**Final project addressing the paper:**

# BP-DIP: A Backprojection based Deep Image Prior

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## Introduction:

**In the paper "BP-DIP: A Backprojection based Deep Image Prior", the researchers tried deblurring a blurred image and restoring it using Deep Image Priors, which is based a CNN, while minimizing the Backprojection objective function.**

**By using Deep Image Priors, we don't have to train our deep neural network on huge datasets and thus we use unsupervised learning techniques hoping that the neural network's architecture will provide a strong prior.**

**Contrary to conventional cases, where the goal is to solve the LS problem, in this paper the researchers tried to minimize the Backprojection problem which yielded in most cases better performances and a smaller number of iterations to solve the problem.**

## Summary of the work:

### Regarding the prior:

**In the researchers' work a Deep Image Prior has been used, other papers have demonstrated that CNNs can be used to solve image restoration problem with no need of offline training using large datasets.**

### Regarding the Backprojection problem:

**In this paper (and also in previous ones), it has been demonstrated that using the backprojection problem in order to restore image has yielded much better results than those of the cases where the LS problem has been used, we will now use some mathematical formulas to describe the problem:**

**If we denote the original image to be $x^*$ then**

$$y = Ax^* + e$$

**is the degraded measurement of the original image (where A is a degradation operator and e is an additive noise).**

**While using DIP we denote the estimated image x to be**

$$x = f_\theta(z)$$

**where $f_\theta(z)$ is a deep CNN (and z is a fixed tensor filled with uniform noise and $\boldsymbol{\theta}$ are the parameters of the CNN).**

**If we use the Backprojection as the fidelity term (the objective function) while dealing with DIP we get that the function which we want to minimize is:**

$$\min_\theta \left\| (AA^T)^{-\frac{1}{2}}(y - Af_\theta(z)) \right\|_2^2 .$$

**In the paper they used this problem to deblur images, so we can replace A with a blur kernel h and thus the problem will be:**

$$\boldsymbol{\min_{\theta} || \left(h * flip(h)\right)^{-\frac{1}{2}} \left(y - h * f_\theta(z)\right) ||_2^2}$$

**Moving the Fourier-Domain we get that the problem can be written this way:**

$$\min_\theta \left\| \mathcal{F}^*\left(\frac{1}{\sqrt{|\mathcal{F}(h)|^2 + \epsilon_1\sigma^2 + \epsilon_2}}\mathcal{F}(y - h * f_\theta)\right) \right\|_2^2$$

**where $\boldsymbol{\sigma}$ is the noise level and $\boldsymbol{\varepsilon_1}$ and $\boldsymbol{\varepsilon_2}$ are regularization parameters.**

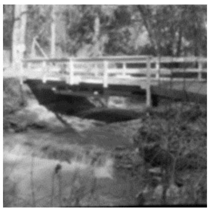
**And so, by solving this optimization problem using Adam or SGD for example we can restore the estimated image from the blurred one.**

## Testing the performance of the algorithm on some of our photos:

**We tested the algorithm on some of the photos provided in the dataset and we got the following results:**



**Original** **Blurred** **Restored with BP-TV**

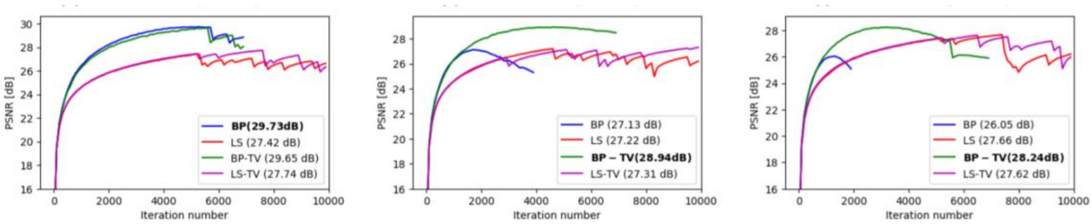




**Original** **Blurred** **Restored with BP-TV**



**Original** **Blurred** **Restored with BP-TV**

**In the paper there have been various good results regarding deblurring of a bunch of photos here are some of the results that the researchers got:**




(g) Gaussian kernel, $\sigma = \sqrt{0.3}$ (h) Gaussian kernel, $\sigma = \sqrt{2}$ (i) Gaussian kernel, $\sigma = \sqrt{4}$

