Inferring the left ventricle dynamical behavior using a free-form deformations model

Antonio Bravo\textsuperscript{a,\*}, Rubén Medina\textsuperscript{b}, Gianfranco Passariello\textsuperscript{c}, Mireille Garreau\textsuperscript{d}

\textsuperscript{a} Grupo de Bioingeniería, Universidad Nacional Experimental del Táchira, Decanato de Investigación, San Cristóbal 5001, Venezuela
\textsuperscript{b} Grupo de Ingeniería Biomédica (GIBULA), Universidad de Los Andes, Facultad de Ingeniería, Mérida 5101, Venezuela
\textsuperscript{c} Grupo de Bioingeniería y Biofísica Aplicada (GBBA), Universidad Simón Bolívar, Sartenejas, Caracas 39000, Venezuela
\textsuperscript{d} Laboratoire Traitement du Signal et de l’Image (LTSI), Université de Rennes 1, Campus de Beaulieu 35042 Rennes Cedex, France

Received 15 October 2006; received in revised form 29 January 2007; accepted 5 February 2007
Available online 16 February 2007

Abstract

A computational 4D (3D + time) model for simulating the dynamical shape of the left ventricle (LV) based on free-form deformations (FFD) techniques is described. The simulation model is useful as a teaching tool for understanding the normal left ventricle motion. The model is also useful for initializing 3D segmentation algorithms and for understanding the relation between pathologies and variation of parameters defining the ventricular function. Validation of this computational model is performed by synthesizing 4D sequences of the left ventricle, comprising the interval going from end-systole to end-diastole. From the resulting 4D shapes, several mechanical parameters such as the left ventricle volume, the radial contraction and torsion are calculated and compared with results of works previously reported based in MR-tagging images. A comparison is also performed with respect to mechanical parameters extracted from the additional time instants in the same multislice computerized tomography (MSCT) database used for extracting the LV wall surfaces required for initialization. First results show a good match between parameters compared.

© 2007 IMACS. Published by Elsevier B.V. All rights reserved.

Keywords: Simulation; Free-form deformation; Left ventricle

1. Introduction

Heart diseases are an important cause of mortality worldwide according to the World Health Organization (WHO), this fact has motivated an important effort of research for understanding the physiopathogenesis of several cardiac diseases [13]. Cardiac motion is an important feature that describes the cardiac function. Physiology and mechanical behavior of the heart are described as normal or abnormal based in the analysis of motion and shape deformation of cardiac cavities. Several parameters are used for quantifying the dynamical function of the heart [16]. The dynamical function of cardiac cavities can be assessed based in bidimensional (2D) and tridimensional (3D) image sequences acquired from several modalities.
Several methodologies for deformable based modeling of cardiac cavities shape have been proposed. Most of these models use some sort of physical principles to determine the shape and motion of objects [9,20]. The free-form deformation constitutes an interesting geometrical tool for modeling and animating non-rigid objects since it enables the manipulation of any shape in a free-form manner. This technique was proposed by Sederberg [19] to sculpt solid geometric models bounded by any analytical surface.

1.1. Left ventricle motion

Cardiac function describes the performance of the heart during the emptying and filling phase of ventricles. In this process, the complex 3D structure, that represents the cardiac muscle, undergoes elastic deformations due to contraction and relaxation of muscles fibers. This mechanism determines the dynamical behavior of the human heart. The left ventricle is considered the main cavity of the heart. This cavity has a complex motion during the cardiac cycle, however, five types of motion components have been identified: (1) translation, (2) rotation, (3) 3D twisting, (4) longitudinal shortening, and (5) radial contraction. These components are varying in space and time. For instance, longitudinal shortening is significantly asymmetric as the plane of the mitral valve descends 1–2 cm towards the apex, but the apex barely moves towards the base of the heart [14]. The radial contraction is also important and it is followed by the longitudinal shortening. The other three movements (translation, rotation and 3D twisting) are of less importance [22] in normal subjects.

1.2. Cardiac motion modeling

Numerical modeling of cardiac cavities considering the actual mechanical properties is a difficult problem that has not been fully solved. Clinical and research applications about cardiac cavities modeling are considerably extensive, a recent review on this subject can be found in [12]. These models have been used for simulation, visualization, planning of surgical interventions and extraction of functional information.

