired photon data are divided among a number of time frames (gates). Classical spatial reconstruction and processing techniques offer noise reduction but they are usually applied on each frame separately and fail to utilize temporal correlation between frames.

Methods: In this work, the authors present a motion-compensated spatiotemporal postreconstruction filter offering noise reduction while minimizing motion-blur artifacts. The proposed method can be used regardless of the type of image-reconstruction method (analytical or iterative). The between-frame volumetric myocardium motion is estimated using a deformable mesh model based on the model of the myocardial surfaces. The estimated motion is then used to perform spatiotemporal filtering along the motion trajectories. Both the motion-estimation and spatiotemporal filtering methods seek to maintain the wall brightening seen during cardiac contraction. Wall brightening is caused by the partial volume effect, which is usually viewed as an artifact; however, wall brightening is a useful signature in clinical practice because it allows the clinician to visualize wall thickening. Therefore, the authors seek in their method to preserve the brightening effect.

Results: The authors find that the proposed method offers better noise reduction than several existing methods as quantitatively evaluated by signal-to-noise ratio, bias-variance plots, and ejection fraction analysis as well as on tested clinical data.

Conclusions: The proposed method mitigates for noise in cardiac gated SPECT images using a postreconstruction motion-compensated filtering approach. Visual as well as quantitative evaluation show considerable improvement in image quality. © 2010 American Association of Physicists in Medicine. [DOI: 10.1118/1.3483098]

Key words: cardiac-gated SPECT, motion compensation, motion estimation, mesh modeling

I. INTRODUCTION

It is well known that noise is a significant problem in cardiac gated single-photon emission computed tomography (SPECT).¹ Spatial smoothing (in the form of spatial regularization or postreconstruction spatial filtering²) fails to exploit the strong temporal correlation between the time frames of the gated sequence. An improvement is to introduce temporal filtering as well; however, temporal filtering that does not explicitly account for myocardium motion³ introduces motion blur that degrades image quality. Preserving accurate myocardium motion is a key objective in gated cardiac SPECT image processing, since the sequence should allow for accurate assessment of myocardium function⁴ via evaluation of the left-ventricle (LV) wall motion, wall thickening, and ejection fraction.⁵

Several methods that reduce motion blur without directly accounting for motion have been proposed in the past. For example, in Refs. 6 and 7, postreconstruction temporal processing methods were reported, where regularization is applied along time-activity curves in order to reduce noise. Spatiotemporal Gibbs priors have also been used within a block iterative MAP reconstruction approach.⁸ The definition of the prior term relies either on a known motion field or on

the assumption that the myocardium motion does not exceed a few pixels. Another different approach which has been presented⁹ is based on the Karhunen–Loève (KL) transform, which was applied on an image sequence and reconstruction was performed in the reduced KL space.

Another motion-compensation technique relies on projection/reprojection of projection images in order to correct for motion in the projection space.¹⁰ Several methods relying on myocardial motion estimation have also been introduced. Simultaneous reconstruction and motion-field estimation has been reported¹¹ in which one iteration of the algorithm consists of an update of the reconstructed image (R-step) followed by an update of the motion-field estimate (M-step). This is done by minimizing a cost function depending on pixel intensity matching, a log-likelihood term, and a strain energy term to regularize the myocardium motion field. Our group has previously developed a 4D (3D space + 1D time) reconstruction method,¹² combining a MAP reconstruction with a temporal prior based on the estimation of myocardial motion field.

Though not considered in this work, estimated myocardium motion offers additional possibilities to quantitatively assess heart functionality such as wall motion,¹³ ventricular

FIG. 1. Mesh model defined on the left ventricle. (a) Transverse and sagittal cross-sections of FBP reconstructed images. (b) Cross-sections with highlighted detected myocardial surfaces. (c) Myocardial surfaces and sampled mesh nodes (dots for support nodes and circles for myocardial nodes). (d) Mesh elements (tetrahedrons) shown between myocardial surfaces.

strain,¹⁴ and ejection fraction.¹⁵ Moreover, the estimated motion field can be further used to perform motion-compensated temporal averaging of the gated sequence, yielding a motion-compensated static image^{16–18} which should have superior noise properties with little motion blur.

Finally, it should be noted that related approaches have been proposed in the context of respiratory motion compensation (e.g., Refs. 19 and 20).

Accurate motion-field estimation is the key to successful motion-compensated methods. Classical motion-field estimation techniques typically either rely on the optical flow^{21,22} or block matching²³ algorithms, the former estimating the distribution of apparent intensity velocities in the images and the latter tracking the motion by matching pixel blocks intensities between time frames. Both methods assume that the intensity of a particular point remains constant in time.^{21,23} The proposed method explicitly relates the change in intensity to a change in apparent volume in order to explicitly account for the myocardial brightening due to the partial volume effect (PVE).²⁴ The origin of PVE is the finite resolution of the SPECT system. It is manifested as an increase in heart wall voxels brightness as the myocardium contracts through the cardiac cycle. Therefore, PVE can degrade the performance of motion-estimation techniques if not accounted for.

