Towards 3-D LV Shape Recovery in Biplane X-Ray Angiography Using Statistical Shape Models

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Abstract

Coronary x-ray angiography has proven to be an efficient method for treatment and diagnosis of cardio-vascular diseases. In clinical practice, quantitative LV analysis is done in 2-D and based on contour data since 3-D information is not available due to projection. In this work, a novel approach for recoverying the 3-D LV shape from bi-planar x-ray images is presented. The sparse and noisy data available for reconstruction necessitates the incorporation of geometric prior information. A statistical shape model of the ventricular 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 the shape model to the x-ray images of the patient, simulated projections of the model are calculated. An optimization procedure mimimizes the difference between simulated and real projection images. The presented method is evaluated using simulated data.

1. Introduction

Interventional x-ray angiography is state-of-the-art in both treatment and diagnosis of cardio-vascular diseases. In case of infarction, the viability of myocardium is evaluated based on x-ray images of the left ventricle (LV). Bi-planar cine-angiographic equipment captures images simultaneously from two different projection directions during 3-5 heart beats opacified with contrast agent. In clinical practice, quantitative analysis of LV function is based on projected end-diastolic (ED) and end-systolic (ES) endocardial contours: ED and ES volumes are approximated to assess ejection fraction (EF) and wall motion is quantified using e.g. the centerline method [1] or the radial method [2]. Instead of evaluating contour information, novel approaches aim at reconstructing the spatio-temporal shape to analyze LV function in 3-D [3]. In this work, a new method for spatial reconstruction is presented.

Several works have addressed the problem of recovering the LV shape from projective x-ray images. While Medina et al. [4] and Moriyama et al. [5] only use contour information, Backfrieder et al. [6] and Prause et al. [7] additionally exploit densitometric information derived from the gray values of the x-ray images. Using more than one bi-planar acquisition [5] increases the data available for reconstruction, but also the x-ray exposure for the patient. However, the problem of recovering the LV from two projections is ill-posed and incorporating prior knowledge of its shape is an important aspect.

The novelty of our LV reconstruction algorithm is that it incorporates a priori information learned from multi-slice CT data in the form of a statistical shape model (SSM). Reconstruction is based on a non-rigid 2-D/3-D registration approach utilizing simulated x-ray projections for model fitting. The application of SSM for reconstruction has been successfully demonstrated for other anatomies [8], [9], [10]. To our knowledge, this is the first time that such an approach is followed to recover the LV shape.

2. Methods

2.1. Statistical shape models

When building a 3-D SSM, 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 s shape vectors form a distribution in a $3n$-dimensional space. This distribution is approximated by $x = \bar{x} + \Phi b$, with $\bar{x} = \frac{1}{s}\sum_{i=1}^{s} x_i$ being the mean shape vector and b being the shape parameter vector. By varying b, new instances of the shape class can be generated. Φ is obtained by performing a principle component analysis (PCA) on the covariance matrix $C = \frac{1}{s-1}\sum_{i=1}^{s}(x_i - \bar{x})(x_i - \bar{x})^T$. 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.

A more detailed explanation about the concept of SSMs can be found in [11].

2.2. Building of LV model

A priori information of the ventricular anatomy is extracted from 15 data sets acquired with a Siemens Somatom Sensation Cardiac 64 multi-slice CT. The scans are performed at 65% of the heart phase (R-R peaks) with 120 kV; a B25f convolution kernel is applied for reconstruction. The volumes have a size of 512×512×230-300 voxels, an effective slice thickness of 0.5 mm and an in-plane resolution of 0.35 mm at average.

The endocardial surface was manually segmented by experts in cardiology. Contours are specified in axial slices by interactively setting control points of a cardinal spline. Due to the high resolution only each fifth slice is segmented; intermediate contours are interpolated.

