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Image Deblurring on Gopro Dataset

Ngo Duy Dat - 20225480

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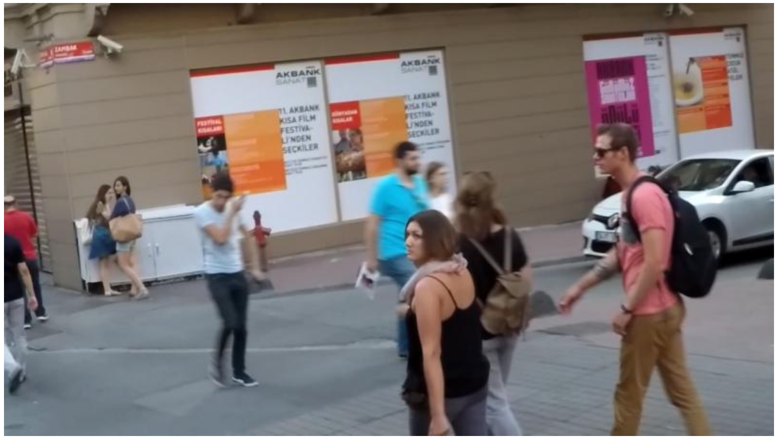
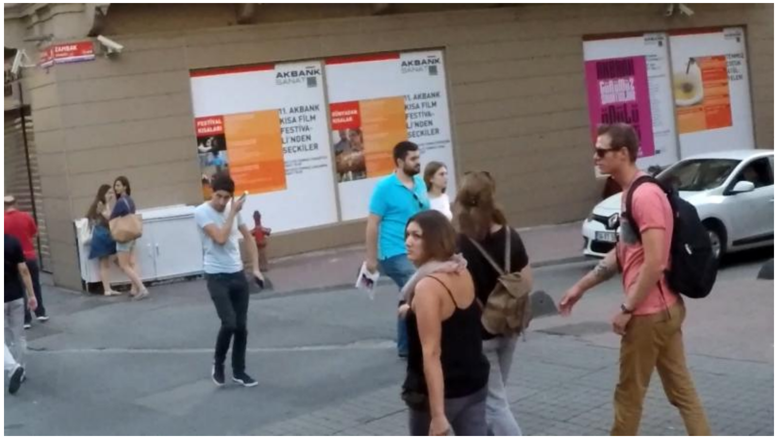
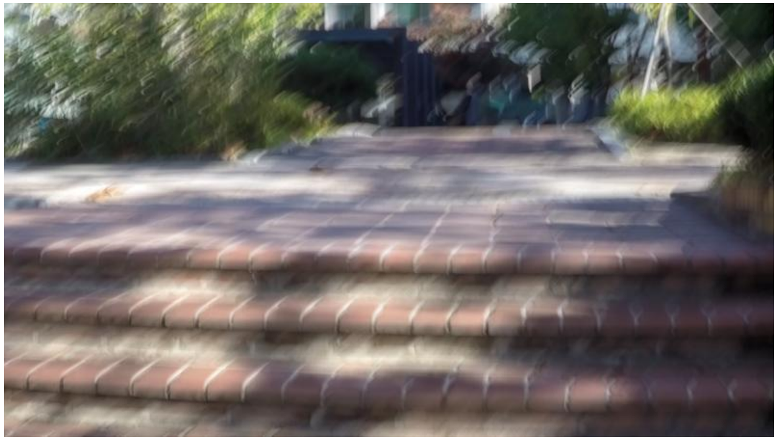
Problem Formulation

- Image deblurring is the task of restoring clear images from those blurred by camera motion or other factors.

