Seminar Machine Learning in MRI

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Goal of this seminar

Deep Convolutional Neural Network for Inverse Problems in Imaging

Kyong Hwan Jin, Michael T. McCann, *Member, IEEE*, Emmanuel Froustey, and Michael Unser, *Fellow, IEEE*

***Abstract*—In this paper, we propose a novel deep convolutional neural network (CNN)-based algorithm for solving ill-posed inverse problems. Regularized iterative algorithms have emerged as the standard approach to ill-posed inverse problems in the past few decades. These methods produce excellent results, but can be challenging to deploy in practice due to factors including the high computational cost of the forward and adjoint operators and the difficulty of hyperparameter selection. The starting point of this paper is the observation that unrolled iterative methods have the form of a CNN (filtering followed by pointwise non-linearity) when the normal operator (H^*H, where H^* is the adjoint of the forward imaging operator, H) of the forward model is a convolution. Based on this observation, we propose using direct inversion followed by a CNN to solve normal-convolutional inverse problems. The direct inversion encapsulates the physical model of the system, but leads to artifacts when the problem is ill posed; the CNN combines multiresolution decomposition and residual learning in order to learn to remove these artifacts while preserving image structure. We demonstrate the performance of the proposed network in sparse-view reconstruction (down to 50 views) on parallel beam X-ray computed tomography in synthetic phantoms as well as in real experimental sinograms. The proposed network outperforms total variation-regularized iterative reconstruction for the more realistic phantoms and requires less than a second to reconstruct a 512 × 512 image on the GPU.**

***Index Terms*—Image restoration, image reconstruction, tomography, computed tomography, magnetic resonance imaging, biomedical signal processing, biomedical imaging, reconstruction algorithms.**

I. Introduction

OVER the past decades, iterative reconstruction methods have become the dominant approach to solving inverse problems in imaging including denoising [1]–[3], deconvolution [4], [5], and interpolation [6]. With the appearance of compressed sensing [7] and the related regularizers such as total variation [1], [2], [4], [8], robust and practical algorithms have appeared with excellent image quality and reasonable computational complexity. These advances have been particularly influential in the field of biomedical imaging, e.g., in magnetic resonance imaging (MRI) [9]–[11] and X-ray computed tomography (CT) [12]–[14]. These devices face an unfavorable trade-off between noise and acquisition time. Short acquisitions lead to severe degradations of image quality, while long acquisitions may cause motion artifacts, patient discomfort, or even patient harm in the case of radiation-based modalities. Iterative reconstruction with regularization provides a way to mitigate these problems in software, i.e. without developing new scanners.

A more recent trend is deep learning [15], which has arisen as a promising framework providing state-of-the-art performance for image classification [16], [17] and segmentation [18]–[20]. Moreover, regression-type neural networks have demonstrated impressive results on inverse problems with exact models such as signal denoising [21], [22], deconvolution [23], artifact reduction [24], [25], signal recovery (model-based restoration) [26], [27], and interpolation [28]–[30]. Central to this resurgence of neural networks has been the convolutional neural network (CNN) architecture. Whereas the classic multilayer perceptron consists of layers that can perform arbitrary matrix multiplications on their input, the layers of a CNN are restricted to perform convolutions, greatly reducing the number of parameters which must be learned.

Researchers have begun to investigate the link between conventional iterative approaches and deep learning networks [31]–[35]. Gregor and LeCun [31] explored the similarity between the ISTA algorithm [36] and a shared layerwise neural network and demonstrated that several layer-wise neural networks act as a fast approximated sparse coder. Similarly, [34] described the usage of iterative gradient descent inferences for maximum a posteriori (MAP) estimation, and the unrolling concept came out in the derivation. In [32], a non-linear diffusion reaction process based on the Perona-Malik process was proposed using deep convolutional learning; convolutional filters from diffusion terms were trained instead of using well-chosen filters like kernels for diffusion gradients, while the reaction terms were matched to the gradients of a data fidelity term that can represent a general inverse problem. In [33], the authors focused on the relationship between l_0 penalized-least-squares methods and deep neural networks. In the context of a clustered dictionary model, they found that the non-shared layer-wise independent weights and activations

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Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

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→ Read

→ Understand

→ Contextualize

→ Assess

→ Present to your peers

→ Summarize in your own words

Seminar structure

MO 10:15 to 11:45

Room 3.17 – Seminarraum, Werner-von-Siemens-Straße 61

Introduction

April 17th: Kick-off

April 24th: MRI refresher lecture (attendance optional)

May 1st: Deadline to pick your paper and presentation slot (via StudOn)
→ First come, first serve, starting today 18:00

Presentations

May 8th, 15th, 22nd, June 12th, 19th, 26th, July 3rd, 10th → 3 presentations per slot

Written report: Deadline July 24th (you are encouraged to submit earlier)

Tasks

Presentation:

- 20 minutes talk + 10 minutes discussion
- Present the paper in your own words
- Target group: your peers
- Spark a discussion
- Mandatory attendance at presentations – you may skip a maximum of two sessions

Written report:

- Approximately 5-7 pages, IEEE Latex style template
- Summarize the paper **in your own words**
- Give an overview of relevant previous work as well as (if applicable) current research that builds on your paper
- What are limitations? Open issues?

Grading:

- 50% report, 50% presentation, bonus for strong participation in discussion

Learning a Variational Network for Reconstruction of Accelerated MRI Data

Kerstin Hammernik,[1*] Teresa Klatzer,[1] Erich Kobler,[1] Michael P. Recht,[2,3] Daniel K. Sodickson,[2,3] Thomas Pock,[1,4] and Florian Knoll[2,3]

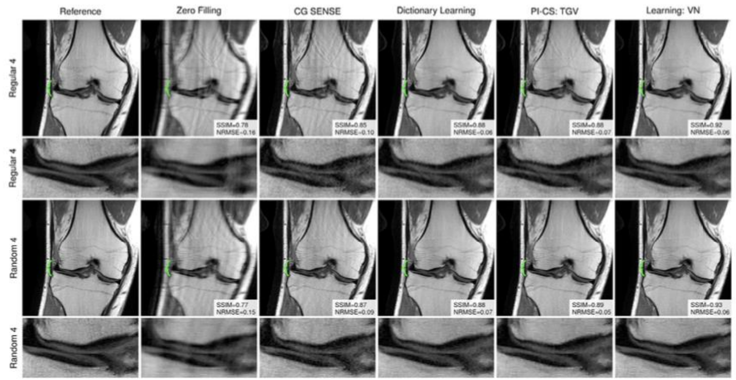
Purpose: To allow fast and high-quality reconstruction of clinical accelerated multi-coil MR data by learning a variational network that combines the mathematical structure of variational models with deep learning.

Theory and Methods: Generalized compressed sensing reconstruction formulated as a variational model is embedded in an unrolled gradient descent scheme. All parameters of this formulation, including the prior model defined by filter kernels and activation functions as well as the data term weights, are learned during an offline training procedure. The learned model can then be applied online to previously unseen data.

Results: The variational network approach is evaluated on a clinical knee imaging protocol for different acceleration factors and

INTRODUCTION

Imitating human learning with deep learning (1,2) has become an enormously important area of research and development, with a high potential for far-reaching application, including in the domain of Computer Vision. Taking encouragement from early successes in image classification tasks (3), recent advances also address semantic labeling (4), optical flow (5) and image restoration (6). In medical imaging, deep learning has also been applied to areas like segmentation (7,8), q-space image processing (9), and skull stripping (10). However, in these applications, deep learning was seen as a tool for image processing and



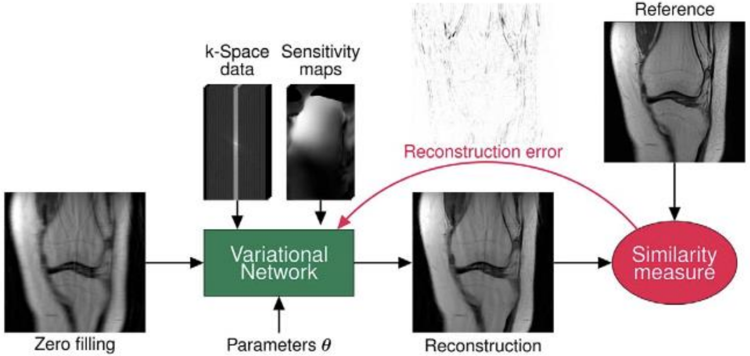


FIG. 2. Variational network training procedure: we aim at learning a set of parameters of the VN during an offline training procedure. For this purpose, we compare the current reconstruction of the VN to an artifact-free reference using a similarity measure. This gives us the reconstruction error which is propagated back to the VN to compute a new set of parameters.

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Pick your paper (1)

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   Akcakaya et al., MRM 2017 (doi.org/10.1002/mrm.27420)
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   Jin et al., IEEE Trans Imag Proc 2017 (doi.org/10.1109/TIP.2017.2713099)
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4. VN for 4D flow MRI
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5. Implicit data crimes
   Shimron et al., PNAS 2022 (doi.org/10.1073/pnas.2117203119)
6. Super-resolution knee
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    Zhang et al., Radiology 2019 (doi.org/10.1148/radiol.2019182304)

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    Cohen et al., MRM 2018 (doi.org/10.1002/mrm.27198)
22. Contrast Agent Reduction
    Gong et al., JMRI 2018 (doi.org/10.1002/jmri.25970)
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    Guo et al., JCMR 2022 (doi.org/10.1186/s12968-021-00834-0)
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    Kleineisel et al., MRM 2022 (doi.org/10.1002/mrm.29357)
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Questions?