METAF2N: BLIND IMAGE SUPER-RESOLUTION BY LEARNING EFFICIENT MODEL ADAPTATION FROM FACES

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Abstract:

Super resolution on real-world, low quality images is challenging due to unknown degradation unlike faces. MetaF2N enables adaptive model fine-tuning using face regions, improving quality without complex degradation modeling. Using one-step fine-tuning for strong image restoration.

Key features:

Efficient Adaptation: Adapts to real-world low-quality images by focusing on face regions.

Single-Step Fine-Tuning: Achieves high-quality restoration with a single fine-tuning step.

Adaptive Loss Weighting: Uses MaskNet to assign dynamic loss weights, minimizing errors in low-confidence areas.

Methodology:

Inner Loop: Extracts degradation representations using low-quality and recovered face pairs. We use GPEN as the pre-trained face restoration model to generate pseudo ground-truth for face regions. And then uses MaskNet to generates adaptive weights based on differences between low-quality and recovered face pairs.

Outer Loop: The SR model is fine-tuned for the whole image using the temporary parameters from the inner loop.

The outer loop loss combines fidelity (L1), LPIPS (perceptual loss), and adversarial losses (GAN). And a discriminator is trained iteratively with the SR network in the outer loop to enhance visual quality.

New Idea:

Self Similarity Loss : While The model effectively minimizes losses comparing the output with the GT images, none of the loss functions assess the quality of the output images themselves. Recognizing that real-world images often exhibit similarities between nearby patches, I sought a method to enhance the realism of my output images.

Image self-similarity leverages repetitive patterns in natural images to improve image restoration by using similar nearby patches. This is quantified through an Exponential Euclidean Distance between patches. To focus on key regions, a mask is generated, highlighting edges and textures by applying the Laplacian operator and thresholding. This mask limits similarity calculations to high-detail areas, creating a Self-Similarity Graph (SSG) that represents the internal structural patterns of the image. This targeted approach enhances the model's ability to restore and sharpen degraded areas effectively. Thus, our loss function gets updated to this:

$$L_{TOTAL} = \lambda_1 L_1 + \lambda_2 L_{lpips} + \lambda_3 L_{adv} + \lambda_4 L_{reg} + \lambda(\| \bar{S}_{SR} - \bar{S}_{HR} \|)$$

Conclusion:

The analysis of my model's results shows comparable or even superior performance to the original paper's benchmarks, with notable reductions in NIQE and FID loss metrics. This improvement indicates enhanced accuracy and effectiveness in image quality restoration. Overall, the model's ability to generate high-quality outputs suggests it effectively addresses image degradations and refines detail more accurately than the baseline approach.

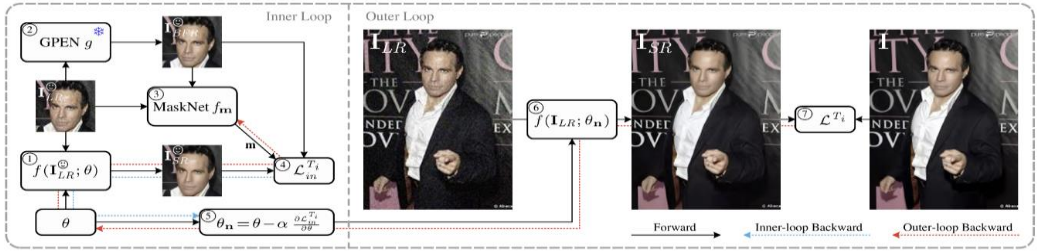

Figure 1: Pipeline of the proposed MetaF2N framework. During inference, the inner loop updates the initial parameter θ via a back-propagation step (dotted blue line), and the obtained θ_n is used to process the whole natural image in the outer loop. For training, the parameter update indeed relies on the gradients of outer loop loss L^{T_i} w.r.t. the initial parameter θ and the MaskNet parameter θ_m (dotted red line).

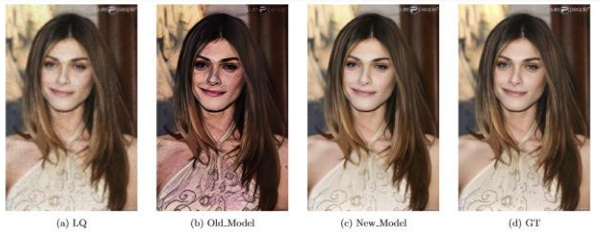

Figure 7: Test Results: CelebA_ood

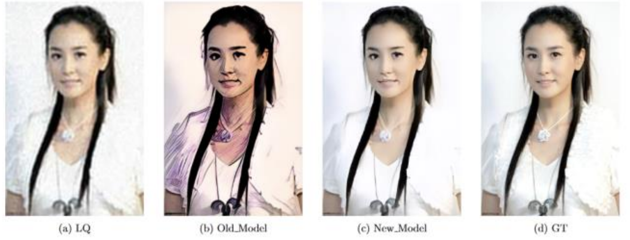

Figure 6: Test Results: CelebA_iid

Figure 3: Test Results: FFHQ_ood

Figure 2: Test Results: FFHQ_iid

Figure 5: Test Results: FFHQ_Multi_ood

Figure 4: Test Results: FFHQ_Multi_iid

My model	Old				New			
Dataset	PSNR	LPIPS	FID	NIQE	PSNR	LPIPS	FID	NIQE
CelebA_iid	17.26	0.4616	130.54	5.56	25.72	0.310	46.5	4.17
CelebA_ood	17.38	0.4648	116.99	5.61	24.88	0.313	44.47	4.44
FFHQ_iid	16.93	0.4589	204.77	5.32	26.13	0.301	46.10	3.94
FFHQ_ood	17.35	0.4536	111.86	5.42	25.34	0.303	45.40	4.21
FFHQ_Multi_iid	16.79	0.4570	134.55	5.23	25.61	0.308	43.85	3.66
FFHQ_Multi_ood	16.85	0.4491	127.59	5.23	25.11	0.312	43.31	3.65

Table 2: Loss Metrics for Various Datasets: My Model

Dataset	PSNR	LPIPS	FID	NIQE
CelebA_iid	25.76	0.289	45.22	4.10
CelebA_ood	25.00	0.297	46.23	4.47
FFHQ_iid	26.30	0.279	44.51	3.94
FFHQ_ood	25.65	0.283	44.30	4.36

Table 3: Loss Metrics for Various Datasets: Mentioned in the paper