Model-Based Visualization for Intervention Planning

Bernhard Preim[1]

1 **Otto-von-Guericke-University of Magdeburg, Dept. for Computer Science, Visualization Group, PO Box 4120, 39016 Magdeburg, Germany**
`preim@isg.cs.uni-magdeburg.de`

Abstract

Computer support for intervention planning is often a two-stage process: In a first stage, the relevant segmentation target structures are identified and delineated. In a second stage, image analysis results are employed for the actual planning process. In the first stage, model-based segmentation techniques are often used to reduce the interaction effort and increase the reproducibility. There is a similar argument to employ model-based techniques for the visualization as well. With increasingly more visualization options, users have many parameters to adjust in order to generate expressive visualizations. Surface models may be smoothed with a variety of techniques and parameters. Surface visualization and illustrative rendering techniques are controlled by a large set of additional parameters. Although interactive 3d visualizations should be flexible and support individual planning tasks, appropriate selection of visualization techniques and presets for their parameters is needed. In this chapter, we discuss this kind of visualization support. We refer to *model-based visualization* to denote the selection and parameterization of visualization techniques based on 'a priori knowledge concerning visual perception, shapes of anatomical objects and intervention planning tasks.

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1 Introduction

Surgical interventions, radiotherapies and other local therapies require a precise understanding of the patient's anatomy. In particular, the location and extent of pathologic variations in relation to vital anatomic structures, such as major blood vessels, is essential to evaluate the resectability and to determine the surgical strategy. Interventions are planned by means of CT or MRI data. Planning involves a systematic exploration of the slices of radiological data. In order to support the mental preparation of surgeons, more and more 3d visualizations are generated. Oblique MPR (multiplanar reformation) slices for instance allow to assess the local cross section of vascular structures and volume rendering is employed to get an overview which is essential for example in case of complex fractures or rare anatomic variants.

Intervention planning can be supported even better if image analysis results, such as segmentation information concerning the relevant objects, are available. For an efficient segmentation, model-based segmentation approaches are often exploited. Statistical models, such as Active Shape Models and Active Appearance Models, employ 'a priori knowledge with respect to the expected shape and grey value distributions [8, 9]. With active contour models-another class of model-based segmentation techniques-deformable models are fitted

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to the segmentation target structure based on a flexible geometric representation such as B-Splines. The process of fitting the model to the target structure is guided by physical principles and constraints which restrict for example the curvature along the path (model assumptions) [24, 27, 39].

Based on image analysis results, visualization parameters can be locally adapted to individual objects or certain categories of anatomic structures, such as nerves or lymph nodes. Since visualizations should provide insights into spatial relations, there is an argument for visualization techniques which "idealize" anatomic structures to some extent to render them more comprehensibly.

The design of "idealized" visualizations requires assumptions or 'a priori knowledge with respect to geometric properties. This gives rise to the term *model-based visualization*. More general, model-based visualization refers to the automatic selection of appropriate visualization techniques. There is a variety of sources which can be exploited to derive such automatic selections. Similar to the model generation process in image segmentation, experience with the visualization of a variety of similar datasets is an essential source of information. In case of clinical applications, "idealized" visualizations must be shown to be "correct enough" to draw reliable conclusions. Therefore we discuss the validation of model-based visualization techniques.

Model-based visualization versus intelligent computer graphics. The (semi-)automatic selection and parameterization of visualization techniques – which we characterized as model-based visualization – might be considered as an instance of *knowledge-based* or *intelligent* computer graphics. However, the typical goals of knowledge-based computer graphics are considerably more ambitious: the automatic selection of appropriate viewpoints and perspectives, the computation of complex layouts, labeling of 3d models, the selection of appropriate levels of detail and the determination of movements of a virtual camera through complex virtual environments are among these goals [21, 12, 6, 16, 22, 36]. The general concept of knowledge-based computer graphics is to hierarchically decompose high-level intent-based specifications into more and more elementary specifications until they are precise enough to be rendered. The results are evaluated with respect to rules and constraints and backtracking mechanisms are employed to initiate new solutions if the initial solutions failed to generate an appropriate result. The goals of model-based visualization are at a lower and more elementary level. Since neither knowledge representations nor backtracking mechanisms are involved, model-based visualization should not be regarded as *intelligent graphics*.

Organization. A general problem for many intervention planning tasks is the generation of geometric models which represent the segmentation results. Due to the large variety of steps and algorithms, a model-based approach is needed for this problem. As a first step, we discuss the appropriateness of mesh smoothing algorithms for different categories of anatomic structures (Section 2). While flat and compact structures can be smoothed satisfactory with general methods, elongated and in particular branching structures require dedicated smoothing approaches. In Section 3, we therefore discuss model-based visualization of vascular structures. In Section 4, we describe the process of generating geometric models for illustrative visualization with a focus on silhouettes and feature lines. Illustration techniques, such as cut-away and ghostviews, and their application are discussed in Section 4. Finally, we provide a general discussion of 'a priori knowledge for visualization purposes in Section 5. In essence, this chapter should rather present a framework for the analysis and refinement of visualization techniques instead of presenting final results.

