Supplementary Material for RAISR: Rapid and Accurate Image Super Resolution

Yaniv Romano, John Isidoro, and Peyman Milanfar, *Fellow, IEEE*

In this supplementary material, we provide various results obtained by RAISR and compare these to state-of-the-art algorithms, both for the conventional SISR problem and real-world scenarios (where the ground truth images are not available).

I. Single Image Super-Resolution

Table I provides a detailed quantitative comparison between various SISR algorithms and the proposed approach, along with the runtime of each method (measured on a 3.4GHz 6-Core Xeon desktop computer). As can be inferred, for upscaling by factors of 2, 3 and 4, RAISR offers a competitive restoration performance to the leading methods with much less computational cost.

II. All in One Enhancement

In the context of $2\times$ upscaling, Fig. 1 – Fig. 16 compare the proposed RAISR to the state-of-the-art methods A+ [1] (with 1024 atoms) and SRCNN [2], [3] on several real-world scenarios. It is important to emphasize that in this case RAISR is more than two orders of magnitude faster than A+ and SRCNN. As such, RAISR makes it possible to enjoy from high-quality and reliable upscaling effect in a real-time memory-limited environment.

This work was performed while the first author was an intern at Google Research. Y. Romano is with the Department of Electrical Engineering, Technion – Israel Institute of Technology, Technion City, Haifa 32000, Israel. E-mail address: yromano@tx.technion.ac.il. J. Isidoro and P. Milanfar are with Google Research, 1600 Amphitheatre Pkwy, Mountain View, CA 94043. E-mail addresses: {isidoro,milanfar}@google.com.