Gopro dataset

- The dataset consists of pairs of a realistic blurry image and the corresponding ground truth sharp image that are obtained by a high-speed camera.
- 3214 pairs : 2103 for training and 1111 for tests

Gopro dataset

Blur	Sharp
	
	

Traditional Methods

Traditional methods

Some common traditional image deblurring methods

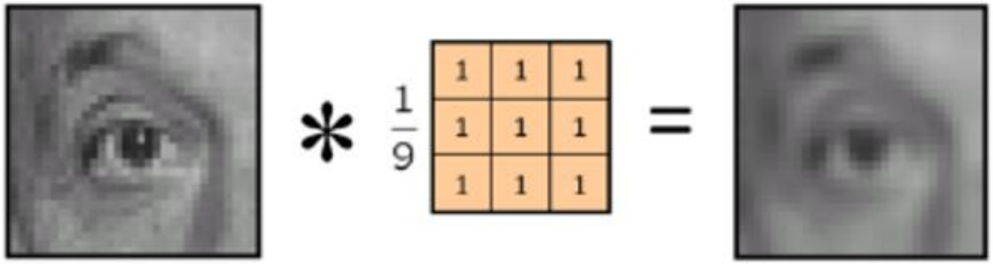
- **Wiener Filtering:** balances deblurring and noise suppression using a statistical model of the signal and noise.
- **Lucy-Richardson Deconvolution:** An iterative algorithm based on maximum likelihood estimation, assuming Poisson noise and known blur kernel.

Blur Kernel

- A blur kernel is a small matrix that represents how a single point spread out of “blurs” in an image.
- Traditional methods model image blurring explicitly as:

$$y = x * k + n$$

where y: blurred image
x: sharp image
k: blur kernel
n: noise



Original

Blur (with a mean filter)

