https://github.com/VladCheremnykh/Kernel_raznos

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Non-uniform Blur Kernel Estimation via Adaptive Basis Decomposition

Course of Machine Learning

Final Project

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Motivation

- Motion blur estimation and restoration are fundamental problems in image processing and computer vision;
- Motion blur is produced by camera or subject movement, inaccurate focusing, low resolution of an aperture, out-of focus and so on;
- Consequences - image quality degradation:
  - Aesthetic blurry images;
  - Performance degradation of subsequent computer vision tasks: tracking, detection, classification, etc.

Problem Statement

In order to get a clearer picture we can either reshoot the same photo or use our knowledge of Machine Learning and reproduce a deblurred image.

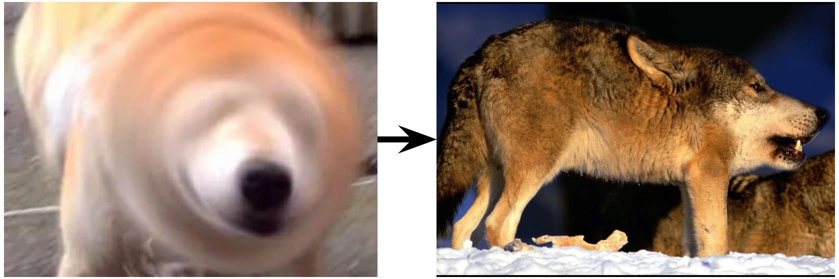

Figure 1. Example of blurred and deblurred images.

In this work we focus on the realistic non-uniform motion blur estimation.

Major goal: provide dense, accurate estimates of non-uniform motion fields via local kernel estimation. Estimate kernels at the pixel level.

Secondary goal: once the motion field has been estimated, perform non-blind image deblurring.

Non-uniform Blur Kernel Estimation via Adaptive Basis Decomposition

Given a blurry image, a neural network predicts a set of kernel basis and corresponding pixel-wise mixing coefficients allowing to deblur the corresponding sharp image by first convolving it with each basis kernel and performing a weighted sum using the mixing coefficients.

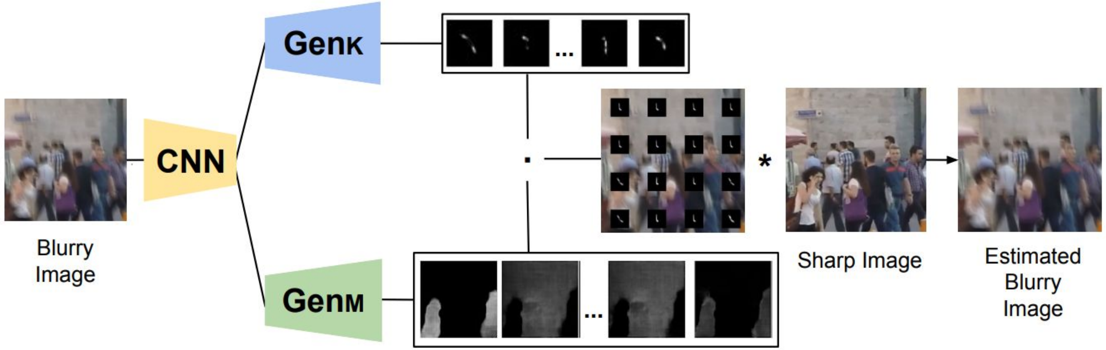

Figure 2. Overview of a Non-uniform method.*

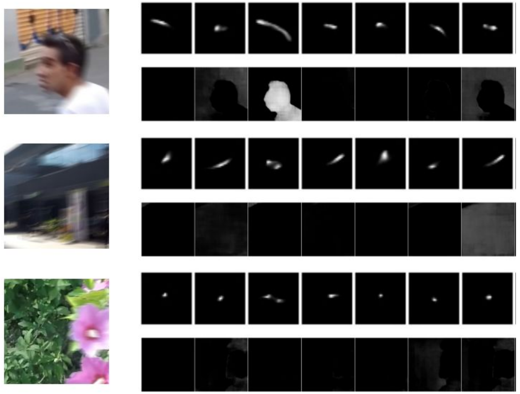

Figure 3. Examples of generated kernels and corresponding mixing coefficients.*

* Non-uniform Blur Kernel Estimation via Adaptive Basis Decomposition // Guillermo Carbajal, Patricia Vitoria, Mauricio Delbracio, Pablo Musé, José Lezama // 1 Feb 2021.

