Efficient Reconstruction of Coronary Vessels from 2D Angiography

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SUMMARY

The recovery of three-dimensional (3D) object information from biplane CT angiographic images is still a challenge in application of modelling coronary vessel trees. The proposed method of 3D reconstruction is obtained from the two-dimensional (2D) corresponding feature points by using triangulation projection based on the rotated mechanical angles of the CT angiographic machine. Those 2D feature points are on the centrelines of vessels. This research also includes how to extract the interested coronary vessels from CT angiographic images and how to represent those vessels as a group of connected 2D points that are on centrelines of them. One of the contributions in the paper is that we developed automatic searching algorithm to obtain the 2D corresponding points from a pair of biplane skeleton images under the two constraints of epipolar lines and corresponding bifurcations. We apply the Lucas-Kanade optical flow algorithm to register the corresponding bifurcations from an image sequence for the application of the proposed searching algorithm. The 3D reconstruction applies the readings of rotated mechanical angles and isocentre of the CT angiographic machine (Siemens Axiom) to establish the biplane image relationships of rotation and translation, and then projects the 2D centrelines of coronary vessels onto 3D world coordinates. Another contribution of the paper is that we apply the back projection algorithm to project the 3D points onto 2D image planes for evaluating the accuracy of the 3D reconstruction. The proposed method has been tested on patient data.

Key Words: *3D reconstruction, biplane angiographic image, coronary vessel.*

1 INTRODUCTION

Coronary vessel disease is one of the main causes of death in the world. The technique of coronary angiography is the conventional method to diagnose coronary disease. The research on 3D modelling of coronary vessels from CT biplane angiographic images has been carried out for many years, e.g. [5, 6, 4]. Many researchers have developed different methods to establish accurate 3D model of coronary vessels from biplane CT angiographic images, e.g. [3, 11]. However, the recovery of 3D object information from biplane CT angiographic images is still a challenge in application to 3D modelling coronary vessels. The main task of 3D reconstruction from biplane angiographic images is to produce a 3D model of coronary vessels with accurate geometrical information. The centrelines of coronary vessels used to reconstruct 3D model are helpful in accurate estimation of geometrical information of the coronary vessels since they can reduce the error of 3D reconstruction which may be caused by, for instance, the deformation of coronary vessels along the cardiac cycle [11]. Skeleton image algorithms can be used to extract the centrelines of vessels [1]. A medial axis extraction algorithm [10] has also shown to be useful to produce centrelines of coronary vessels from the vessel segmentation results since it is effective to identify clearly the medial axis of vessels without complex pruning processes.
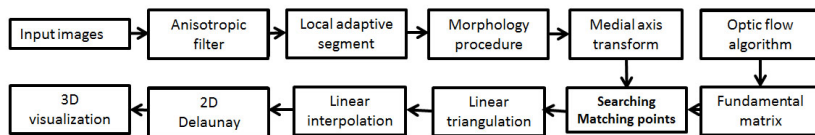
Figure 1: The procedure of the proposed 3D reconstruction.

In this paper, we present a method of 3D reconstruction based on triangulation projection, combined with output from the mechanical rotations and imaging information of the CT machine. One of the contributions in the paper is the development of an automatic searching algorithm that can find the corresponding points from a pair of biplane skeleton images based on the constraints of epipolar lines and two neighbour bifurcations. Anther contribution is that we use the Lucas-Kanade optical flow algorithm to search the corresponding bifurcations from an image sequence for the application of the proposed searching algorithm. Moreover, a new procedure of morphological operations was designed for the application. We developed the back projection algorithm from 3D to 2D for evaluating the accuracy of the proposed 3D reconstruction.

