

Supplementary Material: Guided Volume Editing based on Histogram Dissimilarity

*A. Karimov¹, G. Mistelbauer¹,
T. Auzinger¹ and S. Bruckner²*

*¹Institute of Computer Graphics and Algorithms,
Vienna University of Technology, Vienna, Austria*

*²Department of Informatics,
University of Bergen, Bergen, Norway*

1 Supplementary Material #1: Finding Optimal Bin Size

The only free parameter of our pipeline is the **bin size** b of the histograms. We conducted our experiments on an Intel Core i7-2600K 3.4 GHz CPU with 16 GB of RAM and an NVidia GeForce 680 GPU in order to analyze the correction results with different bin sizes. The bin size, which we use for the histograms, was determined during the correction of four abdominal Computed-Tomography Angiography datasets. The objects had data values from -50 HU (Hounsfield Units) to 250 HU. The slice resolution was 512×512 pixels, and the number of slices ranged from 128 to 384. With different bin sizes we search for a certain correction scenario in each dataset. The bin sizes tried are 1, 2, 4, 8, 16 HU. We checked corrections of all 4 types of defects, each on a specific dataset. Our technique detected the defects properly for every bin size and provided appropriate correction scenarios. We suggest $b = 4$ HU to balance computation time, memory usage and a small number of level of detail adjustments (see Figure 1).

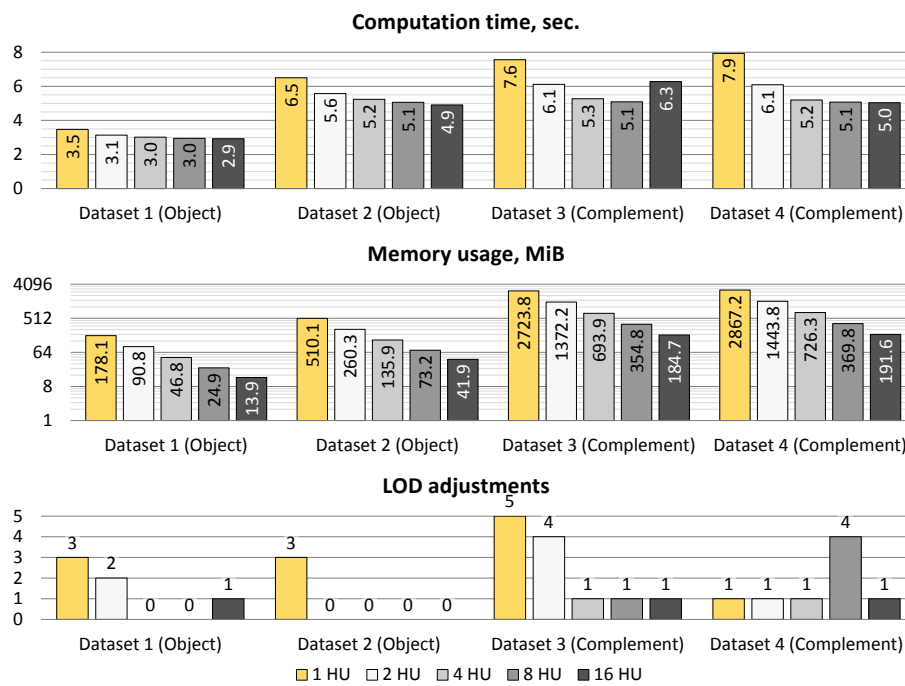


Fig. 1: Analysis of computation time, memory usage and level of detail adjustments with respect to different bin sizes.

2 Supplementary Material #2: Test of the Dissimilarity Measure with Respect to Contrast

In order to evaluate the properties of the dissimilarity measure, which we introduced, we conducted the following two tests on dissimilarity δ_1 :

1. two objects with same data value distribution are split by a one-voxel thick wall between them, which has a different data value distribution
2. two objects with two different data value distributions are located next to each other

The idea behind the tests is to measure the dissimilarity along the skeleton with respect to the varying data value distributions. In the first test, we vary the difference between the means of the objects' distributions and the wall's distribution. In the second test, we vary the difference between the means of two objects' distributions. Each distribution is a Gaussian distribution with standard deviation $\sigma = \frac{32}{3}$ HU (Hounsfield Units). We require that the data value distributions differ, as, otherwise, delineation of the objects cannot be achieved by data values alone.

2.1 Test 1

The test objects are depicted in Figure 2. The parameters are $\mu_1 = 70$ HU, $\mu_2 = \mu_1 + d_1$. The parameter d_1 is varied as follows: 1, 2, 4, 8, 16, and 32 HU. With $d_1 \geq 2$ HU, our technique can clearly separate the two objects, as demonstrated in Figure 2. At $d_1 = 1$ HU, the peak dissimilarity value is not large enough to provide correct delineation, as demonstrated in Figure 3.

