Using Perceptual Difference Model (PDM) to Optimize Regularization Parameters in Parallel Imaging

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INTRODUCTION

We are developing a quantitative method for evaluating image quality, the perceptual difference model (PDM) and using it to develop and optimize fast parallel image reconstruction techniques. PDM is a computerized human vision model that calculates the visual difference between a "test image" and a "gold standard image," which in our parallel imaging experiments correspond to fast images obtained with k-space sub-sampling and slow images obtained with full sampling, respectively. PDM has been shown to correlate well with human observers in a variety of MR experiments including spiral imaging and keyhole imaging [1, 2]. It enables one to evaluate the 1000's of images that are easily generated in reconstruction experiments.

Parallel MR imaging has been widely used to improve image quality and/or shorten acquisition time. SENSE, SMASH, and other hybrid methods reconstruct the image from the arrayed coil data sets. For SENSE, the reconstruction process can be seen as a problem of solving an over-determined large linear function, and the ill-conditioning of the sensitivity map will magnify the small disturbance of the acquired data and result in a bad reconstructed image. King and Angelos [3] proposed to solve this problem utilizing Tikhonov regularization. The success of regularization depends upon the parameter selection method [4, 5], and we are investigating a promising method using PDM.

METHODS

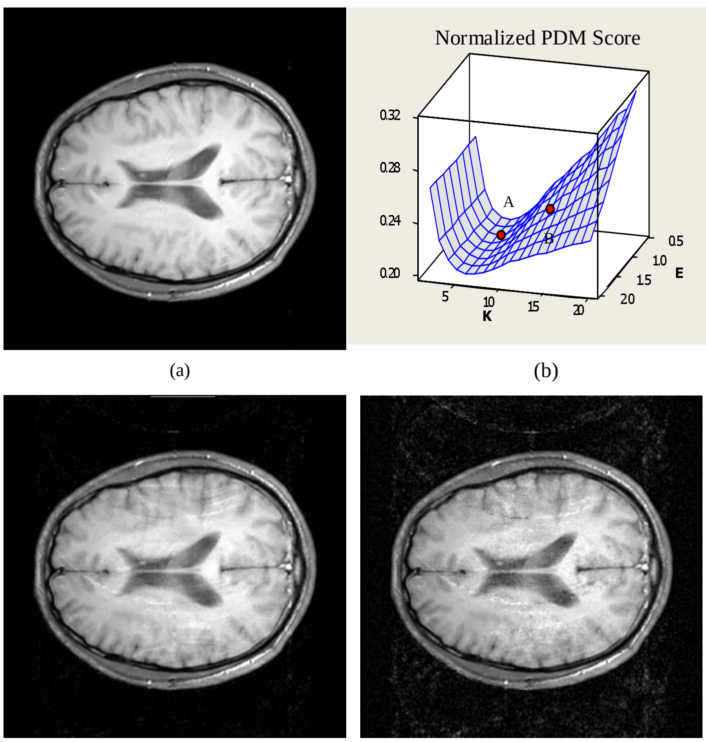
Given the estimated sensitivity map S, measured data *d*, prior image ρ_r and regularization parameter λ, Tikhonov regularization can be expressed as

$$\rho_* = \arg\min\left\{\left\|S\rho - d\right\|^2 + \lambda^2\left\|\rho-\rho_r\right\|^2\right\}$$

The proposed algorithm is to choose λ in a spatially dependent fashion, considering the conditioning of all the equations. First, λ is set to [λmin, λmax], and then is selected point-by-point for in a spatially-adaptive manner. More specifically, set λ(x) to be a linear function of the local condition number of S.

$$\lambda(x) = \frac{\kappa(S)-\kappa_{\min}(S)}{\kappa_{\max}(S)-\kappa_{\min}(S)}\left(\lambda_{\max}-\lambda_{\min}\right)+\lambda_{\min} \qquad \lambda_{\min} = \arg\min_{\lambda}\left\{\frac{\max_i \sigma_i}{\min_i\left(\sigma_i + \lambda^2/\sigma_i\right)} < K\right\}; \lambda_{\max} = \arg\max_{\lambda}\left\{\sum_x \left\|S\rho_{reg}(\lambda) - d\right\| \le \varepsilon\right\}$$

σ is the singular value of S. K and ε are user defined constant, and they are very important to the reconstructed image quality. We will apply PDM to determine the optimal K and ε.



(a) (b)

(c) (d)

Figure 1. Using PDM to optimize parameters K and ε. The gold standard image in (a) is compared to test images such as those in (c) and (d). The surface plot in (b) shows the normalized PDM score changes as a function of K and ε. Point A (K = 5.91, ε = 1.04) is at the minimum and gives the image in (c). Image (d) corresponds to point B (K =15, ε = 1).

EXPERIMENTS

A healthy subject's head images acquired with a four-element head coil are reconstructed with the above method. Fully sampled data were used to construct a "gold standard" image (Figure 1a), and one quarter of the sampled data (R = 4) were used to reconstruct test images. PDM scores determined the visual difference between the two, with a high PDM indicating a poor test image that is visually much different than the gold standard.

RESULTS AND DISCUSSION

Images regularized with different K and ε values are shown in Figure 1. PDM is a smooth function of these parameters, and we can easily determine the best point at A (K = 5.91, ε = 1.04) in Figure 1(b). The image at point B is clearly inferior to the one at A. In other experiments (not shown), PDM correlated well (R=0.95) with human evaluation of parallel image reconstructions. Because of the smooth dependence of PDM upon reconstruction parameters, we have successfully used PDM as a criterion in automated optimization algorithms.

Results show that PDM can be very helpful for selecting free parameters in reconstruction algorithms. Fast parallel imaging is especially amendable because it is relatively easy to design experiments using a full k-space acquisition as the gold standard. Currently, we are using PDM to evaluate a variety of fast MR reconstruction techniques in experiments where we generate 1000's of test images. Without a numerical measure of image quality such as PDM, it would be impossible to design such experiments.

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