Quantitative analysis of left ventricular performance from sequences of cardiac magnetic resonance imaging using active mesh model


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ABSTRACT

In this study, the local and global left ventricular function are estimated by fitting three-dimensional active mesh model (3D-AMM) to the initial sparse displacement which is measured from an establishing point correspondence procedure. To evaluate the performance of the algorithm, eight image sequences were used and the results were compared with those reported by other researchers. The findings were consistent with previously published values and the clinical evidence as well. The results demonstrated the superiority of the novel strategy with respect to formerly presented algorithm reported by author et al. Furthermore, the results are comparable to the current state-of-the-art methods.

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1. Introduction

The death from heart diseases each year contributes to nearly one-third of global deaths throughout the world. The most notable characteristic of the heart is its movement [1]. The cardiac wall motion and quantitative parameters which characterize left ventricular motion, volume of the left ventricle (LV), ejection fraction, amplitude and twist component of cardiac motion are very important diagnostic indices and sensitive indicators for many types of heart diseases. Regional dynamic characterization of the heart wall motion is necessary to isolate the severity and extent of diseases [2]. Quantitative characterization of this motion is essential for the accurate diagnosis and treatment of heart diseases. With the increasingly wider availability of electrocardiographic (ECG)-gated tomographic image sequences, there have been many efforts on image-based analysis of the global and local motion of the heart, especially LV [3]. On the other hand, cardiac magnetic resonance imaging (CMRI) technique can now provide time varying intrinsic, three-dimensional images of the heart with excellent contrast and reasonable spatio-temporal resolutions. While there are rapid ongoing advances in these technological and application areas, cardiac MRI is still largely a “niche” imaging method which has not been widely adopted as a clinical tool yet. By combining and improving analysis approaches of CMRI sequences, it is hoped that effective measures can be taken for analyzing the functional heart quantitatively as well as qualitatively and assessing injuries of the cardiac muscles. However, the ongoing research and rapid development and the growing interest in cardiac MRI by clinicians promise an important clinical role for cardiac MRI in the near future.

Various models have been introduced to study heart wall dynamics [4] because of the specificity of current various cardiac imaging modalities. This specificity does not allow using conventional techniques alone for motion studies with proper precision. The goal of most research efforts has been to reliably recover the dense motion fields from a relatively unconfident sparse set of corresponding feature points. The recovery of the dense field...
motion and deformation parameters for the entire myocardium from the sparse set of displacements/velocities is an ill-posed problem which needs additional constraints to obtain a unique solution in some optimal sense. Various strategies have been proposed over the past ten years with varying degrees of success, including notable examples of mathematically motivated regularization [2,5–6], finite-element method based modal analysis [7–9], spatio-temporal B-spline [10], Fisher estimator with smoothness and incompressibility assumptions [11], statistical model [12–13], deformable superquadrics [14], continuum biomechanics based energy minimization [15–17], constrained local force model [18] and deformable model [19–20].

Conserved volumic [21], continuum mechanical [9,15–17] and deformable models [22–24] have been used to regularize ill-posed problems in many applications in medical imaging analysis and also for cardiac wall motion tracking. The elastic model is designed to reduce bias in deformation estimation and to allow the imposition of proper priors on deformation estimation problems that contain information regarding both the expected magnitude and the expected variability of the deformation to be estimated. In relevant works [15,17], the myocardium is modeled using an elastic volumetric model in terms of hexahedral elements for applying continuum mechanical constraints. The measurements and model are integrated within a Bayesian estimation framework [17]. Pham et al. [9] also proposed an iterative procedure on an active region model that deforms and pulls towards the image edges using the finite element method. Among the large collection of existing segmentation algorithms [4], approaches based on deformable surface have been extensively studied. They showed the relevance of deformable models approaches for LV segmentation due to their ability to introduce prior knowledge. Deformable models are also well suited for cardiac image analysis task [22–24]. The mathematical foundations of deformable models represent the confluence of geometry, physics, and approximation theory. Geometry serves to represent object shape; physics imposes constraints on how the shape may vary over space and time; and optimal approximation theory provides the formal underpinnings of mechanisms for fitting the models to measured data [22]. Among these models, active mesh model (AMM) permits a larger number of degrees of freedom to the object [23]. AMM has the ability to merge the continuum mechanical constrains and a great number of rules in cardiac wall motions. Object tracking in medical imaging using a 2D AMM introduced previously by Lautissier et al. [25]. Algorithms for point-wise tracking and analysis of cardiac motion based on 3D-AMM were presented by former works [26–27]. In pervious study [26], first the 3D epi/endocardial surfaces were extracted from the end-systole (ES) frame. LV was modeled as an elastic wall in a motionless large elastic cube for applying continuum mechanical constraints. For mesh initialization, these surfaces were fed to a 3D Delaunay triangulation and then to a tetrahedralization algorithm. An estimation of the object deformation is achieved based on a set of sparse initial displacement measurements as a result of a robust least square technique. This estimation is then used by the tracking algorithm for measuring the local deformation parameters of the 3D object. In these approaches [26], tetrahedralization of LV cavity as well as the space between the external wall of LV and a distant cube requires a heavy cost in computing. Thus, due to such limitations, former implementation was made on (50%) reduced spatio-temporal resolutions. In other words, half of the data had to be ignored causing a considerable amount of error. This study represents a new approach to overcome these limitations and improve previous works [26–27]. The following contributions are made here:

- Many researcher used an a prior assumption about model such as a cubic includes LV surfaces [26], a half ellipsoid shell [9], balloons [7,22], superquadric [14], a pseudo thin plate splines on the sphere at end-diastole (ED) [20]. In this study, 3D-AMM was initialized directly from the 3D image in ED frame of the cardiac cycle.
- Improving the algorithm efficiency by optimizing the number of mesh elements and applying a volumetric template which covers only LV muscle.
- Due to the heterogeneity of the nodes distribution over the heart wall, in our previous work on the mesh-developing, it is common to find large, thin and low quality and bad shape elements causing errors in the results. Besides, this may cause that during the data extraction the dense of the information on the wall may lessen. This shortcoming is improved through making new slices and its scanning by shape-based interpolation.
- Estimating the displacement field from all points on LV wall or in the myocardium and color kinesis evaluation of LV.
- Fitting 3D-AMM to initial sparse displacements with considering to their confidence.
- For establishing the correspondence points, a robust restricted block matching algorithm was proposed based on weighted-correlation.

This paper is organized as follows: The next section explains the model initialization, the establishing correspondence of the points, fitting 3D-AMM to these sparse points and extracting the local dynamic and global functional LV parameters. Section 3 is devoted to experimental results obtained by applying the algorithm to the two synthetic and six real sequence image sets. Finally, concluding remarks are given in Section 4.

2. Methods

The flow chart of the proposed algorithm for assessing the functioning of LV of the heart which consists of these steps are presented in Fig. 1: After short axis (SA) CMRI, the images of the left ventricular region were selected for all frames and their contrast was increased by windowing. Then, the cardiac cycle was divided into two major phases: the contraction and relaxation by the operator. The ED and ES frames were selected and determined as well as scanning of the epi/endocardial contours was carried out (Section 2.1). To avoid the formation of any low quality pyramid mesh, the number of the slices in each frame of the 3D images was doubled by applying the shape-based interpolation (Section 2.2). Along, with the reduction of the points, epi/endocardial contours of the external and internal surfaces of LV with rather homogeneous distribution are located. In the ED frame, the environmental template is made on the cardiac wall. To apply 3D-AMM in assessing the wall motion, this template is tetrahedralized (Section 2.3). For each couple of correspondent points, a confidence measure was determined to be used in weighted regularization (Section 2.4). Thus, for fitting the model to data and extract the dense field, we used weighted least squares estimation approximation theorem with consideration to continuum mechanical constraints (Section 2.5). Using the basic information regarding the motion of the ventricular wall would result in more effective regularization. At the end, the local and global functional analysis of LV is provided by the dense field (Sections 2.6 and 2.7).

2.1. Segmentation of LV in CMRI image sequences

In all frames, all slices are segmented interactively exactly based on the algorithm introduced by Heiberg et al. [28]. This method is also based on the concept of deformable models, but extended...
with an enhanced and fast edge detection scheme that includes temporal information, and anatomical a priori knowledge. The LV model used in this approach is a time-resolved mesh representation of LV as an open “cone”, sliced along its long axis with an equal number of points for each slice. The number of points for each slice contour is selected to be 80. Toward a fully 3D cardiac wall motion analysis, we will merge the level set procedure [26] to our proposed algorithm.

2.2. Generating intermediate slices

In order to homogenize the scales in 3D, one more slice and its contours was made between each couple of slices. In CMRI, due to the existing imaging system limitations, the SA slices have a minimum thickness of 5 mm ignoring the gap between the slices, where the resolution of the image screen is approximately 1 mm. Hence, in the process of developing the template and the mesh, the distribution of the information assembling on the plane dimension of the SA tends to be undesirably imbalanced. To solve this problem, between each couple of slices, one more slice was made by cubic spline. The external and internal contours of these new images were determined by applying the shape-based interpolation for each epi/endocardial contours separately through the following steps:

Step 1: Determining the map of Euclidean distance of the points from the contour related to the upper and lower slices presupposing that the distances of the points inside the contour are positive and those outside are negative.
Step 2: Computing the mean value of the map of the two upper and lower slices of the first step in all points of the plane.
Step 3: Determining the candidate border points considering that the absolute value of the map interval of these points is below the desired threshold level.
Step 4: As far as the spatial condition is concerned, the candidate border points fall into 80 sectors of the same angle.
Step 5: The mean spatial coordinates of the candidate points in each sector were considered as the border point. The computation of the mean of the candidate points rather than the zero-passing ones in each sector made the proposed shape-based interpolation algorithm more robust to noise.

