Non-Iterative Phase Retrieval With Cascaded Neural Networks

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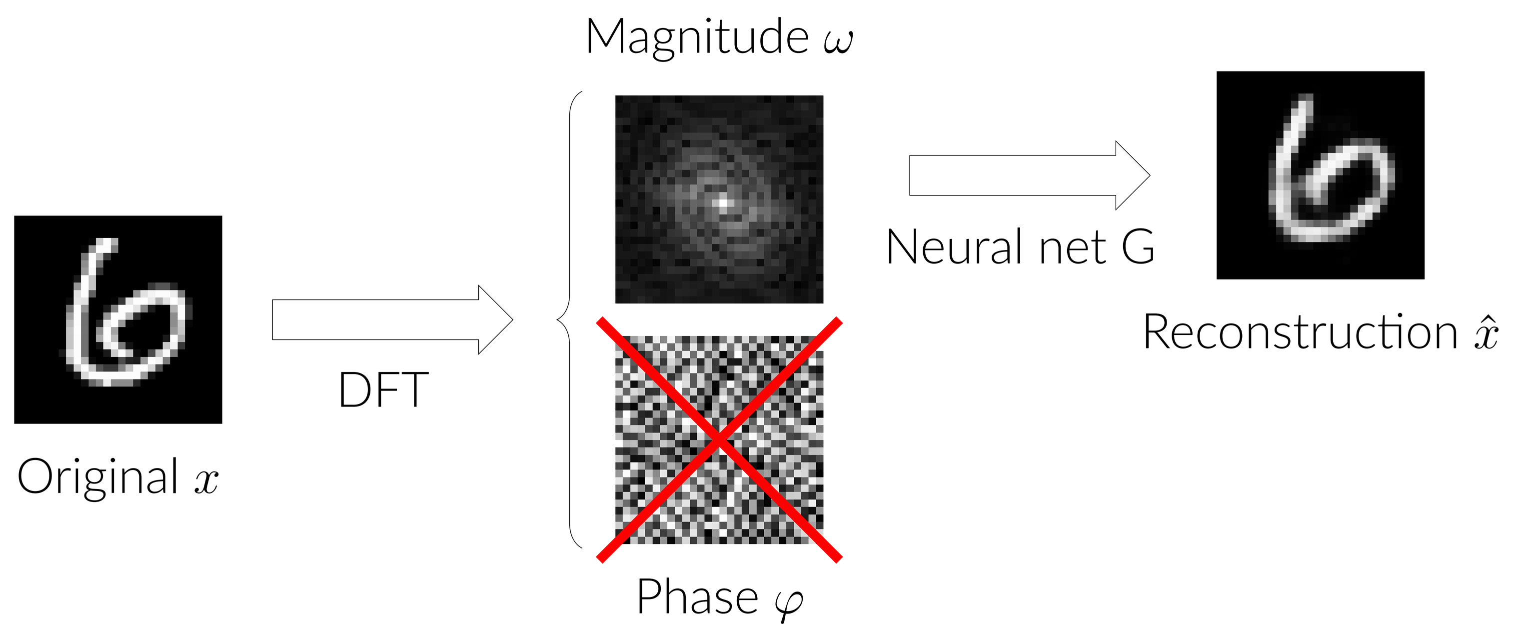
Problem Definition

- Phase retrieval aims at recovering an image x from its Fourier magnitudes

$$\omega = |\mathcal{F}x|, \text{ where } \mathcal{F} \text{ is the two-dimensional DFT.}$$

