Metasurfaces: Contouring with Changing Isovalue

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Abstract

Isosurface extraction is a standard method for volume data exploration, where a surface is extracted according to a chosen isovalue of some trivariate function. Automated isovalue-selection algorithms typically offer a ranking of possible isovalues, from which a user can choose. During isosurface extraction, the isovalue is kept constant throughout the data set. For most biological data, however, it would be desirable to adjust the isovalue locally due to shifts in the "material boundary value." This effect becomes particularly evident when segmenting anatomical branching structures of high fractal dimension. Adjusting isovalues manually is too tedious to be practical. We present an automated contouring approach with locally changing isovalues. We call the resulting surface "metasurface." Metasurface extraction is based on identification of structural information and detection of segments, which allows for local isovalue determination and local isosurface extraction. Our approach blends the contours corresponding to different isovalues.

1 Introduction

Medical imaging techniques like computed tomography (CT), magnetic resonance imaging (MRI), or confocal microscopy today have the precision that allows for acquisition of high-quality "three-dimensional images." Resolution sensitivities are in the range of a few tenths of millimeters for CTs and MRIs, and in the range of micrometers for confocal microscopy. Our work is motivated by the desire to visually explore bio-medical volume data representing branching structures, examples being blood vessels, lung airways, or ganglion dendrites, see Figure 1.[1] High-resolution imaging techniques are capable of capturing branches of a range of many orders, where order refers to the level of a branch in the branching hierarchy.

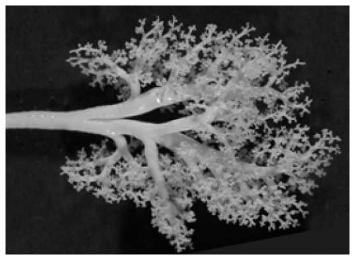

Figure 1: Cast of rat lung.

Isosurface extraction (or contouring) is a standard technique to compute "material boundaries" from volume data. The geometry is used to visualize the structural information of a scanned object or to quantitatively analyze it. Each material boundary (or tissue type in most bio-medical applications) is associated with an isovalue, i. e., a threshold used to separate interior from exterior material. The underlying assumption is that the material properties hardly change in the entire data set. This assumption, however, sometimes needs to be "loosened" when dealing with biological data. In branching data, where partial voluming adds an additional challenge, there appears to be a slight shift in material density when traversing the branching hierarchy, leading to the fact that no global constant isovalue is the perfect choice throughout the whole structure. Instead, one needs to locally adjust the isovalue to the changing material properties.

A locally adjustable isovalue selection allows for the extraction and visualization of all the structural information in the underlying data including features that are mutually excluded when using traditional isosurface extraction. Merely extracting an isosurface and relaxing the surface to match the ma-

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[1]Image courtesy of C.G. Plopper, Department of Anatomy, Physiology, and Cell Biology, University of California, Davis.

terial boundary of the branching structure does not work, since geometry for both large and small features would not be present when starting with one isosurface.

We present an approach to extract contours locally and combine the local contours to define a global surface. Although many segmentation algorithms exist and some of them produce more general results than isosurfaces, no terminology has been specified for such surfaces. To keep the description of our algorithm precise, we need to distinguish between the local isosurfaces an the global surface. Thus, we would like to use the term "metasurface" for the global one with "meta" being the Greek word for "alter" or "change," as "iso" is the Greek word for "same" or "equal." We provide a formal definition:

Definition 1 *Let $f : \mathbf{R}^3 \rightarrow \mathbf{R}$ be a trivariate scalar function. A* metasurface *is defined implicitly as the solution of the equation*

$$f(x, y, z) = f_{iso}(x, y, z) \ ,$$

where $f_{iso} : \mathbf{R}^3 \rightarrow \mathbf{R}$ is a continuous function representing a three-dimensional field of changing isovalues.

Thus, isosurfaces are a subset of metasurfaces, where $f_{iso}(x, y, z) = v_{iso} \in \mathbf{R}$ is a constant. If the isovalue field f_{iso} were known, we could apply standard isosurface extraction to the scalar field $f - f_{iso}$. Unfortunately, f_{iso} is unknown and needs to be determined explicitly or implicitly. The idea behind our algorithm is to partition the domain of scalar field f into small regions, where f_{iso} is approximately constant, to locally extract isosurfaces within each region, and to stitch the isosurfaces together to form the resulting metasurface.

