Vascular modeling from volumetric diagnostic data: a review

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Abstract

Reconstruction of vascular trees from digital diagnostic images is a challenging task in the development of tools for simulation and procedural planning for clinical use. Improvements in quality and resolution of acquisition modalities are constantly increasing the fields of application of computer assisted techniques for vascular modeling and a lot of Computer Vision and Computer Graphics research groups are currently active in the field, developing methodologies, algorithms and software prototypes able to recover models of branches of human vascular system from different kinds of input images.

Reconstruction methods can be extremely different according to image type, accuracy requirements and level of automation. Some technologies have been validated and are available on medical workstation, others have still to be validated in clinical environments.

It is difficult, therefore, to give a complete overview of the different approach used and results obtained, this paper just presents a short review including some examples of the principal reconstruction approaches proposed for vascular reconstruction, showing also the contribution given to the field by the Medical Application Area of CRS4, where methods to recover vascular models have been implemented and used for blood flow analysis, quantitative diagnosis and surgical planning tools based on Virtual Reality.

Keywords: Vessel, CT, MRI, Segmentation, 3D

Introduction

Vascular imaging is been constantly improved by researchers and companies, providing clinicians and surgeons with a large amount of information, that must be understood and interpreted. Several modalities (i.e. CT, MR, Ultrasound and DSA angiography) allow nowadays the acquisition of morphological volumetric data that gives the possibility of recovering precisely structure, local direction and tortuosity of the vessels, information not recoverable through simple 2D imaging. One of the main key to allow an effective use of this information is to build from the data three dimensional geometrical models representing the vessels of interest.

Several techniques have been proposed for this task and it is difficult to present a simple classification of them. Authors, in fact, customize techniques for specific applications (navigation, measurement, simulation, simple visualization, etc.), usually requiring different kind of models with different accuracy (simple visualization usually requires triangulated surfaces without topology control, models to be measured must be closed surfaces with high detail, path planning may require only a curve skeleton reconstruction and so on).

Methods differ also for the required user interaction: algorithms designed for clinical use need a simple initialization, research systems may be more complex.

A very large amount of literature published in recent years on this field and it is honestly difficult to cite all the different methods proposed, so we will limit this review to an overview of the principal approaches and applications, giving only a few references for each category. We apologize with authors of missing important contributions.

We limit our analysis to sufficiently generic vessel lumen/centerline reconstruction methods working on 3D imaging of different types and, in the following sections, we present a short description of images used and reconstruction methods classified in a few groups: first those based on directional filtering in a complete region, then those based on region growing and deformable models, then methods based on contours and tubular structures and finally the most recent ones exploiting shape constraints methods

Additional sections are then dedicated to methods for the reconstruction of complex vascular models including not only lumen and/or curve-skeleton, but also the geometry of tissues around the lumen (i.e. thrombus, calcium) and on the contribution of the Bio Medical Applications Area of the Center of Research, Development and Superior Studies in Sardinia (CRS4) to this research field.

Before starting the survey of the methods applied, we spend also a few words to describe the images used as input data for the reconstruction and the data structure used to represent segmented vessels (sections 1,2).

1. Vascular imaging

3D digital acquisition of vessel structures can be performed in several ways. CT with contrast medium injection is perhaps the most popular method. Multi detector helical scanner allow a sub-millimeter resolution and can be used for the analysis of small vessels. Advantages of the method are non-invasivity, spatial resolution and wide availability.

MRI is also a popular 3D acquisition method. It also provide well contrasted images, even if at lower resolution. It has, however, some limits due to the fact that it should not be used on some patient classes and cannot show calcifications as CT. MRI presents also the possibility of providing functional information. Particularly interesting for vascular analysis is the possibility through phase-contrast imaging, of visualizing velocity information, that can be used in segmentation frameworks, as described, for example, in [1]. We will not describe these methods in the following.

Digital Subtraction Angiography has recently be used also for 3D imaging, allowing the reconstruction of the lumen with very high spatial accuracy. It is, however, a costly and invasive procedure and it is not widely available. Furthermore, it is usually not applied when the vessel is big like the aorta due to the quantity of contrast required and cannot be used when the vessel change shape during the cardiac cycle (like coronary arteries).