In this paper, we propose a postreconstruction motion-compensated four-dimensional filtering method for gated cardiac SPECT images using a deformable mesh model (DMM) of the left ventricle, which can account for PVE and that can be used regardless which image-reconstruction method was utilized. In the proposed method, volumetric myocardium motion is first estimated using a DMM, tracking the myocardium volume through the image sequence. The motion-estimation technique is based on our previous work,²⁵ where a similar approach was presented in a two space dimensions and one time dimension framework (2D space+1D time). The proposed 4D implementation relies on a DMM fitted to the LV, using a LV surface model,²⁶ and it is deformed to track the displacement of the myocardium while accounting for partial volume effect. Next, the estimated motion is used in spatiotemporal filtering to perform smoothing along the motion trajectory while also preserving the PVE. Our motivation for preserving the PVE is based on the fact

that while being an artifact, it remains a useful diagnostic feature for physicians since it provides information on heart wall thickening.¹⁴

The proposed method has been previously introduced²⁵ in a slice-by-slice approach (2D space+1D time). In addition, feasibility studies, in the form of conference papers, of the four-dimensional approach has been reported.^{27–29} In this paper, we provide a full description of a fully four-dimensional method with its implementation, as well as a complete quantitative evaluation. The proposed algorithm is compared to clinically used methods visually as well as quantitatively using peak signal-to-noise ratio (PSNR), bias-standard deviation curves, and ejection fraction (EF) measurements. Results show improvement in image quality when used for images obtained by noniterative reconstruction (FBP) as well as iterative reconstruction [maximum-likelihood expectation maximization (ML-EM)].

The paper is organized as follows. First the methods are described including DMM, motion estimation, and the motion-compensation filtering framework; next, the implementation choices are discussed; and, finally, results of a quantitative comparison are presented.

II. METHODS

II.A. Myocardium deformable mesh model

We will describe deformations (motions) of the LV from any time frame k to l by the following coordinate transformation over the imaging domain $\mathcal{D} \subset \mathbb{R}^3$:

$$\mathbf{x}^l = \mathbf{x}^k + \mathbf{d}^{k \rightarrow l}(\mathbf{x}^k), \quad (1)$$

in which $\mathbf{x}^l, \mathbf{x}^k \in \mathcal{D}$, and the vector-valued function $\mathbf{d}^{k \rightarrow l}(\mathbf{x}^k) \in \mathcal{D}$ represents a volumetric deformation of an incompressible medium between frames k and l . In our implementation, we use a mesh representation of the motion field $\mathbf{d}^{k \rightarrow l}(\mathbf{x})$, in which the domain $\mathcal{D}$ for reference frame k is partitioned into M mesh elements $\mathcal{D}_m$, where $m=1, \dots, M$. These elements are usually polygons with P vertices (in this work, the polygons are tetrahedrons, so that $P=4$). The set of vertices of the mesh elements defines the *mesh nodes* $\{\mathbf{x}_n^k, n=1, \dots, N\}$, where each node location is denoted $\mathbf{x}_n^k$ and where N is the total number of nodes (see Fig. 1). Then, obtaining the nodal displacement from frame k to l is equivalent

lent to obtaining samples of the motion field as

$$\mathbf{d}_n^{k \rightarrow l} = \mathbf{x}_n^l - \mathbf{x}_n^k = \mathbf{d}^{k \rightarrow l}(\mathbf{x}_n^k). \quad (2)$$

Estimation of this nodal displacement will be described in Sec. II B. Once the displacements are obtained, the dense motion field can be approximated using interpolation as

$$\tilde{\mathbf{d}}^{k \rightarrow l}(\mathbf{x}) = \sum_{n=1}^N \mathbf{d}_n^{k \rightarrow l} \phi_n(\mathbf{x}), \quad \mathbf{x} \in \mathcal{D}, \quad (3)$$

where $\phi_n(\mathbf{x})$ is the interpolation function associated with the n th node. Details on the implementation of the mesh generation will be discussed in Sec. III B.

II.B. Motion estimation

Our goal is to find the dense motion field $\mathbf{d}^{k \rightarrow l}(\mathbf{x})$ between time frames k and l . As explained earlier, it is sufficient to have knowledge of the set of nodal displacements, i.e., $\mathbf{D}^{k \rightarrow l} = \{\mathbf{d}_n^{k \rightarrow l}, n=1, \dots, N\}$, which can be found by minimizing the following cost function:

$$J(\mathbf{D}^{k \rightarrow l}) = w E_{\mathcal{M}}(\mathbf{D}^{k \rightarrow l}) + (1 - w) E_s(\mathbf{D}^{k \rightarrow l}), \quad (4)$$

where $E_{\mathcal{M}}(\mathbf{D}^{k \rightarrow l})$ is the matching error measuring dissimilarity between image intensity in frames k and l , $E_s(\mathbf{D}^{k \rightarrow l})$ is a smoothing regularization of the motion field, and $w \in [0, 1]$ is a weighting term that controls the tradeoff between the two terms of the cost function.

