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# VISUAL EVALUATION OF DOWNSAMPLING FILTERS IN RESPECT OF THE TOPOLOGY OF SCALAR FIELDS

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**ABSTRACT**

In general, downsampling filters for structured volumetric grids cannot preserve the topology of a scalar field; thus, the isosurfaces of the downsampled field will not only geometrically but also topologically differ from the isosurfaces of the original field. Since these topological differences are often more important than geometric deviations, the approximate preservation of topological features is an important feature of some downsampling filters in volume visualization. We apply a recently proposed visualization of the topology of scalar fields to visually evaluate three nonlinear downsampling filters, which have been proposed to preserve more topological features than linear downsampling filters. With the help of this evaluation, we can also determine the most suitable filter to compute previews for the mentioned topology visualization.

**KEYWORDS**

Volume visualization, downsampling, filtering, topology, scalar field, isosurface.

## 1. INTRODUCTION

The large size of volume data sets is one of the main challenges in volume visualization. The performance of object-based volume visualization usually increases at least linearly with the amount of data while image-based algorithms require all the data in memory for best performance. For CPU-based implementations this is possible since most computers can be equipped with enough main memory; however, for faster GPU-based implementations the texture memory resources are much more limited and the data transfer bandwidth between main memory and texture memory is too low to allow interactive implementations to transfer all volume data for each frame.

One common solution to this problem of too large data sets is downsampling, which can be used in various ways. For example, the downsampled version of the data set can be employed to quickly compute previews of the final visualization, to compute multiple levels of details (e.g., in the form of a pyramid image) for an adaptive visualization, or simply to visualize a smaller version of the data set instead of the original data set.

While downsampling is a very common technique, very few downsampling filters for scalar volume data have been proposed in the literature. This is particularly surprising since the standard downsampling filter for mip-map texture maps is well-known to result in inferior results for scalar data [LaMar et al., 1999; Kraus and Ertl, 2001]. In fact, the topology of scalar fields changes significantly under most linear downsampling filters. Thus, isosurfaces computed from the downsampled data set will not only differ in their geometry from the original isosurfaces but also in their topology—most notably in the number of their components. Therefore, several nonlinear downsampling filters have been proposed, in particular subsampling [LaMar et al., 1999], topology-guided downsampling [Kraus and Ertl, 2001], and the use of the levels of a min-max octree [Kraus, 2009]. Before these filters are discussed in Section 2.2, we will first discuss a recently proposed technique [Kraus, 2009] to visualize the topology of scalar fields in Section 2.1.

One contribution of this work is to visualize the changes of the topology of selected volume data sets under the mentioned downsampling filters. This allows us to show the topological changes in their entity instead of comparisons of individual isosurfaces as employed previously [Kraus and Ertl, 2001]. Our actual objective, however, is two-fold: Firstly, based on this visual evaluation in Section 3 we can choose an appropriate downsampling filter for previews of the employed topology visualization, and secondly, we can determine appropriate filters for approximate topology preservation in general.

# 2. PREVIOUS WORK

## 2.1 Visualization of the Topology of a Scalar Field

The visual evaluation presented in this work is based on a recently proposed visualization [Kraus, 2009] of the topology—more specifically, the contour tree [Freeman and Morse, 1967]—of scalar fields. To some degree this visualization is related to the function version of volume plots of level set trees [Klemelä, 2004]. Figures 1 to 3 show examples of the employed topology visualization [Kraus, 2009] and selected isosurfaces to illustrate the relation between this visualization and the properties of a scalar field. The visualization is basically a plot of the logarithm of the surface area of isosurfaces on the *y* axis against the isovalue on the *x* axis. Disconnected components of the same isosurface are separated by black lines inside this plot. For example, in Figure 1 a single-component isosurface splits into two components for an isovalue of about 84. For smaller isovalues, the two isosurface components are still connected. In the topology visualization, this corresponds to a separating line that starts at an *x* coordinate of about 84 and a *y* coordinate that divides the total height of the graph into two parts, which correspond to the surface area of the two isosurface components.


Figure 1. Topology visualization and selected isosurfaces of the fuel data set (64×64×64 voxels).