Using 35–40% of the points on the contours for describing the external and internal surface of the heart, the distribution of these describing surfaces are almost homogeneous in three dimensions. Fig. 2 presents the results of the proposed shape based interpolation, intermediate slices, as well as the epi/endocardial contours produced for the ED frame. As this figure shows, the resulting contours conform to the edges of the epi/endocardial surfaces.

2.3. Template-developing and initializing of 3D-AMM

A volumetric template from the 3D image which covers LV muscles environmentally was made and then tetrahedralized it by refined constrained Delaunay tetrahedralization (RCDT) [29]. The proposed model-building method does not depend on prior assumptions about the 3D scene structure; instead it attempts to accumulate this knowledge directly from the images. For this reason, the external and internal surfaces of the heart are formed by combining the points of the epi/endocardial contours generated from the previous step. Since these points must settle in the template for tracking through linear interpolation. Hence, to make the template, the points on the external and internal surface of the template are determined by Eq. (1). Then, all the points of the edges are included in the template:

\[
X_{\text{temp}} = \begin{cases} 
X + \text{sgn}(X_C - X), & X \in \text{Endocardial surface} \\
X - \text{sgn}(X_C - X), & X \in \text{Epicardial surface} 
\end{cases}
\]

where \(X_c\) is the endo/epicardial centeroid of its slice, \(X = [x, y, z]\) is the coordinate point which belongs to endo/epicardial layer and \(X_{\text{temp}}\) is the respected template point. To use 3D-AMM, the template wall must be tetrahedralized. In doing so, the upgraded Delaunay algorithm, RCDT [29], was applied. This kind of tetrahedralization is not only a desired one but also a unique in terms of the size and number of the elements. In addition, the mesh which was constructed using this method places more tetrahedra over high detailed areas. Therefore, we use its geometrical representation to describe the template. The steps for template-making are as follows:

Step 1: Developing new environmental surfaces of the heart wall using Eq. (1).
Step 2: Creating a general point set to satisfy both non-collinearity and non-cosphericity assumptions.
Step 3: Smoothing the surface of template by non-shrinkage Gaussian filter [2].
Step 4: 3D Delaunay triangularization for geometrical representation of LV surfaces.
Step 5: RCDT of the cardiac wall which is represented by the previous step.
Fig. 2. All slices and intermediate slices in ED frame; the intermediate slices and contours, odd slices, are generated by the proposed shape based interpolation.

Fig. 3 illustrates results of the LV wall template for one of 3D image data in the ED phase.

2.4. Obtaining initial sparse field displacement

To track the point on the epi/endocardial surfaces, or to put it differently, the displacement and determination of the initial sparse motion field, a robust restricted block matching algorithm is proposed based on weighted-correlation. To expedite the process, only the correlation of those points were computed that were located in the near spatial sector with those in the last frame. This approach can be implemented on two sequential frames of a 3D sequence image following these steps:

Step 1: Calculating the 3D gradient of the selected points in current frame image by Sobel operator.

Step 2: Determining the discrete gradient direction. There are 13 gradient directions in the discrete 3D image; the 3D space around each point is divided into 13 volumetric sectors. Therefore, a $3 \times 3 \times 3$ mask is defined for each major direction which can be called direction mask.

Step 3: Determining the candidate correspondent points according to the 3D nearest neighbor correspondences in surface.

Step 4: Computing weighted-correlation between $3 \times 3 \times 3$ window with the center of the given point and $3 \times 3 \times 3$ window of the correspondent candidate points after applying direction mask. In this way, more significance is given to the similarity of the grey levels of the corresponding edge pixels.

Step 5: Selecting the point which has the maximum normalized cross correlation as the correspondent point. The displacement sector of the given point ($B_i$) is determined according to the difference of the spatial vector of the two points. The maximum normalized cross correlation value is chosen as a confidence measure ($C_i$).

2.5. Non-rigid motion model: 3D-AMM

According to the model presented in this section, 3D-AMM is deformed and fitted to data which is initial unconfidence sparse motion field derived from point correspondence procedure (Section 2.4). Image deformations result from change in the geometrical viewpoint and physical deformations of the object in the scene. In order to accurately represent these deformations, a novel model incorporating the geometrical and physical characteristics is defined here. We consider LV as a continuous elastic medium. It is submitted to external image forces that push the model’s interfaces towards the image edges. 3D-AMM is a combination of a topological and geometric model of the heart and a constitutive equation defining its dynamical behavior under applied external forces. The equilibrium of the model is obtained when the following global energy functional is minimized:

$$E = E_{\text{Data}} + E_{\text{Elastic}}$$

(2)
where $E_{\text{Data}}$ is the energy due to the external forces and $E_{\text{Elastic}}$ represents the deformation energy of the model.