Ultrasound has been also recently used for the acquisition of 3D data. It is however not suitable for the reconstruction of accurate 3D models due to noise and motion effects and it is usually applied for dynamic analyses. Almost all the 3D reconstruction methods described in the following have been tested and applied on CT and MRI images.

2. Vascular modeling

Vascular reconstruction from a volume dataset can be performed in different ways and vascular models extracted with different techniques may be completely different. The simpler structure that can be used to represent the vascular lumen is a voxelized volume obtained through simple voxel classification: in the 3D grid representing the image acquisition sampling, points(voxels) belonging to the vascular structure of interest are labelled with a flag and differentiated from the background. This structure, usually obtained by simply thresholding the voxel values, does not, however, capture geometrical and topological properties of the vascular tree. Methods for the extraction of volumes/surfaces by thresholding voxel values are often implemented in diagnostic workstation. To visualize the 3D structure software tools extracts and display isosurfaces on the thresholded voxel set (for example with the Marching Cubes method [2]).

A more descriptive model to represent vascular networks and used by several authors consists of storing the vascular centerline (or curve-skeleton) into a well organized data structure.
The curve-skeleton [3] is represented by 1D lines, discretized as node chains, connected at bifurcations, with information associated to nodes like local radii and direction (Fig(1) B). If the vessel is thin and the morphology of the border is not relevant this representation may be sufficient for diagnostic and simulation purposes. For big vessels (i.e. the aorta or when the local shape is relevant (i.e. analysis of plaques, etc.) a more detailed wall model is usually necessary.

To represent the detailed model of the external surface of a vessel, authors use closed triangulated surfaces, or other geometrical structure like extrusions, generalized cylinders and splines. These representations allow the introduction of constraints on topology and curvature (Fig(1) C).

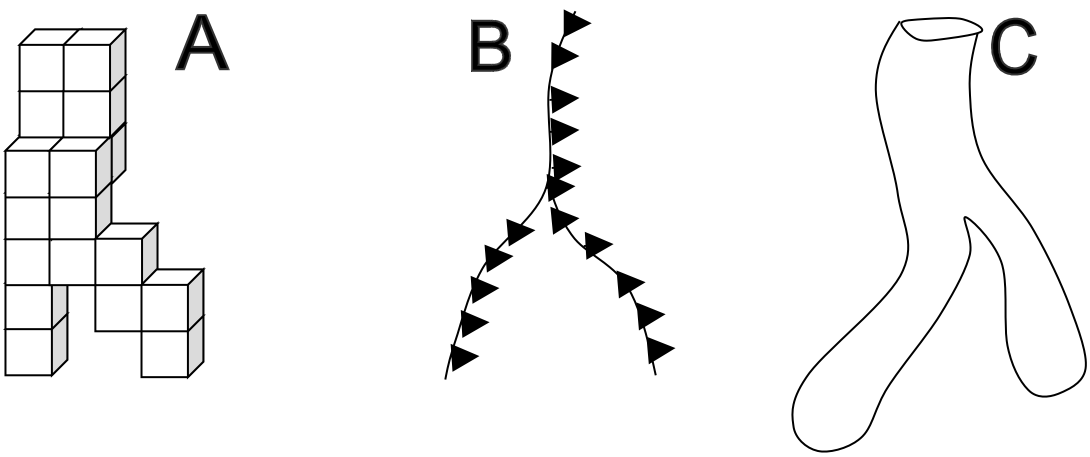

Fig.1: Different data structure representing extracted vessels: A: Classified voxels, B: Centerline points with associated radii, C: Parametric surface representing vascular boundaries.

3. Vessel enhancement with directional filtering

Even from high quality CT or MRI images it is not possible to recover vascular structures by simple thresholding the image grays.

Major limits of this simple approach are sensitivity to noise and artifacts and difficulty in capturing small structures. Furthermore, the color of the contrasted vessels may be irregular due to acquisition timing. Without contrast media, on the contrary, different tissues with similar gray level can create problems near the vessel border.
Authors using simple thresholding methods for vessel analysis (for example Yim and Summers [4] applied therefore methods like adaptive thresholds and data post processing (e.g with morphological operators) to compensate for vascular gray level variations and to remove spurious voxels or holes.

