Training deep learning based image denoisers from undersampled measurements without ground truth and without image prior —Supplementary Material —

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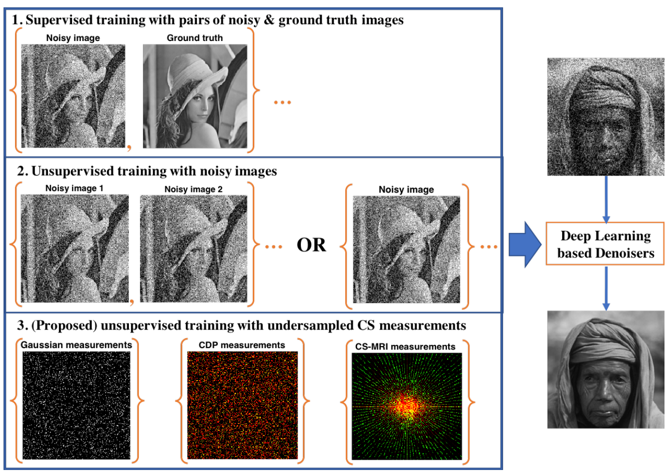

Figure 1: Approaches to train deep learning based denoisers.

In order to train deep learning based image denoisers, there have been two approaches so far: supervised training with pairs of noisy and ground truth images (e.g., [9, 2, 3]) and recently investigated unsupervised training with noisy images only (e.g., [4, 8]). Contrary to above-mentioned methods, we tackled the problem of unsupervised training of image denoisers with undersampled CS measurements. Figure 1 illustrates the clear distinctions between the methods.

1. On training parameters

In this section, we describe how to select tuning hyper-parameters such as ϵ for MC-SURE estimation based on [8] and provide results that demonstrate the importance of our proposed noise estimation method (Eq. (7)) over the previous method ((6) in the main paper) [7].

We selected the value of ϵ in MC-SURE (Eq. (5)) following [8] as shown below:

$$\epsilon = \sigma \times 1.4 \times 10^{-4} \quad \text{for} \quad \sigma \in [0 - 255].$$

Following the training method of DnCNN [9], MC-SURE was also calculated separately for each 50×50 patch in a batch during the training.

The original noise estimation method (Eq. (6)) was not accurate enough for training with MC-SURE. We observed that LDAMP SURE trained with this original method yielded the worst results. Our proposed noise estimation method (Eq. (7)) significantly improved the performance of our LDAMP SURE (see Table 1). We compared the following four methods: BM3D-AMP [5, 6], LDAMP BM3D (the same method as [7], but trained with the results of BM3D-AMP as the ground truth using MSE), LDAMP SURE w/ Prev. Noise Est. (our proposed method, but using the previous noise estimation in [7]), and LDAMP SURE w/ Proposed Noise Est. (our proposed method with the new noise estimation). LDAMP SURE w/ Prev. Noise Est. yielded 10 dB lower than conventional BM3D-AMP, indicating that accurate noise estimation is one of the key factors for successful denoiser training using MC-SURE without ground truth and without additional image prior. In the main paper, we denote "LDAMP SURE w/ Proposed Noise Est." as "LDAMP SURE".

Method	$\frac{M}{N} = 25\%$
BM3D-AMP	31.40 dB
LDAMP BM3D	31.65 dB
LDAMP SURE w/ Proposed Noise Est.	**33.26 dB**
LDAMP SURE w/ Prev. Noise Est.	21.40 dB

Table 1: Avg. PSNR of 100 images of four different methods including our proposed method for CDP measurements.

2. Towards a single denoiser

An extensive study has been performed to understand how the number of denoisers can affect the performance of LDAMP network with the goal of reducing the number of

Networks	Gaussian	CDP	CS-MRI	Trained noise range
LDAMP-9	31.30	**35.07**	**31.41**	$\sigma \in [0-10, 10-20, ..., 300-500]$
LDAMP-4	31.19	32.84	29.64	$\sigma \in [0-50, 50-100, 100-200, 200-500]$
LDAMP-3	31.35	32.96	29.42	$\sigma \in [0-50, 50-150, 150-500]$
LDAMP-3	30.92	33.06	29.47	$\sigma \in [0-100, 100-200, 200-500]$
LDAMP-1	28.45	31.00	28.56	$\sigma \in [0-500]$
LDAMP with BM3D	**31.65**	33.88	31.33	$\sigma \in [0-55]$ and BM3D for larger noise