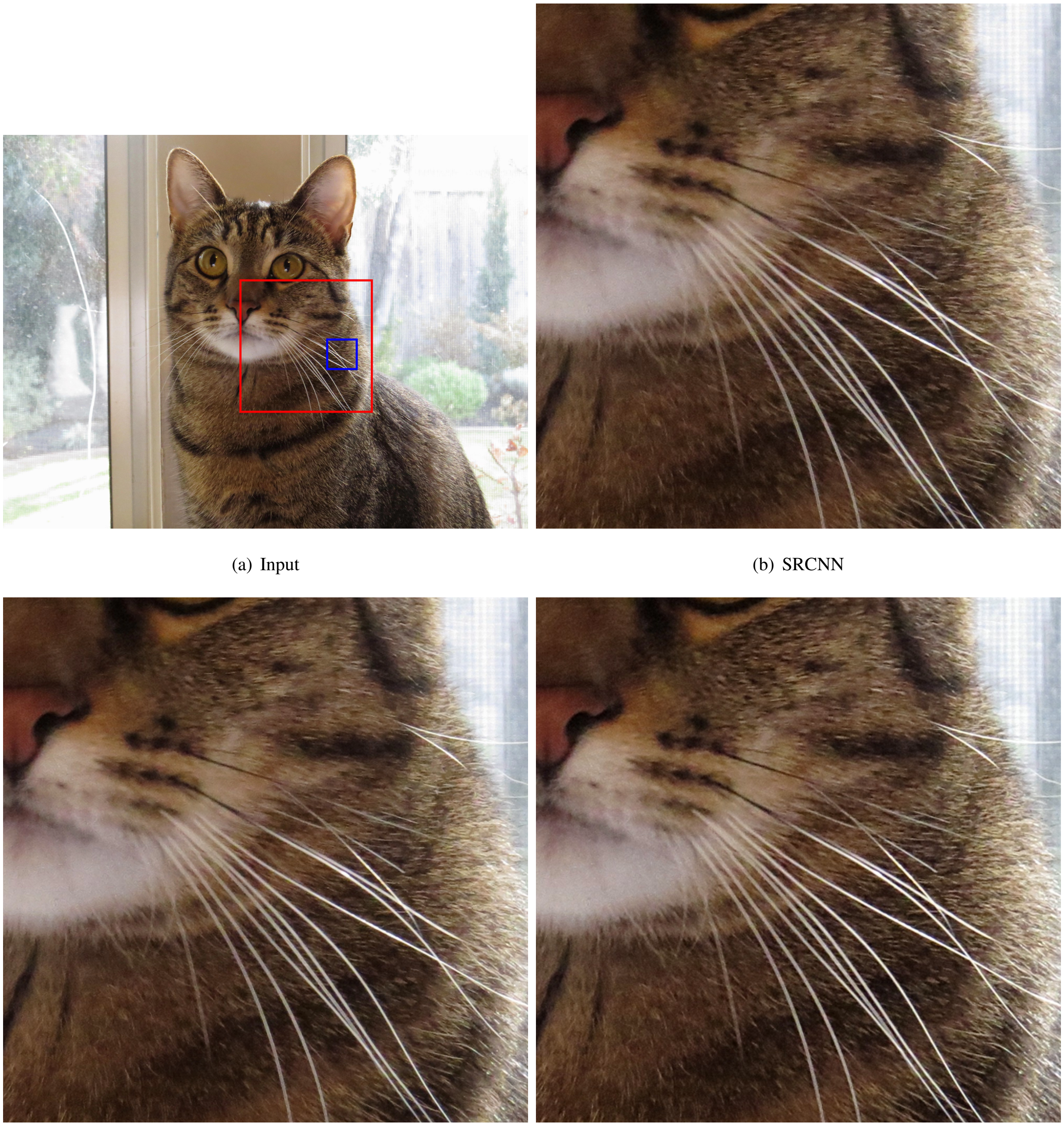
TABLE I

SUMMARY OF THE SISR RESULTS FOR $2\times$, $3\times$ AND $4\times$ UPSCALING. PER EACH METHOD, WE MEASURE THE AVERAGE PSNR AND SSIM (HIGHER IS BETTER) OVER SET5 AND SET14 IMAGES, ALONG WITH THE STANDARD-ERROR OF EACH QUALITY METRIC. WE ALSO PROVIDE THE AVERAGE RUNTIME OF EACH METHOD.

Dataset	**Scaling**	**Bicubic**					**Zeyde et al.** [4]					**GR** [5]				
		PSNR	$\sigma^{\text{err}}_{\text{PSNR}}$	SSIM	$\sigma^{\text{err}}_{\text{SSIM}}$	Time	PSNR	$\sigma^{\text{err}}_{\text{PSNR}}$	SSIM	$\sigma^{\text{err}}_{\text{SSIM}}$	Time	PSNR	$\sigma^{\text{err}}_{\text{PSNR}}$	SSIM	$\sigma^{\text{err}}_{\text{SSIM}}$	Time
Set5	$2\times$	33.661	1.789	0.930	0.019	0.002	35.780	1.603	0.949	0.018	5.815	35.132	1.791	0.944	0.017	0.508
	$3\times$	30.392	1.831	0.868	0.024	0.001	31.901	1.701	0.897	0.022	2.555	31.412	1.822	0.884	0.024	0.289
	$4\times$	28.421	1.847	0.810	0.028	0.001	29.688	1.768	0.843	0.025	1.488	29.336	1.825	0.827	0.028	0.218
Set14	$2\times$	30.232	0.951	0.869	0.020	0.002	31.804	1.017	0.899	0.016	11.496	31.357	0.971	0.897	0.015	1.057
	$3\times$	27.541	0.913	0.774	0.030	0.002	28.666	0.990	0.807	0.028	5.165	28.310	0.943	0.803	0.026	0.616
	$4\times$	26.000	0.880	0.702	0.036	0.002	26.882	0.941	0.734	0.035	3.103	26.599	0.901	0.728	0.033	0.461

Dataset	**Scaling**	**ANR** [5]					**NE+LLE** [6]					**A+ (16 atoms)** [1]				
		PSNR	$\sigma^{\text{err}}_{\text{PSNR}}$	SSIM	$\sigma^{\text{err}}_{\text{SSIM}}$	Time	PSNR	$\sigma^{\text{err}}_{\text{PSNR}}$	SSIM	$\sigma^{\text{err}}_{\text{SSIM}}$	Time	PSNR	$\sigma^{\text{err}}_{\text{PSNR}}$	SSIM	$\sigma^{\text{err}}_{\text{SSIM}}$	Time
Set5	$2\times$	35.833	1.656	0.950	0.017	0.753	35.771	1.659	0.949	0.017	4.282	35.950	1.555	0.951	0.017	0.693
	$3\times$	31.916	1.721	0.897	0.022	0.415	31.835	1.741	0.896	0.022	1.938	32.068	1.681	0.898	0.022	0.375
	$4\times$	29.685	1.790	0.842	0.025	0.297	29.608	1.805	0.840	0.025	1.143	29.827	1.765	0.846	0.024	0.277
Set14	$2\times$	31.795	1.021	0.900	0.016	1.559	31.755	1.019	0.899	0.016	8.665	31.907	1.053	0.901	0.016	1.452
	$3\times$	28.646	0.989	0.809	0.027	0.875	28.595	0.988	0.808	0.027	3.996	28.704	0.987	0.819	0.027	0.801
	$4\times$	26.852	0.938	0.735	0.034	0.632	26.804	0.940	0.733	0.034	2.408	26.993	0.955	0.740	0.035	0.584

Dataset	**Scaling**	**A+ (1024 atoms)** [1]					**SRCNN** [2], [3]					**RAISR**				
		PSNR	$\sigma^{\text{err}}_{\text{PSNR}}$	SSIM	$\sigma^{\text{err}}_{\text{SSIM}}$	Time	PSNR	$\sigma^{\text{err}}_{\text{PSNR}}$	SSIM	$\sigma^{\text{err}}_{\text{SSIM}}$	Time	PSNR	$\sigma^{\text{err}}_{\text{PSNR}}$	SSIM	$\sigma^{\text{err}}_{\text{SSIM}}$	Time
Set5	$2\times$	36.543	1.542	0.954	0.017	0.814	36.656	1.405	0.954	0.017	3.556	36.061	1.354	0.951	0.015	0.018
	$3\times$	32.585	1.541	0.909	0.022	0.422	32.749	1.407	0.909	0.022	3.585	32.172	1.383	0.900	0.019	0.015
	$4\times$	30.279	1.675	0.860	0.023	0.306	30.484	1.465	0.863	0.022	3.523	29.834	1.482	0.848	0.021	0.017
Set14	$2\times$	32.275	1.028	0.906	0.016	1.680	32.454	1.036	0.907	0.015	5.876	32.045	1.018	0.901	0.015	0.034
	$3\times$	29.126	1.040	0.810	0.028	0.899	29.292	1.017	0.821	0.028	5.980	28.821	0.994	0.811	0.027	0.029
	$4\times$	27.317	0.990	0.749	0.034	0.643	27.502	0.974	0.751	0.035	6.512	26.990	0.921	0.738	0.033	0.030



