301: ADAPTIVE LATTICE-AWARE IMAGE DEMOSAICKING USING GLOBAL AND LOCAL INFORMATION

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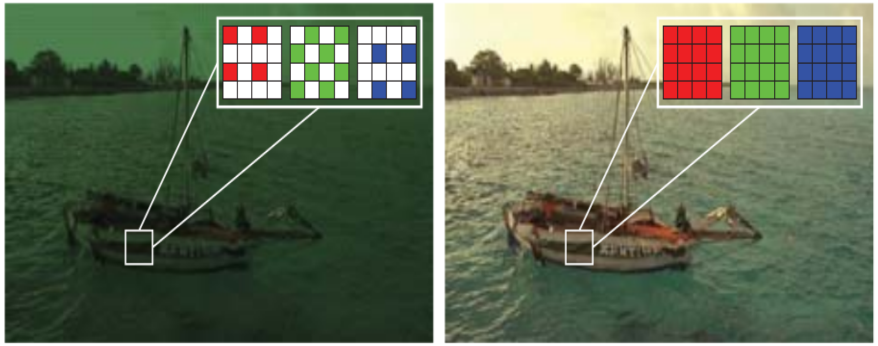
Speaker: Guenet Ilan

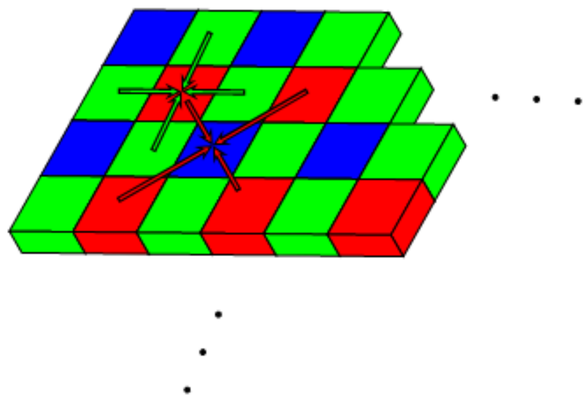
What is demosaicking?



Color filter array (left) and full-color image (right)

- Color filter array (CFA). Only allow single intensity per pixel which result.
- 25% of red, 50% of green and 25% of blue.

What is demosaicking?



Color filter array interpolation

- To render a full-color image, every missing values must be interpolated -> this process is called demosaicking.
- Collection of interpolation algorithms.

CNN (Convolutional Neural Network) based demosaicking

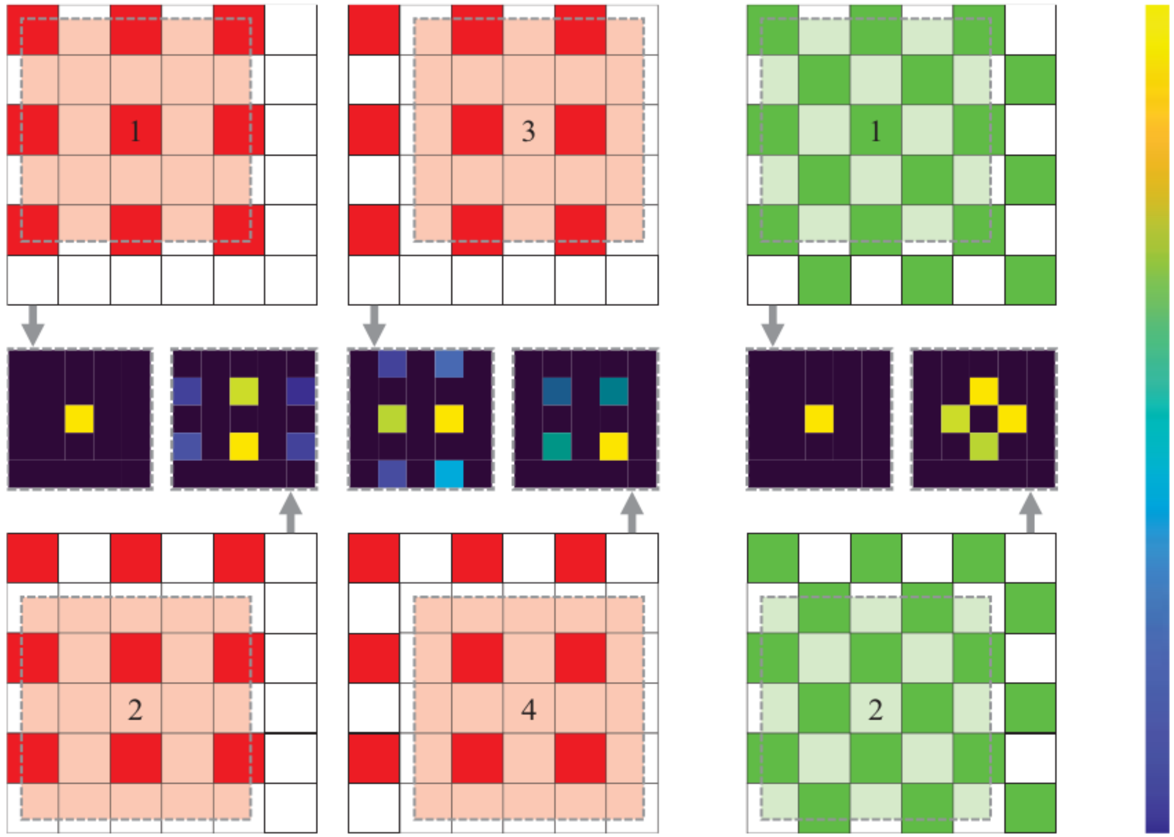
- New way for demosaicking with CNN. Outperform traditional algorithms **BUT** they do not consider lattice structures in CFAs systematically.
- **Solution**
    - **Adaptative lattice-aware Filter generator**: Determines effectively and dynamically the interpolation filters for each pixel.
    - **Local demosaicking**: Use the filter generated by the ALF generator to compute a locally demoisaicked image.
    - **Global refinement unit**: Exploit global image information to refine locally demosaicked images.

