

**Figure 2.12:** Three consecutive angiography image frames (up to down, left to right).

w as not available at a reasonable price, so digital angiographic systems were mostly limited to the on-line review of single patient exams.

### 2.1.2 Advantages of Digital Imaging

The introduction of digital angiographic imaging systems brought many advantages to the practice of cardiac catheterisation. The ability to rapidly recall and play back digital image sequences (figure 2.12) enables the cardiologist to review injection sequences while the patient is still on the examination table. This capability often permits diagnostic and therapeutic catheterisation to be carried out in a single procedure, since it is not always necessary to wait for the film development process to review and diagnose the acquired images. Also, the availability of on-line analytical image processing tools enables the rapid assessment of the efficacy of therapeutic

procedures such as angioplasty (PTCA), and the optimal selection of interventional devices such as the sizing of balloons for dilatation or the selection of intracoronary stents. In addition, digital image processing techniques facilitate the possibility to enhance the acquired images on-line, providing features such as contrast enhancement, noise reduction, and digital zooming of selected regions of interest. Despite the quality of these existing tools, they are all for local analysis in the sense that they are used to process a small portion of a vessel. None of them are able to study the vessel movements and are unable to cover a global tree assessment.

Despite the many advantages of digital image acquisition, there were still a number of technical issues that remained to be solved in order for a fully digital catheterisation laboratory to become a practical reality. The most critical issue was the replacement of the 35-mm cinefilm standard with a digital medium capable of fulfilling the same role as archival and exchange medium. As digital systems were being introduced into the marketplace, several competing solutions were offered by manufacturers and adopted by clinicians, resulting in incompatibilities between acquisition systems. The 35-mm cinefilm, which had been universally accepted and supported as exchange medium, did not yet have a digital counterpart. During the transition period between film and digital systems, many manufacturers offered systems, which supported both acquisition methods simultaneously. This gave cardiologists the advantages of on-line digital acquisition with the flexibility of 35-mm cinefilm for exchange and archival. The high cost of film development, and the promise of cheaper digital archival media however, resulted in the installation of many cine-less acquisition systems. In some cases, analogue Super-VHS tape was used as the sole archival and exchange medium. Although this format is common, and can be used for the exchange of patient images between centres, the resulting image quality is very poor. Due to the limited bandwidth of videocassette recorders, and the lower resolution and poor signal to noise ratio of the recorded images, these video tapes are inadequate for clinical decision making, and are unacceptable to most quantitative coronary arteriography (QCA) core laboratories. Other solutions to replace cinefilm as archival and exchange medium for angiographic image sequences included digital videotapes, videodisks, and magneto-optical disks. The use of these media complicated the exchange of patient data between centres though, since the availability of hardware to read these media was limited. In addition, the large variety of logical media formats, and differences between digital image file formats and computer hardware architectures limited the use of these media for archival purposes within one institution only. A digital exchange medium for the transfer of patient data between hospitals, and for use in multi-centre clinical trials was still missing.

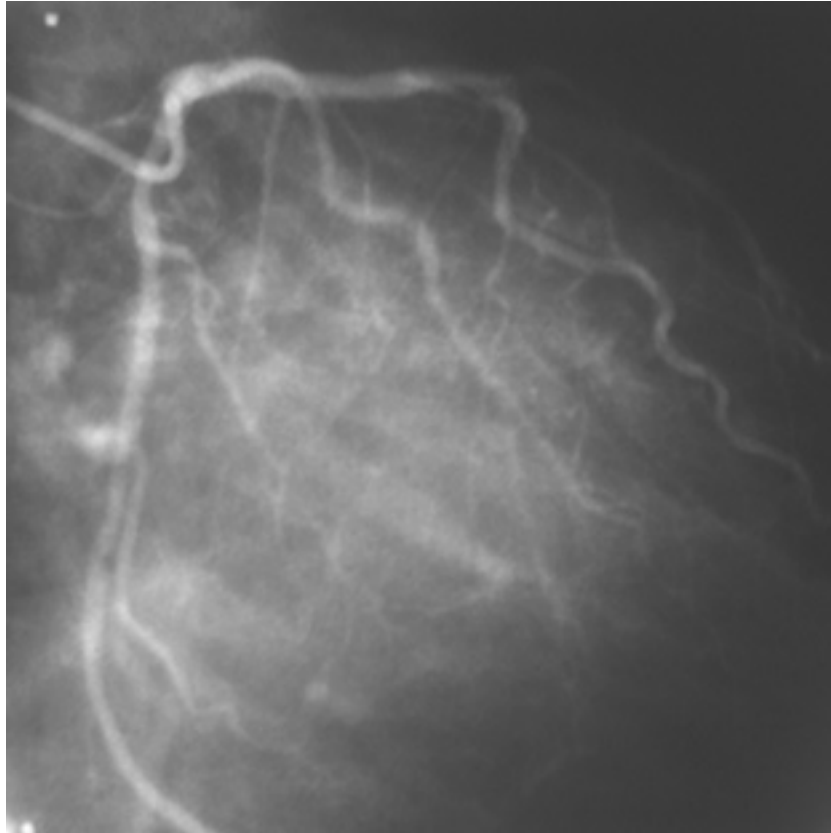
## 2.2 Typical structure of a computer vision system for angiography

