Denoising with Machine Learning

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Add tangent facet that compensates for the perturbed normal such that the average normal of the microsurface remains the geometric normal.
- Compute a combination of scratch BRDFs weighted by area:

\[
\bar{\rho}(\mathbf{x}, \omega_o, \omega_i) = \sum \alpha_k(\mathbf{x}) \rho_{s,k}(\omega_o, \omega_i)
\]

\[
\rho(\mathbf{x}, \omega_o, \omega_i) = \begin{cases} 
\frac{\bar{\rho}}{\bar{\alpha}(\mathbf{x})} & \text{if } \bar{\alpha}(\mathbf{x}) > 1 \\
\bar{\rho} + (1 - \bar{\alpha}(\mathbf{x}))\rho_b & \text{otherwise.}
\end{cases}
\]
Introduction

- Creating images with high samples per pixels (spp) takes a lot of time
- Cut down time by creating low samples images $\rightarrow$ Noisy
- De-Noising techniques
Introduction

Why these papers?

Collection of popular and reproducible image denoising works.

- image-denoising
- benchmarking
- state-of-the-art
- reproducible-research
- implementation
- curated-list
- summary
- inverse-problems
- image-restoration
- image-processing
- performance-analysis
- image-reconstruction
- noise
- noise-reduction
- recovery-image
- denoising-algorithms
- deep-learning
- cnn
- aniv
- art

29 commits 1 branch 0 releases 1 contributor

Branch: master New pull request

Wen Bihan (Asst Prof) add RDN+ (CVPR2018) Latest commit 5291bea 18 days ago

README.md add RDN+ (CVPR2018) 18 days ago

reproducible-image-denoising-state-of-the-art

Collection of popular and reproducible image denoising works.

Criteria: works must have codes available, and the reproducible results demonstrate state-of-the-art performances.

This collection is inspired by the summary by flywh
Introduction

Why these papers?

• Current state of the art models

- CBDNet [Web] [Code] [PDF]
  • Toward Convolutional Blind Denoising of Real Photographs (Arxiv), Guo et al.

- Noise2Noise [Web] [TF Code] [Keras Unofficial Code] [PDF]
  • Noise2Noise: Learning Image Restoration without Clean Data (ICML 2018), Lehtinen et al.

- UDN [Web] [Code] [PDF]
  • Universal Denoising Networks - A Novel CNN Architecture for Image Denoising (CVPR 2018), Lefkimmiatis.

- N3 [Web] [Code] [PDF]
  • Neural Nearest Neighbors Networks (NIPS 2018), Plotz et al.

- NLRN [Web] [Code] [PDF]
  • Non-Local Recurrent Network for Image Restoration (NIPS 2018), Liu et al.

- RDN+ [Web] [Code] [PDF]
  • Residual Dense Network for Image Restoration (CVPR 2018), Zhang et al.

Sparsity and Low-rankness Combined

- STROLLR-2D [PDF] [Code]
  • When Sparsity Meets Low-Rankness: Transform Learning With Non-Local Low-Rank Constraint for Image Restoration (ICASSP 2017), Wen et al.

Combined with High-Level Tasks

- Meets High-level Tasks [PDF] [Code]
  • When Image Denoising Meets High-Level Vision Tasks: A Deep Learning Approach (IJCAI 2018), Liu et al.
Non-Local Neural Networks

NIPS 2018
Introduction

1. Problem
CNN for Denoising

Convolutional Neural Network

- VGG
CNN for Denoising

Convolutional Neural Network

- VGG
  The FC (Fully connected) layer lose every local feature which is important for the image data.
CNN for Denoising

Convolutional Neural Network

• **FCN**
  
  Fully Convolutional Network is the network that has the **convolutional layer only**.

• Since the FCN **does not lose the Local Feature**, most of the **Computer Vision tasks** has been used the FCN structure.
CNN for Denoising

Convolutional Neural Network

- Many denoising models such as KPCN and RDA use the FCN
Recalibrate Features?

- Global Representation
- Global Context
- Long-range Dependencies
- Shorter Paths
Approach

1. Motivation
2. Approach
Problem: Denoising
Solution: Smoothing
Box Filter

\[ BA[I]_p = \sum_{q \in S} B_\sigma(p - q) I_q \]

- \( BA[I]_p \): result at pixel \( p \)
- \( \sum_{q \in S} \): sum over all pixels \( q \)
- \( B_\sigma(p - q) \): normalized box function
- \( I_q \): intensity at pixel \( q \)
Gaussian Filter

\[
GB[I]_p = \sum_{q \in S} G_o(\| p - q \|) I_q
\]
Bilateral Filter

The kernel shape depends on the image content.

