Loss Functions for Image Restoration with Neural Networks

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1 Instructions

Please view this document in full screen (e.g., for Acrobat Adobe Reader CTRL+L on Windows and COMMAND+L on Mac). To compare the images resulting from different networks click the corresponding hyperlinks in the caption.

For each image the reader can either just scroll through the images to see the changes or jump from one image to the other by clicking the figure numbers at the bottom. For each image we provide a couple of details that are worth observing. It is important to see in full-screen mode so that the images are aligned.

We show results for:

- JPEG deblocking,
- joint denoising + demosaicking,
- different training schedules, and
- super-resolution.

JPEG deblocking



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Fig. 1. JPEG deblocking $-\ell_1$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 fails at removing both the artifacts in the sky and the halo introduced by the JPEG compression at the edge of the building. ℓ_1 does better than ℓ_2 , but only Mix succeeds at completely removing the halo and attenuating the artifacts in the sky.

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Fig. 2. JPEG deblocking – Mix

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 fails at removing both the artifacts in the sky and the halo introduced by the JPEG compression at the edge of the building. ℓ_1 does better than ℓ_2 , but only Mix succeeds at completely removing the halo and attenuating the artifacts in the sky.



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Fig. 3. JPEG deblocking $-\ell_2$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 fails at removing both the artifacts in the sky and the halo introduced by the JPEG compression at the edge of the building. ℓ_1 does better than ℓ_2 , but only Mix succeeds at completely removing the halo and attenuating the artifacts in the sky.

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Fig. 4. JPEG deblocking – Ground truth

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 fails at removing both the artifacts in the sky and the halo introduced by the JPEG compression at the edge of the building. ℓ_1 does better than ℓ_2 , but only Mix succeeds at completely removing the halo and attenuating the artifacts in the sky.



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Fig. 5. JPEG deblocking – JPEG

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 fails at removing both the artifacts in the sky and the halo introduced by the JPEG compression at the edge of the building. ℓ_1 does better than ℓ_2 , but only Mix succeeds at completely removing the halo and attenuating the artifacts in the sky.





Fig. 6. JPEG deblocking – ℓ_1

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that Mix produces a result that is sharper than the one produced by ℓ_1 , while better attenuating the halos.





Fig. 7. JPEG deblocking – Mix

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that Mix produces a result that is sharper than the one produced by ℓ_1 , while better attenuating the halos.





Fig. 8. JPEG deblocking – ℓ_2

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that Mix produces a result that is sharper than the one produced by ℓ_1 , while better attenuating the halos.





Fig. 9. JPEG deblocking – Ground truth

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that Mix produces a result that is sharper than the one produced by ℓ_1 , while better attenuating the halos.





Fig. 10. JPEG deblocking – JPEG

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that Mix produces a result that is sharper than the one produced by ℓ_1 , while better attenuating the halos.





Fig. 11. JPEG deblocking – ℓ_1

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Mix outperforms both ℓ_1 and ℓ_2 at removing the artifacts (left patch) and the halos (right patch).





Fig. 12. JPEG deblocking – Mix

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Mix outperforms both ℓ_1 and ℓ_2 at removing the artifacts (left patch) and the halos (right patch).





Fig. 13. JPEG deblocking – ℓ_2

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Mix outperforms both ℓ_1 and ℓ_2 at removing the artifacts (left patch) and the halos (right patch).





Fig. 14. JPEG deblocking – Ground truth

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Mix outperforms both ℓ_1 and ℓ_2 at removing the artifacts (left patch) and the halos (right patch).





Fig. 15. JPEG deblocking – JPEG

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Mix outperforms both ℓ_1 and ℓ_2 at removing the artifacts (left patch) and the halos (right patch).

Joint denoising + demosaicking



Fig. 16. Joint Denoising+Demosaicking – BM3D

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Observe the loss of details for BM3D compared with Mix in the patches on the leaves. Also note the zippering artifacts due to BM3D+demosaicking on the flower, and how they are solved by Mix.



Fig. 17. Joint Denoising+Demosaicking – Ground Truth

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Observe the loss of details for BM3D compared with Mix in the patches on the leaves. Also note the zippering artifacts due to BM3D+demosaicking on the flower, and how they are solved by Mix.



Fig. 18. Joint Denoising+Demosaicking – ℓ_1

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Observe the loss of details for BM3D compared with Mix in the patches on the leaves. Also note the zippering artifacts due to BM3D+demosaicking on the flower, and how they are solved by Mix.



Fig. 19. Joint Denoising+Demosaicking – Mix

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Observe the loss of details for BM3D compared with Mix in the patches on the leaves. Also note the zippering artifacts due to BM3D+demosaicking on the flower, and how they are solved by Mix.



