Investigating effects of different priors for non blind image deconvolution in histopathology images

Motivation

Image deconvolution is an actively studied field in computer vision. The field assumes the following image formation model

$$\vec{b} = \vec{a} * \vec{x} + \eta \tag{1}$$

Where $\vec{b}$ is the procured image that is blurred. The true in-focus image $\vec{x}$ undergoes convolution using some blur kernel $\vec{a}$ and is corrupted with some noise η. In a non-blind image deconvolution problem, generally, the blur kernel is known apriori, hence one can potentially solve the inverse problem using the image formation model. However, the solution is not trivial, as it is an ill-posed problem with many existing solutions. To converge to a solution, lot of different types of priors has been proposed for natural images, however it is not immediately clear if the same assumptions upholds for other kinds of images such as medical images. In this study, I wish to explore different priors for non-blind image deconvolution in histopathology images [1], which are digital images of tissue samples procured at high magnification. In this study, I also propose two new priors, Cross Entropy and KL Divergence and plan to compare it with other priors from the literature.

Related Work

There has been lot of different types of priors or regularizers proposed for the inverse problem. Total Variation[2], a popular regularizer, works based on the assumption that gradients of images are sparse. Although it works well for natural images, it produces staircase effect[3], especially for medical images. There have also been works which have used laplacian norm[4] and L1 norm[4], which has been shown to work well in astronomy. Recently, Hessian Schatten Norm[5] was used as a prior in [6], which was shown to work very well in deconvolution in fluorescence imaging.

Project Overview

In this study, I propose to study different kind of priors for the non-blind deconvolution of histopathology images within Adam optimizer's framework. For the loss function (2), I plan to evaluate the following priors/regularizers ($\Psi(\mathbf{x})$)

$$\text{minimize}_x \frac{1}{2}||\mathbf{Ax} - \mathbf{b}||^2{}_2 + \lambda\Psi(\mathbf{x}) \tag{2}$$

1. Total Variation

2. Laplacian
3. L1-Norm
4. Hessian Schatten Norm
5. Cross Entropy (proposed)
6. KL divergence (proposed)

I will use the dataset from [7], which contains histopathology images, both in-focus and out of focus. For this study, I plan to use only the in-focus set of images. Using a pre-defined blur kernel $\vec{a}$, I plan to simulate blurred images $\vec{b}$. Then I plan to use different priors and solve the inverse decovolution problem using Adam optimizer and evaluate quanlitatively and quantitatively based on Peak Signal to Noise Ratio (PSNR) and Structural Index Similarity(SSIM) values.
Furthermore I propose two priors, Cross Entropy and KL divergence.

Cross Entropy

Let there be two distributions $\mathbb{P}$ and $\mathbb{Q}$, such that, all in-focus images or $\vec{x}$ belongs to in-focus distribution $\mathbb{P}$, and all blurry/out-of-focus images or $\vec{b}$ (in our case simulated) belong to out-of-focus distribution $\mathbb{Q}$. Hence, I would train a simple CNN network which given an image, outputs the probability that it belongs to the in-focus distribution. Hence, we can use this trained network to evaluate the quality of the deconvolved image $\hat{\mathbf{x}}$. Defining the regularizer as

$$\Psi(\mathbf{x}) = -log(T(\mathbf{x})) \tag{3}$$

Where T is our pretrained network, $\Psi(\mathbf{x})$ will be 0 for perfectly restored image $\hat{\mathbf{x}}$ and ∞ for badly restored image. Hence the regularizer should ideally push $\hat{\mathbf{x}}$ as close to the in-focus distribution $\mathbb{P}$ as possible.

KL Divergence

I also wish to use KL divergence as a regularizer, and wish to maximize the KL divergence between the restored images $\hat{\mathbf{x}}$ which should ideally belong to in-focus distribution $\mathbb{P}$ and the blurred images $\mathbf{b}$ which belong to out-focus distribution $\mathbb{Q}$. Defining the regularizer as

$$\Psi(\mathbf{x}) = -D_{KL}(\hat{\mathbf{x}}||\mathbf{b}) \tag{4}$$

To calculate KL divergence, I plan to use similar algorithm from the work [8], where they used Donsker Varadhan Representation[9] to calculate KL divergence,

$$D_{KL}(\mathbb{P}||\mathbb{Q}) = sup_{T:\Omega\rightarrow\mathbb{R}}\mathbb{E}_{\mathbb{P}}[T] - log(E_{\mathbb{Q}}[e^T]) \tag{5}$$

Where T is a neural network, which takes input samples from $\mathbb{P}$ in the left term and input samples from $\mathbb{Q}$ in the right term. For my case, I would first train a network T to minimize equation (5) by using samples of images from in-focus (real $\mathbf{x}$) $\mathbb{P}$ and out-of-focus distribution (simulated $\mathbf{b}$) $\mathbb{Q}$. Then I would use this trained network in the regularizer term (6), where $\hat{x}$ and b corresponds to restored and blurred images. Hence the regularizer should be close to 0 if $\hat{x}$ is not restored properly and have high negative value if $\hat{x}$ is restored properly.

$$\Psi(\mathbf{x}) = -(\mathbb{E}_{\mathbb{P}}[T(\hat{x})] - log(E_{\mathbb{Q}}[e^{T(b)}])) \tag{6}$$

Timeline and Goals

- Week 1: Work on evaluating TV, Laplacian, L1 and Hessian Schatten Norm
- Week 2: Work on KL divergence regularizer
- Week 3: Work on Cross Entropy and report/poster

References

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