The main areas of research in cardiac image analysis in the past 15 years were on geometric and densitometric methods to automate quantitative analysis of coronary arteriograms. The first steps were for assessment of coronary lesion severity in individual segments followed by a growing interest in automated identification and analysis of the entire coronary tree. Over the last few years the attention has directed to research towards three-dimensional reconstruction from biplane projections [34, 42, 39, 77]. Reiber et al. have developed methods for quantitative analysis of stenosis [87]. Sonka et al in [98] have made better measurements on small vessels. Recently, research activities have gone to multimodality imaging fusion. Using new techniques, researchers are trying to match images coming from different equipments. For example, Prause et al. [77] combine data from angiography and intravascular ultrasound images (IVUS) to assist in many measurements and reconstruction tasks.

Despite of the increasing quality of the imaging equipment, the image quality poses a lot of difficulties from a computer analysis point of view. Congenital diseases lead to special topologies (malformation) of the vessel tree. The noise level and artifacts remain high and a fully automatic analysis tool has not been reported. Several methods have been proposed but all of them require user intervention in some degree. All of these research tasks have many common aspects from imaging device characterization up to vessel border detection.

### 2.2.1 Image pre-processing

Image pre-processing includes mask subtraction, background filtering and enhancement of the vascular structures. Some pre-processing is done directly by the imaging equipment (Philips, Siemens and other manufacturers offers images previously enhanced) other after the acquisition process. Among the pre-processing after acquisition, there are three main tasks: contrast enhancement, illumination correction and noise reduction. At this point most authors use well-known algorithms. For contrast enhancement a pixel re-scaling is commonly applied, light correction, when necessary, is carried out by some kind of weighted background subtraction or look-up table modifications and finally noise reduction is carried out using low-pass filtering and to reduce salt and pepper a median or wiener filter is applied. A good survey on image pre-processing and the associated data structures can be found in [97]. In [63] there is an interesting survey on image enhancement in X-ray angiography for still images. Last generation equipment for coronary angiography almost eliminate the need of image pre-processing. The next step toward a computer analysis is information extraction. Figures 2.13 to 2.22 depict the differences between an image acquired from analog (old) equipment and another coming from a last generation angiographic equipment. For the sake of facilitating a detailed visualization, topographic maps are presented for both images. Moreover, a light correction and noise reduction pre-processing is showed for the analog image.

