INSTITUTO DE SISTEMAS E ROBÓTICA
UNIVERSIDADE DE COIMBRA

1st Open day & Workshop @ISR-UC

UniQode®

An integrated solution for secure authentication and traceability

Coimbra | 2022-07-14

vis team
isr-uc

Summary

1. Introduction to UniQode®
2. Research challenges

UniQode®

UniQode®

- Registered Product built in partnership with the Portuguese Mint
- 4 ISR projects since 2017
- 3 patents
- 6 publications

INCMLAB
IMPRENSA NACIONAL CASA DA MOEDA PORTUGAL

UniQode®

UniQode®


COMUNIDADE EUROPEIA | REPÚBLICA PORTUGUESA
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C.1.2 MANUEL JOSÉ FRANCISCO
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C.1.3 AV. ANTÓNIO JOSÉ DE ALMEIDA
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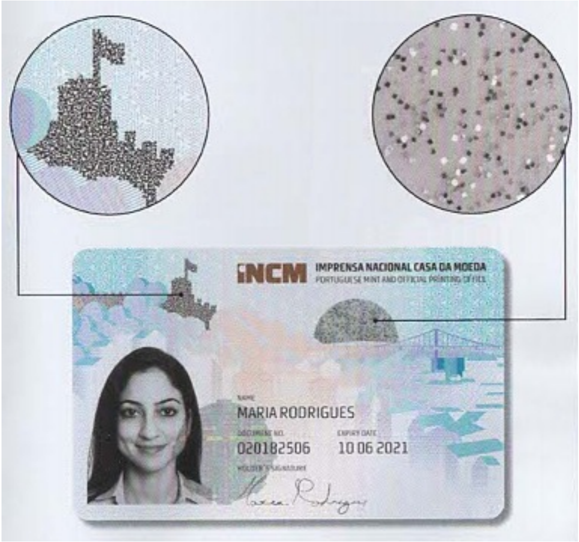
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MARIA RODRIGUES
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UniQode®


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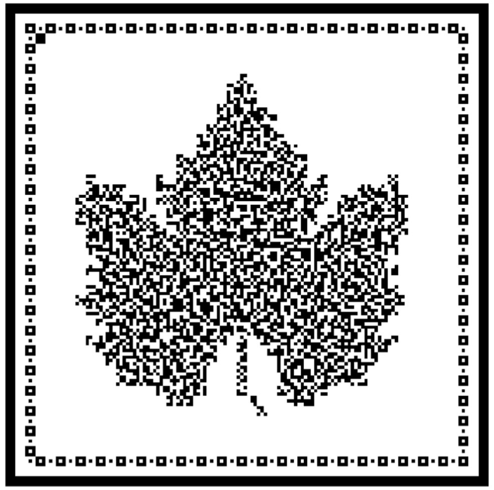
SOGRAPE
AUTHENTICITY
VERIFICATION



UniQode®

UniQode® combines **three** technologies:

PRINTED - GRAPHIC CODE
encodes a message

HOLOGRAPHIC (OVD)
encodes a unique and irreproducible message

GLITTER INKS
encodes a unique and irreproducible message

UniQode®

Glitter particles

Graphic Code

Hologram

UniQode®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SOGRAPE
AUTHENTICITY
VERIFICATION


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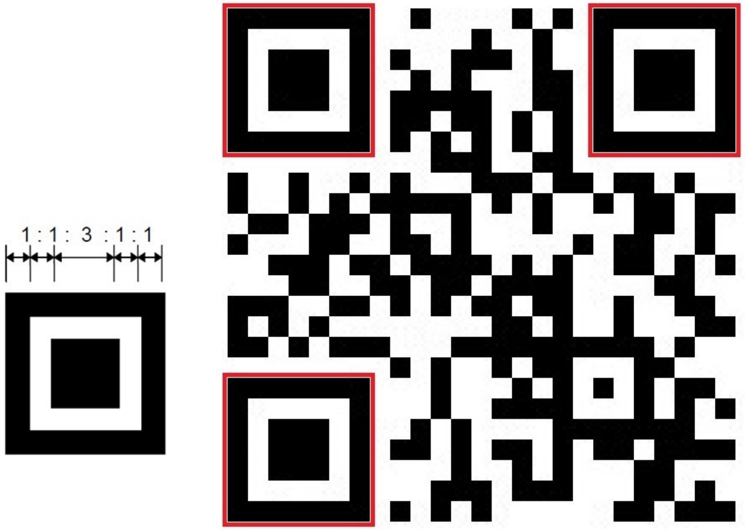
Research Challenges

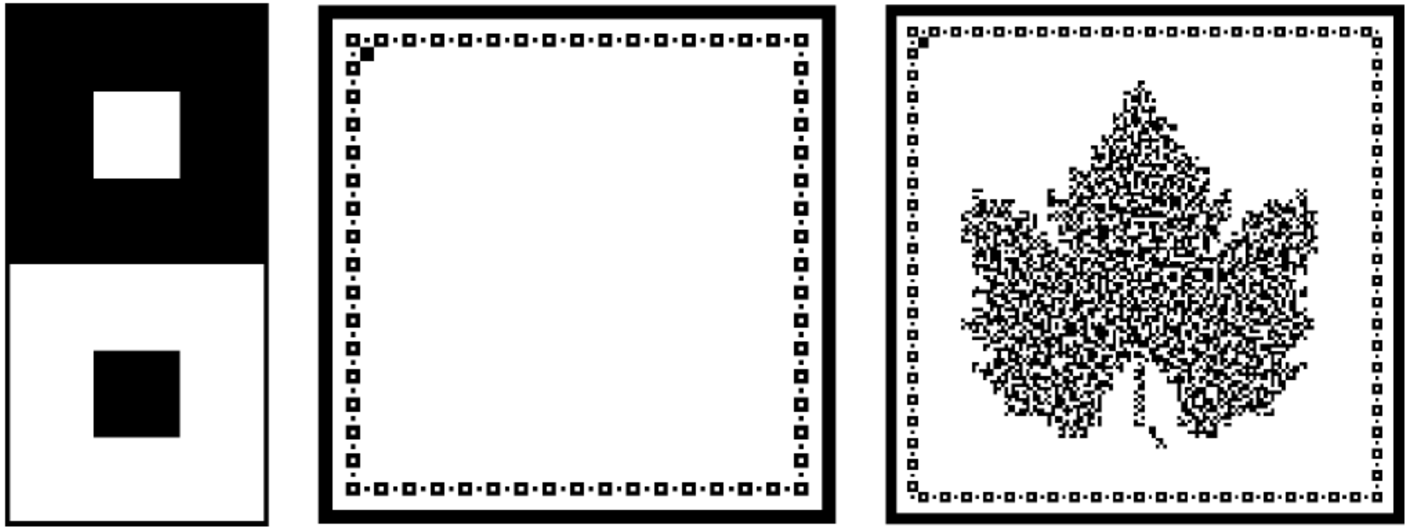
1. Universal Code Rectification
2. Superresolution