2   IMAGING INFORMATION

A Siemens Axiom CT biplane angiographic machine was used to capture the patient data. The gantry motions are characterised by the angle values of CRA/CAU (Cranial/Caudal) and LAO/RAO (Left/Right Anterior Oblique). Each pair of biplane images has the fixed cardiac phase in a pair of angiographic sequences. The corresponding image distance (SD) between the x-ray source and the image intensifier, patient distance (SP) between the X-ray and the patient position, field of view (FOV) and two gantry orientations were automatically recorded and stored with each image file. All of the captured sequences have the imaging resolution of 512×512 pixels with the pixel size of 0.27799 mm.

3   CENTRELINE EXTRACTION

The whole procedure of 3D reconstruction is illustrated in Figure 1. A number of low level image processing algorithms are involved, including anisotropic diffusion, improved local adaptive thresholding algorithm, morphological process, and medial axis extraction. First we apply anisotropic diffusion to remove image noise. This selected approach [9] is a modification of the linear diffusion. We apply four neighbour directions (up, down, left and right) to calculate the anisotropic diffusion of angiographic images. Next, we segment the images based on local adaptive thresholding. This algorithm produces good segmentation for images with uneven illumination distribution. The thresholding algorithm in [2] uses the local mean and the standard deviation of each pixel to compute local threshold. We add local curvature measurement as another constraint to compute the local threshold. Noise in images is assumed to correspond to high curvature. We also remove redundant boundaries at the beginning of calculation as prior knowledge. The, morphological operations are carried out to connect the segments. We apply the dilate operation five times with the 3×3 window first and then use erosion operation three times with the same window size. Finally, we apply close operation two times with the same window size. This morphology procedure not only connects some broken segment areas but also removes small segment areas. The centrelines of vessels are then obtained by using the medial axis extraction algorithm detailed in [10]. In the stage, we not only remove redundant pixels from the segment result but also produce a clean and complete vascular tree for 3D reconstruction. The Figure 2(b) shows an example of the skeletons of vessels resulted from the medial axis extraction.
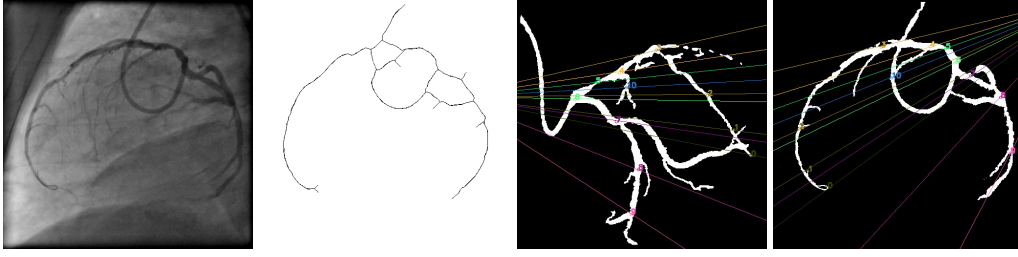
Figure 2: (a) the original image; (b) the skeleton result; (c) and (d) a pair of segmentation results that are labelled the corresponding epipolar lines and bifurcations
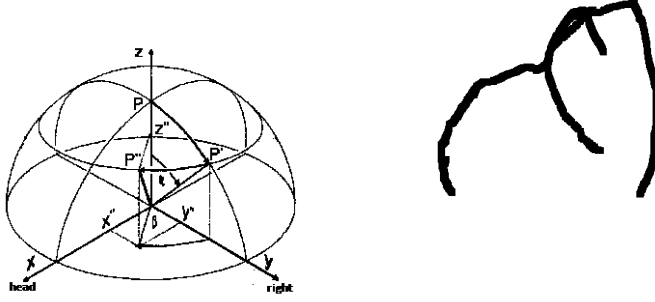

Figure 3: (a) the biplane coordinate; (b) the 3D reconstruction on a view angle.