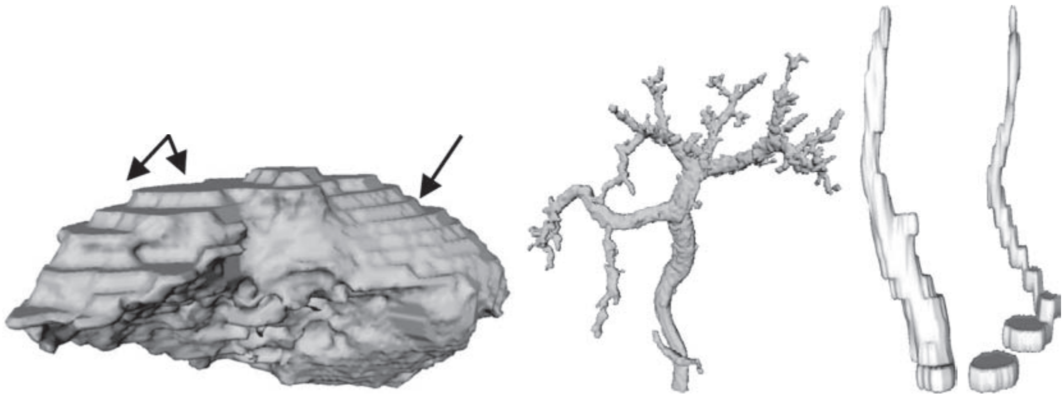

Figure 1 Typical problems of applying Marching Cubes to binary segmented volume data. From left to right: an organ (large compact), a vascular tree (elongated branching), and two individual vascular structures. The arrows in the left image relate to typical problems of visualizing compact objects from data with insufficient slice distance: plateaus and visible staircases arise. Note, that due the oblique course of the vascular structure on the very right, the segmentation results in adjacent slices do not overlap resulting in the generation of several surfaces. Images are courtesy of Jens Haase, University of Magdeburg.

2 Towards Model-Based Surface Extraction and Smoothing

For many rendering options, it is essential to transform segmentation results into (polygonal) surfaces. The usual representation of a segmentation is a binary volume with the same resolution as the original volume data (the set of "1" voxels represents a particular anatomic structure). The common surface extraction technique is the Marching Cubes-algorithm (or one of its refinements which handle ambiguities in a more sophisticated manner). The problem with this general strategy is that Marching Cubes leads to jaggy surfaces if it is applied to binary volume data, in particular if the slice distance is high (e.g. ≥ 5 mm). In some cases, for example when the segmentation results in adjacent slices do not overlap, Marching Cubes would not even generate a connected polygonal surface (Figure 1, right).

A variety of techniques have been developed and discussed to improve the surfaces either before, during or after surface extraction. Before surface extraction, image processing filters may be applied to convert the binary volume in a multivalue volume. In particular, with morphologic filters a good trade-off between accuracy and smoothness can be achieved [28]. Another technique which is applied before surface extraction is the interpolation of intermediate slices. The surface extraction itself may be improved by gradually refining the initial Marching Cubes result when it is strongly discontinuous [7]. Most research however tackles the question how an existing polygonal surface may be smoothed [38].

Smoothing geometric models is a wide topic, similar to smoothing image data. Simple methods tend to remove not only noise but also relevant features. Advanced methods, such as those based on diffusion theory better retain relevant features. The improved quality is attained at the expense of long computation times. However, no single smoothing method is appropriate for all anatomic and pathologic structures. Pathologic structures, for example, should not shrink in the smoothing process, whereas this requirement is less crucial for large organs. Again, the suitable selection, combination and parameterization of smoothing techniques requires 'a priori knowledge with respect to the shapes to which they are applied. Smoothing techniques also alter the geometry and therefore, must be evaluated by measuring distances to "correct" visualizations. The appropriateness of these techniques depends on a

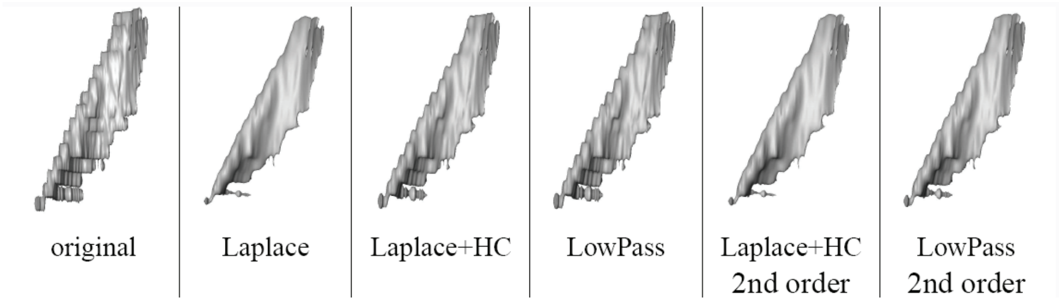

Figure 2 Smoothing results of an elongated surface model (a muscle in the neck region). Images are courtesy of Jens Haase, University of Magdeburg.

large number of parameters:

- *image acquisition parameters*, such as the slice distance.
- *category of anatomic object*. Anatomic objects have strongly different shapes and sizes: elongated, branching, planar, and compact objects occur. Smoothing techniques which are appropriate for one category may lead to inacceptable results for another.
- *task-specific requirements*. Objects which serve as anatomic context should be smoothed strongly even at the expense of accuracy. Objects relevant for the surgical strategy must be more carefully processed since accuracy is more important. For some structures, such as a malignant tumor, accuracy has the utmost priority.

