







Generative Adversarial Network for Denoising Medical Images

DOAN Tien Tai

Supervisor: Asso. Prof. Marie Luong (L2TI) Co-supervisors: Prof. Chevaleyre, Assoc. Prof. Guerif (LIPN) and Dr. Hoang Tung Tran (USTH)

Villetaneuse, July 5th 2017

Outline

- Introduction
- Context
- Methods
- Experiment & Result
- Conclusion

Introduction

Name

DOAN Tien Tai

• From

Hanoi, Vietnam

Education

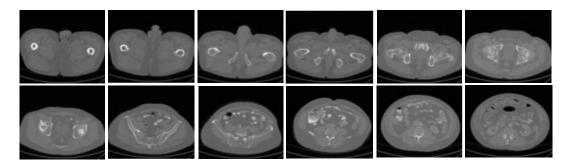
Master student in Information and Communication Technology (ICT) University of Science and Technology of Hanoi (USTH, or Vietnam France University)

Currently work at L2TI & LIPN

M2 Internship (5 months) of Deep Learning for Image Classification and Restoration

Why denoising?

- Computed tomography (CT) scan images [*]:
 - Uses low-radiation X-ray to avoid harmful effects
 - Noisy images: difficult for diagnosing diseases
 - Effective denoising methods are needed



Example of abdominal CT scanned images

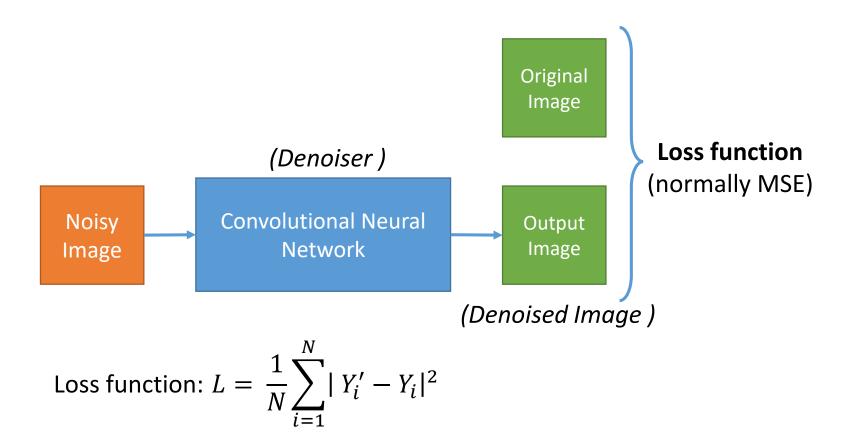
[*] Provided by Asso. Prof. Marie LUONG at L2TI, Paris 13 University

Methods

- A popular approach: Sparse-coding based
 - × Mean Square Error (MSE) based
 - × Slow
- My work
 - Convolutional Neural Networks (Deep Networks)
 - ✓ State-of-the-art results in image denoising
 - × MSE based
 - Generative Adversarial Networks [*]
 - ✓ Loss function is learned

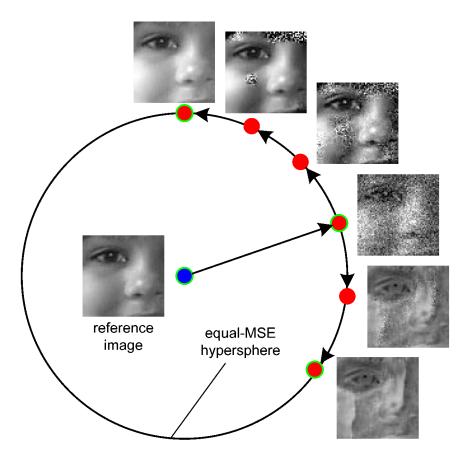
[*] Goodfellow, Ian, et al. "Generative adversarial nets." *Advances in neural information processing systems*. 2014.