The matching error $E_{\mathcal{M}}(\mathbf{D}^{k \rightarrow l})$ is defined as

$$E_{\mathcal{M}}(\mathbf{D}^{k \rightarrow l}) = \sum_{m=1}^M \int_{\mathbf{x} \in \mathcal{D}_m^k} \left(f^k(\mathbf{x}) - f^l(\mathbf{x} + \tilde{\mathbf{d}}^{k \rightarrow l}(\mathbf{x})) \frac{|\mathcal{D}_m^l|}{|\mathcal{D}_m^k|} \right)^2 d\mathbf{x}. \quad (5)$$

In Eq. (5), the total error is a summation over the mesh elements $\mathcal{D}_m^k$ and $|\mathcal{D}_m^k|$ and $|\mathcal{D}_m^l|$ represent the volumes of the m th mesh element in the k th and l th frames, respectively. The ratio $|\mathcal{D}_m^l|/|\mathcal{D}_m^k|$ is used to account for PVE as described next. The numerical calculation of the integration over $\mathcal{D}_m^k$ of the matching error term has been previously reported.³⁰

In the absence of PVE, one can assume that

$$f^k(\mathbf{x}) = f^l(\mathbf{x} + \tilde{\mathbf{d}}^{k \rightarrow l}(\mathbf{x})), \quad \mathbf{x} \in \mathcal{D}, \quad (6)$$

i.e., the intensity of the image at location $\mathbf{x}$ in frame k is preserved when $\mathbf{x}$ is displaced to location $\mathbf{x} + \tilde{\mathbf{d}}^{k \rightarrow l}(\mathbf{x})$ in frame l . The effect of image brightening due to wall thickening in SPECT has been studied²⁴ and it has been shown that the relation between the increase in the number of counts and the wall thickness can be considered to be linear as long as the wall thickness is no larger than 1.80 times the full width at half-maximum (FWHM) of the system resolution. For the data analyzed in this paper, this assumption is acceptable (see Sec. III A). Therefore, Eq. (6) can be modified to include wall thickening by rescaling the pixel intensity with the ratio of the mesh elements volumes as follows:

$$f^k(\mathbf{x}) = f^l(\mathbf{x} + \tilde{\mathbf{d}}^{k \rightarrow l}(\mathbf{x})) \frac{|\mathcal{D}_m^l|}{|\mathcal{D}_m^k|}, \quad \mathbf{x} \in \mathcal{D}_m^k. \quad (7)$$

The intensity increase relates to a change in apparent volume. We have measured the increase in intensity and the apparent myocardial regional volume change. Between end diastole (ED) and end systole (ES), the intensity of the reconstructed image increases by 11% for FBP images (17% for ML-EM), whereas the apparent volume decreases by 11% for both methods. This confirms that the change in voxel intensity due to PVE results in a change of apparent volume. Equation (5) allows for accurate measurement of the dissimilarity between two frames accounting for PVE. Note that by integrating Eq. (7), one can show that

$$\int_{\mathbf{x} \in \mathcal{D}_0^k} f^k(\mathbf{x}) d\mathbf{x} = \int_{\mathbf{x} \in \mathcal{D}_0^l} f^l(\mathbf{x} + \tilde{\mathbf{d}}^{k \rightarrow l}(\mathbf{x})) \frac{|\mathcal{D}_0^l|}{|\mathcal{D}_0^k|} d\mathbf{x}, \quad (8)$$

which reflects the fact that the total activity in the myocardium (denoted by $\mathcal{D}_0^k$ at frame k) is not changing from frame to frame.

The second term in Eq. (4) $[E_s(\mathbf{D}^{k \rightarrow l})]$ represents a smoothness constraint applied on the motion field defined as

$$E_s(\mathbf{D}^{k \rightarrow l}) = \sum_{n=1}^N \|\tilde{\mathbf{d}}_n^{k \rightarrow l} - \bar{\mathbf{d}}_n^{k \rightarrow l}\|^2, \quad (9)$$

where $\bar{\mathbf{d}}_n^{k \rightarrow l}$ is the average displacement of the nodes adjacent to node n . This term penalizes nonuniform motion fields.²⁵ Penalization is used to constrain the motion between adjacent regions and reduce noise effect.

