

Intensity-Based 3D-Reconstruction of Non-Rigid Moving Stenosis From Many Angiographies

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Abstract. This contribution introduces a new *Intensity-based* technique that leads to local 3D-reconstruction of a stenosis from many angiographic views. We examine the reconstruction of a *local* region of a non-rigidly moving heart with unknown motion, using methods of reconstruction of rigid objects and without using ECG-information. Our basic idea is to assume *rigidity* for the ROI, and to *fixate* it by compensating its unknown motion by an additional camera movement. This is achieved using an iterative 2D-3D intensity-based registration approach. To our knowledge the idea of *fixation* of the ROI and the usage of rigid reconstruction algorithm from many angiographic views for local-heart reconstruction has not been yet addressed in literature.

1 Introduction

The early detection and correction of aberrations of coronary vessels is of highest medical importance to avoid occlusions or to minimize the damage of the heart. Image data are usually acquired with cardiac C-arm devices, that allow the acquisition of image sequences (30 Frames/sec) of the beating heart. High-end systems provide two views from different directions to support the physician to conclude the 3D-structure. The 3D-reconstruction of the vessels will lead to an improvement of the workflow and of the treatment. The diagnosis of stenosis does not require the 3D-reconstruction of the whole heart. The region containing just the malformation (region of interest (ROI)) should be sufficient to extract the needed information, such as the degree of stenosis.

3D-heart-reconstruction comprises usually two problems: extraction and tracking of points as well as structure computation. The segmentation of coronary vessels is addressed in [1]. 3D-Reconstruction is mostly reduced to the reconstruction from two views of the same ECG-state [2]. Including all angiographies requires heart-motion estimation and/or compensation [3,4].

In this paper we introduce a new technique that will at least lead to a local 3D-reconstruction of a stenosis. Section 2 states the problem. Sections 3 and 4 explain the chosen procedure. Section 5 presents experiments on generic data. Section 6 concludes and describes future work.

2 Problem statement

The C-arm is rotated around the patient with known projections matrices Let \mathbf{C}_i be the center of the camera at time t_i . The heart is a *deformable* object and is *moving* with unknown motion model. Let the geometric point \mathbf{i}_w denote an arbitrary heart position at t_i . The projection of \mathbf{i}_w through \mathbf{C}_i is referred to by \mathbf{i}_q . The observed point $\mathbf{i} + \mathbf{1}_q$ at t_{i+1} arises from the simultaneous movement of the camera and the unknown non-rigid heart movement between t_i and t_{i+1} . We denote by $\mathbf{H}_{(i,i+1)}^w$ the non-singular 4×4 homogenous matrix describing the 3D-motion of \mathbf{i}_w between t_i and t_{i+1} . The following equation establishes for n frames the relationship between \mathbf{i}_w at t_i and its projection $\mathbf{i} + \mathbf{1}_q$ after motion at t_{i+1} (in homogenous coordinates):

$$\mathbf{i} + \mathbf{1}_q \simeq \mathbf{P}_{i+1} \mathbf{H}_{(i,i+1)}^w \mathbf{i}_w, i = 1, \dots, n, \quad (1)$$

The reconstruction of the small region containing just the stenosis would be sufficient for the physician to extract the needed information. In the following we will keep the heart locally rigid*, i.a all points of the ROI have the same 3D-motion $\mathbf{H}_{(i,i+1)}^w$. The relation in eq. 1 remains if we fix the 3D-point in a *reference position* $\mathbf{0}_w$ and express the relationship wrt. this reference. Besides assuming rigidity for the ROI, it can be generalized to m points:

$$\mathbf{i}_{j\tilde{q}} \stackrel{\simeq}{\sim} \mathbf{P}_i \mathbf{H}_{(0,i)}^w \mathbf{0}_j^i, j = 1, \dots, m, i = 1, \dots, n. \quad (2)$$

The gain of this formulation is that we are now able to compensate the motion of the ROI by integrating its movement into the projection matrix: $\mathbf{P}_i \mathbf{H}_{(0,i)}^w$. The ROI becomes fixed in 3D. Therefore the usage of the filtered-backprojection (FB) [7] based on the updated matrices becomes possible.