Universal Code Rectification

Problem Statement

- Graphics codes have specific patterns to guide the reconstruction
- Algorithms developed for each application



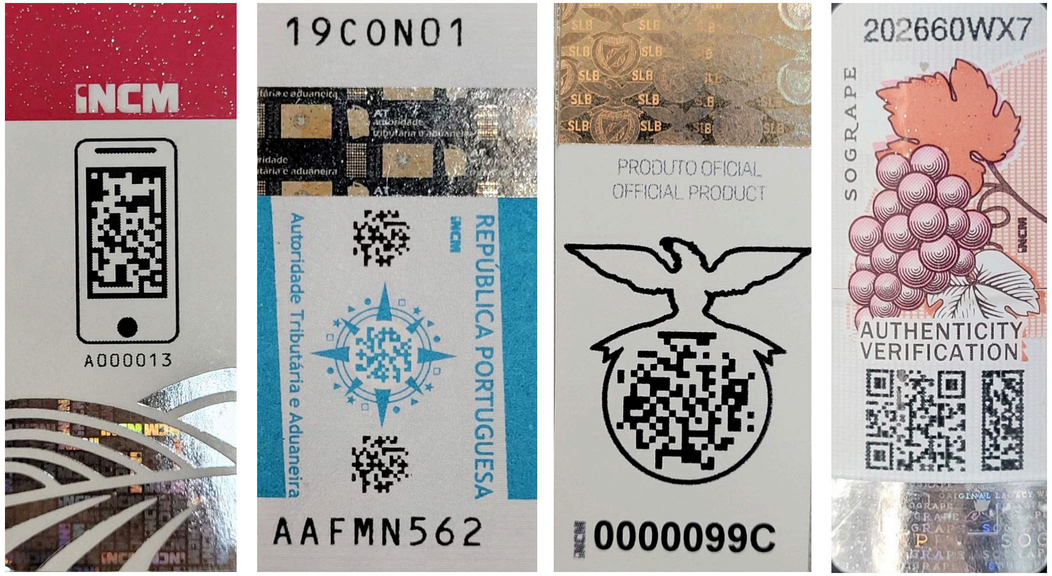


Objectives

- Decode a graphic code with minimal information of finder patterns
- Detect and correct multiple classes of codes with a single algorithm

Proposal

- Graphic codes possess a regular structure with square cells
  - Use that structure to correct orientation and scale



Orientation Correction

Orientation Correction

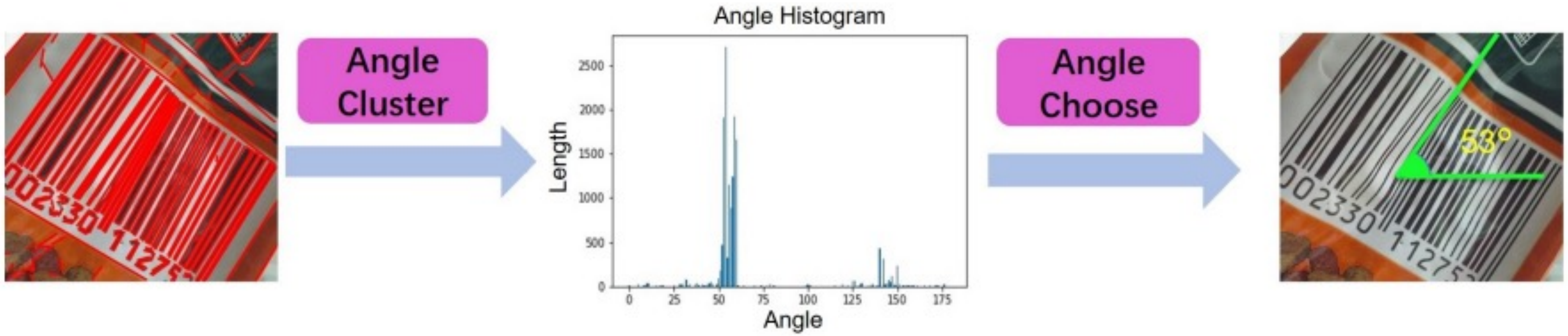


Image taken from: Y. Xiao and Z. Ming, "1D Barcode Detection via Integrated Deep-Learning and Geometric Approach," *Applied Sciences*, vol. 9, no. 16, p. 3268, Aug. 2019, doi: 10.3390/app9163268.

Orientation Correction

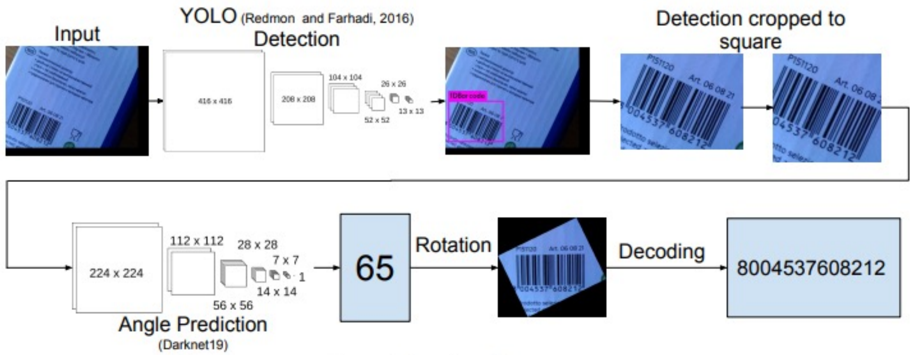


Figure 1: Overview of our system.