4 3D RECONSTRUCTION

Here, present an algorithm for searching corresponding points from a pair of biplane skeleton images. We use epipolar lines and two-neighbour bifurcations as the searching constraints. We selected bifurcations manually on the first pair of biplane images. We then applied the Lucas-Kanade optical flow algorithm [8] to determine those bifurcations on their neighbour frames from the biplane sequences. After obtaining those bifurcations from a pair of biplane images, we use the eight-point algorithm [7] to calculate the fundamental matrix of the pair of images. The fundamental matrix is applied to produce epipolar lines on the pair of images. Under the above two constraints, the proposed searching algorithm can find the corresponding points robustly from a pair of biplane skeleton images. Figures 2(c) and 2(d) shows a pair of segmentation results that are labelled with the corresponding epipolar lines and bifurcations.

For reconstructing the centrelines in 3D, we utilise the triangulation projection algorithm, which is based on the output from the CT angiographic machine. First, we define the 3D coordinate in world space to be $P = [X, Y, Z, 1]$ and its corresponding image coordinates to be $p_{1,2} = [u_{1,2}, v_{1,2}, 1]$, which denotes CRA/CAU view and RAO/LAO view respectively. Second, we use the cone camera model and define the camera matrix, A_1 and A_2, relating to the biplane images respectively as,

$A = \begin{bmatrix} SD & 0 & C_x \\ 0 & SD & C_y \\ 0 & 0 & 1 \end{bmatrix}$ where SD is the distance from X-ray source to image intensifier,

and (C_x, C_y) denote the principal point of the camera, which can be computed through either camera calibration or the imaging centre point as the estimated value. We obtain the image scalars, defined as S_1 and S_2, the ratio between SP and SD from the corresponding image files. From the perspective projection and the linear transformation from 3D world coordinate system to 3D camera coordinate system. They can be formulated as follows:

$$S_1 \times [u_1, v_1, 1]^T = A_1 \times [R_1|T_1] \times [X, Y, Z, 1]^T \tag{1}$$
$$S_2 \times [u_2, v_2, 1]^T = A_2 \times [R_2|T_2] \times [X, Y, Z, 1]^T$$

where the matrices $[R|T]$ are established by the rotation matrix and translation vector of CRA/CAU

view and RAO/LAO view respectively. That is, we use the readings of the gantry rotations of the CT machine to compute $[R|T]_2$, which is corresponding to $[R|T]_1$ as the original orientation and the original point of the world coordinate. We define (α_1, β_1) and (α_2, β_2) to denote the readings of LAO/RAO, and CRAN/CAUD gantrys rotations respectively. The solutions of rotation matrix R_2 and translation T_2 vector in the equation (2) can be derived by

$$R_2 = R_x(\alpha_2) \times R_y(\beta_2) \times R_y(\alpha_1) \times R_x(\beta_1) \tag{2}$$
$$T_2 = R_2 \times [0, 0, I_{so}]^T + [0, 0, I_{so}]^T$$

where I_{so} denotes the isocentre distance of the gantry system obtained from the CT machines specification, and R_x and R_y in a right-hand coordinate shown on the Figure 3(a) can be described below:

$$R_x(\phi) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & cos\phi & -sin\phi \\ 0 & sin\phi & cos\phi \end{bmatrix} \qquad R_y(\phi) = \begin{bmatrix} cos\phi & 0 & -sin\phi \\ 0 & 1 & 0 \\ sin\phi & 0 & cos\phi \end{bmatrix} \tag{3}$$

Linear triangulation method is used:

$$\begin{bmatrix} (a_1^i - u_i \times a_3^i)^T \times R_i \\ (a_2^i - v_i \times a_3^i)^T \times R_i \end{bmatrix} \times P^T = \begin{bmatrix} (u_i \times a_3^i - a_1^i)^T \times T_i \\ (v_i \times a_3^i - a_2^i)^T \times T_i \end{bmatrix} \tag{4}$$

where the a_j^i is the jth row of the camera matrix A_i. An example result is shown in Figure 3. We applied the back projection algorithm from 3D to 2D to test the accuracy of the 3D reconstruction. We obtained the average error of 4.169 pixels for the example shown here.

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