UNIVERSITÉ DE BRETAGNE OCCIDENTALE

DOCTORAL THESIS

Tomographic Image Reconstruction with Neural Networks

Author:
Venkata Sai Sundar KANDARPA

Supervisor:
Dr. Dimitris VISVIKIS

A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

in the

LATIM
Biologie Santé

August 31, 2021

Declaration of Authorship

I, Venkata Sai Sundar KANDARPA, declare that this thesis titled, “Tomographic Image Reconstruction with Neural Networks” and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date:

"Thanks to my solid academic training, today I can write hundreds of words on virtually any topic without possessing a shred of information, which is how I got a good job in journalism."

Dave Barry

UNIVERSITÉ DE BRETAGNE OCCIDENTALE

Abstract

Biologie Santé
Biologie Santé

Doctor of Philosophy

Tomographic Image Reconstruction with Neural Networks

by Venkata Sai Sundar KANDARPA

Neural Networks are extensively used in the field of medical imaging for biomedical image segmentation, cancer diagnosis, image analysis, etc. The advancements in computation power (GPUs) and efficient memory utilization have propelled the spread of deep neural networks into various domains. The main motivation behind the use of neural network approaches is faster prediction (compared to traditional methods) without compromising on the quality of the result. Tomographic image reconstruction has also benefited from the development of neural networks. Medical image reconstruction involves the task of mapping raw measurement data collected by the detector to images that are comprehensible to a radiologist. A medical image reconstruction algorithm essentially approximates this mapping to predict the best possible image. There are established analytical and iterative reconstruction algorithms which have over the years proven to be effective in producing the best image possible. Convolutional neural networks (CNN) specifically have proven to be exceptional in tasks related to images such as denoising, deblurring, and super-resolution. The use of neural networks in Positron Emission Tomography (PET) and Computed Tomography (CT) reconstruction has been explored in this thesis. Novel frameworks called DUG-RECON (Double U-Net Generator) for PET, CT image reconstruction, and LRR-CED (Low-Resolution Reconstruction aware Convolutional Encoder-Decoder) for Sparse-view CT image reconstruction and Total-Body PET image reconstruction are proposed in this manuscript. Quantitative analysis of the images reconstructed with the proposed methods indicated that image quality was either better or on par with standard reconstruction algorithms.

Acknowledgements

The acknowledgments and the people to thank go here, don't forget to include your project advisor…

Contents

List of Figures

List of Tables

List of Abbreviations

LAH	**L**ist **A**bbreviations **H**ere
WSF	**W**hat (it) **S**tands **F**or

Physical Constants

Speed of Light $c_0 = 2.997\,924\,58 \times 10^8\,\mathrm{m\,s^{-1}}$ (exact)

List of Symbols

a	distance	m
P	power	W ($J\,s^{-1}$)
ω	angular frequency	rad

For/Dedicated to/To my…

Chapter 1

Introduction

1.1 Motivation

The use of deep learning in medical imaging has been on the rise over the last few years. It has widely been used in various tasks across medical imaging such as image segmentation (Ronneberger, Fischer, and Brox, 2015; Guo et al., 2019; Sinha and Dolz, 2019; Dolz et al., 2018; Hatt et al., 2018), image denoising (Kadimesetty et al., 2018; Li et al., 2020; Chen et al., 2017; Yang et al., 2018), image analysis (Litjens et al., 2017; Amyar et al., 2019; Cui et al., 2018). Deep learning based algorithms produce faster results along with best possible quality in accordance with existing state of the art methods (Leuschner et al., 2021). Medical Image reconstruction too has benefited hugely with the advancement of deep learning (Reader et al., 2020; Zhang and Dong, 2020). Medical Image reconstruction corresponds to the task of mapping raw projection data retrieved from the detector to image domain data. During the course of this thesis, the focus has been towards positron emission tomography (PET) and computed tomography (CT) image reconstruction. Both these modalities present a unique of set of challenges for image reconstruction.

PET imaging is a form of emission tomography wherein the image reconstruction task revolves around identifying the radio-tracer distribution emitted from the patient. A PET image gives functional information about the organs in a patient making it invaluable for oncology. Some of the challenges in PET image reconstruction are scatter, attenuation and difficulty in identifying the exact annihilation point of the electron-positron. Despite being the most sensitive emission tomography modality, the number of photons captured is low relative to the photons emitted contributing to further image degradation. These challenges result in very noisy images when reconstructed with analytical algorithms. These challenges are addressed by Iterative/Model-based approaches which take into account detector geometry, noise statistics and approximate scatter and attenuation correction resulting in better image quality.

CT imaging on the other hand is an example of transmission tomography. The extent of attenuation undergone by X-Rays that pass through a patient are measured to obtain attenuation maps. In CT imaging research, there has been active interest in sparse-view and low-dose reconstruction scenarios. In both cases, severe artifacts are introduced in reconstructed images either due to incomplete projections or low counts. Many established model-based iterative methods account for the low-dose and sparse-view settings to remove artifacts and noise from the reconstruction (Nuyts et al., 1998; Elbakri and Fessler, 2002; Liu et al., 2013). However, these methods for require the knowledge of the noise and artifacts statistics and generally have longer reconstruction times (Kim, Ramani, and Fessler, 2014).

The main tasks involved in image reconstruction can be broadly categorized into three: sinogram correction, domain translation from sinogram to image, and image correction. Algorithms either tackle the three task individually or simultaneously account for them. One can relate to these tasks in the domain of Computer Vision wherein deep learning architectures have revolutionized the field by producing the state of the art results in most applications (Guo et al., 2016). For example, effective use of deep learning-based methods is seen in dealing with image denoising (Kadimesetty et al., 2018; Li et al., 2020; Chen et al., 2017; Yang et al., 2018), super resolution (Ledig et al., 2017; Lim et al., 2017) and image-to-image translation (Isola et al., 2017; Zhu et al., 2017) tasks. The continuous improvement in the availability of public data has further propelled interest in data-driven medical image reconstruction making it an active area of research. This thesis aims to explore novel deep learning approaches for PET and CT image reconstruction. Most common ways to introduce deep learning architectures in the image reconstruction pipeline are for pre-processing to correct raw projection data from the detector and post-processing to improve images reconstructed with existing methods. Another way is to embed the network into an iterative algorithm to enable faster convergence. The relatively less explored way called direct image reconstruction is to utilize neural networks alone for the entire reconstruction process. In this thesis convolutional neural network (CNN) approaches are proposed for direct image reconstruction with neural networks.

1.2 Thesis Organization

This thesis is divided into six chapters with the first two chapters being introduction and literature review, followed by three chapters that focus on different deep learning methods explored during the thesis, and finally conclusion and perspectives. In the introduction various aspects of PET and CT image reconstruction are discussed along with the relevant background in deep learning background. The second chapter throws light on deep learning applied to medical image reconstruction and reviews the state of the art approaches in the scope of this thesis. In chapter 3 , we discuss reconstruction framework double U-Net generator (DUG) for PET and CT image reconstruction. A novel method for Sparse-view CT reconstruction called low-resolution reconstruction aware convolutional encoder decoder (LRRCED) is covered in chapter 4. A modified version of LRRCED for total body PET is discussed in chapter 5. Potential improvements and ideas for future work are presented in the final chapter.

1.3 Imaging Modalities and Reconstruction Models

1.3.1 PET

PET images provide functional information to the radiologist making them invaluable in image analysis. The application of PET imaging has been on the rise in oncology, cardiology and neuropsychiatry. The increased application lead to the development of many novel reconstruction approaches that lead to improved image quality. This section focuses on the standard analytical and iterative algorithms which are applicable in the context of this thesis.

The aim of image reconstruction in PET is to predict the tracer distribution emitted from the patient. The emission is a result of positron emitting radionuclide injected into the patient which causes positron-electron annihilation. The annihilation results in the production of gamma photons that travel in opposite directions due to the law of conservation of momentum. The simultaneous detection of these photons (also called coincidence events) enables the estimation of tracer distribution in PET imaging. A PET scanner detects the coincidence events through a set of detectors arranged in a circular fashion. This design of the scanner facilitates detection of coincidence photons between a pair of detectors. The centers of two detectors is connected by a straight line called line of response (LOR). Photon pairs that are not subject to scatter are a result of annihilation events that occur along a thin volume surrounding the LOR. In PET, $\boldsymbol{x} = \boldsymbol{\lambda}$ is the distribution of a radiotracer delivered to the patient by injection, and is measured through the detection of pairs of γ-rays emitted in opposite directions (indirectly from the positron-emitting radiotracer).

The measurement $\boldsymbol{y}$ is a random vector modeling the number of detection (photon counting) at each of the n detector bins, and follows a Poisson distribution with independent entries:

$$\boldsymbol{y} \sim \text{Poisson}(\bar{\boldsymbol{y}}(\boldsymbol{x})) \tag{1.1}$$

where $\bar{\boldsymbol{y}}(\boldsymbol{x}) \in \mathbb{R}^n$ is the expected number of counts (noiseless), which is a function of the image $\boldsymbol{x}$.

The expected number of counts is

$$\bar{\boldsymbol{y}}(\boldsymbol{\lambda}) = \boldsymbol{P}\boldsymbol{\lambda} \tag{1.2}$$

where $\boldsymbol{P} \in \mathbb{R}^{n \times m}$ is a system matrix such that each entry $[\boldsymbol{P}]_{i,j}$ represents the probability that a photon pair emitted from voxel j. Image reconstruction is achieved by finding a suitable image $\hat{\boldsymbol{x}} = \hat{\boldsymbol{\lambda}}$ that approximately solves

$$\boldsymbol{y} = \bar{\boldsymbol{y}}(\boldsymbol{x})\,. \tag{1.3}$$

1.3.2 CT

Let an image be represented by $\boldsymbol{x} \in \mathbb{R}^m$ and the scanner measurement by $\boldsymbol{b} \in \mathbb{R}^n$ where m is the number of voxels and n is the number of measurements. In two-dimensional (2-D) CT imaging n depends on the number of detectors N_d and the number of angles N_a. The task of medical image reconstruction corresponds to finding a mapping from $\boldsymbol{b}$ to $\boldsymbol{x}$. The measurement $\boldsymbol{b}$ is a random vector modeling the number of detection (photon counting) at each of the n detector bins, and follows a Poisson distribution with independent entries, i.e.,

$$\boldsymbol{b} \sim \text{Poisson}(\bar{\boldsymbol{b}}(\boldsymbol{x})) \tag{1.4}$$

where, $\boldsymbol{b} = [b_1(\boldsymbol{x}), \dots, b_n(\boldsymbol{x})]^\top \in \mathbb{R}^n$ and $\bar{\boldsymbol{b}}(\boldsymbol{x}) = [\bar{b}_1(\boldsymbol{x}), \dots, \bar{b}_n(\boldsymbol{x})]^\top \in \mathbb{R}^n$ is the expected number of counts (noiseless), which is a function of the image $\boldsymbol{x}$.

The image $\boldsymbol{x} \in \mathbb{R}^m$ is a vectorized input image (also referred to as attenuation) representing the measure of X-rays absorbed or scattered as they pass through the patient. In a monochromatic setting, the expected number of counts $\bar{\boldsymbol{b}}(\boldsymbol{x})$ is given by the Beer-Lambert law, i.e.,

$$\bar{b}_i(\boldsymbol{x}) = I \cdot \exp(-[\boldsymbol{P}\boldsymbol{x}]_i) \quad \forall i = 1, \ldots, n \tag{1.5}$$

where, I is the intensity and $\boldsymbol{P} \in \mathbb{R}^{n \times m}$ is a system matrix such that each entry $[\boldsymbol{P}]_{i,j}$ represents the contribution of the j-th image voxel to the i-th detector. Given the raw projections $\bar{\boldsymbol{b}}$, we take the logarithm as follows

$$y_i = \log\left(\frac{I}{\bar{b}_i}\right) \quad \forall i = 1, \ldots, n \tag{1.6}$$

where we assumed that the intensity I is sufficiently high so that $\bar{b}_i > 0$ for all i. Image reconstruction is based on finding a suitable image $\hat{\boldsymbol{x}}$ that approximately solves

$$\boldsymbol{y} = \boldsymbol{P}\hat{\boldsymbol{x}} \tag{1.7}$$

where $\boldsymbol{y} = [y_1, \ldots, y_n]^\top \in \mathbb{R}^m$. The reconstruction can also be achieved with more sophisticated iterative techniques that account for the stochastic properties of the measurement (1.1) Nuyts et al., 1998; Elbakri and Fessler, 2002.

In a sparse-view setting, the number of rotation angles of the detector is decreased in order to reduce the radiation passing through the patient. This implies a reduction in the number of projection angles in the measurement $\boldsymbol{y}$.

1.3.3 Analytical Reconstruction Algorithms

Analytical algorithms can efficiently solve (1.3) and (1.7) and have been the cornerstone of tomographic image reconstruction. One of the most famous reconstruction algorithms for both PET and CT is the filtered-backprojection (FBP). The projections ($\boldsymbol{y}$) are first filtered (typically with a ramp filter) and then back-projected to get an image. The discrete implementation of the FBP can be written as follows:

$$\boldsymbol{x}(i,j) = \frac{\pi}{N_\phi} \sum_{l=0}^{N_\phi - 1} \boldsymbol{y}_f(s = i\cos\phi_l + j\sin\phi_l, \phi_l) \tag{1.8}$$

where x is the image for a set of pixels (i,j), $\boldsymbol{y}_f$ are the filtered projections obtained by filtering the projections, expressed in terms of radial variable

s and projection angle ϕ, and N_ϕ number of projection angles. The above equation is the approximation of backprojection by a discrete quadrature.

Analytical methods are faster and practical for implementation in a clinical setting but they are vulnerable to noise. The assumptions made in analytical formations are that the measurements are continuous and the solutions are of integral formulation. Sampling is done to the data a posteriori. They are also highly susceptible to system geometry. Since the 80's, model-based iterative reconstruction (MBIR) techniques Shepp and Vardi, 1982; Fessler, Sonka, and Fitzpatrick, 2000 became the standard approach. They consist in iteratively approximating a solution $\hat{\boldsymbol{x}}$ such that $\bar{\boldsymbol{y}}(\hat{\boldsymbol{x}})$ maximizes the likelihood of the measurement $\boldsymbol{y}$. As they model the stochasticity of the system, they are more robust to noise as compared with FBP, and can be completed with a penalty term for additional control over the noise De Pierro, 1995.

1.3.4 Iterative Reconstruction Algorithms

MLEM

TV-PWLS

Appendix A

Frequently Asked Questions

A.1 How do I change the colors of links?

The color of links can be changed to your liking using:

`\hypersetup{urlcolor=red}`, or

`\hypersetup{citecolor=green}`, or

`\hypersetup{allcolor=blue}`.

If you want to completely hide the links, you can use:

`\hypersetup{allcolors=.}`, or even better:

`\hypersetup{hidelinks}`.

If you want to have obvious links in the PDF but not the printed text, use:

`\hypersetup{colorlinks=false}`.

Bibliography

[Amy+19] A Amyar et al. "3-D RPET-NET: development of a 3-D PET imaging convolutional neural network for radiomics analysis and outcome prediction". In: *IEEE Transactions on Radiation and Plasma Medical Sciences* 3.2 (2019), pp. 225–231.

[Che+17] Hu Chen et al. "Low-dose CT denoising with convolutional neural network". In: *2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017)*. IEEE. 2017, pp. 143–146.

[Cui+18] Sunan Cui et al. "Artificial Neural Network With Composite Architectures for Prediction of Local Control in Radiotherapy". In: *IEEE Transactions on Radiation and Plasma Medical Sciences* 3.2 (2018), pp. 242–249.

[Dol+18] Jose Dolz et al. "HyperDense-Net: a hyper-densely connected CNN for multi-modal image segmentation". In: *IEEE Transactions on Radiation and Plasma Medical Sciences* 38.5 (2018), pp. 1116–1126.

[DP95] A. R. De Pierro. "A modified expectation maximization algorithm for penalized likelihood estimation in emission tomography". In: *IEEE Transactions on Medical Imaging* 14.1 (1995), pp. 132–137.

