Learning Continuous Implicit Representation for Near-Periodic Patterns

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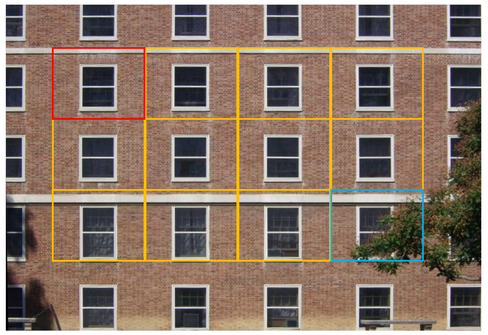
Paper, code are available:
https://armastuschen.github.io/projects/NPP_Net/

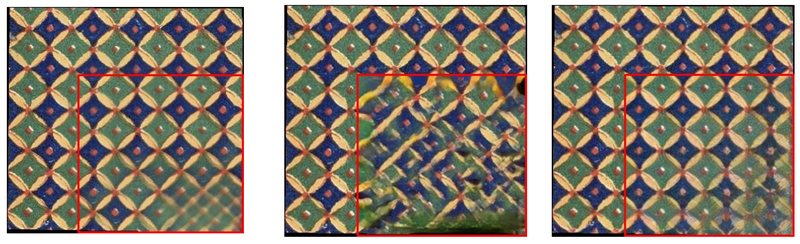
What is Near-Periodic Patterns (NPP)?



(1) **Global Consistency**: a motif (red box) tiles spatially across image (orange boxes).
(2) **Local Variations**: appearance variations in different motifs due to design choice and occlusions (red and blue boxes).

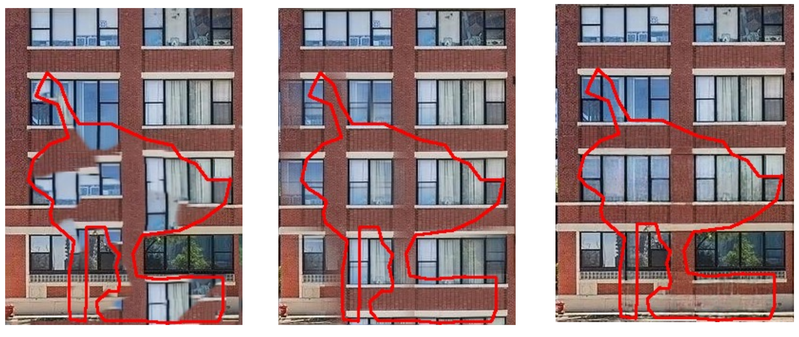
Completing NPP using Existing Methods

PEN-Net (2019) ProFill (2020) Lama (2022)



Existing methods designed for *general scenes* fail in this simple NPP. Pixels inside red boxes are completed (unknown).

Huang et al. (2014) BPI (2020) NPP-Net (Ours)



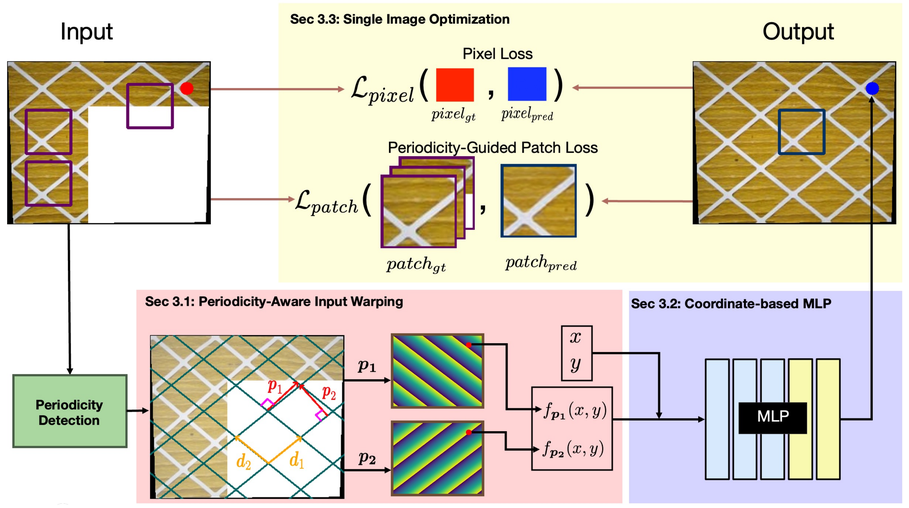
Although existing methods designed for *NPP* work in the previous simple NPP, they fail in this complicated façade NPP. Pixels inside red boxes are completed (unknown).

