

3D Curve Reconstruction by Biplane Snakes

C. Cañero, P. Radeva, R. Toledo, J.J. Villanueva
Computer Vision Center and Dept. Informàtica
Universitat Autònoma de Barcelona
08193 Bellaterra (Barcelona), Spain
cristina@cvc.uab.es

J. Mauri
Cardiac Catheterization Laboratory
Hospital Universitari Germans Trias i Pujol
08916 Badalona (Barcelona), Spain
jmauri@ns.hugtip.scs.es

Abstract

Stent implantation for coronary disease treatment is a highly important minimally invasive technique that avoids surgery interventions. In order to assure the success of such an intervention, it is very important to determine the real length of the lesion as exactly as possible. Currently, lesion measures are performed directly from the angiography without considering the system projective parameters or, alternatively, from the 3D reconstruction obtained from a correspondence of points defined by the physicians. In this paper, we present a method for 3D vessel reconstruction from biplane images by means of deformable models. In particular, we study the known shortcoming of point-based 3D vessel reconstruction (no intersection of projective beams) and illustrate that using snakes the reconstruction error is minimal. We validate our method by a computer-generated phantom, a real phantom and coronary vessels.

1. Introduction

Nowadays, medical imaging techniques are supposed not only to give qualitative information, but also quantitative measurements about the objects to be analyzed. Whereas the technique of angiography has been developed in order to obtain images from the coronary vessels from different views, measurements of the vessels have become necessary very soon. This is the case of the determination of the stent size. When the selected stent is too large, the vessel comes too rigid, otherwise, the lesion is not treated. Obtaining the length of a stenosis is of vital importance for the success of this kind of intervention. In order to obtain these measurements, a view of the affected vessel is taken and the length of the lesion is inferred. The imprecision in the system calibration, as well as the foreshortening due to the view, make these measurements inexact and unreliable. To cope with it we address a three-dimensional reconstruction of the vessel from two views.

There are two main approaches to reconstruct a curve in space: computing the curve which interpolates the corresponding points marked by the user (usually with imprecision) or obtaining the curve whose projections approximate the vessel in the images as well as possible.

There are different works following the bottom-up strategy: Dumay et al. in [1] describe a method for the reconstruction of a point using two views. Wahle et al. in [5] address three dimensional reconstruction of skeletons of the coronary tree from biplane views. Wunderlich et al. in [6] present a procedure in order to obtain the length of a lesion after reconstructing from biplane angiograms. The bottom-up approach has three shortcomings: first, in many cases it is difficult to determine corresponding points. Second, even when the user is helped by the epipolar line [1] to match points in different views, measurement error in the calibration parameters makes fail the epipolarity constraint. Third, the curve is directly interpolated among marked points.

Instead, we consider the second approach proposing a top-down strategy: an elastic curve in the space deforms in order to adapt its projections to the vessels in the images. Therefore, the user initializes the curve by few points in the zone of the vessel to be reconstructed. Then, the curve deforms until its complete adaptation to the vessels in the images. This new kind of deformable curves is called *biplane snake*. Preliminary results of this approach were presented in [4] for orthogonal views. The aim of this paper is to extend the technique and validate it by phantoms and experts; we show the results improvement compared to the bottom-up approach.

The remaining of this paper is organized as follows: section 2 discusses the problem of the 3D reconstruction of a single point and proposes a measure of the reconstruction error. Section 3 extends the technique to the reconstruction of curves introducing the *biplane snakes*. Section 4 presents tests on computer-generated phantoms, mechanic phantoms and also shows its application in a real case. Finally, section 5 states some conclusions and propose several future guidelines.