Section 3 describes the approach for reconstructing the reference pose of the ROI. Section 4 addresses the problem of updating the projection matrices and compensation for heart motion using an intensity-based approach.

3 Computing reference pose

For a number $m \in \mathbb{N}$ of corresponding points in two views (that will be specified in the next section), a reference position is computed using the *optimal triangulation method* [5, p. 305] and the given projection matrices. Due to heart motion this results in 3D-points whose reprojections do not perfectly suit to the given corresponding image-points in remaining frames. As this is not necessary (just "reference points" are needed), we can choose frames which do not correspond to the same ECG-state, as long as the structure of ROI in the two views is preserved.

* The validity of this assumption will have to be justified by experiments.

4 Intensity-based update of Projection Matrices

In order to estimate the ROI-motion we propose to use an intensity-based 3D-2D-Registration approach. Penney designed in [6] an algorithm to obtain the pose of a CT volume wrt. a single fluoroscopy image. The basic idea is to produce digitally reconstructed radiographs(DRR's), which are compared to the fluoroscopy-image using a similarity measure. Given an initial estimate, the pose of the volume is optimized in a six-dimensional search-space.

In order to apply this algorithm we need an initial *good* ROI-volume that will be used for registration. We propose to segment and track *one* single point ($m = 1$) in the ROI, reconstruct a reference-point and perform a first update for the projection matrices as following:

$$\tilde{\mathbf{q}}_i \simeq \mathbf{h}_{(0,i)}^w \mathbf{P}_i \tilde{\mathbf{w}}_0; i = 1, \dots, n, \quad (3)$$

where $\mathbf{h}_{(0,i)}^w$ is a 3×3 homogenous matrix containing the 2D-displacement vector from the projection of \mathbf{w}_0 via \mathbf{P}_i to \mathbf{q}_i . This results in projection matrices $\mathbf{P}_i^0 = \mathbf{h}_{(0,i)}^w \mathbf{P}_i$ which hold one point of the ROI fixed in the reference pose, and compensate its 3D-motion by a 2D-displacement. We used \mathbf{P}_i^0 to reconstruct an initial volume \mathbf{V}^0 . The volume \mathbf{V}^0 is iteratively registered with the C-arm sequence until stabilization of the estimated parameters. In each iteration k the volume \mathbf{V}^{k-1} is registered with each of the frames using its \mathbf{P}_i^{k-1} for initializing the optimization. This yields to \mathbf{R}_i^k and \mathbf{T}_i^k describing the new volume-pose that best align \mathbf{V}^{k-1} with the images. The estimated parameters \mathbf{R}_i^k and \mathbf{T}_i^k are used for updating the projection matrices, that are used for reconstructing \mathbf{V}^k :

$$\mathbf{P}_i^k = \mathbf{P}_i^{k-1} \begin{pmatrix} \mathbf{R}_i^k & \mathbf{T}_i^k \\ 000 & 1 \end{pmatrix}. \quad (4)$$

5 Experiments: Phantom Data

We performed two experiments using sequences of 133 X-ray images taken by Siemens-C-arm during a rotation of 166° . We captured two phantoms: a "non-moving" stenosis made by knead; and a "moving" electrical-connector (see Fig. 2 and 5, left). In all 512×512 gray-images we segmented and tracked a single point of interest (POI). We used the Levenberg-Marquardt-algorithm for the optimization and the gradient-difference[6] as a similarity measure between the fluoroscopy-images and the created DRR for each motion estimates.

Experiment 1: a non-moving stenosis-phantom was considered. The goal is to check the accuracy of segmentation, reconstruction and reprojection in the absence of 3D-motion. The result of this experiment will be taken as a referring point for the amount of error induced by these steps. Fig. 1 shows the volume reconstructed by the FB using the projection matrices, delivered by the calibrated C-arm, as well as the initial volume \mathbf{V}^0 , reconstructed as described in section 4, followed by the results of four iterations of successive registration and reconstruction.