Table 2: Performance of LDAMP networks on 100 test images with 180×180 for $\frac{M}{N} = 25\%$ sampling rate.

denoisers from 9 [7] to 1 or more without losing much performance. All networks were trained on BSD-500 dataset and with a mean square error (MSE) as a loss function. The results are tabulated in Table 2, where the number indicates the number of denoisers in LDAMP. For instance, LDAMP-3 means LDAMP with 3 DnCNN denoisers trained on noise ranges specified in the "Trained noise range" column. It turned out that the more number of DnCNN denoisers and the finer discretization of the noise range are used, the better performance of an LDAMP can be obtained.

On the other hand, we found that the hybrid approach using LDAMP and BM3D could achieve comparable performance with only 1 DnCNN. When we utilized state-of-the-art BM3D denoiser for larger noise levels and use DnCNN at low noise range, comparable reconstruction performance to LDAMP-9 was achieved using only 1 DnCNN. This reduces the network training time significantly. This hybrid method is our proposed LDAMP SURE method in the main paper.

In most cases, our hybrid approach uses only 1 DnCNN denoiser. However, for highly undersampled cases (e.g. $\frac{M}{N} = 5\%$), using more denoisers was necessary to maintain the performance. Thus, we used three blind DnCNN denoisers that were trained for $\sigma_1 \in [0, 55]$, $\sigma_2 \in [55, 110]$, and $\sigma_2 \in [110, 165]$ noise ranges respectively, for $\frac{M}{N} = 5\%$.

3. LDAMP pretrained with TVAL3

In our work we reported the results of LDAMP SURE that was pretrained with BM3D-AMP and then fine-tuned with compressive sensing measurements for all 3 measurement matrices. However, we can also pretrain LDAMP SURE with TVAL3 instead of BM3D-AMP. Thus following the same steps as described in our paper, DnCNN can be pre-trained with the outputs of TVAL3 (we denote this as LDAMP-TVAL3) and then can be fine-tuned using compressive sensing measurements using our proposed LDAMP SURE (we denote this as LDAMP SURE*). These results are reported in Table 3. In our main paper, LDAMP SURE was not able to surpass TVAL3 for CDP case when undersampled measurements are only $\frac{M}{N} = 5\%$. However, by using a different pre-trained network, the same proposed method outperformed other methods including TVAL3.

Methods	PSNR (dB)
NLR-CS	19.00
BM3D-AMP	21.66
TVAL3	22.57
LDAMP-TVAL3	22.72
LDAMP SURE*	**22.88**

Table 3: Average PSNRs of 100 test images with 180×180 reconstructed for CDP at $\frac{m}{n} = 5\%$.

4. Additional results

We report more results for $i.i.d$ Gaussian, CDP, and CS-MRI cases with different compressive sampling ratios in Figures 2 - 7. These results were not included in the main paper due to the page limit. All of our proposed methods here were pretrained with BM3D-AMP and then fine-tuned with compressive sensing measurements. Also, 25 standard grayscale test images can be found in Figure 8.

