Research Project Proposal: Deep Image Denoising

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1. Introduction to the problem

The goal of image restoration is to recover the original, clean image, starting from a corrupted image. Depending on the type of corruption, image restoration tasks can be divided into deblurring, super-resolution, denoising, inpainting, text removal and many others. In particular, image denoising has the goal of estimating the clean image from its observed version corrupted by noise. Modern image denoising lies at the intersection of signal processing, computer science and machine learning. Indeed, recent technological and methodological advances in deep learning have allowed the employment of convolutional neural networks (CNNs) for image restoration purposes.

The obvious application for image denoising is to provide to the user a pleasant and clear image by removing as much noise as possible, without losing details. From a technical point of view, a denoised image is an essential prerequisite for more high-level computer vision tasks and complex deep learning pipelines (e.g. autonomous driving). Moreover, denoiser can be plugged in as a modular part of model-based optimization methods to solve other restoration problems.

The current state of the art methods have achieved great denoising performance and some of them can produce an estimate reasonably fast. A very large variety of deep learning denoisers were proposed in the literature during the last years suggesting different architectures, approaches, noise models, and even brand new CNN units. In our project we will experiment with new modules or architectures rather than focusing on minor variations and fine tuning of existing models.

2. Main related works

Image denoising has been studied for decades and there are several methods that were developed in the first years of the twenty-first century, which achieve very good performance and they had been the state of the art for many years. Among these classic methods, arguably the most famous is BM3D [2], which exploits self-similarity between blocks of pixels and then performs collaborative filtering. With the advent of deep learning, a large number of neural networks have been employed for image denoising, and more in general restoration/enhancement. Among the pioneer methods, it is worth mentioning DnCNN [9], which is basically a plain convolutional neural network, and FFDNet [10] which extend the former requiring a noise level map as input, making the denoiser non-blind. The authors of Noise2Noise [4] showed that, in some cases, it is possible to train a CNN denoiser without requiring clean data for training. NN3D [1] demonstrates how classic non-local filters (e.g. BM3D) and CNN denoisers can team up to increase denoising performance in an iterative manner. In NLRN [5], non-local differentiable operations are enclosed in a module for neural networks and then employed in a recurrent neural network (RNN) for denoising. CBDNet [3] is a CNN trained with a realistic noise model obtaining good results on real photographs benchmarks. The authors of VDN [8] propose a fully Bayesian model of the corruption mechanism and they use a CNN for estimating the hyper-parameters of a variational approximation of the posterior distributions. Almost all the cited networks adopt the simple ℓ_2 loss for training. In [11], it has been highlighted that this choice is not necessarily the optimal one and they propose new losses as mixes of standard losses and perceptual motivated error functions, achieving evident improvements.

3. Research plan

The goal of our research is to develop new ideas that can advance the state of the art in deep image denoising. The main focus will be in proposing new deep architectures, training techniques or single modules that can be plugged into existing CNN or RNN denoisers. Earlier work on deep networks for denoising had a pure machine learning approach, while only recently the architectures started to accommodate the priors that underlie the classic methods. Among these, the rotation/shift equivariance and the importance of the effective receptive field are topics that need to be deepened. A possible research direction is to elaborate how to insert in denoising networks modules or procedures to exploit the rotation and shift equivariance of the denoising problem. We think that a promising idea could be to employ a RNN that receives a shifted/rotated version of the same image in order to force the network to take into account the equivariance properties and at the same time to increase its effective receptive field [6]. Alternatively, we could investigate whether the modules of RotEqNet [7], which provide rotation equivarance for high-level computer vision tasks, can be adapted for restoration purposes, since they likely do not work without modifications because they are meant for high-level tasks such as classification and hence they propagate different types of information.

The nature of the research is theoretical, in the sense that we have to design this new module or architecture, but also comprises the implementation and experimentation of the designed model, testing its performance with widely accepted benchmarks. The tasks in which the research is decomposed are the following:

1. **Study of the state of the art**. Exploration and study of the literature of image denoising with particular focus on deep learning methods for image denoising and restoration. Also other works in deep architectures, as long as they can be adapted to image denoising, are considered.

2. **Familiarise**. Get familiarity with state of the art models and technical details by implementing and training an established deep denoiser architecture, namely FFDNet [10]. In this way we will also become familiar with standard datasets and experimental procedures.

3. **Architecture/module design**. Theoretical design of a new architecture or module for deep image denoising. Ideas from RotEqNet [7] and the use of RNN for exploiting rotation/shift equivariance will be extended.

4. **Implementation**. Software implementation of the designed architecture or module with the aid of one of the available deep learning libraries.

5. **Training and testing**. Training of the implemented model, testing with widely used benchmarks datasets and comparison with state-of-the-art models. The model will be trained with different noise models and a performance assessment will be carried out to understand how much the performance degrades when there is a mismatch in the noise models considered during training and testing.

6. **Writing**. Preparation of a conference paper describing all the achievements.

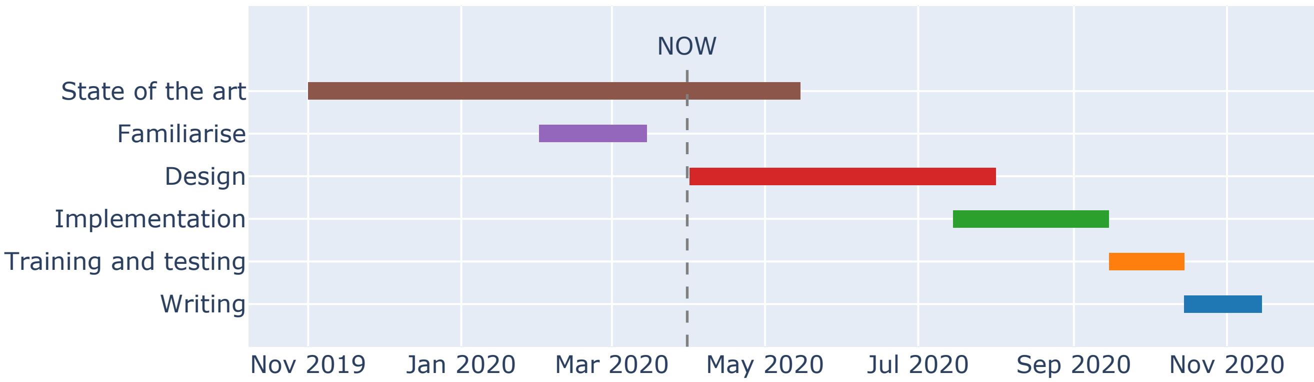

Figure 1: Gantt diagram of the research plan

The desired output of the project will be a working and trained deep image denoiser. The performance of our methods will be compared to the performance of the current state-of-the-art methods with the usual image quality metrics, for instance PSNR and SSIM.

References

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