

Supplementary Material for ‘The Best of Both Worlds: a Framework for Combining Degradation Prediction with High Performance Super-Resolution Networks’

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This document contains a number of supplementary results and figures which support the main text. Please refer to the main manuscript for further details.

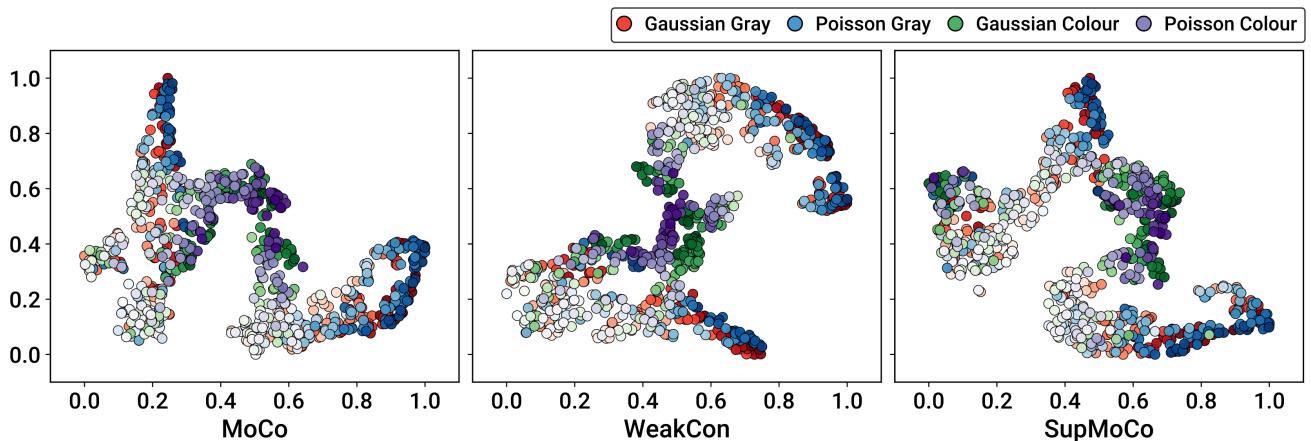
Simple Pipeline Results

Table S1: SSIM SR results corresponding to Table 1 from the main paper. ‘low’ refers to a σ of 0.2, ‘med’ refers to a σ of 1.6 and ‘high’ refers to a σ of 3.0. The best result for each set is shown in red, while the second-best result is shown in blue.

Model	Set5			Set14			BSDS100			Manga109			Urban100		
	low	med	high	low	med	high	low	med	high	low	med	high	low	med	high
Baselines															
Bicubic	0.7909	0.7513	0.6736	0.6803	0.6384	0.5700	0.6452	0.6058	0.5458	0.7716	0.7323	0.6659	0.6376	0.5941	0.5240
Lanczos	0.7986	0.7625	0.6814	0.6888	0.6487	0.5761	0.6534	0.6149	0.5510	0.7775	0.7418	0.6720	0.6452	0.6044	0.5302
Non-Blind															
RCAN	0.8830	0.8783	0.8564	0.7664	0.7632	0.7314	0.7217	0.7170	0.6897	0.9015	0.9000	0.8728	0.7834	0.7760	0.7357
MA	0.8845	0.8837	0.8615	0.7671	0.7669	0.7408	0.7221	0.7212	0.6953	0.9041	0.9047	0.8857	0.7849	0.7812	0.7479
MA (all)	0.8836	0.8828	0.8620	0.7667	0.7670	0.7407	0.7216	0.7213	0.6958	0.9036	0.9051	0.8863	0.7837	0.7808	0.7483
MA (PCA)	0.8846	0.8834	0.8617	0.7677	0.7667	0.7401	0.7224	0.7214	0.6951	0.9040	0.9048	0.8852	0.7852	0.7812	0.7475
SRMD	0.8844	0.8836	0.8622	0.7673	0.7670	0.7406	0.7222	0.7212	0.6956	0.9039	0.9048	0.8855	0.7844	0.7809	0.7477
SFT	0.8847	0.8832	0.8627	0.7677	0.7671	0.7406	0.7228	0.7215	0.6957	0.9043	0.9052	0.8863	0.7859	0.7817	0.7482
DA	0.8845	0.8836	0.8628	0.7676	0.7673	0.7410	0.7221	0.7215	0.6957	0.9040	0.9049	0.8861	0.7846	0.7816	0.7484
DA (all)	0.8847	0.8837	0.8622	0.7666	0.7667	0.7401	0.7217	0.7211	0.6957	0.9033	0.9050	0.8856	0.7822	0.7807	0.7480
DGFMB	0.8845	0.8836	0.8623	0.7672	0.7669	0.7406	0.7224	0.7216	0.6956	0.9041	0.9048	0.8860	0.7850	0.7812	0.7485
DGFMB (no FC)	0.8849	0.8834	0.8625	0.7673	0.7669	0.7406	0.7224	0.7211	0.6954	0.9040	0.9046	0.8856	0.7851	0.7810	0.7479

Complex Pipeline Results

A)



B)