Development of cardiac models for simulation contributes to understand cardiac function and dysfunctions. In cardiac simulation the goal is to improve the understanding of physiological concepts about cardiac dynamics as well as deriving new quantitative parameters. Several research works have been developed for simulating the left ventricle motion. Sideman et al. [21] constructed a left ventricle model considering LV mechanics, perfusion, energetics and electrical activation. The model enabled dynamical simulation of the interacting cardiac functions. In addition, this method was useful for identifying patients pathologies in a non-invasive manner. Chen et al. [4] presented an approach for modeling ventricle shape and motion using angiographic data. Superquadrics shape modeling primitives were used for representing global deformation. Spherical harmonic shape modeling primitives were introduced for representing shape details of the left ventricle. The model considered four motion classes: rigid and non-rigid global motion, local rigid motion and deformation. This model was used to synthesize the dynamics of the left ventricle geometry.

In the last few years, several approaches have been proposed for developing models of cardiac cavities motion, which can be used as prior information for motion tracking. A modeling approach was used by Gérard et al. [9] to track the motion of the left ventricle in 3D echocardiographic sequences. The simulation model was controlled by temporal parameters related to the global contraction and rotation of myocardium: apical contraction, basal contraction, longitudinal contraction and apical rotation. The method performed the segmentation of the ventricular cavity using 3D deformable surfaces, then the simulation model was used for deforming the segmentation result enabling the motion tracking of the 3D surface. Several motion descriptors were estimated from this representation, such as contractility indexes, stress and thickness of the wall. Sermesant [20], presented a 3D simulation model of the heart ventricles that considered the combination of the electrical and biomechanical function. Three information sources were used to construct the model: myocardial geometry, orientation of muscular fibers and parameters of the electrophysiological activity. The proposed model allowed simulation of ventricular dynamics. This model was applied to segmentation of magnetic resonance image sequences allowing the extraction of several quantitative parameters describing the cardiac function. The results obtained were comparable with those previously reported in [9,1]. Chandrashekara et al. [3] have constructed a statistical model from the motion fields estimated at all time instants between end-diastole and end-systole in tagged MR images of different subjects. The statistical model was constructed by performing a principal component analysis (PCA) of the displacement fields in a common coordinate system. The PCA results were used to construct a parametric model, which is used to guide a free-form deformation (FFD) algorithm leading to a robust
deformation model. The model is validated in healthy volunteers considering a set of time frames between end-diastole and end-systole. The main goal was using this statistical motion model for discrimination of cardiac motion in normal subjects and subjects with hypertrophic heart disease.

1.3. Purpose

In this paper, a method for synthesizing 4D (3D + time) left ventricle images using FFD is proposed. The FFD method is used for designing deformation modes that reproduce the components of the left ventricle motion based in prior-knowledge. Additionally, FFD can be applied locally to synthesize certain features related to the irregular shape of the left ventricle walls. The simulation model is useful as a teaching tool for understanding the normal or abnormal motion. As this model is able to simulate the dynamics of the cardiac shape, further applications related to segmentation of left ventricle 3D image sequences could be explored.

2. Model shape

The model is built from a 3D surface representation of the LV extracted at the a preprocessing stage, for only one time instant of the 4D image sequence acquired, from a given imaging modality. A segmentation algorithm based on a 2D active appearance model (AAM) has been used for extracting the endocardial wall in a 3D MSCT database [8]. The 3D surface representation of the LV boundary is inferred using the marching cubes algorithm based on the 3D contour points.

2.1. Boundary extraction

2.1.1. Background in AAM

The segmentation procedure using AAM involves two stages. In the first stage a training procedure is performed based on a set of landmarks describing planar shapes. The second stage corresponds to the segmentation where the active appearance model is perturbed (by varying some of their parameters) in order to generate instances of the model matching the contour and gray-level information in the image [5]. In both stages, each planar shape is represented by \( n \) points as the vector:

\[
X = [x_1, x_2, \ldots, x_n; y_1, y_2, \ldots, y_n]^T
\]

This is an observation in the \( 2n \) dimensional space. Principal component analysis (PCA) is used for dealing with redundancy in the input data after alignment using the procrustes analysis [23]. The resulting shape model is a function of the mean shape \( \bar{X} \), a matrix \( \Phi_s \) which includes the eigenvectors of the covariance matrix of the input data, and a set of parameters \( b_s \) according to:

\[
X = \bar{X} + \Phi_s b_s
\]

The points of the shape are transformed into a modal representation where the modes are ordered according to the percentage of variation that they explain. The gray-level information is also modeled as a texture-model where pixel intensities after normalization are considered. For \( m \) samples over the object, the texture is represented as the vector:

\[
g_m = [g_1, g_2, \ldots, g_m]^T
\]