Initially, we used an additional constraint term to force mesh elements to keep a reasonable volume and penalize small elements. This term was finally discarded since it did not influence the estimated motion. Once estimated, myocardial motion can be used to perform an accurate temporal filter.

II.C. Motion-compensated spatiotemporal filtering

In this section, we describe the proposed motion-compensated temporal filter. If one were to have perfect knowledge of the motion field $\mathbf{D}^{k \rightarrow l} = \{\mathbf{d}_n^{k \rightarrow l}, n=1, \dots, N\}$, temporal averaging weighted by the partial volume effect would be an optimal solution to the filtering problem. However, since one cannot estimate the motion field perfectly, some relaxation of the temporal filter is necessary. Thus, we propose the following form for the temporal filtering:

$$\hat{f}^k(\mathbf{x}) = \sum_{l=1}^K h_{(l-k)} f^l(\mathbf{x} + \tilde{\mathbf{d}}^{k \rightarrow l}(\mathbf{x})) \frac{|\mathcal{D}_m^l|}{|\mathcal{D}_m^k|}, \quad \mathbf{x} \in \mathcal{D}_m^k. \quad (10)$$

Here, the filtered image $\hat{f}^k(\mathbf{x})$ is defined as a weighted sum of the motion-compensated images $f^l(\mathbf{x})$, $l=1, \dots, K$. In Eq. (10), the estimated motion field is introduced via $\tilde{\mathbf{d}}^{k \rightarrow l}(\mathbf{x})$. The term $h_{(l-k)}$ represents the filter kernel and is given by

FIG. 2. Shape of the temporal window controlled by the parameter γ .

$$h_{(l-k)} = \frac{1}{C} \left(1 - \frac{2}{K} \min(|k-l|, K-|k-l|) \right)^\gamma, \quad (11)$$

where C is a normalization term assuring that the sum of the weights is equal to one.

The term γ in Eq. (11) controls the strength of the temporal filter; $\gamma=0$ corresponds to a temporal average with equal weights while, as γ tends to infinity, the smoothing effect vanishes (see Fig. 2).

In addition to temporal filtering, the proposed algorithm performs a low-pass Butterworth filter within the spatial domain of the temporally filtered image sequence in the same fashion as that typically used in the clinic.²

III. IMPLEMENTATION ISSUES

In this section, we detail the implementation of the proposed method. First, the data set used for simulation is presented; next, the mesh-generation and motion-estimation procedures are described.

III.A. Data set

The proposed spatiotemporal processing algorithm was tested using the 4D NURBS-based cardiac-torso³¹ (NCAT) phantom to simulate a clinical Tc^{99m} cardiac gated SPECT perfusion study, with image dimension $64 \times 64 \times 64$ in 16 time frames. An accurate Monte Carlo simulation tool³² (SIMIND) was used to simulate data acquisition, including degradations due camera response, scatter, and nonuniform attenuation. The simulated field of view (FOV) was 40 cm with voxel size of 0.634 cm. The uncorrected system FWHM at the center of the FOV was approximately 1.88 cm. Poisson noise was introduced at a level corresponding to 0.5×10^6 counts originating from the heart region and a total of 16 frames were simulated, in which each frame had 64 projections over 360° and 64×64 projection bins. This corresponds to the Prism 3000 scanner with low energy high resolution collimator.

The volumetric images were reconstructed using FBP and ML-EM,³³ applied on each time frame separately. Reconstruction via the ML-EM algorithm included modeling of

camera response, nonuniform attenuation and scatter correction using the triple-energy-window method.³⁴ Reconstructions from the noiseless data set were also stored and used as a reference for quantitative evaluation.

Note that the NCAT heart wall in the end systole frame has a thickness of around 3.70 cm. The ratio of wall thickness to uncorrected system FWHM at the center of the FOV is 1.97. Recall that the linear intensity increase assumption for PVE was valid for ratios up to 1.80. Thus, at end systole, the linearity condition is not quite met; however, the condition is met in all the other frames. We further note that images reconstructed with iterative ML-EM reconstruction theoretically should not exhibit myocardial brightening, since ML-EM performs resolution recovery correction and the scanner voxel size is only 0.634 cm. Nevertheless, since the iterations are stopped before full resolution recovery is obtained, the images reconstructed via ML-EM are also, in practice, affected by PVE.

In addition to the simulations, the proposed method was applied on five clinical data sets acquired on a Prism 3000 scanner from a Tc^{99m} cardiac gated SPECT perfusion study with image dimension $64 \times 64 \times 64$ in eight time frames. Data were reconstructed using FBP and filtered by the proposed method.

III.B. Mesh generation

The steps to obtain the mesh structure defined on the LV surface model are as follows.

Step 1: Reconstruct the image sequence in the usual way, frame by frame, by FBP or ML-EM (20 iterations).