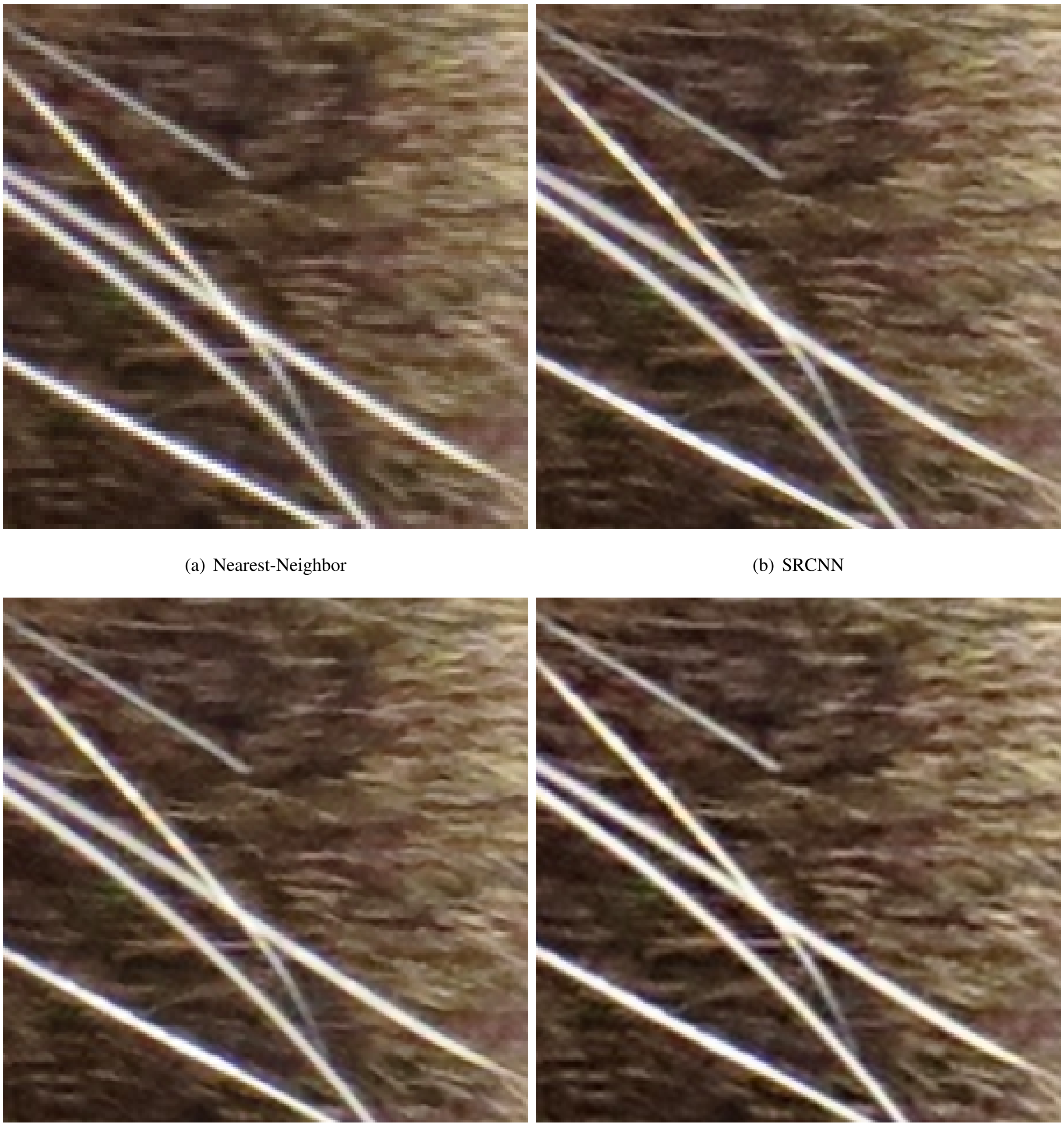
(a) Input

(b) SRCNN

(c) A+

(d) RAISR

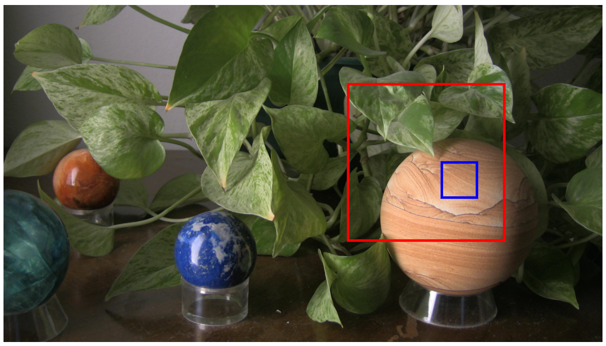
Fig. 1. Visual comparison for upscaling by a factor of 2 of Cat. (a) Input image with two highlighted regions (red and blue rectangles). (b-d) upscaled versions of the red region.



(a) Nearest-Neighbor (b) SRCNN

(c) A+ (d) RAISR

Fig. 2. Visual comparison for upscaling by a factor of 2, showing the blue region from Fig. 1.