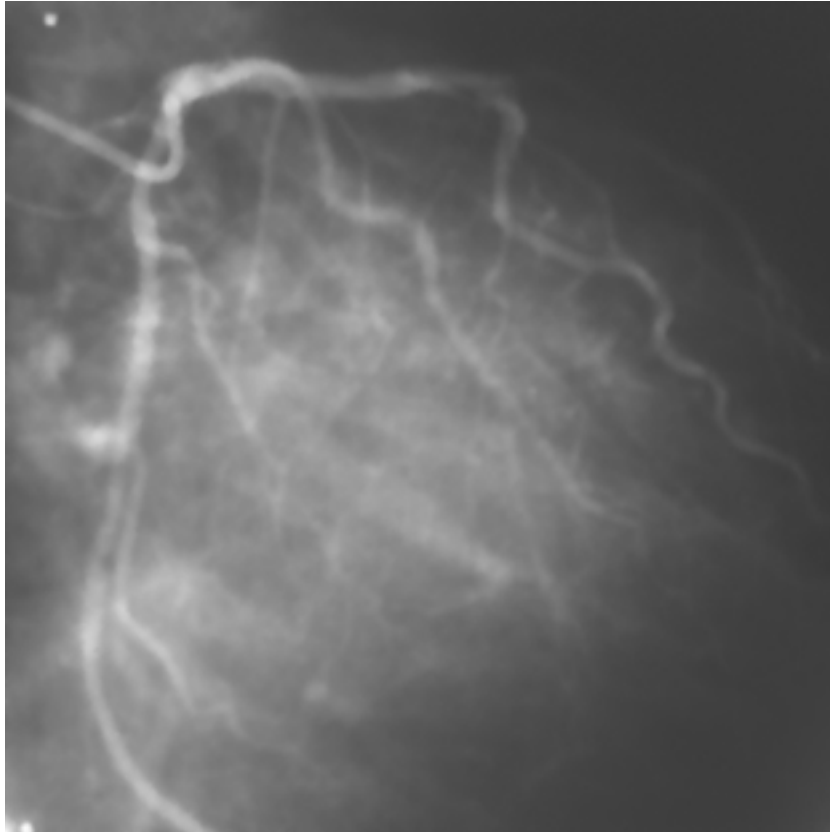


**Figure 2.13:** Angiography from an analog equipment.

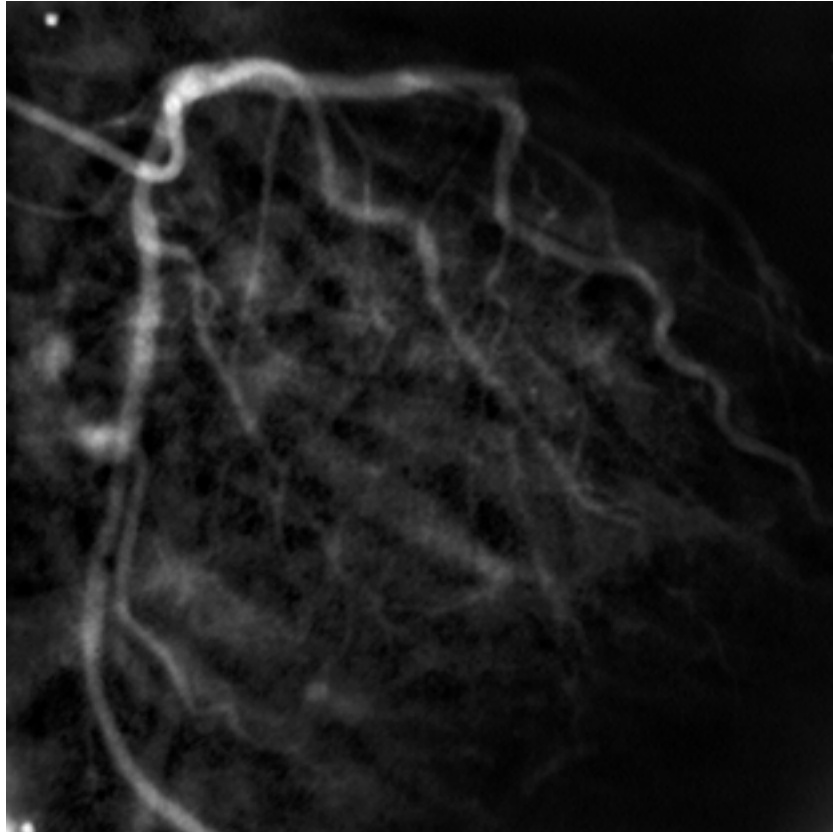
### 2.2.2 Vessel detection

Segmentation of the vessels is the starting point for vessel detection and analysis. Three main approaches to segment and label the vessels of the coronary tree have been reported.

