Model-Based 3-D LV Shape Recovery in Biplane X-Ray Angiography: A-Priori Information Learned from CT

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Abstract

Recovering the 3-D LV shape from non-rotational biplanar x-ray angiograms is a very challenging task. The inherently sparse and noisy data available for reconstruction and the ill-posed nature of the inverse problem necessitate the incorporation of a-priori information. To this end, a statistical shape model of the LV anatomy is learned from high-resolution multi-slice CT data. Reconstruction is based on a non-rigid 2-D/3-D registration technique. To fit pose and shape of the model to the x-ray images of the patient, simulated projections of the model are calculated and the difference between given and simulated projections is minimized. The presented approach is evaluated using simulated and in-vivo angiograms. For patients where both CT and angiograms are available, the reconstructed LV is compared to the true shape known from CT. The defined similarity metrics used for evaluation show a good correspondence between recovered and true shapes.

1. Introduction

In coronary angiography, the gold standard for quantitative left ventricle (LV) analysis is based on the evaluation of endocardial contours gathered from non-rotational 2-D x-ray image sequences. End-diastolic (ED) and end-systolic (ES) volumes are approximated from ED and ES contours by using e.g. the Area-Length method or the Simpson Rule method. Contour information is further utilized by wall motion analysis methods like the Centerline method or the Radial method to quantify myocardial viability. A major drawback of the underlying imaging modality is that 3-D information is lost due to projection. As a consequence, volumetric diagnostic parameters, like ejection fraction (EF), are only approximated and wall motion is only evaluated for surface areas with the boundary visible in the projection image. Instead of evaluating the LV in 2-D, novel approaches aim at reconstructing its spatio-temporal shape to perform analysis in 3-D [1].

In classical computed tomography (CT), several hundreds of projections are acquired by a fast rotating x-ray gantry. Analytical and algebraic iterative reconstruction techniques exploit this dense information to yield voxel values that vary within a continuous range. However, these techniques typically fail if only two (noisy) projections are available. C-arm CT is a relatively young and hybrid type of imaging modality, where the C-arm is rotated during acquisition to increase the number of angiographic projections. Techniques known from CT can then be utilized to address the reconstruction problem [2]. In the catheter lab, however, the application of C-arm CT is challenged by the, compared to conventional x-ray angiography (XA), higher amount of x-ray dose and bolus and the, compared to CT, slower rotational speed of the C-arm when imaging the rapidly moving heart. Whether it will substitute XA as a routine method in future remains to be seen [3].

Unlike classical (continuous) CT, discrete tomography focuses on reconstruction problems where only a small number of projections – as small as two – are available and the object's intensity levels are limited, i.e. discrete, and known a-priori [4]. To solve such underdetermined and ambiguous problems, the use of additional a-priori information is crucial since this can reduce the space of possible solutions and improve the ability to deal with noisy projection data. In [5], post-mortem human LV casts that have been digitized are used as a-priori information. Assuming that ventricular cross-sections follow certain geometric priors (e.g. symmetry, convexity, connectedness) is usually too restrictive. Other approaches often do not incorporate anatomical a-priori information at all [6], [7].

The novelty of our approach is that anatomical a-priori information is learned from high-resolution CT image data and modeled as a statistical shape model (SSM). A non-rigid 2-D/3-D registration method fits the SSM to the angiograms. The application of SSM's for recovering shape from angiography has been successfully demonstrated for hard-tissue objects [8], [9], but not yet for non-rigid contrast-enhanced soft-tissue objects like the LV.