2. Single point 3D-reconstruction

Let F_1, F_2 be the focus position of the X-ray beams in two views, and D_1, D_2 be the projections φ_1, φ_2 of the point D to be reconstructed. Theoretically, the 3D reconstruction of D is the intersection of the projective lines F_1D_1 and F_2D_2 (see figure 1). In practice, projective lines fail to intersect. Dumay et al. in [1] propose as the approximated 3D reconstructed point the point D' which minimises the distance to both projective lines. This point is situated upon a segment perpendicular to both projective lines. The vectorial representation of this segment is as follows:

$$\overline{S_1S_2} \rightleftharpoons (\overline{OF_2} + \sigma \overline{F_2D_2}) - (\overline{OF_1} + \tau \overline{F_1D_1}) \quad (1)$$

where τ, σ are determined from the perpendicular constraints:

$$\overline{S_1S_2} \cdot \overline{F_1D_1} \rightleftharpoons \overline{S_1S_2} \cdot \overline{F_2D_2} \rightleftharpoons 0$$

The backprojection φ^{-1} of D_1, D_2 is expressed as follows [1]:

$$D' = \varphi^{-1}(D_1, D_2) = \overline{OF_1} + \tau \overline{F_1D_1} + \frac{1}{2} \overline{S_1S_2}$$

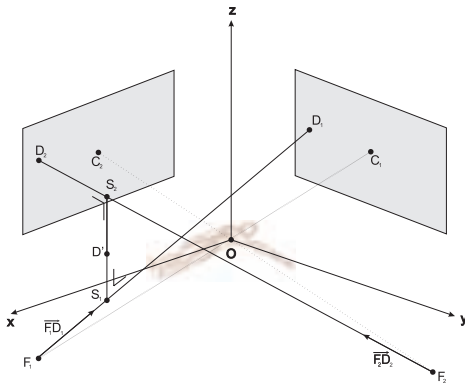


Figure 1. The minimum distance reconstruction of corresponding points D_1 and D_2 .

The distance between projective lines calculated from (1) defines a measure of the reconstruction error as follows:

$$\varepsilon_1(D_1, D_2) = \|\overline{S_1S_2}\| \quad (2)$$

Alternatively, considering D'_1, D'_2 as the projections of D' in both planes, we define the reconstruction error as:

$$\varepsilon_2(D_1, D_2) = \|\overline{D_1D'_1}\| + \|\overline{D_2D'_2}\| \quad (3)$$

It is easy to see that by reducing (3) we reduce (2). On the other hand, error (3) is in the image plane units, and this fact gives numerical stability to our error minimization procedure.

3 3D-reconstruction of a curve

Let us consider a target curve $T(v)$ projected in image planes and a curve $Q(u)$ that is used to reconstruct $T(v)$. Let $Q_i(u), T_i(v)$ be the projections of $Q(u)$ and $T(u)$ in image plane i , respectively. We are interested in the curve which minimizes the following error:

$$\varepsilon(Q(u)) = \sum_{i=1}^2 \int \min_v (||Q_i(u) - T_i(v)||) du \quad (4)$$

Several issues should be discussed. First, it could happen that more than one curve minimizes expression (4). An example of this fact is shown in figure 2. Two pairs of views (fig. 2(a) and 2(c)) with Anterior-Posterior (AP) and Left Lateral (LAT) projections of target curve (dashed lines) and deforming curve (continuous line). In fig 2(b) the reconstructed curve from the pair 2(a) (thick) coincides with the generating (thin) curve. In fig 2(d) (reconstruction from 2(c)) both curves differ in space. To solve this problem an expert's initialization is introduced. Second, feature extraction in real images is not perfect; several vessels will appear in the same image, so a selective and robust method for 3D reconstruction is necessary. To treat all these issues, we develop a model based on the technique of snakes[2]. First, it is able to take into account the expert's initialization. Second, it deforms towards image features under general constraints on model shape. Third, the B-Snakes implementation of Menet et al. in [3] allows to define the curve with only a few control points, which simplifies the initialization but also accelerates the minimization procedure.

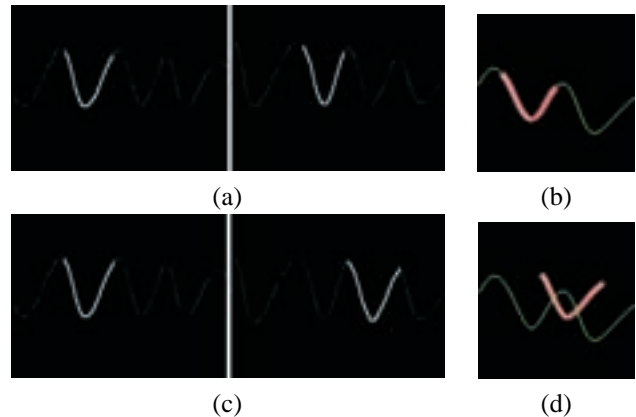


Figure 2. 3D reconstruction could present ambiguity.