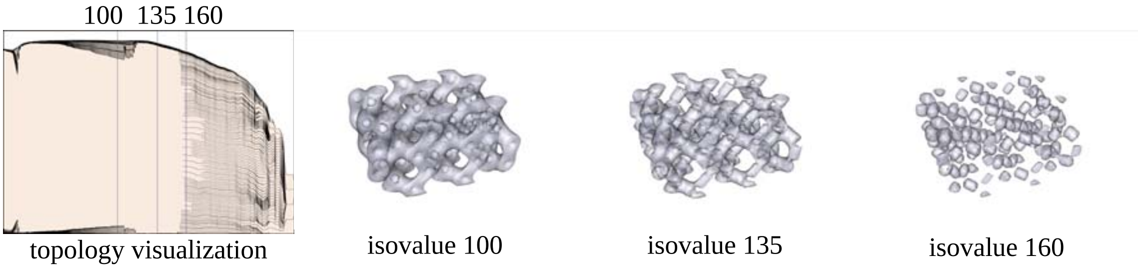



Figure 2. Topology visualization and selected isosurfaces of the silicium data set (98×34×34 voxels).

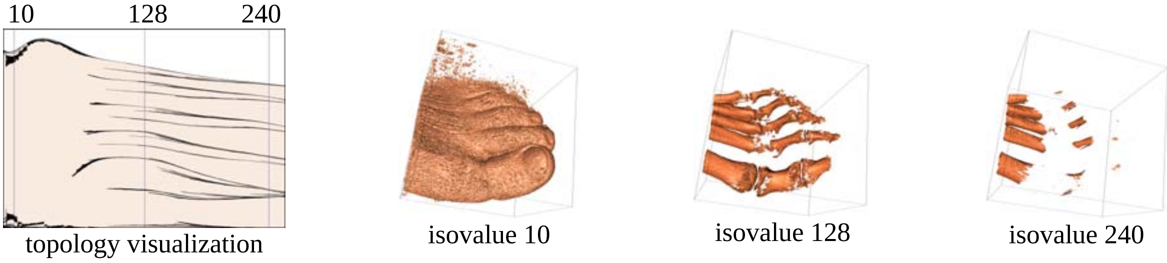



Figure 3. Topology visualization and selected isosurfaces of the foot data set (256×256×256 voxels).

## 2.2 Downsampling Filters for Improved Topology Preservation

Downsampling structured volume data sets is a standard method to increase the performance of volume visualization systems by reducing the amount of data. Unless specified otherwise, we consider downsampling steps that replace groups of 2×2×2 = 8 voxels of the original grid by one voxel of the downsampled grid. To determine the value of the downsampled voxel, a local downsampling filter is applied. As noted by several authors [LaMar et al., 1999; Kraus and Ertl, 2001] linear downsampling filters often tend to produce unsatisfactory results. This is due to the importance of the topology of scalar fields for the topology of its isosurfaces, in particular the number of their components. Since linear downsampling filters tend to change the topology of scalar fields significantly, the resulting isosurfaces change accordingly. Therefore, any visualization that is based on isosurfaces or high-frequency transfer functions will strongly differ from a visualization of the original data. These topological changes can be avoided if the mesh is only filtered [Gingold and Zorin, 2007] but they are inevitable when structured meshes are downsampled.

To minimize the deviations, various alternative downsampling filters have been proposed. In this work we will consider three of them. The first one was suggested by LaMar et al. [1999] in the context of multiresolution volume rendering. They employed subsampling to compute downsampled levels of detail. Specifically, they choose one voxel from each group of 2×2×2 = 8 voxels (always at the same relative position) to represent the whole group in the downsampled data set. While this approach is extremely easy to implement, it significantly improves the rendering results in comparison to linear downsampling filters.