2. Methods

2.1. Statistical Shape Models

To build a 3-D SSM [10], a set of segmentations of the target shape is required. The contour of each shape S_i is described by n landmarks, i.e. points of correspondence that match between shapes, and represented as a vector of coordinates: $x_i = (x_1, ..., x_n, y_1, ..., y_n, z_1, ..., z_n)_i{}^T$. All n_s shape vectors form a distribution in a $3n$-dimensional space. This distribution is approximated by $x = \bar{x} + \Phi b$, with $\bar{x} = \frac{1}{n_s} \sum_{i=1}^{n_s} x_i$ being the mean shape vector and b being the shape parameter vector. By varying b, new instances of the shape class are generated. Φ is obtained by performing a principle component analysis (PCA) on the covariance matrix $C = \frac{1}{n_s - 1} \sum_{i=1}^{n_s} (x_i - \bar{x})(x_i - \bar{x})^T$. PCA yields the principle axes of this distribution; the eigenvalues give the variances of the data in the direction of the axes (= eigenvectors). To reduce noise and dimensionality only those eigenvectors with the largest t eigenvalues are used. t denotes the number of the most significant modes of variation and is chosen so that a fraction f of the total variation is retained, $\sum_{j=1}^{t} \lambda_j \geq f \sum \lambda_j$.

Prior to statistical analysis, location, scale and rotational effects must be removed from the training shapes to obtain a compact model. Commonly, Procrustes analysis is applied to minimize $D = \sum |x_i - \bar{x}|^2$, the sum of squared distances (SSD) of each shape to the mean.

2.2. Modeling of LV Anatomy

A Siemens Somatom Sensation Cardiac 64 multi-slice CT is used to acquire 20 data sets, imaging the human heart in 3-D at high-resolution. The volumes have an effective slice thickness of 0.5 mm and an average in-plane resolution of 0.33 mm. The size of the image mask in the transversal plane is 512×512 pixels; the number of slices varies between 220 and 310. The CT scans are performed at 65% of the heart phase (R-R peaks) with 120 kV.

The endocardial LV surface is manually segmented by experts in cardiology. To obtain an accurate model of the anatomy, details like the atrial emargination, the apex and the aortic valve region are maintained during segmentation. Contours are specified in axial slices by interactively setting/moving control points of a cardinal spline. Due to the high resolution of the CT scans, only each fifth slice is segmented; intermediate contours are interpolated. The surface of an LV is represented as a stack of contours.

Point correspondence among the training shapes is established based on back-propagation of the landmarks on a mean shape [11]. After segmentation, landmark extraction and removing location, scale and rotational effects, the SSM is built as outlined in Sect. 2.1. The first three modes of variation of the final model are illustrated in Fig. 1.

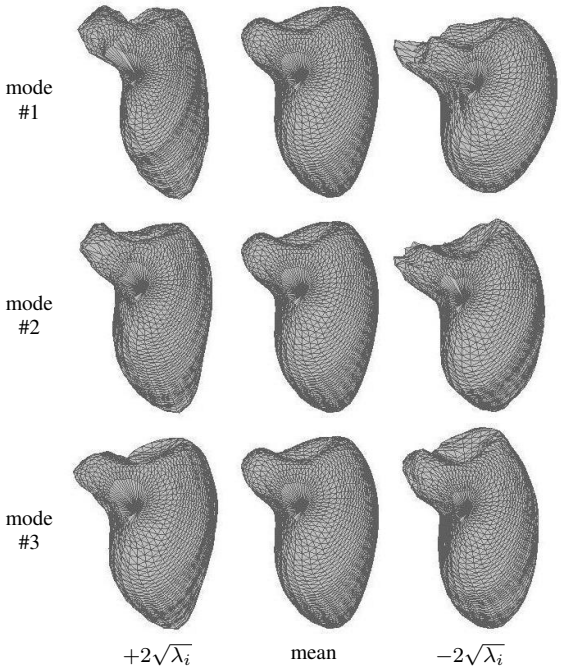

Figure 1. First three modes of variation of the LV SSM.