As a first step, towards a model-based solution, we explored the effects of wide-spread and fast smoothing approaches [2]. We restricted the comparison to smoothing algorithms which have a linear complexity (in each iteration, each vertex is replaced by a weighted sum of its previous position and the positions of adjacent vertices). The Laplace filter, the Laplace-filter with the so-called HC correction [42], and the LowPass filter [38] were considered(Figure 2). Median and average filter, applied to surface normals [44], were also explored but initial results were not encouraging in particular for small objects where new artifacts were created in some cases. The major strength of the latter filters is the preservance of sharp edges as they occur in CAD-models.

Visual quality as well as different metrics (volume preservation, Hausdorff distance to the original model, and the average curvature) were employed to compare different methods. An essential aspect of each filter is the neighborhood which is considered at each point. All filters were implemented with the topological-distance of 1 (only vertices which share an edge with the current vertex) and topological distance of 2 (vertices which are connected to the current vertex by a path of at most two edges are considered). Figure 3 compares smoothing with both neighborhoods.

Each filter was applied to a set of six anatomic objects each representing a different class or category of objects. Each of the filters has two parameters influencing the accuracy and visual quality: the number of iterations and the smoothness factor. The investigation considered 6 weighting factors (from 0.05 to 0.9) and 4 different numbers of iterations (from 5 to 50). The website `http://wwwisg.cs.uni-magdeburg.de/cv/projects/LST/smoothing/` presents all results.

The *LowPass* filter turned out to be the most appropriate fundamental smoothing filter for all reference objects. To smooth compact objects (e.g. organs, lymph nodes), the *LowPass* filter with a 2nd order neighborhood, a weighting factor of about 0.7, and 20 to 50 iterations should be used. A similar smoothing strategy can be applied to planar objects

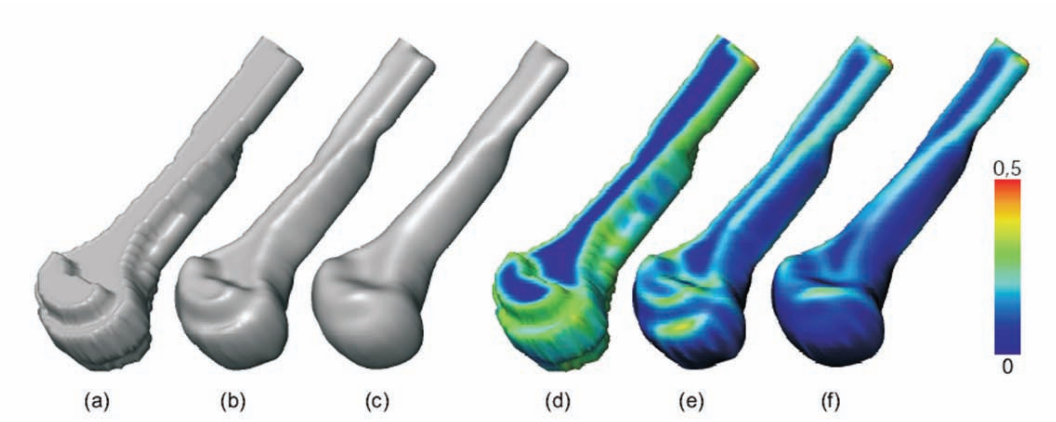

Figure 3 A bone (left) is smoothed with the LowPass-filter with the normal (b) and extended neighborhood (c). The curvature plots show the effect of smoothing on the mean curvature. LowPass-filtering with the extended neighborhood strongly reduces the curvature (f). Images are courtesy of Jens Haase, University of Magdeburg.

(e.g. ligaments), whereas here not more than 20 iterations should be applied. With the recommendations above, the volume of the smoothed models is preserved well: it is exactly preserved for large compact models and for smaller or elongated objects shrinkage was lower than 4% and the Hausdorff distance which is a worst case approximation of the distance error was between 3 to 6 mm. This amount of distance error is reasonable compared to the resolution of the underlying data.

Flat objects (thin objects which might be curved, such as ligaments) with holes and frayed parts should be smoothed with a 1st order neighborhood. Holes cannot be closed by any smoothing algorithm; but at least they should not be enlarged. Elongated objects with many small branches and detached object parts (recall Fig. 1, right) cannot be smoothed appropriately with any of the general smoothing filters. For smoothing simple none branched elongated objects, the *LowPass* filter with a weighting factor of 0.5 and 10 iterations is recommended. The visual results achieved with the Laplace-filter with correction are similar to the *LowPass* filter. However, for larger numbers of iterations and/or larger smoothing factors volume shrinkage (8 to 12%) and Hausdorff distances are larger. The accuracy of the Laplace-filter with HC-correction is considerably better with a 2nd order neighborhood.

2.1 Validation

Similar to new segmentation methods, model-based visualization techniques should be carefully validated with respect to accuracy. This includes qualitative and quantitative comparisons with other methods. Quantitative comparisons are based on metrics which characterize distances between segmentation or visualization results or based on volume overlaps [45]. In particular, the comparison with a "gold standard" is essential. The "gold standard" represents the solution which is regarded as "true" or at least as the most accurate result which could be generated so far. For image segmentation, the manual segmentation of medical experts is usually considered as gold standard.