Non-uniform Blur Kernel Model Architecture

The proposed network is composed by an encoder and 2 decoders. The encoder takes as an input a blurry image. Decoders output the motion kernel basis and corresponding mixing coefficients.

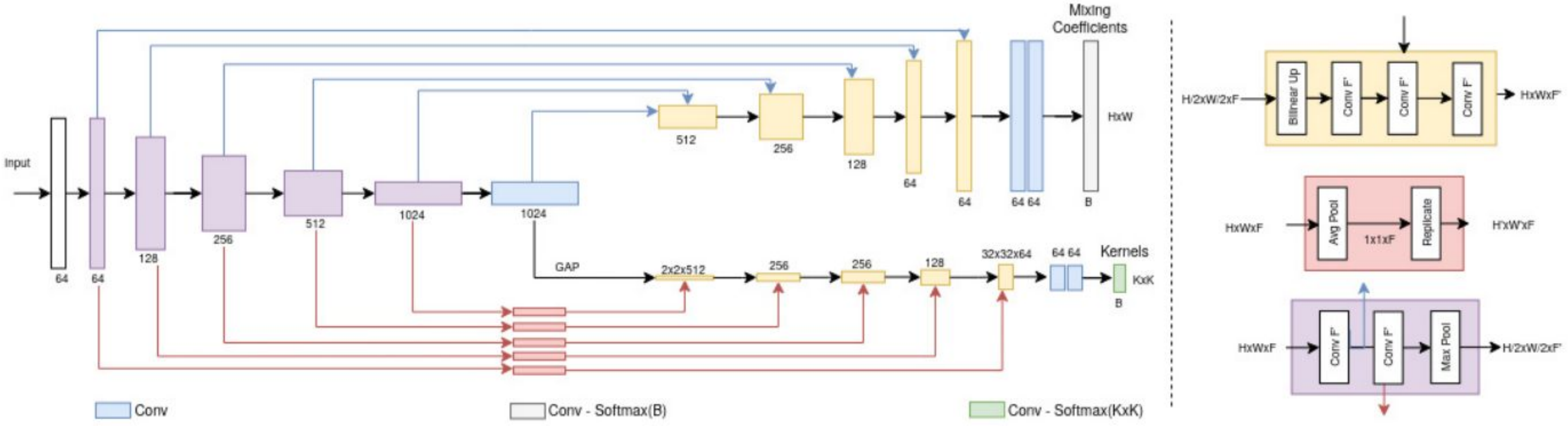

Figure 4. Architecture details.*

* Non-uniform Blur Kernel Estimation via Adaptive Basis Decomposition // Guillermo Carbajal, Patricia Vitoria, Mauricio Delbracio, Pablo Musé, José Lezama // 1 Feb 2021.

DeblurGAN: Blind Motion Deblurring Using Conditional Adversarial Networks

DeblurGAN contains two strided convolution blocks with stride 12, nine residual blocks and two transposed convolution blocks. Each ResBlock consists of a convolution layer, instance normalization layer, and ReLU activation.

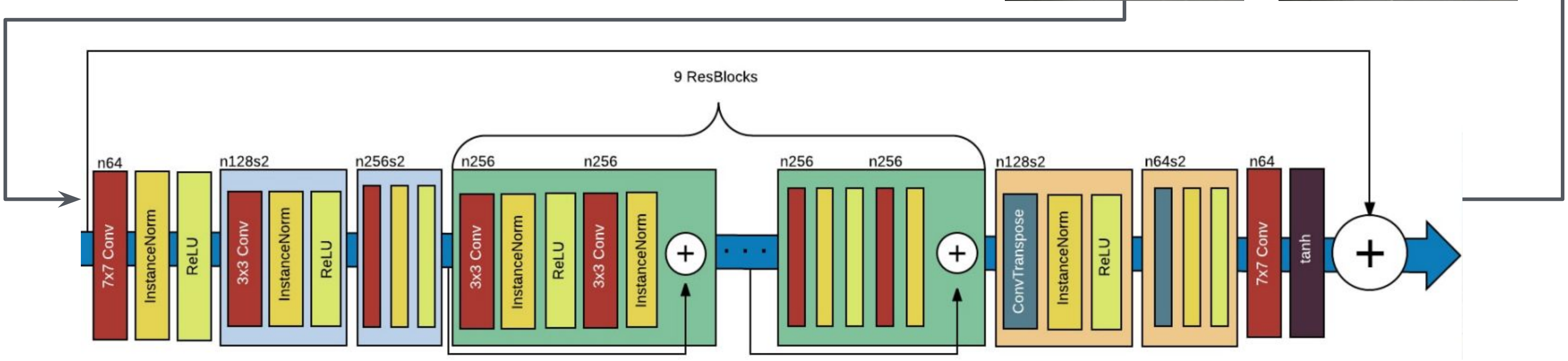

Figure 5. DeblurGAN generator architecture.*

* DeblurGAN: Blind Motion Deblurring Using Conditional Adversarial Networks // Orest Kupyn, Volodymyr Budzan, Mykola Mykhailych, Dmytro Mishkin, Jiri Matas // Nov 2017.