Step 2: Reduce noise by applying temporal summation along the time dimension, producing one static frame, followed by a three-dimensional (spatial) low-pass Butterworth filter with an order of 5 and a cutoff frequency of 0.2 cycles per pixel for FBP images and 0.3 cycles per pixel for ML-EM images. These values for the filter yielded a good mesh structures even in the presence of a defect [see Fig. 1(a)].

Step 3: Fit a left-ventricle model to the result of step 2.²⁶ This procedure performs radial sampling from the heart's center of mass, detects the maximum intensity (midventricle), and detects both the endocardial and epicardial surfaces by finding the location corresponding to 60% decrease from the maximum [see resulting surfaces on Fig. 1(b)].

Step 4: Sample both myocardium surfaces uniformly along concentric circles about the long axis, generating typically 100 mesh nodes [see Fig. 1(c); nodes denoted by circles].

Step 5: Introduce additional support nodes to ensure reasonable triangulation (i.e., avoid degenerate tetrahedrons). A total of 60 nodes are defined around the epicardial surface at a distance of 1.5 times the distance between the endocardial and epicardial surfaces. In addition, ten nodes are defined along the long axis from the base to the apex of the endocardial surface. The final set of nodes therefore typically contains around 170 nodes [see Fig. 1(c); nodes denoted by dots].

Step 6: Merge the nodes into a 3D mesh structure by defining the interconnections between the nodes and the mesh elements using Delaunay triangulation.³⁵ Triangulation uses the quick hull algorithm³⁶ generating around 1000 tetrahedral elements (see Fig. 1(d)).

Step 7: The structure is completed by the addition of stationarity information for the nodes. The endocardial and epicardial surface nodes are defined as nonstationary [denoted by circles in Fig. 1(c)], while the support nodes [denoted by dots in Fig. 1(c)] are defined as stationary. The 3D mesh elements defined between the two heart surfaces correspond to the myocardium and represent the region where the motion estimation is performed. The final structure is then used as an initial mesh for motion estimation.

III.C. Motion estimation

This section details the estimation of the mesh nodal displacement based on the minimization of the cost function expressed in Eq. (4). These displacements are then used as in Eq. (3) to interpolate the dense motion field.

To perform motion estimation, reconstructed images (FBP or ML-EM) are initially processed by a three-dimensional low-pass Butterworth filter with an order of 11 and a cutoff frequency of 0.16 cycles per pixel. The spatial filter offers a tradeoff between noise reduction and preserving the visibility of the heart wall motion. The values above have been chosen empirically to provide a reasonable compromise. Additionally, the initial mesh described previously (Sec. III B) is initially propagated through the time frames, thus yielding a time indexed mesh with no motion. Recall that the initial mesh was generated from a time averaged image and therefore represents an averaged version of the expected final mesh. Note that while mesh nodes lie on the myocardium surfaces, motion estimation is performed volumetrically over mesh tetrahedrons, which include voxels located inside the myocardium.

The myocardium motion is then estimated between successive frames by minimizing Eq. (4). Minimization is performed via gradient descent with a quadratic search algorithm.³⁷ The calculation of the gradient for the matching error $E_M(\mathbf{D}^{k \rightarrow l})$ requires the evaluation of the integral term in Eq. (5) and is therefore nontrivial. For more details, see our previous work.³⁰

Estimation of the motion between successive frames is performed several times around the whole time sequence assuming periodic motion (i.e., $\mathbf{D}^{K \rightarrow K+1} = \mathbf{D}^{K \rightarrow 1}$, where K is the number of frames). The procedure stops when the update does not change the mesh structure, which generally occurs after five to ten global iterations. An example of estimated nodal displacement displayed in three dimensions is shown on Fig. 3 for the NCAT phantom.

The weight w in Eq. (4) has been found empirically to be $w=0.999\,99$ for FBP and $w=0.8$ for EM images, providing a reasonable tradeoff between the smoothness constraint and matching error term. Note that the robustness of the pro-

FIG. 3. Estimated mesh structure for the NCAT phantom at end systole with motion vectors (black arrows) between end systole and end diastole.

posed motion estimation relies on the robustness of the surface detection algorithm which has been previously validated.²⁶

IV. RESULTS

In this section, we present a comparison of the proposed motion-compensated filtering approach with several commonly used postprocessing methods. Our method will be compared to an approach used at the University of Massachusetts Medical School, a temporal filter with kernel $\{\frac{1}{4}, \frac{2}{4}, \frac{1}{4}\}$, followed by a spatial low-pass Butterworth filter with an order of 4 and various cutoff frequencies.³ This method will be referred to as the 121 method. In addition, we will compare the proposed method to a low-pass Butterworth spatial filter with no temporal processing. For quantitative evaluation, the reconstruction of noiseless projections is the reference image against which the different methods are assessed.

The results of postprocessing will be presented for two reconstruction methods, FBP and ML-EM.

