Code Sprint: Benchmarking Deep Learning based CT Image Reconstruction Methods

Date: June 15–24, 2020
The sprint is a virtual event, due to the current pandemic. In addition, we will organize a physical follow-up meeting at the University of Bremen (Germany) when the situation will allow it.

Organization: Maureen van Eijnatten[1], Poulami Ganguly[1], Johannes Leuschner[2,i], Maximilian Schmidt[2]

General introduction

Deep learning has opened up a wealth of promising methodologies for various image analysis tasks such as image classification, object detection, segmentation, and registration. Moreover, deep learning is being increasingly used to solve inverse problems in computed tomography (CT) [1, 2]. In this field, deep learning holds the promise of performing fast and accurate reconstruction of CT images in e.g. high-resolution, limited-angle, or low-dose setups [3, 4, 5, 6]. However, there are still multiple challenges to overcome. Aside from the computational and data-related challenges, solving inverse problems using deep learning possibly requires completely new approaches that allow for the extraction of physically meaningful parameters. In recent years, many different deep learning based methods have been proposed for CT image reconstruction, such as unrolled iterative schemes [7], learned regularizers [8], and post-processing of reconstructed images [9]. However, it remains difficult to compare the performance of these methods across different imaging domains and applications due to a lack of generic benchmarking methods and sufficiently large datasets.

During this Code Sprint, we invite a small group of researchers and software developers to exchange knowledge, write code, form new collaborations and connect with industrial partners in the area of (learned) CT image reconstruction. We will focus on two applications with high relevance and impact: 1) reconstruction of low-dose medical CT images, and 2) high-throughput CT image reconstruction and abnormality detection.

Reconstruction of low-dose medical CT images

In the clinical application of CT, high radiation doses are potentially harmful to the subjects. Therefore, better reconstruction methods for low-dose CT acquisitions are highly desirable.

In order to compare (learned) reconstruction techniques for this application, we will use the low-dose parallel beam (LoDoPaB) CT dataset [10]. This dataset contains more than 40 000 two-dimensional CT images and corresponding simulated low-intensity measurements. The ground truth images of this dataset are human chest CT reconstructions taken from the LIDC/IDRI database [11]. Poisson noise is applied to the projection data after simulation to model the low intensity setup.

High-throughput CT image reconstruction and abnormality detection

When using X-ray tomography in high-throughput settings (e.g. scanning multiple objects per second) such as quality control, inspection of products on conveyor belts, or luggage scanning, very few X-ray projections can be acquired of each object [12]. In such settings, it is essential to incorporate *a priori* information about the object being scanned during image reconstruction. The challenge is to identify and explore how machine learning can be used in the image reconstruction and subsequent decision-making process (e.g. for detecting an internal abnormality in the scanned object) with high computational efficiency.

For this application, annotated CT images of real apples with internal defects will be made available by the innovative fruit sorting company Greefa.

[1]Centrum Wiskunde & Informatica (CWI), Amsterdam
[2]Center for Industrial Mathematics, Bremen
[i]jleuschn@uni-bremen.de

Goal

During the Code Sprint, participants are invited to adapt or implement learned methods to reconstruct CT images based on a medical and/or an industrial training CT dataset (including ground truth reconstructions) that will be provided beforehand. The implemented learned reconstruction methods will be included in the python library DIV$\alpha\ell$ to make them easily accessible to the community. The aim of the Code Sprint is to compare the performance of the implemented methods on a medical and/or an industrial testing CT dataset in a challenge setup.

Output

We aim to publish a comprehensive comparison of the results afterwards. In addition, this Code Sprint will enable easier baseline comparisons when new learned methods emerge. A fair benchmark of learned and classical approaches is an essential next step towards deploying deep learning in medical and industrial CT reconstruction tasks.

Questions for discussion

An important open problem is to define quality measures for reconstructions that consider the needs of the application. For example in medical imaging, the standard metrics (PSNR, SSIM) most likely do not indicate very well whether a doctor could make a better diagnosis based on the reconstruction.

Acknowledgements

We acknowledge the support by the Deutsche Forschungsgemeinschaft (DFG) within the framework of GRK 2224/1 "π^3: Parameter Identification – Analysis, Algorithms, Applications" and the support by the European Union's Horizon 2020 research and innovation programme through the Marie Sklodowska-Curie Innovative Training Network MUMMERING. We thank the company GREEFA for providing data to the participants of the Code Sprint.

