Table 5: Average PSNR and SSIM results on BSD100 for super-resolution.

	PSNR								
	SRCNN	NBSRF	CSCN	CSC	TSE	ARFL+	RED10	RED20	RED30
$s = 2$	31.36	31.30	31.54	31.27	31.18	31.35	31.85	31.95	**31.99**
$s = 3$	28.41	28.36	28.58	28.31	28.30	28.36	28.79	28.90	**28.93**
$s = 4$	26.90	26.88	27.11	26.83	26.85	26.86	27.25	27.35	**27.40**
	SSIM								
$s = 2$	0.8879	0.8876	0.8908	0.8876	0.8855	0.8885	0.8953	0.8969	**0.8974**
$s = 3$	0.7863	0.7856	0.7910	0.7853	0.7843	0.7851	0.7975	0.7993	**0.7994**
$s = 4$	0.7103	0.7110	0.7191	0.7101	0.7108	0.7091	0.7238	0.7268	**0.7290**

comparing to the case in which using separate models for denoising and super-resolution. This may due to the fact that the network has to fit much more complex mappings. Except that CSCN works slightly better on Set14 super-resolution with scales 3 and 4, our network still beats the existing methods, showing that our network works much better in image denoising and super-resolution even using only one single model to deal with complex corruption.

Table 6: Average PSNR and SSIM results for image denoising using a single 30-layer network.

	14 images				BSD200			
	$\sigma = 10$	$\sigma = 30$	$\sigma = 50$	$\sigma = 70$	$\sigma = 10$	$\sigma = 30$	$\sigma = 50$	$\sigma = 70$
PSNR	34.49	29.09	26.75	25.20	33.38	27.88	25.69	24.36
SSIM	0.9368	0.8414	0.7716	0.7157	0.9280	0.7980	0.7119	0.6544

Table 7: Average PSNR and SSIM results for image super-resolution using a single 30-layer network.

	Set5			Set14			BSD100		
	$s = 2$	$s = 3$	$s = 4$	$s = 2$	$s = 3$	$s = 4$	$s = 2$	$s = 3$	$s = 4$
PSNR	37.56	33.70	31.33	32.81	29.50	27.72	31.96	28.88	27.35
SSIM	0.9595	0.9222	0.8847	0.9135	0.8334	0.7698	0.8972	0.7993	0.7276

4 Conclusions

In this paper we have proposed a deep encoding and decoding framework for image restoration. Convolution and deconvolution are combined, modeling the restoration problem by extracting primary image content and recovering details. More importantly, we propose to use skip connections, which helps on recovering clean images and tackles the optimization difficulty caused by gradient vanishing, and thus obtains performance gains when the network goes deeper. Experimental results and our analysis show that our network achieves better performance than state-of-the-art methods on image denoising and super-resolution.

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