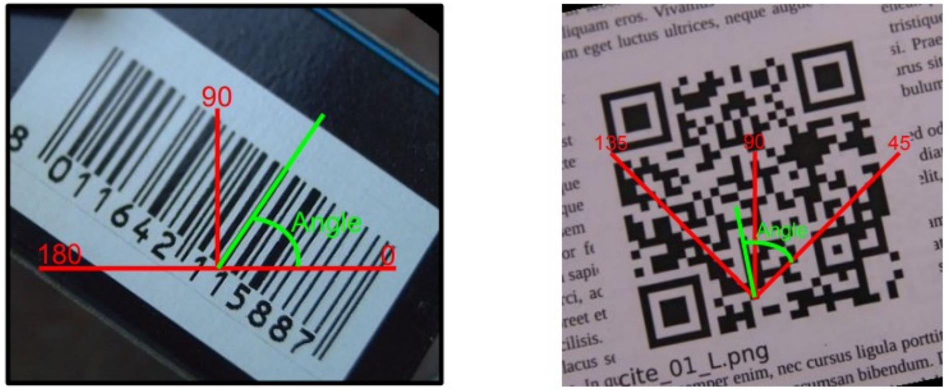
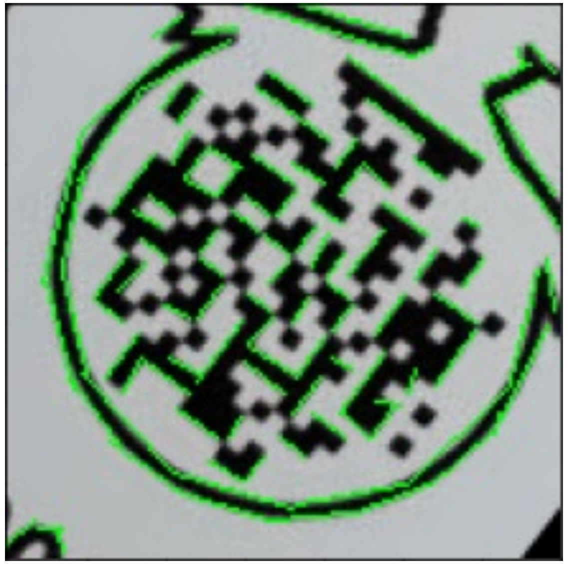


Figure 2: Examples of measuring angle.

Image taken from: D. K. Hansen, K. Nasrollahi, C. B. Rasmusen and T. B. Moeslund, "Real-Time Barcode Detection and Classification using Deep Learning," in *Proceedings of the International Joint Conference on Computational Intelligence*, Madeira, Portugal, 2017, pp. 321-327.

Orientation Correction - UniQode®



Horizontal (or vertical) lines

Perspective Correction

Perspective Correction

Image taken from: K. Chaudhury, S. DiVerdi and S. Ioffe, "Auto-rectification of user photos," in *IEEE International Conference on Image Processing (ICIP)*, Paris, France, 2014, pp. 3479-3483, doi: 10.1109/ICIP.2014.7025706.

Perspective Correction

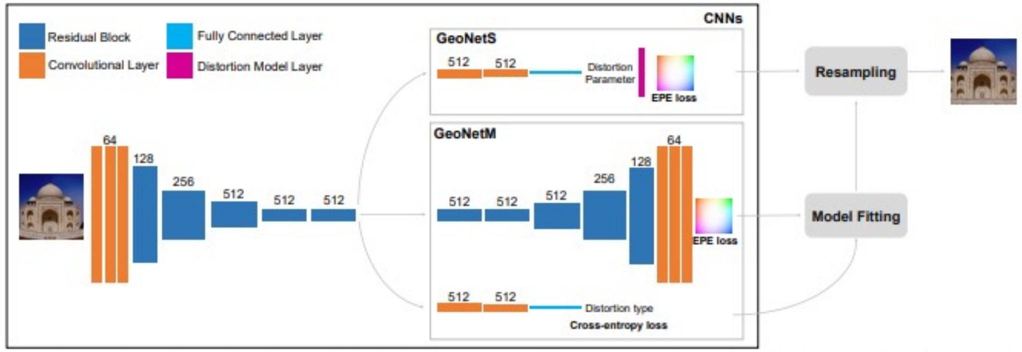


Figure 3. Overview of our entire framework, including the single-model (GeoNetS) and multi-model (GeoNetM) distortion networks (Section 3), and resampling (Section 4). Each box represents some conv layers, with vertical dimension indicating feature map spatial resolution, and horizontal dimension indicating the output channels of each conv layer in the box.

Source Corrected Flow Source Corrected Flow Source Corrected Flow

Figure 5. Results of distortions that we considered. Top row: Barrel distortion, pincushion distortion and shear distortion. Bottom row: rotation, wave distortion and perspective distortion. The flows refer to the flow before model fitting (top), after model fitting (middle), and ground truth (bottom).

Image taken from: X. Li, B. Zhang, P. V. Sander and J. Liao, "Blind Geometric Distortion Correction on Images Through Deep Learning," in *IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, California, USA, 2019, pp. 4850-4859, doi: 10.1109/CVPR.2019.00499.

