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Image Reconstruction Database (ImRiD) for Machine Learning

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INTRODUCTION

- Majority of the image reconstruction models were trained based on a dataset that does not contain raw data. The phase of the image is typically missing or being synthesized[1].
- A standard repository of raw data training dataset which includes phase information is needed for deep learning MRI reconstruction models[2].
- Deep learning model which directly reconstructs raw scanner data can be non-practical due to the heavy memory requirement of the fully connected layers[2]
- Image Reconstruction Database (ImRiD) is designed exclusively for the purpose of training deep learning MR image reconstruction models
- ImRiD provide the MR reconstruction development community a standard database

METHODS

- 3D T_1 weighted MP-RAGE scan of the American College of Radiology (ACR) and Alzheimer's Disease Neuroimaging Initiative (ADNI) phantom were acquired on a 3T Siemens Prisma scanner.
- The acquisition parameters: FOV=256x256x192 mm^3, TI=900 ms, flip angle=8°, TR=2300 ms, isotropic resolution of 1.05 mm with a matrix size of 254 x 254 x 192.
- This was performed to utilize the T_1 targets available in phantoms for quantitative imaging
- The orthogonal slices and arbitrary slices (Figure 2) were chosen by indicating the vector normal to the desired plane.
- Then the corresponding k-spaces mapping can be obtained by performing the inverse Fourier transform. The MATLAB code to leverage these planes are provided in the GitHub repository[3]. The code for arbitrary plane selection is downloadable from ref.[4].
- To demonstrate the importance of phase in MR reconstructions, the k-space from the magnitude of the images was synthesized and multiplied with random phase maps as shown in figure 1a.

Figure 1: Sample Images and Synthesized Phase Map

Figure 1 a shows the random phase map that being applied to the k-space. Figure 1 b and d are actual slice from ACR phantom and ADNI phantom. Figure 1 c and e are same slice but with random phase map that applied to the k-space. Figure 1 f and h are the actual phase angle plots of the actual slice image.

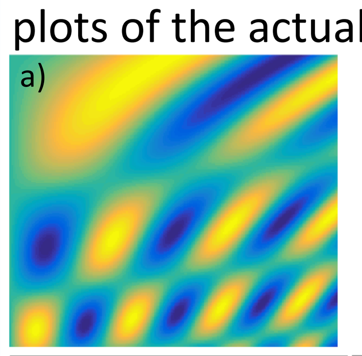
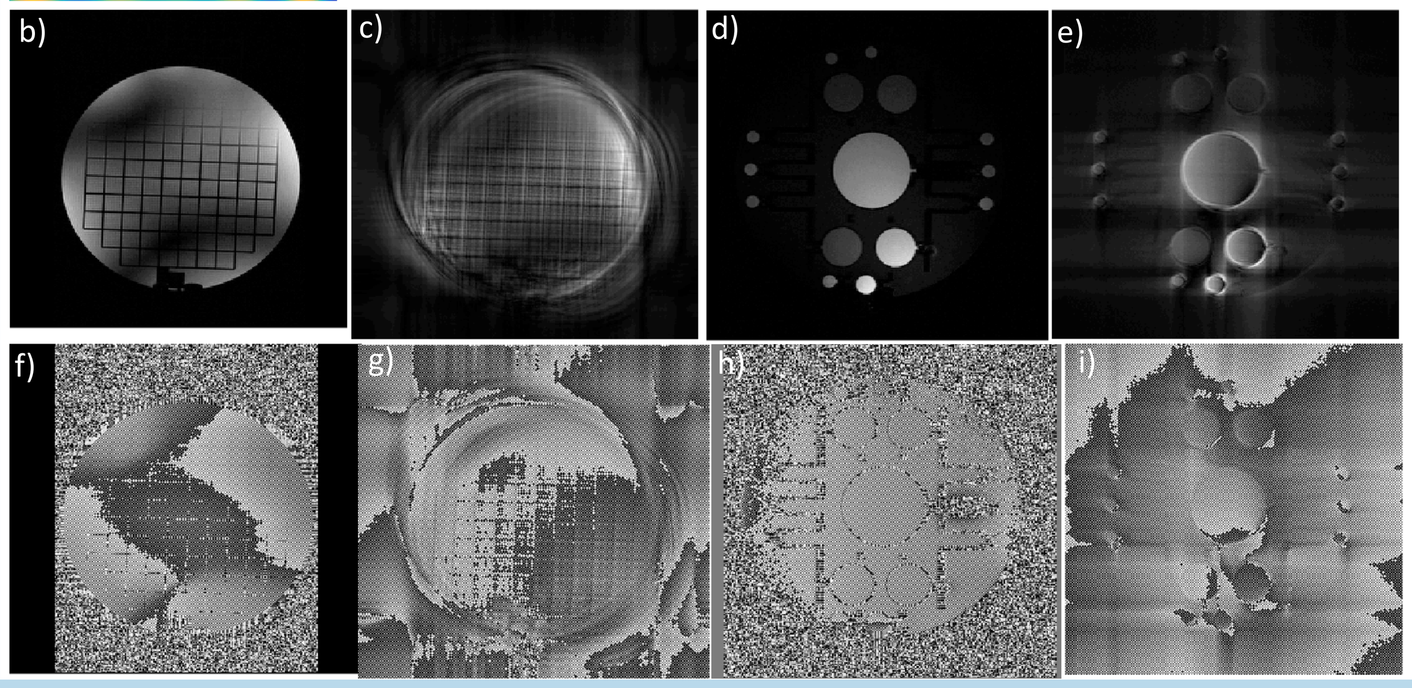


Figure 1 g and i are the phase angle plots that has random phase map applied. The level of clarity indicates the necessary of keeping the phase information in k-space as we do the image reconstruction.



RESULTS

Figure 1 shows an axial slice of the ACR phantom with original (1b,f) and randomly applied phase (1c,g). Figures (1d,h) and (1e,i) correspond to the ADNI phantom. The data is available at ref.[5] for free download.

Figure 2 and 3 show that orthogonal and arbitrary slices are able to be extracted freely with specified normal vector and initial point.

Figure 2: ACR Phantom

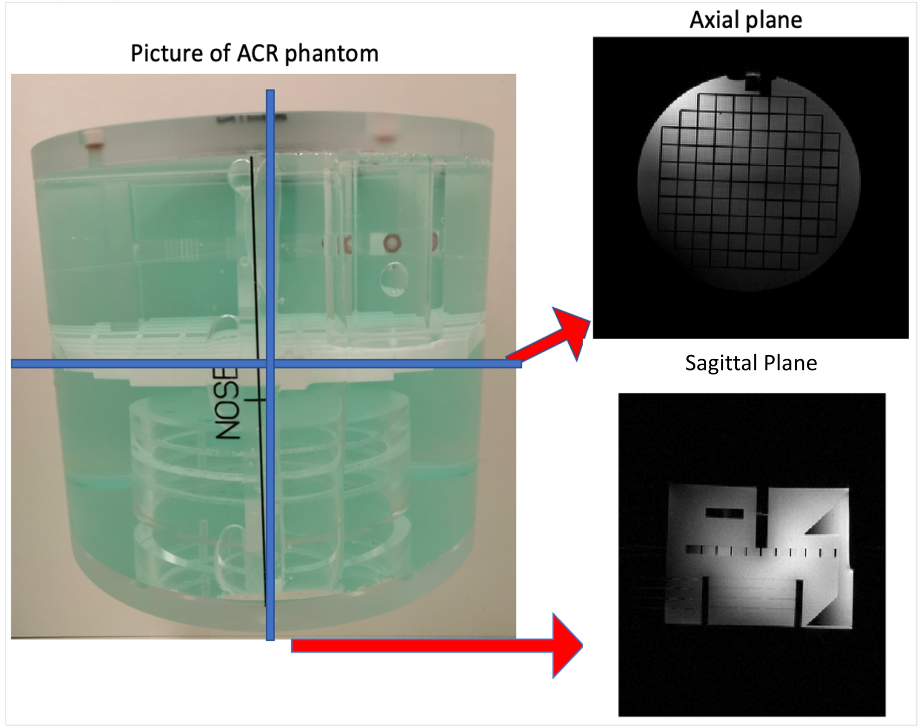


Figure 2 shows orthogonal slice of ACR phantom. Position of the slice is visualized by the blue line in the actual phantom picture.