For model-based visualization, a validation is required to investigate whether the segmentation result is correctly displayed. For our purposes, we considered isosurface rendering with the Marching Cubes method [25] as gold standard (taking 0.5 as isolvalue, when "1" represents foreground voxels and "0" represents background voxels). As has been discussed by [7], Marching Cubes is not the most accurate visualization. However, it is close to it and a more precise visualization (trilinear interpolation) is more complex to implement and considerably slower.

With respect to the smoothing techniques, we evaluated primarily the volume preservation. It is known and not surprising that Laplacian smoothing leads to a strong loss of volume (with larger smoothness factors). The relation between Laplace with correction and the *LowPass* filter as well as the precise influence of the neighborhood on accuracy were not known before.

2.2 Discussion

We derived initial recommendations for smoothing surfaces based on the analysis of widespread and fast iterative methods. It is necessary to include more algorithms, in particular those which adapt the surface normal's [37] and diffusion based methods [11, 37]. So far, our results are limited by the fact that only one segmentation result for each category of anatomic structure is considered. We derived results in a systematic but purely empirical manner. An alternative and more elegant approach would be to derive hypothesis on the suitability of smoothing methods based on an analysis of the properties of the algorithms. We have not investigated so-called normal errors – the angle between the correct surface orientation and the surface computed with a new method. Pommert et al. [32] discussed the validation of medical visualization techniques with respect to distance and normal errors and employed a set of phantoms to study different aspects, such as the influence of the sampling density (see also [31]).

3 Model-based Visualization of Vascular Structures

For intervention planning, it is crucial that spatial relations can be correctly inferred from the visualization. In particular the topology of vascular trees is often essential to decide on the feasibility of a surgical strategy. Moreover, the curvature, the depth relations, and the diminution of the diameter towards the periphery should be depicted correctly. With conventional visualizations, such as Maximum Intensity Projection (MIP) or surface rendering, artifacts arise due to the limited resolution and inhomogeneities of contrast enhancement. Therefore, vascular structures should be reconstructed based on the radiological data of a patient and some model assumptions as to the shape of vasculature [3, 15]. The pioneering work of Barillot et al. [3] is probably the first dedicated effort to generate medical visualizations based on 'a priori knowledge. Healthy vascular structures exhibit a roughly circular cross-section, they are connected with each other and their diameter shrinks from the root to the periphery. Based on these assumptions, a variety of visualization techniques have been developed which use the skeleton and the local vessel diameter as input. Primarily graphics primitives, such as cylinders and truncated cones, were fitted to the skeleton and scaled according to the local vessel diameter [26, 18]. The most advanced explicit reconstruction technique is based on subdivision surfaces [13, 5]. More specialized model assumptions were employed by Puig in [34]. She considered typical elements (cylindrical, stenosis, ...) and branching structures in cerebral vasculature, tried to classify branchings accordingly and used 'a priori knowledge to emphasize the corresponding branching type.

The explicit construction of a geometry however exhibits problems in particular at branchings were discontinuities arise at the joint of truncated cones or cylinders. A superior image quality can be achieved by means of implicit surfaces, where the shape of a vascular system is described by an implicit equation which has to be evaluated along the skeleton.

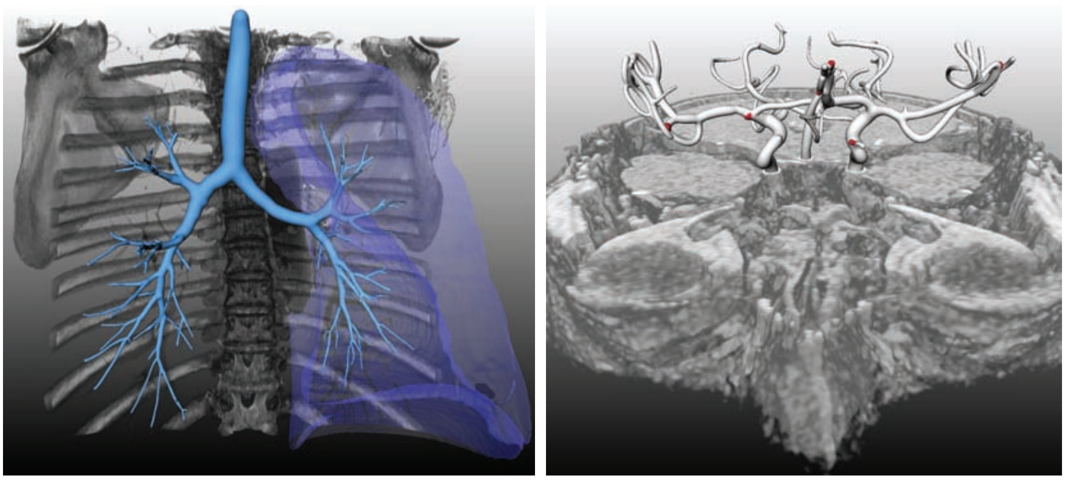

Figure 4 Model-based visualization of vascular structures embedded in direct volume renderings of surrounding structures. Left: The bronchial tree is depicted. Right: a cerebral tree is shown. Images are courtesy of Steffen Oeltze, University of Magdeburg.

The resulting scalar fields are polygonized by means of a threshold. A special variant of implicit surfaces, convolution surfaces, allow to visualize branching skeletal structures by applying a convolution filter to the skeletons. The use of convolution surfaces for medical visualization poses some problems with respect to accuracy; the depicted vascular structures should correctly convey the vessel diameter and the topology of vascular structures. Usually, convolution surfaces exhibit "unwanted effects", such as unwanted blending where two branches are incorrectly merged with each other due to the construction process. Oeltze et al. could show that an appropriate filter selection allows to effectively avoid that the resulting visualizations strongly deviate from the segmentation results on which they are based [29]. Two examples of this work are shown in Figure 4.