Convolutional Neural Network (CNN)



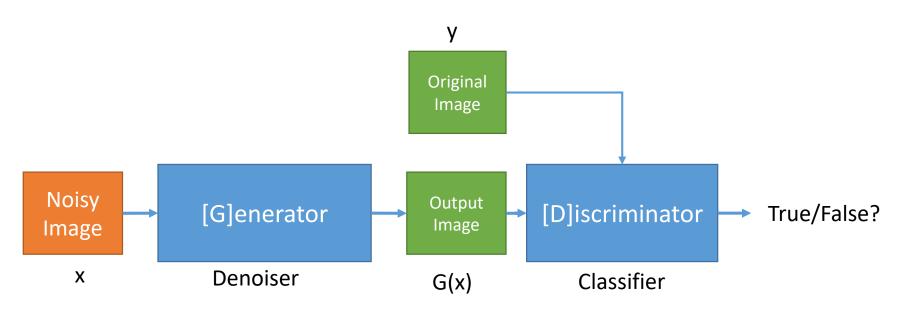
Objective: Minimize the loss function

Low MSE ≠ High Quality



Source: The SSIM Index for Image Quality Assessment http://www.cns.nyu.edu/~lcv/ssim/

Generative Adversarial Network (GAN)



• New loss function:

$$\begin{aligned} L_{GAN}(G,D) &= E_{x,y \sim p_{data}(x,y)} [log D(G(x),y)] \\ &+ E_{x,y \sim p_{data}(x,y)} [log(1 - D(y,G(x)))] \end{aligned}$$

• Objective:

$$G^* = \arg \min_G \max_D \mathcal{L}_{cGAN}(G, D).$$

Generative Adversarial Network (GAN)

• MSE Loss

$$L_{MSE}(G) = E_{x,y \sim p_{data}(x,y)}[|y - G(x)|]$$

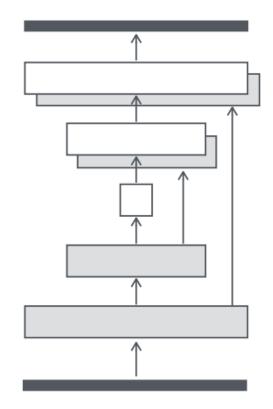
• Final Objective:

$$G^* = \arg\min_{G} \max_{D} L_{cGAN}(G, D) + \lambda L_{MSE}(G)$$

This method is developed from: Isola, Phillip, et al. "Image-to-image translation with conditional adversarial networks." *arXiv preprint arXiv:1611.07004* (2016).

Network structure

- Generator:
 - 7 layers encoder & 7 layers decoder
 - Skip connections
 - Total 54 millions of parameters
- Discriminator:
 - A simple 3-layers convolutional neural network
 - Total 2,7 millions of parameters



An example of a simple auto-encoder with skip connections [*]

[*] Isola, Phillip, et al. "Image-to-image translation with conditional adversarial networks." *arXiv preprint arXiv:1611.07004* (2016).

Experiment

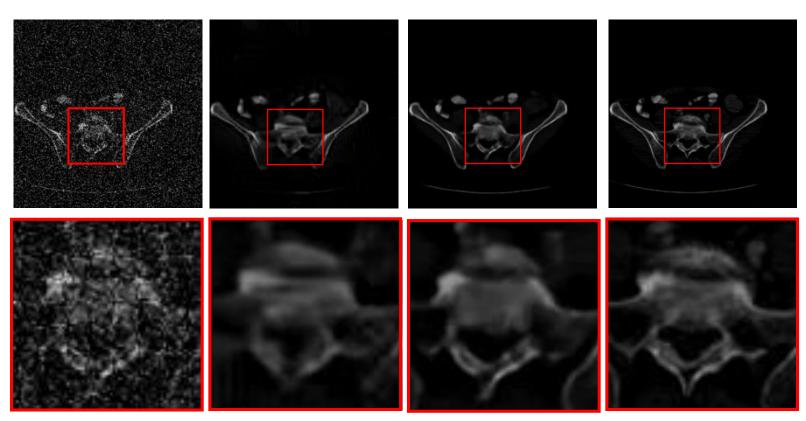
- Dataset:
 - 100,000 images (50% train, 25% validate and 25% test)
 - Adding Gaussian noise $\sigma = 50$
- Training:
 - 20 epochs (took 2 days)
 - Learning rate 0.0001, batch-size 5
- Machine: cluster GAIA gpucreos1
 - Duo GeForce GTX TITAN Black
- Deep learning framework: PyTorch

Results

Noisy image $\sigma = 50$ (PSNR = 19.49 dB) BM3D [*] (PSNR = 31.93dB)

Proposed GAN (PSNR **33.31**dB)

Original image



Performance evaluation of denoising on an image of pelvis bone

[*] Block-matching and 3D filtering (BM3D) algorithm and its extensions http://www.cs.tut.fi/~foi/GCF-BM3D/

Conclusion and future works

- GAN is a very promising approach in image denoising
- In some situations, GAN may generate little wrong details
- Need more research on image denoising using GAN (Eg. take into account of structure-based metrics in the loss function)

Thank you!

Questions & Discussion