Figure 3: ADNI Phantom

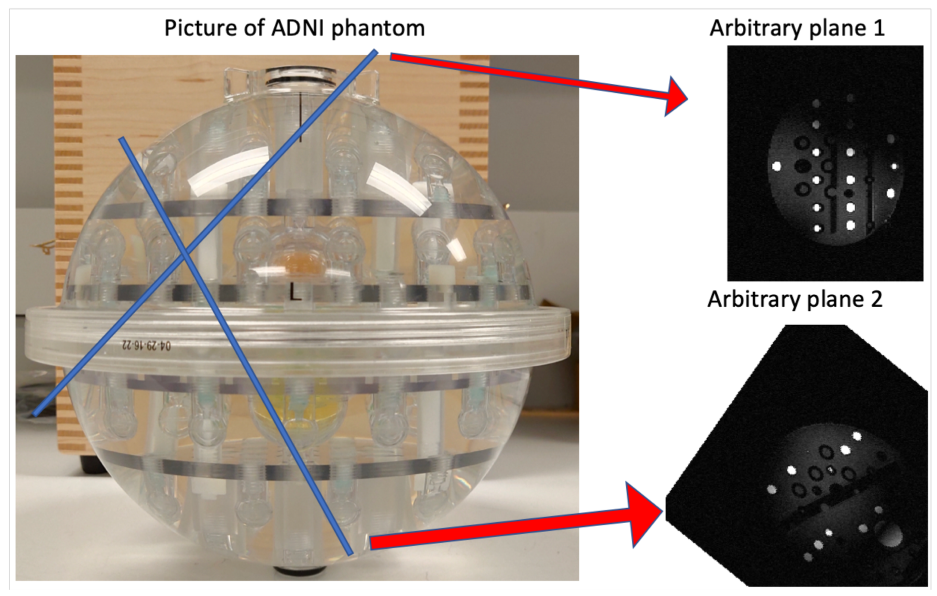


Figure 3 shows arbitrary plane obtained from ADNI phantom data. It illustrates that the arbitrary plane can be specified and obtain from the database.

DISCUSSION

The proposed data set could be utilized as a standard training data for deep learning MR image reconstruction algorithms for the following reasons:

- MR data from these phantoms are typically employed to test/calibrate the system as well as protocols;
- The complex image data captures the phase, noise and related characteristics of the system;
- Image processing algorithms to slice an acquired 3D complex volume with high resolution would provide infinite number of slices and therefore unrestricted size of examples to train on;
- Extension to include acquisition methods tied to hardware such as parallel imaging, selective excitation could be easily and directly incorporated;
- This library could be then also used to under-sample k-space with different non-Cartesian trajectories to perform transform learning of under-sampled data;
- The ground truth/construction of the phantom is well specified and purposely designed.

	Data Construction	Phase	Resolution	Image Dimension	Data Size	K-space Inclusion
ImRiD	Fully sampled k-space and image	Has phase	256x256x192	3D & 2D	Infinite	Yes
Image Net	Meaningful concept and its image	No phase	469x387(avg)	2D	14,197,122	No
HCP	HARDI and DSI to the connections of the brain	No phase	256x256	3D	132	No
IXI	600 healthy brain images	No phase	256x256x150	3D	600	No
Brain Web	Simulated MRI brain Images	No phase	362x434x362	3D	2	No
CIFAR-10	Images of 10 classes	No phase	32x32	2D	60000	No
MNIST	Hand written digits	No phase	28x28	2D	70000	No

CONCLUSION

- The number of training examples that can be obtained from this dataset is infinite.
- Researchers can perform the experiment detailed in this work readily, easily and in line with tests determined by respective guidelines such as those provided by ACR and/or ADNI.
- Phantom tests cover different aspects of MR image quality such as low contrast detectability, resolution, slice thickness, slice accuracy, etc.
- This would allow benchmarking the reconstructions performed using deep learning in line with these prescribed tests by the phantom makers/approvers.
- Reconstruction algorithms trained would cater to multiple anatomies and related artifacts. Therefore, the model would be trained to learn the transform rather than be restricted by the anatomy.
- For a typical training process, the full k-space information of an image can be sub-sampled by any k-space sampling methods the researchers propose (such as radial, spiral). The actual slice image then can be the ground truth that the resampled k-space would be trained against.

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