AUTOMATIC EXTRACTION AND 3D VISUALIZATION OF CORONARY ARTERIES FROM ANGIOGRAPHY SEQUENCES

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ABSTRACT

In this work we explore the feasibility of reconstructing 3D information of coronary arteries and their lesions from coronary angiography sequences. The angiographies were taken during the examination of the vessels with an uncalibrated camera. The camera is still and we assumed that natural movement of arteries is large enough to create the change of view necessary for a stereo effect. We execute an automatic extraction algorithm for the arteries, then we aligned the consecutive pairs of the sequence and finally we used a correlation algorithm to obtain a dense disparity map to finally reconstruct the 3D model of the coronary arteries and their lesions. This preliminary study indicates that this approach could provide a simple way to extract 3D information of the coronary arteries without the use of a stereo image acquisition setup.

KEY WORDS

Coronary angiography, automatic extraction, 3D reconstruction, uncalibrated stereo system.

1. Introduction

Ray X angiography is the classical way to visualize the coronary arteries. These two dimensional projections grouped in sequences where the patient is breathing, are obtained after an invasive catheterization process. The sequence is unique since it is taken with a single view acquisition system, while with a biplane system there are two simultaneous acquisitions. The biplane angiography facilitates 3D modeling of arteries but it suffers of high costs because of the required devices. As a solution, it has been proposed to introduce the movement of the heart to achieve a 3D modeling from a single view angiography sequence.

Most of the works presented about 3D visualization of coronary arteries have been done with biplane systems [1], [2] and [3]; using rotational systems [4], [5]; with a single view system but strongly based in the camera calibration [6] or based in the prior information of the model [7].

The main purpose of this work is to explore the feasibility of reconstructing 3D information of coronary arteries and their lesions using a coronary angiography sequence taken with an uncalibrated camera. The 3D information of the arteries is useful for some cardiovascular illnesses diagnosis such as arterioscleroses. If demonstrated viable, such approach could provide a simple way to extract 3D coronary information without the use of a stereo image acquisition setup and taking advantage of the data presented in every acquired sequence. The camera is still and we assume that natural movement of the arteries caused by patient breathing and heart beating is large enough to create the necessary change of view for the stereo effect. This is important because the coronary angiography capture setup is not made originally for stereoscopic use. We selected those images from the angiography sequences where the contrasting agent is present in the main coronary tree and we preprocessed them for noise reduction. The extraction of the arteries (segmentation) is done automatically for every sequence using the curvilinear structures extraction from differential geometry of the image function approach [8]. We aligned the images with an affine transformation and we calculated the disparity map with an uncalibrated stereo approach [9]. Finally, we created the 3D model of the main artery and other 3D model exclusively of the lesion. Figure 1 shows a general diagram of the proposed method.
This paper is organized as follows. In section 2, we present the set of acquired sequences. Section 3 describes the automatic extraction of arteries approach used for the different sequences. In section 4 we show the algorithm used to calculate the disparity map. Finally, in section 5 we present the results obtained followed by our conclusions and future work.

2. Image acquisition

We used 10 different sequences of coronary angiography of 4 patients with stenosis A type. The images were digitalized directly from the acquisition system of the single view angiographer in DICOM format with a 512 x 512 resolution and 256 values in gray scale. In table 1 we show some examples of the acquired images. Because of the breathing of the patient and the heart beating, there is a natural movement in the arteries during the acquisition process. The extrinsic parameters of the camera (location and orientation) and the intrinsic parameters (focal length, center coordinates of the camera with respect to a reference frame, and pixel size) are unknown, therefore the images are uncalibrated. In figure 2 we show 5 images of one sequence.

The time difference between two consecutive frames is not uniform because the fluorescence evolution in the arteries is not linear. The angiographer captures more images at the beginning of the sequence than at the end. Finally, we made a selection of images suitable for the extraction process, eliminating those where the contrasting agent was appearing and disappearing.

3. Arteries automatic extraction

In order to start the segmentation stage or arteries extraction in an automatic way, we made a preprocessing that consisted on an enhancement of the image followed by the application of some low pass filters to reduce the noise present in the background caused by anatomical structures like the column and heart tissue. The image enhancement phase consists on illuminating the dark zones, and making darker the illuminated ones, for each pixel in the image the new value is given by equation 1.

\[
\text{new} = \text{round}((\text{val} - \text{mean}) \times \text{factor} + \text{orig})
\]  

(1)
where the factor is established in relation to the size of the convolution mask and mean is the average value of the mask.

The smoothing process was made using a convolution of the image with low pass filters like arithmetic median described in equation 2 and the gauss filter given by equation 3. The median filter works by means of definition of an average on the n x n neighborhood of the window. In this case, we applied the arithmetic median filter which calculates the arithmetic median of the window pixels using equation 2.

\[ Ma = \frac{1}{nm} \sum_{(x, y) \in W} f(x, y) \]  

where \( nm \) is the number of pixels in the window \( W \) of \( n \times m \) dimensions. The arithmetic median filter smoothes the local variations inside each image, so it could be implemented by means of a convolution mask where coefficients of the mask are \( 1/nm \). The Gauss filter [10] works by means of a 2D Gaussian kernel with median \( 0 \) and standard deviation \( \sigma \).

\[ G(i, j) = e^{-\frac{(i^2+j^2)}{2\sigma^2}} \]  

In figure 3 we show the results of applying this preprocessing to the original images.

![Original and processed images](image)

Fig. 3. a) Original image of patient 1 b) processed image of patient 1, c) original image of patient 3, d) processed image of patient 3. Notice the new brightness distribution.

Once we made the images preprocessing, we chose the approach of extracting curvilinear structures from the differential geometry of the image function for the segmentation stage. This was done based on the literature about segmentation methods applied to this kind of images [11]. The curvilinear extraction method allows obtaining the skeleton of the main ramification and their extremities because of the multi-scale approach that it uses. We applied the algorithm proposed in [12], where lines in 1D are considered as bar-shaped. It is assumed that an ideal line of width \( 2w \) and high \( h \) has a profile given by equation 4.

\[ f_L(x) = \begin{cases} h, & |x| \leq w \\ 0, & |x| > w \end{cases} \]  

Nevertheless because of the sampling effects it is considered that lines have a parabolic profile approximately given by equation 5.

\[ f_p(x) = \begin{cases} h(1 - (x/w)^2), & |x| \leq w \\ 0, & |x| > w \end{cases} \]  

The algorithm used [12] is based on the detection of lines for this profile. Because of existing noise in real images, the first and second derivates of the image \( z(x) \) should be estimated by convolving the image with the derivates of the Gaussian smoothing kernel given by equation 6.

\[ g_\sigma(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{2\sigma^2}} \]  

To detect salient lines, the magnitude of the second derivate \( z''(x) \) in the point where \( z'(x) = 0 \) is calculated. Bright lines on a dark background will have \( z''(x) \ll 0 \) while dark lines on a bright background will have \( z''(x) \gg 0 \). In 2D, curvilinear structures can be modeled as curves \( s(t) \) that exhibit a characteristic 1D line profile in the perpendicular direction to the line. Figure 4 gives an example of the results that can be achieved with the present approach. Here, dark lines were extracted from an angiography processed image. The preprocessing allowed reducing false arteries detection.

![Extracted centerlines of the main artery](image)

Fig. 4. Extracted centerlines of the main artery.

After we had the main centerline, we used a subpixel accuracy edge detection [13] to find all the edges of the coronary tree. This is illustrated in figure 5.
As a result we have the main artery extracted and represented in figure 6 with some noise removed from the edges.

In figure 7 we show some of the results obtained in the segmentation stage. The extraction process was applied to projections of the different patients. For almost all the images the arteries were correctly extracted (around 70%), only in some of them the process failed because of the lack of illumination in the image. However, these images were eliminated and the other ones were enough to continue with the next stage.