2.3. Recovery of LV Shape

In discrete tomography, a common strategy for solving the underdetermined and ambiguous reconstruction problem is to use numeric optimization [4]. Usually, as an exact solution will not be available, the projections of the recovered object need only be approximately equal to the given projection data. In this work, a non-rigid 2-D/3-D registration approach is followed to minimize the difference between the given projections and the simulated projections derived from the SSM. To transform the SSM from model space to image space the following equation is used:

$$y = R\left((\bar{x} + \Phi b)\, s + T\right)$$

Both shape parameter vector b and the parameters for pose $p = \{R, s, T\}$, i.e. rotation matrix R, scale factor s and translation vector T, have to be found so that the registration error is minimized. Unlike [8] and [9], we derive R from Euler angles to reduce the dimensionality of the registration problem. Orientation in 3-D space is thus described using 3 angles, i.e. $R_{\alpha,\beta,\gamma}$, instead of a 3×3 matrix. To solve the minimization problem, the Nelder-Mead algorithm is applied. Our cost function depends on the shape and pose parameter vector and incorporates contour and densitometric information derived from the given projections P_i and the simulated projections $P_i'(b, p)$:

$$\epsilon(b, p) = \sum_{i=1}^{n_P} \left(\omega_C \epsilon_C(P_i, P_i'(b, p)) + \omega_D \epsilon_D(P_i, P_i'(b, p))\right)$$

The total error ϵ is defined as the weighted sum of contour-related error ϵ_C and density-related error ϵ_D over all $n_P = 2$ projections. ϵ_C is obtained by equiangular sampling of the given and simulated contour and by calculating the SSD for the sampled points. For ϵ_D, the sum of squared difference metric is used. In the case of in-vivo angiograms, the endocardial contour was segmented by experts in cardiology. Densitometric information is derived by means of digital subtraction angiography; logarithmic subtraction is performed due to the exponential attenuation of x-rays. To reduce noise and the inhomogeneous saturation of contrast agent, two frames before and after a frame are used for averaging. In the case of simulated angiograms, contour information is extracted by border detection, whereas densitometric information is measured directly. A simulated projection of the SSM in image space is obtained for a given viewing direction, shape and pose parameter vector by converting the polygonal model into a 3-D binary image, V, and performing ray-casting. The values of V denote the presence/absence of contrast agent.

To generate plausible shapes [10], b is constrained by $\pm 2\sqrt{\lambda_i}$. Unlike [8] and [9], we exploit the training data to derive constraints for p. The training instances in model space are transformed to image space and the range of the components of the pose vector is analyzed. Note that this can be regarded as additional a-priori information.

Our experiments showed that optimizing pose and shape sequentially is more efficient than optimizing both simultaneously. A rigid registration is performed prior to optimization of the deformable parameters.

3. Results

To quantify the difference between original and recovered shape, two geometric and three volumetric similarity metrics are defined for comparing the polygonal models and the binary image representations, respectively.

Similarity of two polygonal models S_1 and S_2 is measured based on a given distance metric d: $sim_d(S_1, S_2) = \frac{1}{2}(\frac{1}{n}\sum_{i=1}^{n} d(p_i, S_2) + \frac{1}{m}\sum_{j=1}^{m} d(q_j, S_1))$, $p_{i=1,\ldots,n} \in S_1, q_{j=1,\ldots,m} \in S_2$. Distance metric d_{min} is defined as the Euclidean distance between point p_i and its closest point on S_2: $d_{min}(p_i, S_2) = \min_{q_j \in S_2} |p_i - q_j|$. Distance metric d_{ortho} denotes the Euclidean distance between p_i and the point obtained by intersecting S_2 with the surface normal at p_i: $d_{ortho}(p_i, S_2) = |p_i - \mathrm{surfn}(p_i) \cap S_2|$.

Let $|V|$ denote the volume of a 3-D binary image V. Volume conformity is measured by calculating the difference of volumes (DOV): $sim_{DOV} = 1 - ||V_{orig}| - |V_{rec}||/|V_{orig}|$. To assess shape conformity, the volume of differences (VOD) metric is used: $sim_{VOD} = 1 - |V_{orig} \oplus V_{rec}|/|V_{orig}|$. An alternative metric for shape conformity, derived from kappa statistic, quantifies the overlap between two binary masks: $sim_\kappa = 2|V_1 \cup V_2|/(|V_1| + |V_2|)$.

Evaluation with simulated data is performed based on leave-one-out experiments. From the segmented CT data sets, all but one are used to learn a SSM. Simulated angiograms are calculated for the left-out data set, and from these angiograms shape is recovered by fitting the learned SSM. The recovered shape is compared with the segmented shape of the left-out data set using the defined similarity metrics. This procedure is repeated for each data set.

