

Supplementary material for the paper:
“Improving Denoising Algorithms via a Multi-Scale Meta-Procedure”
Paper ID: 100

March 28, 2011

1 Training images



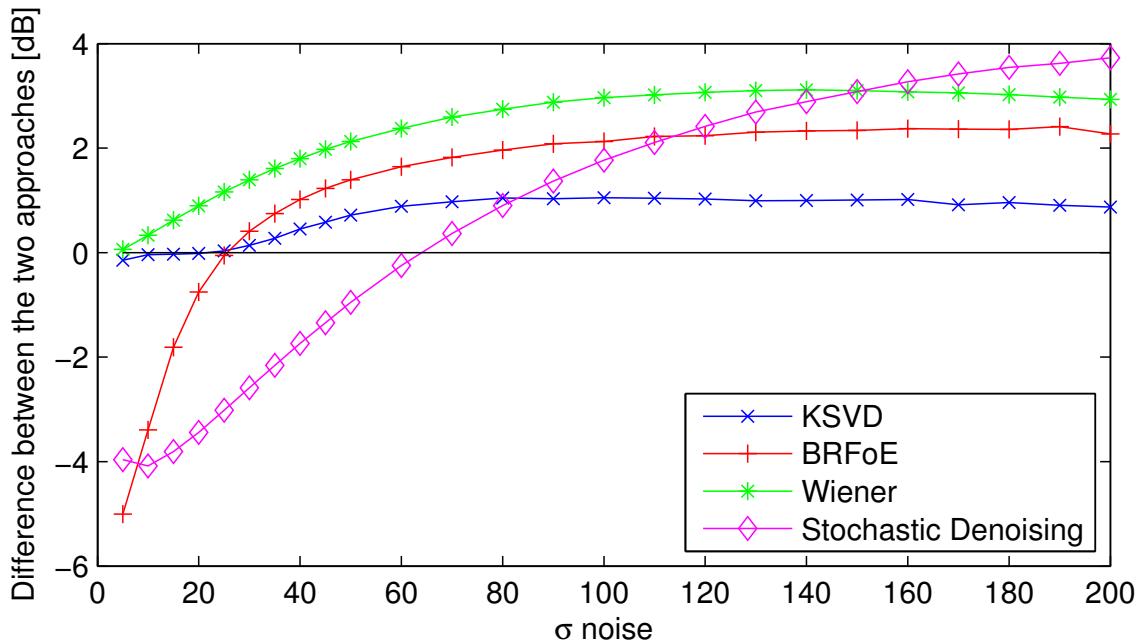
The hyper-parameters of our method were tuned on 20 training images for the Berkeley segmentation. The images are color images, but we worked on black and white versions by averaging the color channels. The images are all either of size 481×321 or of size 321×481 . We removed one pixel row at the bottom of the images and one pixel column at the right of the images in order to create images of size either 480×320 or 320×480 . The reason for this was to create images that are multiples of 8 in height and width.

2 Test images



The 13 test images are usually named “Barbara”, “Boat”, “Cameraman”, “Couple” (or “Living Room”), “Fingerprint”, “Flintstones”, “Hill” (or “Goldhill”), “House”, “Baboon” (or “Mandrill”), “F16” (or “Fighter Jet”), “Lena”, “Man” (or “Pirate”) and “Peppers”. The images “Cameraman”, “House” and “Peppers” are of size 256×256 and all others are of size 512×512 . The images “Baboon” and “F16” were color images which we converted to black and white by averaging the color channels, as we did in the training set. All other images are black and white.

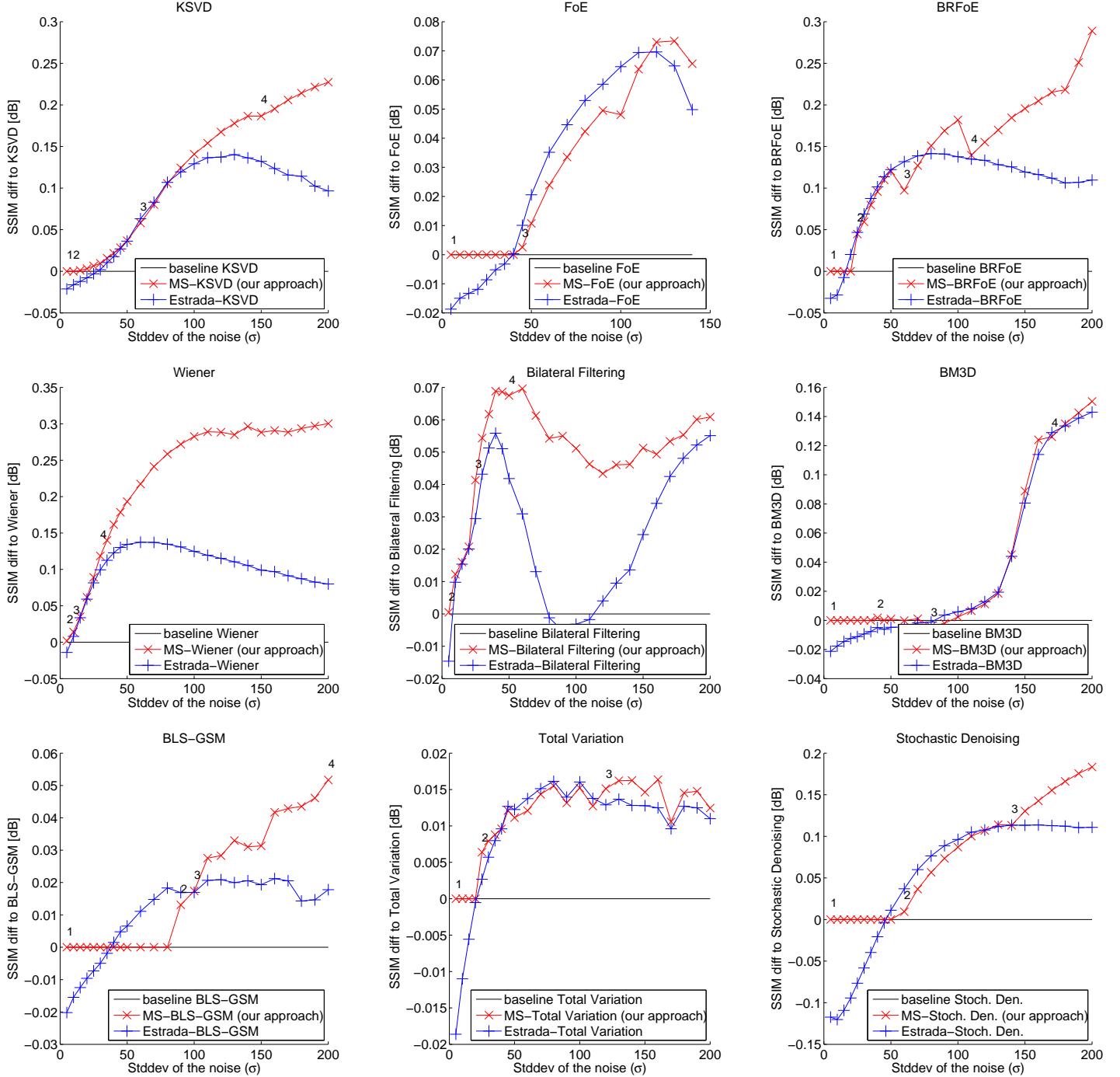
3 Notes on how to denoise lower frequencies



In Sec. 3 (“How to denoise lower frequencies”) of the paper, we explained that first down-scaling, then denoising is preferable to first denoising, then down-scaling. However, we provided results on only one image, for one noise setting and using only one denoising algorithm (KSVD).

To gather statistics, we compared the two approaches on the 20 training images for different noise levels. We chose the algorithms KSVD, BRFoE, Wiener and Stochastic denoising. The figure above reports the average difference between the two methods, where a value larger than 0 indicates that it is better to first down-scale, then denoise than vice-versa. So we see that first down-scaling, then denoising is better than the other way around when the noise is strong.

4 Improvements in terms of SSIM



The most commonly used measure for image quality is the peak signal to noise ratio (PSNR), which is related to the mean squared error. A shortcoming of the PSNR is that it does not take into account the visual appearance of an image. A measure that attempts to address this issue is the structural similarity index (SSIM) [2]. The SSIM is a value ranging between 0 and 1, where higher values indicate higher similarities.

In the paper, we presented improvements achieved by our approach in terms of PSNR. In the figure above we present the same results in terms of SSIM. We see similar trends as for the PSNR: Our approach outperforms the method proposed by Estrada et al. [1] in most cases. The greatest gains are achieved for the methods KSVD, BRFoE and Wiener.