When extracting isosurfaces from volume data, the selection of an appropriate isovalue v_{iso} is often left to the user, who must perform a tedious trial-and-error process to find a suitable value. Obviously, it would be even more tedious to find an appropriate locally changing isovalue-field $f_{iso}(x, y, z)$ in such a trial-and-error process. Thus, our intention was to automate the metasurface extraction process as much as possible.

Some methods exist to automatically determine isovalues from a given volumetric scalar field. The methods typically consider gradient or even higher-order derivative information in addition to the scalar field to generate a list of ranked suggestions for a good isovalue, from which a user can pick the most suitable one. Our metasurface extraction algorithm automatically determines an appropriate field f_{iso}.

The metasurface extraction algorithm consists of multiple steps. First, we identify structural information throughout the volume data, as described in Section 3. The structural information can be used to partition the data set into volumetric segments containing all relevant data, as discussed in Section 4. In Section 5, we locally determine suitable choices for isovalues independently within each segment. Then, we can perform a local isosurface extraction within each segment. A final step combines the local isosurfaces to a global metasurface by blending the surfaces in the transition areas, as described in Section 6. The processing pipeline is shown in Figure 4.

2 Related Work

Isosurfaces are commonly extracted from volumetric scalar fields using marching algorithms for three-dimensional grids. These algorithms go back to the marching-cubes approach [16], which operates on uniform rectilinear grids. Many extensions and improvements have been made to the original approach including the solution of ambiguous cases [7], better triangulations [19], application to tetrahedral grids [6], and a generic algorithm combining previous approaches [2]. A dual contouring approach has been introduced in [9], which has advantages when dealing with adaptively refined grids. The metasurface extraction algorithm presented in this paper adopts the marching nature of existing algorithms, as it consecutively considers one grid cell at a time.

Determining an appropriate isovalue is a challenge inherent in any isosurface extraction method. Early approaches left the choice of an appropriate isovalue to the user. Tedious trial-and-error processes led to the desire to have them replaced by an automated method. A related topic is the choice of appropriate transfer functions for direct volume rendering techniques.

In [18], the trial-and-error process is replaced by producing and displaying a high number of results using various possible transfer functions, which reduces user interaction and makes the selection process more intuitive. In [1], isosurfaces are extracted automatically by examining the gradients of the volumetric scalar field and choosing the isovalue as the maximum of a weighted gradient spectrum. In [12], selection of transfer functions is based on investigating a two-dimensional histogram of scalar values and gradients. This work was extended in [15] by introducing a set of direct manipulation widgets for multi-dimensional transfer functions. In [20], another layer of abstraction is added, as the user operates on the visualization results while the histograms are not transparent to the user anymore.

For the extraction of metasurfaces, we believe that user interaction for selection of an isovalue-field $f_{iso}(x, y, z)$ is no longer an intuitive process. Thus, our goal is to generate a completely automated surface extraction algorithm. To accomplish this goal, we make use of existing automated isovalue selection methods.

Methods detecting more than one isovalue have been used to display multiple isosurfaces (e. g., [5, 10]) but not to adjust isovalues locally or to automatically determine locally changing isovalues. To extract isosurfaces from volume data representing objects with branching structures, surface-growing algorithms have been developed. In [8], three-dimensional regions are grown when the local variation in intensity (scalar value) and gradient are above a certain threshold. In [3] (and to some extend in [13] and [14]), conventional three-dimensional region growing is supplemented with two-dimensional propagation based on local two-dimensional filters. Again, regions are grown when the filtered value based on intensity and gradient lies above a certain threshold. However, leaking due to noise is still a problem and is only dealt with by making certain assumptions about the size of the segmented features or by user intervention.

Segmentation surfaces that do not need to describe an isosurfaces can also be achieved using active surface models including many variations of snakes [11], level-set methods [17] and other deformation models. These methods segment the volume data starting with an initial surface and iteratively adjusting that surface with respect to cost functions. In particular, adaptive level-set methods [4] have proved to be practical for various applications. However, the choice of an appropriate cost function that leads to the determination of a surface desired for our application is not straight forward. A lot of tweaking may be necessary to compromise between following desired features and not producing leaks.