3.1 Validation

In order to validate the convolution surface as viable technique for vascular structures, various experiments with small artificial data have been accomplished to study whether unwanted blending or bulging occurs. Another qualitative part of the validation was to analyze visualization results achieved with "real" patient data and compare them with the results achieved with other model-based techniques. After these tests the width of the convolution filter was adapted and a quantitative validation was based on 10 abdominal CT datasets (patients with liver metastases) with different resolution and distances were computed for each vertex of the resulting polygonal mesh.

Distance metrics, such as mean distance and Hausdorff distance, are primarily relevant for assessing the accuracy of vessel visualization techniques. As the major result of a quantitative validation, Oeltze et al. found that the deviation of "their" variant of convolution surfaces to an isosurface rendering of the segmentation result is on average below half the diagonal size of a voxel. Taking into account that half the diagonal size of a voxel is the uncertainty which is due to resolution of the data, this is an excellent result. Only for a very small fraction of the voxels the distance is up to 3 diagonal voxel sizes [30]. Figure 5 illustrates how the results were achieved and analyzed.

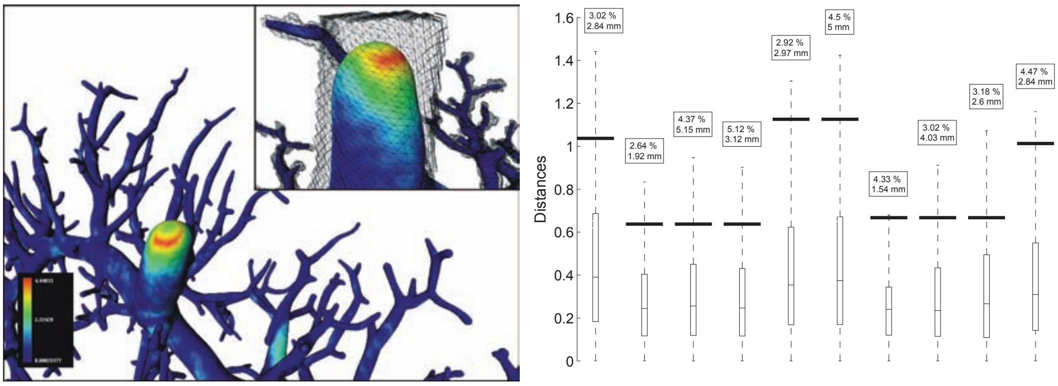

Figure 5 Validation of a model-based visualization techniques. Left: Intensity-coded visualization of the deviation from convolution surface (CS) to isosurface. The strongest deviations occur at the root of the vessel tree (see the inset with the superimposed isosurface in wire-frame mode). Right: Boxplots of the distance measures (in mm) carried out for a comparison of CS and Isosurface based on 10 vascular trees. Each box indicates the lower quartile, median, and upper quartile values. The whiskers extend from each end of the box to show the extent of the rest of the data. The values within each box represent the percentage of data values beyond the ends of the whiskers and the maximum distance. Thick lines indicate the half diagonal voxel size. Images are courtesy of Steffen Oeltze, University of Magdeburg.

3.2 Discussion

Model-based visualization refers to the automatic selection of appropriate visualization techniques. With respect to the visualization of vascular structures this involves an assessment of the local vessel diameter in cross sectional areas.

If it turns out that the assumption of a circular cross section is strongly violated in several adjacent slices, any visualization technique which assumes this property is obviously not suitable. In such cases, a pathology is likely and an isosurface of the segmentation result is a better visualization option. Pathologies such as stenosis or aneurysms occur at small portions of a vascular system. A hybrid combination of isosurface rendering (in pathologic portions) and model-based rendering (in healthy portions) is probably the best choice to depict pathologic vascular systems.

There are some similarities between model-based vessel segmentation and visualization. Model-based vessel segmentation techniques also assume connectedness of vascular structures and try to "bridge" over a few voxels which fail to fulfill a homogeneity criterion due to partial volume effects. An ellipsoidal cross-section is often assumed in vessel segmentation approaches [19]. In general, model assumptions in image segmentation must be less restrictive to cope with the variety of shapes and the imperfect quality of medical image data.

4 Model-based Illustrative Rendering

Conventional 3d visualization includes volume rendering and surface rendering where color and transparency are employed to selectively emphasize anatomic structures. These techniques have obvious limitations if a variety of different objects is relevant for a treatment decision and need to be displayed simultaneously. These limitations recently led to the development of illustrative rendering techniques [4, 17, 40], which can be flexibly combined with conventional medical visualization techniques. These new techniques involve an increased flexibility on the one hand and an increased necessity to adjust parameters on the other hand. In clinical

