Project Title: Sparse Image Reconstruction with Trainable Image priors

Project Supervisor(s) and affiliation(s):

Stamatis Lefkimmiatis, Skolkovo Institute of Science and Technology (Email: s.lefkimmiatis@skoltech.ru)

Project Description:

Sparse image reconstruction refers to the problem of recovering an image from a limited number of measurements. Since this is a highly ill-posed problem, a meaningful reconstruction is only possible if prior information about certain image properties is taken into account. An example of an important real-world problem where sparse image reconstruction methods are typically applied is MRI reconstruction. In this case in order to reduce the scanning time and to avoid image artifacts that can appear because of the movement of the patient, usually only a limited number of k-space data are sampled. Then a sparse image reconstruction technique needs to further process the sampled data in order to recover the missing information.

Current methods that are employed for dealing with this task mainly rely on handcrafted image priors and iterative convex optimization techniques. However, due to their iterative nature, these recovery methods are computationally demanding. The goal of this project is to investigate if an alternative method, which will be based on convolutional neural networks (CNNs) and supervised deep learning, can be used to speed-up the reconstruction time and lead to further improvements in terms of image quality.

Key References:

1) Emmanuel Candès and Michael Wakin, " An introduction to compressive sampling". IEEE Signal Processing Magazine, 25(2), pp. 21 - 30, March 2008

2) Donoho, David L. "Compressed sensing." *IEEE Transactions on information theory* 52, no. 4 (2006): 1289-1306.

3) Compressive Sensing Resources, http://dsp.rice.edu/cs

Ratio of effort: Theoretical/Computational /Programming	Theo:	35%
	Comp:	15%
	Prog:	50%

Recommended Classes/Pre-requisites: Optimization Methods (Term 2), Numerical Linear Algebra (Term 2), Signal and Image Processing (Term 3), Deep Learning (Term 4) / Good programming skills in one of the following programming environments: Python (Tensorflow, Theano), Matlab (MatconvNet), or C/C++ (Caffe).

Suitability: Data Science, Computational Science and Engineering

Safety Training Requirements:

Project Title: Trainable Filters and Shrinkage Functions for Motion Image Deblurring

Project Supervisor(s) and affiliation(s):

Stamatis Lefkimmiatis, Skolkovo Institute of Science and Technology (Email: s.lefkimmiatis@skoltech.ru)

Project Description:

When a photograph is taken under low-light conditions or the scene involves a fast moving object then motion blur appears in the captured image and significantly degrades the image quality. The motion blur is caused by the movement of the object relative to the sensor of the camera during the time that the shutter is open. Both the movement of the object and the camera shake contribute to this blurring effect. This problem is particularly apparent in low-light conditions when the exposure time is longer and can often be in the order of several seconds.

The focus of this project will be on the design of a motion deblurring algorithm that will be able to restore the underlying image from the blurred observation. To deal with this problem conventional algorithms employ hand-crafted regularizers to explore prior information about the image properties. In this project, the goal is to learn instead a suitable regularizer directly from training data. This is possible by designing a suitable neural network and learning the optimal parameters through supervised learning. Such an approach is expected to lead to superior deblurring results while at a significantly reduced computational complexity, which will cast the designed method practical for real-world applications.

Key References:

1) Shan, Qi, Jiaya Jia, and Aseem Agarwala. "High-quality motion deblurring from a single image." In *ACM Transactions on Graphics (TOG)*, vol. 27, no. 3, p. 73. ACM, 2008.

2) Schmidt, Uwe, and Stefan Roth. "Shrinkage fields for effective image restoration." In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2774-2781. 2014.

3) Fergus, Rob, Barun Singh, Aaron Hertzmann, Sam T. Roweis, and William T. Freeman. "Removing camera shake from a single photograph." In *ACM Transactions on Graphics (TOG)*, vol. 25, no. 3, pp. 787-794. ACM, 2006.

Ratio of effort: Theoretical/Computational /Programming	Theo:	35%
	Comp:	15%
	Prog:	50%

Recommended Classes/Pre-requisites: Optimization Methods (Term 2), Numerical Linear Algebra (Term 2), Signal and Image Processing (Term 3), Deep Learning (Term 4) / Good programming skills in one of the following programming environments: Python (Tensorflow, Theano), Matlab (MatconvNet), or C/C++ (Caffe).

Suitability: Data Science, Computational Science and Engineering

Safety Training Requirements:

Project Title: Image Super-resolution with Convolutional Neural Networks

Project Supervisor(s) and affiliation(s):

Stamatis Lefkimmiatis, Skolkovo Institute of Science and Technology (Email: s.lefkimmiatis@skoltech.ru)

Project Description:

Super-resolution (SR) refers to the problem of constructing high-resolution (HR) images from a single or several observed low-resolution (LR) images, thereby increasing the high frequency components and removing the degradations caused by the imaging process of the low resolution camera. The basic idea behind SR is to exploit prior knowledge of image properties and/or combine the non-redundant information contained in multiple low-resolution frames to generate a high-resolution image.

The goal of this project is to investigate whether by using a deep convolutional neural network architecture and supervised learning, it is possible to develop a fast and efficient super-resolution method that will be able to produce super-resolved images of superior quality compared to the ones obtained by current image regularization techniques.