Core Idea:

Prior knowledge of NPP → inject → Implicit NPP representation → preserve → Global Consistency, Local Variations

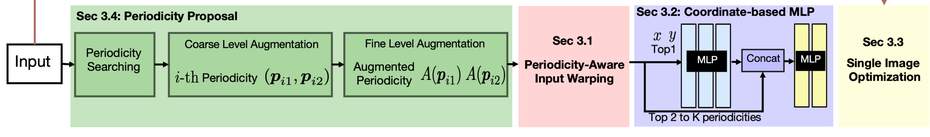
Our primary application is NPP completion, but we also study segmentation and remapping as extension.

Initial Pipeline:



- *Periodicity-Aware Input Warping* (pink) warps input coordinates using detected periodicity.
- *Coordinate-based MLP* (blue) maps warped and input coordinate features to an RGB value.
- *Single Image Optimization* (yellow) uses pixel loss and periodicity-guided patch loss on a single NPP image.

Final Pipeline:



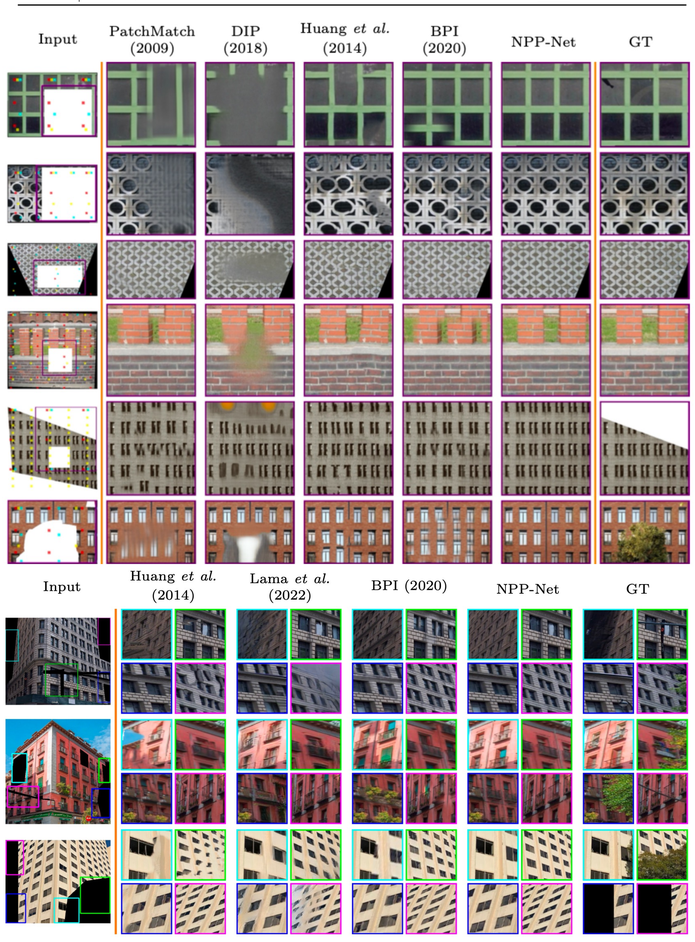
Periodicity Proposal (green) automatically searches and augments the input periodicity to handle inaccurate periodicity detection and encourage the global consistency.

Datasets

- Subset from NRTDB, DTD, Façade datasets.
- Contain 532 images, larger than those used by existing methods (157 images at most).

Completion Result

Category	Method	NRTDB [1]			DTD [10]			Facade [48]		
		LPIPS ↓	SSIM ↑	PSNR ↑	LPIPS ↓	SSIM ↑	PSNR ↑	LPIPS ↓	SSIM ↑	PSNR ↑
Large Datasets	PEN-Net [57]	0.497	0.452	17.97	0.473	0.365	15.81	0.426	0.444	15.78
	ProFill [58]	0.401	0.300	16.35	0.443	0.249	14.30	0.374	0.391	14.73
	Lama [46]	0.196	0.551	18.64	0.274	0.479	16.39	**0.207**	0.468	15.24
Single Image	Image Quilting [11]	0.428	0.074	13.25	0.415	0.077	12.18	0.550	0.002	10.28
	PatchMatch [2]	0.263	0.542	18.14	0.361	0.383	15.47	0.369	0.341	14.22
	DIP [50]	0.554	0.292	16.46	0.659	0.181	13.15	0.582	0.258	15.22
	Siren [44]	0.636	0.084	14.38	0.762	0.080	13.11	0.780	0.052	12.00
	Huang *et al.* [16]	0.287	0.410	16.99	0.302	0.320	14.88	0.387	0.279	13.75
	BPI [23]	0.254	0.442	16.86	0.303	0.305	14.82	0.458	0.173	12.20
NPP-Net	Top3 + Offsets	**0.188**	**0.679**	**21.01**	**0.249**	**0.504**	**18.32**	0.263	**0.485**	**15.93**



More extensions and comparisons in the paper.

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