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(\|I_p - I_q\|) I_q$$
**Non-local Filter**

- Average Similar Pixels
- Do not Average non-Similar Pixels

Problem:
Not Enough Similar Pixels in LOCAL REGIONS

→ Get More Samples in Non-LOCAL REGIONS
Non-local Filter

NL-Means Method:
Buades (2005)

- For each and every pixel $p$: Define a small, simple fixed size neighborhood;
Non-local Filter

NL-Means Method:
Buades (2005)

‘Similar’ pixels $p, q$

$\rightarrow$ SMALL

vector distance;

$|| V_p - V_q ||^2$
Non-local Filter

NL-Means Method:
Buades (2005)

‘Dissimilar’ pixels $p$, $q$
$\rightarrow$ **LARGE**
vector distance;

$\| v_p - v_q \|^2$
Non-local Filter


\[ p, q \text{ neighbors define a vector distance;} \]

\[ \| V_p - V_q \|^2 \]

Filter with this: No spatial term!

\[ NLMF[I][p] = \frac{1}{W_p} \sum_q G_{\sigma s}(\| p - q \|) G_\sigma \left( \| \tilde{V}_p - \tilde{V}_q \|^2 \right) I_q \]

\[ BA[I][p] = \frac{1}{W} \sum_q I_q \]

\[ G[I][p] = \frac{1}{W} \sum_q G_\sigma(\| p - q \|_2) I_q \]

\[ G[I][p] = \frac{1}{W} \sum_q G_\sigma(\| p - q \|_2) G_{\sigma r}(\| I_p - I_q \|_1) I_q \]

\[ NLMF[I][p] = \frac{1}{W} \sum_q G_\sigma \left( \| V_p - V_q \|_2 \right) I_q \]
Non-local Filter

\[ NLMF[I]_p = \frac{1}{W} \sum_{q} G_\sigma (\|V_p - V_q\|_2) I_q \]

Output Value

Representative (Probability Distribution)

Target Value (Pixel)

vs All Values (Pixel)
\[ y_i = \frac{1}{C(x)} \sum_j f(x_i, x_j) g(x_j) \]

Output Value  
Representation (Probability Distribution)  
Target Value (Pixel) vs All Values (Pixel)
Another Representation of Non-Local Pixels

\[ y_i = \frac{1}{C(x)} \sum_j f(x_i, x_j) g(x_j) \]

= Weighted Sum of All Pixels with Similarity + Learning…
Similarity

\[ y_i = \frac{1}{C(x)} \sum_j f(x_i, x_j) g(x_j) \]

- Gaussian
  \[ f(x_i, x_j) = \exp(x_i^T \cdot x_j) \]
- Embedded Gaussian
  \[ f(x_i, x_j) = \exp(\theta(x_i^T) \cdot \phi(x_j)) \]
- Dot Product
  \[ f(x_i, x_j) = \theta(x_i^T) \cdot \phi(x_j) \]
- Concatenation
  \[ f(x_i, x_j) = \text{ReLU}(w_f^T [\theta(x_i) \cdot \phi(x_j)]) \]
Input Representation
For Feature Extraction

\[ y_i = \frac{1}{C(x)} \sum_j f(x_i, x_j)g(x_j) \]

\[ g(x_j) = W_g x_j \]
Non-local Operation Implementation

\[ y_i = \frac{1}{\sum_j \exp(x_i^T \cdot x_j)} \sum_j \exp(x_i^T \cdot x_j) W_g x_j \]
Non-local Operation Implementation

\[ y_i = \frac{1}{\sum_j \exp(\theta(x_i^T) \cdot \phi(x_j))} \sum_j \exp(\theta(x_i^T) \cdot \phi(x_j)) W_g x_j \]
Non-local Operation Implementation

\[ y_i = \frac{1}{N} \sum_j \theta(x_i^T) \cdot \phi(x_j) W_g x_j \]

![Diagram showing the process of non-local operation with reshaping and convolution operations.](image-url)
Non-local Operation Implementation

\[ y_i = \frac{1}{N} \sum_j \text{ReLU}(w_f^T[\theta(x_i) \cdot \phi(x_j)])W_gx_j \]
Non-local Block

\[ z_i = W_z y_i + x_i \]
in Paper (Video case)
Another Representation of Non-Local Pixels

\[ y_i = \frac{1}{C(x)} \sum_{j} f(x_i, x_j) g(x_j) \]

= Weighted Sum of All Pixels with Similarity + Learning?
Experiments

1. Experiments
Noise2Noise: Learning Image Restoration without Clean Data

ICML 2018
Introduction

1. Problem
Introduction – Problem

• Creating images with high samples per pixels (spp) takes a lot of time
• Cut down time by creating low samples images → Noisy
• De-Noising techniques
Additional Approach

- Noise2Noise
  N2N is the current state of the art model for the single RGB denoising problem.