A better approach to localize vessels in 3D directly labeling voxels in image stacks without user interaction consists of enhancing the vascular structure by exploiting its expected elongated morphology. This enhancement can be obtained with directional multi-scale filtering, and has indeed been proposed by many authors. In a few words, at each location of the data set they search for one dimensional directional structures or lines with different thickness.
Vessels are, in fact, characterized, at the scale corresponding to their diameter, by intensity ridges and filters able to capture them may provide not only the localization of vascular centerline points, but also information about local radius.
This approach has been used for example, by Sato et al [5], Frangi et al. [6], Krissian et al.[7,8,9] that proposed "vessel enhancement" filters based on the analysis of the Hessian matrix.
The basic idea of their methods is to compute Hessian matrices (i.e. a matrix with second-order derivatives at different scales and perform eigenvector analysis on them to find and quantify ridges. A scale selection is required to choose the correct scale response for each point, then responses indicate approximately the likelihood of the voxel is part of a vessel and the scale an approximate estimation of the diameter. (see Fig. 2)
Enhancing images this way is effective in background removal and for visualization but it is however only the first step for algorithms trying to recover vascular skeletons or also vascular surfaces with accuracy. Methods used after enhancing are not different from those applied on original images, and we will some of the approaches applied after enhancement in the following sections.
A directional filtering seems to be particularly effective to find regular vascular networks of constant scale, in absence of tissue ambiguities. For more complex structures when accurate lumen surface description must be recovered, a thresholded or tracked enhanced map can be for a centerline detection able to initialize vascular models.

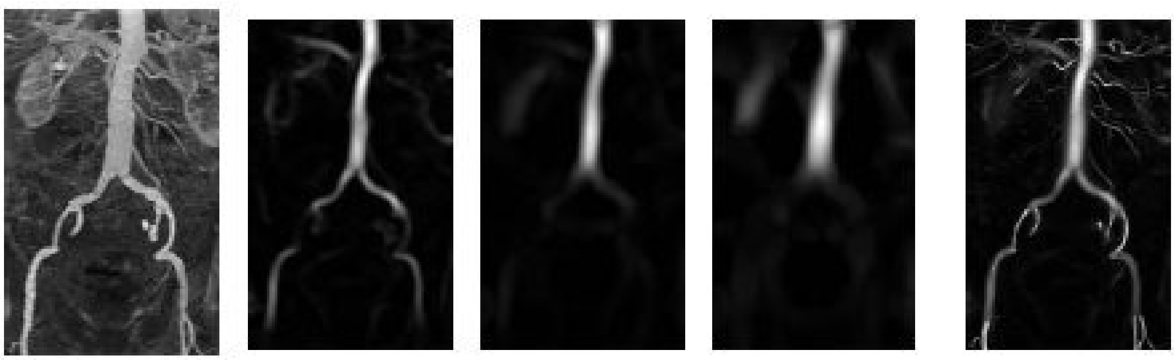

Figure 2: Left image: Maximum Intensity Projection of a MRI scan of the Aorta. Central images: results of vascular enhancement at different scales. Right: MIP projection of the complete vesselness data obtained merging information at different scales (From Frangi et al. [6].)

4. Growing from seeds/skeletons: path planning, region growing, deformable models

With or without vessel enhancement (in some cases it could be better to avoid it because it removes useful information), segmentation methods aim at recovering a curve-skeleton and/or lumen surface or volume from voxelized data. Trying to recover all the vessels with the methods described in full datasets is not useful in practice and would also provide bad results due to ambiguities and noise. In real clinical application *user-interaction* is therefore introduced. Typically the user must click on two points representing the extremes of the vessel branch to be segmented, or just in a point inside the vascular network to be recovered.

The simpler growing method is a voxelized region growing. It can be applied for vessel detection if the vessel is well contrasted. It is however better to introduce shape constraints or noise removal methods in order to avoid false detections or holes. The basic idea is to enlarge the segmented region (starting from the given point) by simply iteratively adding external points near the boundary where the value of the signal is in the range of the vessel lumen.