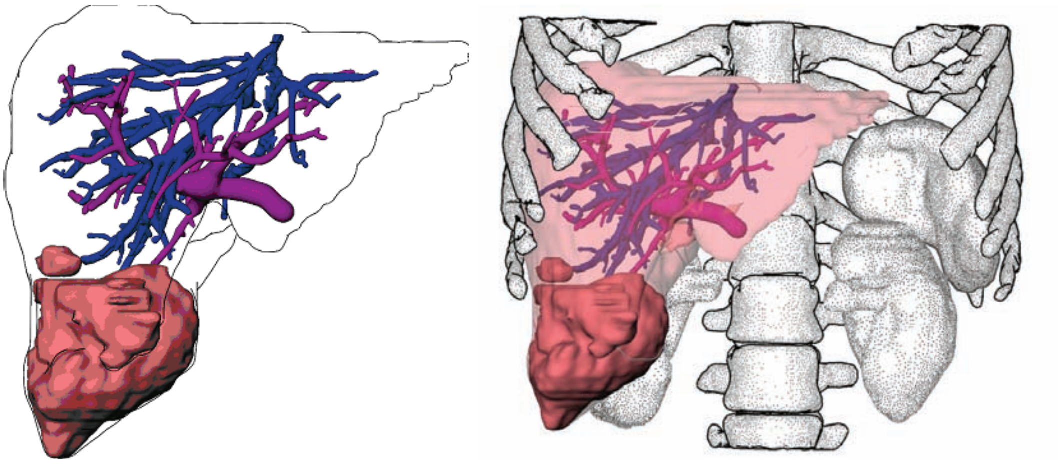

Figure 6 Liver, intrahepatic vasculature as well as a tumor are depicted for intervention planning. Convolution surfaces are used for the vasculature. While the left image is restricted to the liver and their internal structures, the right image also contains surrounding structures as context objects. Stippling is a useful technique for these structures. Left image is courtesy of Christian Tietjen, right image is courtesy of Alexandra Baer (both from University of Magdeburg).

applications, presets are necessary to reduce the interaction effort. These presets must consider which techniques and which parameters of these techniques are appropriate for certain categories of anatomic structures. We regard this as another example of model-based visualization.

Illustrative rendering refers to the use of lines and points as rendering primitives. Silhouette rendering, hatching and stippling are used to render anatomic shapes more comprehensibly. After the pioneering work of Saito and Takahashi [35] a few dedicated therapy planning solutions have been developed, for example radiation treatment planning [20]. Illustrative rendering techniques are based on proven assumptions with respect to shape perception. Object boundaries are recognized faster and more precisely by depicting their silhouettes. Surface orientation is perceived more accurately (compared to shaded surfaces) if hatching lines along the main curvature directions are included [20, 43].

The potential of such visualization techniques for intervention planning can be easily shown. However, for practical use, the selection and parameterization of illustrative rendering techniques must be supported. Our experiments and an informal user study reveal that silhouette rendering is useful for large structures, such as organs (see Figure 6), but not for small structures such as small nodules [40]. Depending on the visualization goal, silhouette rendering may be used as the only rendering mode or combined with surface rendering. The exclusive use of silhouettes clearly indicates that the visualization of an object serves as anatomic context (only). More experiments (more datasets, different visualization goals, ...) and user studies are needed to derive more reliable conclusions.

It is also necessary to investigate the prerequisites for illustrative rendering. A major problem with the automatic use of silhouette and hatching line generation is the smoothness of surfaces. Silhouettes emphasize not only the relevant features of a boundary but also noisy portions which might occur due to smaller segmentation errors or large slice distances. Hatching lines are usually generated by considering curvature directions. Noisy surfaces exhibit frequent strong changes of surface normals and curvatures. Therefore, the hatching directions suddenly change and lead to distracting visualizations. In summary, object shapes

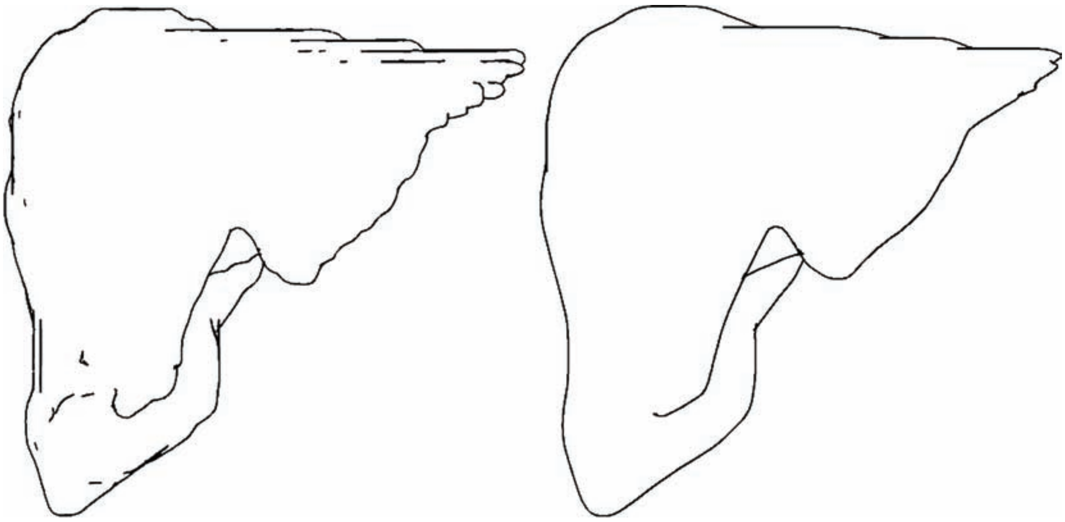

Figure 7 Left: Silhouette generation based on a typical segmentation result of the liver in abdominal CT data. Right: The polygonal model was strongly smoothed (relaxation filter with 7 iterations and relaxation factor 1.0) prior to silhouette generation. Images are courtesy of Christian Tietjen, University of Magdeburg.

resulting from a segmentation process usually require a subsequent smoothing step to be adequate for illustrative rendering (recall Section 2). Figure 7, illustrates how silhouette generation is affected by smoothing.