The medium is considered as a linear elastic solid in continuous form. The elastic energy can then be expressed as follows [30]:

$$E_{\text{Elastic}} = \frac{1}{2} \int_{\Omega} \sigma^T \epsilon \, d \Omega, \quad \text{where} \quad \sigma = K \epsilon \quad (3)$$

The material is considered as transversely isotropic and completely defined by the Young modulus $E$ and the Poisson’s ratio $v$, with the small displacement assumption $\epsilon = E u$:

$$E_{\text{Elastic}} = \frac{1}{2} \int_{\Omega} (S u)^T K (S u) \, d \Omega \quad (4)$$

where $S$ is a differential operator, $K$ is the elasticity matrix and $\Omega$ is the space occupied by the LV muscles. Let $T = \{V, F\}$ be a tetrahedral defined over the template, where $F$ is a set of tetrahedral and $V$ is a set of its vertices. In the discrete form, the elastic energy $E_{\text{Elastic}}$ associated with a plate is given by (5):

$$E_{\text{Elastic}} = \frac{1}{2} \sum_{\epsilon \in F} (S u)^T K (S u) \, d \Omega \quad (5)$$

where $U = \{x_i, y_i, z_i\}, \quad i = 1, 2, \ldots, M$

where $U$ is a vector of elementary deformation, $M$ is the number of vertices and $K$ is the stiffness matrix. The stiffness matrix should be assembled from elementary stiffness matrices associated with each tetrahedral element [30].

The stiffness matrix is then given by (6):

$$K = \sum_{\epsilon \in F} K_{\epsilon}, \quad \text{where} \quad K_{\epsilon} = V e \epsilon B e, \quad e = 1 \ldots \text{Elem} \quad (6)$$

For each element, $K_{\epsilon}$ is the element stiffness matrix, $V_{\epsilon}$ is its volume, $B_{\epsilon}$ is a $6 \times 12$ matrix with elements defined by the orientation of its vertices and $D$ is a $6 \times 12$ matrix defined by the material properties of the deforming body (Fig. 3). The matrix $D$ which proposed by Papademetris et al. [17] is as follows (7):

$$D^{-1} = \begin{bmatrix}
\frac{1}{E_p} & -v_p & -v_p & 0 & 0 & 0 \\
-v_p & \frac{1}{E_p} & -v_p & 0 & 0 & 0 \\
-v_p & -v_p & \frac{1}{E_p} & 0 & 0 & 0 \\
0 & 0 & 0 & \frac{2(1 + v_p)}{E_p} & 0 & 0 \\
0 & 0 & 0 & 0 & \frac{1}{E_f} & 0 \\
0 & 0 & 0 & 0 & 0 & \frac{1}{E_f}
\end{bmatrix} \quad (7)$$

where $E_f$ is fiber stiffness, $E_p$ is cross fiber stiffness, $v_p, v_p$ are the corresponding Poisson’s ratios of them and $G_f$ is the shear modulus across fiber ($G_f = E_f/(2(1 + v_f))$). The fiber stiffness was set to be 3.5 times greater than cross fiber stiffness. The fiber stiffness and Poisson’s ratios are constants corresponding to the approximately incompressible properties (the typical values are $v_p = v_p = 0.4, \quad E_p = 100$). From the above equations, $E_f$ and $G_f$ were calculated.

$E_{\text{Data}}$: Given a set of displacement vector measurements $B$ and confidence measures $C$ from previous stage (Section 2.4). Thus, $E_{\text{Data}}$ is given by (8):

$$E_{\text{Data}} = \sum_{i=1}^{N} \lambda_i^2 \| \delta_i - \delta_i \|^2, \quad (8)$$

where $i = 1, \ldots, N$ and $\delta_i = (\delta_{x_i}, \delta_{y_i}, \delta_{z_i})$

The importance of the $i$th term in the $E_{\text{Data}}$ is tuned by $\lambda_i^2 = c_i$ which is the confidence of the $i$th displacement vector. In Fig. 4, at a point $P$ in the tetrahedron $\Delta p \rho p \rho_{m} \rho_{n}$, the deformation function $d_i(x, y, z)$ is calculated by (9).

$$d_i(x, y, z) = g_k(x, y, z) D_k + g_l(x, y, z) D_l + g_m(x, y, z) D_m + g_n(x, y, z) D_n \quad (9)$$

where $D_i = (dx_i, dy_i, dz_i)$ is the $i$th displacement vertex and $g_i$ is the ratio volume of pyramid fiducial point $P$ and other points except $i$th.
point to the volume of pyramid $\Delta klmn$, for example $g_m$:

$$g_m = \frac{\text{volume of Pyramid } k\ell m\Pi}{\text{volume of Pyramid } k\ell m\Pi}$$