The snake deforms by minimizing its energy, which is defined as follows:

$$E_{total}(Q(u)) = \int E_{internal}(Q(u)) + E_{external}(Q(u)) du$$

Internal forces reduce internal energy preserving the smoothness, and external forces attract the *snake* to the features in the image. In our case, our aim is the 3D reconstruction of the curve so that its projections coincide with the vessels. For this purpose, we define the external energy of the spatial snake as a function of distance of the projected snake to the image features. The 3D snake deforms to adjust its projections to the image vessels. Note that this external energy stems from two images; giving the name of *biplane snakes* to our deformable models. Applying the Euler-Lagrange equation we get [2]:

$$-\frac{\partial}{\partial u}(\alpha Q_u(u)) + \frac{\partial^2}{\partial u^2}(\beta Q_{uu}(u)) + \nabla E_{ext}(Q(u)) = 0$$

We redefine the external force ($\nabla E_{ext}(Q(u))$) of the *biplane snakes* as follows (figure 3):

$$F_{ext}(Q(u)) = \varphi^{-1}[Q_1(u) + \nabla V_1(Q_1(u)), Q_2(u) + \nabla V_2(Q_2(u))] - Q(u) \quad (5)$$

Figure 4 shows an example of the evolution of reconstruction error during deformation of the *biplane snake*. The external energy decreases reducing the real reconstruction error (mean distance of $Q(u)$ to the target curve $T(v)$).

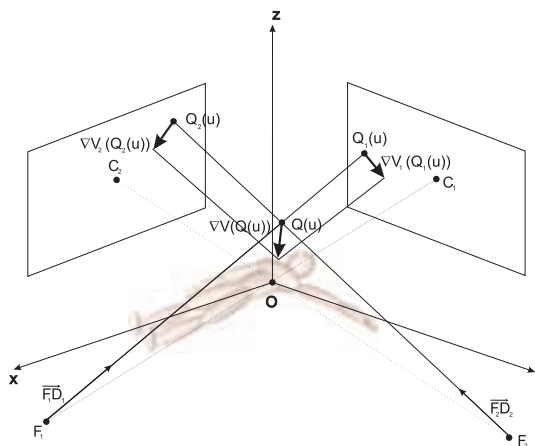


Figure 3. The external force from both projections is backprojected in space.

4 Results

In order to validate the *biplane snake* technique, we do several experiments: tests with computational phantoms, tests with a mechanical phantom and tests with real images of angiography.

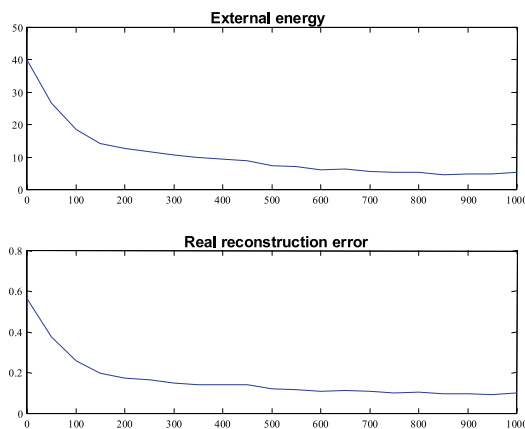


Figure 4. Evolution of the *biplane snake*.

4.1 Tests on computational phantom

The first experiment consists of generating two images with projections of a curve. A user is asked to mark corresponding points of the curve as exactly as possible in order to achieve a manual reconstruction. The epipolar line [1] helps the user on determining the point correspondence. The curve generated by the user is used as initial snake. The deformation of the *snake* is performed until 500 iterations. We do this with 5 different generator curves and 4 experts (*obs1* . . . *obs4*). We repeat the experiment, but now introducing random error in the parameters used to generate the images. Results are shown in figure 5. The mean relative improvement of error was of 9% for the first case (fig. 5(a)) and 12% for the second (fig. 5(b)).