A new method was developed that automatically extracts pseudo-landmarks from the segmented surface [12]: 1) All training shapes are uniformly sampled. Contours are intersected with n_{cp} equiangular rays. A spline connects the i-th sampled contour point of each contour. All n_{cp} splines are intersected with n_c parallel equidistant planes. 2) The sampled shapes are aligned among each other utilizing Procrustes alignment. For pairwise shape registration, the iterative closest point (ICP) algorithm is applied. 3) A mean shape is computed by averaging the contour point coordinates of the aligned shapes. 4) Landmarks on the mean shape are backpropagated to the aligned shapes by creating rays that originate from its centroid and run through its contour points. The intersections of these rays with an aligned shape denote the landmarks.

Once landmarks are determined, the shape model is built as outlined in Section 2.1. The final LV model is described by 2500 landmarks and shown in Figure 1.

2.3. Model fitting

A major difference compared to other works concerning 2-D/3-D registration (see [13] and references therein) is that the shape of the 3-D object to be spatially aligned with its projections is unknown. In this work, a non-rigid registration approach is followed which brings the LV SSM from model space to image space: $y = R([\bar{x} + \Phi b]s) + T$.

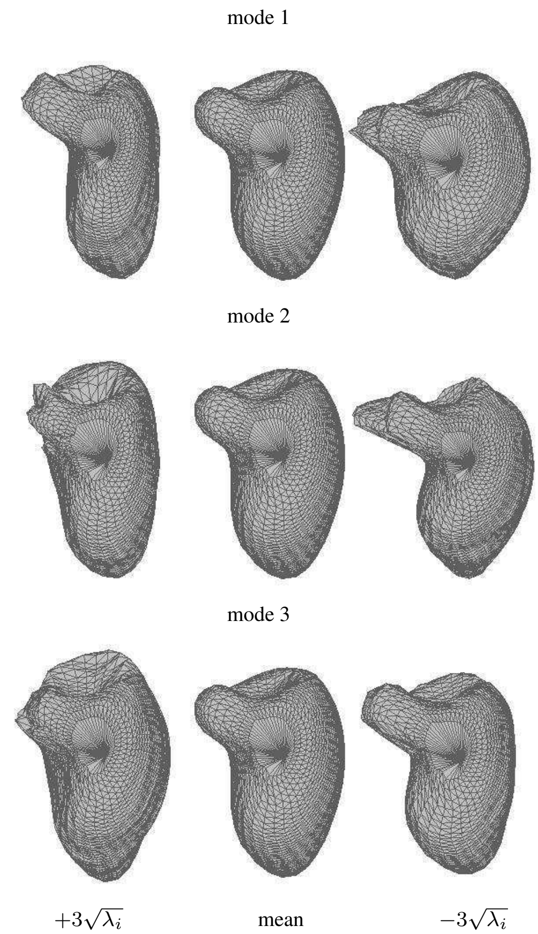

Figure 1. First three modes of variation of the LV SSM.

Both shape parameter vector b and the pose parameters, i.e. rotation matrix R, scale factor s and translation vector T, have to be found so that the registration error is minimized.

In contrast to [8] and [10] we do not use a gradient descent technique for optimization, but, similar to [9], the Downhill Simplex algorithm. To generate plausible shapes [11], shape parameter vector b is constrained by $|b_i| \leq 3\sqrt{\lambda_i}$ during optimization. Unlike [8], [9] and [10] we use quaternions instead of rotation matrices. Thus, the number of parameters needed to represent orientation in the pose vector is reduced by 5 (from 9 to 4).

The cost function to be minimized is based on contour information derived from simulated x-ray projections. For a given pose and shape parameter vector, a simulated projection of the SSM in image space is obtained by first converting the polygonal model into a binary volume, then deriving projection profiles from a given angle θ for each axial slice using the radon transform and, finally, assembling the profiles to a 2-D image. Figure 2 shows simulated projections of the mean model from standard left and right anterior oblique (LAO and RAO) view. The contour-related error for a single projection view is deduced by radially sampling the LV contour in both the simulated and the real projection image and then calculating the SSD between corresponding sampled points, see Figure 3. The total contour-related error is the sum of the SSD of both projection views.

