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Quantitative study of cardiac motion estimation and abnormality classification in emission computed tomography

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Abstract

Quantitative description of cardiac motion is desirable to assist in detecting myocardial abnormalities from gated myocardial perfusion (GMP) emission computed tomography (ECT) images. While “optical flow” type of cardiac motion estimation (ME) techniques have been developed in the past, there has been no quantitative evaluation of their performance. Moreover, no investigation has been performed in terms of applying an ME technique to quantify cardiac motion abnormalities. Using the four-dimensional NCAT beating heart phantom with known built-in motion, the current work aimed at addressing the aforementioned two issues. A three-dimensional cardiac ME technique was developed to search for a motion vector field (MVF) that establishes voxel-by-voxel correspondence between two GMP ECT images. The weighted myocardial strain energy served as the constraint in the process to minimize the difference between one intensity image and the MVF warped other. We studied the convergence of the ME technique using different initial estimates and cost functions. The dependence of estimated MVF on the initialization was attributed to the tangential motion that is undetectable while not suppressed by the strain energy constraint. We optimized the strain energy constraint weighting using noise-free phantom images and noisy reconstructed images, the former against the known MVF and the later in the task of regional motion classification. While the results from the above two studies well coincide with each other, we also demonstrated that upon appropriate optimization the ME method has the capability of serving as a computer motion observer in separating simulated noisy reconstructed GMP SPECT images corresponding to hearts with and without regional motion abnormalities.

I. INTRODUCTION

Gated myocardial perfusion (GMP) emission computed tomography (ECT) plays an important role in the assessment and risk stratification of patients with coronary artery disease and left ventricular dysfunction [1], [2]. Feasibility of detecting cardiac motion for more accurate quantitative estimates of myocardial perfusion has been examined on patient data based on tracking right ventricular insertion points in normal subjects or perfusion defect zones in abnormal subjects [3]. Quantitative description of the cardiac movement may assist in locating the myocardial motion abnormalities, especially when perfusion abnormality is absent [4]. Since the myocardium is a non-rigid structure that bends and stretches during the cardiac cycle, simple motion models such as a six parameter rigid-body

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description are inadequate to describe the motion. A three-dimensional (3D) map of motion vectors at the same resolution as the perfusion image allows for better description of the complex myocardial motion.

Before introducing cardiac motion estimation (ME) methods that have been developed and applied to ECT/CT images, we acknowledge the work done on tagged magnetic resonance imaging (MRI) technique [5], [6], which provides an intuitive way to observe and confirm cardiac motion. Tagged MRI generates a series of magnetic resonance images with spatially encoded magnetic saturation planes or tags created within the tissues being imaged. The difference in intensity between tagged and untagged regions allows tracking of the motion of underlying tissues. Methods have been developed to analyze the cardiac motion from tagged MR images. Young et al. [7] presented a method for tracking stripe motion in the image plane and showed how the information could be incorporated into a finite element model of underlying deformation. The method provides a framework to combine high level global constraints (e.g., smoothness and connectivity) with low-level local constraints (e.g., dark, linear features). Park et al. [8], [9] presented a technique using a class of physics-based deformable models, which allow parameterized deformations that captured the motion of the left ventricle (LV). Ozturk et al. [10] used four-dimensional (4D) B-splines to interpolate the motion between the tracked myocardial points. The 4D displacement field formed from combining the two-dimensional (2D) fields derived from the short-axis and long-axis image planes could be used to track the deformation of points anywhere within the myocardium.

Many cardiac ME methods developed for ECT/CT images are based on the well-known optical flow determination method proposed by Horn and Schunck [11]. Optical flow is defined as the distribution of apparent velocities of movement of brightness patterns in an image. Using the brightness constraint, the motion component in the direction of the local gradient of the image intensity function may be estimated. This phenomenon is known as the aperture problem and only at image locations where there is sufficient intensity structure can the motion be fully estimated [12], [13]. The velocity of a surface that is homogeneous or containing texture with a single orientation cannot be recovered optically. In Horn and Schunck [11], the brightness constraint was used in conjunction with a regularization term. Regularization by requiring a slowly varying optical flow field was introduced to disambiguate normal measurements.

Attempts have been made to apply the Horn and Schunck method directly to 2D cardiac images [14], [15]. However, the 2D estimation is inadequate to describe the true heart motion vector which is distributed and oriented in 3D. Song and Leahy proposed a method for computing the 3D motion vector field (MVF) directly from 3D CT heart images [16]. In this approach, incompressibility and divergence-free constraints were imposed on the velocity field of the deforming heart. The motion computing problem was then formulated as minimizing a penalty function that accounts for physical and smoothness constraints in a 3D space. The algorithm was applied on simple simulated images as well as cine CT images of a human heart. The authors, however, made no claim as to the correctness of the computed fields although they stated that visually reasonable estimates of the heart velocity field were obtained.