References

[1] Simon Arridge, Peter Maass, Ozan Öktem, and Carola-Bibiane Schönlieb. Solving inverse problems using data-driven models. *Acta Numerica*, 28:1–174, 2019.

[2] Kyong Hwan Jin, Michael T McCann, Emmanuel Froustey, and Michael Unser. Deep convolutional neural network for inverse problems in imaging. *IEEE Transactions on Image Processing*, 26(9):4509–4522, 2017.

[3] Saiprasad Ravishankar, Jong Chul Ye, and Jeffrey A Fessler. Image reconstruction: From sparsity to data-adaptive methods and machine learning. *Proceedings of the IEEE*, 108(1):86–109, 2019.

[4] Eunhee Kang, Junhong Min, and Jong Chul Ye. A deep convolutional neural network using directional wavelets for low-dose x-ray ct reconstruction. *Medical physics*, 44(10):e360–e375, 2017.

[5] Tatiana A Bubba, Gitta Kutyniok, Matti Lassas, Maximilian Maerz, Wojciech Samek, Samuli Siltanen, and Vignesh Srinivasan. Learning the invisible: A hybrid deep learning-shearlet framework for limited angle computed tomography. *Inverse Problems*, 35(6):064002, 2019.

[6] Allard A Hendriksen, Daniël M Pelt, Willem Jan Palenstijn, Sophia B Coban, and Kees Joost Batenburg. On-the-fly machine learning for improving image resolution in tomography. *Applied Sciences*, 9(12):2445, 2019.

[7] Jonas Adler and Ozan Öktem. Learned primal-dual reconstruction. *IEEE transactions on medical imaging*, 37(6):1322–1332, 2018.

[8] Sebastian Lunz, Ozan Öktem, and Carola-Bibiane Schönlieb. Adversarial regularizers in inverse problems. In *Advances in Neural Information Processing Systems*, pages 8507–8516, 2018.

[9] Daniël M Pelt, Kees Joost Batenburg, and James A Sethian. Improving tomographic reconstruction from limited data using mixed-scale dense convolutional neural networks. *Journal of Imaging*, 4(11):128, 2018.

[10] Johannes Leuschner, Maximilian Schmidt, Daniel Otero Baguer, and Peter Maass. The lodopab-ct dataset: A benchmark dataset for low-dose ct reconstruction methods, 2019.

[11] Samuel G. Armato III, Geoffrey McLennan, Luc Bidaut, Michael F. McNitt-Gray, Charles R. Meyer, Anthony P. Reeves, Binsheng Zhao, Denise R. Aberle, Claudia I. Henschke, Eric A. Hoffman, Ella A. Kazerooni, Heber MacMahon, Edwin J. R. van Beek, David Yankelevitz, Alberto M. Biancardi, Peyton H. Bland, Matthew S. Brown, Roger M. Engelmann, Gary E. Laderach, Daniel Max, Richard C. Pais, David P.-Y. Qing, Rachael Y. Roberts, Amanda R. Smith, Adam Starkey, Poonam Batra, Philip Caligiuri, Ali Farooqi, Gregory W. Gladish, C. Matilda Jude, Reginald F. Munden, Iva Petkovska, Leslie E. Quint, Lawrence H. Schwartz, Baskaran Sundaram, Lori E. Dodd, Charles Fenimore, David Gur, Nicholas Petrick, John Freymann, Justin Kirby, Brian Hughes, Alessi Vande Casteele, Sangeeta Gupte, Maha Sallam, Michael D. Heath, Michael H. Kuhn, Ekta Dharaiya, Richard Burns, David S. Fryd, Marcos Salganicoff, Vikram Anand, Uri Shreter, Stephen Vastagh, Barbara Y. Croft, and Laurence P. Clarke. The lung image database consortium (lidc) and image database resource initiative (idri): A completed reference database of lung nodules on ct scans. *Med. Phys.*, 38(2):915–931, 2 2011.

[12] Yoseob Han, Jingu Kang, and Jong Chul Ye. Deep learning reconstruction for 9-view dual energy ct baggage scanner. *arXiv preprint arXiv:1801.01258*, 2018.