4.2 Tests on physical phantom

In order to demonstrate that real length measurements obtained by *biplane snakes* are correct, we constructed a wire phantom simulating a vessel. Then, we took images of the phantom from different points of view with the angiography acquisition system in clinical conditions. Finally, we reconstructed the same wire segment from several projections and, marking on the beginning and the end of the segment of the obtained curve, we computed its length. We repeated this procedure ten times for each pair of projections using different snake initialisations. Figure 6 shows the statistics of the error done when measuring the length of a segment of 32mm (for an explanation of the abbreviations see [1]). Note that the mean error is $< 0.6mm$, which met the requirement in the clinic.

4.3 Tests on real vessels in angiography

Finally, we have tested our technique in order to reconstruct coronary vessels in different real angiography cases.

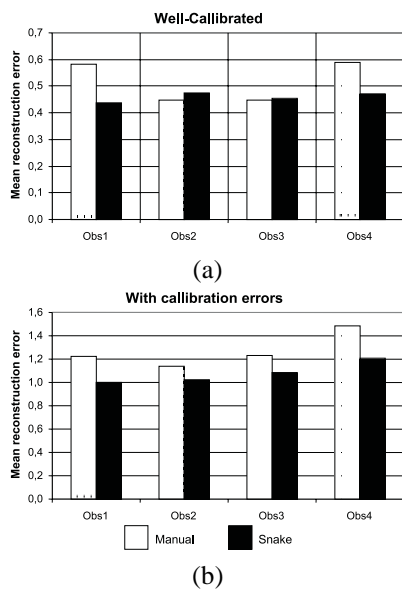


Figure 5. Mean reconstruction error for computational phantom.

Error [mm]	AP-LAT	RAO30-LAT	RAO30-LAO60
Mean	0.59	0.59	0.55
Max	2.20	1.50	1.40
Variance	0.34	0.19	0.14

Figure 6. Mean length measurement error for physical phantom.

Figure 7 shows a reconstruction of the left coronary of a patient from their projections AP and RAO30 (see figure 7(a) and 7(b)). Three curves are reconstructed adapting its projections to the images as shown in figures 7(c) and 7(d). The user can then interact with the point of view of the 3D reconstruction (see figure 7(e) and figure 7(f)) and get absolute length of the vessel segments.

5 Conclusions

In this paper, we address the problem of the 3D reconstruction of coronary vessels by biplane snakes. To this purpose we rest on biplane snakes to deform in space adjusting its projections to the vessels in the angiography. We show that gain of 3D reconstruction by biplane snakes is obtained in precision of measurements as well as time of computation due to the reduced user interaction. Tests on 3D reconstruction of computer-generated phantoms show that the biplane snake meaningfully reduces the reconstruction error in case of uncalibrated acquiring system. Tests on a wire phantom show that average error of length measurements is in the

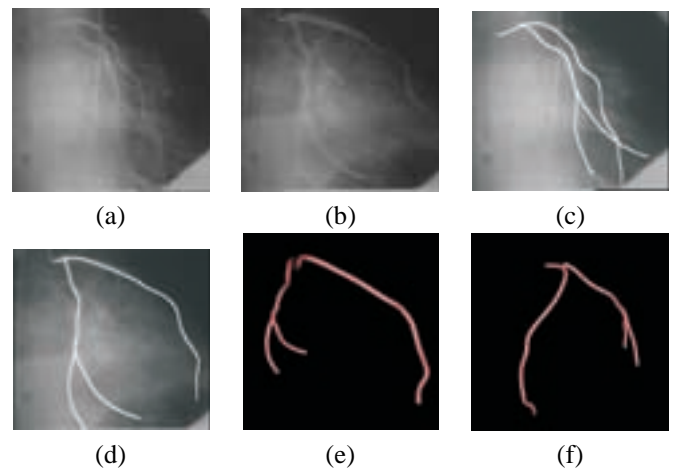


Figure 7. Reconstruction of left coronary main vessels of a patient.

permissible clinical limits. Finally, different tests on 3D reconstruction of real vessels are carried on and validated by a physician team.

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