A visualization similar to rendering metasurfaces may be generated by direct volume rendering techniques when applying multi-dimensional transfer functions [15]. However, no boundary surface is extracted that could be used for further processing including quantitative analysis.

3 Identifying Structural Information

Let the trivariate function f be the representation of a scanned object. In bio-medical imaging applications, f represents density or similar intensity values of scanned materials or tissue types. The materials range from gases and liquids to solids of varying density like bones. In particular, for objects with branching structure, one can distinguish between gases or liquids inside the branching structure, the branching structure itself given by tube-like branches and joints of branches, and gases or liquids surrounding the branching structure.

Our first goal is to identify the structural information in the volume data. By structural information we refer to the parts of the data that possibly contain information about the structure of the scanned object. We separate structural information from internal or surrounding material in a crude pre-segmentation. We want to define masks to "mask out" material not to be considered for further investigation. A mask can be represented by the union of intervals from the range of function f.

The function f is given in a discrete fashion, as a volumetric grid used to approximate a scalar field. The scanning procedure of bio-medical imaging techniques typically results in a stack of two-dimensional images, which can be arranged to form a three-dimensional regular rectilinear grid with grid cells being cubes or cuboids. Masks can operate on this discrete data structure determining for each grid cell whether it contains structural information (see Figure 4).

The simplest case for the definition of the mask is given when density/intensity values of non-structural parts, i. e., of internal and surrounding material, are approximately known and, in addition, structural parts are known to have different density/intensity values. The mask can directly be defined as the interval I including exactly the known density values for non-structural parts. All grid cells that only contain values within the range of interval I are "masked out."

In case no a-priori knowledge about the underlying data is given, we have to automatically determine an appropriate mask. An automated isovalue-selection algorithm applied to the entire data set can be used for this purpose. Any of the approaches described in Section 2 can be used. We decided to use an approach based on two-dimensional histograms, where the two dimensions are given by density/intensity values and their gradients, which proves to be sufficient. From the histogram we can deduce which values are likely to describe structural and non-structural information, respectively. We base our decision on the assumption that solids have higher densities than gases or liquids. We pick values with respect to high density-gradient peaks from the two-dimensional histogram in the upper density region. We define our mask by an interval describing densities of non-structural information chosen with a certain error tolerance. The error tolerance is introduced based on the fact that, in case of doubt, it is better to choose a smaller interval in order to "mask out" less.

Once the masks have been applied, we can compute local bounding volumes. A bounding volume is a section of the data set that contains part of the relevant structural information. The data structure of a bounding volume is a collection of adjacent grid cells, often approximating the discretized version of a bounding box.

When considering branching structures, the data set has many tube-like branches winding or stretching through the volumetric domain. The idea for the selection of the size $\mathbf{s} = (s_1, s_2, s_3)$ of a bounding volume is that bounding volumes should be limited by the diameter of the branches to be extracted. To determine an appropriate value for $\mathbf{s}$, we extract an isosurface using the "best" global isovalue derived from the two-dimensional histogram as described above. Based on the isosurface, we can approximate the average diameter $\overline{d}$ of the branches. The average diameter is just a rough estimate derived from the diameter of some extracted tubes. If existent, a priori-knowledge can be used instead. The size $\mathbf{s}$ of the bounding volumes is set to $\mathbf{s} = (\overline{d}, \overline{d}, \overline{d})$.

Using $\mathbf{s}$ as a guiding value, we partition the volumetric domain of our data set such that each grid cell that has not been "masked out" belongs to exactly one bounding volume. Because of prior masking, bounding volumes are not necessarily box-shaped (see Figure 4).

4 Detecting Segments

Based on the identification of structural information using masks and the size of bounding volumes, we detect individual segments. The idea is to detect small segments of a branch that can be stitched together to define the entire branch, while the geometry of each segment can be computed locally and independently of the other segments.

Segments are detected in a constructive way while traversing the volumetric grid. A segment S is constructed by starting with a grid cell, which contains structural information, and exploring its neighbor cells. If any of the neighbor cells also contain structural information, we add them to segment S. Progressively, we explore the neighbors to possibly add more cells to segment S, proceed with their neighbors, and so on. The exploration strategy is defined by a breadth-first search. The search terminates when none of the neighbors can be added to the current segment S or when segment S has reached its maximum size limited by the bounding volume size.