5 Visual comparison for the “Barbara” image



noisy $\sigma = 200$
PSNR: 7.59dB, SSIM: 0.074



ground truth



denoised with BM3D
PSNR: 18.88dB, SSIM: 0.429



denoised with MS-BM3D
PSNR: 20.96dB, SSIM: 0.591

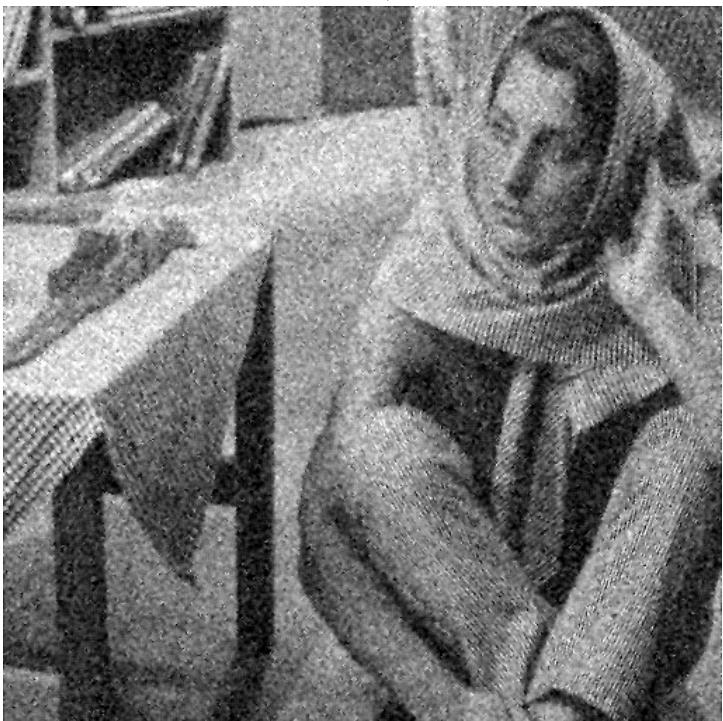
The images above show the results obtained with BM3D and MS-BM3D (our approach) when noise with $\sigma = 200$ is added to the “Barbara” image. In the noisy image, one can barely recognize the original image content. BM3D is able to partially recover the image, but also introduces many artifacts. Surfaces that should be smooth look very grainy. Some patches are completely black, which further degrades the image quality. Combining BM3D with our multi-scale approach (MS-BM3D) produces an image with fewer artifacts. Surfaces appear smooth again and it is easier to recognize the original image content. Even some details are recovered: For instance part of the texture of the table cloth is discernible.



noisy $\sigma = 50$
PSNR: 14.77dB, SSIM: 0.44



ground truth



denoised with Wiener
PSNR: 20.77dB, SSIM: 0.579



denoised with MS-Wiener
PSNR: 22.99dB, SSIM: 0.731

The image “Barbara” has been corrupted with AWGN ($\sigma = 50$) and denoised with Wiener and MS-Wiener. The image produced by MS-Wiener looks much smoother than the one produced by Wiener (without multi-scale extension).



noisy $\sigma = 50$
PSNR: 14.77dB, SSIM: 0.44



ground truth



denoised with KSVD
PSNR: 25.35dB, SSIM: 0.791



denoised with MS-KSVD
PSNR: 26.08dB, SSIM: 0.842

The image “Barbara” has been corrupted with AWGN ($\sigma = 50$) and denoised with KSVD and MS-KSVD. With KSVD, regions of the image that should be smooth appear “wavy”. These low-frequency artifacts are due to the fact that KSVD denoises images patch by patch: Adding Gaussian noise with mean 0 will result in noise vectors with a non-zero average value on small patches. The smaller the patch size, the more dramatic this effect. Applying our multi-scale approach (MS-KSVD) reduces this effect: Few artifacts are visible in the smooth regions of the image, yet fine details have not been deteriorated.

6 Visual comparison on all images

We now display the images produced by the nine denoising algorithms in the plain and multi-scale settings (i.e. plain vs. our approach) for all images in the test set. We will use three different noise levels: $\sigma = 50$, $\sigma = 90$ and $\sigma = 130$. We report the PSNR and SSIM of each image.