ALF (Adaptive Lattice-aware Filter) generation

Goal: determines effectively and dynamically the interpolation filters for each pixel.
Consider the lattice.

- For each pixel compute the coefficients of three filters of size 5x5 to interpolate respectively the red, green and blue.
- Adaptive to the traits of the local area
- Use DenseNet neural network
- Train 3 generators for the 3 colors
- From I^m (input mosaic image) generate $F^R_{x,y}, F^G_{x,y}, F^B_{x,y} \in \mathbb{R}^{5\times 5}$

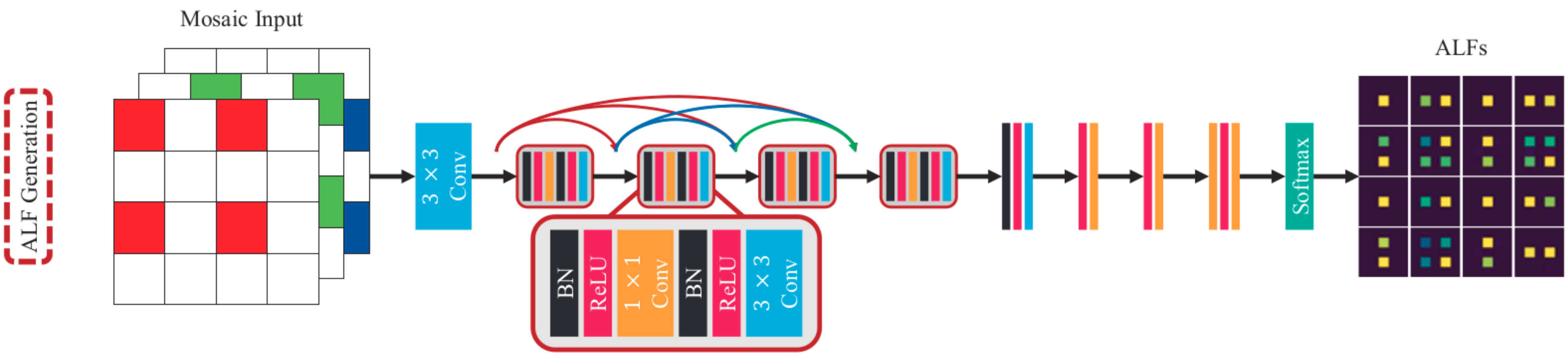
Example of generated filters



Different possible layouts of generated filters for the red channel (left) and green channel (right). The blue channel behaves like the red channel

ALF generation (DenseNet)

- **Densely connected convolutional network** as backbone of the network
- Each layer produces feature maps
- Connect all layers directly with each other $x_l = H([x_0, x_1, ..., x_{l-1}])$
- **Reduce** the number of parameters
- **Strengthen** features propragation



Adaptive lattice-aware filter generator using a densely connected convultional network

G. Huang, Z. Liu, L. Van Der Maaten and K. Q. Weinberger, "Densely Connected Convolutional Networks," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 2261-2269, doi: 10.1109/CVPR.2017.243.

Local demosaicking

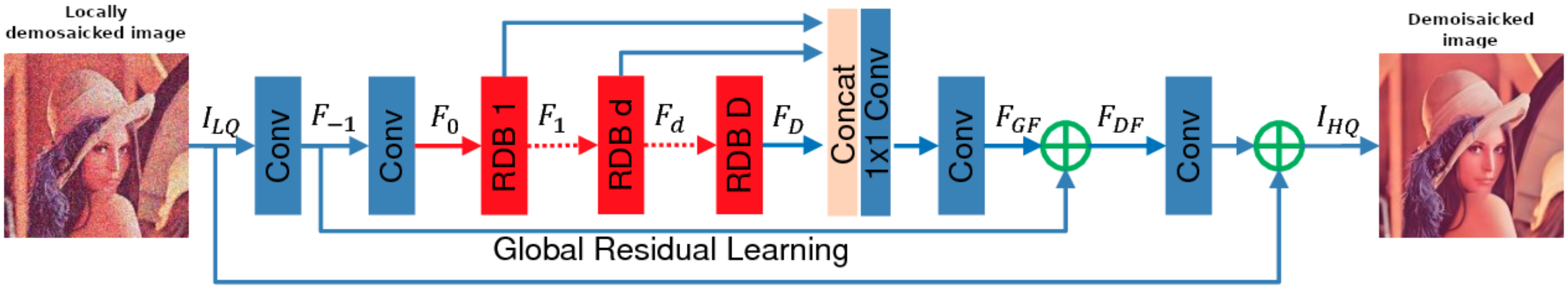
Goal: Use the filters generated by the ALF generator to compute a locally demoisaicked image.

- Use the **information in the neighborhood** of each pixel only
- Divide I^m into 3 channels (R^m, G^m, B^m)
- For each pixel convolute a channel with its corresponding generated filter. $G^{dm}(x, y) = \sum_{i=-2}^{2} \sum_{j=-2}^{2} F_{x,y}^{G}(i, j) G^m(x + i, y + j)$
- $(R^{dm}, G^{dm}, B^{dm}) = I^{md}$ such that I^{md} is the locally demosaicked image.

GRU (Global Refinement Unit)

Goal: Exploit global information to refine locally demosaicked images efficiently.

- Based on the **residual dense network**.
- Better and quicker convergence
- Extract abundant local features
- Dilated convolutions to exploit global information more effectively



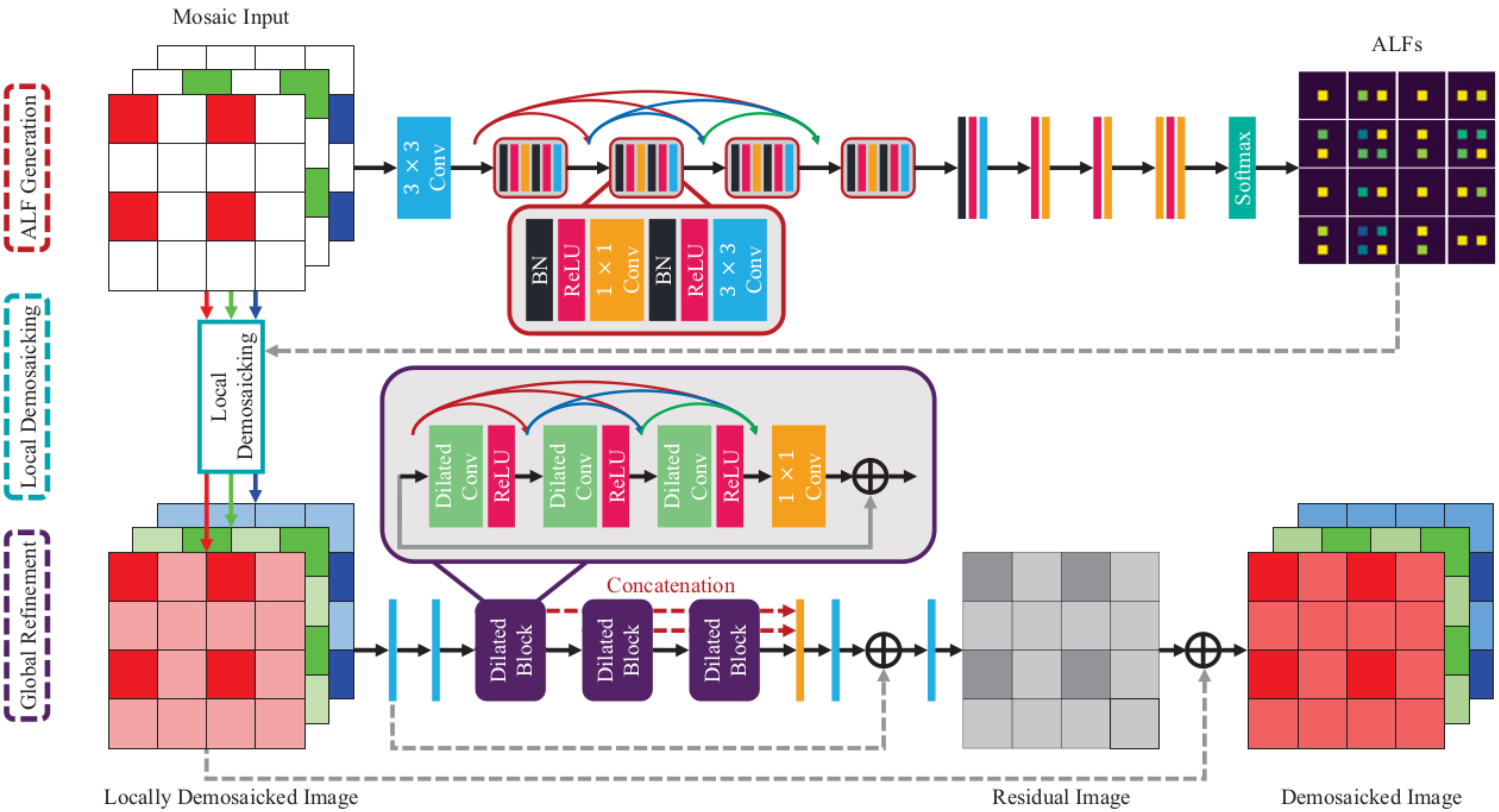
Example of an use-case of a residual dense network