Klein *et al.* [17] investigated the tracking of torsion of the LV using an ME algorithm described by Klein and Huesman [18]. The estimation problem was solved to find an MVF consistent with elastic material properties that best matches a deformed time frame to the reference frame. The authors applied the cardiac ME algorithm to gated PET, cine MR, and tagged MR images of healthy volunteers. The short-axis views of estimated MVF from gated PET images revealed that the radially-directed component of the heart motion was represented but the torsional component appeared lost. Although showing highly resolved

boundaries of the myocardium, the cine MR cardiac images, being relatively featureless within the boundaries, did not appreciably augment the ability of the ME technique. Torsional motion was estimated from the tagged MR images because of the useful image features contained. The authors came to the conclusion that typical gated cardiac PET images from healthy subjects were so uniform that they do not possess a sufficiently rich feature space to track the local features within the myocardial walls. Similar conclusions have also been reached in work by Gilland *et al.* [19], Cao *et al.* [20], and Mair *et al.* [21] with regard to the estimated MVFs from phantom images and SPECT patient images.

While cardiac MVF estimation techniques for GMP images have been developed and implemented in different situations, there has been no *quantitative* evaluation¹ on an estimated MVF. Some of the study mentioned above only quantified the cardiac MVF [16], some others did visual comparison of the estimated MVFs with an estimated “gold standard” [17]. Moreover, no investigation has been performed in terms of applying an MVE estimation technique as a computer motion observer to detect motion abnormalities. Using the 4D non-uniform rational B-spline (NURBS)-based CArdiac-Torso (NCAT) phantom with a beating heart insert with known MVFs, we studied the convergence of a 3D cardiac ME method, and optimized its performance in detecting regional motion defects in the absence of perfusion abnormalities. In section II, we present the cardiac ME algorithms and the initial estimates applied in this study. In section III, we describe the 4D NCAT phantom and its built-in MVF and then the optimization and convergence studies for the ME methods. We also present the regional motion defect detection studies using both noise-free and noisy reconstructed images. Section IV shows the results of the studies performed in section III using the ME methods described in Section II. Section V offers discussion on the acquired results followed by section VI which summaries the work in this manuscript.

II. CARDIAC MOTION ESTIMATION METHODS

A. Cardiac motion estimation algorithms

The cardiac ME task can be treated as a constrained minimization problem. We first present a cardiac ME algorithm that seeks to determine the MVF that is consistent with the modeled elastic properties of cardiac tissue, at the same time best matches (warps) the heart voxels in one frame to those in an adjacent frame [18]. Then we present a second algorithm with its cost function modified from the cost function of the first algorithm. We call the first one the *original* algorithm and the second one the *modified* algorithm.

The original ME algorithm computes the MVF between two consecutive GMP images (heart region separated from rest of the body) directly in the 3D space. It assumes that the intensity of myocardium does not change between frames. The estimation problem is solved by finding the MVF $\mathbf{m}$ that minimizes the cost function consisting of an image matching error term $E_I(\mathbf{m})$ and a weighted regularization term $\alpha E_S(\mathbf{m})$

$$E_I(\mathbf{m}) + \alpha E_S(\mathbf{m}), \quad (1)$$

where α is the weight. 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 a given MVF

¹Evaluation of the estimated MVF with respect to a “true” MVF quantitatively.

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

where $\mathbf{r}$ is the 3D spatial coordinate of a voxel, f_1 and f_2 are the intensity images from which an MVF is to be estimated, $\mathbf{m}$ is the 3D MVF that supposedly warps f_1 to f_2 . The strain energy function for a linear isotropic elastic material [22] is chosen to serve as the regularizing constraint

$$E_S(\mathbf{m}) \triangleq \frac{1}{2} \sum_{\mathbf{r}} (\lambda(u_x + v_y + w_z)^2) + \sum_{\mathbf{r}} (\mu(u_x^2 + v_y^2 + w_z^2)) + \frac{1}{2} \sum_{\mathbf{r}} (\mu[(u_y + v_x)^2 + (u_z + w_x)^2 + (v_z + w_y)^2]), \quad (3)$$

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 $\partial u / \partial x$. The parameters λ and μ are the 1st and 2nd Lamé constants, which arise in strain-stress relationships. One set of Lamé constants uniquely defines the elasticity property of the modeled myocardium. As a result, the choice of λ and μ affects the performance of the motion estimation technique. In this study, the shear modulus μ is determined from the cross-fiber equibiaxial data and λ is calculated from the μ value and the bulk modulus determined from an LV finite element model developed by Veress *et al.* [23].