Image “Barbara” with $\sigma = 50$



Image “Boat” with $\sigma = 50$



Image “Cameraman” with $\sigma = 50$



noisy

PSNR:14.93dB, SSIM:0.179



ground truth



KSVD

PSNR:25.44dB, SSIM:0.704



MS-KSVD

PSNR:25.44dB, SSIM:0.716



FoE

PSNR:24.63dB, SSIM:0.756



MS-FoE

PSNR:24.07dB, SSIM:0.715



BRFoE

PSNR:20.92dB, SSIM:0.449



MS-BRFoE

PSNR:22.68dB, SSIM:0.602



Wiener

PSNR:21.17dB, SSIM:0.374



MS-Wiener

PSNR:23.73dB, SSIM:0.689



BilateralFiltering

PSNR:22.51dB, SSIM:0.576



MS-BilateralFiltering

PSNR:24.30dB, SSIM:0.703



BM3D

PSNR:26.03dB, SSIM:0.777



MS-BM3D

PSNR:25.90dB, SSIM:0.770



BLS-GSM

PSNR:25.45dB, SSIM:0.725



MS-BLS-GSM

PSNR:25.45dB, SSIM:0.725



TV

PSNR:24.44dB, SSIM:0.749



MS-TV

PSNR:24.21dB, SSIM:0.743



