

Cross-scale self-similarity super-resolution of single MRI slice-stacks

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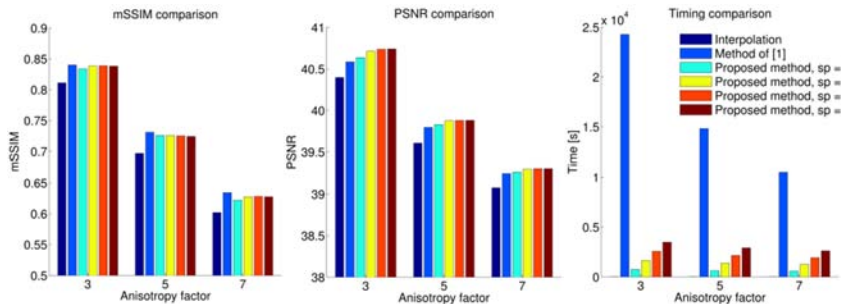
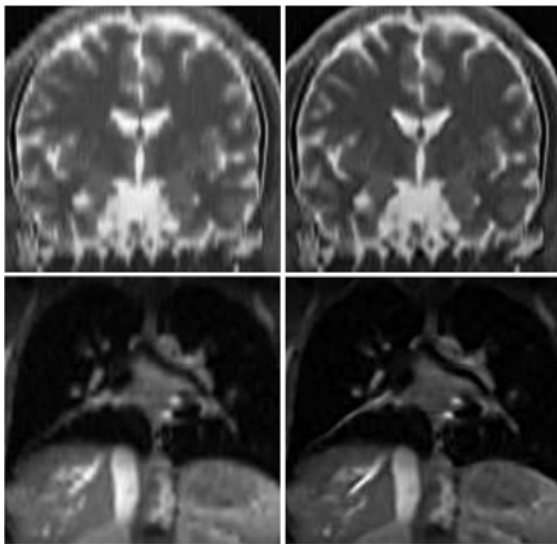
Purpose:

In MRI-sequences which require long repetition times, direct 3D acquisition often leads to infeasible acquisition times. In such cases, 2D multi-slice imaging is a common alternative. However, due to hardware limitations and other factors, the slices of such acquisitions are usually thick relative to the in-plane resolution. Such anisotropy hampers both visualization and analysis of the underlying anatomy. Less blocky images can be achieved by interpolation in the slice-selection direction. While interpolation techniques are fast, they rely on very limited local information to fill in the missing voxels and do not recover information that was removed by the sampling. Recently, a new idea for super-resolution (SR) of MRI slice-stacks was proposed. It exploits the fact that both high-resolution (HR) and low-resolution (LR) image content is present in such images [1]: In-plane slices contain HR content, while the orthogonal planes containing the slice-selection direction are of low anisotropic resolution. The method relies on the powerful assumption of self-similarity of local image structures across the two scales. In this work we present a different approach to take advantage of the same underlying idea. Our technique tailors the general dictionary-based SR method developed in [2] for the case of an MRI slice-stack: The relationship between the two slice-stack scales is captured in a pair of trained dictionaries. These can subsequently be applied to improve the resolution in the LR image planes one by one. Our method is up to an order of magnitude more efficient than that of [1] and it achieves better or comparable results.

Methods:

The HR in-plane slices X_{HR} of the MRI slice-stack are used for training. From the HR slices a corresponding LR set of slices Z_{LR} are generated by applying an approximation of the slice-selection point-spread function and down-sampling in one dimension. Z_{LR} is then up-sampled by cubic interpolation into of target X_{LR} HR grid size. From X_{LR} , feature images are generated by applying a gradient and a Laplacian filter in the low-resolution direction of each slice. From each voxel location in these two sets of slices, 2D patches are extracted and vectorized. The vectors of corresponding location in the feature images are concatenated in to a single feature vector \mathbf{x}_{LR} . PCA is optionally applied on the matrix \mathbf{X}_{LR} of column-wise concatenated vectors \mathbf{x}_{LR} for dimensionality reduction and a LR dictionary \mathbf{D}_{LR} is trained on the features using K-SVD [3]. HR features \mathbf{x}_{HR} are vectorized patches from $X_{diff} = X_{HR} - X_{LR}$. They are extracted at locations in X_{diff} corresponding to the locations of $\{\mathbf{x}_{LR}\}$. The HR dictionary \mathbf{D}_{HR} is trained by using the matrix \mathbf{A}_{LR} of sparse coding vectors obtained from the training of \mathbf{D}_{LR} , and minimizing $\|\mathbf{D}_{HR}\mathbf{A}_{LR} - \mathbf{X}_{diff}\|^2$, implying that \mathbf{A}_{LR} aims to bring the best possible prediction for the difference patches. All of the above corresponds to the training process. In the actual SR phase, each LR plane Y_{LR} along one of the two HR directions is processed by first up-sampling it by cubic interpolation into Y of HR grid size. Second, features are extracted from Y as before, and then these vectors are projected onto the PCA subspace. Each patch can be encoded sparsely using \mathbf{D}_{LR} and e.g. a pursuit algorithm. The obtained sparse coding vector is applied to \mathbf{D}_{HR} , resulting in a HR patch estimate. These patches are inserted into an estimate \hat{Y}_{diff} , in which overlapping patches are averaged, and added to Y to obtain the HR estimate \hat{Y}_{HR} .

Synthetic MRI from BrainWeb [4] was used for quantitative experiments. A 1x1x1 mm noise-free T2-weighted image was downloaded as a HR reference. LR images were based on a T2-weighted image of resolution 1x1x1 mm and a noise-level of 3%. Axial slice stacks of 3, 5, and 7 mm slice thickness were generated by applying a Gaussian point-spread function in the slice-selection direction and down-sampling. Lung MRI (TE=2.2s, TR=0.75s, FA=35deg., NEX=1, resolution 1.56x1.56mm, slice thickness = 8mm, courtesy of H. Tiddens and P. Ciet, Erasmus MC, Rotterdam) was used for further qualitative validation of the method.



Results:

Left figure: qualitative results. Top row: coronal view of reconstruction of an axial BrainWeb slice-stack with 5 mm thick slices. Bottom row: coronal view of reconstruction of an axial lung slice-stack. Left/right column: cubic interpolation/proposed method (PM). PM uses a dictionary of 1000 atoms, a sparsity-level of 1 and a patch-size of 7x7 voxels. Right figure: quantitative results. PM is compared to cubic interpolation and the method of [1] in terms of (left to right) mean structural similarity index (mSSIM), peak signal-to-noise ratio (PSNR), and computation time. In the experiments of PM and that of [1], patch sizes of 7x7 voxels are used. In PM dictionaries of 1000 atoms and varying sparsity-levels, sp , are used. On the x-axis the anisotropy factor (ratio of slice thickness to in-plane resolution) of the LR slice-stacks is given.

Conclusions:

The proposed method is clearly better than interpolation, visually as well as quantitatively. It also outperforms the method of [1]. In particular, while the quality measures of the proposed method are similar or slightly superior to those of [1], the total processing time is up to an order of magnitude lower. In addition, solving the MR single-image SR problem using the framework of learned dictionaries opens a wealth of opportunities for taking advantage of the many recent results in this field.

References:

[1] Plenge et al, MICCAI 2013, p.123-130. [2] Zeyde et al, Proc. Curves & Surf. 2009, p.711-730. [3] Aharon et al, IEEE Trans Sig Proc, 54(11):4211-4322, 2006. [4] Cocosco, NeuroImage, 5(4), 1997.