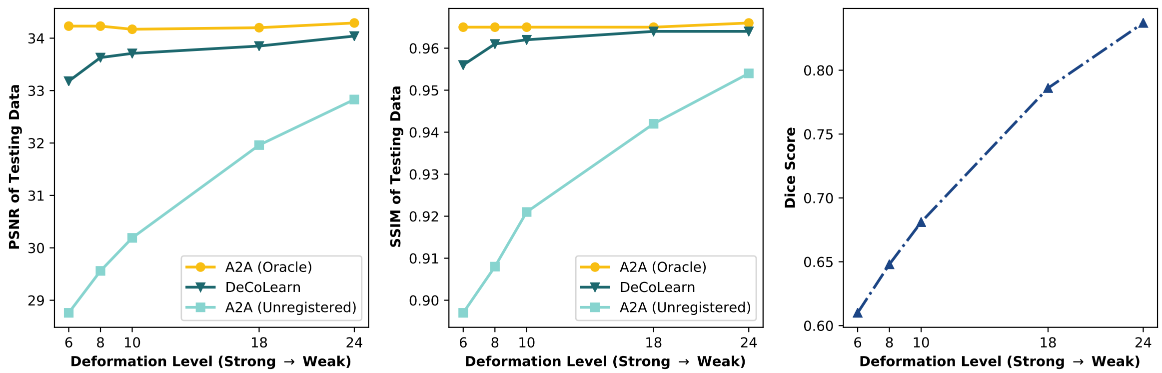
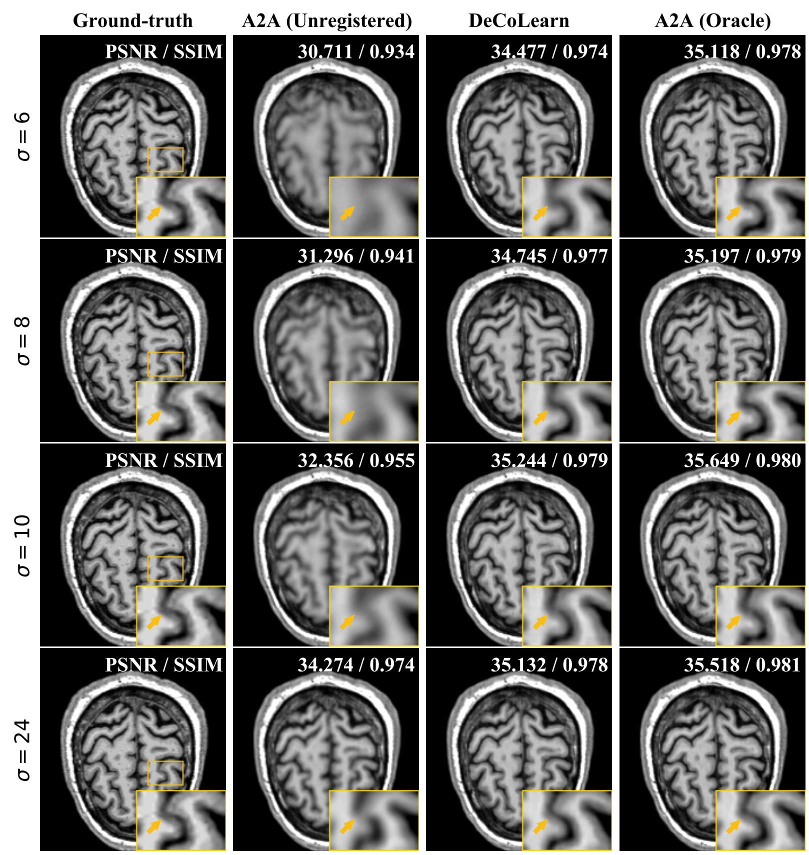
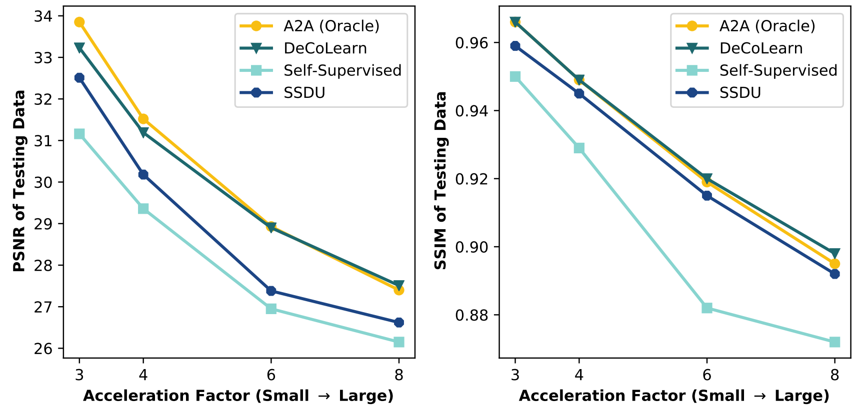