Stochastic

PSNR:22.45dB, SSIM:0.517



MS-Stochastic

PSNR:22.45dB, SSIM:0.517

Image “Couple” with $\sigma = 50$



Image “Fingerprint” with $\sigma = 50$

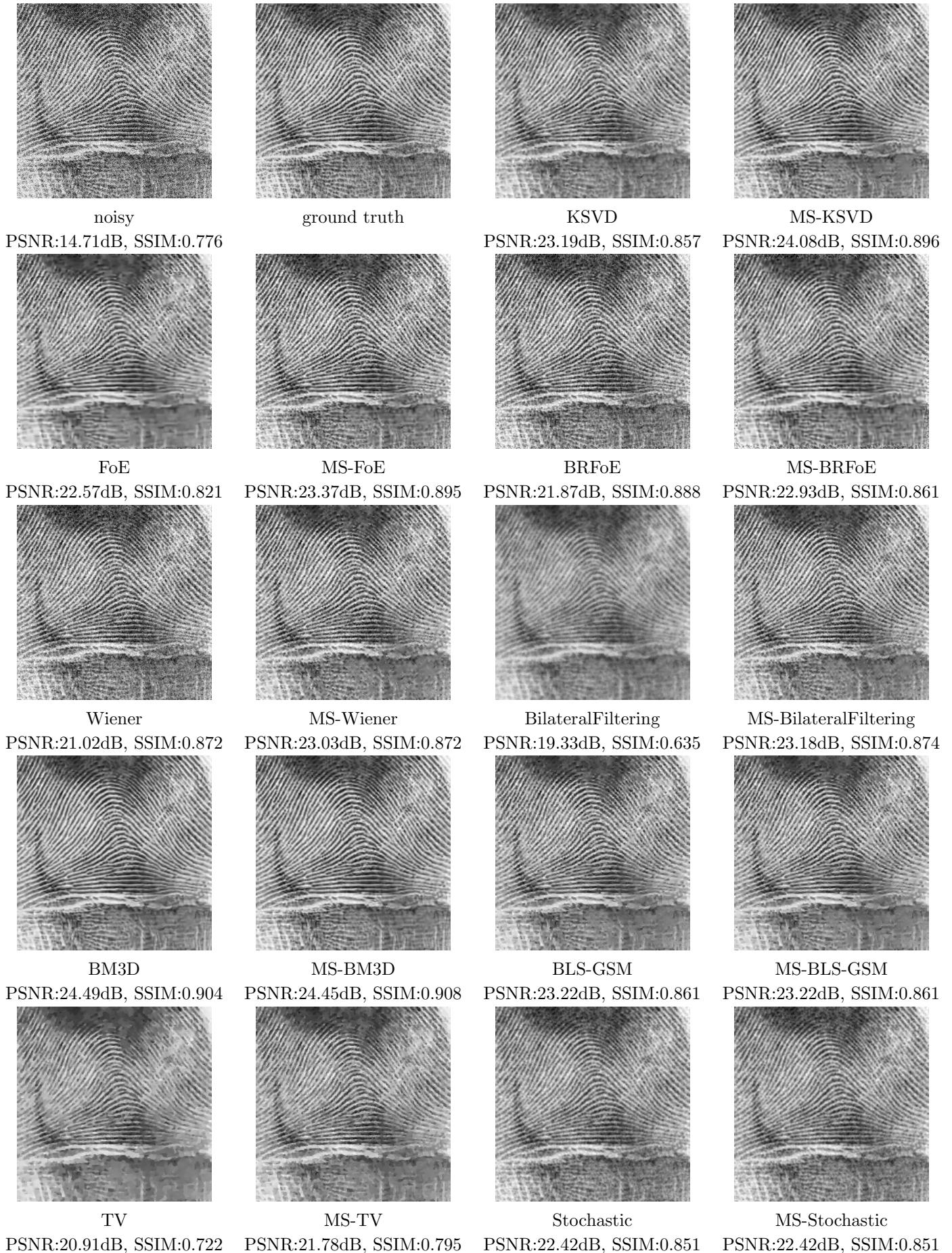


Image “Flintstones” with $\sigma = 50$

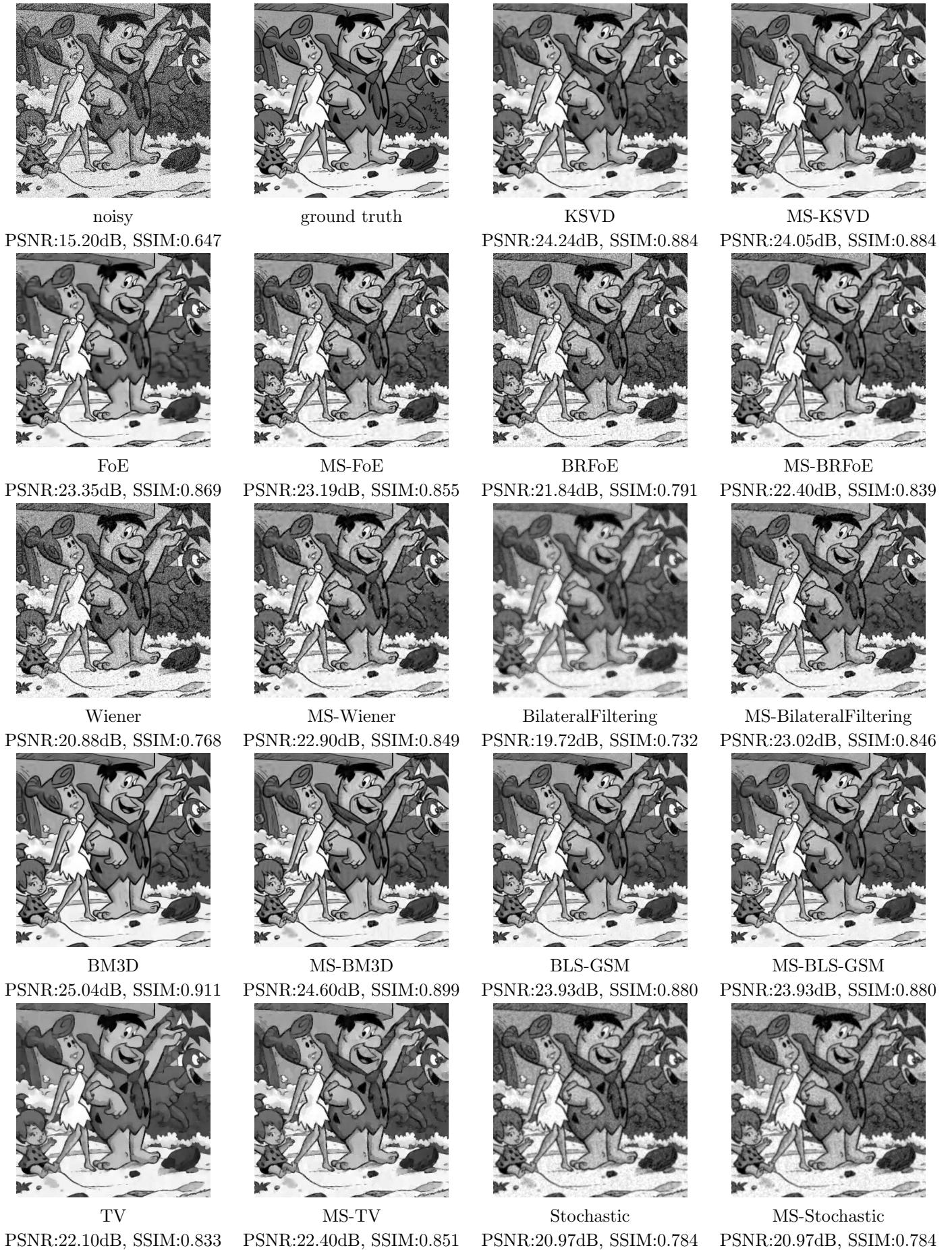


Image “Hill” with $\sigma = 50$



Image “House” with $\sigma = 50$



Image “Baboon” with $\sigma = 50$

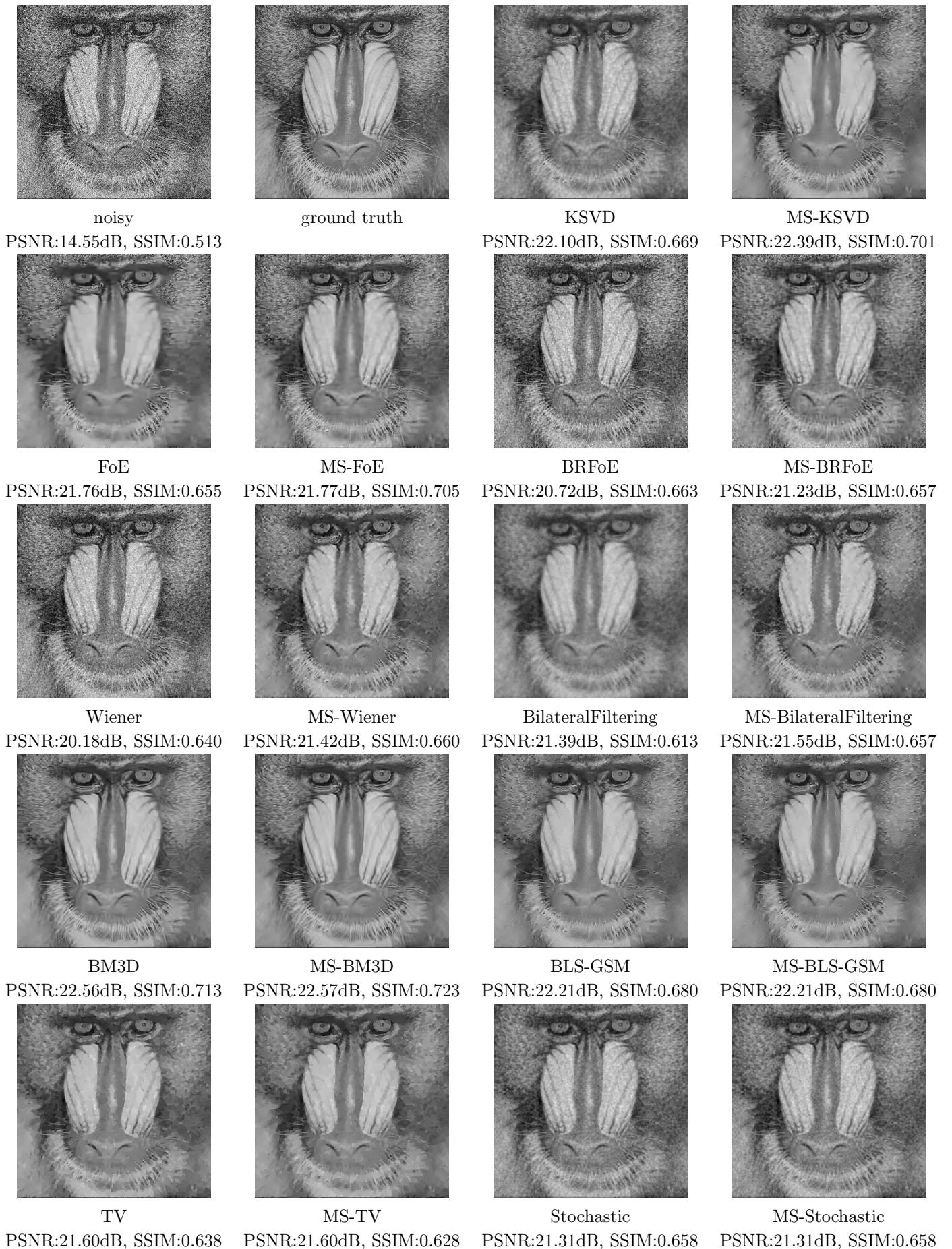


Image “F16” with $\sigma = 50$

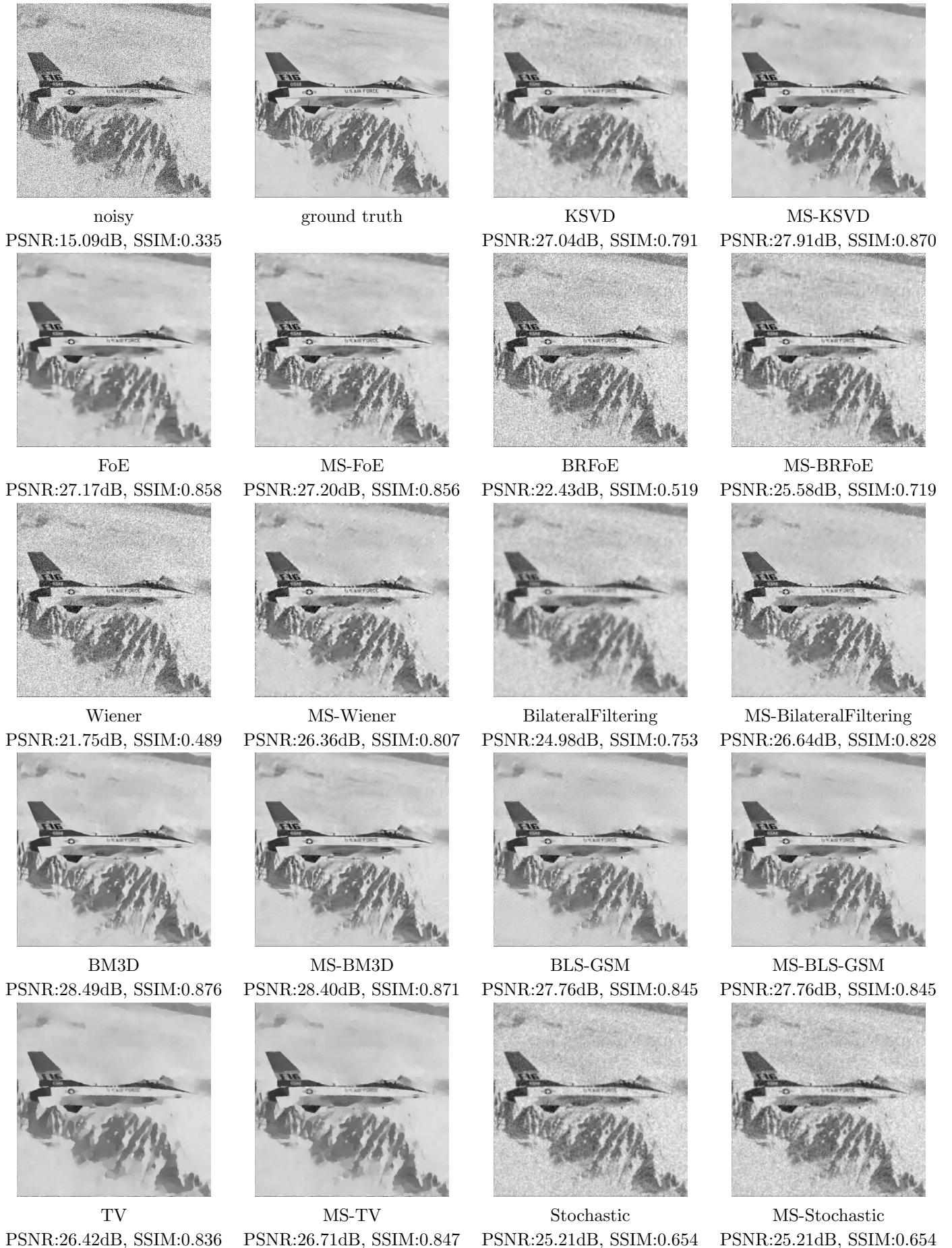


Image “Lena” with $\sigma = 50$



Image “Man” with $\sigma = 50$



Image “Peppers” with $\sigma = 50$



Image “Barbara” with $\sigma = 90$



Image “Boat” with $\sigma = 90$



Image “Cameraman” with $\sigma = 90$



noisy

PSNR:10.88dB, SSIM:0.086



ground truth



