

Angiographic Images Segmentation Techniques

Francisco J. Nóvoa

University of A Coruña, Spain

Alberto Curra

University of A Coruña, Spain

M. Gloria López

University of A Coruña, Spain

Virginia Mato

University of A Coruña, Spain

INTRODUCTION

Heart-related pathologies are among the most frequent health problems in western society. Symptoms that point towards cardiovascular diseases are usually diagnosed with **angiographies**, which allow the medical expert to observe the bloodflow in the coronary arteries and detect severe narrowing (**stenosis**). According to the severity, extension, and location of these narrowings, the expert pronounces a diagnosis, defines a treatment, and establishes a prognosis.

The current modus operandi is for clinical experts to observe the image sequences and take decisions on the basis of their empirical knowledge. Various techniques and **segmentation** strategies now aim at objectivizing this process by extracting quantitative and qualitative information from the **angiographies**.

BACKGROUND

Segmentation is the process that divides an image in its constituting parts or objects. In the present context, it consists in separating the pixels that compose the coronary tree from the remaining “background” pixels.

None of the currently applied **segmentation** methods is able to completely and perfectly extract the vasculature of the heart, because the images present complex morphologies and their background is inhomogeneous due to the presence of other anatomic elements and artifacts such as catheters.

The literature presents a wide array of coronary tree extraction methods: some apply pattern recognition

techniques based on pure intensity, such as **thresholding** followed by an analysis of connected components, whereas others apply explicit vessel models to extract the vessel contours.

Depending on the quality and noise of the image, some **segmentation** methods may require image pre-processing prior to the **segmentation** algorithm; others may need postprocessing operations to eliminate the effects of a possible oversegmentation.

The techniques and algorithms for vascular **segmentation** could be categorized as follows (Kirbas, Quek, 2004):

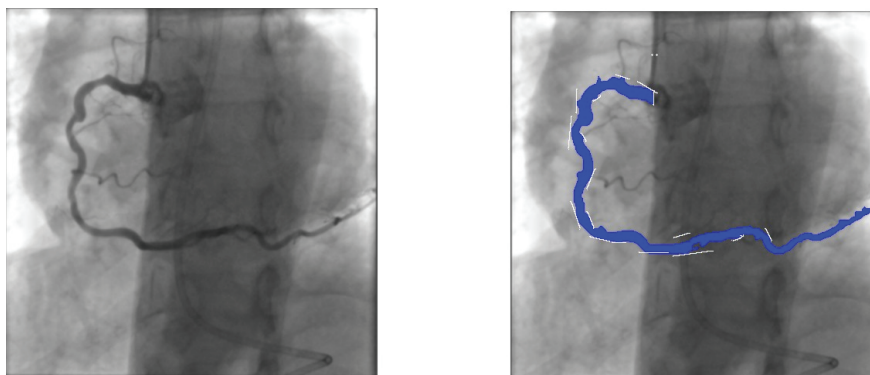
1. Techniques for “pattern-matching” or pattern recognition
2. Techniques based on models
3. Techniques based on tracking
4. Techniques based on artificial intelligence
5. Main Focus

This section describes the main features of the most commonly accepted coronary tree **segmentation** techniques. These techniques automatically detect objects and their characteristics, which is an easy and immediate task for humans, but an extremely complex process for artificial computational systems.

Techniques Based on Pattern Recognition

The pattern recognition approaches can be classified into four major categories:

Figure 1. Regions growth applied to an angiography



A

Multiscale Methods

The multiscale method extracts the vessel method by means of images of varying resolutions. The main advantage of this technique resides in its high speed. Larger structures such as main arteries are extracted by segmenting low resolution images, whereas smaller structures are obtained through high resolution images.

Methods Based on Skeletons

The purpose of these methods is to obtain a *skeleton* of the coronary tree: a structure of smaller dimensions than the original that preserves the topological properties and the general shape of the detected object. Skeletons based on curves are generally used to reconstruct vascular structures (Nyström, Sanniti di Baja & Svensson, 2001). Skeletonizing algorithms are also called “thinning algorithms”.

The first step of the process is to detect the central axis of the vessels or “centerline”. This axis is an imaginary line that follows each vessel in its central axis, i.e. two normal segments that cross the axis in opposite sense should present the same distance from the vessel’s edges. The total of these lines constitutes the skeleton of the coronary tree. The methods that are used to detect the central axes can be classified into three categories:

Methods Based on Crests

One of the first methods to segment angiographic images on the basis of crests was proposed by Guo and

Richardson (Guo & Richardson, 1998). This method treats **angiographies** as topographic maps in which the detected crests constitute the central axes of the vessels.

The image is preprocessed by means of a median filter and smoothed with non-linear diffusion. The region of interest is then selected through **thresholding**, a process that eliminates the crests that do not correspond with the central axes. Finally, the candidate central axes are joined with curve relaxation techniques.

Methods Based on Regions Growth

Taking a known point as seed point, these techniques segment images through the incremental inclusion of pixels in a region on the basis of an *a priori* established criterion. There are two especially important criteria: similitude in the value, and spatial proximity (Jain, Kasturi & Schunck, 1995). It is established that pixels that are sufficiently near others with similar grey levels belong to the same object. The main disadvantage of this method is that it requires the intervention of the user to determine the seed points.

O’Brien and Ezquerro (O’Brien & Ezquerro, 1994) propose the automatic extraction of the coronary vessels in angiograms on the basis of temporary, spatial, and structural restrictions. The algorithm starts with a low-pass filter and the user’s definition of a seed point. The system then starts to extract the central axes by means of the “globe test” mechanism, after which the detected regions are entangled through the graph theory. The applied test also allows us to discard the regions that are detected incorrectly and do not belong to the vascular tree.

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