(a)

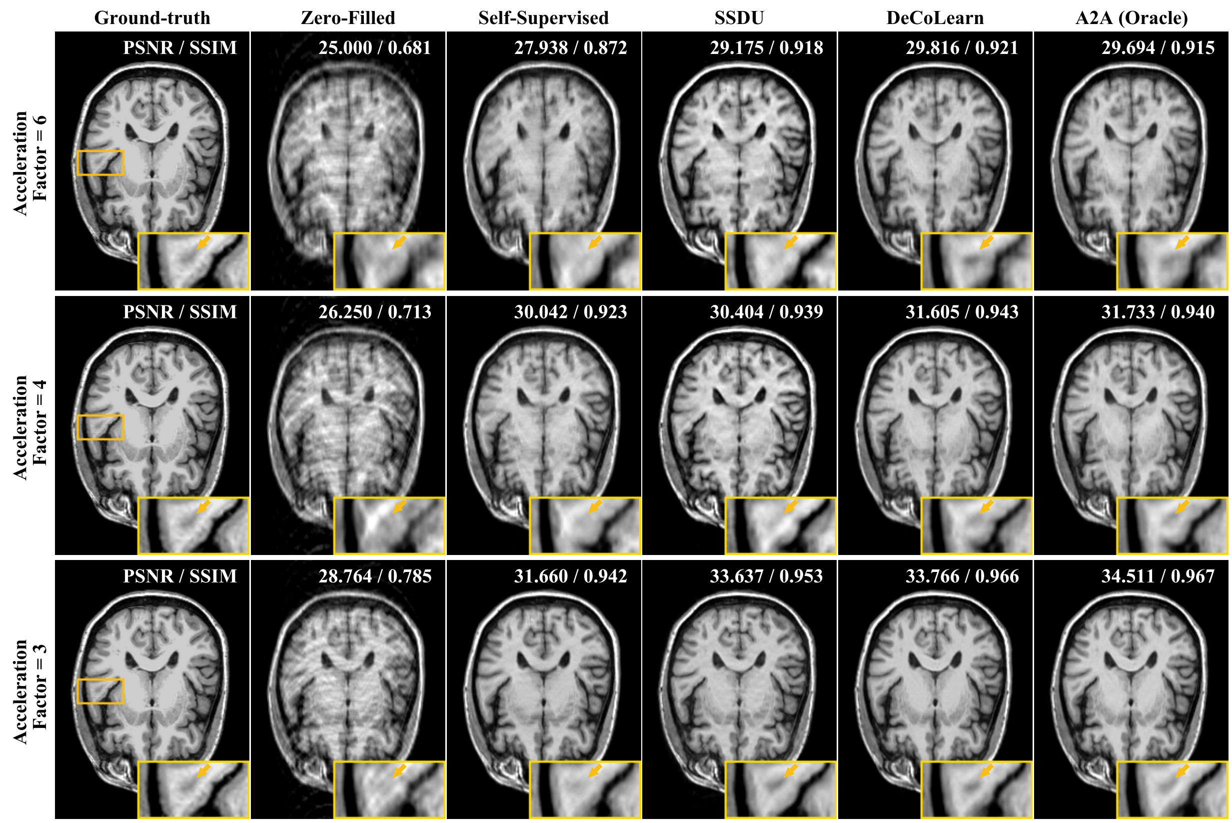


(b)