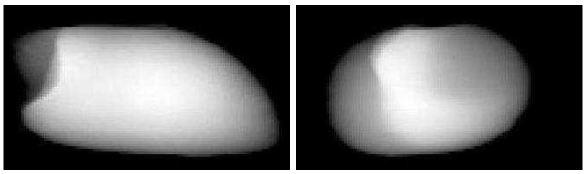

Figure 2. Simulated x-ray projection of the mean shape model from standard LAO and RAO view.

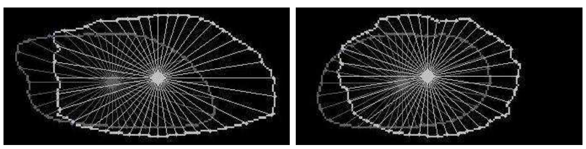

Figure 3. Contour information used for model fitting. The model contour is in dark, the original contour in bright color.

3. Results

The presented method is implemented using Matlab and the Insight Segmentation and Registration Toolkit (ITK). For evaluation, leave-one-out experiments are performed.

From the segmented CT data sets, all but one are used to learn a shape model. Simulated projections are calculated for the left-out data set, and from these projections shape is recovered by fitting the learned model. The recovered and the original LV shape are converted into binary volumes (v_{rec}, v_{orig}) and compared based on two volumetric measures: difference of volumes, $DOV = 1 - |vol(v_{orig}) - vol(v_{fitted})|/vol(v_{orig})$, and volume of differences, $VOD = 1 - vol(xor(v_{orig}, v_{fitted}))/vol(v_{orig})$. These evaluation steps are performed for each data set. The resulting statistics are listed in Table 1.

Table 1. Comparison of original and recovered volume.

	difference of volumes (%)	volume of differences (%)
mean	94.27	74.14
std	4.41	5.13
min	85.95	65.86
max	99.10	81.06

The experiments show that the original volume can be recovered at high accuracy (94.27% at average), even if only contour information is incorporated for reconstruction. However, the VOD measure indicates that there's still place for improvement concerning shape conformity.

Figure 4 shows one reconstruction result of the leave-one-out experiments, convergence is shown in Figure 5.

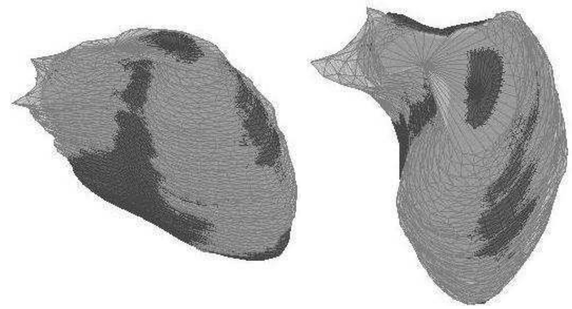

Figure 4. Reconstruction example showing original shape (bright) and recovered shape (dark).

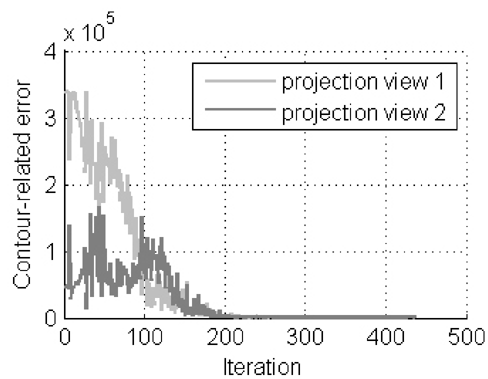

Figure 5. Convergence of reconstruction example.

4. Discussion and conclusions

A novel method for reconstructing the LV shape from bi-planar x-ray images is presented. One major difference to other works in this field is the incorporation of geometric prior information, extracted from high-resolution multi-slice CT data and modeled as a SSM. Reconstruction of the LV shape is based on a non-rigid 2-D/3-D registration approach utilizing simulated x-ray projections. The model is fitted by minimizing the difference between real and simulated projection images.