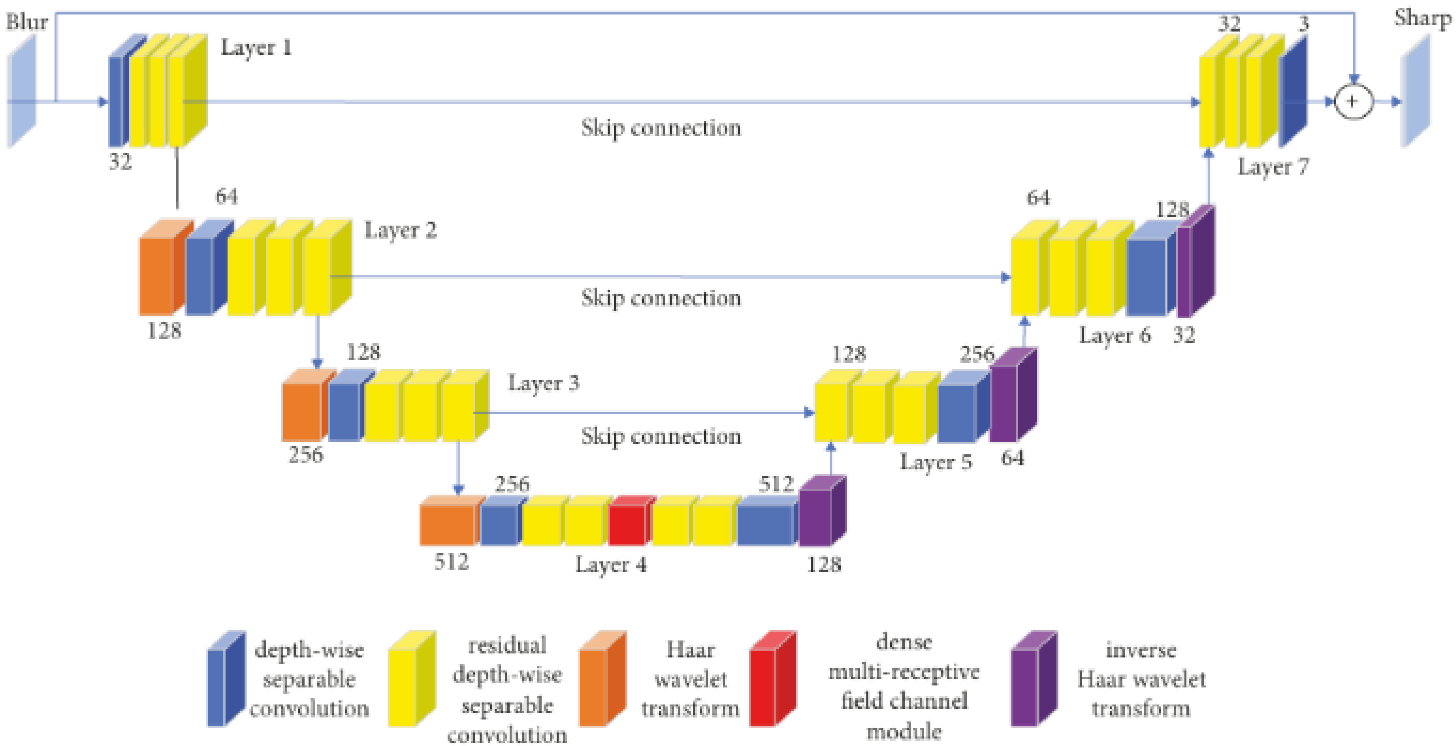
Problem with traditional methods

- Traditional methods heavily depends on known blur kernel to reverse the process of blurring image.
- This is not suitable for the task of deblurring on Gopro dataset:
  - GoPro images suffer from complex, spatially varying blur due to fast camera motion.
  - In GoPro images, different parts of the image are blurred differently.

Improved Unet model

Overall Architecture

A U-shaped architecture with an encoder, a bottleneck, and a decoder:



Haar wavelet transform

Haar wavelet transform divide image into 4 subbands to achieve different image frequency information.

a	b	a	b
c	d	c	d
a	b	a	b
c	d	c	d

$$x1 = \begin{bmatrix} a & a \\ a & a \end{bmatrix},$$

$$x2 = \begin{bmatrix} b & b \\ b & b \end{bmatrix},$$

$$x3 = \begin{bmatrix} c & c \\ c & c \end{bmatrix},$$

$$x4 = \begin{bmatrix} d & d \\ d & d \end{bmatrix},$$

$$I_{HL} = \frac{(-x1 - x2 + x3 + x4)}{2},$$

$$I_{HL} = \frac{(-x1 + x2 - x3 + x4)}{2},$$

$$I_{HH} = \frac{(x1 - x2 - x3 + x4)}{2},$$

$$I_{LL} = \frac{(x1 + x2 + x3 + x4)}{2}.$$

Inverse Haar wavelet transform

Inverse Haar wavelet transform recover the original matrix by calculating x1, x2, x3, x4.

