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Untrained Deep Networks in Computational Imaging and Sensing: A Short Review

Farhad Niknam*

Department of Geotechnical Engineering, Shahid Beheshti University, Tehran, Iran

Abstract

Physics-based image formation models enable computationally obtaining meaningful information by processing other forms of information which can be acquired through measurements. In practical situations however, the inner functionalities of the system which create the impulse response function are usually unknown, and due to noise, measurements are unreliable. Before Deep Neural Networks (DNNs) taking over, Compressed Sensing (CS) techniques were primarily being used to address this lack of information by imposing assumptions into the problem. But this switch to DNNs came with the price of mass data acquisition for training to leap over the never-ending problem of algorithmic fidelity in CS methods. Recently, deep image prior and untrained or semi-trained networks, while leveraging the power of DNNs and algorithms, have become successful to be considered as potential answers to the desire of finding a cost-efficient yet powerful solution. In this paper, we briefly have a look at the recent breakthroughs conducted over this concept to solve various imaging problems.

Keywords: Deep neural networks • Compressed sensing • Convolution neural networks

Introduction

Deep Neural Networks (DNN) has led to state-of-the-art results in signal processing and inverse problems with a superior accuracy. Furthermore, their high capability in handling nonlinearity have induced a common compliance in simply choosing data oriented supervised DNN models over conventional algorithmic approaches [1-4]. But this shift in paradigm comes with the expenses of preparing massive datasets. This requirement becomes increasingly serious when the expenses rise dramatically for domains such as biological or astronomical imaging. Furthermore, trained DNNs suffer from generality issue, and they are only suitable for specific tasks that they were trained for. Optimized feature spaces are built upon a set of features which were given in the training dataset and the performance of DNN models may drop dramatically on totally different test samples.

After the introduction of Deep Image Priors (DIP), untrained networks have gained interest for signal reconstruction and inverse problems [5]. It was shown that the feature extraction property of Convolution Neural Networks (CNN), if trained on a single image of interest, can effectively produce an organic image prior. This image prior enables the network to accurately reproduce the image with a reduced set of features which filters out high spatially varying structures such as noise. This idea was initially demonstrated on various linear problems such as denoising, restoration, inpainting, and super-resolution.

Meanwhile, DNN priors found their way into nonlinear inverse problems and Compressed Sensing (CS) as well [6,7]. A DNN is versatile enough to allow integration of mathematical extensions, like signal formation algorithm, to the cost function. The resulting model is capable of inversely reconstructing the desired information from a set of input measurements through an optimization process. Furthermore, the learned regularization in CNNs has shown a promising performance in solving undetermined problems. The inherent generality and controllability of untrained networks in addition with their precision, effectively fills the gap between the mathematical approaches relying on inaccurate hand-crafted priors and supervised DNNs requiring extensive amount of training information.

***Address for Correspondence:** Farhad Niknam, Department of Geotechnical Engineering, Shahid Beheshti University, Tehran, Iran; E-mail: farhad.niknam@outlook.com*

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Literature Review

Untrained networks in imaging problems

Quantitative Phase Microscopy (QPM) refers to a category of algorithmic imaging approaches which enables numerical reconstruction of phase information of microscopic samples by a set of intensity measurements and allows imaging of label-free transparent phase specimen e.g. unstained cells and tissues [8]. The underdetermined and nonlinear nature of phase reconstruction problems mandates an inverse procedure based on the physics of the image formation process which is generally challenging to solve without obtaining multiple diversified measurements or having a precise knowledge about the system [9].

As demonstrated in, an encoder-decoder DNN accompanied with the free-space optical propagation algorithm can reconstruct the phase image of transparent micro-samples using the intensity distribution of their coherent diffraction pattern measured on a sensor array [10]. The physics-based model designed on top of the untrained network produces an optimized learned prior which enables recovering the phase information without any training or prespecified constraint. Even though in the off-axis holographic microscopy method used in this work, the forward problem is well-defined, and the measured information is enough to directly retrieve the phase and amplitude terms, the high quality of the outcomes clearly shows the performance gained by the sample-specific deep image priors [11].

However, for many applications, the problem is highly underdetermined due to poorly known system under-sampled measurements. Errors originating from noise, aberrations, or misalignments may also cause this issue. One great advantage of the physics-based optimization formulation is enabling incorporation of multiple physical models to retrieve different sorts of data simultaneously. This allows even solving a problem without properly knowing the crucial system parameters and finding them during the optimization [12,13].