The second downsampling technique was proposed by Kraus and Ertl [2001], who called it “topology-guided downsampling.” It first computes critical vertices (maxima, minima, and saddle points) in a tetrahedralization of the structured volume data set. For the downsampling of 2×2×2 = 8 vertices into one vertex, the data value of one vertex is chosen. To this end, the algorithm prefers maxima and minima over saddle points and saddle points over regular points. If there are multiple maxima or minima among the eight vertices, the algorithm chooses the scalar value of the maximum or minimum with the largest absolute difference to the average scalar value. A particular feature of this method is that it preserves small and/or thin isosurface components in the downsampled data set, which are lost or broken into multiple components if a linear downsampling filter is applied.

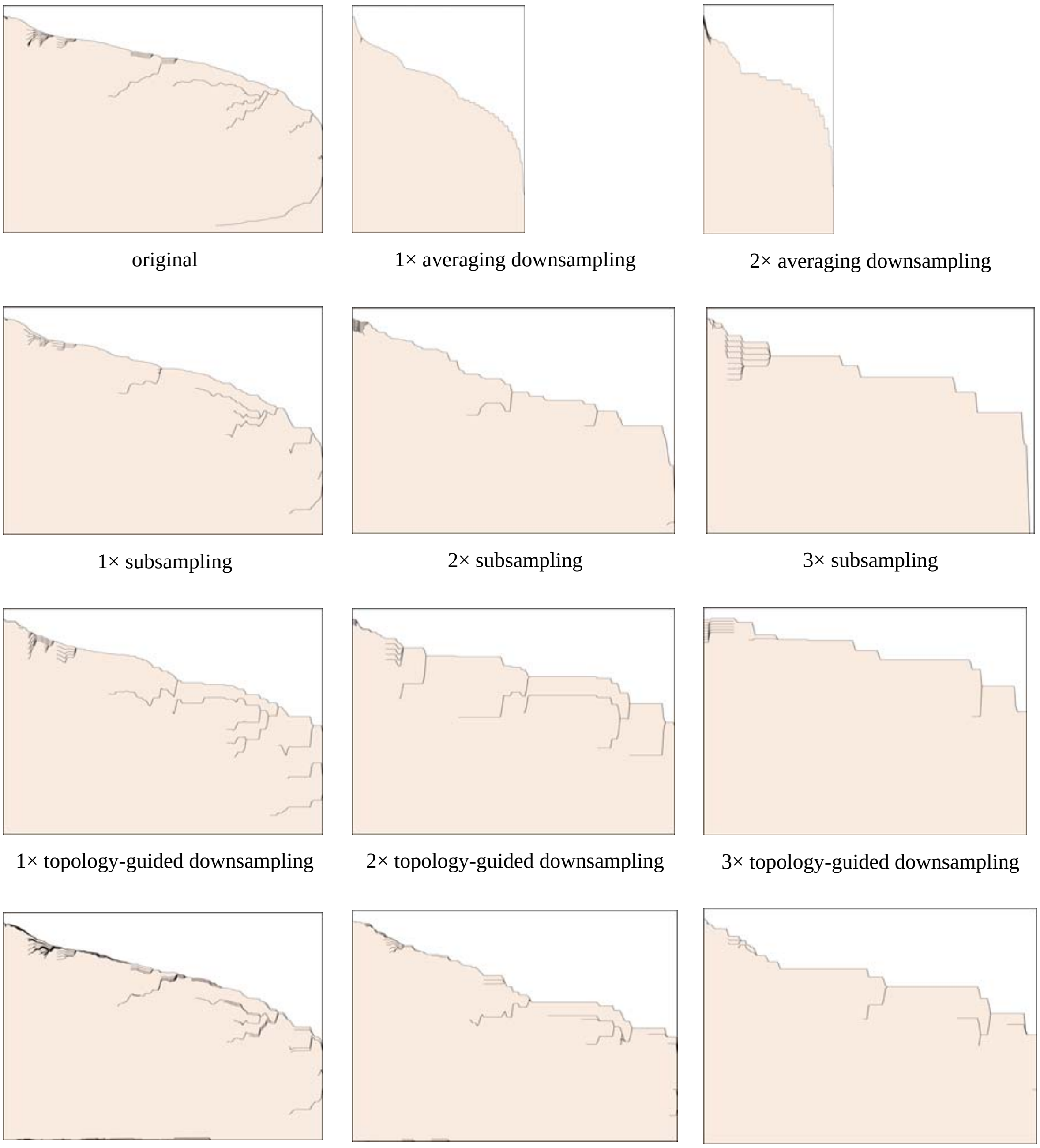
The third candidate in our evaluation was suggested as part of the employed topology visualization [Kraus, 2009]. This visualization uses min-max intervals for all voxels to compute the topology of the scalar field. Moreover, a min-max octree is employed to accelerate this computation. Thus, it is straightforward to use any level of this min-max octree to compute an approximate visualization of the topology of the original data set.