After one segment has been completed, we iterate our procedure to construct more segments. As long as there are grid cells that are identified to contain structural information and do not belong to any of the segments extracted so far, we generate new segments.

5 Local Isosurface Extraction

Since the detected segments are of limited size, we can assume that the changes of the isovalue-field f_{iso} within the bounding volume of a segment are very small. Thus, we set $f_{iso} = v_{iso}$ for a constant value $v_{iso} \in \mathbf{R}$ and apply an isosurface extraction method to extract the desired material boundaries locally for each segment, see Figure 4.

To determine the local isovalue v_{iso} for a segment S, any of the automated isovalue computation methods described in Section 2 can be applied. We have tried algorithms based on one- and two-dimensional histograms, i. e., based on density/intensity values solely or on density/intensity values and their gradients, respectively. For the chosen examples, a one-dimensional histogram-based approach was sufficient.

For implementation efficiency and simplicity purposes, we store the automatically determined isovalue v_{iso} in each grid cell of segment S. When doing so for all segments detected in the previous step, we obtain a discrete representation of our isovalue-field f_{iso}. Standard isosurface extraction algorithms can be applied globally to extract the individual local isosurfaces for each segment. The only difference to traditional isosurface extraction is that the isovalue is not a constant but is being looked up for each grid cell individually.

We have implemented a marching cubes-like approach that traverses the volumetric grid once. Grid cells that do not contain any structural information are tagged (see Section 3) and can be skipped.

6 Blending Isosurfaces

Let S_1 and S_2 be two adjacent segments. Each segment has an automatically detected isovalue associated with it. Let v_1 be the isovalue for segment S_1 and v_2 be the isovalue for segment S_2. When isosurfaces of two adjacent grid cells are extracted with respect to different isovalues, the two extracted isosurface components do not match generally on the shared cell faces. Figure 5 shows four selected possible cases that can emerge on the shared cell face.

The surface as a whole is discontinuous. Such artefacts are known in the context of extracting isosurfaces from adaptively refined grids. Such discontinuities are often referred to as "cracks." In our case, however, the representation of the scalar field is continuous (assuming piecewise linear interpolation), which we can use to "fix the cracks" in the sense of contour stitching.

In marching cubes-like isosurface extraction, the vertices of the resulting triangular mesh (the so-called "isopoints") lie on the edges of the grid. To resolve the discontinuities in our surface, we have to ensure that the isopoints on the shared edges for segments S_1 and S_2 coincide.

The marching-cubes case-table leads to different possible constellations on the shared face. In the regular case, as depicted in Figure 5(a), we can blend the contours (shown as dotted and dashed lines, respectively) by relaxing the local isosurfaces to match the contour with respect to the "average" isovalue $v_{1,2} = \frac{v_1+v_2}{2}$ (shown as a solid line). In case the two contours do not intersect the same edges of the shared face, as depicted in Figures 5(b), the shared face reflects a transition with respect to the marching-cubes cases. To accommodate for such a transition, the two contours are relaxed to a contour that contains face vertices. In case of topological changes, as depicted in Figures 5(c)-(d), we can proceed in the same way. The contour lines may degenerate to points at the cell vertices.

The resulting surface is a metasurface without discontinuities.

7 Results

Figures 2 and 6 show the results we obtained when applying our metasurface extraction approach to the data set of a rotational x-ray scan of the arteries of the right half of a human head. The x-ray scan exhibits an aneurism.[2] The goal was to extract the geometry of the arteries' branching structure. The data size is 256^3 with a $1:1:1$ spacing.

In Figure 2, we compare the results from isosurface extraction (using a traditional marching cubes-like approach) with the results from our metasurface extraction approach. The upper row shows an isosurface extracted from the entire volumetric data set (Figure 2(a))[3] and from a part of the volumetric data set (Figure 2(b)). The branches in Figure 2(b) are not connected, as the branching structure continues outside the chosen volumetric domain. The middle row shows a metasurface. The metasurface extraction algorithm was also applied to the entire data set (Figure 2(c)) and the chosen part (Figure 2(d)). Our metasurface approach is capable of extracting much more structural branching information when compared to the standard isosurface approach.

