Medical Image Denoising Using Convolutional Denoising Autoencoders

Lovedeep Gondara - Simon Fraser University

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Project Recap

- Low Dose Fluoroscopy for Orthopedic Surgery
- Team Members: Mariya Kazachkova, Michael Mudgett
- Mentors: Mathias Unberath, PhD, Bastian Bier, Nico Zaech, Nassir Navab, PhD, Greg Osgood, MD

Project Recap

- Goal: reduce total radiation inflicted on patient through x-ray imaging during orthopedic surgery while increasing the temporal resolution of X-ray imaging
- Project goal: Combine MC-GPU simulated images with deep learning to ultimately make low dose fluoroscopy usable during orthopedic surgery
 - Minimum deliverable: Denoising neural network



Paper Selection

- Architecture proven to work for medical images
- Good results with small dataset

Problem Statement

- Deep learning is great, but requires a large amount of training/validation data and great computational power
- The above requirements are not always readily available
 - Need for methods that can work with small datasets and low computational power

Background

• Denoising Autoencoder



Hubens, N. Deep inside: Autoencoders – Towards Data Science. Towards Data Science (2018). Available at: https://towardsdatascience.com/deep-inside-autoencoders-7e41f319999f. (Accessed: 12th March 2018)

What the authors did - Data

• Two datasets

- Mini-MIAS database of mammograms (MMM)
 - 322 Images (1024x1024 resolution)
- Dental Radiography Database
 - 400 images (1935x2400)
- Resized to 64x64
- Added noise
 - Gaussian and Poisson

| Noise type | corruption parameters |
|------------|------------------------------|
| Gaussian | $p=0.1, \mu = 0, \sigma = 1$ |
| Gaussian | $p=0.5, \mu = 0, \sigma = 1$ |
| Gaussian | $p=0.2, \mu = 0, \sigma = 2$ |
| Gaussian | $p=0.2, \mu = 0, \sigma = 5$ |
| Poisson | $p=0.2, \lambda = 1$ |
| Poisson | $p=0.2, \lambda = 5$ |



What the authors did - Testing

- Implemented Network using Keras
- Trained using Acer Aspire M5 notebook (no GPU!!)
- Structural Similarity Index Measure (SSIM)
 - Index of 3 measures:
 - Luminance
 - Contrast
 - Structural changes

| | input 1 (Input) | inpu | t: (N | (None, 1, 64, 64) | | |
|---------------------------------|---|--------|--|---|---|--|
| | mpot_1 (inputLayer) | output | | at: (None, 1, 64, 64) | | |
| | | | | | | |
| | | * | inout | (None 1 | 64 64 | |
| convolution2d_1 (Convolution2D) | | outou | t (None 64 | (None 64 64 6 | | |
| | | | outpu | [[[[[]]]]] | . 04, 0 | |
| | | + | | | | |
| maxpooling2d_1 (MaxPooling2D) | | | input | : (None, 64 | (None, 64, 64, 6 | |
| | | | outpu | t: (None, 64 | (None, 64, 32, 3 | |
| | | 1 | | | | |
| | | input | : (None, 64 | (None, 64, 32, 3 | | |
| convolution2d_2 (Convolution2D) | | | outpu | t: (None, 64 | (None, 64, 32, 3 | |
| | | | | | | |
| maxpooling2d_2 (MaxPooling2D) | | + | innut | None 64 | 22.2 | |
| | | g2D) | outou | ti (None 64 | (None, 64, 32, 3 | |
| | | | outpu | L (None, 04 | , 10, 1 | |
| | | + | | | | |
| convo | olution2d 3 (Convolutio | m2D) | input | : (None, 64 | , 16, 1 | |
| | convolution2d_5 (convolutio | | outpu | (None, 64, 16, 1 | | |
| | | Ļ | | | | |
| | | | | | (None, 64, 16, 1 | |
| | | | input | : [(None, 64 | , 16, 1 | |
| upsan | npling2d_1 (UpSamplin | g2D) | outpu | : (None, 64 t: (None, 64 | , 16, 1 | |
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What the authors did - Results

- 1st row: original
- 2nd row: noisy image
 - Gaussian noise (mu= 0, σ = 1, p = 0.1)
- 3rd row: denoised using CNN DAE
- 4th row: denoise using median filter



What the authors did - Results

- Produced results for denoising images with high noise
 - Image barely recognizable to human eye
- Combined training data
 - Training set = mammograms and dental images
 - Produced results slightly better than using only one dataset









What the authors did - Significance

- Effective denoising of medical images using a small dataset and low computational power
- Can combine heterogeneous datasets to increase sample size
- Future work:
 - Find optimal architecture for small sample denoising
 - Using known denoising techniques to preprocess images before running them through the CNN DAE

My Assessment

| Pros | Cons |
|---|--|
| Provides way for deep learning to work in medical field | Reproducibility? |
| Uses two different datasets | No result present of network working with actual noisy image |
| Varies the amount and type of noise | Would have liked more comparison to existing methods |

Back to our project

- Architecture described in this paper will be the beginning of our minimum deliverable
- Will use Dental Radiography Dataset to test network prior to obtaining simulated images
- Look into using SSIM to quantitatively compare produced images with their starting points

Thank you!

Citation:

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