Perspective Correction

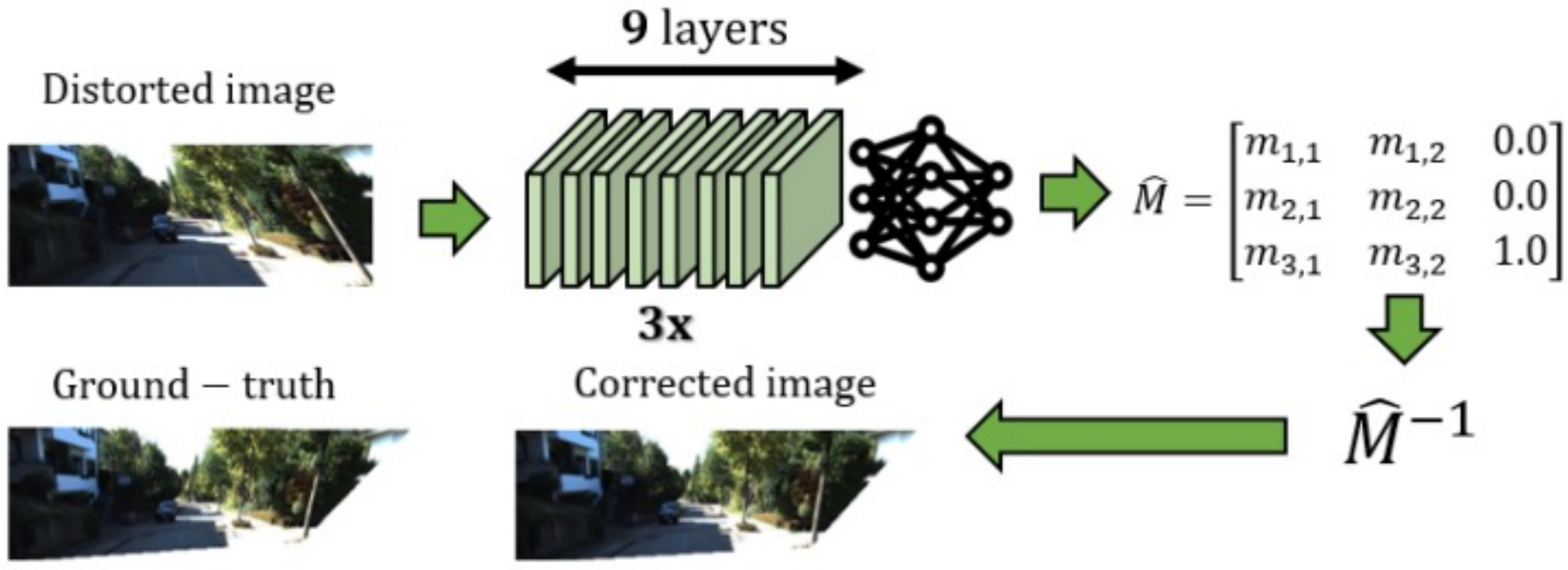
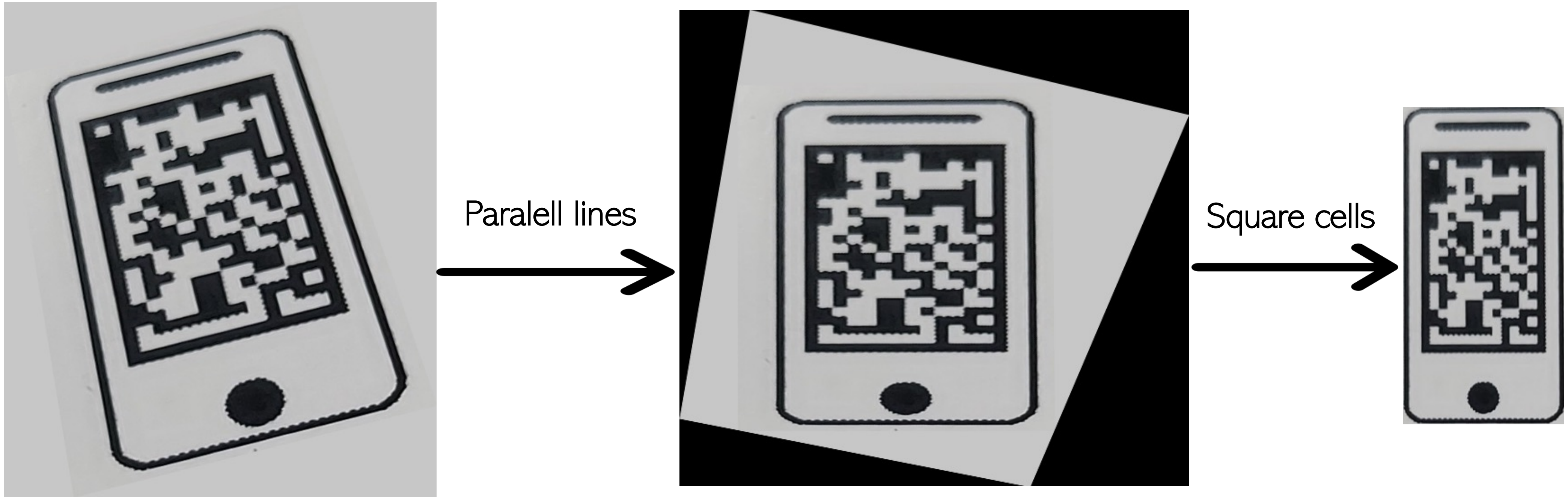


Image taken from: N. P. Del Gallego, J. Ilao, and M. Cordel, "Blind First-Order Perspective Distortion Correction Using Parallel Convolutional Neural Networks," *Sensors*, vol. 20, no. 17, 2020, doi: 10.3390/s20174898

