

# Physics-Aware Deblurring with Coded Exposure

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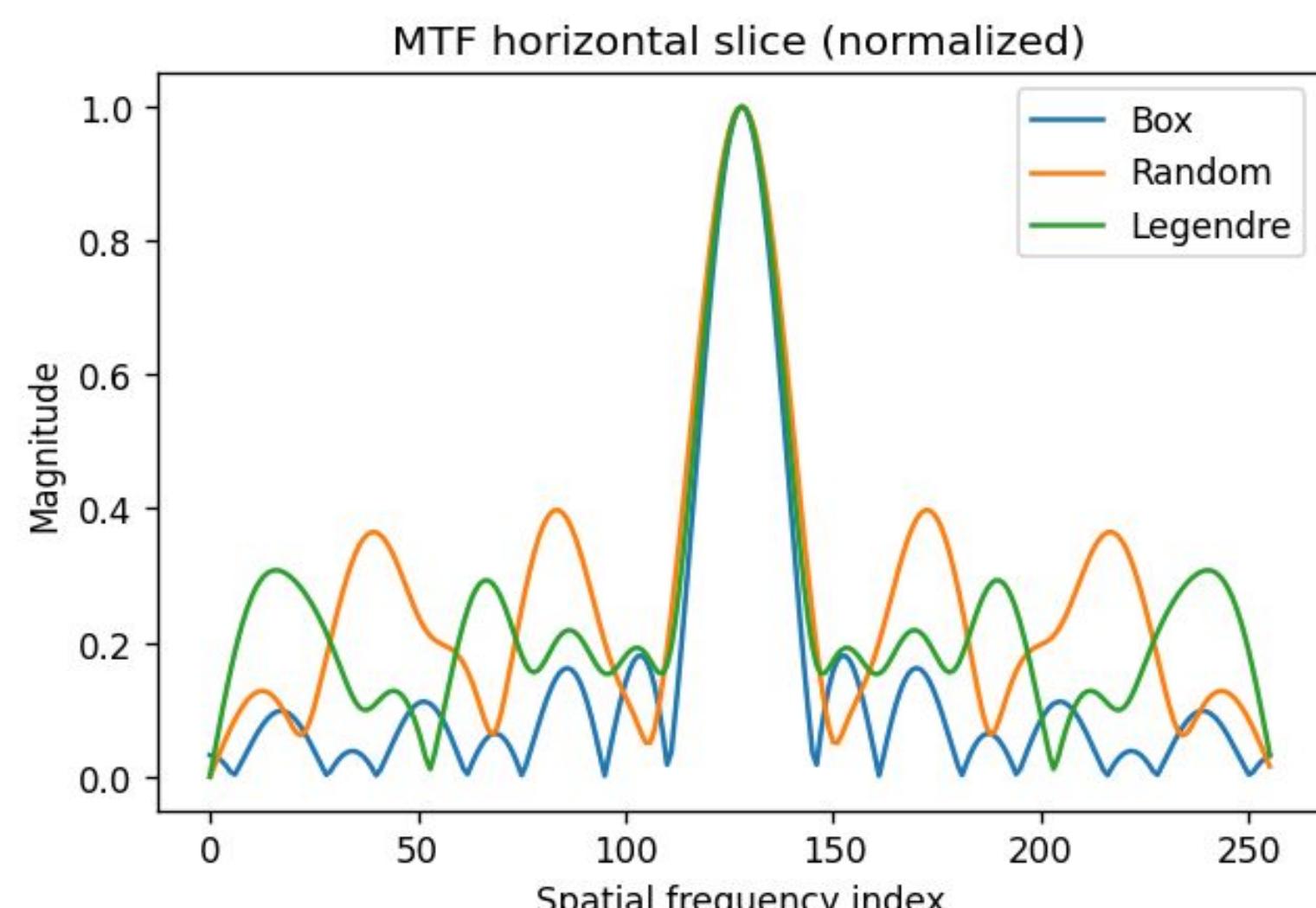
## Motivation

Real imaging systems such as smartphones, drones, and robotic cameras often operate under severe motion.

Coded-exposure imaging attempts to preserve recoverable information by modulating the shutter with a temporal code  $c(t)$ . The observation can be modeled as

$$Y(\omega) = H(\omega)X(\omega) + N(\omega)$$

in the frequency domain. The term  $H(\omega)$  is the optical transfer function whose magnitude is the Modulation Transfer Function (MTF). The MTF determines how much contrast survives at each spatial frequency.



\* Legendre-coded exposure (green) preserves higher and more uniform MTF than box (blue) or random (orange)

## Related Work

We follow the Plug-and-Play ADMM paradigm, coupling a physics-driven solver with a deep prior:

- **The Engine (ADMM):** Iteratively enforces agreement with the coded-exposure forward model and measurement noise statistics.
- **The Deep Prior (PnP):** A pretrained CNN denoiser replaces handcrafted regularizers and restores texture during the iterative updates.