Y. Zhang, Y. Tian, Y. Kong, B. Zhong and Y. Fu, "Residual Dense Network for Image Super-Resolution," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2018, pp. 2472-2481, doi: 10.1109/CVPR.2018.00262.

Network training

- Minimize objective function given by $\mathcal{L} = \mathcal{L}_{local} + \mathcal{L}_{global}$ where:
  - $\mathcal{L}_{local} = \frac{1}{WH} \sum_{x=1}^{W} \sum_{y=1}^{H} \| I^{dm}(x,y) - \bar{I}(x,y) \|_1$
    - Compare a locally demoisaicked image I^{dm} with the ground truth $\bar{I}$
  - $\mathcal{L}_{global} = \frac{1}{WH} \sum_{x=1}^{W} \sum_{y=1}^{H} \| \mathcal{R}(x,y) - \mathcal{R}_{GRU}(x,y) \|_1$
    - Compare a defined residual image $\mathcal{R} = \bar{I} - I^{dm}$ with the predicted residual image $\mathcal{R}_{GRU}$.
  - The minimization of $\mathcal{L}_{global}$ **depends on** $\mathcal{L}_{local}$
- Adam Optimizer with a learning rate of 10^{-4}, a batch size of 4 for 60 epochs

Overall architecture



Overall architecture of the proposed solution

Experiment results

- Flickr500 (500 images) dataset for training
- Kodak (12 images) and McMaster (18 images) dataset for evaluation
- **Peak signal-to-noise ratio** (PSNR) score: ratio between the maximum possible power of a signal and the power of corrupting noise (computing with a **Mean Square Error**) that affects the fidelity of its representation.
- Higher PSNR indicates that the reconstruction is of higher quality

Results comparison

	Kodak	McMaster
Menon et al.	39.19	32.27
Zhang and Wu	40.11	34.47
Kiku et al.	39.17	36.89
Gharbi et al.	41.20	39.50
Tan et al.	42.12	37.29
Kokkinos and Lefkimmiatis	41.50	39.70
Proposed	**43.19**	**39.82**

Every reference given here can be found in the paper

Conclusion

- 3 steps:
  - **Filters generations** adapted the to pixel neighborhood
  - **Local demosaicking** by interpolating the input with the generated filters
  - **Refine** locally demoisaicked images by using a residual dense network
- To obtain a **globally demoisaicked full-color image**
- **State-of-the-art** demoisaicking technique (outperform others)

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- G. Huang, Z. Liu, L. Van Der Maaten and K. Q. Weinberger, "Densely Connected Convolutional Networks," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 2261-2269, doi: 10.1109/CVPR.2017.243.
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