

Adaptive Image Reconstruction for EPR

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Abstract

In this work, we introduce an adaptive algorithm which, using the information of first few projections, estimates the total number of projections required for the given object. It would be extremely useful to predict beforehand the number of projections required for the object under study because different objects require different number of total projections for similar reconstruction quality. Furthermore, the performance of the suggested algorithm can be enhanced if we collect projections at non-uniformly spaced angles. Hence, we also suggest a mean square error (MSE)-based scheme to collect projections at non-uniformly spaced angles. Simulation and experimental results indicate that for some configurations, we can save 50% or more projections while for other configurations the improvement is marginal.

Introduction

In EPRI, slow data acquisition is one of the limiting factors in obtaining the high-resolution images, especially in the case of living systems. Furthermore, some objects, depending on their spectral and anisotropic characteristics, require much smaller number of projections (N) to generate reasonable reconstruction while other objects may need significantly larger N to generate similar results. Hence, we suggest an adaptive technique which can reduce the acquisition time considerably.

Method

There are three main factors that influence the total number of projections required for the given object. Firstly, we consider spectral spread (S) that measures the spread of k -space. In inverse Fourier transform (IFT) based direct method [1], we take FT of each individual projection and place it in 2D frequency space (k -space) at the orientation along with the projection was taken. In this way data is more concentrated at the center of 2D frequency space and it gets sparse as we move away from the center towards higher frequencies. If the k -space of an object shows considerable amount of energy in higher frequencies, we need more projections for such object so that we have enough data to perform reasonable interpolation in the higher frequency region where data is lesser concentrated. Secondly, we consider image spread (I) that indeed represents the power spectral density (PSD) of k -space. A smaller image spread suggests a highly correlated k -space data, which in turn implies that interpolation in k -space would be efficient, and consequently the error introduced by interpolation would be smaller even with lesser number of projections. Thirdly, anisotropy (A) of the object is taken into account. We suggest a technique that can make use of this anisotropy to acquire the projection at non-uniform angles [2]. After acquiring first 20 projections, we calculate the combined factor (CF) from S, I, and A. This CF is used to estimate how many projections we need to acquire in total.

Results

Simulations: Training and test phantoms were generated in MATLAB. We obtained the MSE vs. N curve for each phantom and calculated the slope of the curve. Value of N, where slope of the curve fell below a selected value, was decided to be the number of required projections (P) for that phantom. Moreover, CF was calculated for each phantom. CF vs. P was linear fit which was used to predict P for the test phantoms. Fig. 1 shows training and test (last two) phantoms. Fig. 2 shows simulation results where (o) indicate training phantom and (*) indicate test phantom.

Experiment: Two phantoms were generated using capillary tubes filled with LiPC. One phantom was I-shaped while other was U-shaped. The experiment was carried on L-band (1.2 GHz) EPRI system [3]. Total of 256 projections were obtained with the scan time of 5.6 s. Image reconstructed using 256 projections was used as reference image shown in Fig. 3. As in the case of training phantoms, we calculated CF and P for both phantoms. P was also estimated from the corresponding CF using the linear fit obtained from training phantoms. Actual value and estimated value of P were compared. Fig.4 indicates that estimated P for U-shaped phantom exactly matches the actual P, and for I-shaped phantom estimated P is only one projection off the actual value.

Conclusions

We suggested and tested an adaptive technique which using the information of first 20 projections can estimate the total number of projections required for the given object. Using this approach we may save up to 50% of the data acquisition time.

References

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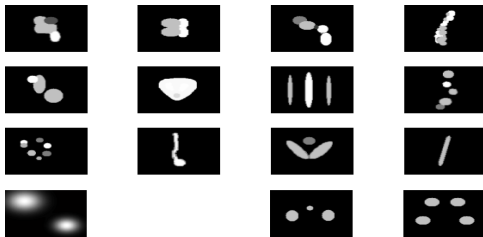


Fig. 1. Training and test phantoms

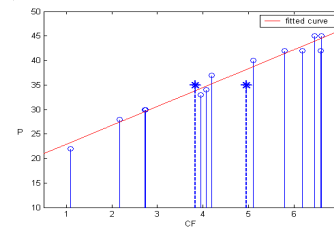


Fig. 2. CF vs. P for training and test phantoms

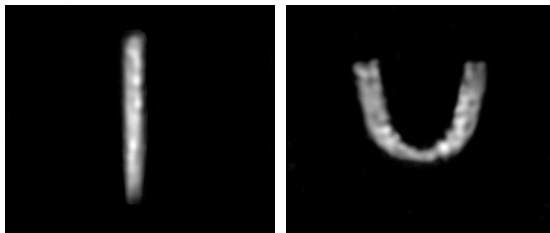


Fig. 3. Reconstructed I-shaped and U-shaped phantoms

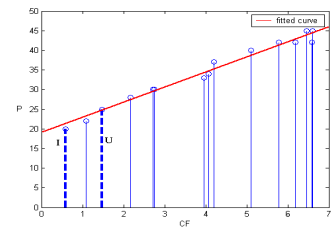


Fig. 4. CF vs. P for training and actual phantoms