We observed that the data set contains noise. Our segment detection algorithm is sensitive to noise, as it detects even very small segments. An automated approach cannot distinguish between noise and actual small features without using heuristics. Thus, we incorporated an optional user intervention mechanism applied during segment detection to reduce or even eliminate noise. As we keep track of the size of the segments we detect, we can suppress segments up to a given size. Ideally, all segments of a size below a certain threshold represent noise and all segments of a size above the threshold represent features of the structure. What is left to the user is to select the threshold from an interval with range zero to bounding volume size. This selection is as simple as adjusting a single slider and comparable to choosing the size of a 3D low-pass filter in a preprocessing. To make our algorithm completely automatic (even for data containing noise), we set the threshold by default to an empirically de-

[2] Data set courtesy of Philips Research, Hamburg, Germany.
[3] Also cf. http://www.volvis.org/.

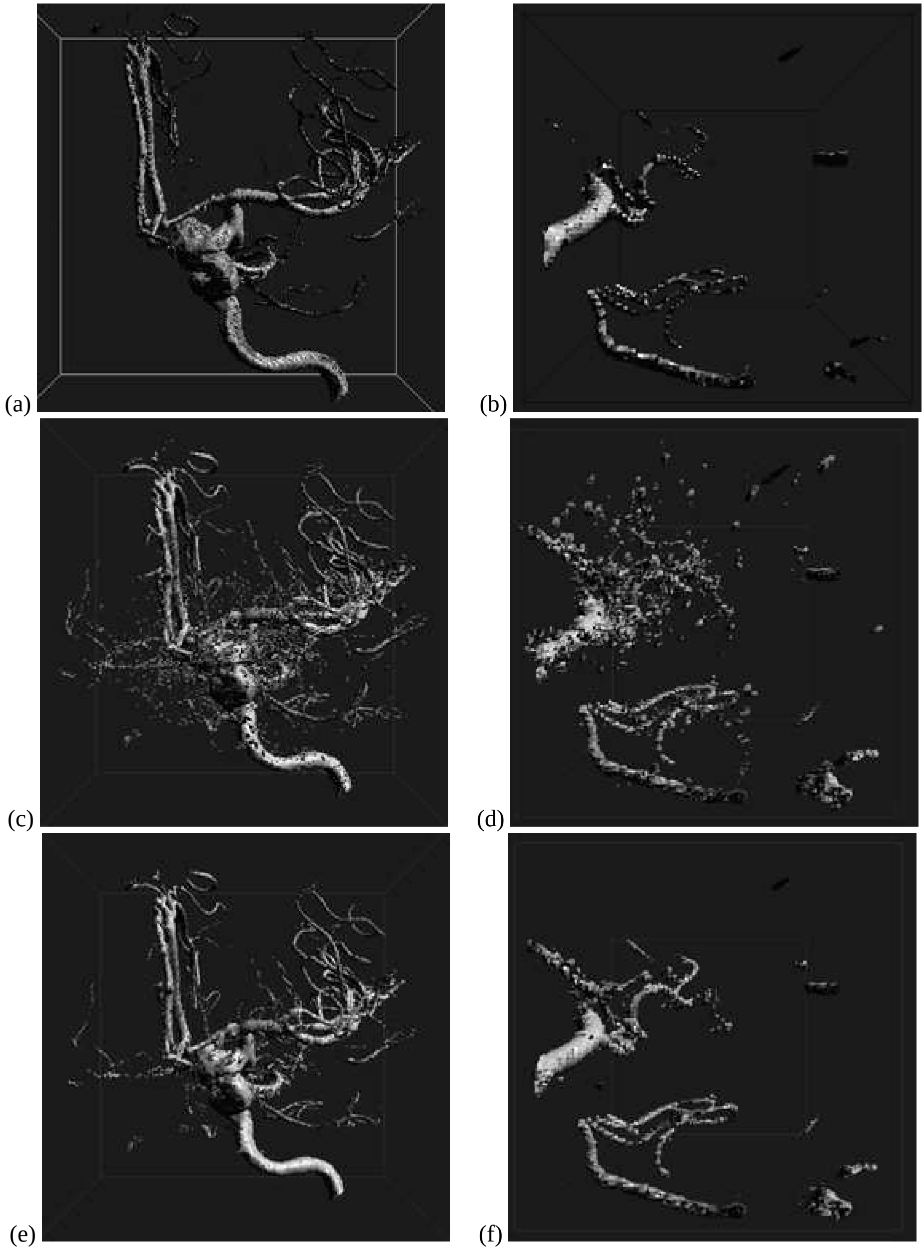

Figure 2: Isosurface extraction (upper row) compared to metasurface extraction without (middle row) and with cutting of noise (lower row). Algorithms were applied to aneurism data set (left column) and a part of the aneurism data set (right column). Metasurface extraction was capable to extract much more structural information of branching structure including branches of high order.