Then for the set of displacement vector measurements $B$, estimated $B$ which obtained from the model is given by $B = AU$ where

$$A = \begin{pmatrix} Q & 0 & 0 \\ 0 & Q & 0 \\ 0 & 0 & Q \end{pmatrix}_{3N \times 3M},$$

$$Q_{ij} = \begin{cases} g_j(x_i, y_i, z_i), & j = \{k, l, m, n\}, (\hat{x}_i, \hat{y}_i, \hat{z}_i) \in \Delta P_k P_l P_m P_n \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

2.5.1. Fitting the model to data

For estimation of the model parameters, the displacement vectors of M vertex: $U$, the global energy functional (2) is minimized by (11):

$$\arg \min \{ \sum_{i=1}^{N} \lambda_i^2 \| \delta_i - \delta_i \|^2 + \lambda_C U^T K U \} \quad \text{where } i = 1, \ldots, N \tag{11}$$

$\lambda_C$ is the global regularizing factor. The above minimization (11) is seen to be equivalent to the minimization (12):

$$\min \{ ||UAU - \lambda B||^2 + \lambda_C U^T K U \}$$

where

$$B = [\delta x_1, \ldots, \delta y_1, \ldots, \delta z_1, \ldots]^T$$

and

$$\lambda = [\lambda_1, \ldots, \lambda_N], \quad i = 1, \ldots, N \tag{12}$$

The solution of (11) is (12), which gives the displacement of all vertices of the mesh. Then, the displacement of all points of LV muscle will be obtained by linear interpolation [9]. Eq. (12) is solved by Moore–Penrose inverse matrix (13):

$$\hat{U} = (\lambda A^T A + \lambda_C K)^{-1} \lambda A^T B \tag{13}$$

2.6. The global functional analysis of LV

In practice, one of the assessments of cardiac function still relies on the variation of simple global volumetric measures like left ventricular volume (LVV) and mass (LVM), over time. According to 3D-AMM, in the output of the model, there are representations of wall and epicardial/endocardial surfaces by tetrahedra and triangles for all frames respectively. Thus, LV Wall and LV cavity are represented by them. Summation of the tetrahedron volumes is simply calculated by Eq. (14) and LVV and LVM are provided for all frames:

$$\text{LVV} = \sum_{i=1}^{M_1} V_{\text{tet}}, \quad \text{where } M_1 : \text{the number of elements in LV cavity}$$

$$\text{LVM} = \sum_{i=1}^{M_2} V_{\text{tet}}, \quad \text{where } M_2 : \text{the number of elements in LV wall}$$

$$V_{\text{tet}} : \text{volume of } i\text{th tetrahedron}$$

$$V_{\text{tet}} = \frac{1}{6} (\det(Tet^i)) \tag{14}$$

where Tet$^i$ is the tetrahedron matrix according to coordinate of vertices $nmlk$:

$$\text{Tet}^i = \begin{bmatrix} n_i & m_i & l_i & 1 \\ m_i & n_i & k_i & 1 \\ l_i & k_i & n_i & 1 \\ k_i & l_i & m_i & 1 \end{bmatrix}$$

2.7. Estimation of path length and strain

Path length and strain measures are proposed by many researchers for assessing the proper functioning of the heart [2]. It is revealed that the changes in motion parameters (path length, and strain measures) between normal and injury region are significantly different and indicative of the myocardial function, and these changes can be used to diagnose the location and extent of myocardial injury, validated using post mortem triphenyl-tetrazolium chloride staining technique [2].

The path length of any myocardial point is the sum of the magnitudes of all displacement vectors of that point over the cardiac cycle, and it measures the overall motion of the point. For estimation of displacement vectors of each point, on LV wall or in the myocardium, we used Eq. (9) over the entire cycle. According to the fact that the deformation of all elements in the template over the entire cardiac cycle, is clarified by the model and each fiducial point (on LV wall or in the myocardium) which belongs to one of the tetrahedral elements is due to the definition of the template. Therefore, all of the displacement vectors of this point are clarified by linear interpolation of vertex points such as Eq. (9) during the entire cycle.

Strain is a dimensionless quantity measuring the percent change in length at different points of a deforming continuous body. Lagrangian strain [30] maps are produced from our model by describing the deformation of LV in the Lagrangian reference frame. The ED frame is considered as the reference frame. Once a displacement vector field is available, the strain of deformation can be computed at each myocardial point. In the Lagrangian reference frame, the mapping $\Gamma(X)$ warps $X$ into $x$. Then, the Lagrangian strain tensor is defined as

$$E = \frac{1}{2} (C - I) \quad \text{and} \quad C = F^T F \tag{15}$$

where $C$ is the Cauchy–Green deformation tensor and $I$ is the identity matrix. This can also be deduced directly from the definition in Eq. (15). Consequently, $E$ can be expressed as follows:

$$E = \frac{1}{2} (F^T F - I) \quad \text{where } F_{ij} = \frac{\partial x_i}{\partial x_j} \quad i, j = 1, 2, 3 \tag{16}$$

The quantity $M^T EM$ will give the value of the normal strain in the direction given by the unit vector $M$. Due to the ventricular geometry, it is appropriate to calculate the myocardial strains based on the radial, circumferential and longitudinal directions.

