Intermodality image guided MRI super-resolution

Jianhua Yan[1], Jason Chu-Shern Lim[1], and David W Townsend[1]
[1]*A*STAR-NUS, Clinical Imaging Research Center, Singapore, Singapore, Singapore*

Target audience: Clinicians and researchers who want to improve resolution of low-resolution MRI to match with other high-resolution MRI.

Purpose: Image resolution of MRI is limited by several factors such as hardware, signal to noise ratio, hardware and time limitations or patient's comfort. In typical clinical settings, several types of images are obtained with different voxel resolutions. Typically, resolution of through-plane is lower than that of in-plane. In many applications, such as image segmentation or registration, voxel size of low-resolution (LR) image is desired to match with a higher-resolution dataset[1]. Traditionally, interpolation techniques such B-spline interpolation were applied[2]. Super-resolution technique has been emerged as an effective way to improve the resolution, signal-to-noise ratio and acquisition time trade-offs compared with direct high-resolution (HR) acquisition [3,4]. Here, an alternative super-resolution method with intermodality priors from another HR MRI is proposed. In particular, we aim to improve resolution of LR T2-weighted image with help of HR T1-weighted image.

Methods: The key assumption of the proposed method is a local linear model between the HR MRI (*I*) and the output (*Q*). We assume that *Q* is a linear transform of *I* in a local window ω_k centered at the pixel *k*: $Q_i = a_k I_i + b_k, \forall i \in \omega_k$ where a_k and b_k are some linear coefficients assumed to be constant in ω_k. This local linear model ensures that *Q* has an edge only if *I* has an edge. To determine the linear coefficients, we need constraints from the LR image (*P*). We seek a solution that minimizes the difference between *P* and *Q* while maintaining the linear model. Specifically, we minimize the following cost function in the window ω_k after considering degradation factor *H* including sub-sampling, blurring and geometric transformation: $E(a_k, b_k) = \sum_{i \in \omega_k} \left(\left(a_k (H \otimes I)_i + b_k - P_i \right)^2 + \varepsilon a_k^2 \right)$, which is the linear ridge regression model and can be easily solved to get closed-form solution for a_k and b_k, where ε is a regularization parameter penalizing large a_k. Since a voxel *i* is involved in all the overlapping windows ω_k that covers *i*, so the value of Q_i is not identical when it is computed in different windows. A simple strategy is to average all the possible values of Q_i. However, there are some cases where this assumption may not hold. For example, multiple sclerosis lesions are clearly visible in T2-weighted images but not in T1-weighted images (see Fig.1 and Fig.2, red arrow). In this case, the HR T1-weighted image is not a relevant candidate to guide the super-resolution process. An adaptive scheme was used. If there are outliers in the LR image (can be achieved by a local edge detector function), the LR image itself was used to guide the super-resolution so that the flat information from HR image will not be enforced in this case.

HR T1-weighted and HR T2-weighted image were simulated with Brainweb[5]. Using the HR T2-weighted image, we have generated LR images with an in-plane resolution of 1mm x 1 mm and a slice thickness of 5 mm. As in the Brainweb, the point spread function is modeled with a boxcar function. Intensities of Brainweb images have been normalized between 0 and 255. In order to investigate robustness of the proposed method, except for non-pathological brain data, pathological brain (sclerosis) was also simulated. In addition, the influence of Rician noise was also investigated, where both LR images and HR reference images were corrupted with Rician noise level of two percent of the brightest tissue. Mean squared error (MSE) was used to evaluate the image quality.

Results and Discussion: Fig. 1 illustrates ground truth images and images produced by traditional B-spline interpolation and the proposed method under the different situations (normal anatomical model without noise; multiple sclerosis anatomical model without noise; normal anatomical model with Rician noise; multiple sclerosis anatomical model with Rician noise). Visually, the structure can be much better delineated with the proposed method and sclerosis lesion (red arrow in the T2-weighted images) can also be effectively preserved even without corresponding structural information the HR T1-weighted image (shown in Fig.2). In addition, the images from the proposed method are also less noisy due to inherent smoothing operation in the proposed model. Fig.3 shows the percentage reduction of MSE for the proposed method over the B-spline interpolation. As expected, more reduction exists for the noiseless case.

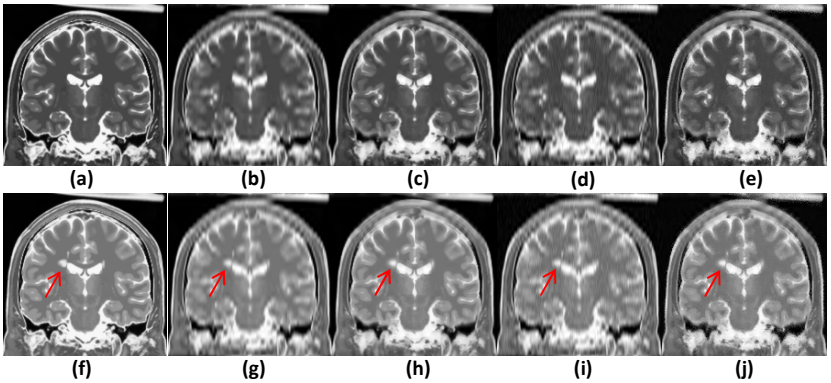

Fig. 1 The first row and second row show images of non-pathological brain and pathological brain (multiple sclerosis), respectively (a) and (f): ground truth; (b) and (g): B-spline interpolation for noiseless case; (c) and (h): proposed method for noiseless case; (d) and (i) B-spline interpolation for noise case; (e) and (j): proposed method for noise case

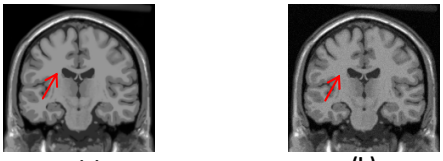

Fig. 2 T1-weighted image (a): noiseless (b): noisy

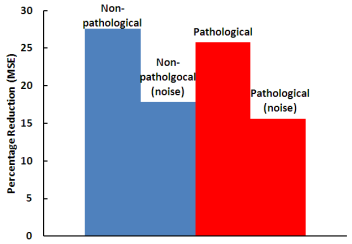

Fig. 3 Percentage reduction (MSE) of proposed method over B-spline interpolation

Conclusion: In this abstract, a new super-resolution method was proposed by utilizing the local linear model between the HR image and LR image. Preliminary results with normal and pathological (sclerosis) data from Brainweb demonstrated the proposed method can give lower MSE when compared with traditional B-spline interpolation technique and structure can be much better delineated.

References:

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