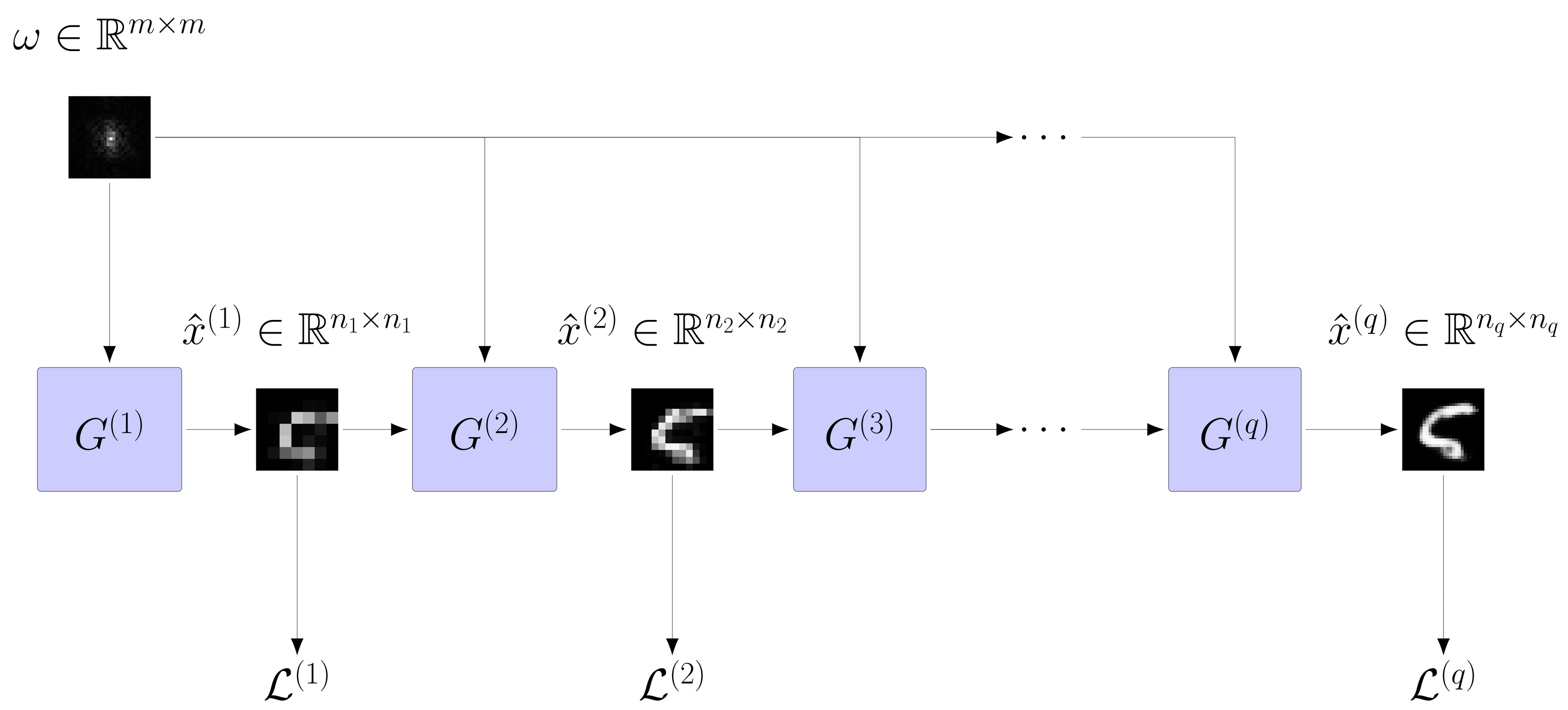


- Most information about the image is contained in the phase φ.

Proposed Method

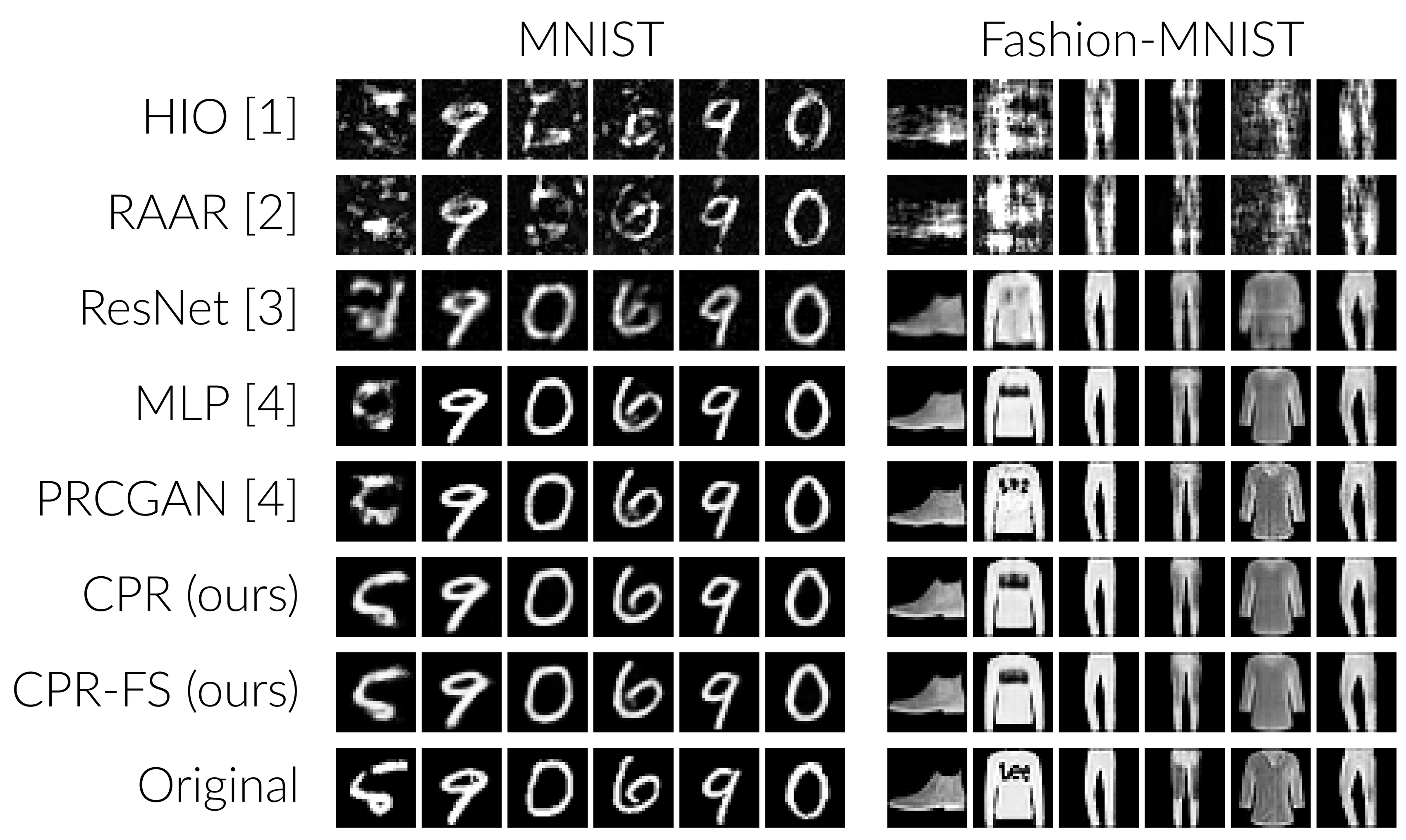
- We propose to use a neural network cascade $G^{(1)}, \ldots, G^{(q)}$ for Fourier phase retrieval.
- The magnitude image is fed to each of the networks.
- The sub-networks are updated stage-wise, i.e., we use $\mathcal{L}_1$ to update $G^{(1)}$, then the output of $G^{(1)}$ is passed as additional input to $G^{(2)}$ and so on.
- The first few networks focus on reconstructing a sub-sampled instance of the image, whereas the last sub-network predict the image at full-resolution.
- Alternatively, sub-sampling can be omitted. We denote this approach as CPR-FS.