References

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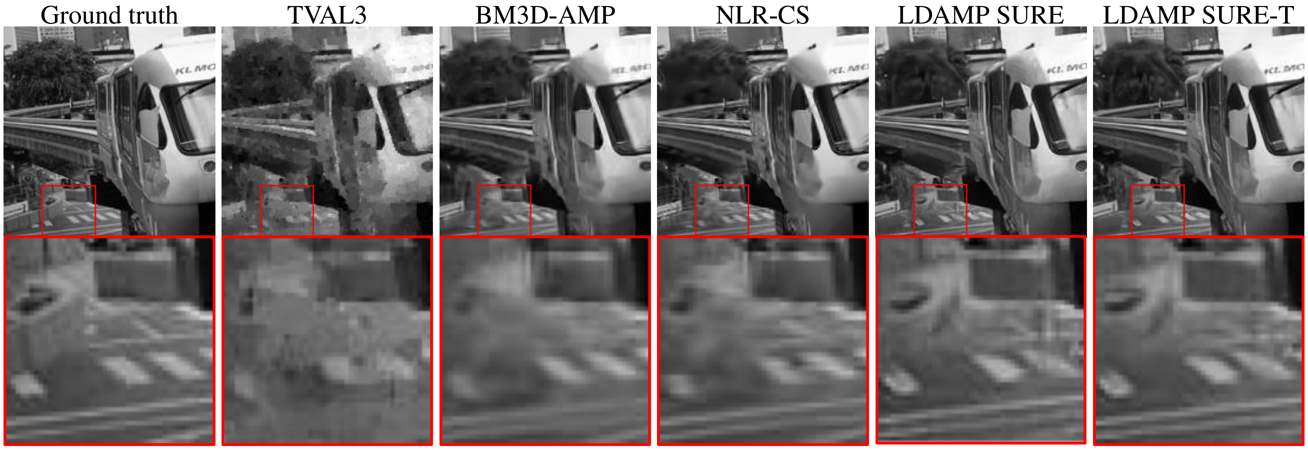
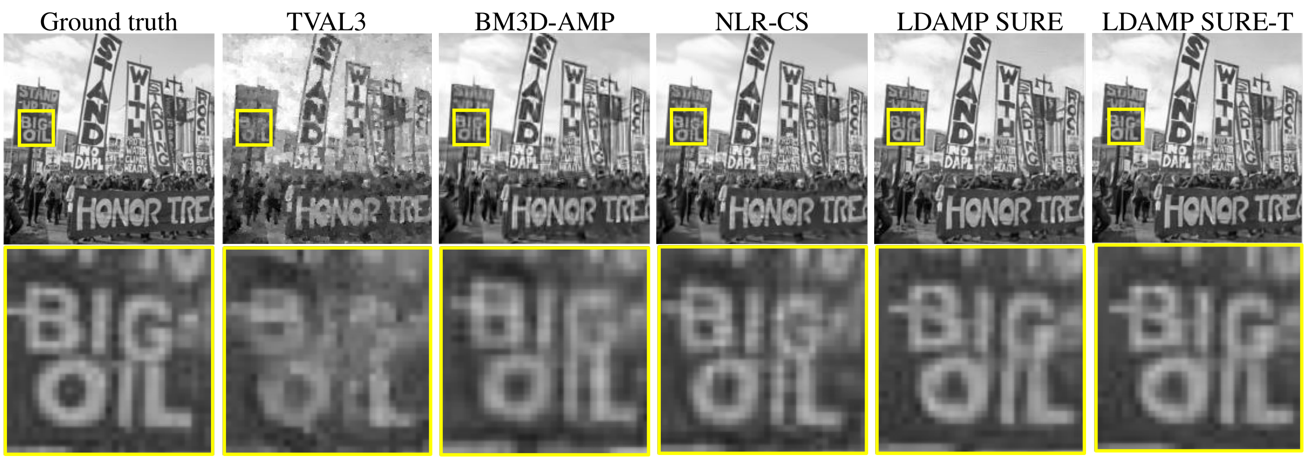


(a) PSNR (b) 23.53 dB (c) 26.03 dB (d) 27.04 dB (e) **27.91 dB** (f) **28.17 dB**

Figure 2: Reconstructions of 180×180 test image (DIV2K dataset [1]) with $i.i.d.$ Gaussian measurement matrix for $\frac{m}{n} = 0.15$ sampling rate.



(a) PSNR (b) 21.73 dB (c) 24.96 dB (d) 26.96 dB (e) **27.72 dB** (f) **27.83 dB**

Figure 3: Reconstructions of 180×180 test image (DIV2K dataset [1]) with $i.i.d.$ Gaussian measurement matrix for $\frac{m}{n} = 0.25$ sampling rate.

