

# Improved Random Sampling Reconstruction for In-Vivo Data Using Discrete Cosine Transform

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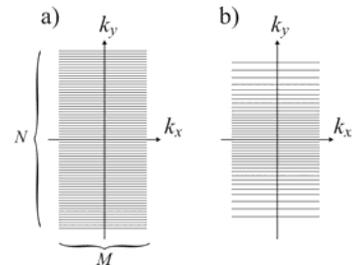
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**INTRODUCTION.** It has been shown that signals or images having a sparse or compressible representation in a given domain can be reconstructed from a few randomly drawn samples, obtained from a domain whose components are linear combinations of the pursued image. The process minimizes the L1 norm of the sparse domain coefficients, keeping the consistency between the acquired samples and the resulting image [1]. Phantoms usually allow an exact reconstruction because, in general, their images have a sparse representation, hence, are easily compressed. However, it has been difficult to achieve good results with in vivo images. To tackle this problem, we hypothesize that a windowed 2D-DCT (2D-Discrete Cosine Transform) of in vivo images, JPEG like, allows concentration of the image content in a few coefficients with a good combination of localization (window size) versus frequency. Therefore, we propose an MRI reconstruction from undersampled data based on the DCT, using adaptive and non-uniform  $k$ -space undersampling mainly concentrated in the low frequencies.

**PROPOSED METHOD.** Previous work [1,2,3] has demonstrated the feasibility of exact or approximate reconstruction of compressible signals from a small number of random samples. Here we propose a complex MRI image reconstruction method, in which the 2D-DCT is computed for small image windows of size  $w \times w$ , avoiding discontinuities by means of overlapping the windows through the reconstruction process. The approach is based on the fact that for small windows the information concentrates in the lower frequencies of the 2D-DCT. Moreover, compared to other transforms the DCT allows a minimum number of coefficients for linearly behaving image intensity. The problem to solve is

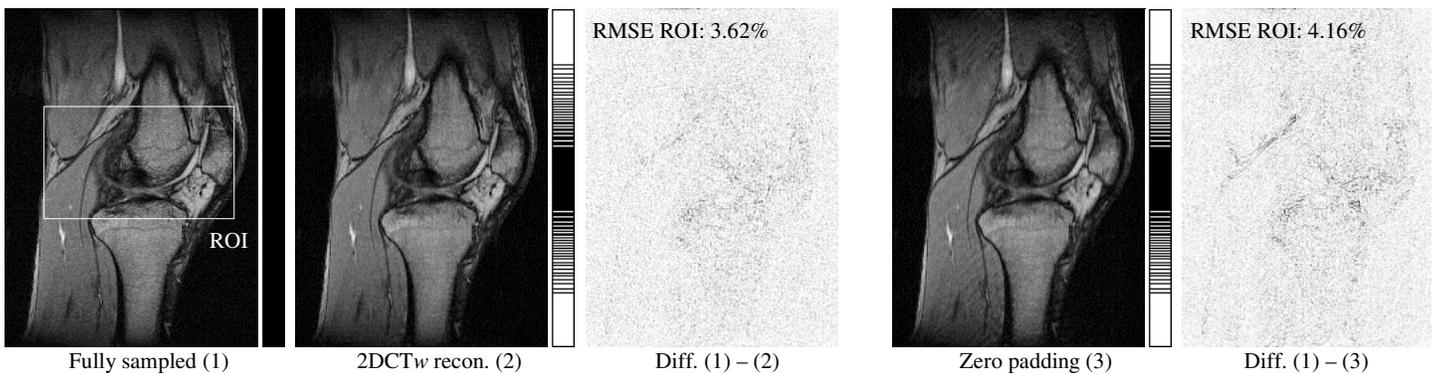
$$\min \|2DCTw[m]\|_1 \quad s.t \quad W_{\Omega}m = \hat{m}_{\Omega},$$

where  $2DCTw$  is the function that split the image into windows of size  $w \times w$ , computes their 2D-DCT, and applies a weighting mask to penalize the higher frequencies;  $m$  is the desired image;  $W_{\Omega}$  is a matrix containing the undersampled 2D-Discrete Fourier Transform (2D-DFT), and  $\hat{m}_{\Omega}$  are the  $k$ -space samples actually acquired. We look for the image with the least amount of coefficients in the  $2DCTw$  domain which in turn are concentrated at low frequencies, keeping the consistency between the acquired samples and the resulting image. We propose a sampling pattern with a heavier concentration at the center of  $k$ -space. The central section sampling complies with  $\Delta k_{min}$ , and the higher frequencies are undersampled with an increasing spacing towards the edges of the  $k$ -space. It is done adaptively, starting from the center towards the edges, and depending on the number of samples. The proposed undersampling pattern of the  $k$ -space, shown in Fig. 1-b, is sustained by the fact that MRI image contents concentrate at low frequencies, but higher frequencies are also important to preserve detail.



**Fig. 1.** a) Fully sampled  $k$ -space; b) Proposed sampling pattern of  $k$ -space.

**RESULTS.** Results are shown for a  $256 \times 256$  sagittal knee image, obtained using a GRE sequence with TE = 20ms and TR = 500ms, using a Philips GyroScan T5-NT at 0.5T. The selected samples cover only 45% of  $k$ -space, with 47 central lines according to the proposed undersampling pattern. The window size used here is  $8 \times 8$ . Aliasing artifacts in the  $2DCTw$  reconstructed image are practically removed, and the image clearness is remarkably improved when compared to zero padding reconstruction. Difference images to compare reconstructions and fully sampled image are also shown, as well as RMSE values of the difference images for the defined region of interest (ROI). The  $2DCTw$  reconstruction does not match the fully sampled image completely, although they are perceptually very similar. Minimization was implemented using a POCS algorithm modification.



**CONCLUSIONS.** The proposed method allows excellent reconstruction for heavy  $k$ -space undersampling. Concentrating samples at the lower frequencies allows much better results than randomly sampling images without sparse representation and with information gathered in the low frequencies, as is the case in MRI images. Therefore, fully sampling the center of  $k$ -space is justified in order to have a good initial image approximation for the reconstruction. The method is efficient since the data is sampled using a 2DFT trajectory and consequently does not need gridding. Off-resonance conditions negatively affect the reconstruction, causing estimation errors in the real and imaginary  $k$ -space components. This fact prevails for T2-weighted images that involve long TE. However, our method still achieves better reconstruction than zero-padding for this kind of images. Our approach shows that with less than half the samples it is possible to reconstruct a high quality image. This technique could be extended for parallel imaging and for dynamic imaging applications.

## REFERENCES

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