Fig. 20. Joint Denoising+Demosaicking – ℓ_2

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Observe the loss of details for BM3D compared with Mix in the patches on the leaves. Also note the zippering artifacts due to BM3D+demosaicking on the flower, and how they are solved by Mix.



Fig. 21. Joint Denoising+Demosaicking – MS-SSIM

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Observe the loss of details for BM3D compared with Mix in the patches on the leaves. Also note the zippering artifacts due to BM3D+demosaicking on the flower, and how they are solved by Mix.



Fig. 22. Joint Denoising+Demosaicking – SSIM₅

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Observe the loss of details for BM3D compared with Mix in the patches on the leaves. Also note the zippering artifacts due to BM3D+demosaicking on the flower, and how they are solved by Mix.



Fig. 23. Joint Denoising+Demosaicking - SSIM₉

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Observe the loss of details for BM3D compared with Mix in the patches on the leaves. Also note the zippering artifacts due to BM3D+demosaicking on the flower, and how they are solved by Mix.



Fig. 24. Joint Denoising+Demosaicking - Noisy

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Observe the loss of details for BM3D compared with Mix in the patches on the leaves. Also note the zippering artifacts due to BM3D+demosaicking on the flower, and how they are solved by Mix.



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Fig. 25. Joint Denoising+Demosaicking – BM3D

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 produces splotchy artifacts in the sky patch. MS-SSIM removes them, but changes the color of the sky. Mix (ℓ_1 combined with MS-SSIM) achieves the desired result. Also, focus on the patch from the top of the building to notice how SSIM₅ and SSIM₉ produce an increasingly large "halo" of noise around the edge, which is removed by MS-SSIM (See main paper for the explanation).

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Fig. 26. Joint Denoising+Demosaicking – Ground Truth

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 produces splotchy artifacts in the sky patch. MS-SSIM removes them, but changes the color of the sky. Mix (ℓ_1 combined with MS-SSIM) achieves the desired result. Also, focus on the patch from the top of the building to notice how SSIM₅ and SSIM₉ produce an increasingly large "halo" of noise around the edge, which is removed by MS-SSIM (See main paper for the explanation).



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Fig. 27. Joint Denoising+Demosaicking $-\ell_1$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 produces splotchy artifacts in the sky patch. MS-SSIM removes them, but changes the color of the sky. Mix (ℓ_1 combined with MS-SSIM) achieves the desired result. Also, focus on the patch from the top of the building to notice how SSIM₅ and SSIM₉ produce an increasingly large "halo" of noise around the edge, which is removed by MS-SSIM (See main paper for the explanation).

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Fig. 28. Joint Denoising+Demosaicking – Mix

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 produces splotchy artifacts in the sky patch. MS-SSIM removes them, but changes the color of the sky. Mix (ℓ_1 combined with MS-SSIM) achieves the desired result. Also, focus on the patch from the top of the building to notice how SSIM₅ and SSIM₉ produce an increasingly large "halo" of noise around the edge, which is removed by MS-SSIM (See main paper for the explanation).



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Fig. 29. Joint Denoising+Demosaicking $-\ell_2$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 produces splotchy artifacts in the sky patch. MS-SSIM removes them, but changes the color of the sky. Mix (ℓ_1 combined with MS-SSIM) achieves the desired result. Also, focus on the patch from the top of the building to notice how SSIM₅ and SSIM₉ produce an increasingly large "halo" of noise around the edge, which is removed by MS-SSIM (See main paper for the explanation).

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Fig. 30. Joint Denoising+Demosaicking – MS-SSIM

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 produces splotchy artifacts in the sky patch. MS-SSIM removes them, but changes the color of the sky. Mix (ℓ_1 combined with MS-SSIM) achieves the desired result. Also, focus on the patch from the top of the building to notice how SSIM₅ and SSIM₉ produce an increasingly large "halo" of noise around the edge, which is removed by MS-SSIM (See main paper for the explanation).



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Fig. 31. Joint Denoising+Demosaicking – SSIM₅

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 produces splotchy artifacts in the sky patch. MS-SSIM removes them, but changes the color of the sky. Mix (ℓ_1 combined with MS-SSIM) achieves the desired result. Also, focus on the patch from the top of the building to notice how SSIM₅ and SSIM₉ produce an increasingly large "halo" of noise around the edge, which is removed by MS-SSIM (See main paper for the explanation).

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Fig. 32. Joint Denoising+Demosaicking – SSIM₉

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 produces splotchy artifacts in the sky patch. MS-SSIM removes them, but changes the color of the sky. Mix (ℓ_1 combined with MS-SSIM) achieves the desired result. Also, focus on the patch from the top of the building to notice how SSIM₅ and SSIM₉ produce an increasingly large "halo" of noise around the edge, which is removed by MS-SSIM (See main paper for the explanation).