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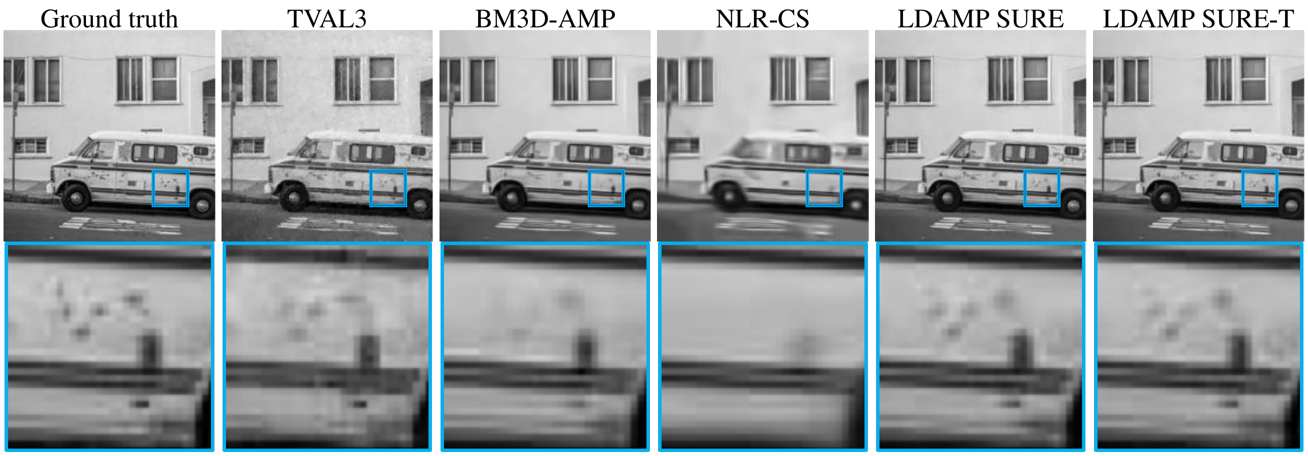
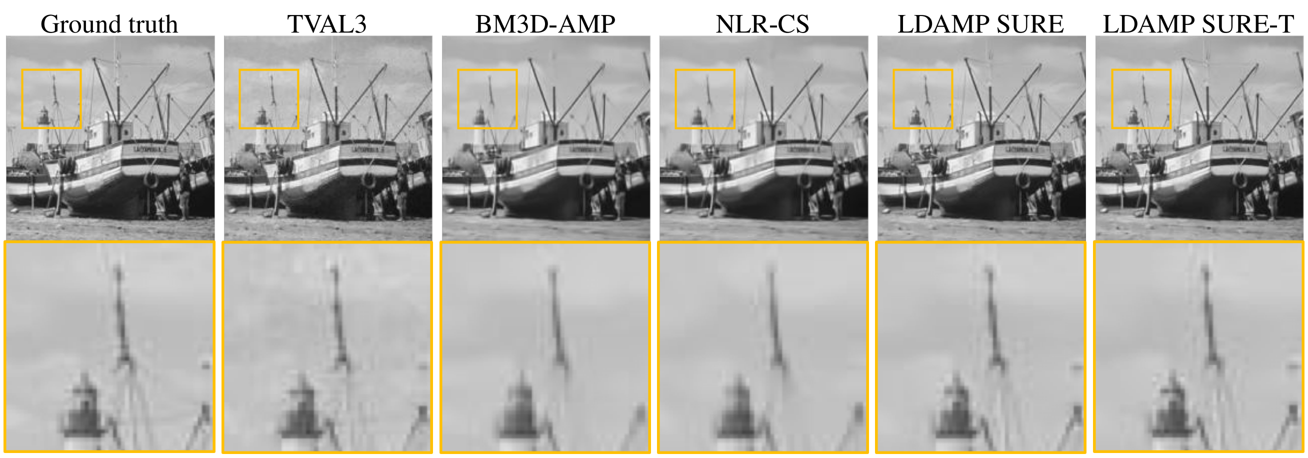


(a) PSNR (b) 29.49 dB (c) 32.83 dB (d) 24.98 dB (e) **34.76 dB** (f) **34.34 dB**

Figure 4: Reconstructions of 180×180 test image with CDP measurement matrix for $\frac{m}{n} = 0.15$ sampling rate.



(a) PSNR (b) 34.00 dB (c) 31.74 dB (d) 31.86 dB (e) **34.89 dB** (f) **35.24 dB**

Figure 5: Reconstructions of 180×180 “Boat” test image with CDP measurement matrix for $\frac{m}{n} = 0.25$ sampling rate.