## 3. COMPARISON

To compare the three downsampling methods discussed in Section 2.2, we computed topology visualizations of several publicly available data sets [Bartz, 2005]. We have chosen three data sets with very different characteristics in order to cover a wide range of applications and data sets.

## 3.1 Experimental Results

For each of the data sets we present topology visualizations after applying each of the three downsampling methods, i.e., subsampling, topology-guided dowsampling, and min-max octree levels. Each method is applied up to three times. For comparison, topology visualizations of the original data and of the data after one and two averaging downsampling steps are included. The averaging downsampling just averages groups of 2×2×2 = 8 voxels to determine the voxels of the downsampled data set.



original | 1× averaging downsampling | 2× averaging downsampling

1× subsampling | 2× subsampling | 3× subsampling

1× topology-guided downsampling | 2× topology-guided downsampling | 3× topology-guided downsampling

1st min-max octree level | 2nd min-max octree level | 3rd min-max octree level

Figure 4. Topology visualization of various versions of the fuel data set (see also Figure 1).

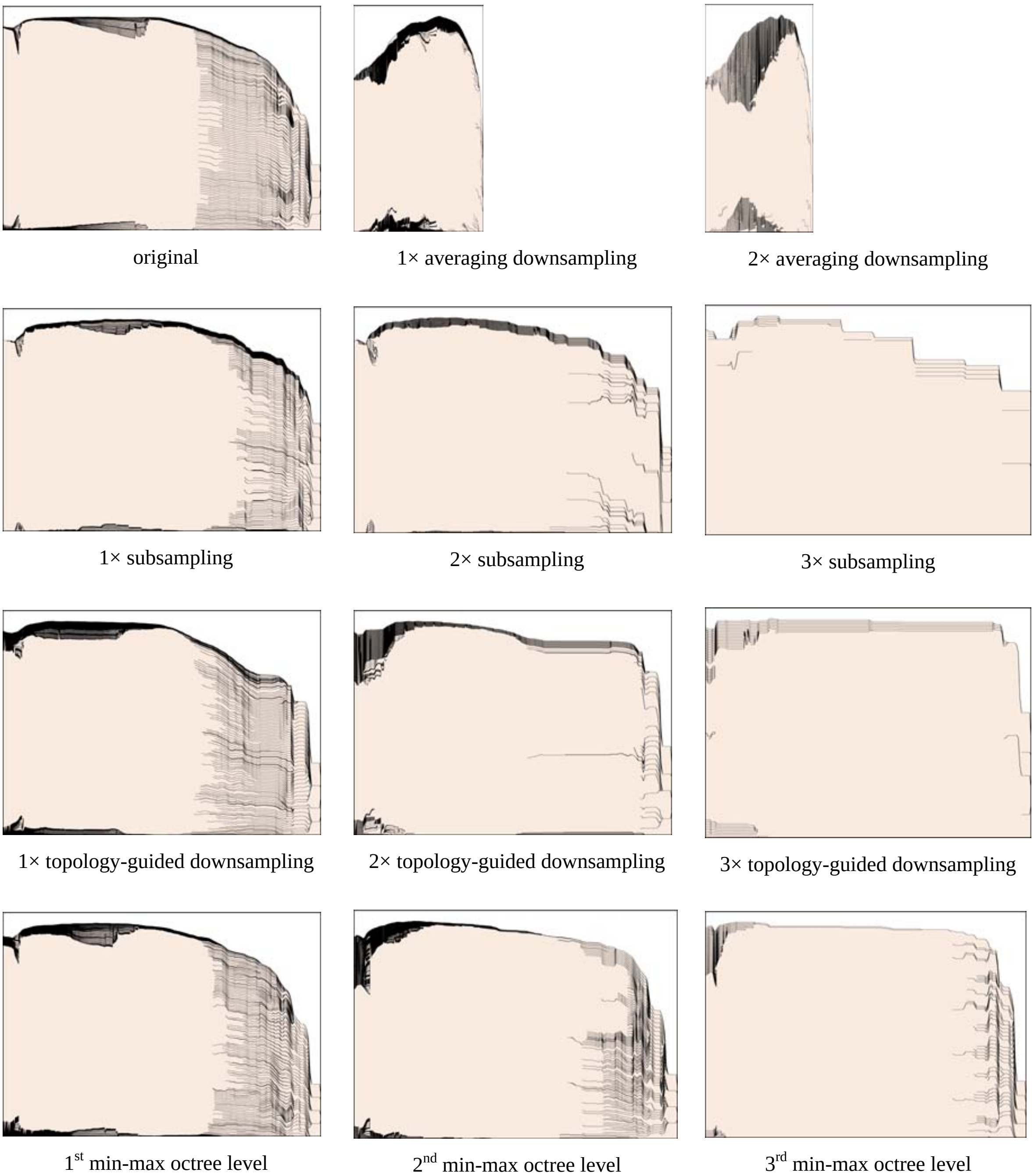
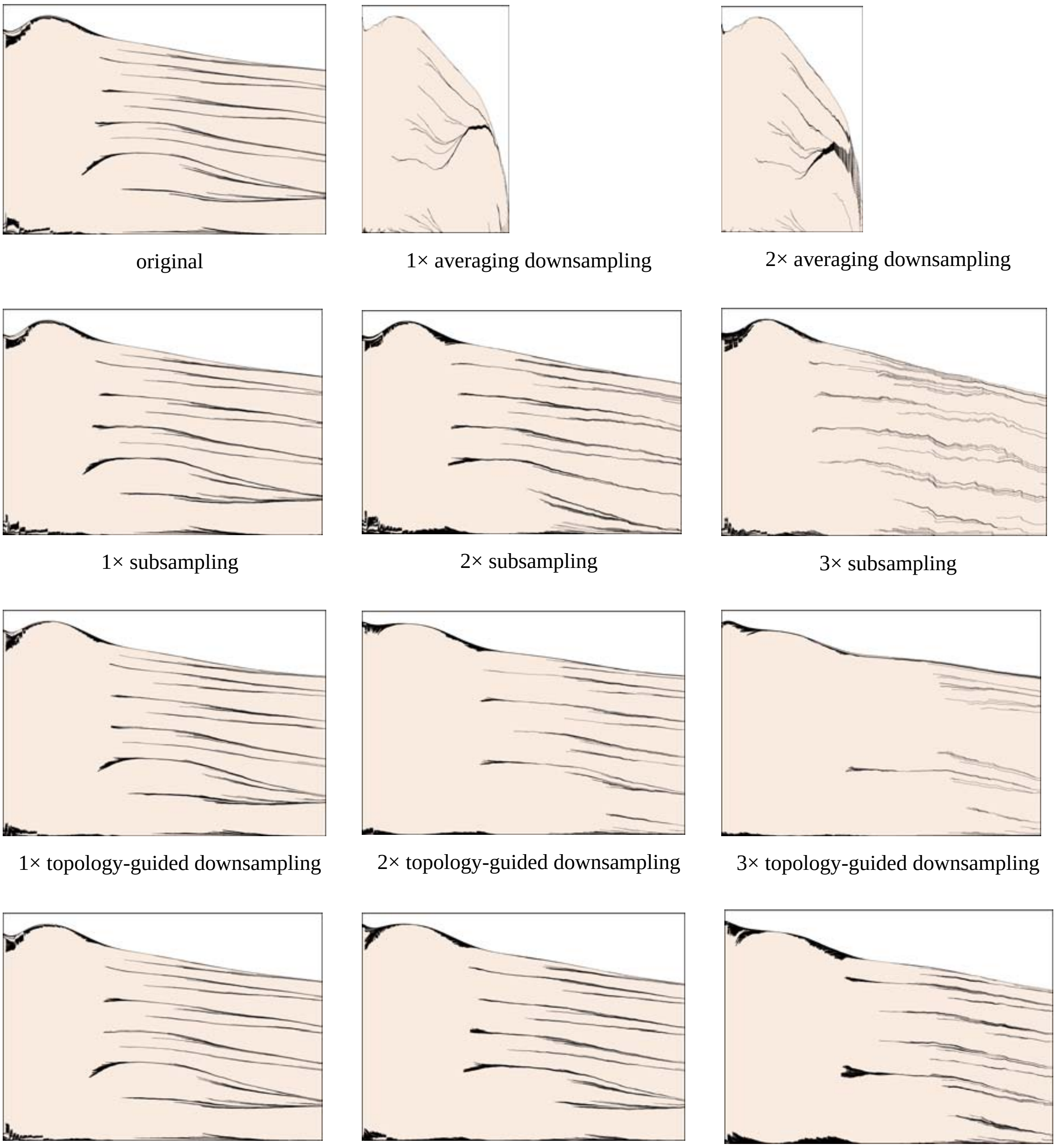