Key References:

1) Wang, Zhaowen, Ding Liu, Jianchao Yang, Wei Han, and Thomas Huang. "Deep networks for image super-resolution with sparse prior." In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 370-378. 2015.

2) Kim, Jiwon, Jung Kwon Lee, and Kyoung Mu Lee. "Accurate image superresolution using very deep convolutional networks." *arXiv preprint arXiv:1511.04587* (2015).

Ratio of effort: Theoretical/Computational /Programming	Theo:	35%
	Comp:	15%
	Prog:	50%

Recommended Classes/Pre-requisites: Optimization Methods (Term 2), Numerical Linear Algebra (Term 2), Signal and Image Processing (Term 3), Deep Learning (Term 4) / Good programming skills in one of the following programming environments: Python (Tensorflow, Theano), Matlab (MatconvNet), or C/C++ (Caffe).

Suitability: Data Science, Computational Science and Engineering

Safety Training Requirements:

Project Title: Universal CNNs for Blind Image Denoising

Project Supervisor(s) and affiliation(s):

Stamatis Lefkimmiatis, Skolkovo Institute of Science and Technology (Email: s.lefkimmiatis@skoltech.ru)

Project Description:

Recently many powerful techniques that are based on convolutional neural networks have been proposed in the literature for tackling the problem of image denoising. While their performance has been shown to be superior than other existing nonmachine learning denoising methods, their main limitation is that these networks need to be trained for all possible noise levels. If a network trained for a specific noise level is applied on an image corrupted by a noise of a different level, then the result is far from optimal. This can be a serious limitation in practice and hinders the wider applicability of such image denoising techniques.

The goal of this project is to investigate whether it is possible to modify existing CNN architectures that are designed for image denoising or design new deep models so that a single instance of the network can handle several noise levels without compromising the final image quality.

Key References:

1) Schmidt, Uwe, and Stefan Roth. "Shrinkage fields for effective image restoration." In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2774-2781. 2014

2) Chen, Yunjin, and Thomas Pock. "Trainable Nonlinear Reaction Diffusion: A Flexible Framework for Fast and Effective Image Restoration." *arXiv preprint arXiv:1508.02848* (2015).

3) Lefkimmiatis, Stamatios. "Non-Local Color Image Denoising with Convolutional Neural Networks." *arXiv preprint arXiv:1611.06757* (2016).

Ratio of effort: Theoretical/Computational /Programming	Theo:	35%
	Comp:	15%
	Prog:	50%

Recommended Classes/Pre-requisites: Optimization Methods (Term 2), Numerical Linear Algebra (Term 2), Signal and Image Processing (Term 3), Deep Learning (Term 4) / Good programming skills in one of the following programming environments: Python (Tensorflow, Theano), Matlab (MatconvNet), or C/C++ (Caffe).

Suitability: Data Science, Computational Science and Engineering

Safety Training Requirements:

Project Title: Non-local Image Demosaicing with Deep CNNs

Project Supervisor(s) and affiliation(s):

Stamatis Lefkimmiatis, Skolkovo Institute of Science and Technology (Email: s.lefkimmiatis@skoltech.ru)

Project Description:

Image demosaicing refers to the problem of reconstructing a full color image from the incomplete color samples output from an image sensor overlaid with a color filter array (CFA). This is a very important problem in image processing and has a high practical interest since almost all modern digital color cameras use an image demosaicing algorithm to produce color images.

The main goal of this project is the design and supervised training of a deep learning network for image demosaicing, and the comparison of its performance with current state-of-the-art demosaicing algorithms. In this context, the core idea that will be pursued is the design of a non-local deep image model, which will be able to explore the very important non-local self-similarity property of natural images, and investigate if its use can lead to further improvements in terms of reconstruction quality compared to local image methods that have been employed so far.

Key References:

1) Khashabi, Daniel, Sebastian Nowozin, Jeremy Jancsary, and Andrew W. Fitzgibbon. "Joint demosaicing and denoising via learned nonparametric random fields." *IEEE Transactions on Image Processing* 23, no. 12 (2014): 4968-4981.

2) Klatzer, Teresa, Kerstin Hammernik, Patrick Knobelreiter, and Thomas Pock.
"Learning joint demosaicing and denoising based on sequential energy minimization."
In *Computational Photography (ICCP), 2016 IEEE International Conference on*, pp. 1-11. IEEE, 2016.

3) Gharbi, Michaël, Gaurav Chaurasia, Sylvain Paris, and Frédo Durand. "Deep joint demosaicking and denoising." *ACM Transactions on Graphics (TOG)* 35, no. 6 (2016): 191.

4) Lefkimmiatis, Stamatios. "Non-Local Color Image Denoising with Convolutional Neural Networks." *arXiv preprint arXiv:1611.06757* (2016).

Ratio of effort: Theoretical/Computational /Programming	Theo:	35%
	Comp:	15%
	Prog:	50%

Recommended Classes/Pre-requisites: Optimization Methods (Term 2), Numerical Linear Algebra (Term 2), Signal and Image Processing (Term 3), Deep Learning (Term 4) / Good programming skills in one of the following programming environments: Python (Tensorflow, Theano), Matlab (MatconvNet), or C/C++ (Caffe).

Suitability: Data Science, Computational Science and Engineering

Safety Training Requirements: