MRI TGV BASED SUPER-RESOLUTION

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Introduction

Spatial resolution in MRI is limited by several factors such as acquisition time, gradients amplitude and performance or signal to noise ratio. In some applications, in particular when co-registration between modalities is needed, such as fMRI and 3DT1-IR, the acquired image needs to be upsampled to a higher resolution so common interpolation methods have been typically applied to increase this new apparent spatial resolution. In the last years super resolution (SR) techniques have emerged as an effective alternative in the case of single MRI high-resolution reconstruction[1, 2]. In this work we adapt a variational SR model proposed and validated for MRI by Joshi et al.[1] to the use of the 2nd order Total Generalized Variation (TGV) instead of the Total Variation (TV) originally used. TGV regularization has been recently introduced as a better model for MRI reconstruction because it overcomes the TV assumption of piecewise constant images not valid in practical MRI situations[3].

Model Proposed

Following Joshi et al.[1], let f be the observed low resolution image and u the unknown high resolution image, given a linear downsampling operator D and S the transpose (upsampling) operator. The observation model is written as: $f = D(u) + \eta$ where η is an additive Gaussian white noise with 0 mean and variance σ^2. We can obtain u as the solution of the problem: $u = \min_u \left\{ TGV_\alpha^2(u) + \frac{\lambda}{2} \left[\|f - D(u)\|_2^2 - \sigma^2 \right] \right\}$ where TGV_α^2 is the 2nd order TGV defined as $TGV_\alpha^2 = \min_v \alpha_1 \int_\Omega |\nabla u - v| + \alpha_0 \int_\Omega |\mathcal{E}(v)|$ with $\mathcal{E}(v) = \frac{1}{2}(\nabla v + \nabla v^T)$ denoting the symmetrized gradient (see Knoll et al. [3] for more details). The upsampling operator used in this work was the 3rd order B-spline interpolation. For the minimization an efficient primal-dual algorithm as presented in Knoll et al. [3] was implemented.

Material and methods

The proposed algorithm was implemented in MATLAB code. For comparison purposes the images were also reconstructed with the Linear, Cubic and B-spline interpolation as implemented on MATLAB 7.10. Two sets of images were used to test our SR technique. The first experiment consisted in reconstructing downsampled versions of the HR Brainweb phantom T1 weighted volume of 181x217x180 voxels (voxel size=1x1x1mm) (available in http://brainweb.bic.mni.mcgill.ca/brainweb/). Following Manjon et al.[2] the volume was downsampled in the z direction to simulate a slice thickness of 2 and 4mm. We tested also the fully reconstruction with a central slice which was downsampled to half size and then reconstructed to the original dimensions. We repeated this test contaminating the low resolution slice with Gaussian noise to asses the robustness of the method in the presence of noise. The standard deviation of the noise was fixed to the 4 and the 10 % of the maximum intensity of the image. The second set of images consisted on real scan data obtained from a healthy-young subject (24y). We acquired 2 volumes of a 3DT1 SPGR sequence with matrix sizes 256x256 (voxel size=0.9375x0.9375mm) and 512x512 (voxel size=0.4688x0.4688mm), 26 slices, TR=17.212, TE=8.252, TI=500ms, flip angle=12, slice thickness 2.1mm. The slices were downsampled (to 128x128 in the first case and to 256x256 for the second volume) previously to the reconstruction with the proposed algorithm and the interpolation methods. Peak Signal to Noise Ratio (PSNR) was used to assess the image quality.

Results

The results of the phantom brain reconstruction are displayed in Table 1. The proposed method outperforms the interpolation techniques for all the tests. The differences become higher when noise is introduced, suggesting a better robustness of our approach. When real MRI are considered, our SR method also obtain the best results as it can be seen in Table 2. A visual inspection of the reconstruction of the 512x512 T1-w image with the different methods can be observed in Figure 1. The details, specially the edges and the contrast, are better preserved for the proposed reconstruction method (boxed in the image) fitting with what PSNR values indicated.

Reconstruction test	Slice thickness of 1mm from 2 mm	Resolution of 216x180 from 108x90 image	Resolution of 216x180 from 108x90 contaminated image with 4% noise	Resolution of 216x180 from 108x90 contaminated image with 10% noise
Linear Interp.	34.41	30.70	28.44	23.44
Cubic Interp.	37.03	33.26	28.41	21.84
Splines Interp.	37.87	34.29	28.22	21.28
Proposed	**39.12**	**35.87**	**29.92**	**25.56**

Table 1: PSNR obtained for the different methods in the phantom reconstruction

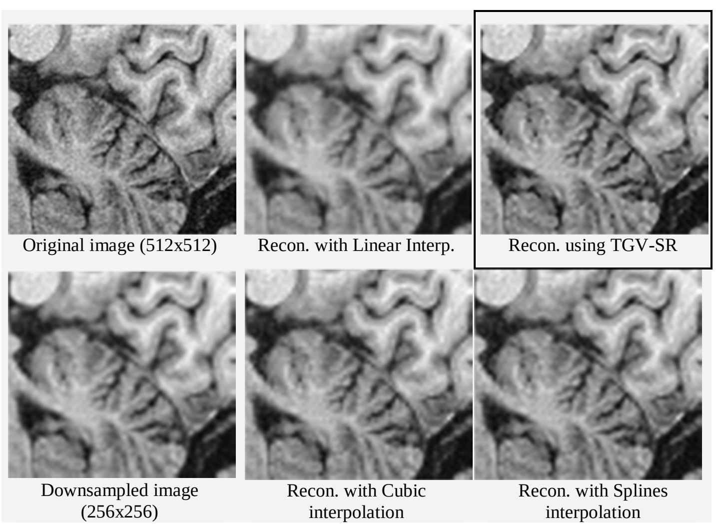

Figure 1: A detail of the original and the reconstructed real MRI (512x512)

Reconstruction test	Resolution of 256x256 from 128x128 image	Resolution of 512x512 from 256x256 image
Linear Int.	34.41	30.70
Cubic Int.	37.03	33.26
Splines Int.	37.87	34.29
Proposed	**39.12**	**35.87**

Table 2: PSNR obtained for the reconstruction of the T1-w real MRI

Conclusions

A new variational SR method has been presented taking into account the recently proposed TGV operator. It outperforms the results obtained with the standard interpolation techniques for the image resolution enhancement. Further work includes a parametric study and to explore other options for the upsampling operator. As a future goal we are now planning to use this variational Superresolution method to be applied in clinical routine related to structural (DTI) and functional (ASL) assessment in the study of Neurological disorders and Neurodegenerative diseases.

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2. Manjón J V, Coupé P, Buades A, et al.: Non-local MRI upsampling. Med. Image Anal. 14(6) 2010, pp. 784-792.
3. Knoll F, Bredies K, Pock T, et al.: Second Order Total Generalized Variation (TGV) for MRI. Magnet. Reson. Med. 65(2) 2011, pp. 480-491.