The MVF $\mathbf{m}$ is estimated using an iterative method that updates the current estimate $\tilde{\mathbf{m}}$ by minimizing the quadratic approximation of the cost function [21]. The conjugate gradient algorithm is applied to find the estimate that minimizes the convex function

$$Q(\mathbf{m}) + \alpha E_S(\mathbf{m}), \quad (4)$$

where

$$Q(\mathbf{m}) = \sum_{\mathbf{r}} [f_1(\mathbf{r}) - f_2(\mathbf{r} + \tilde{\mathbf{m}}(\mathbf{r})) - (\mathbf{m}(\mathbf{r}) - \tilde{\mathbf{m}}(\mathbf{r})) \cdot \nabla f_2(\mathbf{r} + \tilde{\mathbf{m}}(\mathbf{r}))]^2, \quad (5)$$

is the first order Taylor series approximation of $E_I(\mathbf{m})$. The selection of the weighting factor α is studied in the coming sections.

It is noticed that the regularizing constraint (3) in the cost function of the original ME algorithm enforces certain relationship among the estimated motion vector components. However, this constraint (3) does not separate edge-orthogonal motion from tangential motion and therefore does not penalize tangential motion that is not detectable from images. For the sole purpose of studying convergence and quantitative performance, we add another regularization term to the original cost function and make it the modified ME algorithm.

This added term, $E_T(\mathbf{m}) \triangleq \sum_{\mathbf{r}} \|\mathbf{m} \times \nabla f_2\|^2$, and its weighting factor β makes the modified cost function

$$E_l(f_1, f_2, \mathbf{m}) + \alpha E_s(\mathbf{m}) + \beta E_t(\mathbf{m}). \quad (6)$$

We adopt similar minimization process applied to the original cost function. Iterative method is used to update the MVF to minimize the first-order Taylor approximation of the modified cost function

$$Q(\mathbf{m}) + \alpha E_s(\mathbf{m}) + \beta E_t(\mathbf{m}). \quad (7)$$

The selection of weighting parameter α and β will be described in the coming sections.

B. Initial Estimates

To study the convergence and to optimize the performance of the ME algorithms presented in the previous section, we applied three initial estimates. The first one is the straightforward *zero initial estimate*, with motion vector magnitudes on all voxels set to zero. The second one is the *edge-orthogonal initial estimate*, which were created to study the convergence of the original ME algorithm in the edge-orthogonal direction. The last one is what we call the *NCAT initial estimate*, which comes from the 4D NCAT beating heart phantom we use in this study. Note that the latter two initial estimates are only used for proof-of-principle studies, which are designed to evaluate the ME algorithms. We are not going to use them, especially the NCAT initial estimate, in application of the ME algorithms such as regional motion defect detection.

The motion vectors of the edge-orthogonal initial estimate were set as the relative intensity changes between the two image frames along the gradient directions, when the gradients were larger than certain threshold ε

$$\mathbf{m}(\mathbf{r}) = \begin{cases} \frac{f_1(\mathbf{r}) - f_2(\mathbf{r})}{\|\nabla f_2(\mathbf{r})\|} \cdot \frac{\nabla f_2(\mathbf{r})}{\|\nabla f_2(\mathbf{r})\|} & \text{if } \|\nabla f_2(\mathbf{r})\| \geq \varepsilon \\ \mathbf{0} & \text{if } \|\nabla f_2(\mathbf{r})\| < \varepsilon \end{cases}. \quad (8)$$

For normalized noise-free phantom images, the threshold ε was set to a small number (e.g. 0.01).

The 4D NCAT phantom consists of a cardiac MVF that represents the true motion vectors at each voxel in the myocardium between each two consecutive gated frames. The MVF only covers voxels on the myocardium. We generated the NCAT initial estimate by extrapolating the motion vectors on the myocardium into the immediate neighbor regions (three voxels next to the edges). Note that the MVF on the myocardium was kept unchanged. Compared with the MVF of the NCAT, this modified NCAT initial estimate avoids abrupt motion magnitude changes over the edges of the myocardium (resulting in lower cost function value).