One of the typical drawbacks of simple region growing based on single thresholds related to the gray level of contrast medium is that contrast level is not constant during the acquisition and therefore a single threshold is not able to capture the whole morphology. Eiho et al. [10] solved this problem implementing a branch based region growing method adapting locally the stopping criteria to segment vessels on MRA images.

Another example of simple region growing application can be found in a paper by Sherbondy et al [11] using growth from seeds based on Perona-Malik's anisotropic diffusion to recover vessels from CT images. The peculiarity of their method is the use of GPU for computation.

The most popular ad advanced "growing" segmentation methods are, however, those base on surface evolution, i.e. it is a surface and not a volume that grows inside the lumen until the border is not reached. With this method, surface constraint keeping the surface smooth and limiting the effect of noise in the data can be added to the algorithm.

Two main approaches are used: deformable models implemented with discrete meshes and level sets. Readers interested in a more general survey on deformable surfaces implementations can find an extensive classification in the paper by Montagnat et al. [12].

Deformable models are the 3D extension of the popular "snakes", introduced in 1988 by Kass et al [13], and consist of parametric surfaces, usually discretized in implementation as polygonal meshes, evolving under potential fields depending on elastic parameters keeping the surface regular and image forces trying to make the surface attracted by the limits of the regions to be segmented.

An overview of medical applications of deformable models can be found in the paper by Terzopulos and McInereney [14]., showing also advantages/drawbacks of different implementations. The usual approach for vascular segmentation consists of making a closed surface grow until the correct boundaries are reached, initializing it near a seed inside the lumen, using an inflating force to move mesh nodes outward and blocking them through the action of forces based on edges strength or gray level differences. This method has the great advantage of directly providing a surface that can be rendered and measured, while after the application of regionalization methods surfaces must be computed typically using the Marching Cubes algorithm [2]. Furthermore, elastic and rigid forces act as basic shape constraints that allow the surface to pass over small irregularities, noise, etc.

Implementation problems may be found in the handling of the geometrical structure (necessity of resample the mesh, detection of auto-intersection, etc).

Simplex Meshes introduced and applied by Delingette in 1996 [15] are particular discrete surface meshes where each node is connected to three neighbors, allowing a simple calculation of of the curvature parameters used to constrain the evolution. For their properties they have been extensively exploited by other authors to solve the problem of Aortic segmentation [16,17,18]. This is a typical problem where it is not possible to recover the lumen surface with tubular models due to

the large size and irregularity, so region growing or deformable surfaces are the elective segmentation methods.
A different deformable model for the segmentation of the aorta has been presented in [19], using a iterative mesh nodes displacement with a "velocity" similar to that used in the level set model propagation described later.

Deformable surfaces implemented as discrete closed meshes have the property of maintaining a fixed topology and avoid the presence of holes. This is a very good property for applications where quantitative measurements should be performed. It is, however, considered a drawback when complex and small structures must be detected or in presence of objects with complex or changing topology. A framework to evolve discrete deformable surfaces able to change their topology (T-surfaces) has been developed by Terzopulos and McInereney and successfully applied to vascular image segmentation (aorta from CT, cerebral vasculature from MRI) in [20]. Another possibility for topology change is to detect self collision and reparametrize surfaces when this occurs, like proposed by Pietroni et al. [21].

