Improvements in Line Scan Diffusion Weighted Image Reconstruction with a Least Norm Algorithm

J. Chen[1,2], K. Butts Pauly[2]

[1]Electrical Engineering, Stanford University, Stanford, CA, United States, [2]Radiology, Stanford University, Stanford, CA, United States

Introduction

Line scan diffusion imaging (LSDI) has been shown to be relatively insensitive to motion artifacts as it is insensitive to view-to-view motion (1). Compared to other diffusion weighted imaging techniques, LSDI may be the easiest one to implement in terms of gradient amplitude and slew rate. However, the LSDI image is inherently blurred in the line scan direction due to its approximately triangular shape point spread function (PSF), which is illustrated in Fig.1. The width of the PSF could be decreased by exciting ultra thin slices. However, to achieve a half maximum width of 1 mm at an LSDI inclination angle of 45, the 90° and 180° slice thickness would have to be 0.7 mm. In this work, we use a least norm (LN) algorithm (2) to increase the resolution of line scan images without requiring ultra thin slices.

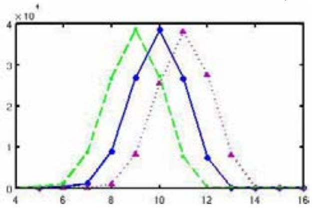

Fig.1 Measured slice profiles of three adjacent lines in the line scan direction. The large overlap between lines caused the blurring.

Theory and Method

Conventional 2DFT image can be represented by a matrix M_i. If the image resolution is high enough compared to the underlying object structure, each element of M_i could be approximated as the amplitude of all the magnetization within that voxel. Thus in LSDI, when two oblique slices are excited and the signal from the cross section is acquired, it could be viewed as several elements in one row of M_i are selected, weighted and summed to form on element in the acquired image M_{lsdi}. How these elements are selected and weighted depends on the shape of the PSF, i.e. slice thickness and LSDI inclination angle. The whole process could be simplified as one matrix operation, $M_{lsdi} = A \times M_i$. With the knowledge of A (shape of the PSF), we could extract the high-resolution image M_i out of the LSDI image.

Since some part of the information would be lost due to the wide PSF, A is a fat matrix. For example, if the size of M_i is 106×256 and the full width of the triangle is 7, A should be 100×106. This condition is underdetermined, and there are many solutions for M_i. Assuming A is full rank, one of the solutions is the least norm solution $M_{ln} = A^T (AA^T)^{-1} M_{lsdi}$. M_{ln} has the smallest norm of any solution. An LSDI images is acquired on the 0.5T Signa SP open MRI system (GE, Milwaukee, WI). The head coil was used as transmitter and receiver. Other imaging parameters are TE/TR = 70/150 ms, FOV = 32 cm, LSDI FOV = 16 cm, slice selective thickness = 5mm, bandwidth = 7.81 kHz, NEX = 1, LSDI angle = 70°, b = 10 seconds/mm^2. An LN image is generated from the acquired LSDI image using the least norm method.

Results

Improved image resolution can be appreciated around the high-resolution structures (dashed arrow and arrow head) in the LN reconstructed image in Fig.2. One useful application of the LN method is to recover dropped lines. These arise from intraview motion in the presence of diffusion weighted gradients (1). Fortunately, the information from the dropped line has been preserved when its neighbor lines were acquired due to the wide PSF. In Fig3 (a), two lines are manually taken out to simulate the motion artifact. Compared to the previous example, this equation is further underdetermined. The least norm method can recover these two lines. A is reapplied to the LN solution to obtain the corresponding LSDI image. The result shown in Fig 3(b) is very close the Fig.2 (a) although the image is reconstructed with less information. Detailed structures are regained by the LN method as illustrated in Fig.4 with only small errors (arrow heads) at the two dropped lines.

Conclusion and Discussion

In this work we present a technique using the least norm algorithm to improve the image quality of line scan diffusion imaging. The method can be used to obtain high resolution in the reconstructed image, or to remove the motion artifact in LSDI. The tradeoff with the LN algorithm is a loss in SNR. This is because that the signal in the LN image comes from only one line of the object, while the signal from the LSDI image is the sum of several lines of the object. This tradeoff between SNR and resolution is universal in MR imaging. One advantage of LN is that once the high-resolution image is reconstructed, it could be convolved with any filter to optimize the tradeoff between SNR and resolution. On the other hand, since the noise is Gaussian white noise in the LSDI image as $n \sim \mathcal{N}(0,\Phi)$, after linear operation $\Sigma = A^T (AA^T)^{-1}$, the noise in the LN image is still Gaussian distributed $\hat{n} \sim \mathcal{N}(0, \Sigma\Phi\Sigma^T)$. However, the covariance matrix $\Sigma\Phi\Sigma^T$ has non-zero off-diagonal elements introduced by the LN method. This means that the noise is no longer white after the reconstruction, and the correlation could be used to build a filter to improve the SNR in the LN image.

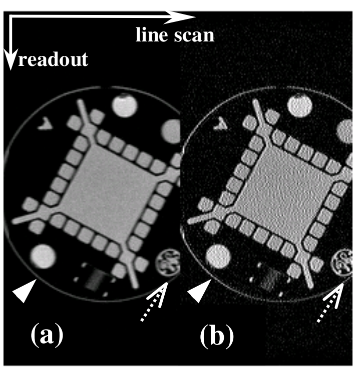

Fig.2 Line scan image (a) and its least norm solution (b). The image resolution is enhanced. The line scan direction and the readout direction are labeled on the figure.

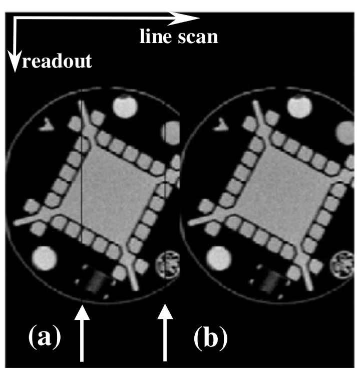

Fig.3 (a) (M_i') is obtained by setting two lines in Fig.2 (a) to zero. The least norm solution M_{ln}' is calculated. (b) shows the result of A×M_{ln}', which is almost identical to Fig.2 (a)

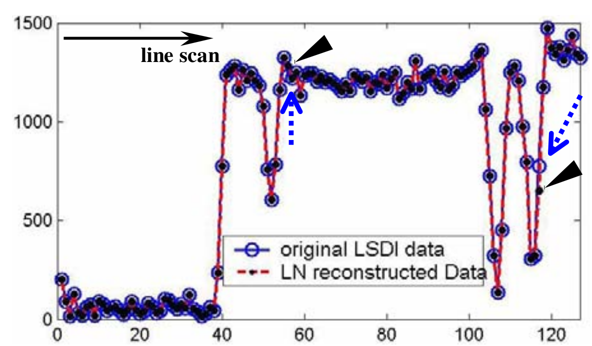

Fig.4 The comparison between the cross sections of the original LSDI (M_i) and the LN reconstructed image from the dropped data (M_i'). At the two dropped lines, the LN reconstructed value (arrow heads) are very close to the original data (dashed arrows). The spatial frequency is maintained in the lines scan direction.

Reference

(1) Gudbjartsson H, et al. MRM 1996 (36):p509-519

(2) Boyd S. Stanford University EE263 lecture notes

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