MetaHDR: Model-Agnostic Meta-Learning for HDR Image Reconstruction

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Motivation

In Low Dynamic Range (LDR) to High Dynamic Range (HDR) conversion, there exists a nonlinear mapping between the scene radiance and the pixel values.

Existing deep learning models learn a single nonlinear mapping across all scenes, cameras, etc.

We propose the use of a meta-learning framework that learns an infinite set of nonlinear mappings by producing a set of meta-parameters which capture the common structure of LDR-to-HDR non-linear mapping.

At test time, given specific examples of LDR images in a scene, our model can quickly adapt to the optimal task-specific nonlinear mapping.

Background & Related Work

Problem: Given n LDR images ($n > 0$), produce 1 HDR image. Example input below[1]. Image borders added for visual clarity.

$\mathcal{D}_i$

With an input image spanning many exposures, we can perform HDR image fusion based on a set of computed exposure weights. [2]

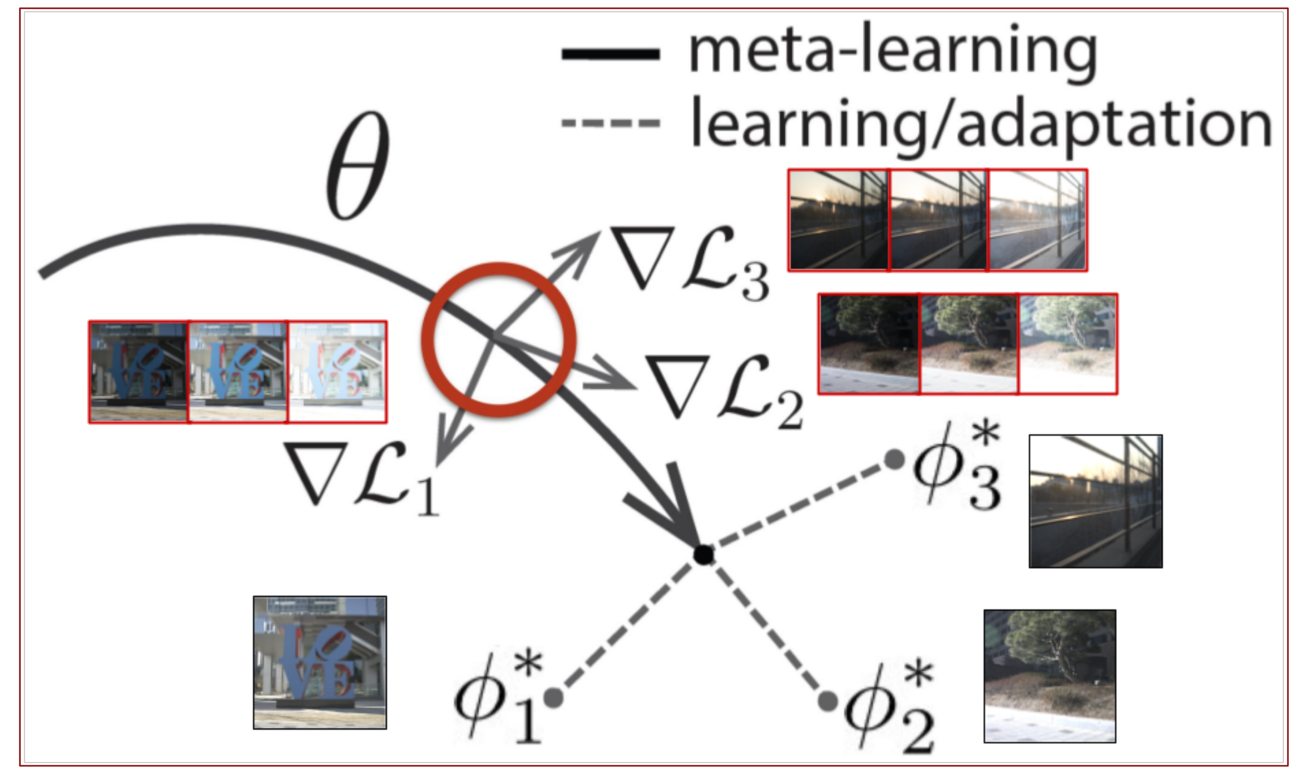
Nonlinear mappings can be learned by assuming consistency across multiple images. Historically, this has been done through deep-CNN architectures. [3]