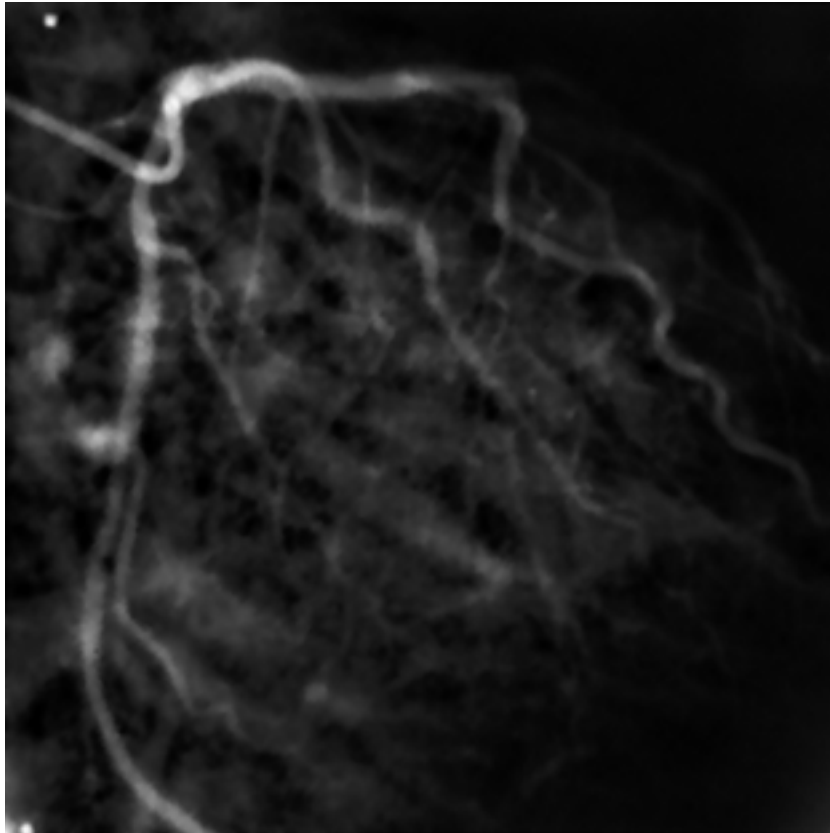
1. Scanning: consists of edge or ridge extraction usually by a mask convolution with the angiography (the whole image). A second step implies recognition of the vascular structure by chaining the centerline points while excluding heuristically noise points. Most of the reported image feature detectors are conventional. P olier et al. [76] use a Laplacian and a Gaussian, Zhang [117] uses a hat transform. Recently, ridge detector based on level-set theory has been used too [59]. Our experience with the ridge detectors revealed the presence of too much false responses.



**Figure 2.14:** Angiography from an analog equipment filtered.



**Figure 2.15:** Angiography from an analog equipment after light correction.



**Figure 2.16:** Angiography from an analog equipment after light correction and noise filtering.

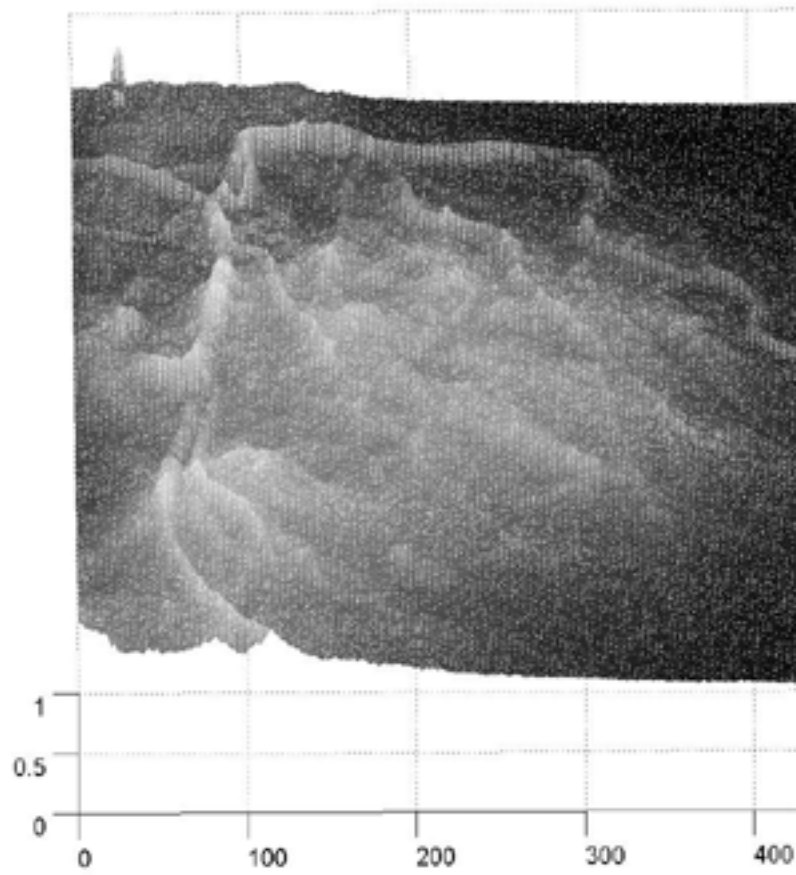


Figure 2.17: Topographic map of an angiography from an analog equipment.