Perspective Correction - UniQode®



Perspective Correction - UniQode®

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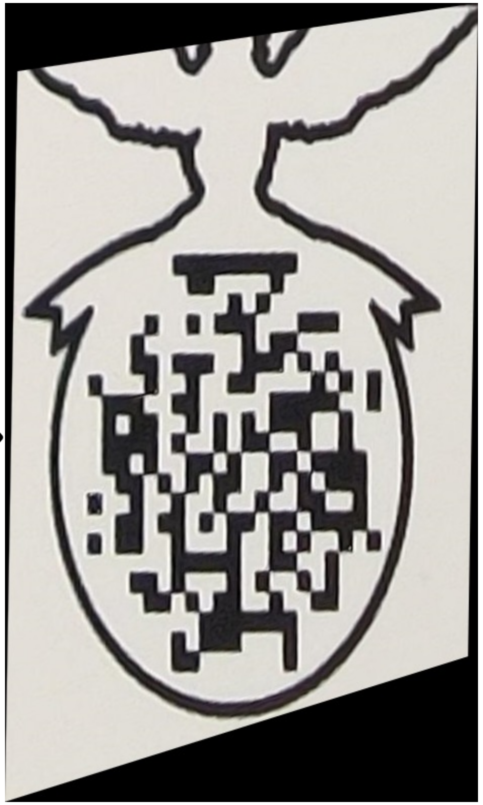

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Perspective Correction - UniQode®

Superresolution

SIREN: Sinusoidal Representation Networks

Implicit Neural Representations with Periodic Activation Functions

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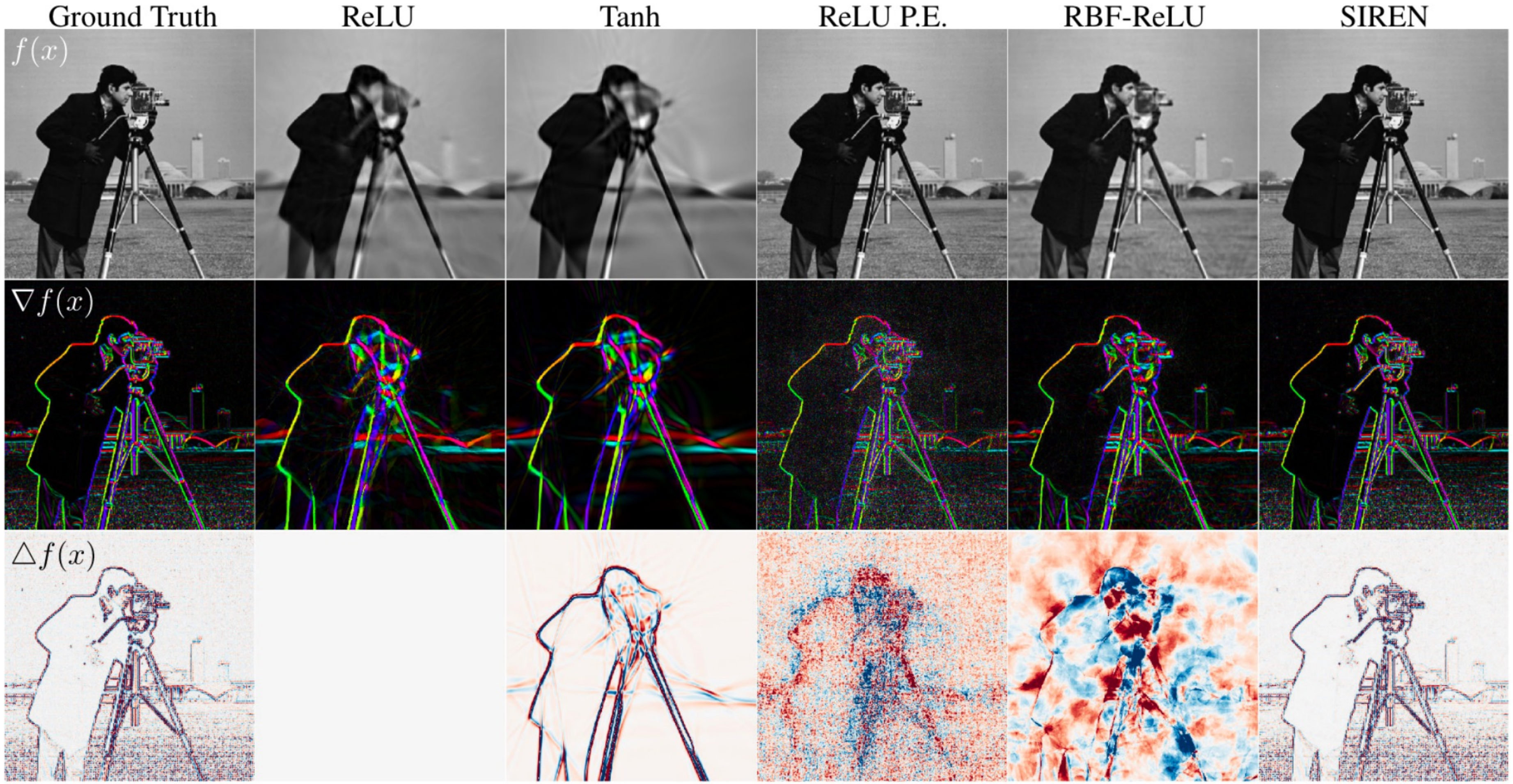
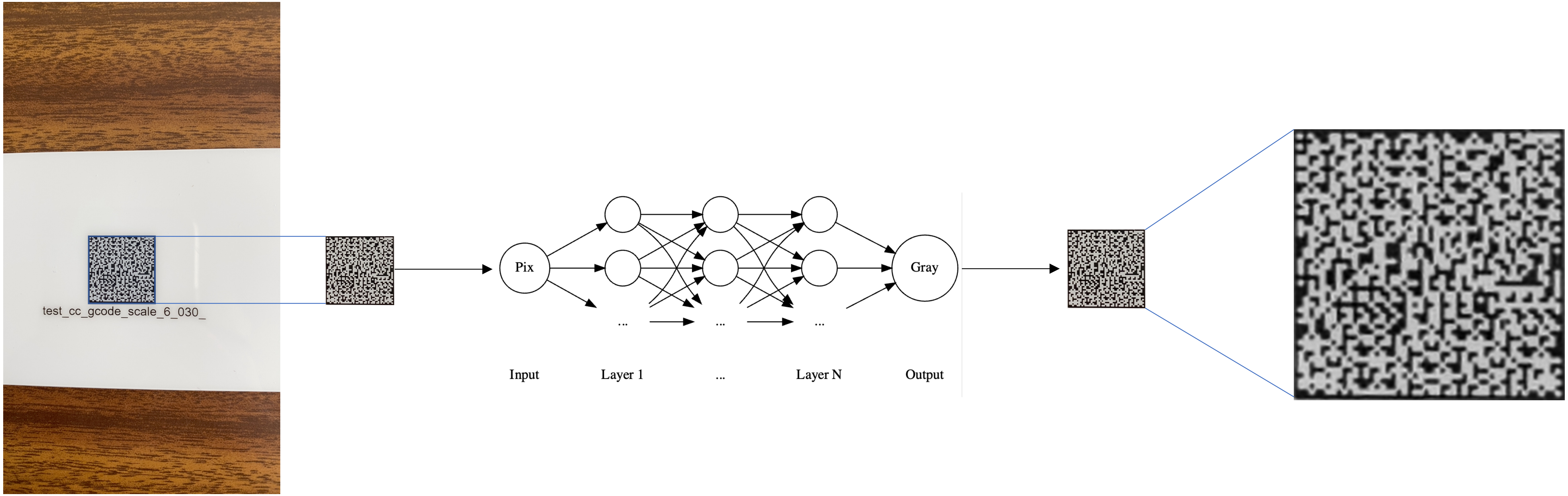