$$x1 = \frac{(I_{LL} - I_{HL} - I_{LH} + I_{HH})}{4},$$

$$x2 = \frac{(I_{LL} - I_{HL} + I_{LH} - I_{HH})}{4},$$

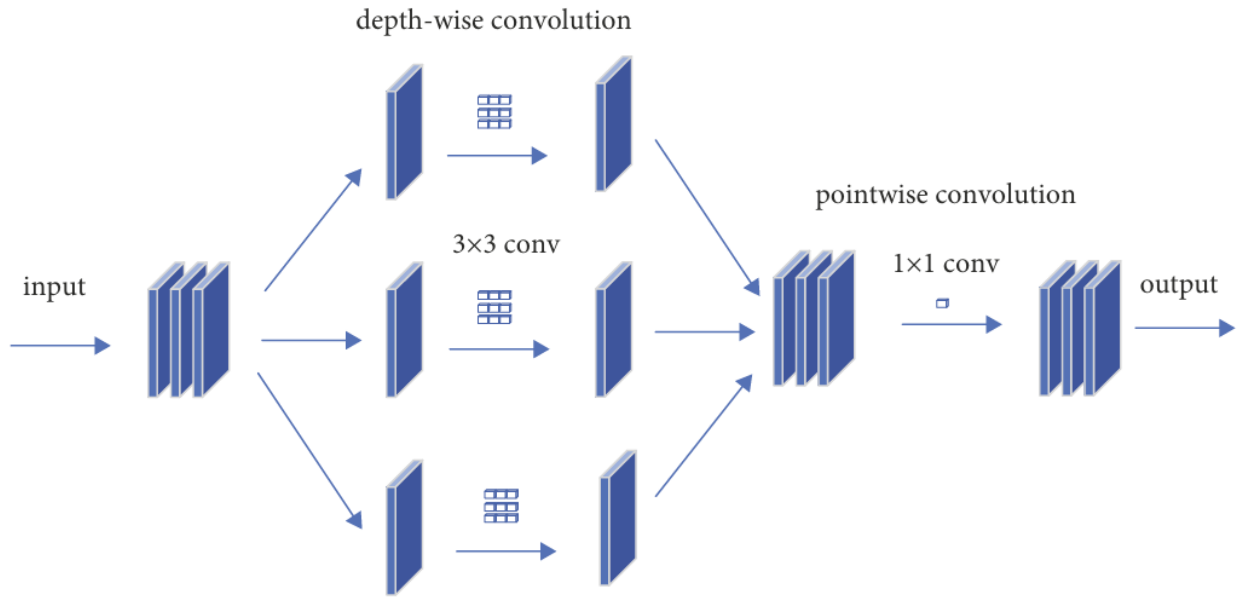
$$x3 = \frac{(I_{LL} + I_{HL} - I_{LH} - I_{HH})}{4},$$

$$x4 = \frac{(I_{LL} + I_{HL} + I_{LH} + I_{HH})}{4}.$$

Depth-wise seperable convolution (DSC)

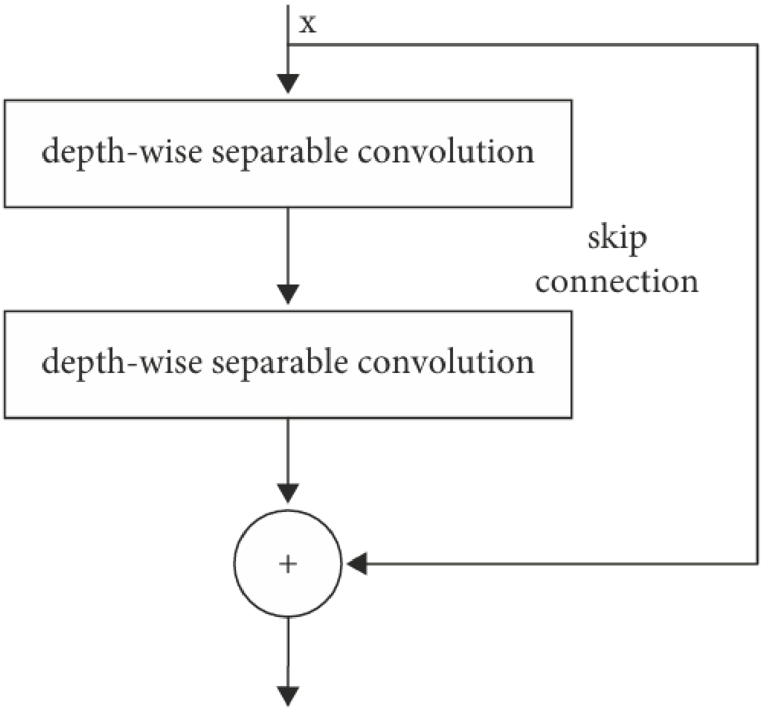
Depth-wise convolution block use depth-wise convolution instead of standard convolution, which :