(a) Input

(b) SRCNN

(c) A+

(d) RAISR

Fig. 3. Visual comparison for upscaling by a factor of 2 of Leaves. (a) Input image with two highlighted regions (red and blue rectangles). (b-d) upscaled versions of the red region.

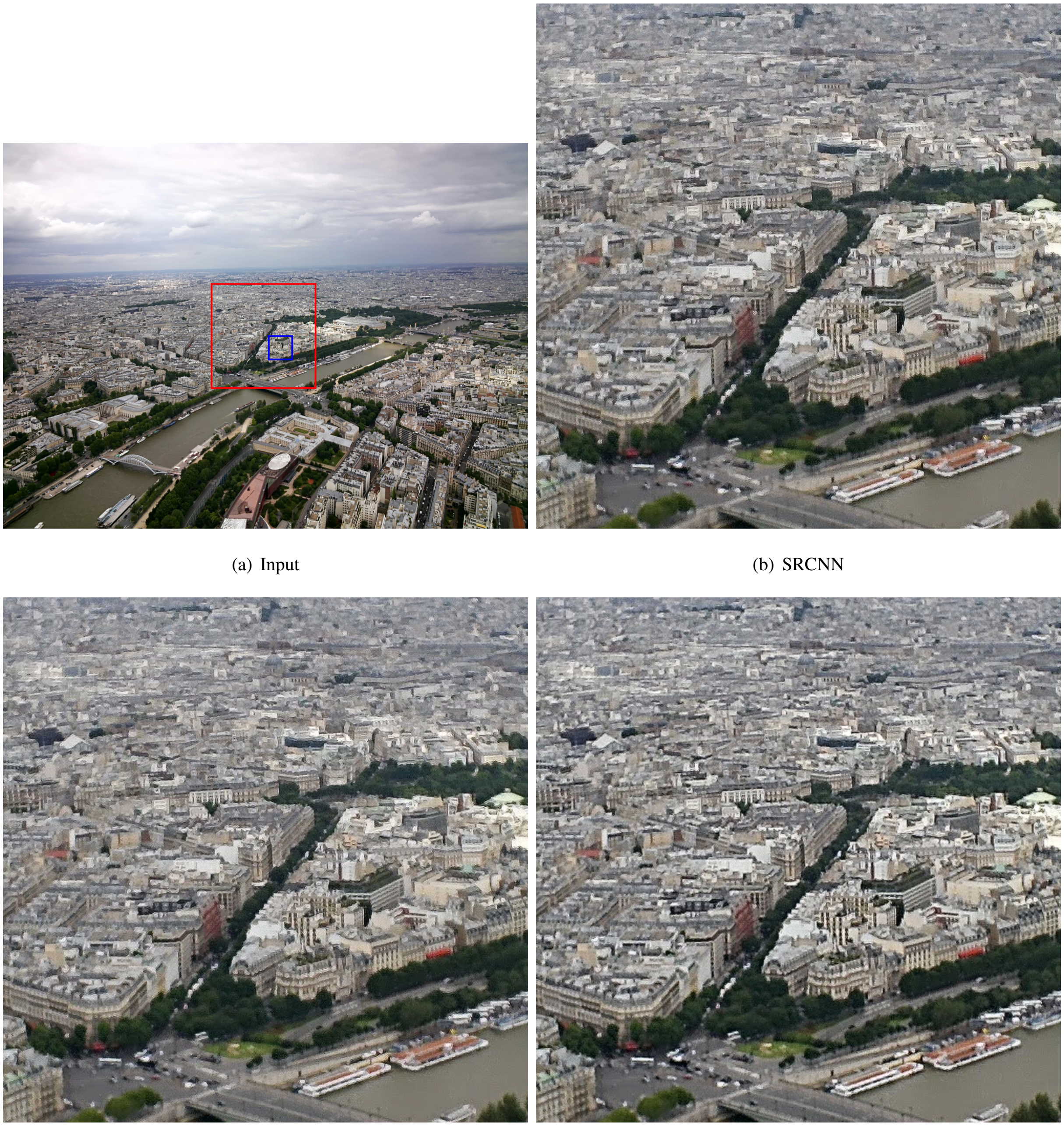
(a) Nearest-Neighbor

(b) SRCNN

(c) A+

(d) RAISR

Fig. 4. Visual comparison for upscaling by a factor of 2, showing the blue region from Fig. 3.