Building on this foundation, prior work has explored key directions relevant to ours:

- Jeon, Lee, and Han introduced a modified Legendre coded-exposure pattern [1] that creates long, low-autocorrelation binary shutter codes for motion deblurring.
- Song *et al.* introduced a quality-aware deblurring model [2] that conditions its restoration on image-quality metrics, conceptually similar to our physics-aware scheduling strategy.

## References

[1] Jeon, H.-G., Lee, J.-Y., Han, Y., Kim, S.-J., & Kweon, I. S. (2013). *Fluttering Pattern Generation Using Modified Legendre Sequence for Coded Exposure Imaging*. In *Proceedings of the IEEE International Conference on Computer Vision*

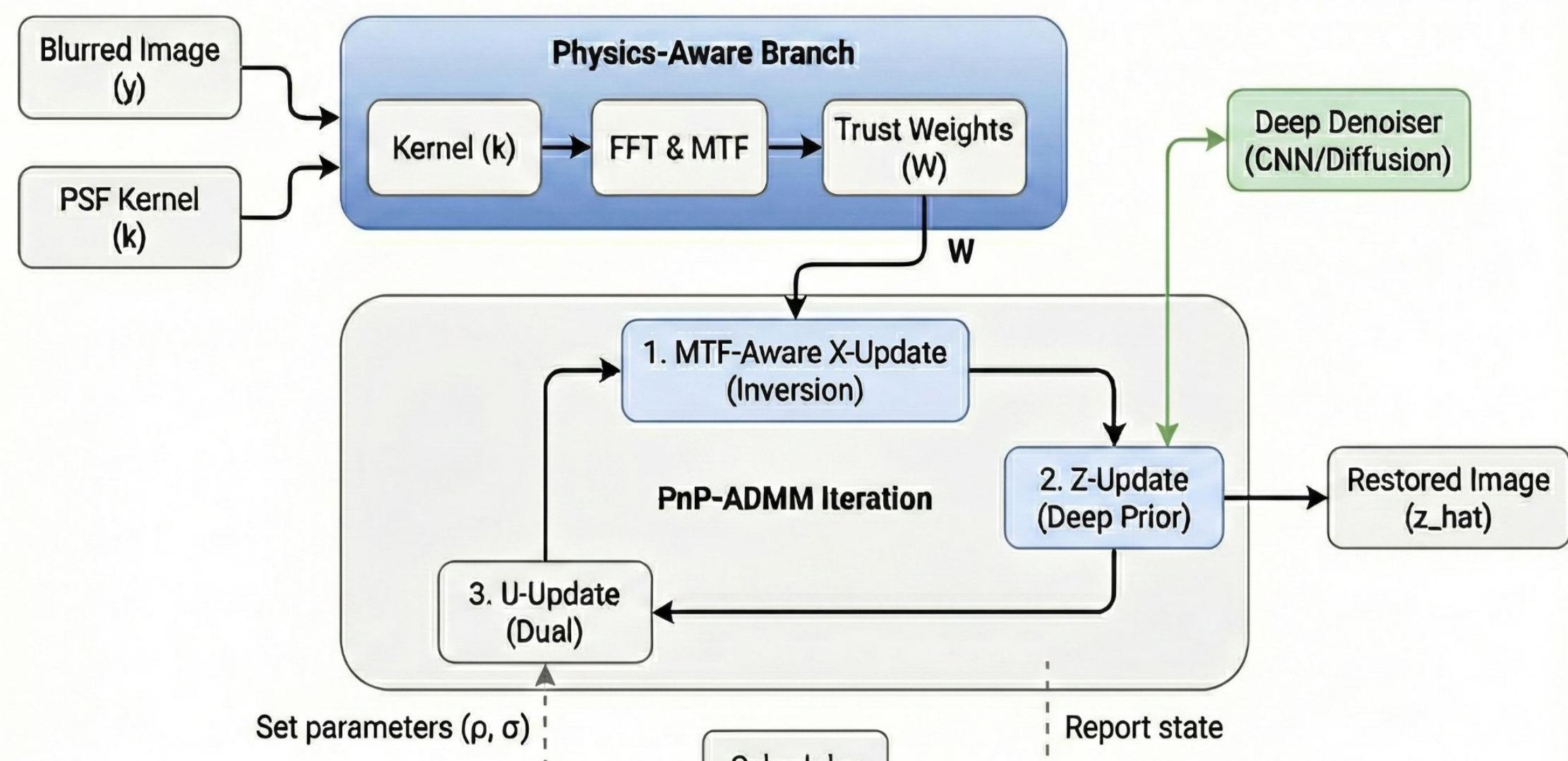
[2] Song, T., Li, L., Wu, J., Dong, W., & Cheng, D. (2024). *Quality-aware blind image motion deblurring*. *Pattern Recognition*, 153, 110568.

## New Technique

We inject "optical intelligence" into the standard PnP framework.

- **Physics-Aware Weighting (The Core Novelty)** Pre-computes frequency-domain "Trust Weights" ( $W$ ) based on the kernel's MTF.
- **MTF-Selective Data Consistency** Modifies the standard ADMM inversion step by injecting Trust Weights.
- **Adaptive Physics Scheduler** Eliminates manual tuning by dynamically adjusting parameters ( $\rho, \sigma$ ) at every iteration.