The texture inside the shape is sampled using a piece-wise affine warp based on the Delaunay triangulation of the mean shape. A normalization of the texture information is performed and then PCA yields the following representation:

\[
g = \bar{g} + \Phi_g b_g
\]

where \( \bar{g} \) is the mean texture, \( \Phi_g \) includes the eigenvectors of the covariance matrix and \( b_g \) is the set of deformation parameters. The combined formulation leads to the appearance model. As there are correlations between the shape and texture variations, a concatenated vector is generated as:

\[
b = \begin{pmatrix} W_s b_s \\ b_g \end{pmatrix} = \begin{pmatrix} W_s \Phi_s^T \\ \Phi_g^T \end{pmatrix} \begin{pmatrix} X - \bar{X} \\ g - \bar{g} \end{pmatrix}
\]
where $W_s$ is a diagonal matrix whose entries are the weighting parameters that account for the differences of units between shape (distances) and gray-level models (pixel intensities) [6]. A third PCA is applied to this vector leading to the combined model:

$$b = Qc$$  \hspace{1cm} (6)

where $Q$ is a matrix of eigenvectors and $c$ is a vector of appearance parameters controlling both shape and gray-level of the model. Shape and texture can then be synthesized from the model in Eq. (5) as:

$$X = \bar{X} + \Phi S^{-1}Q_s c, \quad g = \bar{g} + \Phi G Q_g c$$  \hspace{1cm} (7)

To use this AAM for segmentation requires an optimization process where the differences between the input image and the one synthesized by the model are minimized.

### 2.1.2. Training procedure

In the training procedure several tasks are performed. The first task is the manual tracing, by a medical expert, of a set of points located in each left ventricle contour. As for the AAM algorithm, a set of landmarks is required that should be in correspondence within the population of shapes. The algorithm proposed by Hill et al. [10] for automatic landmark identification is used. A set of two hundred and twenty-four 2D images extracted from the 4D multislice sequence is considered as a training set and 102 landmark points are used in each image for modeling the left ventricle shape. Combination of shape variability and texture variability after using PCA on the combined information leads to a compact appearance model that is used for performing a robust 2D segmentation.

### 2.1.3. Segmentation

Segmentation is carried out as an optimization procedure where the difference between the synthesized object obtained from AAM and the actual image is minimized. An iterative algorithm is used for the optimization. At each iteration, a controlled perturbation of the parameters of the model is introduced in order to approach the target ventricle shape. By adjusting the combined model parameters and pose (which defines the position, size and orientation of the shape), the texture mode, $g_{\text{model}}$, can be deformed to fit the image texture, $g_{\text{image}}$, by minimizing the square error:

$$E = \sum_{i=1}^{m} (g_{\text{model}}(i) - g_{\text{image}}(i))^2 = \sum_{i=1}^{m} (\delta g_i)^2 = ||\delta g||^2$$  \hspace{1cm} (8)

Since the model has many parameters, this is a difficult optimization problem [5]. The optimization is usually performed under the assumption of a linear relationship between parameters change $\delta c$ and pixel differences $\delta g$

$$\delta c = R \delta g$$  \hspace{1cm} (9)

Matrix $R$ is determined from a set of 105 experiments on the training set. This set of experiments is fed into a multivariate linear regression framework. Each experiment consists in displacing the model parameters $c$ and the pose parameters $t$ by a known amount and measuring the difference between the texture described by the model and the actual texture in the image located at the corresponding pixels (see [23] for details). The pose parameters are given by:

$$t = (s_x, s_y, t_x, t_y)^T$$  \hspace{1cm} (10)

where $s_x = s \cos(\theta) - 1$ and $s_y = s \sin(\theta)$ are the combined scaling and rotation with $\theta$ being the rotation and $s$ the scale parameter; additionally, $t_x$ and $t_y$ are the translation parameters.

### 2.2. Left ventricle geometrical model

The geometrical model of the left ventricle is constructed using the 3D points $p(x, y, z)$ detected from the 4D image dataset during the segmentation stage. Each segmented contour, is parameterized using a 2D B-spline which is sampled to generate a discrete set of evenly distributed points. From this set of points, the endocardial wall is reconstructed using the marching cubes algorithm [17]. The reconstructed surface is smoothed using a Gaussian filter that reduces apparent faceting. With this purpose, the Visualization Toolkit libraries [18] were used. The LV surface is cut at the level of the aortic valve to exclude these anatomical structures.
3. Motion model

The simulation process incorporates five parameters for describing the left ventricle motion. These parameters are extracted from works previously reported in the literature. Among the possible types of deformation, our model considers longitudinal shortening, radial contraction, circumferential shortening and torsion. The algorithm is implanted using a hierarchical deformation approach, where global deformations are applied first, followed by local deformations.

