Compressed Sensing for Active Feedback Contrast-Enhanced In Vivo Tumor Imaging

L. Vu[1], J. Furuyama[1], T. Goldstein[2], S. Osher[2], and Y-Y. Lin[1]

[1]Chemistry and Biochemistry, UCLA, Los Angeles, CA, United States, [2]Applied Mathematics, UCLA, Los Angeles, CA, United States

Introduction

It has recently been demonstrated that the use of nonlinear active feedback fields can be useful in the detection of early tumors [1]. One particular example is the application of a weak continuous wave (CW) in the presence of radiation damping-like active feedback fields [2]. The non-linearity of the active feedback effect makes the spin evolution highly sensitive to both initial conditions as well as small variations in magnetic properties in the sample. Consequently, the optimal set of parameters (CW strength, active feedback strength, active feedback phase, evolution time, etc) may not be known ahead of time and must sometimes be obtained through trial and error. As a result, the determination of the optimal set of parameters can be both tedious as well as time consuming.

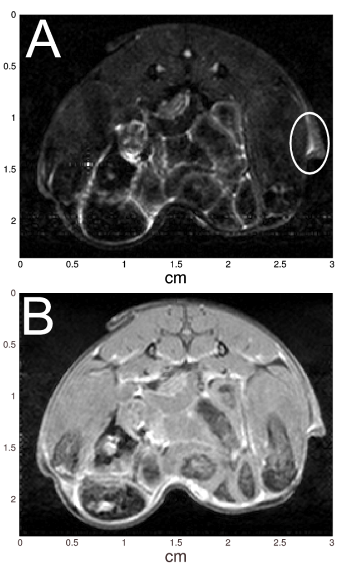
An image that is sparse can be described in some transform domain by fewer coefficients than the full image itself. Images with high-contrast are expected to be sparse in a specific transform domain as they contain very little information beyond the location of a tumor, as can be seen in Fig. 1A. The situation is very different for a low-contrast image, which contains much more information and is thus not as sparse, as is seen in Fig. 1B. The highly theoretical field, known as *compressed sensing*, proposes the ability to reconstruct sparse images that have been significantly under-sampled, not satisfying the Nyquist criterion. As a result the compressed sensing algorithms would be expected to perform much more efficiently on high-contrast images, allowing for a significant reduction in acquisition time. The corresponding acceleration is thus useful in the determination of the optimal parameters used in the detection of early tumors. We show the limit of acceleration as well as discuss possible k-space trajectories to further enhance the improvement of the compressed sensing algorithms.

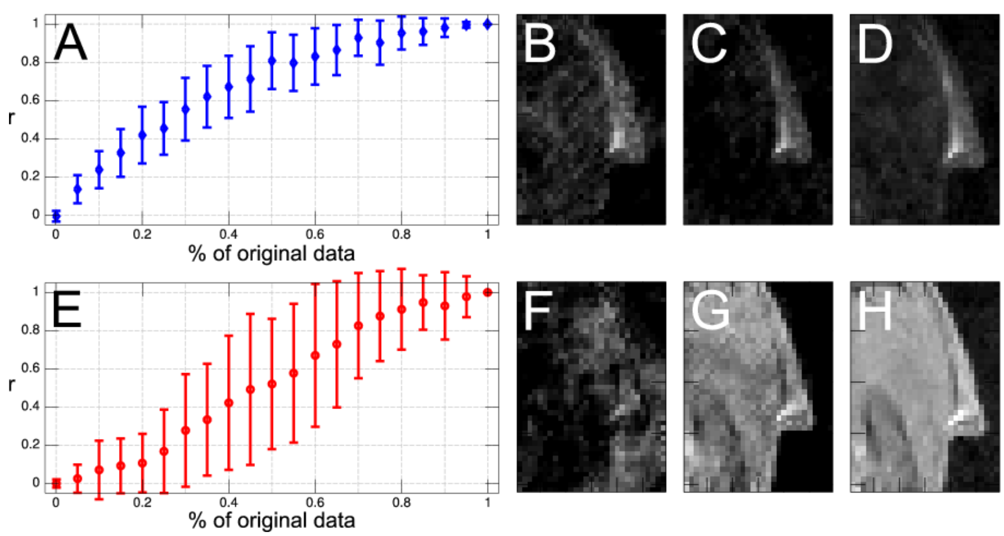
Theory and Methods

For this particular work, we employed the Split-Bregman method for problems. The performance of the algorithm is assessed by deleting random data points from the original k-space data and then comparing the reconstructed image with the original. Random points were deleted by creating a random matrix, which is thresholded in order to keep a certain amount of data. The random nature of the deleted points requires the processing of multiple sets in order to get a good measure for the efficiency and consistency of the algorithm. To numerically quantify the efficiency of the algorithm, the two-dimensional correlation coefficient, r, was calculated between the reconstructed image and the original image. The algorithm was tested 50 different times with varying amounts of kept data for both a high-contrast active feedback in vivo tumor image (Fig. 1A) as well as a low-contrast proton density in vivo tumor image (Fig. 1B).

Results

The performance of the algorithm as a function of the amount of kept data can be seen in Fig. 2A for the high-contrast and Fig. 2E for the low-contrast images. It can be seen that the average correlation coefficient is noticeably higher for the high-contrast image, along with smaller standard deviation bars indicating a high consistency as well. Examples of reconstructions of the high-contrast data can be seen for 40% (Fig. 2B), 65% (Fig. 2C), and 100% (Fig. 2D) of the data kept, along with reconstructions for the low-contrast data can be seen for the same 40% (Fig. 2F), 65% (Fig. 2G) and 100% (Fig. 2H) of the data kept. It can thus be seen that since the high-contrast images contain much less information to begin with, the reconstruction efficiency is much higher than for low-contrast images which contain more information. In order to ensure satisfactory high-contrast reconstruction, it would appear that at least 50% of the original data should be kept, whereas for low-contrast reconstruction, a much higher amount, >80%, is required considering the fluctuations in the performance.





Discussion

The ability to successfully reconstruct images without having to collect the entire k-space is valuable for parameter optimization and can lead to a higher success rate for the detection of early tumors. Other k-space trajectories can be used to further improve the performance of the algorithm, such as concentrating the kept data points towards the center of k-space, while deleting more points around the edges (results not shown). As a result, strategic k-space sampling (beyond purely random) can be employed to further accelerate data acquisition.

References

[1] S. Y. Huang et al., MRM 56, 776 (2006). [2] J.K Furuyama et al. Preceedings from ENC (2008).

Figure 1. A.) Sample high-contrast active feedback in vivo rat image with human breast cancer. **B.)** Sample low contrast proton density in vivo rat image with human breast tumor.

Figure 2. A.) Plot of the average high-contrast correlation coefficient vs. % of original data kept, with error bars showing the standard deviations. Examples of reconstruction using **B.)** 40%, **C.)** 65%, and **D.)** 100% of the original data. **E.)** Plot of the average low-contrast correlation coefficient vs. % of the original data kept.