Figure 1: Quantitative evaluation under deformations of different strengths at undersampling rate of 33%: *(a)* PSNR and SSIM values obtained over the test set and *(b)* visual illustration of the results, where visual differences are highlighted by yellow arrows in the magnified regions. *A2A (Unregistered)* learns directly from unregistered measurements, leading to blurring under strong deformations. Since DeCoLearn compensates for the deformation by jointly optimizing a registration module, it significantly outperforms the traditional A2A. Note that *A2A (Oracle)* is trained on registered measurements that are usually unavailable in practice. This figure shows that DeCoLearn maintains its ability to learn from unregistered data by nearly matching *A2A (Oracle)* over many deformation strengths.



(a)



(b)

Figure 2: Quantitative evaluation on simulated measurements and real deformation over different acceleration factors: *(a)* PSNR and SSIM values obtained over the test set and *(b)* visual illustration of the results. SSDU and *Self-supervised* train CNNs without ground-truth by using two non-overlapped subsets of the undersampled measurements as training targets for each other. *A2A (Oracle)* is an idealized oracle method trained on registered measurements. The visual differences are highlighted in *(b)* using yellow arrows in the magnified regions. Note how DeCoLearn outperforms SSDU over all acceleration factors by nearly matching the performance of the idealized *A2A (Oracle)*.

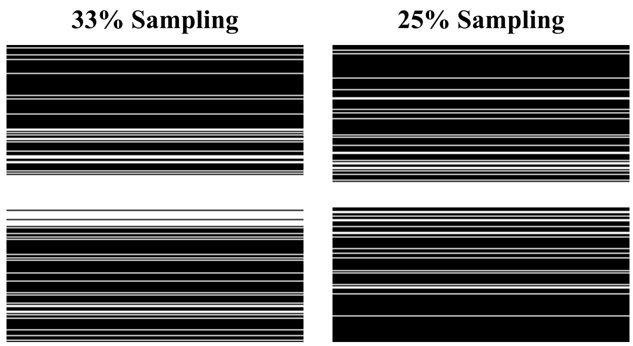
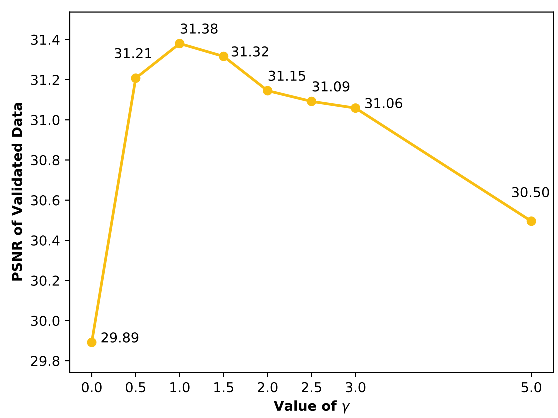
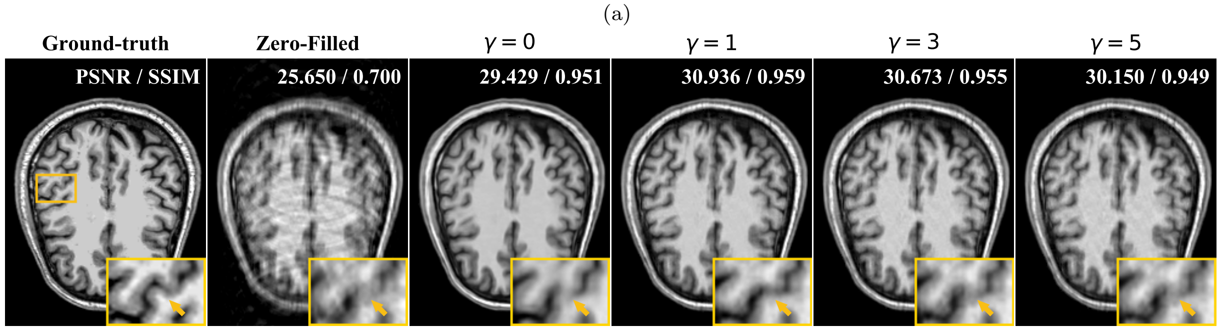


Figure 3: Illustration of synthesized sampling masks used in the experiments of simulated measurements. *Left*: a sampling mask with undersampling region being 33% of the whole k-space; *Right*: a sampling mask with undersampling region being 25% of the whole k-space.