- Reduce computational cost
- Allow multi-scale feature extraction



Residual depth-wise seperable convolution

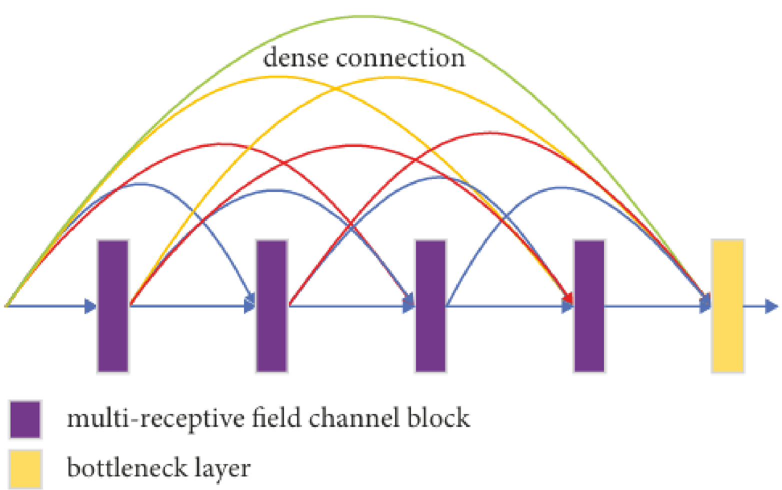
The residual DSC block consists 2 DSC blocks and addition of skip connections, which solves the problem of gradient descent.



Dense multi-receptive field channel(DMRFC) module

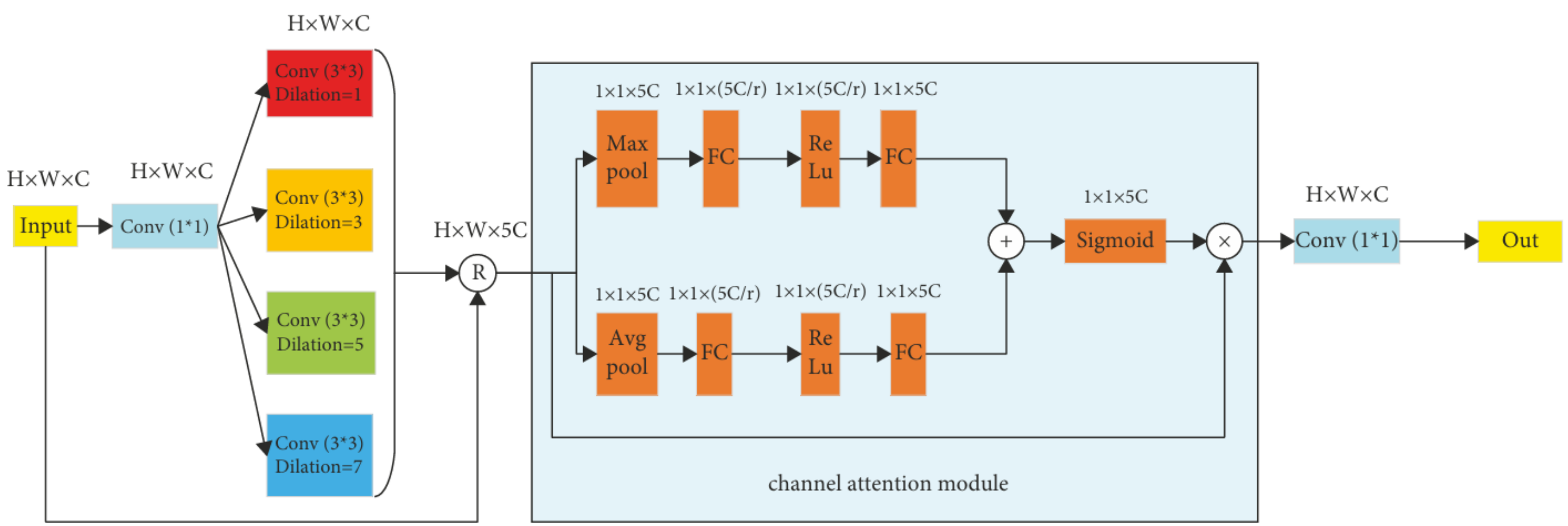
The DMRFC module is composed of four multi-receptive field channel(MRFC) blocks and a bottleneck layer:

- MRFC blocks: obtain deep sematic information from image
- Bottleneck layer: reduce number of feature for computational efficiency



