Blind Deconvolution Using Constrained Deep Image Prior

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Abstract

In this poster we study the problem of blind deconvolution. This problem can be formulated as an energy minimization one, but it was showed in [1] that the desired solution has a higher energy than the no-blur solution. The need of suitable regularizers for the kernel, to avoid trivial solution, motivated the research in this field. According to [2] the Total Variation is a good regularizer on the reconstructed kernel but Favaro and Perrone in [3] observed that the results obtained with the algorithm of Chan and Wong are due to some internal parameters choices.

The main purpose of this work is to exploit the expressiveness of the Deep Image Prior [4], to re-parameterize the initial problem and to avoid the convergence to the blurry input (as reconstructed image) and the Dirac delta (as estimated blur). The resulting algorithm is an iterative alternating energy minimization where at each step the minimization is performed on the neural networks parameter space and the inner problem is solved by means of an iterative scheme derived from a constrained reformulation.

Introduction

We are interested in the solution of the **blind deconvolution** problem.

$$v = \bar{k} \otimes \bar{u} + \eta \tag{1}$$

where $\otimes$ denotes the 2D convolution operator, $\bar{k}$ is the blur kernel, $\bar{u}$ is the latent clean image and η is the additive white Gaussian noise (AGWN).
The two unknowns are both:

- the original clean image $\bar{u}$
- the blur kernel $\bar{k}$

The inverse problem (1) can be reformulated as an optimization problem [2].

$$(u,k) = \underset{(u,k)}{\operatorname{argmin}} \|k \otimes u - v\|_2^2 + \lambda\psi(u) + \tau\phi(k)$$
$$\text{s.t.} \quad \sum_j k_j = 1, \quad k_j \geq 0 \quad \forall\, j, \quad u_i \in [0,1] \quad \forall\, i \tag{2}$$

That can be solved using an alternating minimization (AM) iterative scheme.

$$\begin{cases} u_{t+1} = \underset{u}{\operatorname{argmin}} \|k_t \otimes u - v\|_2^2 + \lambda\psi(u) & (3) \\ k_{t+1} = \underset{k}{\operatorname{argmin}} \|k \otimes u_{t+1} - v\|_2^2 + \tau\phi(k) & (4) \end{cases}$$

Method

In [5] it was proposed to exploit the Deep Image Image Prior [4] both for the image and the kernel.
Formally two neural networks are considered as parametrization:

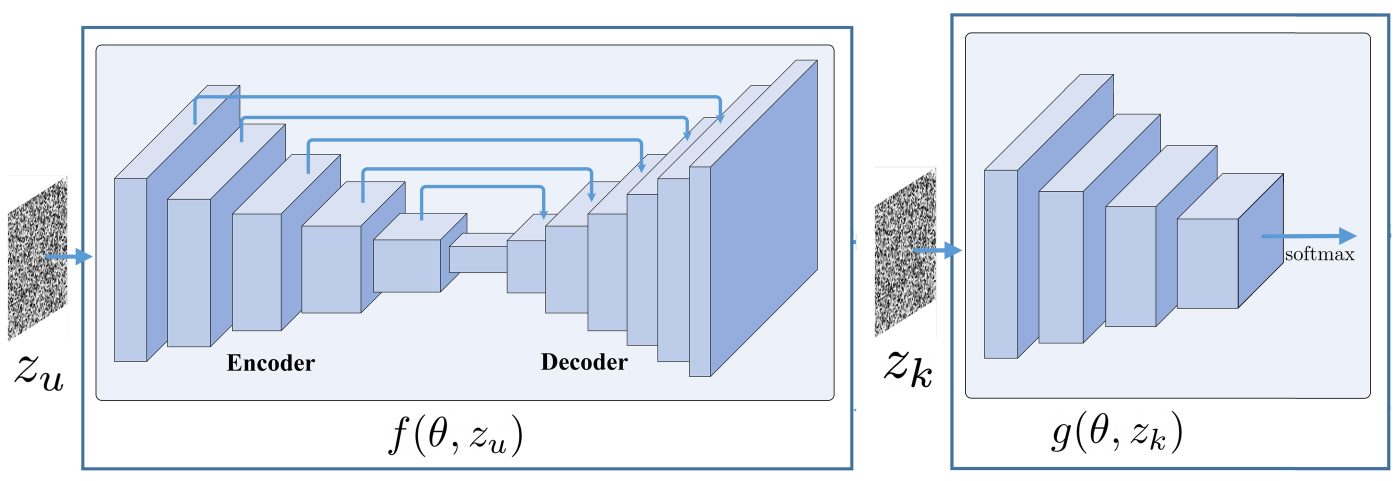
- $u = f(\theta, z_u)$ encoder-decoder with skip connections
- $k = g(\theta, z_k)$ plain convolutional neural network with softmax activaion function