IV.A. Visual comparison

First, we present images for visual comparison. These images are obtained for optimal PSNR described later. Note that for spatial filter only and the 121 method, the optimal cutoff frequency of the spatial filter was obtained close to the one used in clinical practice (Butterworth filter with an order of 4 and a cutoff frequency of 0.22 cycles per pixel) at the University of Massachusetts Medical School.

Figures 4 and 5 show horizontal long-axis and short-axis views of postprocessed images obtained by FBP reconstruction. Images are shown at ED and ES for (a) FBP reconstruction of noiseless projections, (b) FBP reconstruction followed by a spatial filter only (clinical parameters), (c) 121 method, and (d) proposed 4D motion-compensated spatiotemporal filtering method. Visual inspection shows that the proposed method achieves better noise reduction than the clinical methods, while preserving best the shape and uniformity of the myocardium. In addition, these images also show

FIG. 4. Horizontal long-axis view of images filtered after FBP reconstruction at the ED and ES frames. (a) Reconstruction from noiseless projections, (b) spatial only, (c) 121 method, and (d) proposed method.

that the PVE, which tends to be attenuated by the 121 method, is preserved when using the proposed filtering method. Besides, if one reviews cines of the image sequence, it is apparent that the myocardium motion is best preserved by the proposed method. Similar conclusions can be drawn from the postprocessed ML-EM data presented in Figs. 6 and 7.

Finally, in Fig. 8, we present the postprocessing of clinical data obtained from five patients and reconstructed by FBP. One can observe similar improvements as previously described. These representative clinical examples (four males, including one with a perfusion defect, and one female) illustrate the feasibility of the proposed method but more clinical evaluation will come in the future.

Next, to confirm this visual improvement, we provide a full quantitative evaluation using simulated data.

IV.B. Noise reduction measurement

Here, we present a quantitative assessment for noise reduction properties of the proposed method. As a quality metric, the PSNR was computed between the reference image (reconstruction from noiseless projections) and the different postreconstruction methods. PSNR was calculated for the 4D image as follows:

$$\text{PSNR} = 10 \log_{10} \frac{N_x \times N_y \times N_z \times K \times \max(\mathbf{f})}{\|\mathbf{f} - \hat{\mathbf{f}}\|^2}, \quad (12)$$

where N_x , N_y , and N_z correspond to the volumetric image size in voxels, K is the number of time frames, $\mathbf{f}$ is a vector

FIG. 5. Short-axis view of images filtered after FBP reconstruction at the ED and ES frames. (a) Reconstruction from noiseless projections, (b) spatial only, (c) 121 method, and (d) proposed method.

FIG. 6. Horizontal long-axis views of images filtered after EM reconstruction at the ED and ES frames. (a) Reconstruction from noiseless projections, (b) spatial only, (c) 121 method, and (d) proposed method.

containing all pixels of the reconstructed image sequence using noiseless projections, and $\hat{\mathbf{f}}$ is the image sequence after reconstruction and postprocessing.

Figure 9(a) shows the influence of the temporal filter strength when applying filtering on the NCAT projections reconstructed using FBP. This figure shows that the proposed method achieves better noise reduction than both spatial filtering and the 121 method. At the optimal point ($\gamma=0$), the proposed method improvement is 1.7 dB over the 121 method and 4.2 dB over spatial filtering only. These curves were estimated over 50 noise realizations and corresponding error bars of three standard deviations are plotted. Figure 9(b) reports the PSNR measurements as a function of the spatial filter strength (ω_c , cutoff frequency of the spatial filter). The curves show that the proposed method achieves better noise reduction than the clinically available approaches for any level of spatial smoothing.

Similarly, Fig. 10 shows the PSNR curves for postreconstruction of ML-EM image sequences. The proposed method achieves improvement of 2.5 dB compared to the 121 method and 5.2 dB compared to the spatial only filtering method. Note the general greater PSNR values, which are due to the fact that the ML-EM method utilize camera response model, nonuniform attenuation, and scatter correction.

In PSNR figures, optimal points for each method are denoted by square symbols. The images presented in Sec. IV A for visual comparison correspond to these optimal points.

FIG. 7. Short-axis views of images filtered after EM reconstruction at the ED and ES frames. (a) Reconstruction from noiseless projections, (b) spatial only, (c) 121 method, and (d) proposed method.

(PATIENT A – Healthy male)

(PATIENT B – Healthy male)

(PATIENT C – Healthy male)

(PATIENT D – Male with apical perfusion defect)

(PATIENT E – Healthy female)

FIG. 8. Horizontal long-axis views for five clinical data sets at the ED and ES frames filtered by (a) spatial only, (b) 121 method, and (c) proposed method. Note that patient D is affected by a severe perfusion defect in the apical region.