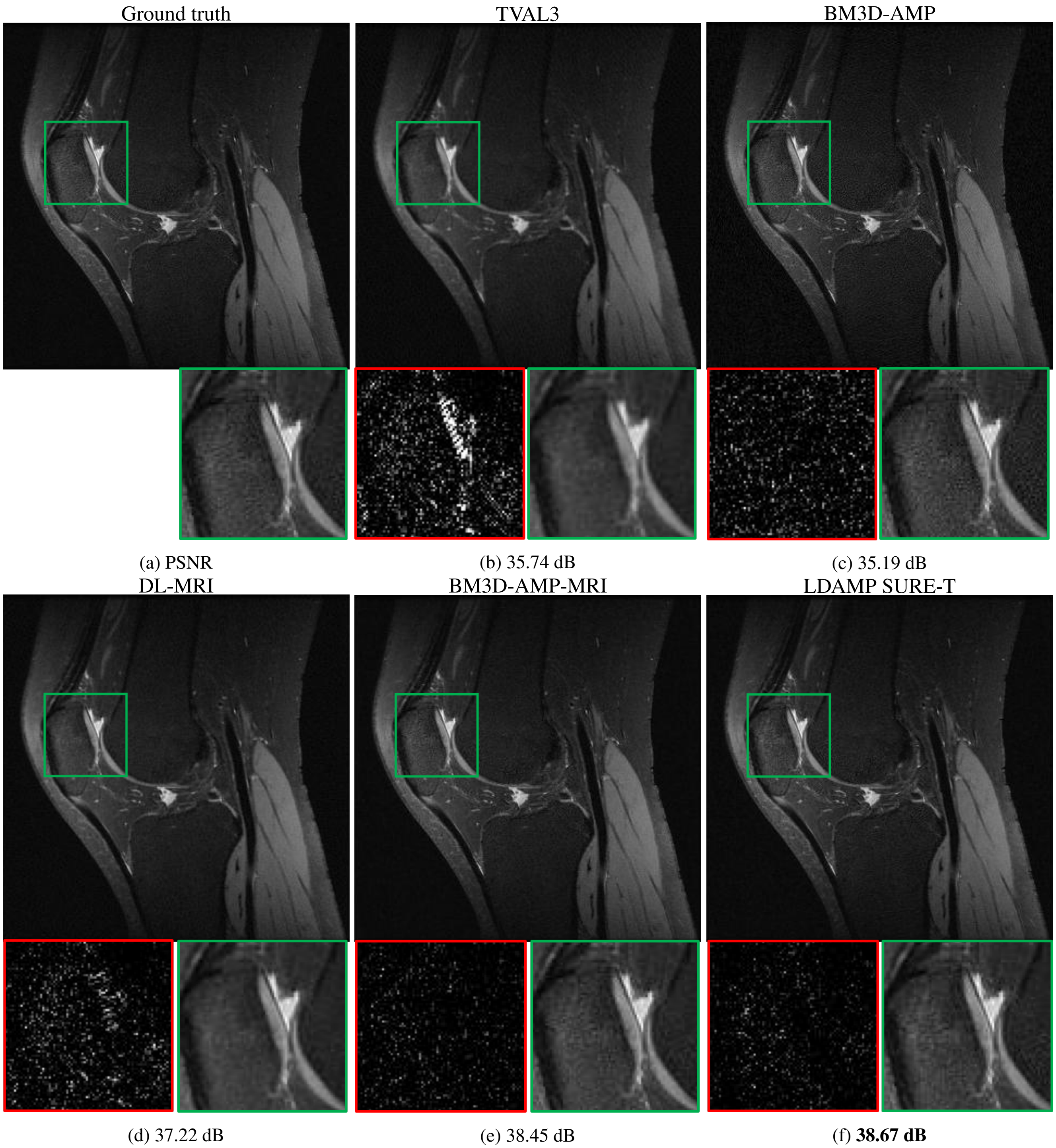


Figure 6: Reconstructions of 180×180 test image with CS-MRI measurement matrix for $\frac{m}{n} = 0.50$ sampling rate. Red box corresponds to a residual between the ground truth and reconstructed image, while green box is an enlarged region of the recovered image.