Fig. 1. Left: Ideal volume of static-stenosis. Right: 3D-Reconstruction results

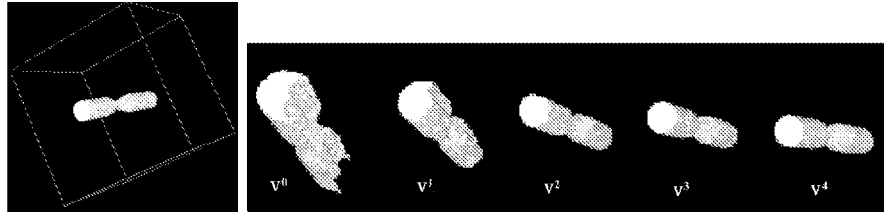


Fig. 2. Left: Phantom stenosis. Right: Pose of Camera centers before and after motion compensation

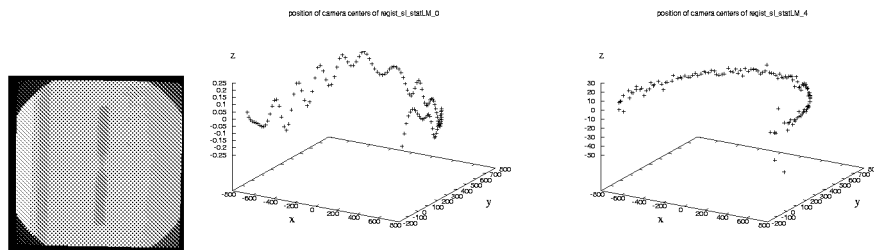


Fig. 2 shows the initial and final poses of camera centers.

Experiment 2: a real moving object with unknown 3D-motion was considered. Fig. 3 shows the volume reconstructed by using the projection matrices delivered by the calibrated C-arm, as well as the volumes V^0 til V^5 , results of five iterations.

Fig. 4 shows the initial and final poses of camera centers.

Discussion: The artifacts in experiment 1 in V^0 are due to the errors in the initial update of P_i^0 . These are due to incorrect segmentation and detection of the POI. The artifacts have to be compensated by additional camera motion (s. Fig. 2,right). It should be mentioned, that the poses in Fig. 2 do not show the orientation of the camera axis. Nevertheless the positions induce a certain smoothness, that could be used to introduce motion constraints.

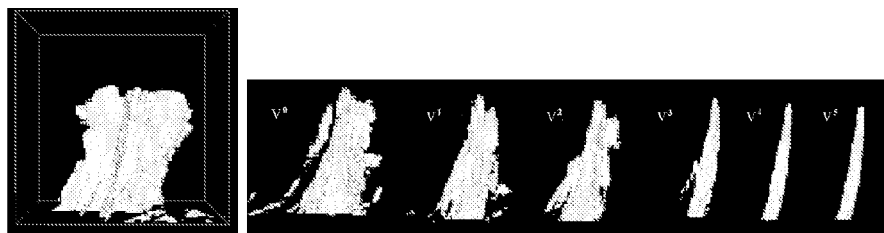
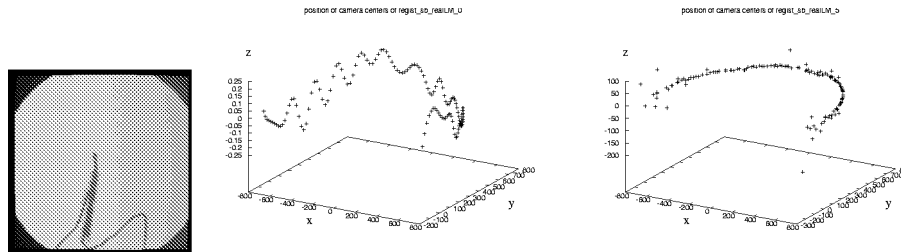


Fig. 3. left: Original volume of electrical connector. Right: 3D-Reconstruction results

Fig. 4. Left: electrical connector. Right: Pose of Camera centers before and after motion compensation



Experiment 2 proves experimentally the idea of fixation since the object is really moving. The artifacts in V^5 are due to the convergence of the optimization algorithm in local minima. Current work is focusing on a refined registration using gradient projections at edge points [8].

6 Conclusion

The possibility to compensate the motion of a local non-rigid heart region by an additional camera motion, while keeping the region of interest fixed has been examined. This has the advantage to use known algorithms of volume reconstruction for fixed objects. Future work will concentrate on the development of rigorous criteria for termination and reconstruction accuracy, propagating motion constraints and testing on anatomical images.

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