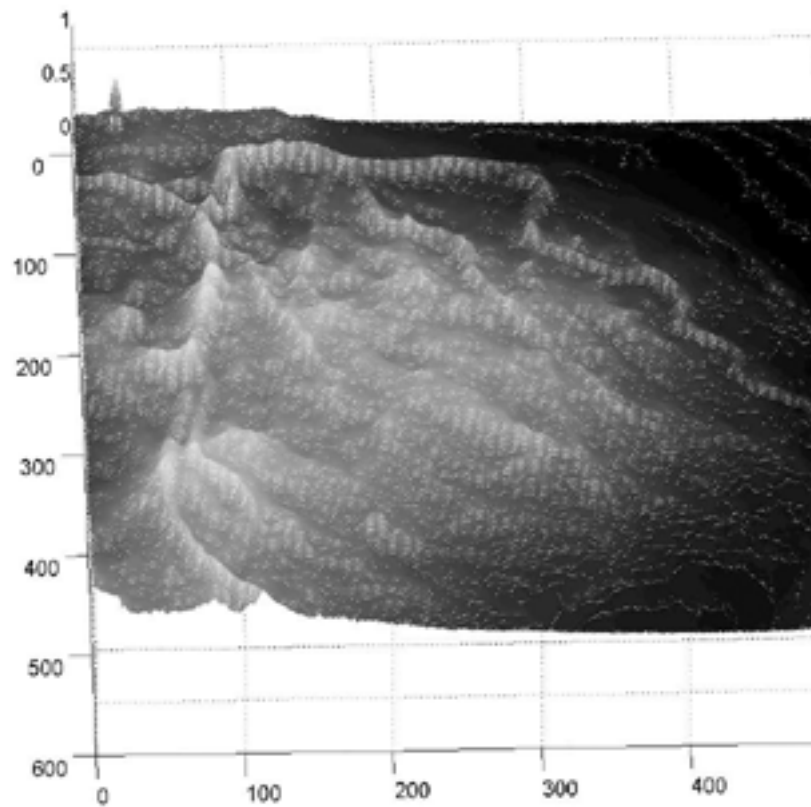
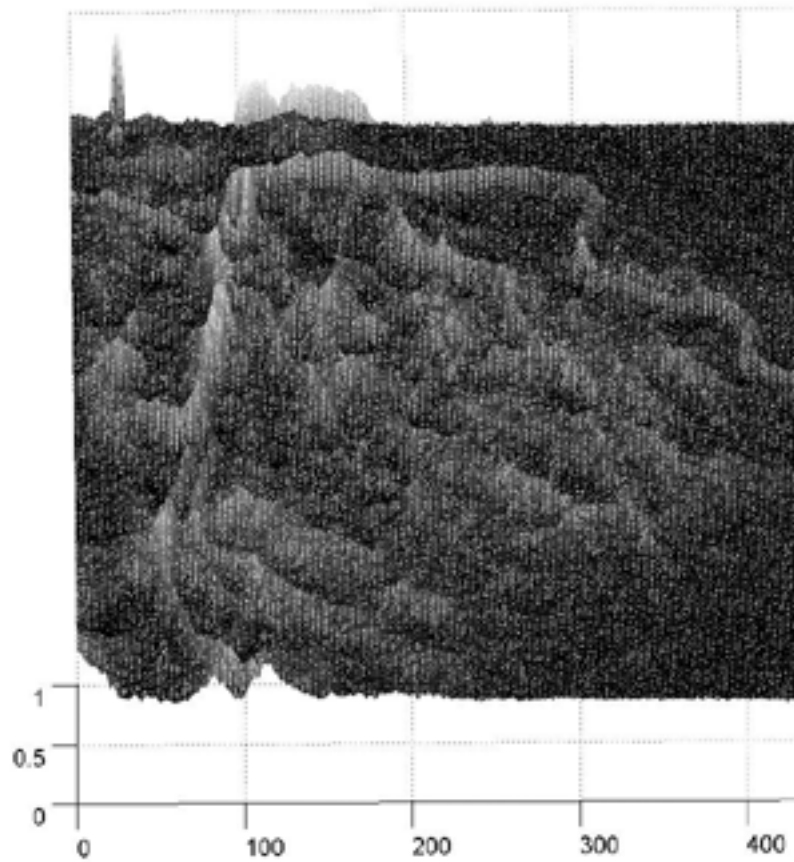
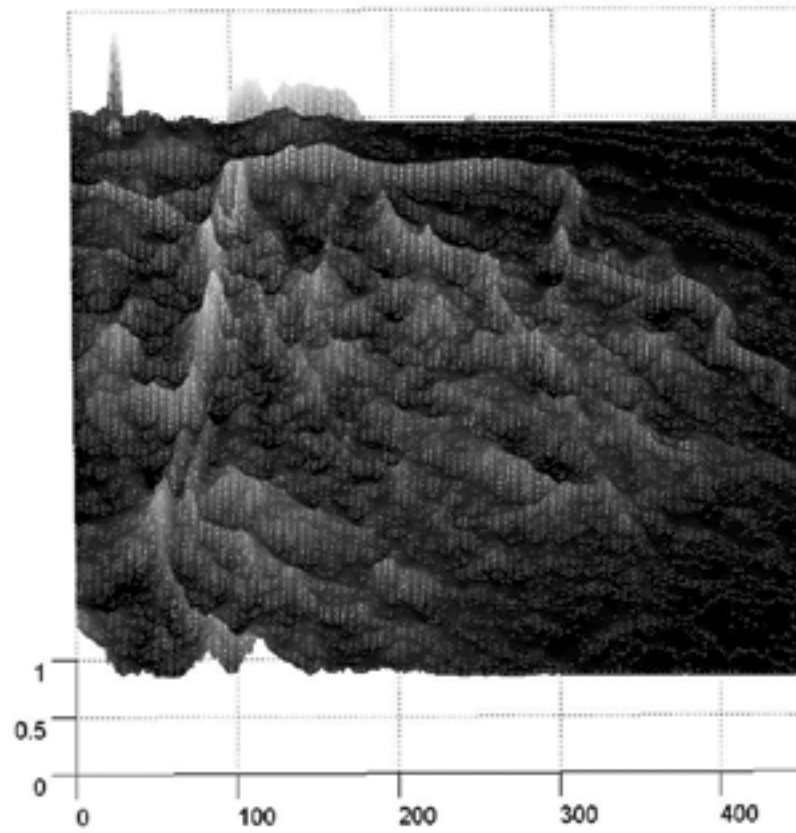