Illustrative techniques enrich the expressiveness of medical 3d visualizations by emphasizing silhouettes or characteristic features, such as ridges and valleys. This development is not finished yet; new hatching and stippling techniques (see Fig. 6, right) are devised which convey geometric properties such as curvature.

These new techniques exhibit considerably more parameters than silhouette rendering. The analysis of anatomic structures and the evaluation of sample image should lead to recommendations how to apply such techniques for certain anatomic structures.

5 Exploration of Nodules and Lymph Nodes with Cutaways and Ghosting

Emphasis techniques are useful to support the perception of relevant anatomic or pathologic structures. What is *relevant* is determined by the user, by either selecting an object name in a list or by picking its visual representation. A wide variety of emphasis techniques exists [33]. The selection should again consider geometric properties and 'a priori knowledge of the objects. As an example, we discuss emphasis techniques which were developed to support the exploration of lymph nodes, lung nodules and other pathologic structures.

The occurrence and localization of enlarged and potentially malignant lymph nodes is an essential information for planning surgical interventions, for example, in the neck region [23]. By contrast to vascular structures, lymph nodes, tumors and lung nodules do not exhibit a complex topology. Instead they are rather small and compact. They are explored together with adjacent structures in order to evaluate whether these structures are infiltrated. Without other structures displayed, small nodules cannot be localized. Often, it is a severe problem to display these structures simultaneously with sufficient opacity.

Cutaways – originating from technical illustrations – might be applied. Cutaway views

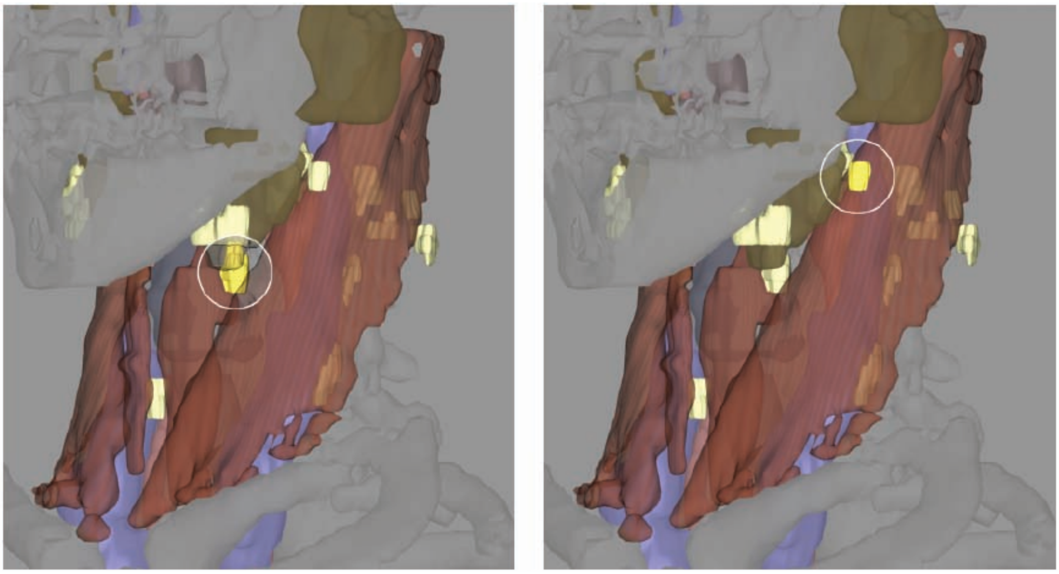

Figure 8 Lymphnodes in the neck region are emphasized by means of cylindrical ghostviews. A sequential exploration of all lymph nodes is supported taking into account the lymph node's size and position. Image is courtesy of Arno Krueger, University of Magdeburg.

are generated by removing a geometric shape to expose hidden objects. Instead, cutaways are applicable to show compact small objects. Compactness and relative size can be geometrically analyzed.

As a variation of cutaway views the cut region can be displayed transparently instead of a complete removal. This technique is referred to as ghostview (Feiner and Seligman [12]). An essential decision in the use of cut-away views and ghostings is the selection of a cut geometry. It should be regular to be recognizable as an illustration technique (anatomical shapes are not regular). The shape should "fit" to the objects which should become visible (see also [41] for a discussion of cutaways and related smart visibility techniques). Since lymph nodes, nodules, and metastasis have roughly circular shapes (model assumption), cylinders are appropriate cut-regions. Figure 8 shows cylindrical ghostviews used for neck dissection planning. Intervention planning, however, requires a systematic exploration of all enlarged lymphnodes. Based on this task knowledge, an exploration technique is needed which supports a sequential emphasis of all relevant lymphnodes. In [23], we suggested to use the Tab-key in order to emphasize all lymphnodes based on a sequence which considers size and local coherency.