The main other approach to compute surface evolution is the use of implicit formulations like front propagation using level sets [22]. The idea is to evolve a N+1 dimensional potential which zero-level set is the surface of interest. The evolution is usually due to a speed function based on curvature and images and has the property of naturally handling changes in topology. Drawbacks in this case are computational cost, difficulty in introducing strong shape constraints and the necessity as for simpler region growing of extracting surfaces later for visualization. Several authors, however, used level sets to segment vascular structures starting from the basic works of Malladi et al. [23] and Caselles [24]. Efficiency have been increased with the introduction of the "fast marching" technique by Sethian [22], limiting the surface evolution to growth. Adaptation to this algorithm to tubular structures like vessels may consists of avoiding leakages by freezing surfaces points assumed to have reached the borders and leave the evolution free only in the vascular fronts, like in Deschamps et al. [25]. Manniesing and Niessen [26] adapted locally thresholds in velocity terms of a front propagation algorithm to have a more precise segmentation of vessels, still initialized from seed points.
It is evident that the limits of discretized meshes coincide with the advantages of level sets and vice versa. To exploit advantages from both the approaches, Magee and Bullpitt [27] used level sets and deformable discrete surfaces together to recover the structure of Abdominal Aortic Aneurysms.
Also Chen and Amini [28] presented a segmentation of vascular structures from MRI images obtained through different steps: first applying multiscale enhancement, then level sets to describe the vascular volumes and finally building the vascular surface with Delaunay triangulation and using a deformable model for the final vascular surface refinement.

5. "Tubular" models

Some papers do not describes methods to directly recover 3D geometries from 3D data, but build vessels' geometres working 2D sections of the data set. Tubular structures can be, in fact, easily recovered by using 2D contour extraction on consecutive slices (approximately) perpendicular to the vessel. This approach has been used in the ViVa Project [29] or in Wang et al. [30], where 3D tubular branches are extracted from slices perpendicular to vessel direction joining them into intersecting mesh structures, and finally handling branches intersections. In the first paper authors work mainly on vessels perpendicular to CT slices, so original images can be used, in the second they first recover a curve skeleton with a path planning algorithm described in [31]. It must be noted that similar path planning methods also recover the lumen geometry.
Tubular models of this kind are often referred to as "generalized cylinders" and are often used to model vessels after the multiscale filtering described in the previous section.
Krissian et al.[8] used, after the multiscale filtering, a simple model of cylindrical vessel with Gaussian cross section to recover vascular networks with associated local diameters. Frangi et al. [32] proposed the use of deformable contours implemented as B-splines driven by filter responses

to detect locally and interactively the centerline and built surfaces as spline surfaces initialized as tubular structures around the centerline. Aylward and Bullitt [33] recently proposed a similar method defining optimal-scale measures for handling noise, discontinuities and singularities, building more accurate centerlines.
Another 3D “tubular” model has been recently proposed by Yim et al [34]. They describe a specific mesh model exploiting a tubular coordinate system and methods to avoid self-intersections and maintain an even vertex spacing. Even if interesting, the method has still the problem of requiring a complete preliminary recovery of the vessel centerline (not described by authors) and may be also consider more a model refinement method than a vessel segmentation one.

6. Recent advances: new shape constraints for deformable models

Deformable models can be used successfully for vessel detection, the main limit in the use of their generic implementations is that the evolution is driven by “local” parameters and in presence of missing information in images this may cause leakages and other errors. They however are usually preferred to “strong” model based methods because the initialization of these methods is extremely difficult due to the great variability in vascular morphology.
The most interesting trend in vascular segmentation techniques consists therefore in the introduction of “light” shape or evolution rule constraints.
Nain et al. [35] proposed the use of a shape-driven flow to derive an active contour/surface model that penalize leakage considering 3D regional information. The method is effective in some cases, the obvious drawback is the computational cost due to the use of non-local information to constrain locally the surface and the risk of missing vascular continuity.
Lorigo et. al [36] proposed the use of an evolving 1D line in a codimension 2 space (i.e. in 3D). they found an elegant formulation for evolving a similar structure similarly to the front propagation method. The vessel is modeled as a curve with local diameter information and energy function to be minimize depend only on the principal component of the local curvature. The drawback of the method consists in missing the complexity of the vascular surface, limiting, as other methods, the reconstruction to a centerline-radius structure.
Vassilevskij and Siddiqi [37] changed the classical gradient based constraint to find boundaries in a front propagation model by maximizing rhe flux of the gradient vector through the evolving surface. Algorithm is initialized placing seeds in regions of high inward flux and seems to provide an optimal detection of elongated structures; it cannot, however, due to locality, prevent large leakages in case of missing information.
Shape constraints to avoid leakage can be more easily introduced on 2D sections if the vessel is modeled as a tubular structure made joining curve sections (see Section 5).