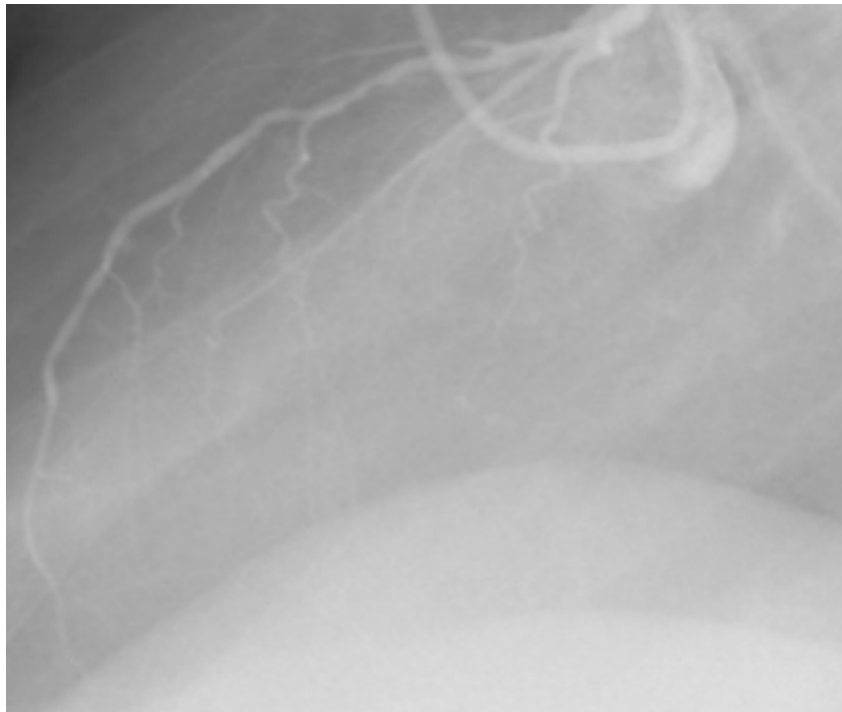
Figure 2.18: Topographic map of an angiography from an analog equipment filtered.