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Losses Calculation

Forward model:

$$\boxed{v_i = R\left(\langle \mathbf{u}_{nn(i)}, \sum_{b=1}^{B} m_i^b \mathbf{k}^b \rangle + n_i\right)^{1/\gamma}}$$

We aim to minimize: $L_{reblur} + L_{kernel}$.

At training time, for the synthetic dataset, we have:

- The sharp image uGT
- The blured image vGT
- The ground truth kernels and mixing coefficients that were applied to each pixel, kGT.

Given a blurry image vGT, we aim to find the global kernel basis and per-pixel mixing coefficients to minimize:

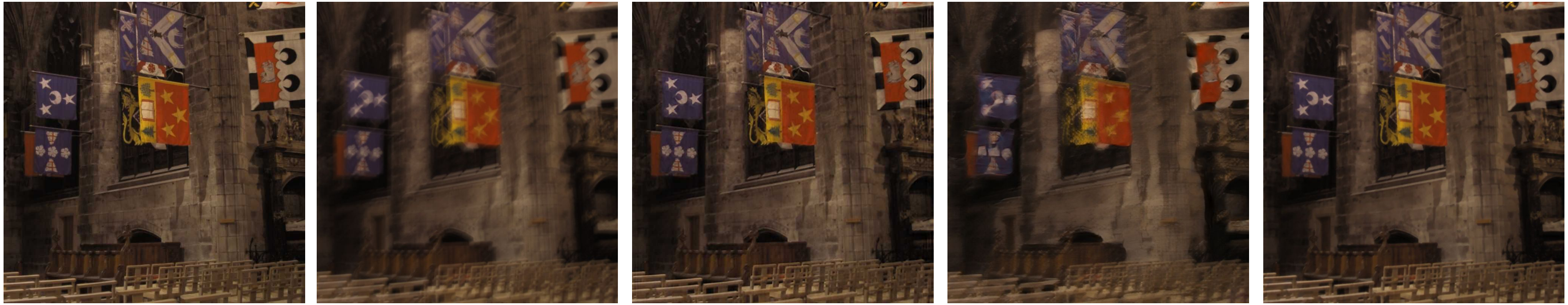
$$\mathcal{L}_{kernel} = \sum_i w_i \left\| \sum_{b=1}^{B} m_i^b \mathbf{k}^b - \mathbf{k}_i^{\mathrm{GT}} \right\|_p^p$$

Given the ground truth per-pixel blur kernels, computed kernel basis and mixing coefficients, the kernel loss is:

$$\mathcal{L}_{reblur} = \sum_i w_i \left(v_i^{\mathrm{GT}} - v_i\right)^2$$

Results

Sharp | Blurry | Hirsch | DeblurGAN | Adaptive



PSNR Expected	27.58	33.16	NA	35.19
PSNR Calculated	27.58	33.16	26.98	34.47

Zoomed results

Blurry

DeblurGAN

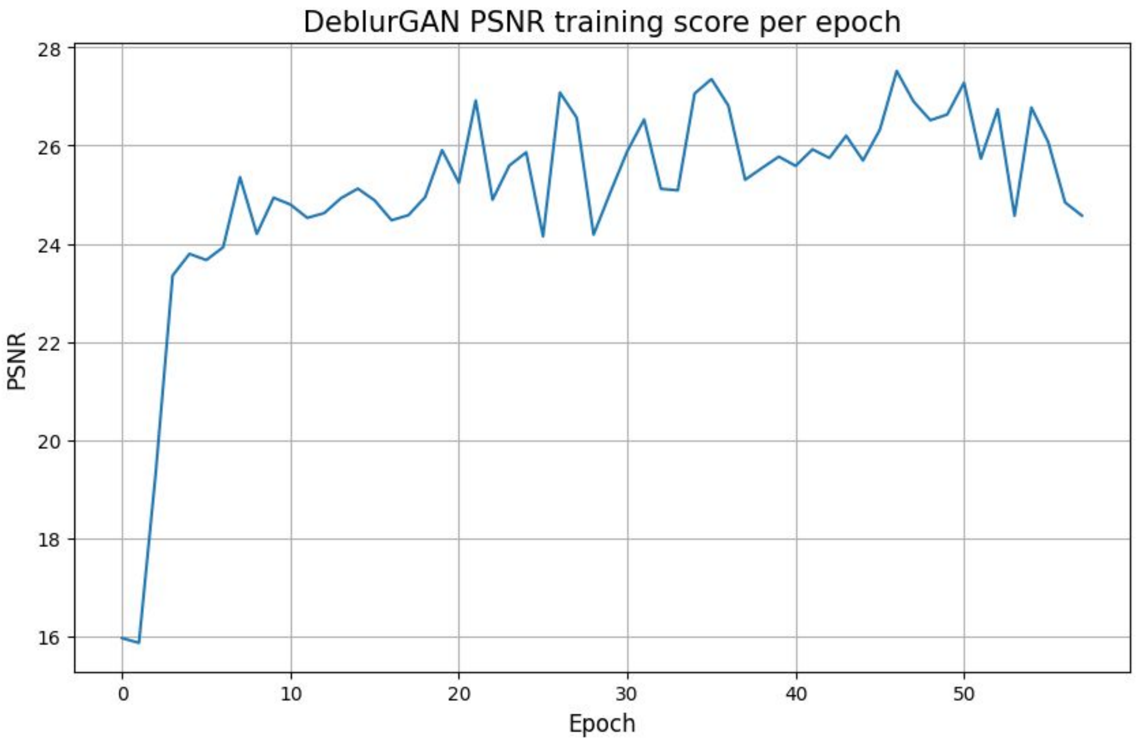
Adaptive

Metrics

Method	KOHLER		GOPRO	
	PSNR	SSIM	PSNR	SSIM
DeblurGAN	25.97	0.75	32.12	0.98
Adaptive	26.86	0.80	31.21	0.91
Reference value Adaptive	28.39	0.82	NA	

Non-Uniform model trained with our code

DeblurGAN Training process



- The model was trained on GoPro dataset during 60 epochs
- The total number of epochs for full model training is 300
- As it can be seen, the PSNR score has tendency to increase during the training

Discussion of the Results and Suggestions for Improvement

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In this work, we have conducted a research on 2 methods of image deblurring - Adaptive basis decomposition and DeblurGAN.

We have figured out that our calculations are accurate for the Hirsch method, which proves that we have defined the correct metrics. However, we encountered the following problem: the results for the Adaptive method differ from the reference value by ~0.7 dB. It can be assumed that authors falsified the results, since they did not make the training model publicly available and their article was not published.

Our suggestions how to improve results:

- Create a python code instead of Matlab for PSNR calculation of Kohler dataset;
- Validate author’s results.

Thanks for your attention!

Task Description

As a reference, we had 2 scientific papers, one of which describes a Non-uniform motion deblurring model, another one describes a DeblurGAN model.

Tasks:

1. Use pre-trained Non-uniform model and compute PSNR and SSIM metrics for both Kohler and Gopro datasets. Compare results with the reference.
2. Use pre-trained DeblurGAN model and follow the same steps. In case if results are worse, we can try to retrain a model.
3. Write a code to train a Non-uniform model. Plot training and validation metrics depending on number of epoch. Compare results.
4. *In case of failure in task 3, try to reproduce tables 1 & 2 from the DeblurGAN paper and train the networks from scratch.

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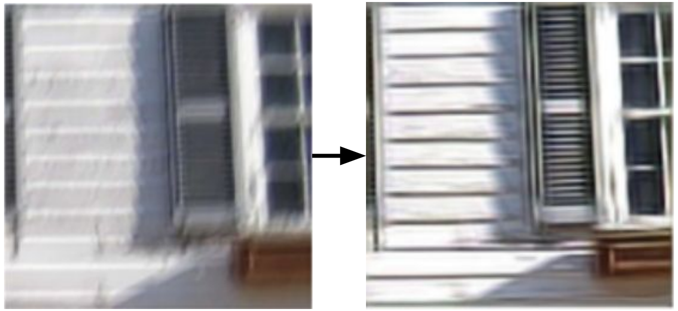

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* Deep learning based image processing approaches for image deblurring // V. Gampala, M. Sunil Kumar, C. Sushama, E. Fantin Irudaya Raj // Materials Today: Proceedings, 2020.