7. Centerline/path finding

The curve-skeleton or centerline of the vessel is extremely important in vascular reconstruction: it can be used as a guide for virtual navigation, as a reference for radius measurement, to initialize tubular models for refined segmentation, to approximate locally the blood flow direction and more.
Methods to recover paths in vessels are the same used in generic virtual endoscopy. They usually require a seed point or start and end point and try to follow the centerline of the structure. A few path finders works without a preliminary segmentation of the volume of interest.
Wesarg and Firle [38] proposed a simple “corkscrew” algorithm to compute skeletons and approximate diameters, based on 1D iterative search of borders in rotating directions. It seems to provide successful results on CT scans even if with rough accuracy and may have problems with noise.
Flasque et al. [39] used an iterative search of vessel centers from a starting point using a limited search space of adaptive size where input data (binarized voxels) are interpolated to obtain subvoxel accuracy. Bifurcations are also handled with an analysis of region limits.

Olabarriaga et al. [18] compute centerline of a single vessel branch from two points applying minimum cost path on enhanced voxel data. A reference for minimum cost path extracting from couple of points is the paper of Wink [40].

The most widely applied methods to compute vascular centerlines are, however, performed together or after a lumen complete vascular lumen segmentation step. Skeletonization of a known structure, given voxelized volume or the enclosing surface is, however, a difficult problem with and there is a large related literature on the subject. In 3D the skeletonization problem is much more complicated than in 2D, where skeletons can be easily extracted with a medial axis transform [41]. The ``medial axis'', i.e. the set of centers of balls which touch the object boundaries in two or more points is, in 3D is a surface. For a three dimensional object it is even difficult to give an accepted definition of curve-skeleton, usually considered a set of one voxel thick lines with particular properties, i.e. it is centered, connected and smooth. The problem is well addressed in a recent research paper by Cornea et al., describing also classes of algorithms for the curve-skeleton extraction [3]. The most intuitive approach for curve-skeletons extraction is the topological thinning, consisting in an iterative removal of "external" voxels of the volume without changing topology [42]. Another popular approach, applied in popular virtual endoscopy has been proposed by Paik [31]: it is based on the computation of medial axis and an iterative adaptaition of a path toward it.
Other methods are based on the computation of distance functions are described in [43,44,45,16]. For example Zhou and Toga [43] compute a "distance from seed" map and a "distance from border" map. Shortest paths are generated through the first one and then are centered with different approaches and curve modeling through the use of the other distance map.
Methods using as input the triangulated meshes describing the vascular orders have been proposed as well and are usually based on the computation of the Voronoi diagram of the mesh nodes[46]. The computational cost of the methods is, however, relevant.

8. Complex models with different tissues

Big vessels like the Aorta can be analyzed considering also different tissue structures around the lumen. This is particularly important if the model is used for elastic simulation, but it is also relevant for surgical planning.
With the current image resolution is, of course, impossible to recover the structure of vascular walls tissues, but it is, however, possible, from CT scans to recover the structure of at least two materials related to the vascular structure: thrombus, i.e. deposit of particles inside vessel walls, and calcified plaques. If calcium is well separated from other tissues having an high HU level and can be segmented just with a thresholding and Marching Cubes isosurface computation, as done in [16], thrombotic tissue, that may occupy a relevant space between vascular wall and blood and should be detected when analyzing aortic rupture risk, is not easy to be segmented due to its similarity with surrounding materials. Giachetti et al. applied Fourier constrained 2D snakes to recover thrombus limits (see Fig. 3). De Brujne et. al. [47] proposed the use of Active Shape Models [48] to limit the variability of curves and avoid leakage. Olabarriaga [18] segmented vascular walls in presence of thrombus without shape constraints, but applying a particular image force obtained by training a k-NN classifier for 1D border profiles recognizing voxels as "internal", "external" or "border".