[EF02] I. A. Elbakri and J. A. Fessler. "Statistical image reconstruction for polyenergetic X-ray computed tomography". In: *IEEE Transactions on Medical Imaging* 21.2 (2002), pp. 89–99.

[FSF00] J. A. Fessler, M. Sonka, and J. M. Fitzpatrick. "Statistical image reconstruction methods for transmission tomography". In: *Handbook of medical imaging* 2 (2000), pp. 1–70.

[Guo+16] Yanming Guo et al. "Deep learning for visual understanding: A review". In: *Neurocomputing* 187 (2016), pp. 27–48.

[Guo+19] Zhe Guo et al. "Deep learning-based image segmentation on multimodal medical imaging". In: *IEEE Transactions on Radiation and Plasma Medical Sciences* 3.2 (2019), pp. 162–169.

[Hat+18] Mathieu Hatt et al. "The first MICCAI challenge on PET tumor segmentation". In: *Medical image analysis* 44 (2018), pp. 177–195.

[Iso+17] Phillip Isola et al. "Image-to-image translation with conditional adversarial networks". In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017, pp. 1125–1134.

[Kad+18] Venkata S Kadimesetty et al. "Convolutional neural network-based robust denoising of low-dose computed tomography perfusion maps". In: *IEEE Transactions on Radiation and Plasma Medical Sciences* 3.2 (2018), pp. 137–152.

[KRF14] Donghwan Kim, Sathish Ramani, and Jeffrey A Fessler. "Combining ordered subsets and momentum for accelerated X-ray CT image reconstruction". In: *IEEE Transactions on Medical Imaging* 34.1 (2014), pp. 167–178.

[Led+17] Christian Ledig et al. "Photo-realistic single image super-resolution using a generative adversarial network". In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017, pp. 4681–4690.

[Leu+21] Johannes Leuschner et al. "Quantitative Comparison of Deep Learning-Based Image Reconstruction Methods for Low-Dose and Sparse-Angle CT Applications". In: *Journal of Imaging* 7.3 (2021), p. 44.

[Li+20] Meng Li et al. "SACNN: Self-Attention Convolutional Neural Network for Low-Dose CT Denoising with Self-supervised Perceptual Loss Network". In: *IEEE Transactions on Medical Imaging* (2020).

[Lim+17] Bee Lim et al. "Enhanced deep residual networks for single image super-resolution". In: *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*. 2017, pp. 136–144.

[Lit+17] Geert Litjens et al. "A survey on deep learning in medical image analysis". In: *Medical image analysis* 42 (2017), pp. 60–88.

[Liu+13] Y. Liu et al. "Total variation-Stokes strategy for sparse-view X-ray CT image reconstruction". In: *IEEE Transactions on Medical Imaging* 33.3 (2013), pp. 749–763.

[Nuy+98] John Nuyts et al. "Iterative reconstruction for helical CT: a simulation study". In: *Physics in Medicine & Biology* 43.4 (1998), p. 729.

[Rea+20] Andrew J Reader et al. "Deep learning for PET image reconstruction". In: *IEEE Transactions on Radiation and Plasma Medical Sciences* 5.1 (2020), pp. 1–25.

[RFB15] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation". In: *International Conference on Medical image computing and computer-assisted intervention*. Springer. 2015, pp. 234–241.

[SD19] Ashish Sinha and Jose Dolz. "Multi-scale guided attention for medical image segmentation". In: *arXiv preprint arXiv:1906.02849* (2019).

[SV82] L. A. Shepp and Y. Vardi. "Maximum Likelihood Reconstruction for Emission Tomography". In: *IEEE Transactions on Medical Imaging* 1.2 (1982), pp. 113–122.

[Yan+18] Qingsong Yang et al. "Low-dose CT image denoising using a generative adversarial network with Wasserstein distance and perceptual loss". In: *IEEE Transactions on Radiation and Plasma Medical Sciences* 37.6 (2018), pp. 1348–1357.

[ZD20] Hai-Miao Zhang and Bin Dong. "A review on deep learning in medical image reconstruction". In: *Journal of the Operations Research Society of China* (2020), pp. 1–30.

[Zhu+17] Jun-Yan Zhu et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks". In: *Proceedings of the IEEE international conference on computer vision*. 2017, pp. 2223–2232.