(a) Input

(b) SRCNN

(c) A+

(d) RAISR

Fig. 5. Visual comparison for upscaling by a factor of 2 of Paris. (a) Input image with two highlighted regions (red and blue rectangles). (b-d) upscaled versions of the red region.

(a) Nearest-Neighbor

(b) SRCNN

(c) A+

(d) RAISR

Fig. 6. Visual comparison for upscaling by a factor of 2, showing the blue region from Fig. 5.

(a) Input

(b) SRCNN

(c) A+

(d) RAISR

Fig. 7. Visual comparison for upscaling by a factor of 2 of Restaurant. (a) Input image with two highlighted regions (red and blue rectangles). (b-d) upscaled versions of the red region.

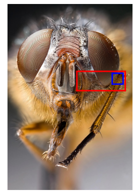
(a) Nearest-Neighbor

(b) SRCNN

(c) A+

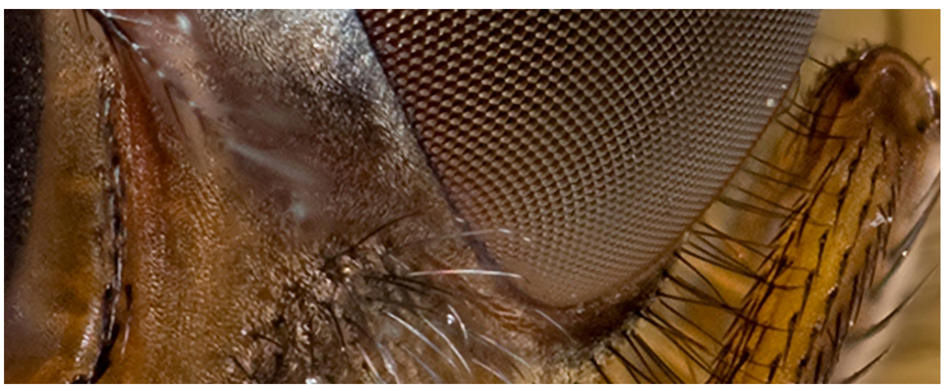
(d) RAISR

Fig. 8. Visual comparison for upscaling by a factor of 2, showing the blue region from Fig. 7.