The minimization problems (3) and (4) are re-parameterized and the minimization is performed on the neural networks parameter space.

$$\begin{cases} u_{t+1} = f(\theta^*, z_u) \Longleftarrow \theta^* \in \underset{\theta \in \mathbb{R}^s}{\operatorname{argmin}} \|k_t \otimes f(\theta, z_u) - v\|_2^2 + \lambda\psi(f(\theta, z_u)) & (5) \\ k_{t+1} = g(\theta^*, z_k) \Longleftarrow \theta^* \in \underset{\theta \in \mathbb{R}^s}{\operatorname{argmin}} \|g(\theta, z_k) \otimes u_{t+1} - v\|_2^2 + \tau\phi(g(\theta, z_k)) & (6) \end{cases}$$

A constrained reformulation of the iterative algorithm proposed in [6], based on the Augmented Direction Multipliers Method (ADMM), it is used to inexactly solve (5) without the need of the regularization weight λ.

$$u_{t+1} = f(\theta^*, z) \leftarrow \begin{cases} \theta^* \in \underset{\theta \in \mathbb{R}^s}{\operatorname{argmin}}\ \psi(f(\theta, z)) \quad \text{s.t.} \quad f(\theta, z) \in D_{\sigma_\eta} \\ D_{\sigma_\eta} := \{ f(\theta, z) \in \mathbb{R}^n \mid \|k_t \otimes f(\theta, z) - v\|_2^2 \leq \tau\sigma_\eta^2 m \} \end{cases} \tag{7}$$



(a) Image Generator (b) Kernel Generator

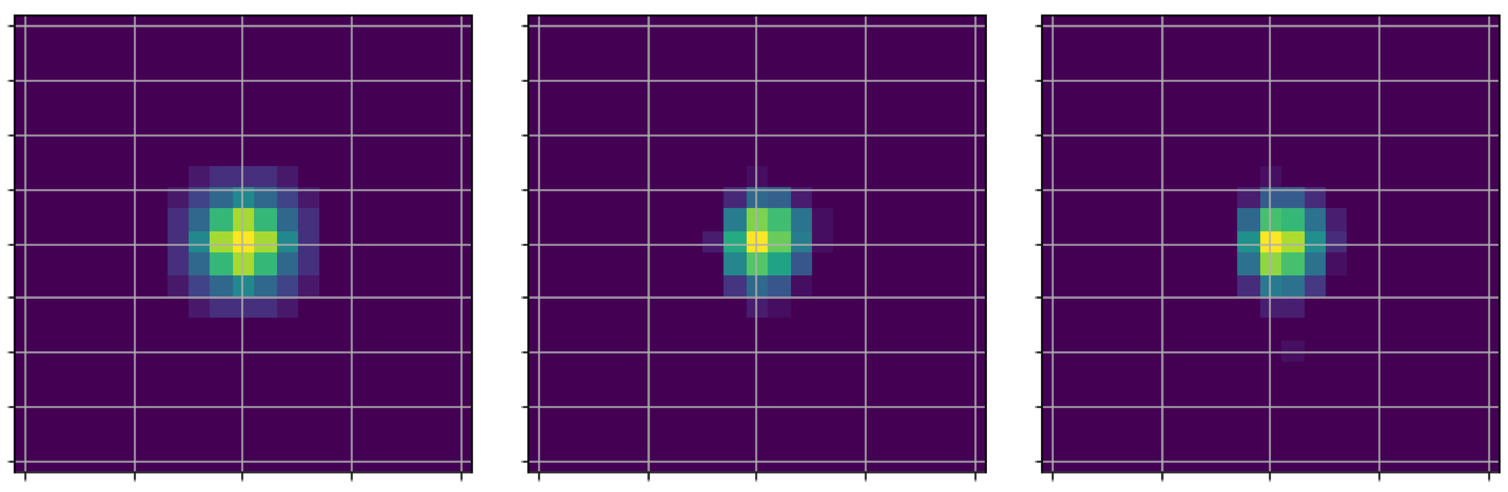
Fig. 1: Network architectures

Results

Experiment settings

- Gaussian noise $\sigma_\eta = 5$
- Gaussian kernel 21×21 with $\sigma_k = 1.6$
- Results obtained performing 5000 global iterations
- The problem (7) is inexactly solved performing only an iteration of the inner algorithm.

(a) Ground Truth (b) Reconstruction (c) Corrupted



(a) Original kernel (b) Reconstructed kernel at 2500 itr. (c) Reconstructed kernel at 5000 itr.

Future Work

- Automatic techniques for the selection of the regularization weight τ.
- Different parametrization for the kernel and its prior/regularizer.
- Characterization of the kernels space with a trained encoder-decoder.

References

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