Figure 5. Topology visualization of various versions of the silicium data set (see also Figure 2).



original — 1× averaging downsampling — 2× averaging downsampling

1× subsampling — 2× subsampling — 3× subsampling

1× topology-guided downsampling — 2× topology-guided downsampling — 3× topology-guided downsampling

1st min-max octree level — 2nd min-max octree level — 3rd min-max octree level

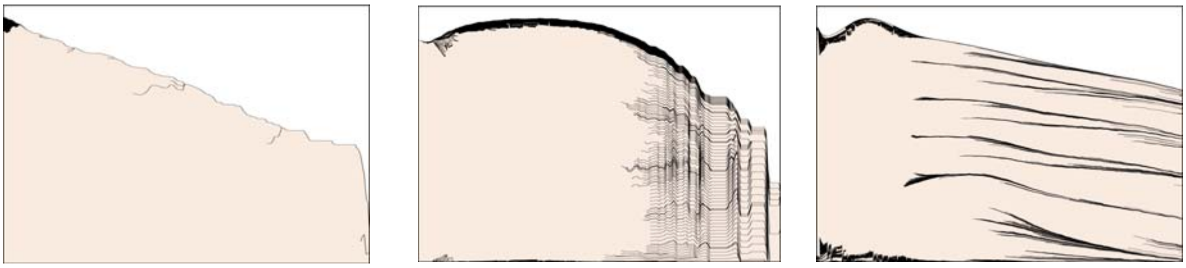
Figure 6. Topology visualization of various versions of the foot data set (see also Figure 3).

## 3.2 Discussion

The experiments presented in the previous section show that averaging downsampling changes the range of the scalar data (and therefore the width of the plots) as well as the topology of the scalar field significantly. In fact, most averaging downsampling filters “flatten” maxima and minima such that the surrounding isosurface components stay disconnected only for a small data range, which does not include the data value of the original maximum or minimum. Thus, averaging downsampling is neither useful for previews of the topology visualization nor for downsampling with approximate topology preservation in general.

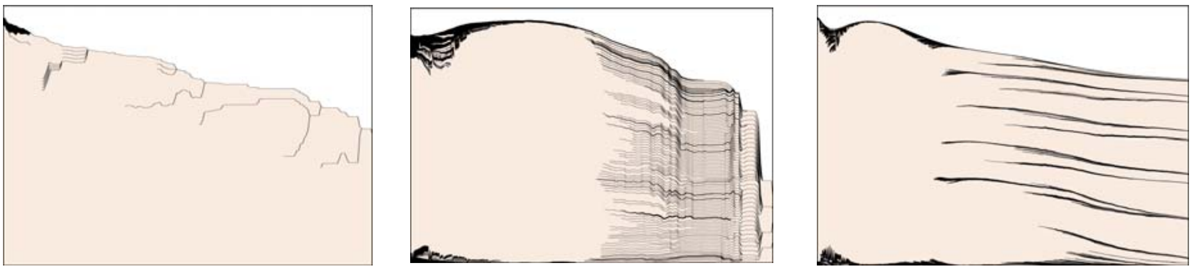
One of the unexpected results of this study was the failure of the topology visualization to represent the topology of some of the downsampled data sets. In particular, the topology of the silicium data set after two downsampling steps using subsampling or topology-guided downsampling is not well visualized. This becomes apparent in a visualization of the twice downsampled and once trilinearly upsampled data sets as shown in Figure 7 for subsampling and Figure 8 for topology-guided downsampling. Upsampling does not change the topology but improves the quality of the topology visualization as it alleviates some of the employed approximations. While the visualizations of the fuel and foot data set do not change strongly in comparison to the twice downsampled versions in Figures 4 and 6, the visualizations of the silicium data set is quite different from the versions in Figure 5.