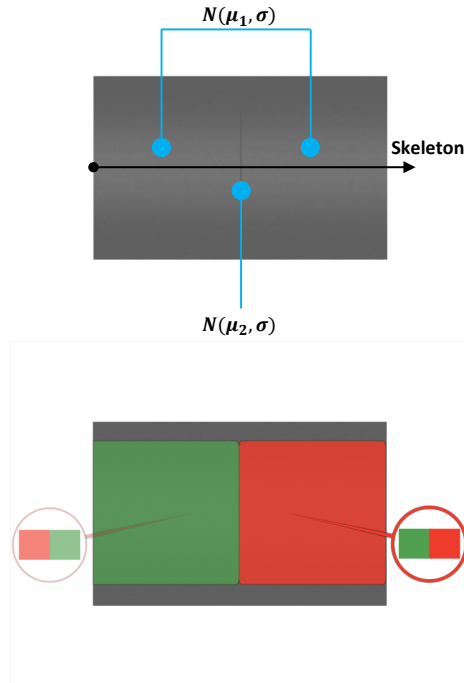


Fig. 2: Test 1: structure of the test objects and the editing result for the case of $d_1 = 2$ HU.

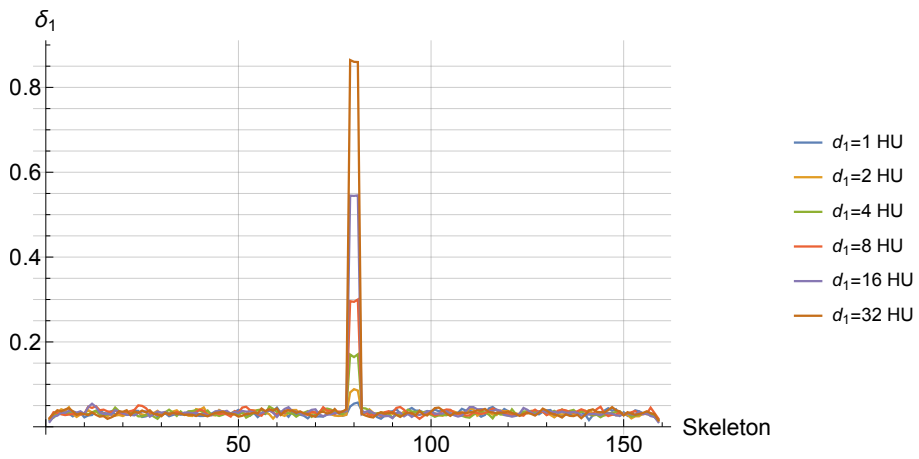


Fig. 3: Test 1: dissimilarity values δ_1 along the skeleton with respect to different $d_1 = |\mu_1 - \mu_2|$.

2.2 Test 2

The test objects are depicted in Figure 4. The parameters are $\mu_4 = 70$ HU, $\mu_3 = \mu_4 + d_2$. The parameter d_2 is varied as follows: 1, 2, 4, 8, 16, and 32 HU. With $d_2 \geq 2$ HU, our technique can clearly separate the two objects, as demonstrated in Figure 4. At $d_2 = 1$ HU, the peak dissimilarity value is not large enough to provide correct delineation, as demonstrated in Figure 5.

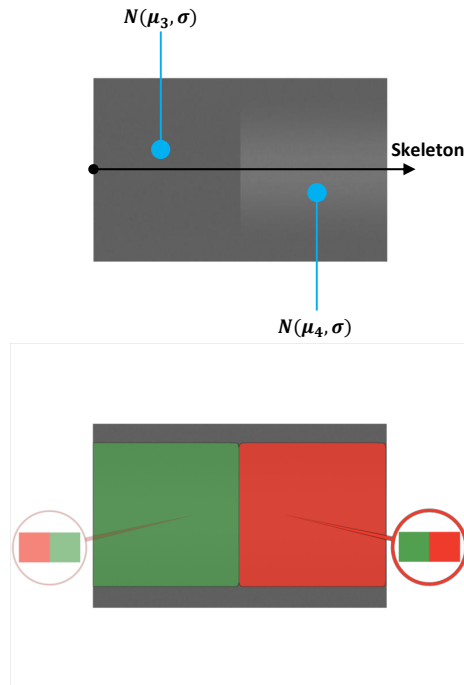


Fig. 4: Test 2: structure of the test objects and the editing result for the case of $d_2 = 2$ HU.

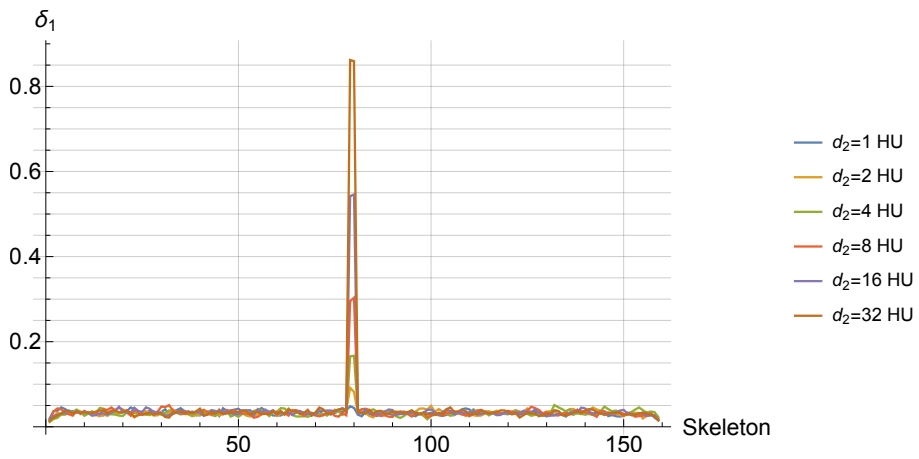


Fig. 5: Test 2: dissimilarity values δ_1 along the skeleton with respect to different $d_2 = |\mu_3 - \mu_4|$.