2.8. Visualization of the result

At the conclusion of model fitting, a sequence of the $T = (V, F)$ sets is obtained. At each point on this sequence, the LV wall is represented by sets of tetrahedra with given geometry and topology in a 3D space. Hence, 3/2D representation can be obtained which is a combination of geometry, anatomy and local indices such as strain and path-length. By assembling tetrahedra/triangles, cardiac wall/surfaces can be produced during the cardiac cycle as a cine-loop. The value of the local quantities can be computed by the model and indicated on the wall using the color coding
for quantifiers. Using this color coding, Fig. 5 denotes that the behavior of strain in LV derived from synthetic image sequence. Fig. 5 is the presentation of radial, circumferential and longitudinal Lagrangian strain quantities in ED and ES phases. For color kinesis evaluation of LV, a propounded way is the 2D visualization of the original anatomical data together with analyzed result in polar representation or bulls-eye map. From the clinical point of view, this representation could be considered as an advantage considering that cardiologists are already familiar with “bulls-eye” maps that are often used for representing myocardial perfusion during nuclear medicine studies. The result of the regional parameters (strain or path length) can be visualized per slice as color overlay on the original anatomical image data and for all slices together in a bulls-eye representation.

3. Results

For evaluation of this proposed algorithm, eight sequence sets, six real (five volunteers and a patient) and two synthetic groups were used. The deformation field within the myocardium was reconstructed for each set over the entire cardiac cycle. Then, strain and path-length computed from the proposed algorithm. For two synthetic sequence sets, the path-length were compared to those obtained from analytical model of CMRI simulator. Finally, the
trajectories which obtained from both estimated and analytical procedures also compared.

3.1. Synthetic sequence CMRI

A computational simulator to generate two sets of gradient spine echo synthetic image sequence was used. The simulator incorporates a parametric model of LV motion introduced by Arts et al. [31] and applying it to a confocal prolate spherical shell, resembling the shape of LV. Each point of this shell is displaced in the space due to the kinematic model of LV which is proposed by Arts et al. [31]. The model is made to assume a configuration representing one of 60 phases in the cardiac cycle. A gradient-echo CMRI imaging sequence with intersecting the shell and the plane at a desired orientation was simulated. For definition of the grey level in images, each common point between the plane and shell was set to 100 (dark) and others to 255 (white). The inverse motion map is presented analytically, allowing point-wise correspondences to be made between points at any two frames. Then, there is the true 3D motion in the output so that the motion estimation algorithm can be compared against the truth. In order to assess the robustness of the proposed method, we contaminated these images with

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<td>9</td>
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Fig. 7. Root mean square errors of motion fields versus frame, provided from synthetic image sequences at 0 dB SNR.

Fig. 8. The cardiac MRI data of the patient: Horizontal line consists of frames 1, 3, 5, 7, 9, 11, 13, 15, 17, 19 and 21 of each slice and 12 slices for the vertical line, base to apex.
normal distributed random noise in the determined level of SNR. Another imaging sequence was generated similarly, but mechanical parameters were changed in the lateral apical region as a simulation of hypokinetic heart disease region. The motion in center of this region was 75% of a normal zone. Assuming LV wall volume is constant and almost equal 100 cm$^3$ and LV cavity volume changes from 60 to 120 cm$^3$ during a cardiac cycle. The specification of confocal prolate spherical shell model is as follows:

$$
x = \delta \sinh \lambda \sin \eta \cos \varphi
$$

$$
y = \delta \sinh \lambda \sin \eta \sin \varphi
$$

$$
z = \delta \cosh \lambda \cos \eta
$$

where $\delta = 5$, $\lambda : 0.4$–$0.6$

$0 \leq \eta \leq 120$, $0 \leq \varphi \leq 360$

The shell intersects with 64 parallel planes in equal distance. The result of this simulation was 64 images for each frame. The size of these images is 64 $\times$ 64, and their resolution is 1.1 mm in all direction. Then the size of the image sequence set of 64 $\times$ 64 $\times$ 60 $\times$ 64 is decreased to 64 $\times$ 64 $\times$ 15 $\times$ 64, as the standard CMRI sequence.