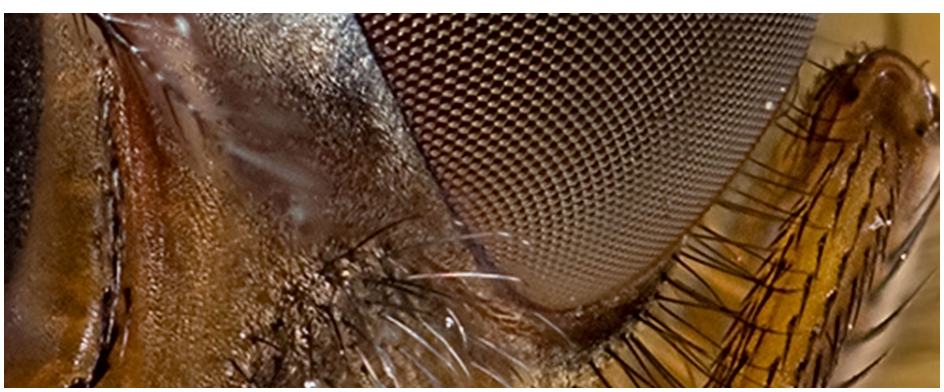


(a) Input

(b) SRCNN

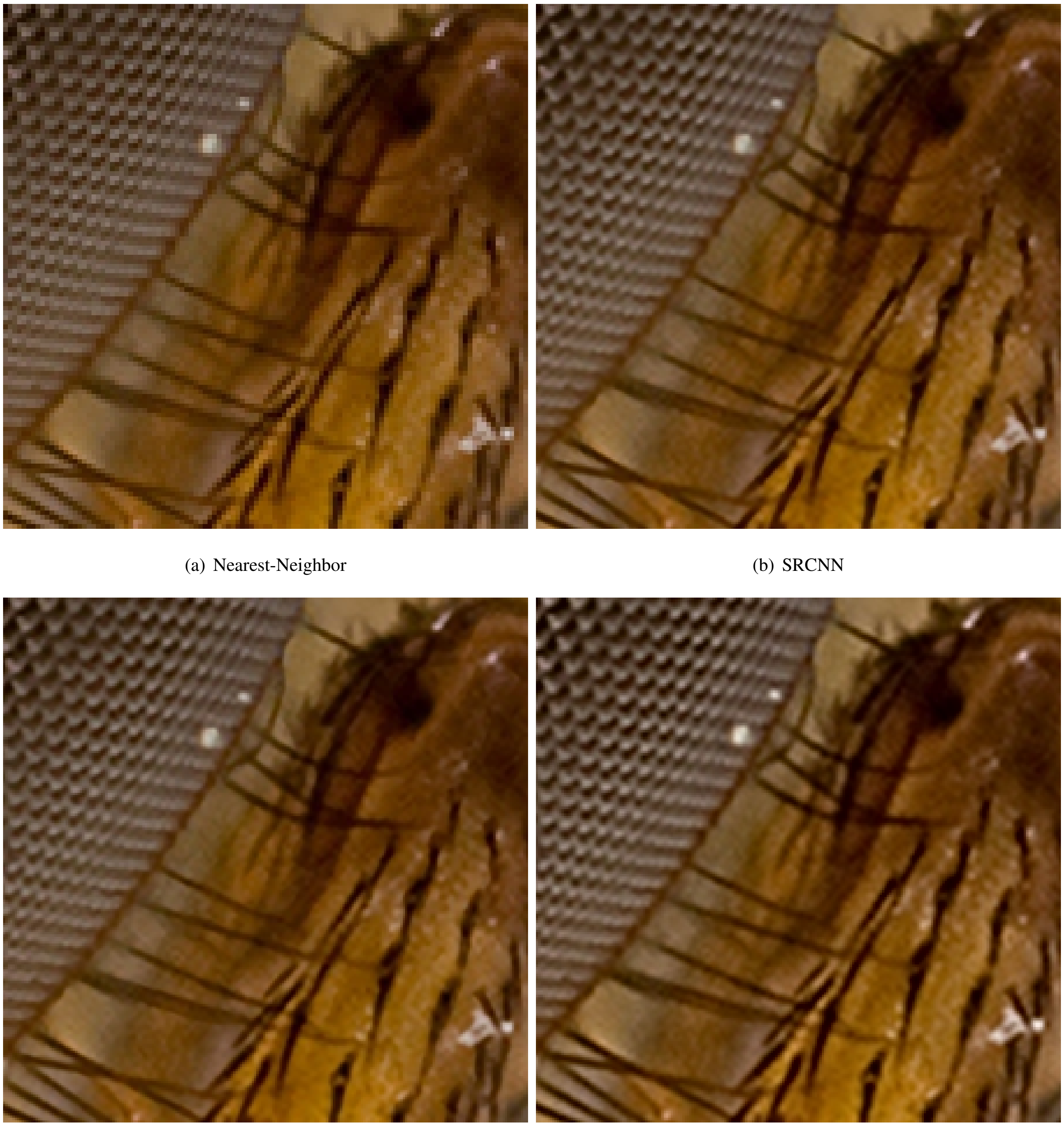


(c) A+



(d) RAISR

Fig. 9. Visual comparison for upscaling by a factor of 2 of Bug. (a) Input image with two highlighted regions (red and blue rectangles). (b-d) upscaled versions of the red region.