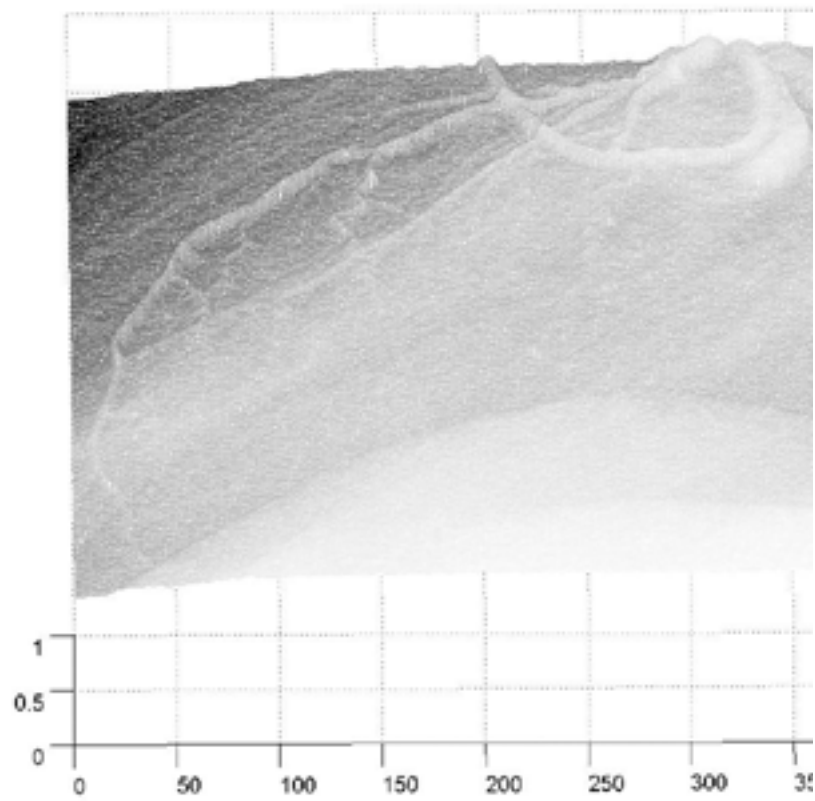
**Figure 2.19:** Topographic map of an angiography from an analog equipment after light correction.



**Figure 2.20:** Topographic map of an angiography from an analog equipment after light correction and noise filtering.



**Figure 2.21:** Angiography from a last generation equipment (digital).



**Figure 2.22:** Topographic map of an angiography from a last generation equipment (digital).

2. Tracking begins at an *a-priori* known position of the vessel in the image. In a single pass operation, feature extraction and vessel structure recognition are performed. By its own nature, a tracking strategy is computationally more efficient than scanning. In [101], Sun proposes the following strategy: given a starting point and direction, a line profile extracted some pixels ahead in that direction is used to compute the centerline of a vessel and a new forward direction for the tracking. Barth et al. [7] use a curve sampling profile instead of a straight line for tracking the whole tree. Dumay [34] uses a moving circle, image resampling and gray level profile information to track.
3. Knowledge-based approach. This approach comes from the fact that general approaches like the ones commented above have not given the expected results (for example, they are not able to discriminate the vessels accurately). Different authors [39, 100, 95] have done research based on expert systems as a way to recognize and/or reconstruct the vessels. Many of them used two projections and structural knowledge, while others rely on vessel models [69, 42]. To represent and manage the knowledge, embedded rule-based systems or custom models are used. Dumay represented the knowledge by graphs [34]. Rule-based systems use to be slow and difficult to tune.

The low-level image-processing techniques explained in the first two points use only local information, hence are error prone. Therefore, such techniques require considerable amount of expert intervention. Summarizing, segmenting structures from coronary angiography images and building a compact geometric representation of the vessels is difficult due to many factors. Complexity and variability of the anatomic shapes, shortcomings typical of sampled data such as sampling artifacts, spatial superposition, low image quality, etc. increase the ambiguities of image interpretation. These drawbacks lead authors to consider the addition of knowledge (third point) to obtain better results. Adding knowledge is achieved either by expert systems (ruled based systems) or using vessel models. All of them either use scanning or tracking methods as part of the low-level vessel segmentation process. Our approach is to use deformable models and statistical vessel descriptions to cope with the inherent difficulties to vessel detection in angiographic images.