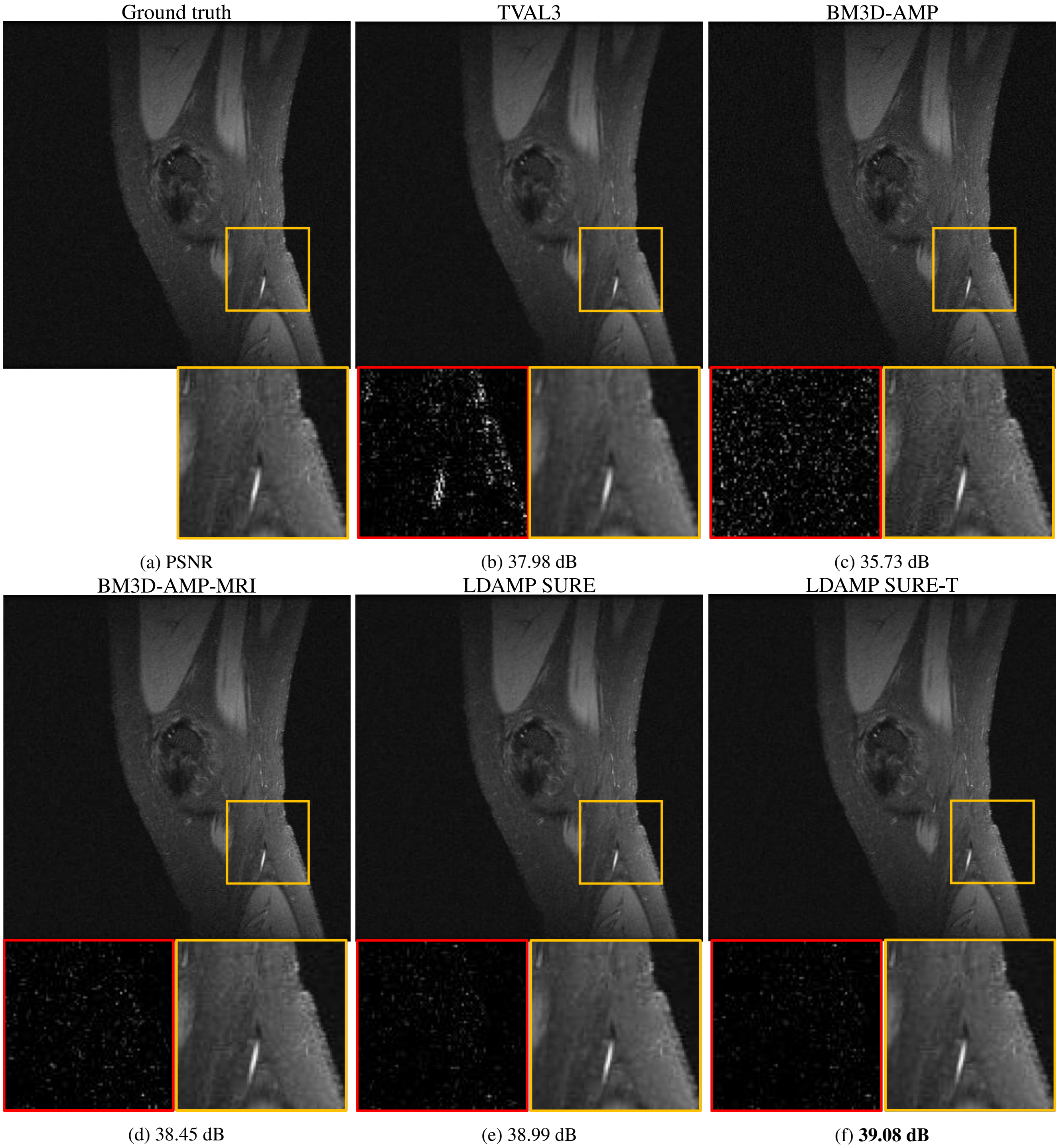


Figure 7: Reconstructions of 180×180 test image with CS-MRI measurement matrix for $\frac{m}{n} = 0.60$ sampling rate. Red box corresponds to a residual between the ground truth and reconstructed image, while yellow box is an enlarged region of the recovered image.

Figure 8: The twenty five standard test images used as a part of the test dataset for Gaussian measurement matrix and CDP experiments.