KSVD

PSNR:21.95dB, SSIM:0.467



MS-KSVD

PSNR:22.65dB, SSIM:0.640



FoE

PSNR:21.62dB, SSIM:0.669



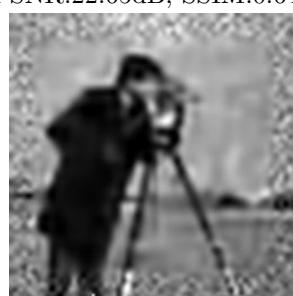
MS-FoE

PSNR:22.06dB, SSIM:0.637



BRFoE

PSNR:17.00dB, SSIM:0.285



MS-BRFoE

PSNR:20.31dB, SSIM:0.507



Wiener

PSNR:17.01dB, SSIM:0.225



MS-Wiener

PSNR:21.34dB, SSIM:0.599



BilateralFiltering

PSNR:20.82dB, SSIM:0.515



MS-BilateralFiltering

PSNR:22.07dB, SSIM:0.618



BM3D

PSNR:23.56dB, SSIM:0.700



MS-BM3D

PSNR:23.19dB, SSIM:0.691



BLS-GSM

PSNR:22.72dB, SSIM:0.603



MS-BLS-GSM

PSNR:22.71dB, SSIM:0.615



TV

PSNR:22.33dB, SSIM:0.687



MS-TV

PSNR:22.22dB, SSIM:0.683



Stochastic

PSNR:20.41dB, SSIM:0.351



MS-Stochastic

PSNR:20.47dB, SSIM:0.519

Image “Couple” with $\sigma = 90$