Table 1. Evaluation of simulated angiograms.

Sim. Metric	Mean	Std.	Min.	Max.
d_{min} (mm)	2.61	0.65	1.65	3.53
d_{ortho} (mm)	2.49	0.77	1.38	3.72
DOV (%)	94.56	3.55	87.35	98.73
VOD (%)	78.17	5.30	68.88	84.91
κ (%)	87.12	2.53	82.54	90.18

The DOV metric in Tab. 1 shows that the original volume is approximated at high accuracy. This is essential for assessing volume-based diagnostic parameters, like EF. Concerning shape conformity we can see that a high overlap between the two shapes is achieved, although the VOD is still improvable. The distance metrics d_{min} and d_{ortho} are near the mean reconstruction error of 2.3 mm [11].

Evaluation of in-vivo angiograms is performed as follows: 1) a SSM is learned from 19 data sets, with the CT data set corresponding to the angiogram being excluded, 2) the model is fit to the in-vivo angiograms, and 3) the recovered shape is compared with the true 3-D shape of the excluded CT data set using the defined similarity metrics. The angiograms are acquired using a Siemens Bicor and a Siemens AXIOM Artis dBC system, capturing images of 512×512 pixels and 8-bit gray level depth at a frame-rate of 25fps. For temporal registration with CT data, the ECG information accompanying the angiograms is utilized.

Table 2. Evaluation of three in-vivo angiograms.

Sim. Metric	#1	#2	#3	Mean	Std.
d_{min} (mm)	2.43	2.32	2.95	2.57	0.34
d_{ortho} (mm)	2.36	2.05	3.36	2.59	0.68
DOV (%)	98.01	92.87	82.11	91.00	8.11
VOD (%)	74.72	80.13	68.12	74.32	6.01
κ (%)	87.49	90.41	79.75	85.88	5.51

The results for three in-vivo angiograms are given in Tab. 2. Our experiments indicate that values similar to the evaluation with simulated data are achieved, although the number of data sets is relatively small. For example #3, the reconstruction yields suboptimal results. The best shape conformity is achieved for example #2.

Finally, Fig. 2 shows one reconstruction result of the leave-one-out experiments.

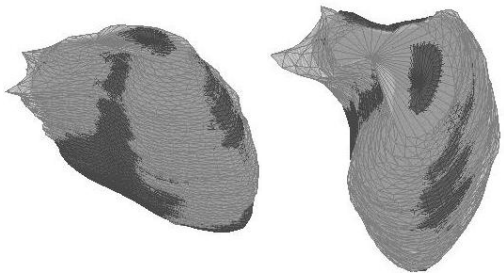

Figure 2. Reconstruction example showing original shape (bright) and recovered shape (dark).

4. Discussion and Conclusion

A new method for recovering the LV from non-rotational bi-planar x-ray images is presented. The novelty of our approach is that anatomical a-priori information about the LV is learned from high-resolution CT data and modeled as SSM. Reconstruction is based on a non-rigid 2-D/3-D registration technique which fits the SSM to the angiographic projections.

When only two (noisy) projections are available, the reconstruction problem usually becomes underdetermined and ambiguous. In such cases, the incorporation of a-priori information plays a crucial role, since this helps in limiting the space of possible solutions and often improves the ability to deal with noisy data.

Using a SSM for reconstruction allows to generate statistically plausible and patient specific shapes. In contrast to other LV SSM's often found in literature, anatomical areas like the atrial concavity, the aortic valve region and the apex are preserved in our model. This is necessary to generate complete contour and densitometric information during registration. Further note that these areas overlap with the ventricular cavity in projection images and are therefore hard to recover without prior knowledge.

Evaluation with both simulated and real patient data shows promising results. The LV volume is recovered at high accuracy. This is important for assessing volumetric diagnosis parameters, like EF. Concerning shape conformity, the overlap between original and recovered volume is high, though there is still place for minor improvements.

Future work will focus on evaluating our approach with more in-vivo angiograms and on improving the non-rigid 2-D/3-D registration.

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