V. Sitzmann, J. Martel, A. Bergman, D. Lindell, G. Wetzstein, "Implicit Neural Representations with Periodic Activation Functions". In: *Conference on Neural Information Processing Systems (NeurIPS)*, Vancouver, Canada, 2020, pp. 7462-7473, https://proceedings.neurips.cc/paper/2020/file/53c04118df112c13a8c34b38343b9c10-Paper.pdf



V. Sitzmann, J. Martel, A. Bergman, D. Lindell, G. Wetzstein, "Implicit Neural Representations with Periodic Activation Functions". In: *Conference on Neural Information Processing Systems (NeurIPS)*, Vancouver, Canada, 2020, pp. 7462-7473, https://proceedings.neurips.cc/paper/2020/file/53c04118df112c13a8c34b38343b9c10-Paper.pdf

Known Limitations

- Each network encodes a single signal (wave, image, 3D mesh,...)
  - We may use meta-learning, or some latent representation to learn a family of signals

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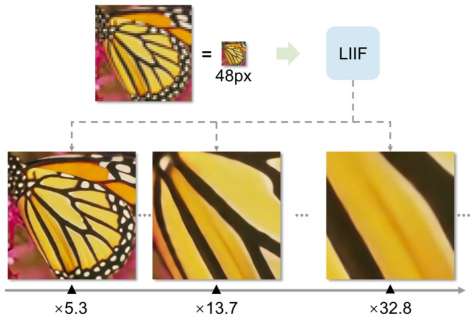
- Each network encodes a single signal (wave, image, 3D mesh,...)
  - We may use meta-learning, or some latent representation to learn a family of signals

Learning Continuous Image Representation with Local Implicit Image Function

Yinbo Chen, UC San Diego
Sifei Liu, NVIDIA
Xiaolong Wang, UC San Diego



GRADIENT ORIGIN NETWORKS

Sam Bond-Taylor* **& Chris G. Willcocks***
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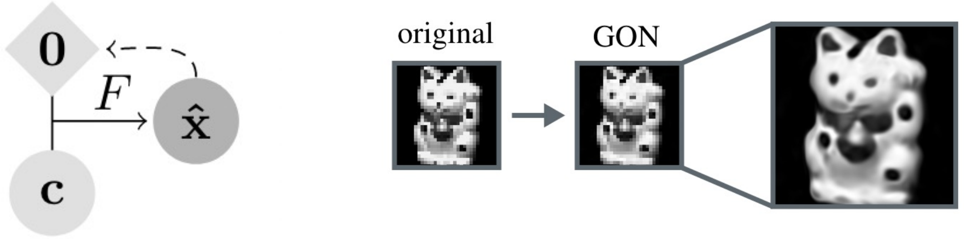
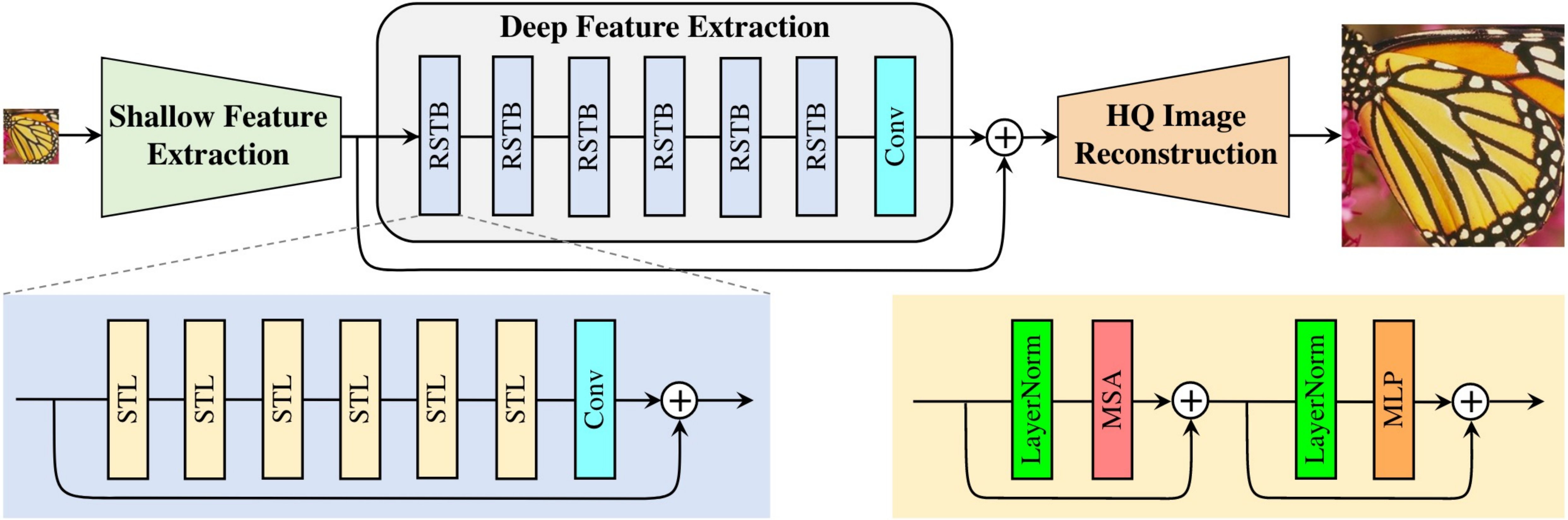