III. MATERIALS AND EXPERIMENTAL DESIGNS

A. Four-dimensional NCAT phantom and its built-in MVF

The evaluation and optimization of the ME technique were performed using the 4D NCAT phantom, which has become a standard tool in the field of nuclear medicine, with the

beating heart insert that realistically models the cardiac motion [24]. We used the 4D NCAT phantom to generate GMP SPECT images of the beating hearts and the MVF representing frame to frame built-in motion. The MVF of the beating heart in the 4D NCAT phantom serves as the true MVF for quantitative evaluation of the estimated MVF.

Cardiac motion in the 4D NCAT phantom was modeled by defining time-position cubic NURBS curves for each of the control points of the heart surfaces. The time-position curves were originally derived from normal human gated tagged MR images [24]. From the continuous time-position curves defined for the control points, any number of time frames over the cardiac cycle can be produced. Multiple 4D surfaces were created for the LV spanning its entire volume. The multiple surfaces within the LV wall were spline-interpolated over the thickness of LV, creating a 4D NURBS solid model for the LV wall. This 4D solid model of the LV wall has the ability to generate the motion of any point within the volume of the LV wall at any time during the cardiac cycle [24].

Figure 1 shows the 2D quiver plots of the 3D MVF of the 4D NCAT LV wall on a short-axis slice and a long-axis slice at end-diastole. It is difficult to display 3D motion vectors on top of a 3D intensity image, so we present the in-plane components of the 3D MVF on short-axis and long-axis slices of the phantom heart images. The voxel size is 0.31^3 cm^3 and the presented short-axis slice is the 16th slice of the 31 slices ($\sim 10 \text{ cm}$) covered by the entire LV, counted from the apex. Note the counter-clockwise twisting motion in the short-axis slice and the longitudinal motion toward the apex in the long-axis slice.

B. Optimization and convergence studies

The studies in this subsection were designed to evaluate the proposed algorithms. We used noise-free images and initial estimates such as the NCAT initial estimate presented in II.B, which are not accessible in practice, only for the purpose of proof of principle. The application of the proposed methods to detect regional motion defects in realistically achievable situations is described in the next subsection, III. C.

1) Strain energy weighting factor optimization—The ME algorithms described in II.A are based on the optical flow algorithm, with performance depending on the form and weight of the regularizing constraint. For the original ME algorithm, it is critical to find the balance between the image matching term $Q(\mathbf{m})$, which acts as the driving force pushing one frame to match the other, and the constraint term $\alpha E_S(\mathbf{m})$, which shapes the estimated MVF according to the strain energy model. Using the NCAT initial estimate, we studied the effect of the weighting factor α on the estimated MVF from the phantom heart images modeling a normal-beating heart. The use of the known MVF as an initial estimate in the motion estimation process is to optimize the weighting factor on the strain energy in the original ME algorithm.

For this optimization process, we used the end-diastolic frame and its adjacent frame (of a 16-gate scheme) in the contracting process since the motion between these two frames is the largest among those between all adjacent frames. The original ME algorithm was applied to the two normalized image frames, where intensity values of the images were scaled linearly with the maximums set to 1. The α values from 10^{-4} to 1 were tested, with each tested value an order of magnitude greater than the preceding value. For each tested α value, we calculated the root-mean-squared (RMS) errors of the estimated MVF components u , v , and w against the known MVF on the entire LV myocardium. The tested α value that minimizes the RMS errors is the optimized strain energy weighting factor.

2) Convergence studies—To study the convergence of the ME algorithms, we applied the three initial estimates (described in II.B) and compared the estimated MVF

quantitatively. We defined a region of interest (ROI) which is a pie-shaped wedge on the anterior-lateral region of the LV (Figure 2). The pie-shaped wedge is centrally located at mid-range of the long axis of the LV. This is the region where the motion defect will be located in the coming studies. The motion vectors on the ROI were decomposed into radial, circumferential, and longitudinal components. For estimated MVF obtained from different combinations of ME algorithms and initial estimates, we compared the average magnitudes of the three components on each ROI-covered short-axis slices.

C. Regional motion defect detection

In this subsection, the experiments were designed to demonstrate the capability of proposed ME methods in regional motion defect detection. The performance of the proposed algorithms was first evaluated with noise-free images. More importantly, we then applied and optimized the ME algorithms using noisy reconstructed SPECT images that were realistically simulated. Only the zero initialization that is available in real situation is used in studies of this subsection.