- We will try to merge N2N and KPCN model if we have enough time.

[Lehtinen et. al. 18] Noise2Noise: Learning Image Restoration without Clean Data, ICML2018
Problem

Current Denoising

- Current models take the noisy input and learns to produce the clean target.

[Lehtinen et. al. 18] Noise2Noise: Learning Image Restoration without Clean Data, ICML2018
Problem

Current Denoising

- However, in some cases, getting a clean image target with zero noise (Ground Truth) is impossible.
- Medical image such as MRI scan, Montecarlo rendering image are one of those cases.

[Lehtinen et. al. 18] Noise2Noise: Learning Image Restoration without Clean Data, ICML2018
Problem

Current Denoising

• In these cases, normal supervised learning method is not the best because the target itself is noisy.

[Lehtinen et. al. 18] Noise2Noise: Learning Image Restoration without Clean Data, ICML2018
Approach

1. Motivation
2. Approach
Motivation

Current Denoising

• How the RGB camera get clean image?
Motivation

Current Denoising

• If the camera sensor shot only one time, the image must be noisy too.

• However, the camera takes many shot during the exposure time, and take average of the color value after the filtering. In this way, we can remove the noise of the image.
Motivation

Current Denoising

• Therefore, when the camera gets not enough number of light signal (short exposure), the camera will produce the noisy image.

\[ x \times 10 = \]
Motivation

Current Denoising

• This method is possible because the random noise on the camera sensor is **Zero mean**.
Approach

Supervised Denoising

- Current models take the noisy input and learns to produce the clean target.

[Lehtinen et. al. 18] Noise2Noise: Learning Image Restoration without Clean Data, ICML2018
Supervised Denoising

- The model takes the difference between the target and prediction for the loss value.

[Lehtinen et. al. 18] Noise2Noise: Learning Image Restoration without Clean Data, ICML2018
Approach

Supervised Denoising

- The model takes the difference between the target and prediction for the loss value.
Approach

Supervised Denoising

• However, in some cases, there is no GT target.
Approach

Unsupervised Denoising

• Therefore, instead of predicting the clean target, N2N infer another noisy data.
Unsupervised Denoising

- If the mean of the noise is zero, the average of the gradients that model takes is same with the gradient to the ground truth.
Approach

What’s the difference with taking average directly from noisy images?

- In order to get a meaningful ground truth, large number of images are required. N2N learn to find the mean value with only few random samples.
Experiments

1. Experiments
Experiment

Characteristics of N2N

• During the **training**, the N2N model **cannot succeed** in transforming one instance of the noise to another. Therefore, the training loss does not decrease well.

• However, it shows almost similar performance with supervised model at the **test accuracy**.

[Lehtinen et. al. 18] Noise2Noise: Learning Image Restoration without Clean Data, ICML2018
Experiment

Removing texts

- The ‘clean target’ below means the Supervised learned model with clean data, and rest of the results are produces by N2N.

\[
p \approx 0.04 \quad p \approx 0.42
\]

Example training pairs  | Input (\( p \approx 0.25 \)) | \( L_2 \) | \( L_1 \) | Clean targets | Ground truth
\hline
17.12 dB | 26.89 dB | 35.75 dB | 35.82 dB | PSNR

Figure 3. Removing random text overlays corresponds to seeking the median pixel color, accomplished using the \( L_1 \) loss. The mean (\( L_2 \) loss) is not the correct answer: note shift towards mean text color. Only corrupted images shown during training.
Experiment

Monte Carlo rendering denoising

- The ‘clean target’ below means the Supervised learned model with clean data, and rest of the results are produces by N2N.
- It takes 9 channel (RGB, RGB albedo, 3D normal vector of each pixel)

Figure 7. Denoising a Monte Carlo rendered image. (a) Image rendered with 64 samples per pixel. (b) Denoised 64 spp input, trained using 64 spp targets. (c) Same as previous, but trained on clean targets. (d) Reference image rendered with 131072 samples per pixel. PSNR values refer to the images shown here, see text for averages over the entire validation set.
Additional Approach

• **Noise2Noise**
  
  N2N is the current state of the art model for the single RGB denoising problem.

• We will try to merge N2N and KPCN model if we have enough time.

[Lehtinen et. al. 18] Noise2Noise: Learning Image Restoration without Clean Data, ICML2018
Thank You!
Reference

[Liu et. al. 17] Learning Efficient Convolutional Networks through Network Slimming, ICCV2017

[Zhang et. al. 18] Image Super-Resolution Using Very Deep Residual Channel Attention Networks, ECCV2018

[Lehtinen et. al. 18] Noise2Noise: Learning Image Restoration without Clean Data, ICML2018