SwinIR: Image Restoration Using Swin Transformer



(a) Residual Swin Transformer Block (RSTB)

(b) Swin Transformer Layer (STL)

Image taken from: J. Liang, J. Cao, G. Sun, K. Zhang, L. Van Gool and R. Timofte, "SwinIR: Image Restoration Using Swin Transformer," *IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, 2021, pp. 1833-1844, doi: [10.1109/ICCVW54120.2021.00210](https://doi.org/10.1109/ICCVW54120.2021.00210)

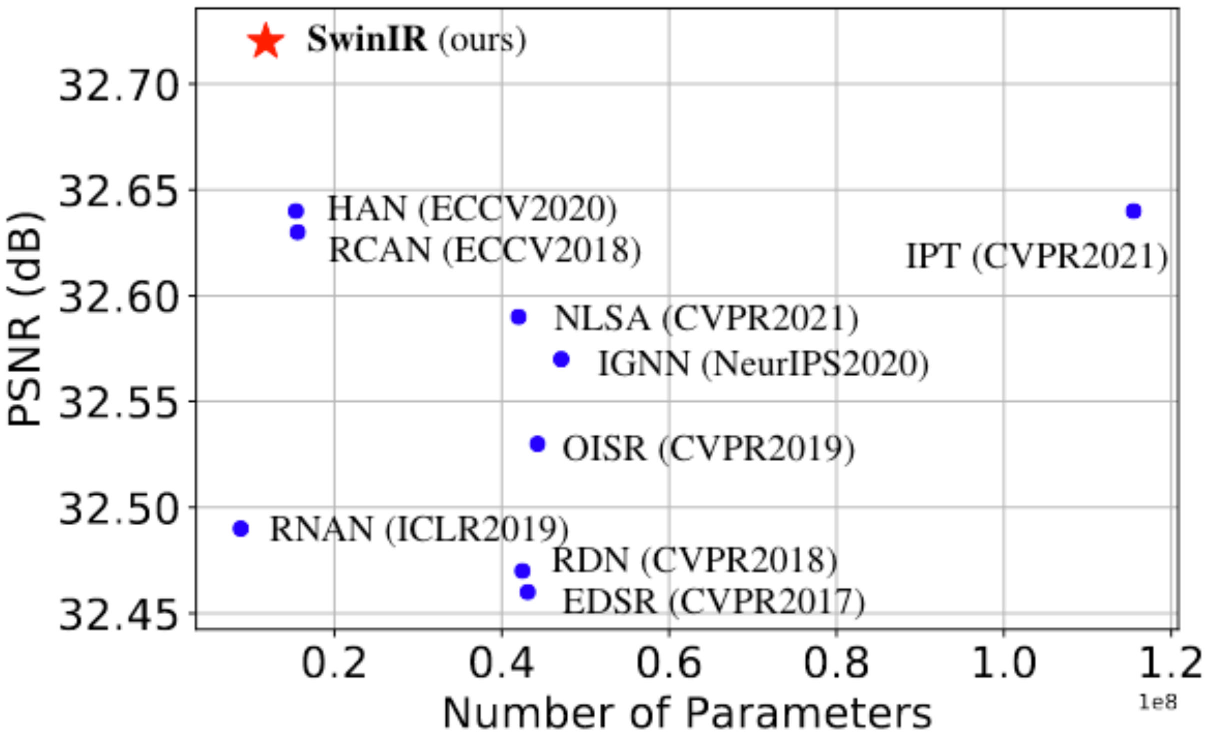
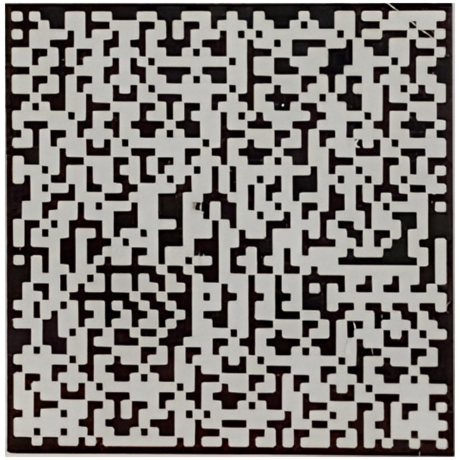