4. 3D reconstruction of the coronary arteries and their lesions

In this stage, we used an uncalibrated stereo approach. The temporal change between sequence images is equivalent to the two different positions obtained in a stereo system. Disparity vectors between images are established instead of motion vectors. Assuming a conventional stereo geometry, only scalar disparities could be established in a horizontal direction [14]. We performed two types of experiments. For the first one we used the entire image to reconstruct a coronary 3D model, and for the second one we selected the lesion from the image to obtain its 3D model, see figure 8.

Since stereo correspondence needs to have a rectified image pair, we aligned image pairs with an affine transformation. For this purpose the correspondence points between images were calculated with the Structure and Motion toolkit [15]. With this tool we used the Harris corner detector to find similar features between images and then we used the affine transformation to translate the images to the same y axis. Figure 9 illustrates the rectified images from figure 8.

With every rectified pair we tested a stereo correspondence algorithm based in a block matching approach. Block matching methods seek to estimate disparity at a point in one image by comparing a small region about that point (the template) with a series of small regions extracted from the other image (the search region). Three classes of metrics are commonly used: correlation, intensity differences and rank metrics [16].
We chose the Normalized Cross Correlation (NCC) as correspondence method which is the standard statistical method for determining similarity. This metric is given by equation 7.

$$\sum_{u,v} (I_1(u,v) - \bar{I}_1 \cdot (I_2(u + d,v) - \bar{I}_2))$$

\[
\frac{\sum_{u,v} (I_1(u,v) - \bar{I}_1)^2 \cdot (I_2(u + d,v) - \bar{I}_2))^2}
\]

where $I_1$ and $I_2$ represent the corresponding sample means.

The calculated disparity map gives an estimation of the depth in the model, so the next step was to interpolate the image with this map to create the 3D model. We chose to create all the models in the VRML format.

5. Results and Conclusion

Results

We obtained 3D models of the main coronary ramifications and also 3D models of particular lesions. All the models were created for VRML visualization because it could be read in any explorer and it could be integrated in almost any system. The models were also created in VTK format, which offers tools to continue with this work. Figures 10 and 11 show the 3D models for the main coronary ramification and a particular lesion respectively.

![Fig. 10. 3D model in VRML of the main coronary tree presented in sequence 1 of patient 1, a) lateral view b) front view.](image)

![Fig. 11. 3D model in VRML of the lesion presented in sequence 2 of the right artery from patient 3.](image)

Future work

Currently we are integrating the 3D models of lesions from a sequence, that is, we are applying the ICP algorithm (iterative closest points) from the created 3D models of each pair of images of every patient using VTK [17]. This allows us to identify the correspondence between points of the models and take them to the same coordinate system, all of this to optimize the visualization of the current model. Another work in progress is the evaluation of certain basic features that could be extracted from our model, such as volume, curvature and morphology to take more advantages from the 3D model beyond visualization.

Conclusion

This method offers the advantages of using a well known stereo approach, without the necessity of having all its initial setup and the prior information about the model. Another advantage, according to the specialist point of view, is that we achieve a relative depth of the injured segment which allows identifying in a better way (compared to 2D projections) whether the lesion is concentric or not and the lesion’s percentage of obstruction. As disadvantages we have a lack of information to detect overlapping of vessels and existing occlusions. Even though, this problem could be solved using a labeling method of the arteries proposed in [18].

From the medical point of view, the contribution of the 3D visualization achieved in this research could be seen in different ways. Firstly, the visualization of the lesion in a 3D model facilitates the creation of a mental conception that helps the physician to diagnose the patient and gives a spatial impression in a more natural way than the one given by radiography. Besides, the 3D model can be rotated, zoomed and cut in an arbitrary and interactive way. A second application is achieved because of the mode of virtual visualization in X-ray. With this, it is possible to rotate a model of the pathology to an optimal point of view to acquire the scene with these rotation and translation angles with the angiographer device.
Finally, as stated before, it could be possible to generate a quantitative measure, related to the state of health of the arteries that most of the times indicates the severity of several illnesses.

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References