Image “Fingerprint” with $\sigma = 90$

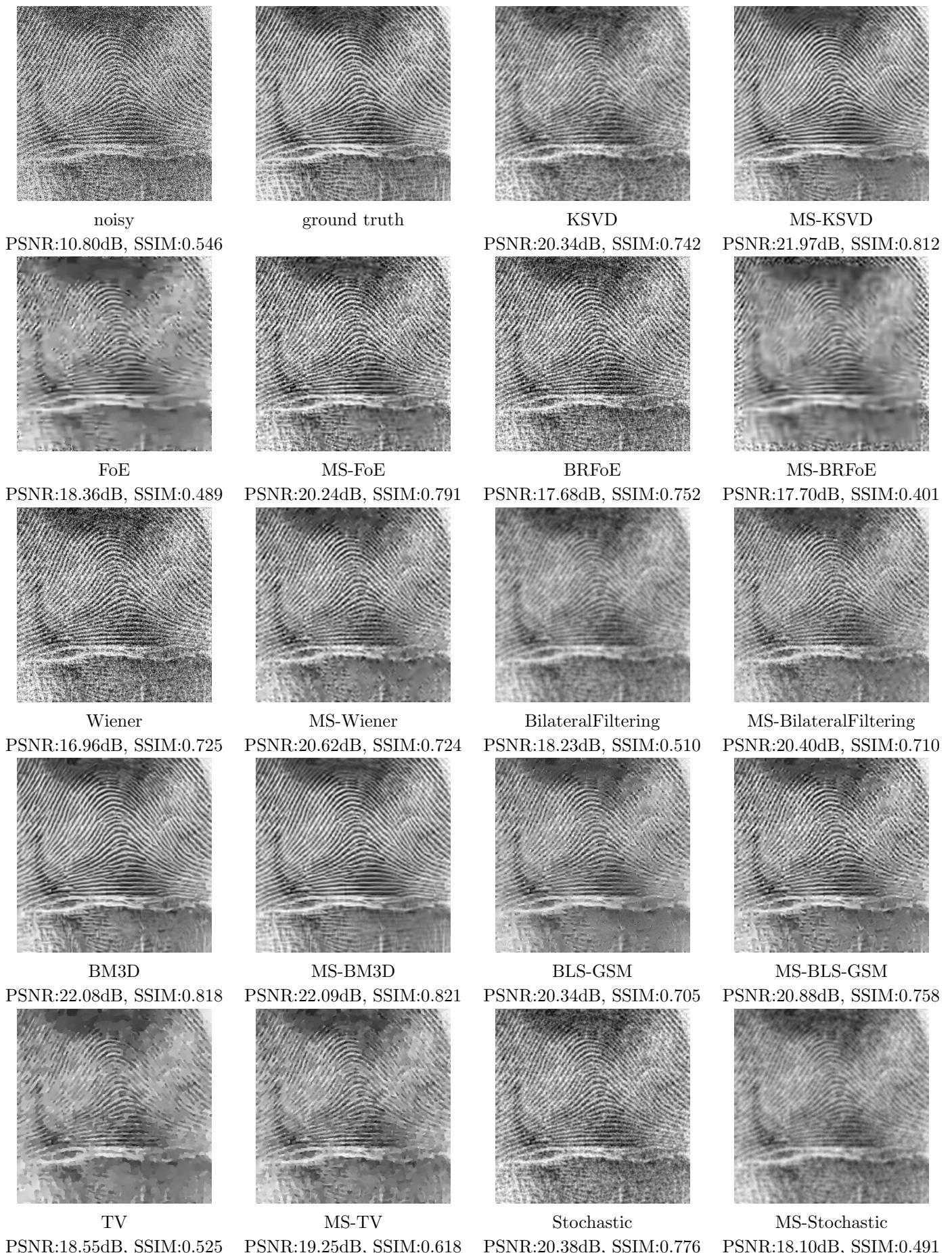


Image “Flintstones” with $\sigma = 90$

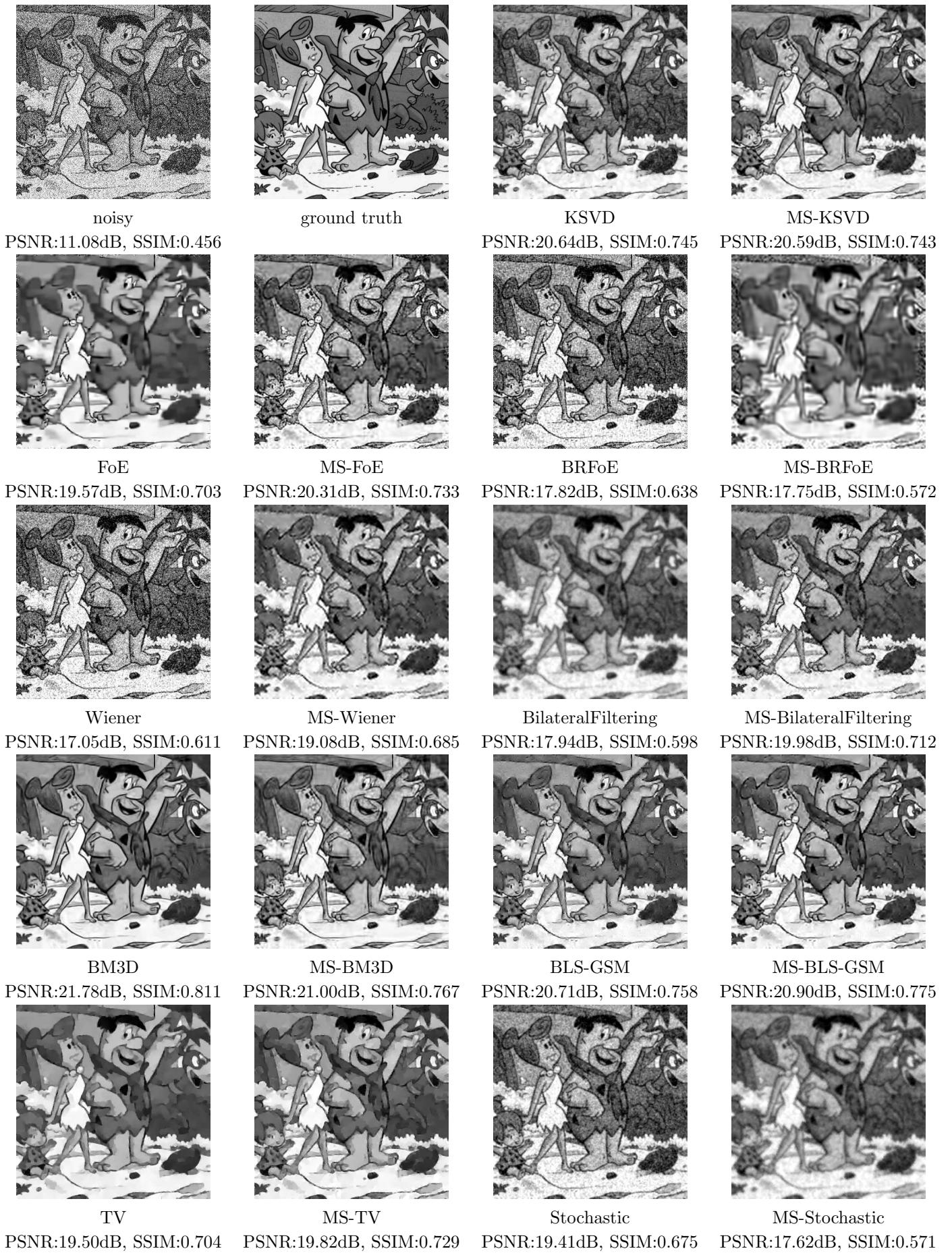


Image “Hill” with $\sigma = 90$



Image “House” with $\sigma = 90$

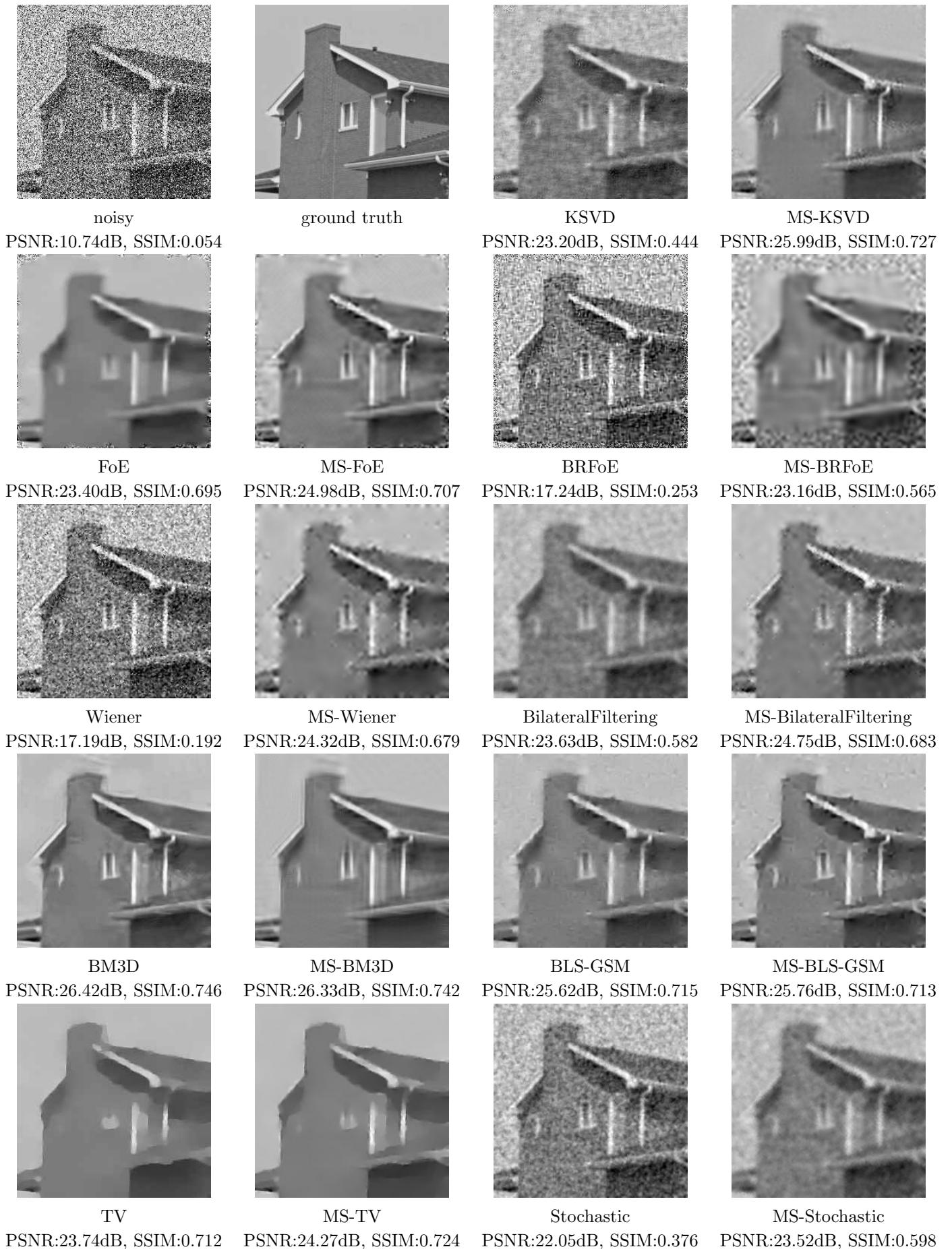


Image “Baboon” with $\sigma = 90$

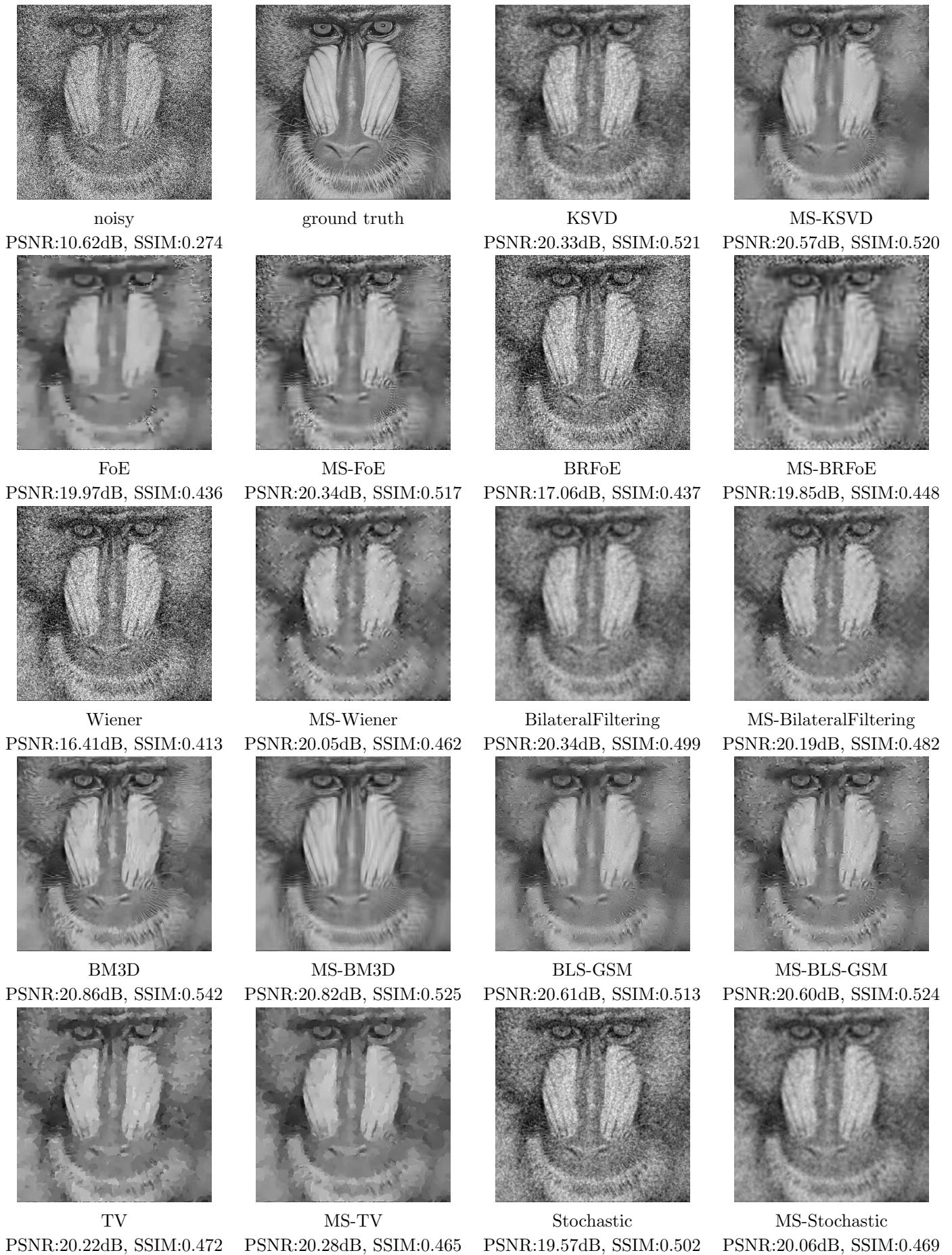


Image “F16” with $\sigma = 90$

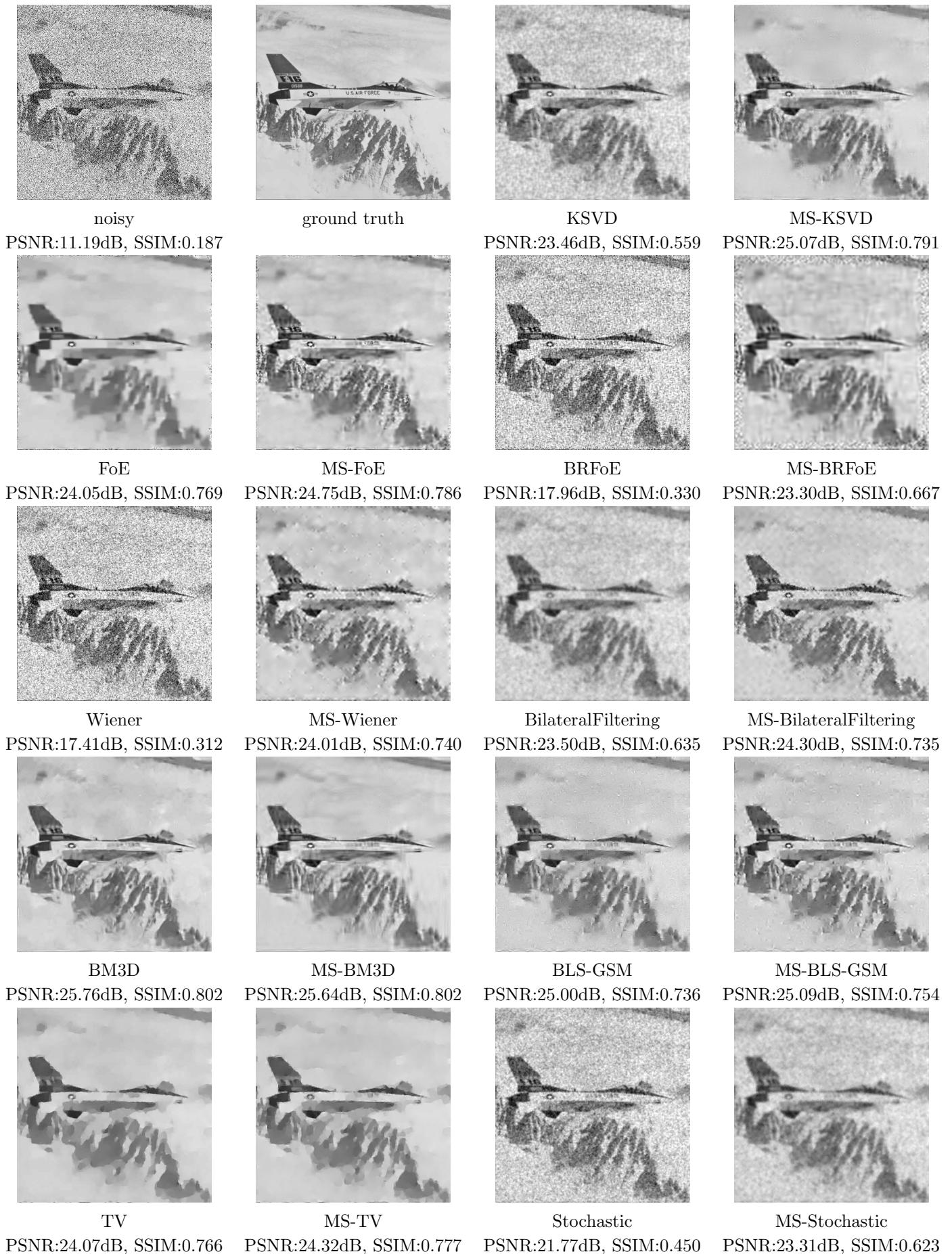


Image “Lena” with $\sigma = 90$



Image “Man” with $\sigma = 90$



Image “Peppers” with $\sigma = 90$



Image “Barbara” with $\sigma = 130$



Image “Boat” with $\sigma = 130$



Image “Cameraman” with $\sigma = 130$



noisy

PSNR:9.02dB, SSIM:0.050



ground truth



KSVD

PSNR:19.49dB, SSIM:0.300



MS-KSVD

PSNR:21.31dB, SSIM:0.591