1) Quantification of regional motion defect using noise-free images—As mentioned in the Introduction section, a goal of ME is for computer-aided diagnosis through detecting cardiac motion defects using the estimated MVFs, especially in circumstances where perfusion abnormalities are absent. Before applying ME to noisy reconstructed images, we first studied the performance of the original ME method using phantom images corresponding to abnormally beating hearts. Different levels of regional motion defects can be set on an ROI over the LV, such as the ROI described in the previous section (Figure 2). For example, for a 50% motion defect, the magnitudes of the motion vectors at the center of the ROI are reduced to 50% of the normal magnitudes, gradually increasing back (transition region size can be specified) to normal over the edges of the ROI, in both short-axis and long-axis directions. We study two levels of regional defects, one is 50% and the other is 0% of the normal motion magnitude (motion magnitudes were reduced to 0 at the center of ROI). We applied zero initial estimate in the ME process and calculated the ratio of estimated abnormal to normal motion magnitudes. The recovered ratios of motion defect were then compared to the true levels of regional defect (50% and 0%), which indicate the performance of the ME method in motion defect detection.

2) Regional motion classification from noisy reconstructed images—Using the zero initial estimate, we investigated regional motion classification from the simulated noisy images. The estimated MVF was used to distinguish normal beating hearts from those with regional motion defects. The ME technique was applied as a computer observer to detect motion defects similar to the Channelized Hotelling Observer used in detecting perfusion defects [25], [26].

We first generated noise-free 16-gate GMP SPECT projection data from a 4D NCAT phantom with normal heart motion and phantoms each with a regional motion defect of different levels. Three levels of defect, 50%, 75%, and 85%, were studied respectively. 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° with a parallel-hole low-energy high-resolution (LEHR) collimator. The projection modeled the effects of non-uniform attenuation, collimator-detector response, and scatter. The slab-derived scatter estimation method was used to model the scatter effect [27]. After projection, the data was collapsed to pixel size of 0.312^2 cm^2 . The projection data from each of the phantom models were scaled to the corresponding count level of a typical $^{99\text{m}}\text{Tc}$ patient GMP SPECT study [28]. Poisson noise fluctuations were then added to generate 40 realizations of noisy projection datasets for both the normal and defect motion cases. A 4D MAP-RBI-EM image reconstruction

algorithm with corrections of attenuation, collimator-detector response, and scatter was used to reconstruct the noisy projection datasets [29]. The original ME method with zero initial estimate was applied to estimate the MVF from the reconstructed images of each noise realization. The radial motion magnitudes in the voxels within the ROI were averaged to represent the regional radial motion from each noise realization.

The regional radial motion estimated from the normal and abnormal beating heart images were tested for Gaussian distribution using the Lilliefors test [30]. The signal-to-noise ratio (SNR) for detecting the regional motion defect (of a given level) was then calculated using the following equation:

$$\text{SNR} = \frac{\langle r \rangle_n - \langle r \rangle_a}{\sqrt{\frac{1}{2}\sigma_n^2 + \frac{1}{2}\sigma_a^2}}, \quad (9)$$

where $\langle r \rangle_n$ and $\langle r \rangle_a$ are the average values of regional radial motion over the normal and abnormal noise realizations, σ_n and σ_a are the variances, respectively. The area under the curve (AUC) is calculated from the SNR through the relationship:

$$\text{AUC} = \frac{1}{2} + \frac{1}{2} \text{erf}\left(\frac{\text{SNR}}{2}\right), \quad (10)$$

where erf is the error function defined by $\text{erf}(z) = \frac{2}{\sqrt{\pi}} \int_0^z \exp[-y^2] dy$ [31]. The AUC value reflects the detectability of the regional motion defect. We studied the effect of the strain energy weighting factor α on the calculated AUC value.

IV. RESULTS

A. Optimization and convergence studies

1) Strain energy weighting factor optimization—In III.B.1, we described the method to determine the optimized strain energy weighting factor α using the NCAT initial estimate in estimating the MVF of a normal-beating heart. We examined the convergence of the iterative process of the original ME algorithm and also calculated the RMS errors of the components of the MVF estimation in the x, y and z directions for each α . The cost function was found to converge to a steady value after fewer than 3 updates of $\tilde{\mathbf{m}}$ when α was larger than or equal to 10^{-2} . When $\alpha \leq 10^{-3}$, the cost function value oscillated between iterations with variations around 10% after 30 through 100 iterations. The RMS errors at the 30th iteration was calculated for $\alpha = 10^{-3}$ and $\alpha = 10^{-4}$. The RMS errors in the x, y, and z directions on the LV were plotted as a function of the weighting factor α in Figure 3. The difference among the estimated MVF components with different strain energy weighting factor value is noticeable, with α of 10^{-2} performing the best.