6 Discussion

The previous sections presented a variety of examples where visualization techniques have been fine-tuned to particular target structures such as nodules and vascular structures. "Model-based" techniques are also needed for a variety of other applications, such as the visualization of diffusion tensor data, where 'a priori knowledge on white matter tracts and their branchings is incorporated in the visualization and clustering of fiber tracts [14, 46].

Similar to segmentation problems, the suitability of visualization techniques depends on the object shape, size and on the occurrence of other objects in the neighborhood. In many intervention planning applications, image analysis is regarded as a challenge and visualization as a simple matter of using some wide-spread commercial rendering system. This is an over-simplified view of the difficult problem of conveying the essential information to the user. Visualization, on the other hand, can benefit from the substantial work on representing 'a priori knowledge for image segmentation. Smoothness constraints as they are used for Active Contours are relevant for silhouette rendering: If segmentation results fail to meet smoothness constraints, they cannot be directly employed for silhouette generation.

Model-based image segmentation recently started to represent not only one "target" structure, but also spatial relations of adjacent structures, see e.g., the Active Structural Shape Models developed by [1]. Similarly, the effectiveness of visualization techniques applied to one anatomic structure depends on the visualization techniques applied to other anatomic structures which are displayed simultaneously. Therefore, it is essential that intervention planning tasks are carefully studied in order to determine which collections of objects are explored simultaneously. These collections should be provided as predefined selections and the default visualization techniques should be chosen in such a way that the whole collection is comprehensibly displayed. As a simple example, colors and transparencies of such objects should be selected such that contrasts are easily perceived and all relevant objects are sufficiently visible.

Comparison of model-based segmentation and visualization. In Table 1, we compare information used for model-based segmentation and visualization. While the distribution of grey values of the target structures in CT and MRI data is valuable information for model-based segmentation, this information is not relevant for model-based visualization. Derived information such as gradient magnitude or curvature metrics is essential for edge-based segmentation, such as Live Wire. For visualization, these metrics can be regarded as indicators for the certainty of the visualization. Primary tumors for example, often have weak borders and their precise extent is uncertain. This information can be employed to select a visualization technique which conveys this uncertainty (for example a semitransparent volume rendering instead of a "perfect" shiny isosurface). We regard as geometric shape any shape descriptor; such as compactness or anisotropy. Assumptions related to shape descriptors are useful to identify the target structure and to visualize it appropriately. Similar, topology information, such as connectedness and the number of holes is essential for segmentation and visualization. The use of structural information for image analysis was clearly demonstrated. For visualization, it can be used for the design of color mapping schemes which employ information on adjacency of structures. Finally, visualization strongly benefits from research in visual perception. Whether something can be perceived at all, whether color differences can be discriminated, whether objects can be discriminated at a glance ("preattentive" vision) is dependent on the selection of visualization parameters. A variety of user studies have been carried out and provide a valuable source for 'a priori knowledge (recall Colin Ware's book [43]). Finally, task knowledge can be exploited to derive which objects are essential for certain tasks and to guide the selection of visualization parameters.

Despite the similarities between model-based segmentation and visualization there are also fundamental differences. Model-based segmentation is employed to automatically segment one target structure (with rather fixed topology). Model-based visualization is more general and refers to classes of anatomic structures, such as vascular systems or lymph nodes. Moreover, model-based segmentation is adapted to particular image data, such as T2-weighted MRI data, whereas model-based visualization does not consider the modality of the imaging device.

While there is one correct segmentation, there are potentially many appropriate visualization settings for a particular set of anatomic structures. The suitability of visualization

Table 1 Model-based segmentation and visualization

Information	**Model-based segmentation**	**Model-based visualization**
Grey value distribution	x	-
Gradient magnitude/ curvature metrics	x	x
Geometric shape	x	x
Topology	x	x
Structural relation between objects	x	x
Visual perception	-	x
Task knowledge	-	x

parameters depends on user preferences, previous experiences and on the visual capabilities of a particular user. The exploration of 3d models with appropriate interaction facilities is desirable and may lead to additional insights. In particular, rotation and zooming provide insight into spatial relations. However, the unrestricted exploration involves too many parameters. Therefore, a model-based approach is desired to start the exploration with a meaningful combination of visualization techniques.

7 Concluding Remarks

We introduced model-based visualization as a concept where the appropriateness and parameterization of visualization techniques is carefully adapted to the shape and size of the object, and to the context of its visualization in intervention planning. To realize model-based visualizations, the shape of the target structure has to be analyzed, for example, with respect to the branching pattern. The wide literature on shape description may be employed to select appropriate shape descriptors (see e.g. [10] for a recent book on shape classification).

We argue that model-based visualization is an essential goal in order to effectively exploit the huge space of visualization options. The fully interactive specification of all visualization parameters is not feasible since it is time-consuming and leads to visualization results which are neither optimal nor reproducible. Although we presented concepts and solutions for some specific problems, many aspects of model-based visualization require a more in-depth analysis. Even the visualization of vascular structures – probably the aspect which deserved most attention so far – requires the refinement of existing solutions, for example to better represent vascular structures at locations where the cross section is notably not circular.

There is an urgent need for further research in the adaptation of visualization techniques to intervention planning tasks. In particular, the appropriateness of visualization techniques must be assessed by the target users: medical doctors who prepare for complex interventions. Prospective user studies are required which compare visualization techniques with respect to their consequences for the surgical strategies. We restricted the discussion in this paper to static visualizations. The model-based generation of animation sequences for intervention planning is an interesting challenge for future research.

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