(a) Nearest-Neighbor

(b) SRCNN

(c) A+

(d) RAISR

Fig. 10. Visual comparison for upscaling by a factor of 2, showing the blue region from Fig. 9.

(a) Input

(b) SRCNN

(c) A+

(d) RAISR

Fig. 11. Visual comparison for upscaling by a factor of 2 of Newspaper. (a) Input image with two highlighted regions (red and blue rectangles). (b-d) upscaled versions of the red region.

(a) Nearest-Neighbor

(b) SRCNN

(c) A+

(d) RAISR

Fig. 12. Visual comparison for upscaling by a factor of 2, showing the blue region from Fig. 11.

(a) Input

(b) SRCNN

(c) A+

(d) RAISR

Fig. 13. Visual comparison for upscaling by a factor of 2 of Playground. (a) Input image with two highlighted regions (red and blue rectangles). (b-d) upscaled versions of the red region.

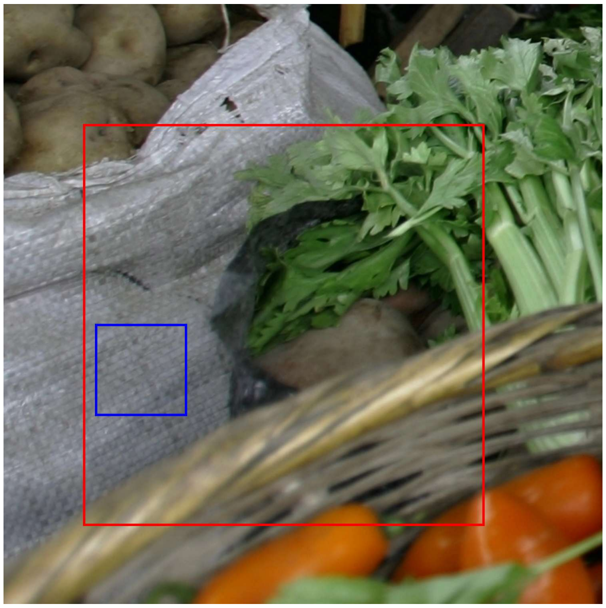
(a) Nearest-Neighbor

(b) SRCNN

(c) A+

(d) RAISR

Fig. 14. Visual comparison for upscaling by a factor of 2, showing the blue region from Fig. 13.



(a) Input

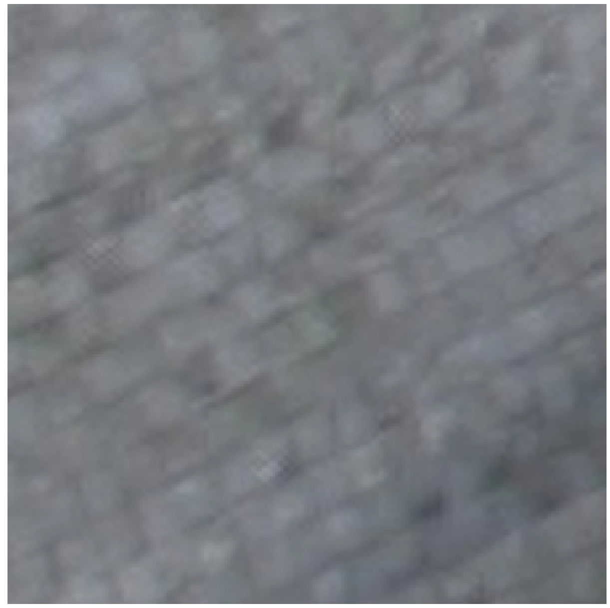
(b) SRCNN

(c) A+

(d) RAISR

Fig. 15. Visual comparison for upscaling by a factor of 2 of Market. (a) Input image with two highlighted regions (red and blue rectangles). (b-d) upscaled versions of the red region.

(a) Nearest-Neighbor



(b) SRCNN

(c) A+

(d) RAISR

Fig. 16. Visual comparison for upscaling by a factor of 2, showing the blue region from Fig. 15.

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