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An Energy Preserving Upscaling Technique for Enhanced Volume Rendering of Medical Data

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Abstract In this paper we describe an edge-directed optimization-based method for volumetric data supersampling. Our method faces the problem of partial volume effect by upscaling the volumetric data, subdividing voxels in smaller parts and performing an optimization step keeping constant the energy of each original subdivided voxel while enhancing edge continuity. Experimental tests show the good quality of the results obtained with our approach. Furthermore, we show how offline 3D upscaling of volumes can be coupled with recent techniques to perform high quality volume rendering of large datsets, obtaining a better inspection of medical volumetric data.

Keywords Interpolation, Partial Volume, Multi-resolution volume rendering

1 Related Work

A lot of research effort has been spent on digital image or video upscaling, and several super-resolution methods have been recently proposed, e.g. edge-based ([7]), optimization-based [1, 3] or example-based methods ([2, 6]). These techniques, however, are rarely applied to voxelized volumes captured by diagnostic modalities. The reason is probably the lack of applications due to the difficulty in processing and visualizing the large volumes produced. Medical volumes are sometimes upscaled only in Z-direction to overcome the problem of relevant slice spacing. This is done by interleaving in the stack new ”interpolated” slices computed with methods based on preserving continuity of segmented structures [5] or through deformable registration of consecutive slices [8]. In this way it is possible to reduce the ”partial volume” effect that makes the physical value measured at each voxel location not tissue-specific. In this paper we propose a new volume upscaling method similar to 2D edge-directed algorithms and show a possible application of the technique. The method relies on the assumption that the energy or density measured inside each voxel is equal to the sum of those that would have been acquired in the region by a sensor with higher resolution and on the assumption of local smoothness of second order derivatives of the gray level. In this way we can reduce partial volume effect and obtain more accurate results in tissue classification tasks. We show then that this kind of processing can be useful to obtain high resolution detail in volume rendering, improving the visual analysis of the imaged anatomy. Recent multi-resolution methods are, in fact, able to handle huge voxelized volumes allowing their interactive visualization. This means that through an off-line volume upscaling and the use of such techniques it is possible to improve the quality of the 3D visual analysis of medical data.

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2 Methods

The proposed upscaling technique enlarge images by subdividing original voxels into smaller ones. In this way it is possible to obtain integer scale factors along each direction. We implemented two schemes, one splitting each voxel in two parts along the z direction, obtaining a slice-based interpolation and another subdividing each voxel in eight smaller ones (isotropic $2\times$ zooming). The algorithm then computes new voxel values through an optimization scheme driven by two constraints. The first is the constancy of the sum of the gray levels inside each splitted voxel (a physically grounded constraint: the energy captured by the sensors in a region should be the same in the case of a high resolution or low resolution device). The second is the continuity of the second order derivatives of the gray level, that has shown good results in 2D image upscaling [3], reducing artifacts of upscaled images. The greedy optimization procedure consists of an iterative processing of splitted voxels. At each

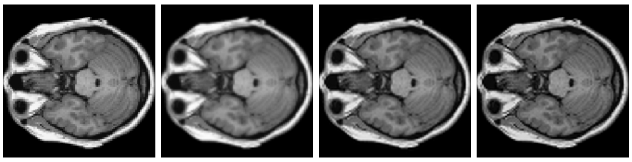

Fig. 1 The visual quality of corresponding slices of volumes upscaled (2x) with different methods is clearly different. From left to right: Nearest neighbor, Linear interpolation, that appear quite smoothed, Spline interpolation, still a bit smoothed, and proposed method, providing extremely sharp images.

iteration, for each splitted voxel, a local energy function is computed for unchanged gray level values and ”perturbed” configurations obtained adding a small value to one smaller pixel and subtracting the same value to another (unchanged average value in the splitted voxel). The large volumes produced by our volume upscaling technique can be integrated within a state-of-the-art multiresolution framework for for GPU volume rendering in order to produce fast an accurate visualizations of large volumes and improve their medical analysis. Based on the framework proposed by Gobbetti et al. [4], we propose to introduce in the preprocessing stage a previous step for generating, using our upscaling technique, the new leafes of the volume to be stored as the maximum detailed version of the volume in the out-of-core database. Then, the preprocessing stage starts filtering the data by taking this new computed leafes to generate all the octree piramid data structure. The multiresolution framework maintain an out-of-core octree representation of the volume, and an adaptive loader executed on the CPU updates view and transfer function dependent subvolume bricks maintained on GPU memory by asynchronously fetching data from octree. In this way, even if the original data cannot be stored in the GPU memory, the volume can still be interactively inspected, and it is possible to obtain the maximal visual quality for each part of the dataset just controlling the camera viewpoint and transfer function parameters.

3 Results

We tested both the z-upscaling and the isotropic upscaling on different MRI and CT datasets. For all the data sets we created downsampled versions with half resolution only along the z direction or in all three directions. We then upscaled the simulated low resolution acquisitions with different methods, comparing the result with the original datasets using two error measures: Peak Signal to Noise Ratio (PSNR) and the number of largely different voxels (LDVN), i.e. the number of voxels differing more than a threshold from the original value, related to possible errors in voxel classification. For the z-upscaling we obtained, on average, an improvement in the PSNR obtained comparing upscaled and original data of 2.63dB over linear interpolation and of 1.02 dB over spline interpolation (Octave implementations). LDVN was reduced of the 12.5% with respect to linear interpolation and of 5.4% with respect to spline interpolation. For the isotropic $2\times$ upscaling we obtained, on average, a PSNR increased of 3.85dB over linear interpolation and of 0.63dB over spline interpolation. LDVN was reduced of 12.7% with respect to linear inrerpolation and of 3.4% with respect to spline interpolation. Fig. 1 shows sections of volumes enlarged with different methods: the new method provides images with sharper detail. If we inspect with volume rendering techniques corresponding details of original and upscaled volumes it is possible to see the advantages of the new edge adaptive interpolation with respect to simple linear/cubic interpolators applied in the ray casting sampling. Figure 2 shows the detail of a CT acquisition of a contrasted iliac bifurcation at original resolution and $2\times$ upsampled. Small structures appear clearly sharper and more contrasted with the proposed offline upscaling. These results encourage us to go on testing smart interpolation approaches integrated in the rendering preprocessing.

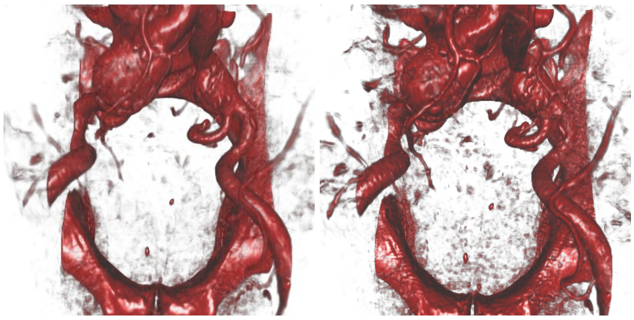

Fig. 2 The new adaptive volume upsampling (right) allows a sharper rendering of small details (look at thin vessels) with respect to original volume (left), using the same transfer function and sampling rate.

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