Fig. 3: Aortic lumen reconstruction with skeleton (dark gray) thrombus (wireframe) and plaques (light gray) from CRS4 AQUATICS project

8. CRS4 contribution

CRS4 is a multidisciplinary research center located in Sardinia, Italy, where high performance computation is applied to several fields, like energy, computational fluid dynamics, computer graphics, telecommunications and more.
The Bio Medical Application area of CRS4 is active in the field of medical data processing, with application in image based diagnosis, applications of Virtual Reality in medicine and Hospital Data information handling.
Researchers of the area are active in the field of vascular analysis since mid 90's. Most of their work have been realized within the framework of European projects. For example during the ViVa (Virtual Vascular) Project, patient specific volume meshes representing arteries were constructed with ad hoc segmentation tools and optimized in order to run patient specific simulations of blood flow inside the vessels with a Navier Stokes finite element solver. The peculiarity of the implementation of the method was the possibility of decomposing the mesh domain in regions at different resolution and run the simulation in parallel.
During the AQUATICS (Aneurysm QUAntification through an Internet Collaborative System) project, aimed at supporting the planning of endovascular procedures for the repair of Abdominal Aortic Aneurysms, a Web based measurement system to perform on the vascular model built all the evaluations required by the clinical applications. Major contribution in vascular segmentation techniques were realized in the period by building a system for complete reconstruction of vascular models, using Simplex Mesh balloons to recover lumen surface, Fourier constrained 2D snakes to segment thrombus, isosurface extraction to recover calcified plaques and a voxel coding elastic method to recover the vascular skeleton, shown in Fig. 4.
The quality of the models was also checked during the period with a validation phase where diagnostic measurements were performed on models built from scans performed at the University of Innsbruck on a plastic phantom of an Abdominal Aortic Aneurysm filled with contrast medium. The effects of user interaction during the segmentation phase were also proved to be not relevant for measurement quality. CRS4 is still working to improve segmentation quality by investigating different geometric models to represent the arterial shape and new image forces depending on texture descriptors.

9. Conclusions

We presented an overview of different approaches applied to solve the problem of vascular image segmentation. Different methods have been applied with success especially on CT and MR data. Current methodologies can extract pathways and walls and can detect pathologies with good precision, particularly if contrast media can be injected into blood enhancing the vascular lumen. The reconstructed geometries provide a lot of useful diagnostic information and can be used for surgical planning or to realize patient-specific blood flow simulations.

The main limits of the reconstruction techniques consists in a reduced possibility of detecting correct geometry and topology in the case of very small vessels, noisy images (like US), non contrasted images, and in the necessity, for some of the techniques described of user interaction and parameters tuning that make them not suitable for a simple clinical application.

The increasing quality of imaging modalities is, however, constantly reducing these problems, so that in the near future the major challenge for a wide exploitation of 3D shape reconstruction techniques (applied to vessels, but also to other structures) will probably be to reach a better collaboration between IT specialists and physicians in order to design and validate quickly new diagnostic applications of existing technology.

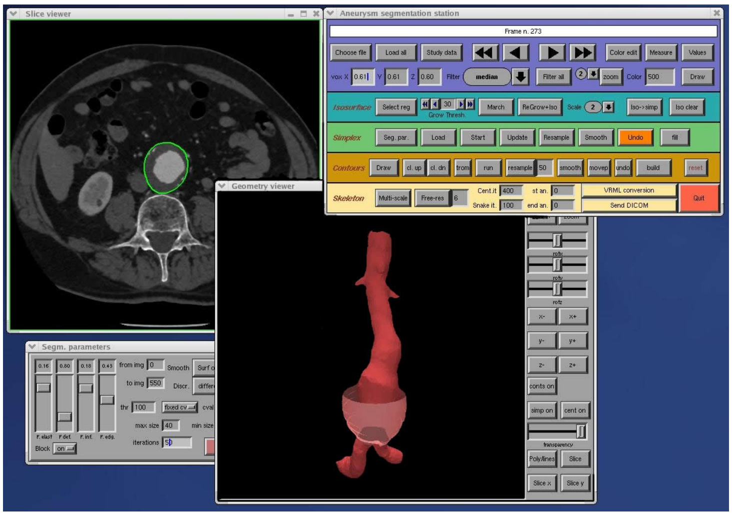

Fig. 4: Segmentation procedure with deformable surface for the lumen and constrained 2D snakes for the external walls, from CRS4 AQUATICS project

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