We also studied the effect of the Lamé constants on the estimated MVF. Based on Veress et al. [23], we determined the 1st Lamé constant or the shear modulus μ to be 2.5K Pa and the 2nd Lamé constant λ to be 193.3. For the optimized $\alpha = 10^{-2}$, we varied the λ value with μ set as 2.5K Pa and we also varied the μ value with λ set as 193.3. The RMS errors of the estimated MVF components were calculated from which we found that the above λ and μ values selected based on the experimental data and model study [23] were optimal. Since the optimization study is very similar to the strain energy weighting factor optimization described in the last paragraph, we will not show more details here.

As mentioned earlier, with the NCAT initial estimate, the optimized value as 10^{-2} was *also* the smallest α (among the tested values) that leads to fast convergence (fewer than 3 updates) of the ME process. This further confirmed that, the strain energy function (including the Lamé constants), which was chosen to model that of the myocardium independent of creation of the NCAT phantom images and MVFs, served as an appropriate constraint for the cardiac motion estimation.

Parenthetically, one must note that we only employ the NCAT initial estimate to show the importance of optimizing the strain energy weighting in the ME algorithm. As demonstrated in Figure 3, the value of the constraint weighting factor affects the estimated MVF significantly; when the factor is not chosen properly, the estimated MVF can be quite different from the “true” MVF even when the “true” MVF is used as the initial estimate. As stated in III.C.2, we further performed the study on the optimization of the stain energy weighting with zero initial estimate, in the task of motion defect detection from noisy reconstructed images, and the results are to be shown in Section IV.B.2.

2) Convergence studies: in edge-orthogonal and tangential directions—The convergence study started with comparing estimated MVFs obtained from the original ME algorithm with the zero initial estimate and the NCAT initial estimate. The study in the last section indicated that when the NCAT MVF was used as the initial estimate, the smallest α leading to fast convergence of the ME process also resulted in the estimated MVF with the smallest RMS errors. In the case with zero as the initial estimate, we also used the smallest α that leads to fast convergence of the ME process, which was also 10^{-2} . Figure 4 shows the quiver plots of the estimated in-plane components of MVFs from the zero initialization (*O Init*) and from the NCAT initialization (*N Init*) with the optimized α value. From these plots, we see the clear difference between the results in both the short-axis and the long-axis slices. The quantitative comparison of these two MVFs will be shown later in this section (Figure 6).

Knowing that different initial estimates result in different MVF estimations, we first studied the convergence of the original ME algorithm in the direction orthogonal to the edges of the myocardium. The resulting MVFs (average magnitudes on each short-axis slices covered by the ROI) obtained from using the zero and the edge-orthogonal initial estimates, together with the known NCAT MVF, are plotted in Figure 5. They demonstrate the results from the edge-orthogonal initial estimate are close to the results from zero initialization, although they both differ from the known truth. We also used an initial estimate which has motion magnitudes half of the described edge-orthogonal intensity change (8) as the initial estimate and a similar MVF was obtained (not shown). These results suggest that the original cost function may have a minimum in the edge-orthogonal direction.

As mentioned in II.A, the modified cost function added a constraint to penalize tangential motion that is not detectable from the images. Plotted in Figure 6 are four sets of results, from the combinations of original and modified cost functions and NCAT and zero initializations, respectively. The weighting factor β in (7) was chosen to make the resulting $\alpha E_s(\mathbf{m})$ and $\beta E_t(\mathbf{m})$ values in the cost function comparable. The plots show that the results from applying NCAT initial estimate to the modified cost function were close to the results from applying zero initialization to both the original and the modified cost functions. We also applied an initial estimate that had half the magnitude of the NCAT initial estimate to the modified cost function. The resulting MVF was very similar to the MVF from applying NCAT initial estimate to the modified cost function. The added constraint aiming at suppressing the tangential motion did not affect the estimated MVF when zero initialization was used. But it suppressed the tangential motion in the NCAT MVF so that the resulting

MVF from using the NCAT initial estimate were similar to that using zero as the initial estimate in all radial, circumferential, and longitudinal directions.

Thus we confirm that the strain energy constraint (3) does not suppress the tangential component contained in the NCAT initial estimate, which can not be detected when zero initial estimation is applied. The results in Figure 5 indicate that the original cost function (1) may have a minimum in the edge-orthogonal direction. But it does not have a minimum in the tangential plane (i.e. directions perpendicular to the intensity gradient). When motion is suppressed in the tangential directions by the added term in the modified cost function (7), nearly identical results are reached from different initial estimates.