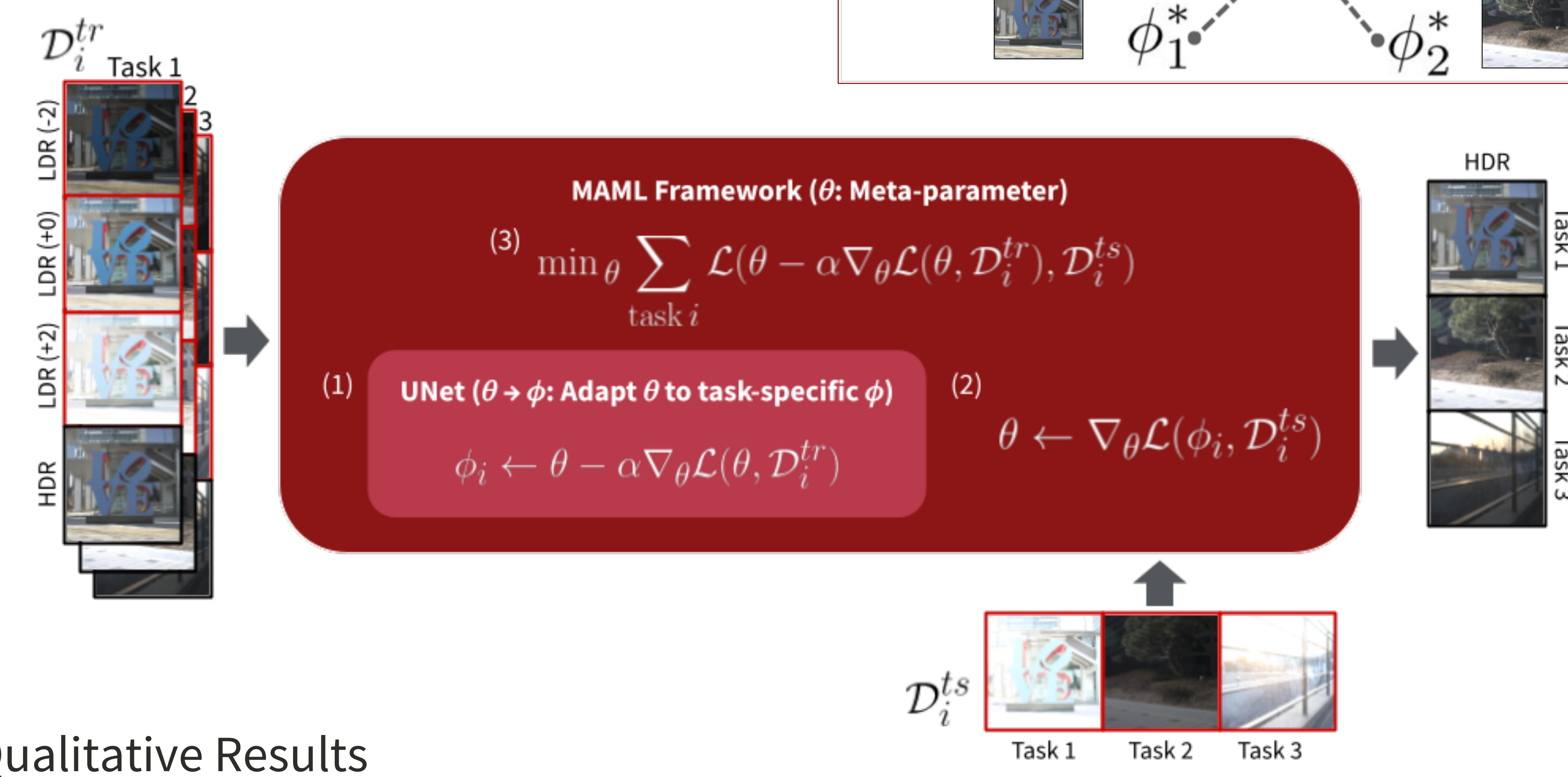
* Equal contribution

Approach & Model Architecture

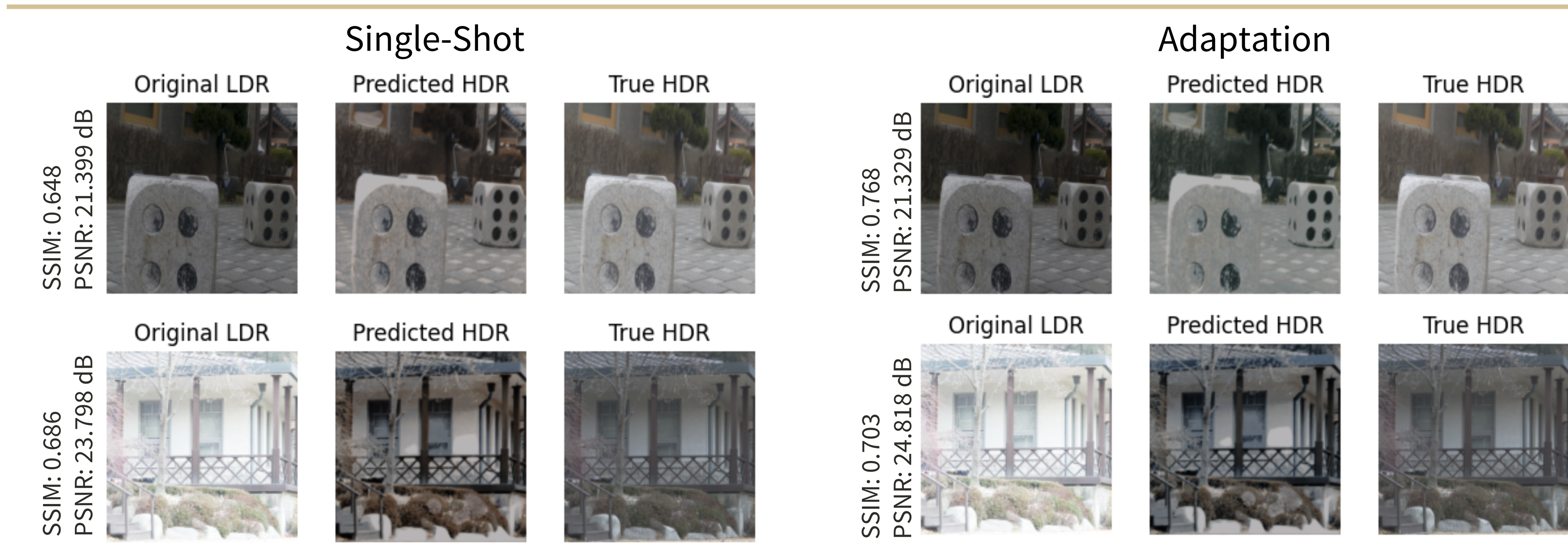
A set of scene-exposures is interpreted as a task. For i tasks in a batch, pass through the MAML[4] model. The loss function[5] incorporates similarity and L1 distance. One pass involves 3 steps:

1. Compute task-specific ϕ_i for the UNet by optimizing meta-params θ (i.e., weights).
2. Use ϕ_i to compute HDR for test LDR image.
3. Accumulate loss and adjust meta-params θ.





Qualitative Results



Note: All predicted HDR and true HDR images have been gamma corrected for visualization.

Quantitative Results

	SSIM† (↑)		PSNR† (dB) (↑)	
	Label[2]	Label[3]	Label[2]	Label[3]
LDR No Recon.	0.489		12.200	
Single Shot	0.666	0.687	19.577	19.713
Adaptation with True HDR[2]	0.683	0.701	19.967	20.125
Adaptation with Simulated HDR[3]	0.687	0.698	19.753	19.790

† Averaged over all meta-test set images.
Note: Labels refer to labels used for task-specific adaptation in meta-training.

Discussion

Conclusion: Our novel approach for HDR image reconstruction generates comparable results to state-of-the-art. Model performs well in the single-shot setting. Few-shot setting improves results.

Challenges: Color saturation was hard to maintain between input and output.

Limitations: While single-shot reconstruction works, the model performs better when given more LDR exposures per scene. Labels need to simulated at meta-test time for model adaptation.[3]

Future Work: Incorporate loss functions that prioritize saturated pixels during reconstruction. Train with more exposures per scene, and a wider variety of scenes.

References

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[4] Finn et. Al. ICML, pages 1126–1135. PMLR, 2017.
[5] Marnnerides et. Al. Eurographics, Vol:37, 2018