Neural Network Cascade



- $G^{(1)}, \ldots, G^{(q)}$ are multi-layer perceptrons with three hidden layers.
- $\mathcal{L}^{(1)}, \ldots, \mathcal{L}^{(q)}$ are mean-absolute-error or mean-squared error.

Results on MNIST and Fashion-MNIST



Quantitative Results

	MNIST			EMNIST		
	MSE	MAE	SSIM	MSE	MAE	SSIM
HIO [1]	0.0441	0.1016	0.5708	0.0653	0.1379	0.5241
RAAR [2]	0.0489	0.1150	0.5232	0.0686	0.1456	0.4973
ResNet [3]	0.0269	0.0794	0.6937	0.0418	0.1170	0.5741
MLP [4]	0.0183	0.0411	0.8345	0.0229	0.0657	0.7849
PRCGAN [4]	0.0168	0.0399	0.8449	0.0239	0.0601	0.8082
CPR (ours)	**0.0123**	**0.0370**	**0.8756**	0.0153	0.0525	0.8590
CPR-FS (ours)	0.0126	0.0373	0.8729	**0.0144**	**0.0501**	**0.8700**

	Fashion-MNIST			KMNIST		
	MSE	MAE	SSIM	MSE	MAE	SSIM
HIO [1]	0.0646	0.1604	0.4404	0.0835	0.1533	0.3414
RAAR [2]	0.0669	0.1673	0.4314	0.0856	0.1559	0.3208
ResNet [3]	0.0233	0.0820	0.6634	0.0715	0.1711	0.3783
MLP [4]	0.0128	0.0526	0.7940	0.0496	0.1168	0.5991
PRCGAN [4]	0.0151	0.0572	0.7749	0.0651	0.1166	0.5711
CPR (ours)	0.0115	0.0503	0.8077	0.0447	0.1068	0.6488
CPR-FS (ours)	**0.0113**	**0.0497**	**0.8092**	**0.0433**	**0.1034**	**0.6626**

Conclusion

- Our proposed method does not fail to reconstruct unusual images as often as the compared methods. See first MNIST example.
- Both CPR and CPR-FS produce reconstructions with fewer artefacts.

References

[1] James R Fienup. Phase retrieval algorithms: a comparison. *Applied optics*, 21(15):2758--2769, 1982.

[2] D Russell Luke. Relaxed averaged alternating reflections for diffraction imaging. *Inverse problems*, 21(1):37, 2004.

[3] Yohei Nishizaki, Ryoichi Horisaki, Katsuhisa Kitaguchi, Mamoru Saito, and Jun Tanida. Analysis of non-iterative phase retrieval based on machine learning. *Optical Review*, 27(1):136--141, 2020.

[4] Tobias Uelwer, Alexander Oberstraß, and Stefan Harmeling. Phase retrieval using conditional generative adversarial networks. In *2020 25th International Conference on Pattern Recognition (ICPR)*, pages 731--738. IEEE, 2021.

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