3.1. Free-form deformation

Free-form deformation is a useful method to perform deformation of objects by adjusting several control points. The method is based on embedding an object in a region of the space called deformation region. Each point of the object has a unique parameterization in the 3D space, that defines its position in the region. The deformation region is a parallelepiped that has an associated local coordinate system. The origin of the local coordinate system \(X_0\) is located on a vertex of the parallelepiped and the axes \((U, V, W)\) are located on the three edges whose intersection is \(X_0\). A point in the local coordinate system is expressed as \(X = X_0 + uU + vV + wW\), where \((u, v, w)\) according to linear algebra are given by:

\[
\begin{align*}
u &= \frac{V \times W(X - X_0)}{V \times W \cdot U}, \\
v &= \frac{U \times W(X - X_0)}{U \times W \cdot V}, \\
w &= \frac{U \times V(X - X_0)}{U \times V \cdot W}
\end{align*}
\]

A grid of control points in the 3D space denoted by \(P_{ijk} = [p_i \ p_j \ p_k]\) is formed by the intersection of \((l+1)\) planes perpendicular to the \(U\) direction, \((m+1)\) planes perpendicular to the \(V\) direction and \((n+1)\) planes perpendicular to the \(W\) direction. These control points are defined by:

\[
P_{ijk} = X_0 + \frac{i}{l}U + \frac{j}{m}V + \frac{k}{n}W
\]

When the grid is deformed, object points are adjusted accordingly. Such adjustment, is defined by a deformation function that establishes the correspondence between initial object points and deformed object points. The deformation of the object is defined by a trivariate tensor product of Bernstein polynomial functions. The deformed position \(X_d\) of an arbitrary point \(X\) in the Cartesian space is determined after evaluation of the following Bernstein polynomial:

\[
X_d = \sum_{i=0}^{l} \sum_{j=0}^{m} \sum_{k=0}^{n} (C_l^i C_m^j C_n^k (1 - u)^{l-i} u^i (1 - v)^{m-j} v^j (1 - w)^{n-k} w^k)
\]

where \((u, v, w)\) represents the coordinates of the point \(X\) given by (11).

Performing a local isolated deformation requires ensuring that the continuity of the surface of the object is not lost [7]. A sufficient condition for maintaining such continuity is to avoid that control points on the \(k\) planes adjacent to the local grid can be displaced as shown by [19]. The deformation process is applied hierarchically [7].

3.2. Deformation modes

At this stage, deformation modes describing the dynamical behavior of the LV cardiac cavity are selected. Deformation modes provide a manner to directly specify the range of permissible shapes in the animation of an object. These deformation modes are chosen based on prior-knowledge about motion of the cardiac cavity. In general, the left ventricle cavity has five types of motion when the heart evolves from the end-systole to the end-diastole (see Section 1.1). The deformation modes must be defined such that deformations associated to the FFD correspond with the type of movement associated to LV. Three deformation modes are considered for applying to the left ventricular surfaces: translation, rotation and dilatation. Translation allows to simulate the apex motion. Rotation is used to simulate the 3D twisting motion: the control points (12) located in the superior half of the deformation grid are rotated with respect to the longitudinal axis in the opposite direction to the control points located in the inferior half. Dilatation allows to synthesize the longitudinal shortening and radial contraction.

Deformation modes are specified by a deformation vector \(d_{ijk} = [d_i \ d_j \ d_k]\) whose components determine the maximum displacement in the control points along each of the axes. Vector values are established according to myocar-
dial contractility indexes and the torsion index between end-diastole and end-systole reported in [15]. Contractility indexes represent the radial contraction ($a_1$, $a_2$) and longitudinal ($a_3$) contraction of the LV. $a_1$ captures the motion of the free wall, the index $a_2$ represents the wall motion perpendicular to the septum and $a_3$ represents the motion along the longitudinal axis of the LV. Additionally the torsion index ($\tau$), represents the rotation of the heart from left to right while the cavity evolves to the end-systole phase.

4. Simulation model

There are four parts in the simulation model: (1) LV surface is embedded in a deformable region and each point is mapped to the local coordinate system using Eq. (11), (2) in each deformation region a grid of control points is generated, (3) these surfaces are then deformed according to deformation modes (Section 3.2), and (4) the new position of points in the surfaces after the deformation is determined using Eq. (13).