termined value. The lower row of Figure shows 2 the results. Again, we applied the metasurface extraction algorithm to the entire data set (Figure 2(e)) and the chosen part (Figure 2(f)).

Coloring of isosurfaces is usually done using a single color, which does not add any information about the data set (see Figure 2). When extracting metasurfaces, the surface can be colored with respect to the locally changing isovalue, as shown in Figure 6. We defined a one-dimensional continuous transfer function, which assigned each value of the range of the scalar function f a color. Each local isosurface is drawn in the color assigned to the isovalue that was used to extract the local isosurface. Figures 6(a) and (b) illustrate the coloring of metasurfaces without and with cutting using the surfaces from Figures 2(c) and (e), respectively. We used a color map ranging from bright yellow to dark red, and flat shading to emphasize the change in color. The colors indicate the shift in density/intensity values for different-order branches in the branching structure data.

In Figure 3, we apply isosurface and metasurface extraction to a part of a data set with low signal-to-noise ratio. The data set represents a CT scan of a canine lung.[4] While the extracted branches are disconnected for the isosurface in Figure 3(a) due to noise, the metasurface in Figure 3(b) exhibits the geometry of a branching structure. Compared to Figure 1, we did not capture all branches, which is primarily due to the resolution of the scanning technique (branches in the subpixel range).

The results show that approach can automatically obtain locally adjusting segmentation results in a general setting. No manual tweaking of several parameters is necessary, and there are no obvious flaws (such as leaking artefacts) in our segmentation.

The complexity of our metasurface extraction algorithm is linear in the number of grid cells. In our current implementation, we iterate three times through all grid cells. This number could be reduced to two by combining the segment detection with the local isosurface extraction step. The computation times for the shown examples are in the range of a few seconds. For larger data sets we believe that using a hierarchical volumetric data organization would be beneficial, especially when larger blocks of volumes exist that do not contain structural information.

[4] Data set courtesy of E.R. Wisner, Department of Surgical and Radiological Sciences, University of California, Davis.

The results document that metasurface extraction is superior to a marching-cubes-like isosurface extraction method when it comes to the extraction of branching data with a shift in material boundary values. It remains to compare our approach to region-growing or active-surface/level-set approaches. For future work, we plan on implementing other state-of-the-art approaches and comparing them to our approach in a user study: Experts in lung anatomy are to evaluate all methods pointing out their advantages and drawbacks.

8 Conclusions and Future Work

We have presented an algorithm for the extraction of metasurfaces. Metasurfaces are "material boundary surfaces extracted with changing isovalue." The motivation for introducing metasurfaces is the desire to extract material boundaries from volumetric bio-medical imaging data, especially when considering objects with branching structure. Often, one can observe density shifts in the boundary material, which requires the adaption of the isovalue during boundary surface extraction.

Our metasurface extraction algorithm is based on detection of structural information using a masking technique, size estimation for boundary volumes, volume partitioning into segments, local isosurface extraction, and blending of local isosurfaces. We applied our methods to objects with branching structure and achieved a significant improvement in results when compared to traditional isosurfacing approaches. Features mutually excluded by standard isosurfacing techniques can be incorporated into one surface.

An obvious target for improvement is the size of the bounding volume, which currently is defined globally. As we extract isosurfaces locally, the bounding volume size should vary locally. We also plan on investigating how we can make isovalues vary continuously rather than in discrete steps. Continously changing isovalues would make the blending step obsolete.