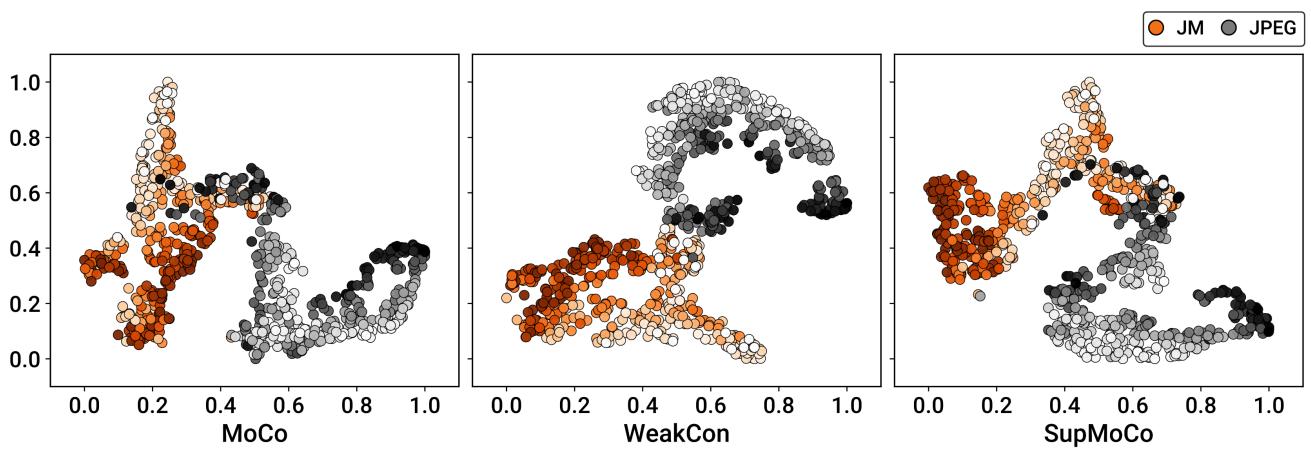


Figure S1: t-SNE plots (perplexity value of 40) showing the separation power of the different contrastive learning algorithms considered on the complex pipeline. All models were evaluated at epoch 2000. The test dataset consisted of 2472 images (8 sets of 309 images of BSDS100/Manga109/Urban100) degraded using the full complex pipeline (random degradation parameters). Only 800 images (randomly selected) are plotted per panel, to reduce cluttering. Each dimension was independently normalised in the range [0, 1] after computing the t-SNE results. A) t-SNE plots with each image coloured according to the noise applied. The colour intensity of each point corresponds to the noise magnitude (in the range [1, 30] for Gaussian noise and [0.05, 3] for Poisson noise). All three encoders are capable of separating noise magnitudes, but lose the ability to distinctly separate the two noise classes. B) t-SNE plots with each image coloured according to the compression applied. The colour intensity of each point corresponds to the compression level, which is in the range [30, 95] (higher is better) for JPEG and [20, 40] (lower is better) for JM H.264. All three encoders are capable of separating compression magnitudes, but struggle to separate the two compression types when the compression is very low.

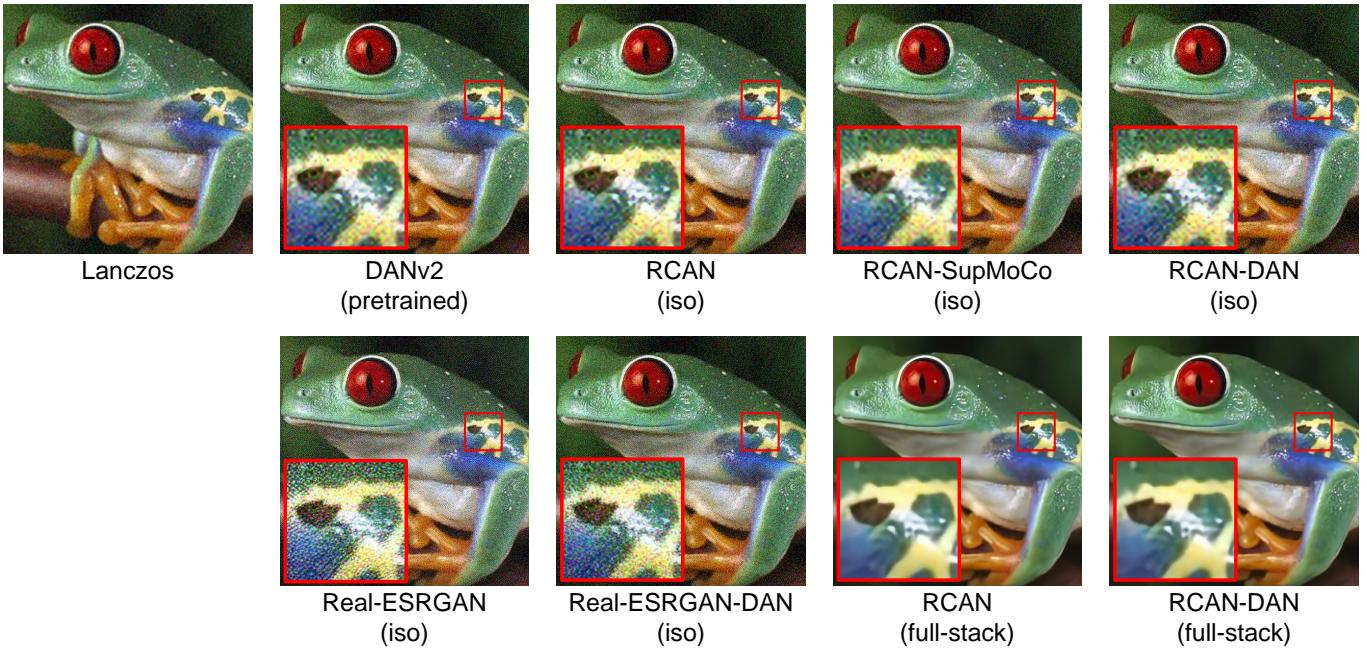


Figure S2: Comparison of the SR results of various models on the frog image from RealSRSet. All simple pipeline models (marked as iso) are incapable of removing the noise from the image. The complex pipeline models (marked as full-stack) produce significantly improved results.