In a successful demonstration of this self-calibrating model concept, a deep decoder network could reconstruct a phase image

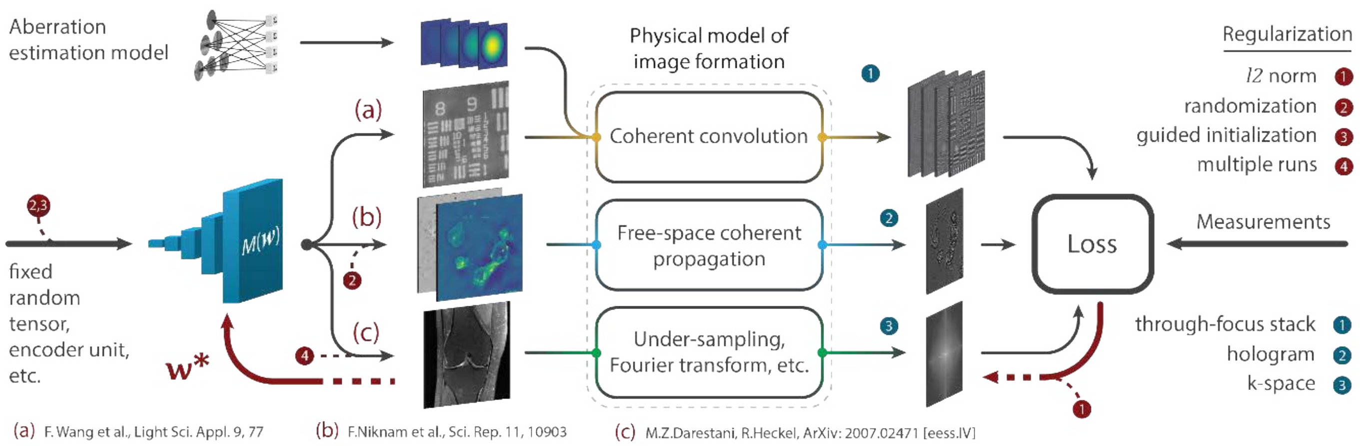

Figure 1. Examples of UDN models to reconstruct different types of signals. Note: (a) Self-calibrating phase retrieval, (b) Single-shot lens less in-line holography, (c) Fast-MRI.

using multiple defocus intensity measurements without knowing their axial displacement values (Figure 1) [14,15]. The self-calibration part is made of an aberration estimation model consisting of Zernike polynomials which are densely connected to a layer of neurons. This model aims to estimate the wave front aberrations at the pupil plane caused by defocus for each measurement. Hence, through the optimization steps, a hypothetical phase image will be reconstructed that corresponds to the observable field on the sensor plane based on the estimated coherent pupil functions of the system.

Another existing challenge for computational imaging modalities is fast imaging with compressive measurements. Particularly, in coherent imaging approaches, the phase map or phase-amplitude complex-valued mixed image is difficult or impossible to retrieve by a single magnitude-only measurement which clearly limits the throughput. Traditionally, one need to obtain multiple phase shifted images or employ off-axis geometry to resolve this issue [9,16]. Alternatively, the object field can be inversely recovered using coherent propagation principles while being constrained by strict sample-dependent assumptions such as sparsity [17].

One obvious example is digital holographic imaging which normally requires multiple measurements, each with a well-characterized tweak in a system parameter, to robustly recover the whole phase/amplitude image in an in-line scheme. However, the same information could be retrieved using an off-axis scheme by a spatial phase-shift imposed by a precisely known angle between the two interfering beams of object and reference. The ultimate objective in such a problem is to compressively reconstruct the whole complex-valued object field with a single shot which not only removes all these complications, but also enables real-time image acquisition by a simple setup. But such a severe under-sampling makes the problem extremely ill-posed that cannot be solved without inflicting tight restrictions on the solutions by regularization.

Discussion

In a recent demonstration, holograms captured from cell specimen by a lensless in-line holographic microscope were unprecedentedly reconstructed using an untrained deep decoder network by a single hologram [18]. The accuracy of the results was quite comparable with of those obtained by traditional multi-image-based phase recovery techniques using 6 to 8 holograms. This was simply achieved by enforcing some general regularization on the network such as l2 or the so-called weight decay and periodic network randomization. Such accomplishments for under-sampled measurements by untrained networks were also achieved for lensless 2D imaging, single-shot video acquisition, and hyperspectral imaging as well [19].

Although untrained networks have shown impressive results in computational imaging and CS problems and, by far, outperformed traditional methods, they are slow, computationally expensive, and their quality of outcomes greatly depends on the network architecture. In another attempt for under-sampled signal reconstruction, some enhancements in deep decoder network's architecture and its optimization procedure led to significant improvements in fast MRI imaging, both in speed and fidelity respect to the prior implementations of untrained networks for similar applications and surpassed the traditional sparsity-based CS techniques in quality [20]. The newly suggested Conv-Decoder can reconstruct under-sampled MRI images closely resembled with the state-of-the-art end-to-end supervised DNN models and thanks to the proposed guided initialization, it can provide the same results 10x faster.

Conclusion

The considerable success of learned priors in a wide range of computational imaging and sensing applications without making any dramatic change in the primary idea implies that untrained networks will probably perform effectively on other inverse problems as well. Replacing the predefined priors and parameters with the learned ones can create a generalized model structure against various conditions for which the only variable would be the physical model. A DNN incorporated with a physical model is general enough to be used relatively untouched for any application. Moreover, the demonstrated ability of UDNs in solving underdetermined ill-posed problems that were once impossible to solve with a proper quality indicates it would find a greater audience for various applications in the future. Although optimization speed and memory intensiveness of UDNs are still open problems, they will have less importance in the future with the continuous annual growth in GPUs and TPUs power, or the possible emergence of publicly available quantum computers and quantum-computer-compatible neural networks frameworks.

Conflict of Interest

Author has nothing to disclose.

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