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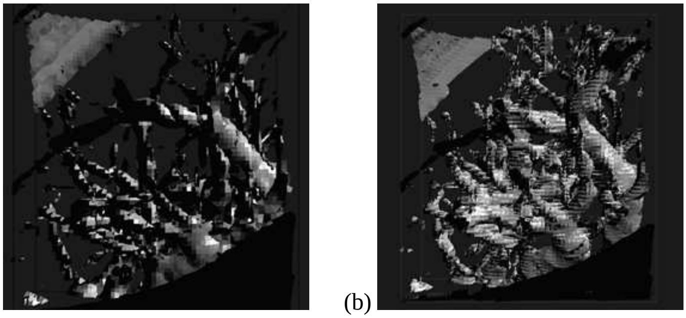

(a) (b)

Figure 3: Isosurface (a) and metasurface (b) extracted from a canine lung data set.

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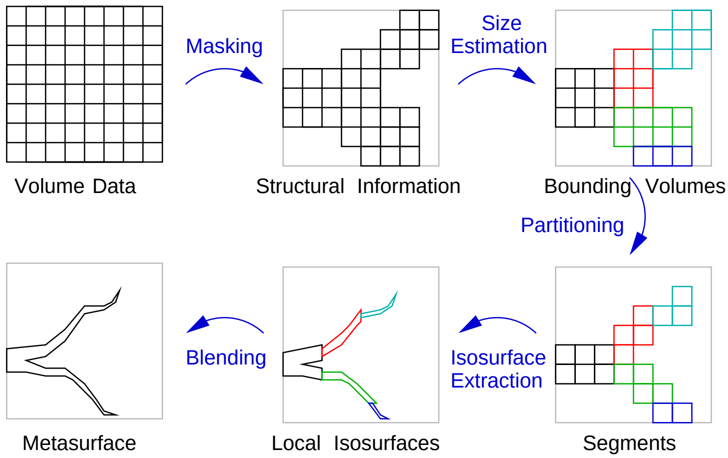

Figure 4: Processing pipeline for metasurface extraction.

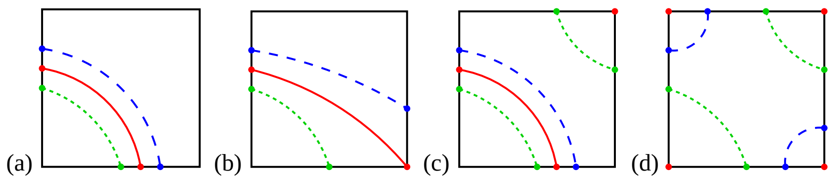

Figure 5: Blending (solid lines) of contours (dashed and dotted lines) on a common face: (a) Regular case. (b) Geometrical change. (c),(d) Topological change.

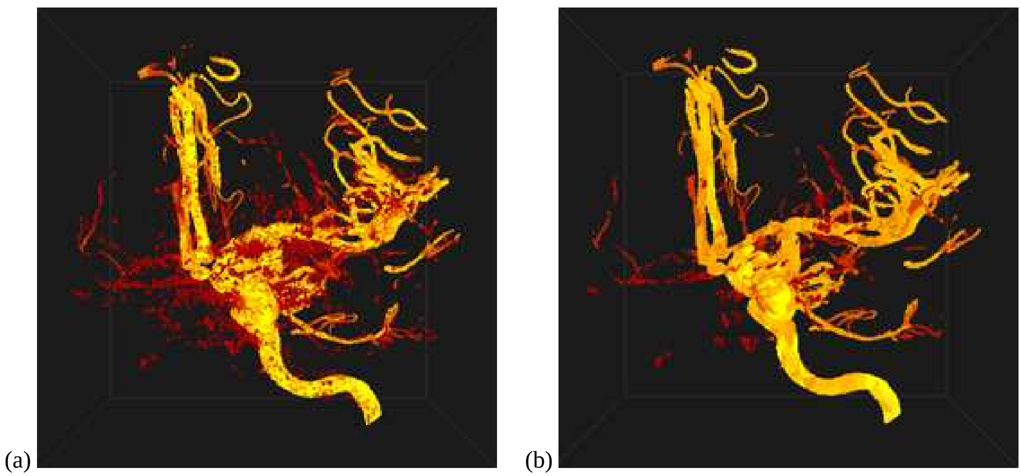

Figure 6: Colored metasurfaces extracted from aneurism data set without (a) and with cutting of noise (b). Colors refer to locally chosen isovalue using one-dimensional continuous transfer function.