Validation of the proposed method is estimated on these synthetic image sequences for which a ground truth about the LV volume is known. For this reason, the displacement of points on all contours are achieved from the analytical generator and estimated by the proposed method during an entire cardiac cycle. The mean square error is calculated by the following equation:

$$
RMSE(f) = \frac{1}{N\text{Nod}} \sqrt{\sum_{i=1}^{N\text{Nod}} ||\mathbf{U}_f^i - \mathbf{\bar{U}}_f^i||^2}
$$

Table 2

<table>
<thead>
<tr>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
<th>C6</th>
<th>Mean ± S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>LVV (%)</td>
<td>2.05</td>
<td>2.71</td>
<td>2.15</td>
<td>5.41</td>
<td>4.56</td>
<td>5.73</td>
</tr>
<tr>
<td>LVVSTD (%)</td>
<td>1.87</td>
<td>1.7</td>
<td>1.86</td>
<td>6.21</td>
<td>5.60</td>
<td>6.41</td>
</tr>
<tr>
<td>LVM (%)</td>
<td>5.53</td>
<td>2.19</td>
<td>6.98</td>
<td>6.21</td>
<td>6.16</td>
<td>6.15</td>
</tr>
<tr>
<td>LVMSTD (%)</td>
<td>4.50</td>
<td>1.78</td>
<td>3.95</td>
<td>3.65</td>
<td>4.18</td>
<td>4.11</td>
</tr>
<tr>
<td>Run (s)</td>
<td>18.1</td>
<td>24.8</td>
<td>21.6</td>
<td>13</td>
<td>17.2</td>
<td>13.6</td>
</tr>
</tbody>
</table>
where $\vec{U}_f^i$ and $\vec{U}_f^i$ are the estimated and analytical displacement vector of $i$th node in the $f$th frame, respectively. Also $|| \cdot ||$ is the norm of a vector, $\text{RMSE}(f)$ is mean square errors in the $f$th frame. “NFrame” and “NNod” are the number of frames and nodes, respectively. For reporting purposes, the LV was divided into three slices, each consisting of eight sectors. Bulls-eye of path-length estimated motion field of two synthetic image sequence sets is shown in Fig. 6. There are significant differences between the values of the apical and hypokinetic area and the hypokinetic region completely revealed. The extraction of motion field is also robust to noise. Fig. 7 demonstrates the MSE of motion field versus frame, where the mean error value of all frames is $0.45 \pm 0.015$ mm at $0 \text{ dB SNR}$. The comparison of this result with the previous version [27], shows 53% improvement in performance. Thus, it seems that the proposed approach is robust. Despite the meshing object was refined, the running time of the algorithm was half of the previous algorithms [26], because of the ability of the proposed model which eliminates nodes and elements outside the cardiac wall.

### 3.2. Real sequence

The results of evaluation on six sets of Gradient-Echo images are given in this section. MR imaging was performed on a 1.5T scanner (Symphony Siemens, Germany) located at Isfahan MRI Center, Isfahan, Iran. SA images through LV were obtained with the turboGSE cine technique using the following parameters: TR = 42–44 ms, TE = 1.38–1.45 ms, FA = 53°, SL = 5 mm and resolution in plane = $256 \times 256$. The protocol is called tf2d20_12slices_shph_12bh. With this protocol, short breath-hold scans and multi

**Fig. 12.** The uniformed and normalized path-length bulls-eye of midmyocardial points provided from the patient’s images analysis.

**Fig. 13.** 3D motion field with cardiac wall in ES.

**Fig. 14.** Mapping of the endocardial surface: endocardial surface is rendered light red with deformation of an embedded curvilinear (a) ED phase, (b) ES phase with patch transformation and (c) ES phase.
slice applications in one breath-hold are possible. Contrast is a function of $T_1/T_2^*$ and independent of TR. Table 1 are consisting of the data specifications.

The patient was a 67-year-old man with 70% stenosis of left anterior descending artery in the recent angiography and hypokinetic septum on echocardiography and also ECG evidence of myocardial infarction of septal wall. The MRI cardiac data of the patient is shown in Fig. 8. In these images, the region containing LV is selected; hence, the size of the image matrix is reduced to $109 \times 86$.

The global cardiac function parameters provided by the proposed algorithm were compared with result from expert manual segmentation. The normalization of the errors by expert manual segmented results arranged in 0–100 with running time per slice as presented in Table 2. Running time has potential to reduce by modification of program efficiency. This result shows that the provided LVV and LVM are fairly accurate. Over the six real image sequences, the mean error LVV is below $4 \pm 2\%$.

Viewing the cardiac wall/surfaces in a cine-loop provides a good impression of the overall 4D left ventricular motion. The video of the estimated LV endocardial surface sequence is provided by assembling the fitted triangles of cardiac surfaces in the Appendix B. By assembling the fitted tetrahedra of active mesh, Fig. 9 displays the extracted cardiac wall in six phase of cardiac cycle. Fig. 10 shows the result of mapping the trajectory of a set of the middle myocardial points in 2D. Color kinesis evaluation of LV is seen in Figs. 11 and 12. The 3D motion fields mapping is also shown in Fig. 13. The 3D motion field in this figure is the difference between position vectors in ED and correspondence points in ES. This field is uniformly sparse due to limitation of the presentation. Consequently, the algorithm is capable of obtaining and visualizing the local parameters in all points of myocardium or LV surfaces such as path-length or strains and 3D motion field.