### 2.2.3 3D reconstruction of coronary vessels

Angiography imaging devices lead to bidimensional representation of three dimensional organs (in our case coronary arteries). The images are obtained at an *a priori* point of view. 3D reconstruction of coronary vessels aims to obtain the three dimensional shape and dimensions from the bidimensional images. Gensini [40] showed that a 3D reconstruction from an orthogonal pair of digital subtraction angiography (DSA) images without using *a-priori* knowledge is impossible. Similarly, Sueten [100] concludes that automatic reconstruction from a stereoscopic pair by stereo matching is feasible but very difficult and could be significantly simplified using interpretation knowledge. Since then, many authors used different strategies to cope with this constraint. They used *a-priori* knowledge from mean approximation up to sophisticated

expert systems and vessel models. Dumay [34] uses conventional reconstruction theory with biplane angiograms and an arithmetic mean approximation to obtain the 3D vessel. The obtained spatial model is used to compute the best projection angles. In [18], Chen et al. follow a similar approach. Nguyen et al. in [69] use a model for the reconstruction of the skeletal structure of coronary arteries from a succession of frames of a single-view cineangiogram using assumptions about the vessel trajectories. This approach has the advantage that the vessel is reconstructed without a biplane acquisition system, being a fact that biplane systems are expensive and not always available. The authors model the heart as an expanding and contracting ellipsoid assuming invariant swapping angles. Using this model, they infer the 3D placement of the vessels.

When the reconstruction is obtained from static biplane images, a model of the heart is not necessary. However, a biplane acquisition system is very expensive and extra knowledge is still necessary to avoid ambiguities.

Both reconstruction techniques, from a single-view and from biplane-views, have common problems. They rely on accurate segmentation of the vessels to solve the matching between 2D points. Even using the support of epipolar geometry, it is not easy to obtain an optimal matching in the biplane case. Deformable models are also used for 3D reconstruction. Typically the user initializes the vessel model. Once located near the object of interest, it deforms into place. Users could then use the interactive capabilities of these models and manually fine-tune them. Furthermore, once the user is satisfied with the result on an initial image frame, the fitted contour model may then be used as the initial boundary approximation for neighboring frames. These models are then deformed into place and again propagated until all slices have been processed.

Radeva et al. [84] use the same technique (snakes) to optimise the correspondence problem reconstructing a vessel from angiographic images. In this work, the matching is done optimizing a whole curve instead of a set of isolated 2D points. The main difference regarding the methods explained above comes from the global curve processing, minimizing the errors produced on individual points. As stated above, all the methods add some knowledge to obtain a correct reconstruction, but in our case we try to also minimize the reconstruction uncertainty.

#### 2.2.4 Motion extraction and representation

Many different approaches to motion estimation are reported in computer vision. In [16] Blake et al develop a Kalman filter application together with a persistent template as shape subspaces configuring a framework for tracking visual contours. In [17], Blake and Isard show the use of B-spline curves to track contours restricting the shapes to affine transformations and also explains the use of principal component analysis (PCA) to the same aim.

The research contributions to the dynamics of the coronary tree are not very broad. Coatrieux et al. [21] combines motion estimation with frame-to frame structure detection. After detection of a vessel centerline the motion is estimated using a gradient based method. Ruan et al. [92] makes a 3D reconstruction of a moving arterial network from a pair of angiographic image sequence. After vessel centerline detection

the  $2D$  motion is estimated and then, the  $3D$  motion is reconstructed. Puentes et al. [80] describe the motion of coronary arteries in  $2D$  and  $3D$ . They define a set of motion features splitting the vessels in segments and transform the features into symbolic labels to provide information to a knowledge-based system.

We [106] propose a Kalman filter and snake approach. A semantic network was developed to make a static structural model. Then, to estimate the motion, the network uses a Kalman filtering device guided by the trajectory model. The vessel deformation is detected in an energy-minimization procedure applying the active contour model (snake) technique. A complete spatio-temporal description of the vessels (not just of sparse set of points) is obtained using a compact bi-dimensional B-spline representation where the movement of the vessel model is uniquely determined from the movement of the B-spline control points. In this two-dimensional B-spline dynamic model the directions determined by the iso-parametric curves correspond to the spatial and temporal vessel position, respectively.

## 2.3 Summary

The chapter has offered an anatomy description of the coronary tree, introduced the angiographic imaging as a technique used to deal with the coronary stenosis. Related with this image modality, the chapter has described the most used projections to obtain different views of the coronary arteries. A comparison between the analogue (older) and digital equipment is done, emphasizing the advantages of the digital imaging. Then the focus is directed towards the computer vision elements currently used to build computer assisted software systems for angiography imaging.