B. Regional motion defect detection

1) Quantification of regional motion defect using noise-free images—As described in III.C.1, we studied the performance of the ME algorithm in regional motion defect detection using zero initialization. Keeping in mind that tangential motion is not detected as demonstrated from the convergence studies, we compared the estimated normal and abnormal radial motion on the ROI. The average radial motion components of estimated MVFs, from phantom images corresponding to normal motion, regional 50% defect motion, and regional 0% motion (as explained in III. C.1.), on each short-axis slices in the ROI were plotted in Figure 7(a). The ratios between the estimated normal radial motion averages and the estimated 50% defect radial motion averages on short-axis slices were plotted in Figure 7(b). The ratios between the estimated normal radial motion averages and the estimated 0% defect radial motion averages on short-axis slices were plotted in Figure 7(c). For comparison, the given true ratios of the normal and abnormal radial motion were also plotted. As demonstrated by Figure 7(b) and Figure 7(c), the ratios of the estimated normal and abnormal radial motion are close to the true ratios. From this study, we conclude that although the estimated radial motion components did not match the known ones (see Figure 5(a) for the normal case), the difference between the estimated normal and abnormal radial components well reflects the level of motion abnormality.

2) Regional motion defect classification from noisy reconstructed images—As shown in the previous subsection, results from zero initial estimate reflect the level of motion defect from noisy-free phantom images. In this subsection, we present the results of applying zero initial estimate in the study of regional motion classification from noisy reconstructed images. The regional radial motion magnitudes estimated from the noisy reconstructed normal (and abnormal) beating heart images were tested and confirmed to follow Gaussian distribution. The AUC values that reflect detectability of abnormal motion (of given defect levels) were calculated for different values of strain energy weighting factor α , as shown in Figure 8. The choice of α affects the performance of the ME method considerably, in terms of distinguishing abnormally beating hearts from normal ones. The α value maximizing the defect motion detectability index (AUCs) from noisy GMP SPECT reconstructed images matches the α value that minimizing the RMS errors of MVF from ideal images (shown in Figure 3). Comparing the maximum AUC values for each of the motion defect level, we see that classification of abnormal motion gets harder (AUC value decreases) as the defect motion magnitude gets closer to the normal motion. For the specific ROI we study here, the detection of motion defect levels smaller than 15% reduction of the normal motion may not be feasible (AUC<0.65).

V. DISCUSSION

As mentioned in the Introduction section, the “optical flow” type of cardiac ME methods similar to what we presented in this study have been used by different groups of researchers.

Without quantitative evaluation, they all showed that the twisting motion of the LV could not be detected when the image of the myocardium was featureless. Some investigators claimed that although the twisting motion could not be detected from cardiac ECT images, the radial motion could be accurately represented [17].

The study we present here consisted of the difficult and realistic case of having no perfusion defects, as such exhibiting nearly uniform intensity in the myocardium. This case allows a thorough study of the limitations and capabilities of the “optical flow” type approaches. As shown in Figure 5, when zero initialization was applied, the circumferential (twist) motion and the longitudinal (cross-plane) motion that did not cause intensity change of the myocardium in the ROI could not be detected. Without the detection of these tangential motion components (especially the longitudinal motion that crosses the short-axis planes), the estimated radial motion was shown to deviate from the known radial motion. This is because, in terms of matching one image to the other, the motion components in the three directions are correlated with one another.

With optimized weighting, the strain energy constraint well maintains the relationship among the motion components of the NCAT initial estimate in the radial, circumferential, and longitudinal directions. But this constraint does not suppress tangential motion that causes no intensity change between frames. The original cost function (1) does not have a global minimum as the estimated MVF highly depends on the initialization. Through the study of an added term that aimed to suppress motion perpendicular to the intensity gradient (6), we confirmed that the difference between estimated MVFs from zero and NCAT initial estimates using the original ME algorithm was due to the motion components in the undetectable tangential directions contained in the later.

With the limitations of the ME algorithm demonstrated, we also showed its capability of serving as a computer motion observer. As presented in Section IV.B, with zero initialization applied, although the estimated radial motion did not represent the true radial motion, the level of defect could be correctly detected. The zero initialization was then applied to noisy reconstructed images for the defect motion classification task. It was shown that the strain energy weighting factor α affects the results of motion defect classification as significantly as it affects the RMS errors of MVFs estimated from phantom images. The optimized α values from the two studies (shown in Figure 3 and Figure 8) are the same. Moreover, with the capability of motion abnormality detection and defect level quantification, the ME algorithm has the potential for clinical applicability in GMP ECT imaging to provide valuable diagnostic information on identification and grading of regional myocardial dysfunction [32–36].