The CT data used in this work shows the ventricle at high accuracy and is suitable for learning a detailed anatomical model. The sparse data available for LV shape recovery necessitates the incorporation of geometric prior information. Using an approach based on SSM improves robustness and allows generating plausible and patient-specific shapes. Unlike other LV SSMs often found in literature, anatomical areas like the atrial concavity, the aortic valve region and the apex are preserved. This is necessary to generate complete contour and densitometric information by the simulated projections during registration. Another important reason is that these areas overlap with the ventricular cavity in projection images and are therefore hard to recover; an aspect not yet addressed in previous work. Using a model-based reconstruction approach helps in recovering these areas.

Once a ventricle is reconstructed, its volume can be measured directly and needn't be approximated from its projected contour.

Future work will focus on improving the SSM and the non-rigid 2-D/3-D registration. Incorporation of densitometric information is currently work in progress. The presented approach will be further evaluated using real patient data.

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References

[1] Sheehan F, Bolson E, Dodge H, Mathey D, Schofer J, Woo H. Advantages and applications of the centerline method for characterizing regional ventricular function. American Heart Association Circulation 1986;74:293–305.

[2] Gelberg H, Brundage B, Glantz S, Parmley W. Quantitative left ventricular wall motion analysis: A comparison of area, chord and radial methods. American Heart Association Circulation 1979;59:991–1000.

[3] Swoboda R, Carpella M, Steinwender C, Gabriel C, Leisch F, Backfrieder W. From 2d to 4d in quantitative left ventricle wall motion analysis of biplanar x-ray angiograms. In Computers in Cardiology 2005. IEEE Computer Society Press, 2005; 977–980.

[4] Medina R, Garreau M, Toro J, Breton H, Coatrieux JL, Jugo D. Markov random field modeling for three-dimensional reconstruction of the left ventricle in cardiac angiography. IEEE Transactions on Medical Imaging 2006;25(8):1087–1100.

[5] Moriyama M, Sato Y, Naito H, Hanayama M, Ueguchi T, Harada T, Yoshimoto F, Tamura S. Reconstruction of time-varying 3-d left-ventricular shape from multiview x-ray cineangiocardiograms. IEEE Transactions on Medical Imaging 2002;21(7):773–785.

[6] Backfrieder W, Carpella M, Swoboda R, Steinwender C, Gabriel C, Leisch F. Model based lv-reconstruction in bi-plane x-ray angiography. In Medical Imaging 2005: Image Processing, volume 5747. SPIE, 2005; 1475–1483.

[7] Prause GPM, Onnasch DGW. Binary reconstruction of the heart chambers from biplane angiographic image sequences. IEEE Transactions on Medical Imaging 1996; 15(4):532–546.

[8] Benameur S, Mignotte M, Parent S, Labelle H, Skalli W, de Guise J. 3d/2d registration and segmentation of scoliotic vertebrae using statistical models. Computerized Medical Imaging and Graphics 2003;27(5):321–337.

[9] Fleute M, Lavallée S. Nonrigid 3-d/2-d registration of images using statistical models. In MICCAI '99: Proceedings of the Second International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer-Verlag, 1999; 138–147.

[10] Lamecker H, Wenckebach TH, Hege HC. Atlas-based 3d-shape reconstruction from x-ray images. In ICPR '06: Proceedings of the 18th International Conference on Pattern Recognition. IEEE Computer Society, 2006; 371–374.

[11] Cootes TF. Statistical models of appearance for computer vision. Technical report, May 2004.

[12] Swoboda R, Scharinger J. A 3-d statistical shape model of the left ventricle - geometric prior information for recovering shape from projective bi-planar x-ray images. In Proc. 32nd Workshop of the Austrian Association for Pattern Recognition, volume 232. books@ocg.at, 2008; 53–61.

[13] van de Kraats E, Penney G, Tomazevic D, van Walsum T, Niessen W. Standardized evaluation methodology for 2-d-3-d registration. IEEE Transactions on Medical Imaging 2005;24(9):1177–1189.

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