(a)

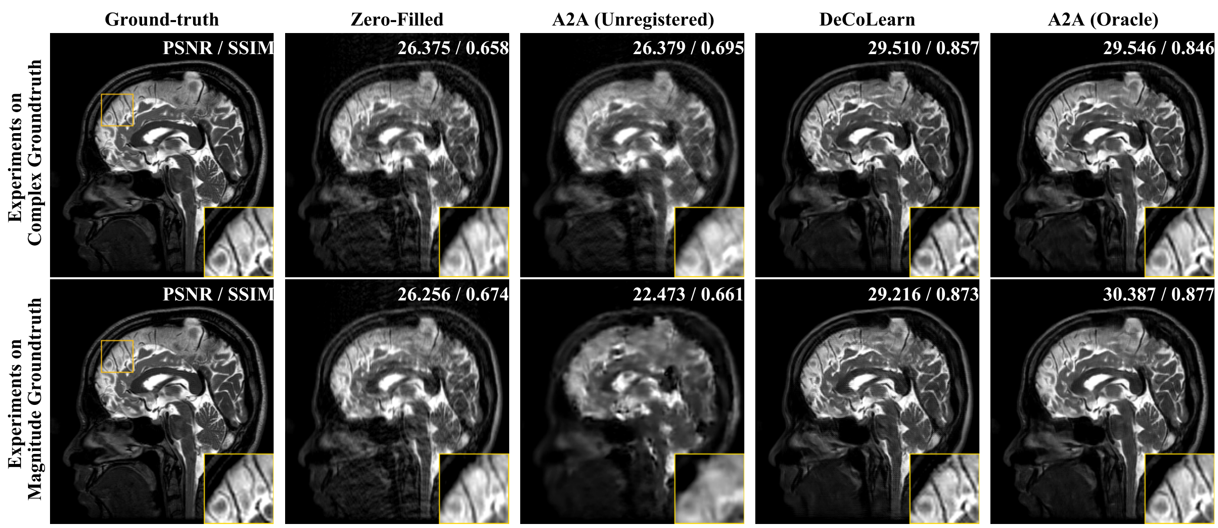


(b)

Figure 4: Quantitative evaluation of DeCoLearn on simulated measurements over different values of trade-off parameter γ in the reconstruction loss: *(a)* illustration of average PSNR values obtained over the validation set and *(b)* visual examples of the reconstruction results over the test set, where the visual differences are highlighted by using yellow arrows in the magnified regions. In practice, we choices the value of γ among $[0.5, 1.0, 1.5, 2.0, 2.5, 3.0]$ that achieves the highest PSNR on the validation dataset. This figure shows that the performance of DeCoLearn can be improved by using the optimized value of the trade-off parameter γ.

Measurements Simulated from	*Complex Ground-truth*		*Magnitude Ground-truth*	
Schemes	PSNR (dB)	SSIM	PSNR (dB)	SSIM
Zero-Filled	27.85	0.694	27.81	0.712
A2A (Unregistered)	28.22	0.720	25.71	0.758
DeCoLearn	**32.47**	**0.888**	**32.14**	**0.907**
A2A (Oracle)	33.01	0.892	33.71	0.909

(a)



(b)

Figure 5: Quantitative evaluation of DeCoLearn on a new brain MRI data that is publicly available in `https://github.com/hkaggarwal/modl`: *(a)* average PSNR and SSIM values obtained over the test set and *(b)* visual examples of the reconstruction results. We simulated the unregistered measurements with the sampling rate being 33% and σ being 18 (corresponds to moderate deformation). Note that the complex- and magnitude-groundtruth correspond to the same fully-sampled k-space data. This table demonstrates that DeCoLearn can achieve an equivalent performance when conducting experimented by using either complex- or magnitude-groundtruth.