IV.C. Bias-standard deviation

Next, bias-standard deviation curves are presented using $T=50$ noise realizations. Bias and standard deviation were computed on a small region of interest (ROI) located on the inferior wall at the end diastole (see Fig. 11). Our analysis is based on the absolute value of the bias in ROI estimation, expressed as a percentage

$$b = \frac{|\overline{[\mathbf{f}^k]_{\text{ROI}}} - \hat{\mu}^k|}{\overline{[\mathbf{f}^k]_{\text{ROI}}}} \times 100\%, \quad (13)$$

where $\overline{[\mathbf{f}^k]_{\text{ROI}}}$ is the average image intensity over the region of interest ROI in the k th frame of the reference image and $\hat{\mu}^k$ defined as

$$\hat{\mu}^k = \frac{1}{T} \sum_{t=1}^T \overline{[\hat{\mathbf{f}}_t^k]_{\text{ROI}}}. \quad (14)$$

Here, $\overline{[\hat{\mathbf{f}}_t^k]_{\text{ROI}}}$ is the average intensity over the region of interest ROI in the k th frame of the postprocessed image for the t th noise realization.

Similarly, the standard deviation over the ROI is computed using

$$\text{std} = \frac{\sqrt{1/(T-1) \sum_{t=1}^T (\overline{[\hat{\mathbf{f}}_t^k]_{\text{ROI}}} - \hat{\mu}^k)^2}}{\overline{[\mathbf{f}^k]_{\text{ROI}}}} \times 100\%, \quad (15)$$

using the same notations as in Eq. (14).

First, we present the results when postprocessing FBP images. Curves obtained for the end diastolic frame for varying

FIG. 9. PSNR as a function of the temporal filter strength γ for (a) a spatial filter fixed at its optimal cutoff frequency and (b) a temporal filter fixed at its optimal strength ($\gamma=0$). Images were reconstructed via FBP.

temporal filtering strength γ and spatial cutoff frequency ω_c are shown in Figs. 12(a) and 12(b), respectively. Note that better methods have curves exhibiting smaller bias and standard deviation. The proposed method results in generally lower bias and standard deviation when compared to clinical methods, confirming that the proposed filtering algorithm seems to outperform other clinical methods. In addition, this analysis was performed on postprocessed images reconstructed via ML-EM at the end diastole as shown on Figs. 13(a) and 13(b). The figures show that the proposed method achieves better performance than available clinical methods when reconstructing images via ML-EM.

IV.D. Ejection fraction

Finally, we evaluate the influence of postreconstruction filtering on estimation of the LV end diastolic volume (EDV), end systolic volume (ESV), and EF as reported by CORRIDOR4DM software. For reference, the NCAT true values are EDV=117.00 mL, ESV=48.12 mL, and EF=58.87%. This feature was evaluated since LV ejection fraction is a

useful tool for detection of heart failure symptoms.⁵ Here, the presented results indicate that the proposed method preserves this feature. From our experience, inaccurate filtering can lead to apparent reduction in the ejection fraction measurements. The results for postprocessing of FBP image are reported in Table I for FBP reconstruction where optimal values are taken for each method, and in Table II for postprocessing of ML-EM image. The values show that the proposed method accurately approaches the reference value, thus mitigating the degrading effect of filtering on cardiac sequences. This confirms that the proposed method preserves heart motion and therefore potentially can improve clinical diagnostic. Note that EDV and ESV estimated on ML-EM reconstructed images are much closer to the true values. This explains a smaller improvement in terms of ejection fraction for ML-EM images than for FBP images.

V. DISCUSSION

The aim of this work was to establish cardiac motion estimation and motion-compensated postreconstruction pro-

FIG. 10. PSNR as a function of the temporal filter strength γ for (a) a spatial filter fixed at its optimal cutoff frequency and (b) a temporal filter fixed at its optimal strength ($\gamma=1$). Images were reconstructed via EM.

FIG. 11. Region of interest used for bias-standard deviation curve at the ED.

processing methods that can be applied regardless of the image-reconstruction methods used. In our experiments we applied these to two of the most dominantly used reconstruction methods, FBP and iterative ML-EM with a camera response model, nonuniform attenuation, and scatter correction.

The critical step of motion-compensated processing is the estimation of cardiac motion. If the motion can be characterized accurately, motion-compensated temporal averaging can yield excellent results. If the cardiac motion is estimated with lesser accuracy, weaker temporal filtering should be utilized. The required level of accuracy in motion estimation is a function of the amount of noise present in the image. For example, in FBP reconstructions, which are usually noisy and blurry, the optimal temporal filter parameter (as judged by PSNR) was found to be $\gamma=0$, which corresponds to temporal averaging.

This indicated that the estimated motion is sufficiently accurate. ML-EM reconstructed images reached a maximum PSNR at $\gamma=1$ and PSNR value of 36.3 dB; however, using $\gamma=0$ yielded a PSNR of 36 dB, which is only slightly below the optimal value. This indicates that in both cases we have an accurate estimation of the motion field.