As the last note, we emphasize that the ME algorithm developed and the simulation study presented here are a preliminary step of a series of studies aiming for clinical application. The normal motion (healthy baseline state) has been assumed only for evaluating the ME algorithm with simulated images. In order to detect motion defects from patient images without assuming knowledge on the baseline state, we will establish a “normal” MVF from averaging the MVFs of a number of “normal patients”. In addition, we will also determine the heterogeneity among “normal” patients with a very low likelihood of coronary artery disease. For diagnosis, the deviation of the estimated MVF values from those of the “normal” file will be calculated and expressed in terms of percent difference. Abnormality will be defined when the percent difference is larger than the variability calculated from the “normal” population.

VI. CONCLUSIONS

By using the 4D NCAT phantom with known cardiac MVFs, this study was aimed to quantitatively study a 3D cardiac ME method which estimates the MVF from two GMP ECT images with and without a regional cardiac motion defect using a constrained minimization algorithm. The modeled myocardium strain energy serves as the constraint for minimizing the difference between one gated image frame and the adjacent one warped by the MVF.

We quantitatively demonstrated the difference between the estimated MVFs from different initialization and studied the convergence of the original and modified ME algorithms. It was noted that the strain energy constraint did not suppress tangential motion contained in the NCAT MVF. With an extra term aiming to eliminate motion perpendicular to the intensity gradient (i.e., along the tangential plane), the modified cost function seemed to have a global minimum.

Using simulated noisy GMP SPECT images, we have applied the cardiac ME technique as a computer motion observer in classifying normal versus regional defects myocardial motion in the absence of perfusion defects. The performance of the algorithm in this classification task was found to be affected by the weighting factor value considerably, as also shown in the noise-free image case. The optimization of the ME technique for reducing RMS errors of estimated MVF from noise-free images provides guideline for reaching optimal performance in motion classification of noisy GMP SPECT images. Upon appropriate optimization, the ME method can serve as a computer motion observer in separating simulated noisy reconstructed GMP SPECT images corresponding to hearts with and without regional motion abnormalities.

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(a) (b)

Fig. 1.

Two-dimensional quiver plots of the in-plane components of the 3D MVF of the 4D NCAT phantom on (a) a short-axis slice and (b) a long-axis slice of the LV wall at end-diastole.

Fig. 2.

Schematic diagrams showing (a) short-axis and (b) long-axis views of the LV. The shaded ROI has parameters specified as: $\theta_{\text{center}} = 45^\circ$, $\Delta\theta = 60^\circ$, and $\Delta Z = 3\text{cm}$. A motion vector is decomposed into radial (R), circumferential (C), and longitudinal (L) components as demonstrated.

Fig. 3. RMS errors of the estimated MVF components in the x , y , and z directions, i.e., RMS_u , RMS_v , and RMS_w , as a function of the strain energy weighting factor α .

Fig. 4. Two-dimensional quiver plots of the in-plane components of the estimated 3D MVF on (a) a short-axis slice and (b) a long-axis slice of the LV (same slices as shown in Fig. 1), zero (*0 Init*) vs. NCAT (*N Init*) initialization.

Fig. 5. Average magnitudes of (a) radial, (b) circumferential, and (c) longitudinal components on short-axis slices in the ROI, known MVF (*NCAT*), estimated MVFs from edge-orthogonal (*E Init*) and zero (*0 Init*) initializations.

Fig. 6. Average magnitudes of (a) radial, (b) circumferential, and (c) longitudinal components on short-axis slices in the ROI, estimated MVFs from using the NCAT initial estimate or the zero initial estimate with the original (N Init or 0 Init) or the modified (MC N Init or MC 0 Init) cost functions.

Fig. 7.

(a) Average magnitudes of radial components on short-axis slices in the ROI, estimated MVFs from normal (*Normal*), 50% defect (*50% Dft*), and 0% defect (*0% Dft*) cases. (b) Ratio of the normal to the 50% abnormal radial motion magnitudes for the known NCAT MVFs (*NCAT*), and that for the estimated MVFs from zero initial estimate (*0 Init*). (c) Same as (b) other than for 0% abnormal radial motion magnitudes.

Fig.8.

AUC values of the regional radial motion (motion defect levels of 50%, 75%, and 85%) as a function of the strain energy weighting factor α , motion estimated from simulated reconstructed noisy GMP SPECT images using the original ME algorithm with zero initial estimate.