**It's obvious from the results that the BP algorithm tops the "conventional" minimization problem and especially when the TV regularization is being used.**

## Limitations of the work:

**Sometimes BP-DIP on its own can have a drop in performance when deblurring an image, the reason for that is sensitivity to noise, in order to solve that we can use some helpful regularizations, for example in the paper, the researchers used TV.**

**Maybe we could also add some hyper-parameters to dampen the effect of noise.**

## Applying the method to a new problem:

**We can use the Backprojection loss function in a problem which we faced previously in this semester: Burst Image Deblurring.**

**In this problem we take a burst shot of a certain scene and get some blurred images, in our case we take 100 shots of a certain scene.**

**We use these 100 shots as the prior to our estimator and try to minimize the Backprojection, in other words we try to find the optimal motion blur (PSF) while solving the BP problem.**

**Here we don't use the Deep Image Prior, instead we use the 99 blurred images, because we think that they will give us a better estimation and so we can overfit the model better.**

## The algorithm:

**1. Calculating the pior:**

**Lets denote the frame k of the blurred image to be $v_k$ for every k=0.....99**

**And so the prior would be:**

**prior=** $\sum_{k=0}^{99} \frac{|V_k|^p}{\sum_{i=0}^{99} |V_k|^p} V_k$

**2.By denoting the PSF kernel of frame 100 to be h then we get that the minimization problem would be :**

$$\hat{h} = \min_{\theta} \left\| \mathcal{F}^{*}\left(\frac{1}{\sqrt{|\mathcal{F}(h)|^{2} + \epsilon_{1}\sigma^{2} + \epsilon_{2}}}\mathcal{F}(y - h * \mathrm{p}\ )\right\|_{2}^{2}$$

**where p is our prior.**

**3. And so we would recover the original image $\hat{x}$**

$$\hat{x} = \hat{h}^{-1}y$$

## Results that we got in this part:

**In contrast to what we believed this method did not yield good results, in fact the results that we got were quiet bad.**

**We tried to know what the reason behind this "bug" in the algorithm was, but found that the algorithm has nothing wrong about it.**

**In the end we concluded the the only thing that could be wrong would be the prior itself, the same prior that we created using the 99 frames with motion blur.**

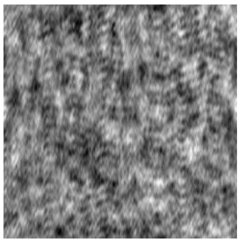
If we examine the paper one again we notice that they used the BP to recover blurred frames, while having a constant "type" of blur kernel throughout the same expirament.

In our case however, each frame has a totally different motion blur kernel, this yield the result of a "noisy" prior which does not have a clear distribution function, and thus we got poor results.

<u>Some of the results:</u>

Original

Blurred

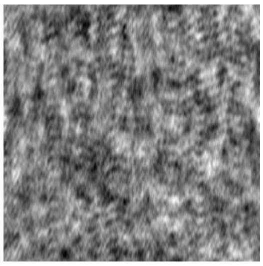


Restored with BP

```
PSNR Value is :
23.486500066732074
```

Original

Blurred



Restored with BP

```
PSNR Value is :
34.74490348677701
```

Here we see that the algorithm surprisingly yields poor results.

**Other ideas considering the BP-DIP paper:**

**We also thought about combining the two subjects in super-resolution problem, especially after reading the Deep Image Prior paper (lecture), we thought about combining the DIP and BP in a super- resolution problem and think that it would yield good results, in contrast to the situation reagarding burst image deblurring.**

## Summary

**The BIP-DIP is a fast algorithm to solve the problem of deblurring, the BP minimization problem is relatively not as popular as the LLS method, but in the paper it is shown that it's as very efficient algorithm to deblur images, especially when commbined with a Deep Image Prior and TV-Regularization.**

**This algorithm is relatively new (especially DIP), and has lots of potential applications such as Super-Resolution and Inpainting.**

**In the experiment that we made, the algorithm did not deliver the results that we wished for, but neverthuless we found this algorithm very helpful**

**in understanding the importance of a prior in estimating the blur kernel.**

**We had lots of fun working on this project and do hope that you also had fun reading it 😊**