In Fig. 11, the normalized mean values of five volunteers’ path length visualized by bulls-eye. Decrease in kinesis on septum, especially in basal and middle septal region is clarified by position of the region between two ventricular and specificity of basal region (membrane tissue). According to normalized mean values of five normal volunteers, the path-length results of patient’s images analysis are uniformed and normalized. These normalized and uniformed values are illustrated in Fig. 12 by bulls-eye. In this figure, the path length below 50% as a severe hypokinetic region and between 50% to 75% is labeled as a moderate hypokinetic region. At a glance the hypokinesis of the middle and apical septal region is significant. These results are consistent with the clinical evidence of the patient as well.

Fig. 14 illustrates the LV endocardial surface of a normal subject in the ES phase with an embedded curvilinear quadrilateral. It shows that the quadrilateral is deformed to ED phase, by apply-

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**Fig. 15.** Normal strain plots across a normal human data set for each of the 16 regions of the left ventricle. The different geometric shapes (circle, diamond, and square), represents the radial, circumferential, and longitudinal strain values, respectively. The x-axis is the time in milliseconds during systolic interval and the y-axis is the strain value.
ing the derived transformer. It can also be seen that the curvilinear quadrilateral moved outward (radial expansion), downward (longitudinal shortening), rotated and slanted (circumferential twist).

The temporal evolutions of the three axial strain components at different regions of LV from ED to ES are shown in Fig. 15. For the purposes of strain analysis, the LV was divided into three longitudinal levels (apical, mid-ventricular, and basal level). The mid-ventricular and basal levels were further subdivided into six sub-regions (anterior-septal, anterior, lateral, posterior and inferior–septal sub-region) and four sub-regions for the apical level (septal, anterior, lateral, and posterior sub-region). At all longitudinal levels and all sub-regions, the average radial, circumferential, and longitudinal strains generally increased their magnitude as the cardiac cycle reached ES. At ES, the average radial and circumferential strains reached around 0.3 and −0.15, respectively. The longitudinal strains were relatively small compared with their two strains which, indicate that thickening of the myocardium is primarily in the radial direction and that shortening is in the circumferential direction. To less extent, shortening of the myocardium is undergone in the longitudinal direction. To evaluate the performance of the algorithm, the above strain measurements were compared with other works [32–34]. The average regional radial strains were well agreed with the previous studies at all longitudinal levels except for the regional radial strains in septum of apical level [32–34]. In B-spline model approach [32], the radial strain decreased to about −0.2 but in elastically deformable model [34], the radial strain reached about +0.3. Our proposed value in this case is equal to +0.1. The results of circumferential and longitudinal strains were the same as those obtained from other results [20,32–34].

3.3. Interpretation of results

Fig. 15 represents average radial, circumferential, and longitudinal strains for normal ones. The radial strains remained positive for the 16 regions indicative of the systolic thickening of LV. Both the circumferential and longitudinal strains were negative. Circumferential shortening during LV contraction has resulted in the negative strain values in the circumferential direction while compression in the longitudinal direction has caused negative longitudinal strains. The results are also comparable with other relevant works [20,32–34].

4. Discussion and conclusions

This work represented a new method for reconstructing and tracking the myocardial LV motion for assessing myocardial viability by reconstructing 3D displacement fields based on AMM. 3D-AMM is a generalization of the original elastic model which penalizes deformations away from a preset value as opposed to simply all deformations. The novelty of the method may be included the model initializing, new fast 3D block matching algorithm and fitting the model. Extraction of the dense 3D myocardial displacements and 3D myocardial strain maps are available. The advantages of the method are its independence on image modality, point-wise tracking and capability of doing global functional and deformation analysis as well as its swiftness (according to Table 2) and also robust tracking algorithm. It may be used for analysis of the full 3D dimensional deformation field of LV. To do so, SA images (CMR) of LV were applied. These abilities are illustrated with results from reconstruction of the deformation field within the myocardium for the five normal volunteers, one patient and two synthetic data sets of image sequences. According to Table 2, some global cardiac function parameters provided by the proposed algorithm are fairly accurate. The 3D motion of LV was tracked throughout the entire cardiac cycle, and a quantitative strain analysis was carried out. The findings showed that the strain measurements were generally found to be consistent with mentioned published values. The results from quantitative analysis on patient data set are also consistent with the clinical evidence of that patient.

Further and future study may involve the assessment and improvements of the tracking software for larger data sets. Unfortunately, the researchers failed to get access to CMRI sequences with implanted markers for comparison between marker trajectories and trajectories which have been derived from the proposed algorithm. We will merge the algorithm with the level set segmentation procedure which was presented in FIMH2007. Some works are in progress to integrate cardiac muscle nonlinearity into this model. In addition, to combine the proposed restricted block matching algorithm with other similarity measures which seems to be a better choice for obtaining initial displacement data and then gain access to more accurate external forces are planning.

References