Each 3D point in the grid at time instant $t_r$($P^r_{ijk}$) is modified for obtaining the corresponding point at instant $t_{r+1}$($P^{r+1}_{ijk}$), according to the following relation:

$$P^{r+1}_{ijk} = P^r_{ijk} + d^r_{ijk}$$

(14)

where $d^r_{ijk} = [d_i\ d_j\ d_k]$ represents the deformation vector that allows the displacement of points in the grid between two consecutive time instants.

The elements of the deformation vector are obtained from parameters $a_1$, $a_2$, $a_3$ and $\tau$ reported by [15] according to:

$$d^r_{ijk} = [a^r_2 + \gamma^r_i, a^r_1 + \gamma^r_j, a^r_3]$$

(15)

where

$$\gamma^r_i = p_i \cos \tau^r - p_j \sin \tau^r, \quad \gamma^r_j = p_i \sin \tau^r - p_j \cos \tau^r$$

(16)

and where $a^r_1$, $a^r_2$, $a^r_3$, and $\tau^r$ represent values of radial contraction, longitudinal contraction, and torsion for the time instant $t_r$, respectively.

We assume that variations of $a_1$ are oriented along the V direction whereas variations of $a_2$ are oriented along the U direction of the local coordinate system. The longitudinal contraction index $a_3$ acts in the W direction. The values of $\gamma_i$ and $\gamma_j$ synthesize the twist of ventricle around the W axis on the local coordinate system. The control points on each plane UV of the grid are rotated according to the value given by the torsion index $\tau$. The deformation process considers a grid of size $7 \times 7 \times 7$ (343 control points) that affects endocardial surface.

The previous procedure expresses the global deformation; however, with this approach it is not possible to synthesize several features related to the irregular shape of the endocardial wall [11]. Such cases include the translation of the distal portion of the LV when going from the end-diastole to end-systole and the relaxation of regions where the papillary muscles are located. Local deformation are implemented, for overcoming these difficulties, by considering local grids overlaid in a particular region using the hierarchical deformation approach [7].

5. Validation and experimental results

5.1. Data source

The input images are a sequence of MSCT images acquired on a healthy volunteer (36 years, without pathology) with a 16-slice CT system (LightSpeed-16 General Electric Medical Systems) at 400 mA. The tube voltage was 120 $kV_p$ and the section thickness was 0.625 mm. The data acquisition was triggered by the R wave of the electrocardiographic (ECG) signal. Each image is quantized with 12 bits per pixel and the size is $512 \times 512$ pixels. The 4D MSCT database has eighteen 3D objects, each one representing a time instant of the cardiac cycle. The size of each 3D object is $512 \times 512 \times 352$. 
5.2. Left ventricle surface model generation

The training and segmentation of images was performed using the application interface (API) developed by Stegman et al. [23] from the IMM at The Technical University of Denmark. The training procedure is performed on the selected 2D images in the set. Validation of the segmentation approach is performed by quantifying the difference between the left ventricle shape obtained with respect to the left ventricle shape manually traced by a cardiologist. The error is expressed as the distances between the manual and automatic segmentation. The error obtained (mean ± S.D.) for the end-systolic (end-diastolic) MSCT volume phase is $9.45 \pm 1.05$ mm ($2.85 \pm 2.13$ mm). Although segmentation procedure is not the main issue of this work.

The segmentation process provide a set of planar contours. These myocardial sample points are used to construct the discrete geometric model of the left ventricle by means of the marching cubes technique. Fig. 1 shows the left ventricle surface model constructed at end-systole phase.

5.3. Simulation results

LV shape constructed from the MSCT database at end-systole phase is assumed as the LV model in the time instant $t_0$. The parameters used in the simulation process are derived from a experiment on a human heart [15]. These parameters were extracted (using a motion estimation algorithm) from MR-tagging database acquired on a healthy subject, and
they were expressed as a function of the MR-tagging volume number between end-diastole and end-systole phases. We have assumed that parameters variation when going from end-diastole to end-systole and vice versa, follows a symmetrical behavior. The contraction indexes $a_1$, $a_2$, $a_3$ are unitless parameters and the torsion $\tau$ is in $^{\circ}$.

From the initial 3D LV model, the rest of shapes corresponding to time instants between end-systole and end-diastole are successively generated using the deformation approach described in Section 4. A total number of twenty-seven 3D images are generated for a cardiac cycle. Fig. 2 shows 12 synthesized images.