### MTF-Aware PnP-ADMM Algorithm

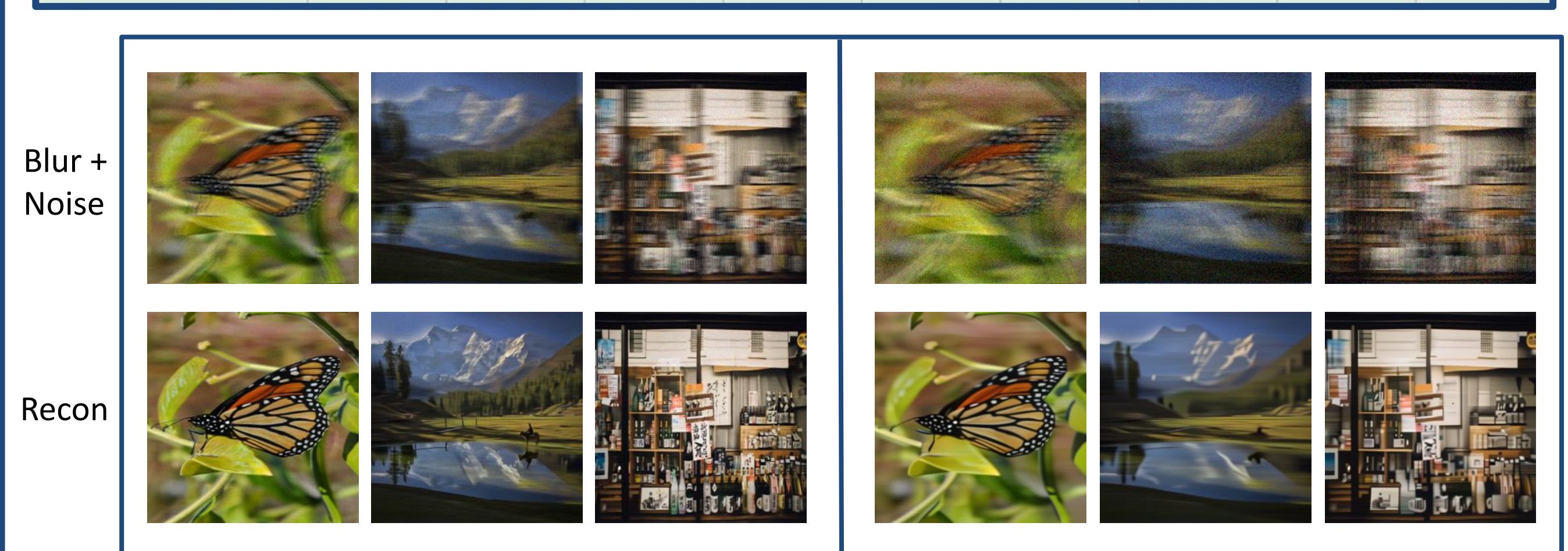


## Experimental Results

- We compare our method against classical (**Richardson–Lucy**) and learned PnP baselines (**DnCNN**, **DRUNet**) under identical coded-exposure settings.
- Quantitative evaluation uses **PSNR**, **SSIM**, and **LPIPS** across multiple shutter codes (**Box**, **Random**, **Legendre**).

Method	PSNR (Higher is Better ↑)			SSIM (Higher is Better ↑)			LPIPS (Lower is Better ↓)		
	Box	Random	Legendre	Box	Random	Legendre	Box	Random	Legendre
Richardson-Lucy	19.01	19.00	19.02	0.388	0.387	0.388	0.636	0.619	0.623
Adam w/ DnCNN	18.70	22.36	22.49	0.401	0.540	0.544	0.497	0.372	0.367
ADMM w/ DrUNet	22.99	23.94	23.69	0.680	0.688	0.679	0.373	0.314	0.319
Physics-Aware (Ours)	<b>24.32</b>	<b>28.12</b>	<b>29.27</b>	<b>0.718</b>	<b>0.804</b>	<b>0.853</b>	<b>0.386</b>	<b>0.217</b>	<b>0.211</b>

Method	PSNR (Higher is Better ↑)			SSIM (Higher is Better ↑)			LPIPS (Lower is Better ↓)		
	Box	Random	Legendre	Box	Random	Legendre	Box	Random	Legendre
Richardson-Lucy	18.35	18.63	18.63	0.319	0.324	0.325	0.686	0.661	0.665
Adam w/ DnCNN	12.45	17.05	17.08	0.143	0.281	0.282	0.700	0.574	0.572
ADMM w/ DrUNet	12.03	13.40	13.05	0.107	0.157	0.153	0.652	0.585	0.602
Physics-Aware (Ours)	<b>20.79</b>	<b>23.59</b>	<b>24.04</b>	<b>0.541</b>	<b>0.675</b>	<b>0.693</b>	<b>0.539</b>	<b>0.422</b>	<b>0.409</b>



Left: Physics-Aware Deblurring on mildly blurred and noisy inputs.

Right: Physics-Aware Deblurring on severely blurred and noisy inputs.