Figure 10(b) shows another interesting feature of the proposed method. For ML-EM reconstructions, as seen on Fig. 10(b), the spatial filter seems to have little effect on the PSNR (for reasonable cutoff frequencies, i.e., between 0.2 and 1 cycle per pixel). This suggests that the proposed method using ML-EM reconstructed images does not require any spatial smoothing to improve image quality; the motion-compensated temporal filter seems to be sufficient.

TABLE I. Ejection fraction measurement for the different methods (FBP reconstruction). Values were obtained using the INVIA CORRIDOR4DM software (except for the true NCAT value obtained from the NCAT program).

Method	EF (%)	EDV (mL)	ESV (mL)
True	58.87	117	48.12
Ref	48	114	60
SO	33.80 (± 5.98)	114.80 (± 9.68)	76.10 (± 9.59)
121	37.90 (± 3.78)	111.70 (± 5.70)	69.20 (± 5.03)
MC	47.67 (± 2.45)	107.50 (± 8.03)	56.10 (± 6.21)

The bias-standard deviation curves represent a statistical analysis of the ROI estimate over 50 noise realizations. One can interpret bias as the accuracy of the regional image intensity estimation, while standard deviation describes the variability of the estimate. As shown in Figs. 12 and 13, strong filtering (spatial or temporal) results in high bias and low standard deviation. For a fixed level of bias, the proposed method results in smaller standard deviation than the clinical methods to which it is compared. Equivalently, for a given standard deviation, the bias resulting from motion-compensated processing is lower than traditional processing. Note that the abrupt transitions in the curves [Figs. 12(a) and 13(a)] are due to a sign change caused by the absolute value operator in the bias definition [see Eq. (13)].

The proposed algorithm has been tested on five clinical data sets (Fig. 8), including one with a perfusion defect in the apical region. Figure 8 (patient D) shows the filtered images with different methods. It suggests that the proposed method accurately reduces noise even in the case of severe perfusion defect and may be expected to improve visibility of subtle perfusion defects. Moreover, by avoiding motion-blur artifacts, clinical diagnosis relying on cardiac motion may be significantly improved by the proposed method. We have shown and quantified image quality improvement when using the proposed motion-compensated filtering approach and

FIG. 12. Bias-standard deviation curve for FBP images at the ED with (a) varying temporal filter strength and (b) varying spatial cutoff frequency. For (a), the cutoff frequency of the spatial filter was fixed to $\omega_c=0.27$. For (b), the temporal filter parameter was fixed to $\gamma=0.33$.

FIG. 13. Bias-standard deviation curve for FBP images at the ED with (a) varying temporal filter strength and (b) varying spatial cutoff frequency. For (a), the cutoff frequency of the spatial filter was fixed to $\omega_c=0.33$. For (b), the temporal filter parameter was fixed to $\gamma=0.33$.

presented results showing that the proposed method improves accuracy of ejection fraction readings obtained using the clinical software (INVIA CORRIDOR 4DM (Ref. 38)). Finally, we have reported results on several real patients including one with a severe perfusion defect. Visual considerations for real patients also suggest that the proposed method can improve image quality and therefore diagnosis accuracy for both perfusion defect detection and myocardial motion assessment.

VI. CONCLUSION

We have developed and evaluated an accurate postreconstruction motion-compensated spatiotemporal filtering algorithm for cardiac gated SPECT images. The proposed method relies on a deformable mesh model based on a left-ventricle surface model to track heart wall motion. Estimated motion is used for temporal filtering along the motion trajectories, thus reducing motion-blur artifacts. The proposed method was tested using the NCAT phantom and simulating a SPECT system with the SIMIND package. The proposed method was evaluated on images reconstructed by both FBP and ML-EM methods. Visual inspection, noise evaluation, as well as measurement of statistical properties, demonstrate that the proposed motion-compensated filtering method outperforms several existing clinical postprocessing methods. In addition, we have shown that heart wall motion is accurately

preserved when evaluating ejection fraction by the CORRIDOR 4DM software.

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^{a)}Electronic mail: brankov@iit.edu

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TABLE II. Ejection fraction measurement for the different methods (EM reconstruction). Values were obtained using the INVIA CORRIDOR4DM software (except for the true NCAT value obtained from the NCAT program).

Method	EF (%)	EDV (mL)	ESV (mL)
True	58.87	117	48.12
Ref	60	95	38
SO	57.32 (± 4.33)	99.02 (± 4.30)	42.10 (± 3.02)
121	56.06 (± 5.25)	97.72 (± 4.51)	42.92 (± 4.40)
MC	56.00 (± 5.07)	95.01 (± 4.99)	41.68 (± 2.93)

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