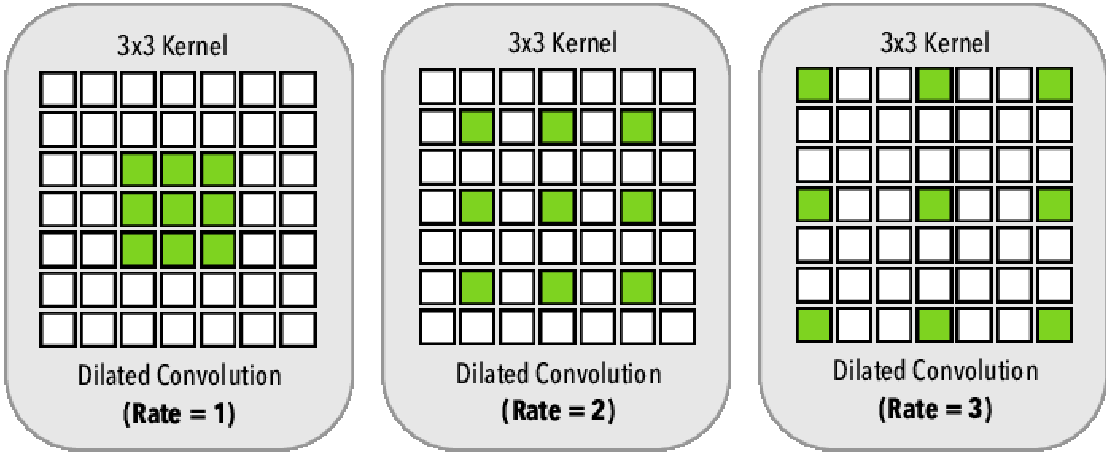
Multi-receptive field channel (MRFC) block

- Extract features in 4 paralleled branches with different dilation rate, allow simultaneously perceive features at multiple scales.
- Channel attention module capture most important feature and amplify them



Multi-receptive field channel (MRFC) block

- Different dilation rate allows capture features at multi-scale, which is essential for image deblurring.



Training Setup

Loss function

- Structural similarity index (SSIM) is a metrix to measure the similarity between 2 images

$$\mathrm{SSIM}(\mathbf{x}, \mathbf{y}) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{\left(\mu_x^2 + \mu_y^2 + C_1\right)\left(\sigma_x^2 + \sigma_y^2 + C_2\right)}.$$

- The loss function used here is the combination of SSIM loss and MSE loss, w1 is a hyperparameter set at 0.001.

$$L_{\mathrm{SSIM}} = 1 - \mathrm{SSIM}\,(R, S),$$

$$L_{\mathrm{total}} = L_{\mathrm{MSE}} + w_1 L_{\mathrm{SSIM}}.$$

Training detail

- The model is trained over 1000 epochs
- The learning rate initially is 1e-4, is gradually decreased until 1e-5
- The optimizer is Adam
- The model is trained on Kaggle

Result

Peak Signal-to-Noise Ratio (PSNR)

- PSNR measures the quality of a reconstructed image by comparing it to its original, perfect version

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{RMSE}^2}\right),$$

Where:

- MAX is the highest pixel value of the deblurred image
- RMSE is the root mean squared error between deblurred image and the sharp image

Result

- We evaluate the model using 2 metrics: PSNR and SSIM

	Our model	Deblur-GAN V2	Restormer
PSNR ↑	28.85	29.55	32.92
SSIM ↑	0.8688	0.932	0.961

Result


Blurred Image
Ground Truth Sharp
Predicted Deblurred
Blurred Image
Ground Truth Sharp
Predicted Deblurred
Blurred Image
Ground Truth Sharp
Predicted Deblurred

Conclusion

Conclusion

- This project has successfully implemented an Unet-based model for image deblurring task on GoPro Dataset.
- The model has achieved the result of 28.85 for PSNR and 0.8688 for SSIM.
- However, the deblurred images generated still lack sharp details and struggle with human faces.
- Further work:
  - Further training for more epochs, optimizing hyperparameters
  - Leverage transformer-based models to achieve state-of-the-art result

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