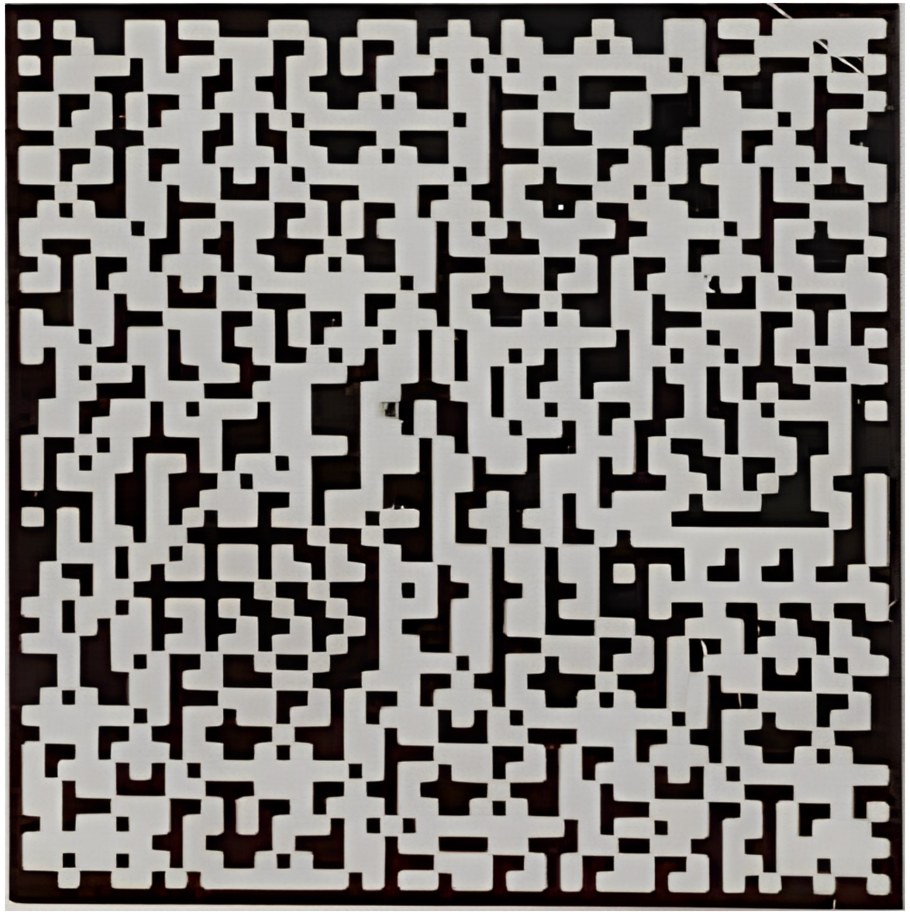
Figure 1: PSNR results v.s the total number of parameters of different methods for image SR (×4) on Set5 [3].

Image taken from: J. Liang, J. Cao, G. Sun, K. Zhang, L. Van Gool and R. Timofte, "SwinIR: Image Restoration Using Swin Transformer," *IEEE/CVF International Conference on Computer Vision Workshops (ICCVW)*, 2021, pp. 1833-1844, doi: 10.1109/ICCVW54120.2021.00210

261x263

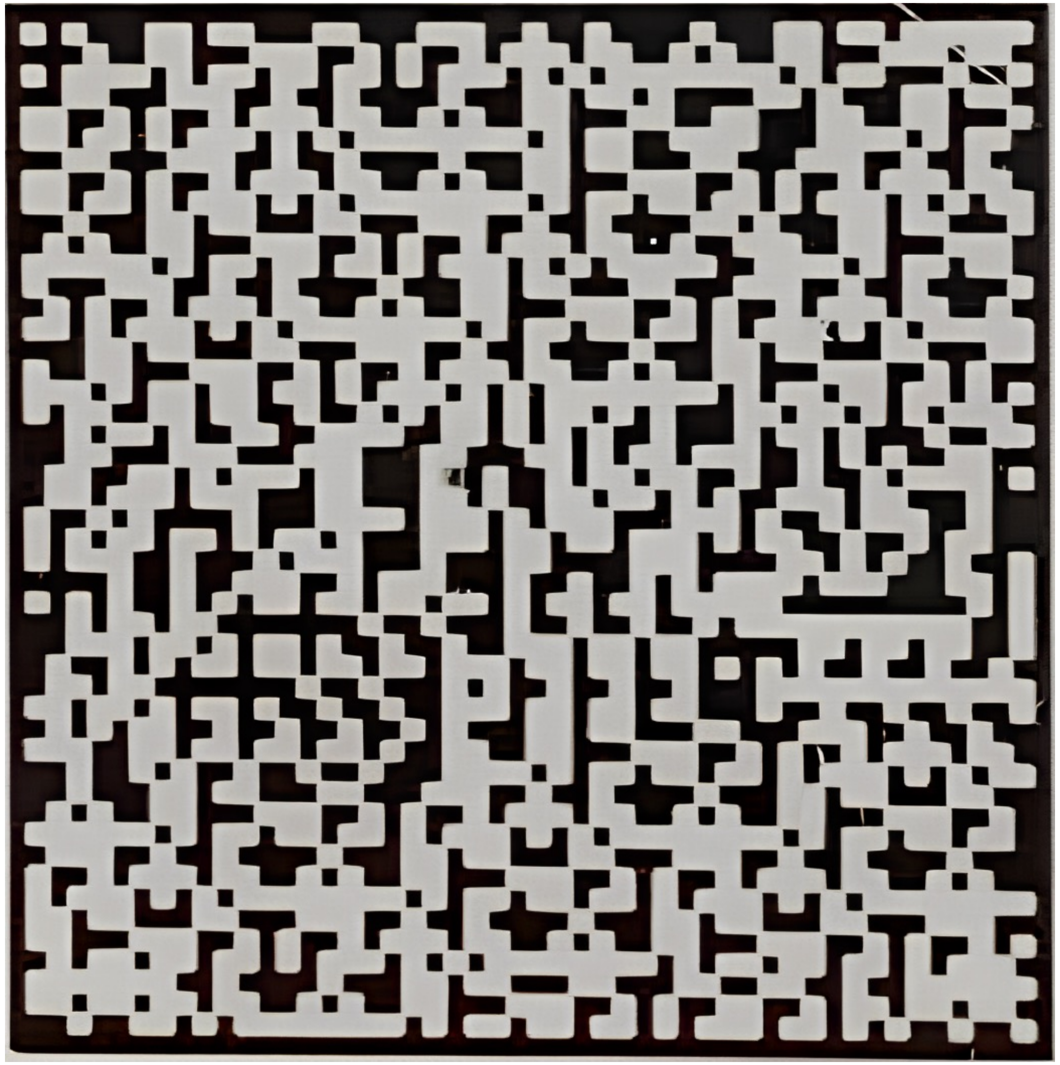


522x526



1044x1052

PS: Using pretrained models without fine-tuning on UniQode® images



SwinIR – x2 Superresolution Results

- Inference time: ~0.80 s
- PSNR: ~19.70 dB
- SSIM: ~0.85

Questions?