FoE

PSNR:19.11dB, SSIM:0.593



MS-FoE

PSNR:20.54dB, SSIM:0.584



BRFoE

PSNR:14.58dB, SSIM:0.201



MS-BRFoE

PSNR:18.67dB, SSIM:0.476



Wiener

PSNR:14.38dB, SSIM:0.158



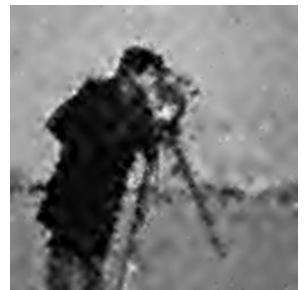
MS-Wiener

PSNR:20.04dB, SSIM:0.552



BilateralFiltering

PSNR:19.95dB, SSIM:0.483



MS-BilateralFiltering

PSNR:20.78dB, SSIM:0.577



BM3D

PSNR:21.72dB, SSIM:0.630



MS-BM3D

PSNR:21.60dB, SSIM:0.646



BLS-GSM

PSNR:21.04dB, SSIM:0.508



MS-BLS-GSM

PSNR:21.16dB, SSIM:0.594



TV

PSNR:21.11dB, SSIM:0.647



MS-TV

PSNR:20.76dB, SSIM:0.623



Stochastic

PSNR:18.41dB, SSIM:0.259



MS-Stochastic

PSNR:19.83dB, SSIM:0.441

Image “Couple” with $\sigma = 130$



Image “Fingerprint” with $\sigma = 130$

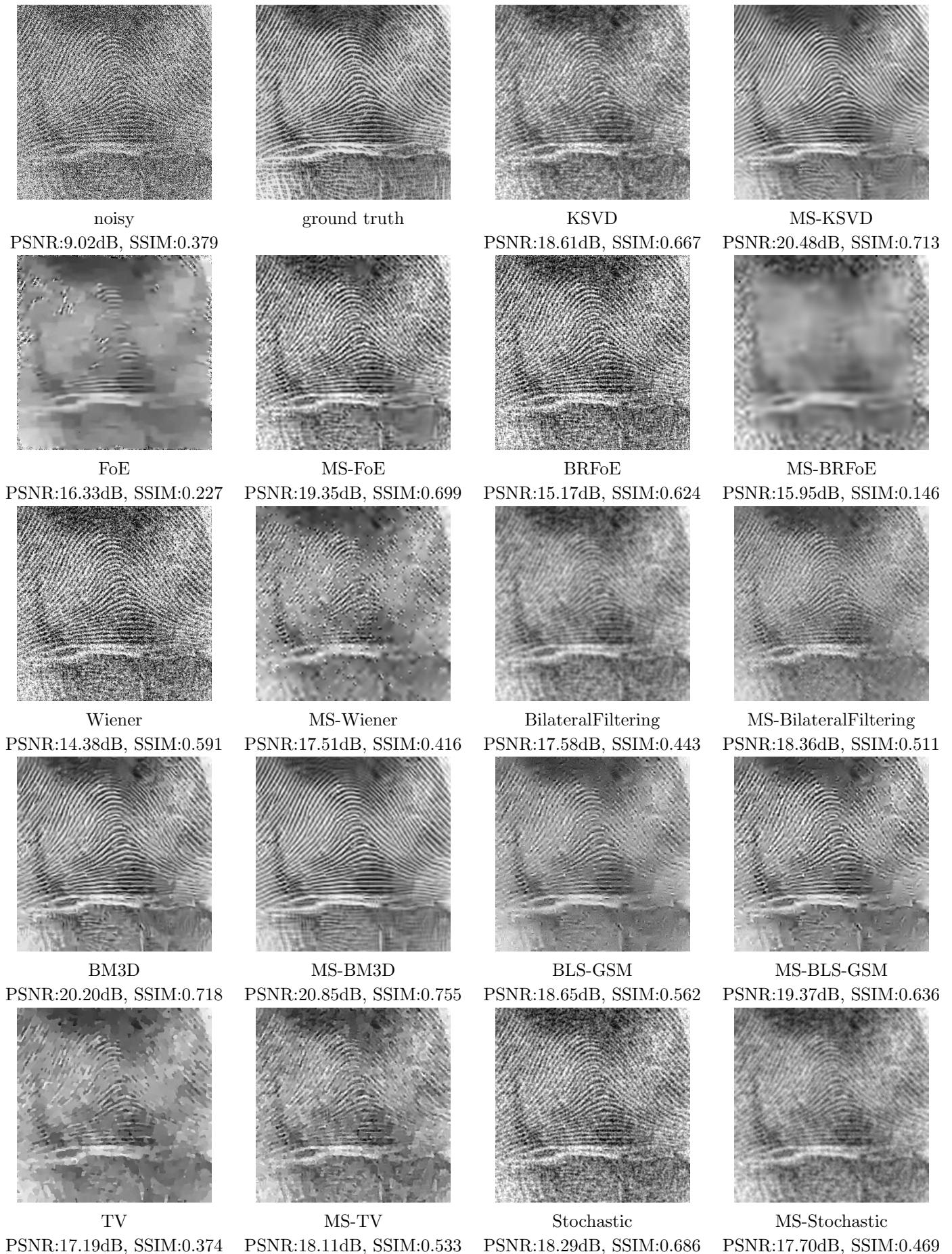