This failure of the topology visualization is due to the high density of critical points in this particular data set as shown in Figure 2. In the second downsampling step neighboring maxima and minima are so close to each other that neither subsampling nor topology-guided downsampling can pick one sample for each maximum and minimum. The situation is different, however, for the fuel data set, where topology-guided downsampling can still choose the maxima at the cost of geometrically distorting the isosurface while more of the maxima are lost by subsampling. Thus, the fuel data set demonstrates that topology-guided downsampling can perform significantly better than subsampling in respect of topology preservation—at least for some data sets.



fuel data set silicium data set foot data set

Figure 7. Topology visualizations after two subsampling steps followed by one upsampling step.



fuel data set silicium data set foot data set

Figure 8. Topology visualization after two topology-guided downsampling steps and one upsampling step.

While upsampling can improve the quality of the topology visualization, it also increases the amount of data. Therefore, it is in general preferable to reduce the number of downsampling steps instead of adding further upsampling steps. For the min-max octree levels upsampling could be applied to the original data but this approach would first increase the amount of memory and was therefore not included in our evaluation.

In general, the subsampling filter worked quite well, in particular in comparison to the averaging downsampling filter. In data sets of higher resolution with few isosurface components, such as the foot data set (Figure 6), subsampling introduces some spurious components, but the overall topology is preserved very well even after three downsampling steps. However, topology-guided downsampling and the levels of a min-max octree work better for smaller and/or thinner components as demonstrated by the fuel data set (Figure 4) and the silicium data set (Figure 5). For specific data sets, however, subsampling may be a viable alternative to the more costly downsampling methods, in particular if the costs of the implementation are important.

Some of the advantageous results of the topology-guided downsampling method are obtained by geometrically magnifying isosurface components as seen in the example of the fuel data set (Figure 4). If these distortions are inacceptable, subsampling can be considered as an alternative. In the context of the employed topology visualization, the min-max octree levels tend to produce more detailed results than topology-guided downsampling. However, for other applications of downsampling, e.g., multi-resolution volume rendering, the min-max octree is usually not applicable and therefore topology-guided visualization is preferable.

In summary, the use of the min-max octree is the best choice to accelerate the employed topology visualization while topology-guide downsampling is preferable for more general applications. In specific cases, subsampling should also be considered as it is a very efficient and easily implementable alternative. Averaging downsampling is not a viable alternative unless the preservation of topology is unimportant.

## 4. CONCLUSION

We have employed a recently proposed visualization technique [Kraus, 2009] to evaluate the effect of various downsampling filters in respect of the preservation of the topology of scalar volume fields. Our results revealed certain limitations of this visualization for data sets with (artificially) dense critical points. On the other hand, this work also showed that the proposed visualization can be used to successfully analyze image operations such as downsampling techniques.

Our evaluation confirms that the downsampling method proposed in [Kraus, 2009] is in fact appropriate for this specific visualization technique. It also confirms that topology-guided downsampling [Kraus and Ertl, 2001] and subsampling [LaMar et al., 2001] are suitable techniques, while averaging downsampling is not appropriate if the topology of a scalar field is important.

Future work includes the evaluation of other image operations in three and two dimensions, e.g., edge-enhancing filters. In fact, to our knowledge, the effect of most image operations on the topology of scalar fields has not been studied yet.


## ACKNOWLEDGEMENT

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