Fig. 33. Joint Denoising+Demosaicking – Noisy

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note that ℓ_2 produces splotchy artifacts in the sky patch. MS-SSIM removes them, but changes the color of the sky. Mix (ℓ_1 combined with MS-SSIM) achieves the desired result. Also, focus on the patch from the top of the building to notice how SSIM₅ and SSIM₉ produce an increasingly large "halo" of noise around the edge, which is removed by MS-SSIM (See main paper for the explanation).


Fig. 34. Joint Denoising+Demosaicking – BM3D

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Please compare the sharpness of BM3D and Mix on the eye and mouth of the dog. Also, compare the details on the tongue between ℓ_1 and Mix, particularly the crease on the tongue.



Fig. 35. Joint Denoising+Demosaicking – Ground Truth

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Please compare the sharpness of BM3D and Mix on the eye and mouth of the dog. Also, compare the details on the tongue between ℓ_1 and Mix, particularly the crease on the tongue.





Fig. 36. Joint Denoising+Demosaicking – ℓ_1

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Please compare the sharpness of BM3D and Mix on the eye and mouth of the dog. Also, compare the details on the tongue between ℓ_1 and Mix, particularly the crease on the tongue.



Fig. 37. Joint Denoising+Demosaicking – Mix

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Please compare the sharpness of BM3D and Mix on the eye and mouth of the dog. Also, compare the details on the tongue between ℓ_1 and Mix, particularly the crease on the tongue.



Fig. 38. Joint Denoising+Demosaicking $-\ell_2$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Please compare the sharpness of BM3D and Mix on the eye and mouth of the dog. Also, compare the details on the tongue between ℓ_1 and Mix, particularly the crease on the tongue.



Fig. 39. Joint Denoising+Demosaicking – MS-SSIM

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Please compare the sharpness of BM3D and Mix on the eye and mouth of the dog. Also, compare the details on the tongue between ℓ_1 and Mix, particularly the crease on the tongue.



Fig. 40. Joint Denoising+Demosaicking – $SSIM_5$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Please compare the sharpness of BM3D and Mix on the eye and mouth of the dog. Also, compare the details on the tongue between ℓ_1 and Mix, particularly the crease on the tongue.



Fig. 41. Joint Denoising+Demosaicking – SSIM₉

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Please compare the sharpness of BM3D and Mix on the eye and mouth of the dog. Also, compare the details on the tongue between ℓ_1 and Mix, particularly the crease on the tongue.



Fig. 42. Joint Denoising+Demosaicking – Noisy

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Please compare the sharpness of BM3D and Mix on the eye and mouth of the dog. Also, compare the details on the tongue between ℓ_1 and Mix, particularly the crease on the tongue.



Fig. 43. Joint Denoising+Demosaicking – BM3D

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note how Mix preserves the subtle structure on the power line better than ℓ_1 . Also, switch between SSIM₅, SSIM₉, and MS-SSIM to appreciate the noise halos around the star (see also paper).



Fig. 44. Joint Denoising+Demosaicking – Ground Truth

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note how Mix preserves the subtle structure on the power line better than ℓ_1 . Also, switch between SSIM₅, SSIM₉, and MS-SSIM to appreciate the noise halos around the star (see also paper).



Fig. 45. Joint Denoising+Demosaicking – ℓ_1

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note how Mix preserves the subtle structure on the power line better than ℓ_1 . Also, switch between SSIM₅, SSIM₉, and MS-SSIM to appreciate the noise halos around the star (see also paper).



Fig. 46. Joint Denoising+Demosaicking – Mix

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note how Mix preserves the subtle structure on the power line better than ℓ_1 . Also, switch between SSIM₅, SSIM₉, and MS-SSIM to appreciate the noise halos around the star (see also paper).



Fig. 47. Joint Denoising+Demosaicking – ℓ_2

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note how Mix preserves the subtle structure on the power line better than ℓ_1 . Also, switch between SSIM₅, SSIM₉, and MS-SSIM to appreciate the noise halos around the star (see also paper).



Fig. 48. Joint Denoising+Demosaicking – MS-SSIM

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note how Mix preserves the subtle structure on the power line better than ℓ_1 . Also, switch between SSIM₅, SSIM₉, and MS-SSIM to appreciate the noise halos around the star (see also paper).



Fig. 49. Joint Denoising+Demosaicking – $SSIM_5$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note how Mix preserves the subtle structure on the power line better than ℓ_1 . Also, switch between SSIM₅, SSIM₉, and MS-SSIM to appreciate the noise halos around the star (see also paper).



Fig. 50. Joint Denoising+Demosaicking – $SSIM_9$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note how Mix preserves the subtle structure on the power line better than ℓ_1 . Also, switch between SSIM₅, SSIM₉, and MS-SSIM to appreciate the noise halos around the star (see also paper).