Image “Flintstones” with $\sigma = 130$

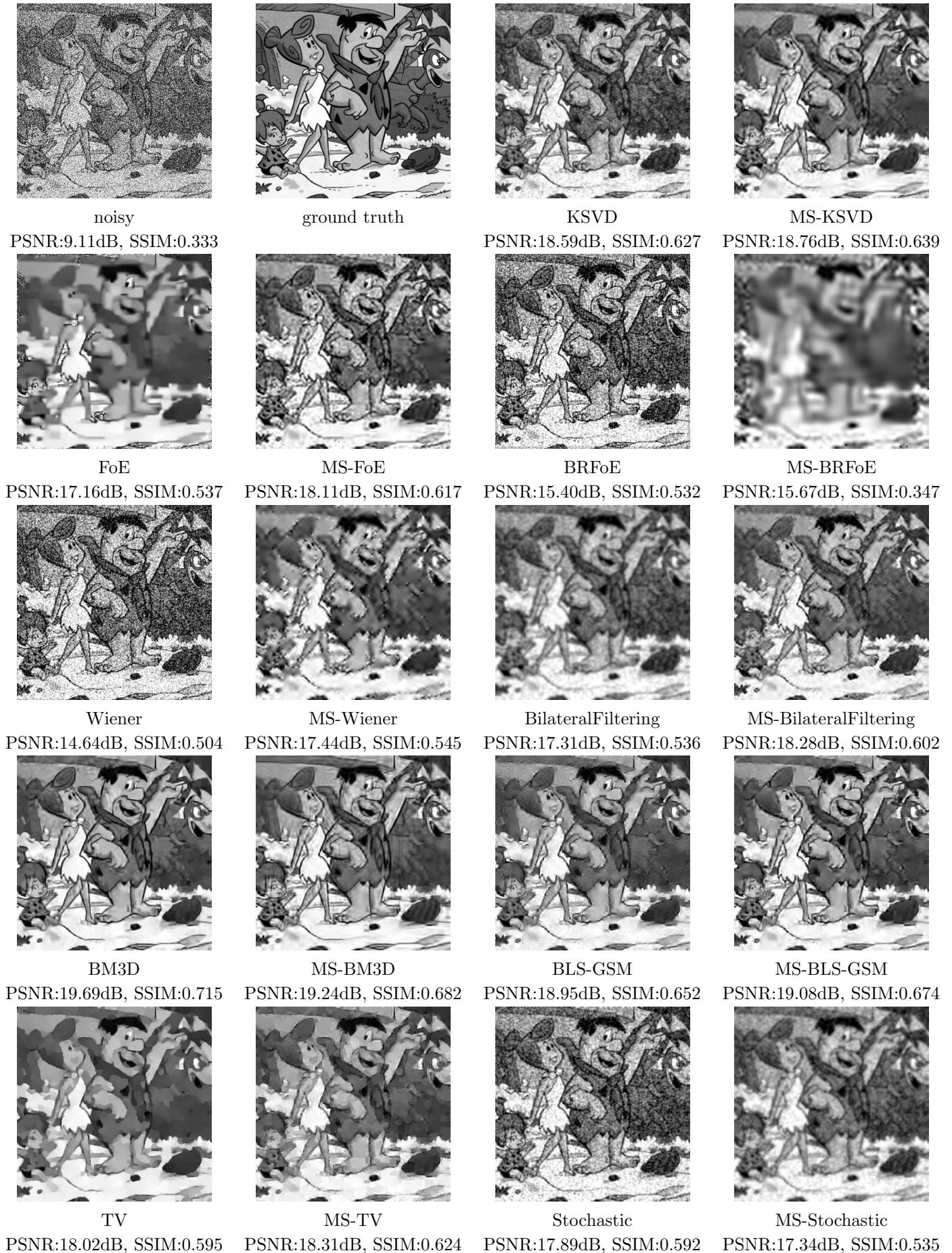


Image “Hill” with $\sigma = 130$



Image “House” with $\sigma = 130$



Image “Baboon” with $\sigma = 130$

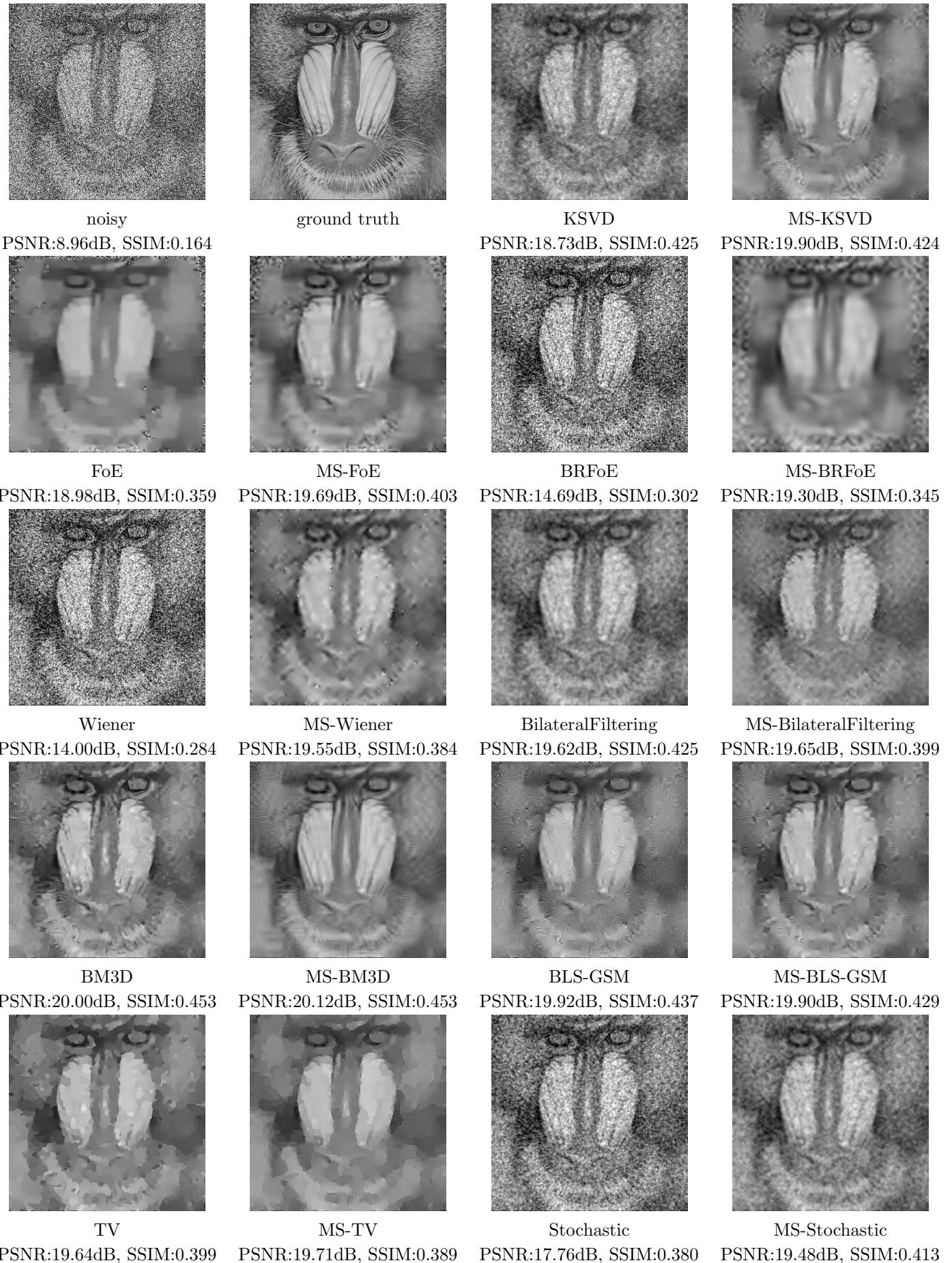


Image “F16” with $\sigma = 130$

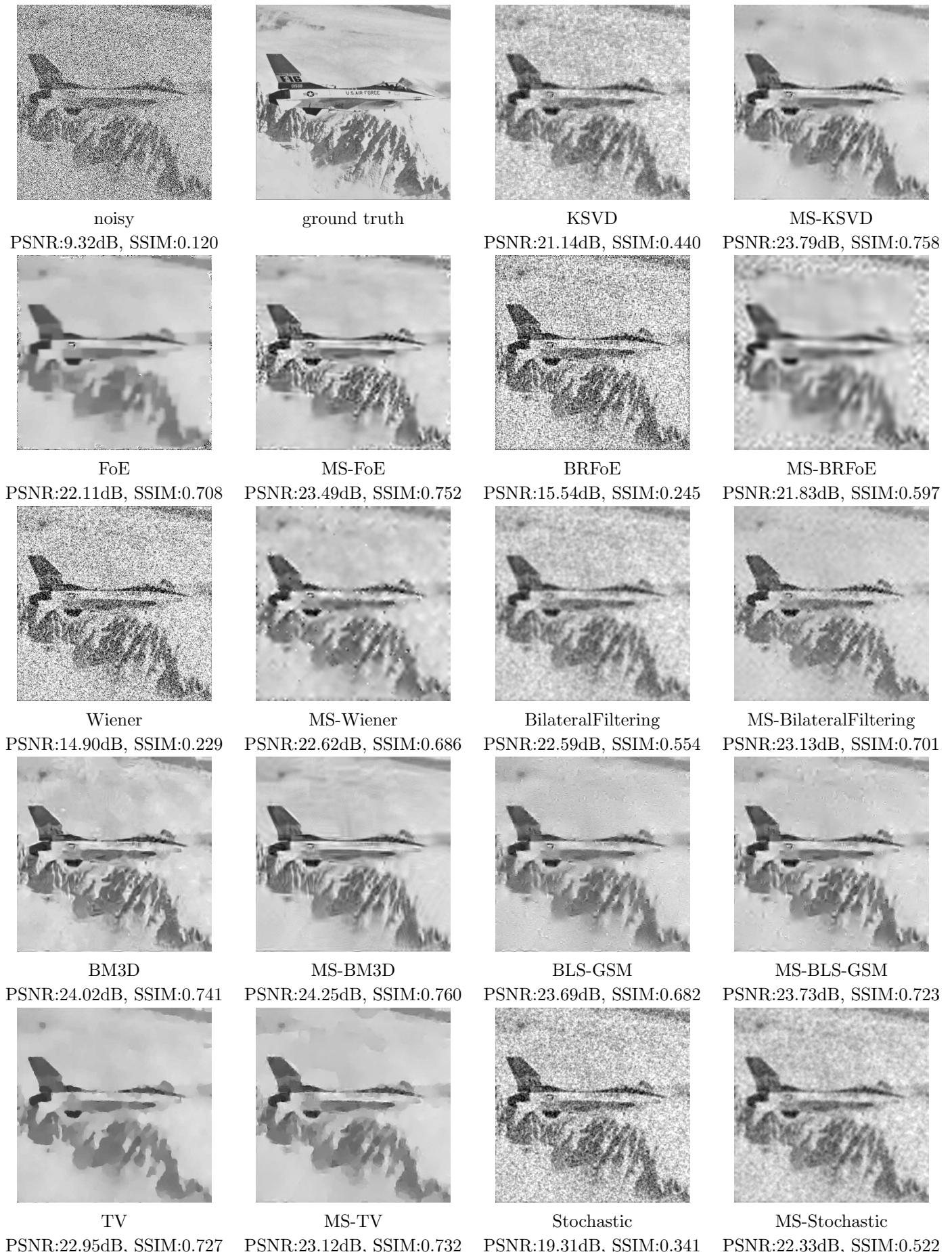


Image “Lena” with $\sigma = 130$



Image “Man” with $\sigma = 130$



Image “Peppers” with $\sigma = 130$



References

- [1] Estrada, F., Fleet, D., Jepson, A.: Stochastic image denoising. In: Proceedings of the British Machine Vision Conference (BMVC) (2009)
- [2] Wang, Z., Bovik, A., Sheikh, H., Simoncelli, E.: Image quality assessment: From error visibility to structural similarity. *IEEE Transactions on Image Processing* 13(4), 600–612 (2004)