Several motion parameters are calculated from the synthesized 4D image sequence. Average radial contraction index and the torsion index are estimated in three planes located at 10 mm below the base, at the equator and at 10 mm above the apex. Average radial contraction index is a parameter that represents the average of radial distances (measured along an axial plane) from the endocardial wall to the center. The torsion angle is defined as the angle between a radial line traced joining the gravity center of the slice and a endocardial contour point at time $t$ and the radial line joining the gravity center and the corresponding endocardial contour point for the $t+1$ time instant. Contraction indexes are expressed normalized with respect to the value obtained in end-diastole.

Values found for the average radial contraction index in the endocardial wall (Fig. 3) are comparable with those extracted from MR-tagging, like the reported by [9,20,1].

In Fig. 4 we can observe that the amplitude of torsion is higher at the apex than the torsion at the base of endocardial wall. Additionally, the rotation angle is opposite between the base and the apex. These features are normally found in the ventricular dynamics of healthy subjects [22]. These torsion values are also comparable with those reported in [9,20,1].

The motion parameters are also alike to the results obtained using a method for estimating the deformation field of the LV wall applied on the same 4D MSCT database used to construct our geometrical initial model [2]. The minimal and maximal torsion values obtained from synthesized images are $-2.99^{\circ}$ and $12.08^{\circ}$, respectively. These
Table 1
Comparison of motion parameters between the simulation model and the original MSCT database [2]

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Plane</th>
<th>Synthesized images</th>
<th>MSCT database</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average radial contraction</td>
<td>Apex</td>
<td>18.17 ± 13.92%</td>
<td>18.52 ± 16.82%</td>
</tr>
<tr>
<td></td>
<td>Equator</td>
<td>16.58 ± 13.49%</td>
<td>15.57 ± 9.44%</td>
</tr>
<tr>
<td></td>
<td>Base</td>
<td>14.34 ± 12.11%</td>
<td>16.14 ± 9.52%</td>
</tr>
<tr>
<td>Torsion</td>
<td>Apex</td>
<td>5.20 ± 2.84°</td>
<td>8.66 ± 5.94°</td>
</tr>
<tr>
<td></td>
<td>Equator</td>
<td>2.35 ± 2.46°</td>
<td>3.18 ± 1.57°</td>
</tr>
<tr>
<td></td>
<td>Base</td>
<td>−0.91 ± 0.86°</td>
<td>−0.99 ± 1.84°</td>
</tr>
</tbody>
</table>

values reported in [2] were −3.6° and 16.4°, respectively, when they were estimated directly from the original MSCT database. Table 1 shows the mean ± S.D. values of the average radial contraction and torsion indexes calculated from the simulated data and the real data.

6. Conclusions

A system for simulating the motion and deformation of the left ventricle has been implemented. This methodology allows a better knowledge of the LV cavity motion and deformation by synthesizing 4D (3D+time) sequences of such cavity that describe its dynamical behavior during the cardiac cycle. Mechanical parameters, such as: contraction indexes and the torsion index were calculated from the synthesized sequences and qualitatively compared with works previously reported. Result of this comparison shows that our simulation model has a dynamical behavior close to a real left ventricle.

The proposed approach uses the FFD algorithm for integrating the anatomical model constructed from a MSCT database with a priori-knowledge about the ventricular dynamics. This approach takes into account five components of the left ventricular motion: (1) translation, (2) rotation, (3) 3D twisting, (4) longitudinal shortening, and (5) radial contraction of the ventricular cavity.

A quantitative validation stage using a method for estimating the deformation field for the left ventricle wall from MSCT sequences is implemented. The estimated parameters from the simulation show a good match with respect to parameters extracted from the multislice CT sequence. We are investigating the application of this methodology for the synthesis of ventricular dynamics in non-healthy patients. This application would be a useful teaching tool for understanding the normal or abnormal motion of the LV.

Further research involves incorporation of the proposed model to an approach for left ventricle segmentation using 3D deformable surfaces. Based in this framework, the next step will concern the development of a complete approach to track the motion of the left ventricle in 4D image sequences, using the information obtained from our model.

Acknowledgments

The authors would like to thank the Investigation Deans Office of Universidad Nacional Experimental del Táchira and CDCHT from Universidad de Los Andes. Authors would also like to thank Herve Le Breton and Dominique Boulmier from the Centre Cardio-Pneumologique in Rennes, France for providing the human MSCT database.

References