Fig. 51. Joint Denoising+Demosaicking – Noisy

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note how Mix preserves the subtle structure on the power line better than ℓ_1 . Also, switch between SSIM₅, SSIM₉, and MS-SSIM to appreciate the noise halos around the star (see also paper).

Comparisons of different training schedules



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Fig. 52. Comparison of different training schedules on denoising+demosaicking $-\ell_1$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Here we compare the output of the networks trained alternating ℓ_1 and ℓ_2 . In the paper we show that a network trained with ℓ_2 gets stuck in a local minimum. When ℓ_2 is used to train a network that was pre-trained with ℓ_1 , the ℓ_2 loss decreases but the result is not as good as with the other losses in flat regions, such as the sky.

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Fig. 53. Comparison of different training schedules on denoising+demosaicking – Mix

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Here we compare the output of the networks trained alternating ℓ_1 and ℓ_2 . In the paper we show that a network trained with ℓ_2 gets stuck in a local minimum. When ℓ_2 is used to train a network that was pre-trained with ℓ_1 , the ℓ_2 loss decreases but the result is not as good as with the other losses in flat regions, such as the sky.



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Fig. 54. Comparison of different training schedules on denoising+demosaicking – ℓ_2

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Here we compare the output of the networks trained alternating ℓ_1 and ℓ_2 . In the paper we show that a network trained with ℓ_2 gets stuck in a local minimum. When ℓ_2 is used to train a network that was pre-trained with ℓ_1 , the ℓ_2 loss decreases but the result is not as good as with the other losses in flat regions, such as the sky.

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Fig. 55. Comparison of different training schedules on denoising+demosaicking $-\ell_1 + \ell_2$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Here we compare the output of the networks trained alternating ℓ_1 and ℓ_2 . In the paper we show that a network trained with ℓ_2 gets stuck in a local minimum. When ℓ_2 is used to train a network that was pre-trained with ℓ_1 , the ℓ_2 loss decreases but the result is not as good as with the other losses in flat regions, such as the sky.



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Fig. 56. Comparison of different training schedules on denoising+demosaicking $-\ell_2 + \ell_1$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Here we compare the output of the networks trained alternating ℓ_1 and ℓ_2 . In the paper we show that a network trained with ℓ_2 gets stuck in a local minimum. When ℓ_2 is used to train a network that was pre-trained with ℓ_1 , the ℓ_2 loss decreases but the result is not as good as with the other losses in flat regions, such as the sky.

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Fig. 57. Comparison of different training schedules on denoising+demosaicking – Ground Truth

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Here we compare the output of the networks trained alternating ℓ_1 and ℓ_2 . In the paper we show that a network trained with ℓ_2 gets stuck in a local minimum. When ℓ_2 is used to train a network that was pre-trained with ℓ_1 , the ℓ_2 loss decreases but the result is not as good as with the other losses in flat regions, such as the sky.



Loss Functions for Image Restoration with Neural Networks

Fig. 58. Comparison of different training schedules on denoising+demosaicking – Noisy

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Here we compare the output of the networks trained alternating ℓ_1 and ℓ_2 . In the paper we show that a network trained with ℓ_2 gets stuck in a local minimum. When ℓ_2 is used to train a network that was pre-trained with ℓ_1 , the ℓ_2 loss decreases but the result is not as good as with the other losses in flat regions, such as the sky.

Super-resolution



Fig. 59. Super-resolution – Ground truth

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note the artifacts on the wing for ℓ_2 .



Fig. 60. Super-resolution – Low Resolution interpolated

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note the artifacts on the wing for ℓ_2 .



Fig. 61. Super-resolution $-\ell_1$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note the artifacts on the wing for ℓ_2 .



Fig. 62. Super-resolution – Mix

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note the artifacts on the wing for ℓ_2 .



Fig. 63. Super-resolution $-\ell_2$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Note the artifacts on the wing for ℓ_2 .



Fig. 64. Super-resolution – Ground truth

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Both ℓ_1 and Mix produce an image that is sharper than ℓ_2 , see for instance the necklace.



Fig. 65. Super-resolution – Low Resolution interpolated

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Both ℓ_1 and Mix produce an image that is sharper than ℓ_2 , see for instance the necklace.



Fig. 66. Super-resolution $-\ell_1$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Both ℓ_1 and Mix produce an image that is sharper than ℓ_2 , see for instance the necklace.



Fig. 67. Super-resolution – Mix

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Both ℓ_1 and Mix produce an image that is sharper than ℓ_2 , see for instance the necklace.


Fig. 68. Super-resolution $-\ell_2$

Please switch between the output of the different networks clicking on the links below (Figures numbers).

Both ℓ_1 and Mix produce an image that is sharper than ℓ_2 , see for instance the necklace.

Ground truth 64, LR interpolated 65, ℓ_1 66, Mix 67, ℓ_2 68.