Non-Uniform Blind Deblurring by Reblurring

Team DIPhodaa

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Github Link - https://github.com/alti-tude/blind_deblurring

AIM

An approach for blind image deblurring,which handles non-uniform blurs.

Overview

Scenario

Images taken in our daily lives are often corrupted ey blur.

Major causes of blur

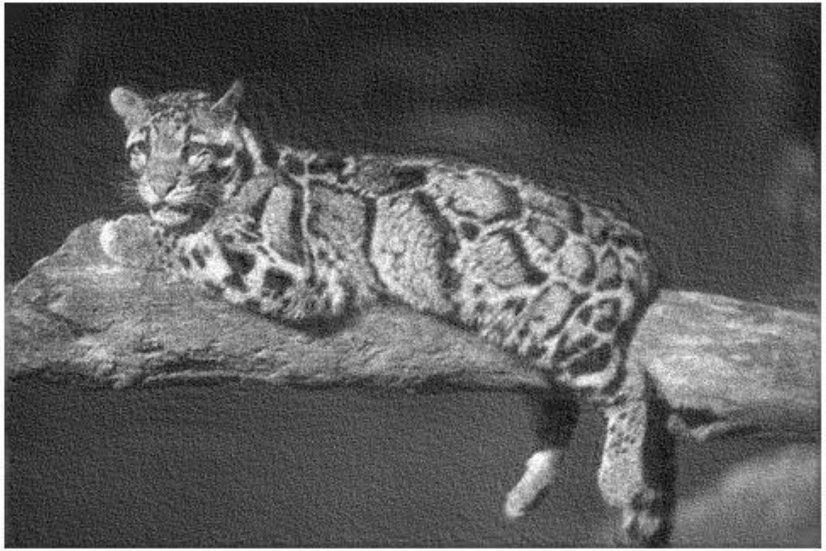
- Camera motion
- Defocus
- Movement of rigid or non-rigid objects in the scene

Blind Deblurring

Recovering the sharp image solely from the blurry image without any knowledge of the blur function, has been the focus of many studies in the past years.

Corrupted Image

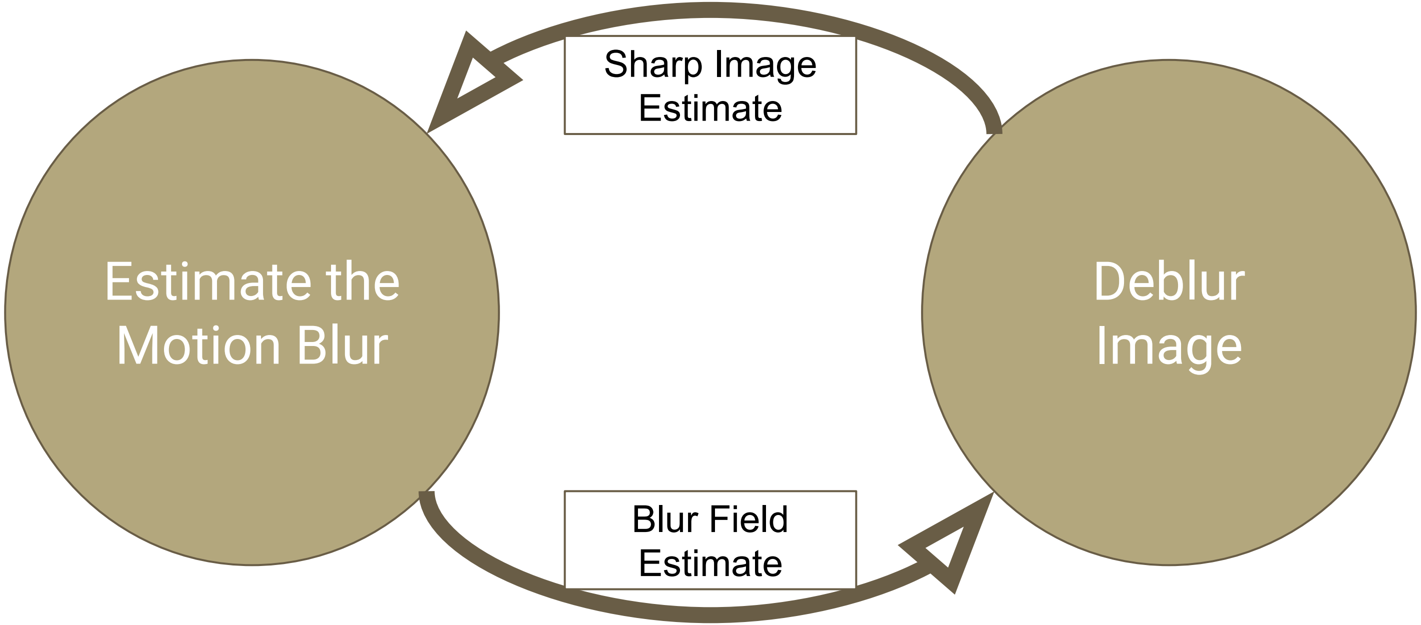
Restored Image



Corrupted Image

Restored Image

Pipeline

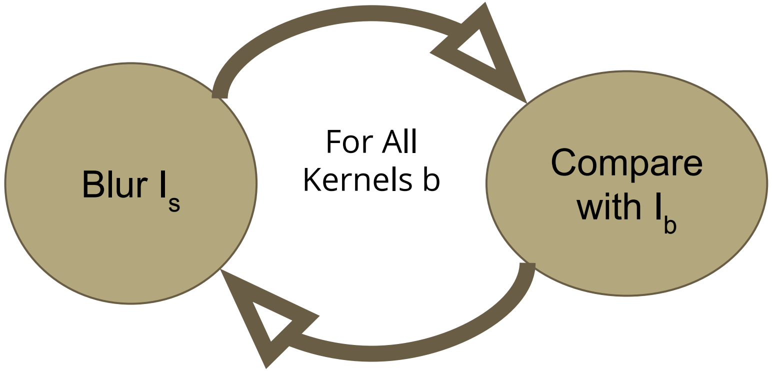

Sharp Image
Estimate
Estimate the
Motion Blur
Deblur
Image
Blur Field
Estimate

Reblurring

Reblurring

- The blur field in this case is undirected (since (u, v) and (−u,−v) induce the same blur).

- Have we had the sharp image I_s, we could have simply blurred the entire image with various blur kernels $b(r, \theta)$ of different lengths r and orientations θ, and then choose for each pixel(x, y)the blur $b(r, \theta)$ for which its surrounding patch in $I_s * b(r, \theta)$ is closest to the one in the input blurry image I_b.



Reblurring

- However we do not have I_s . However, we can

$$I_b * b(r^*, \theta^*) = I_b$$

- Now after adding the noise, our blur kernel estimate becomes -

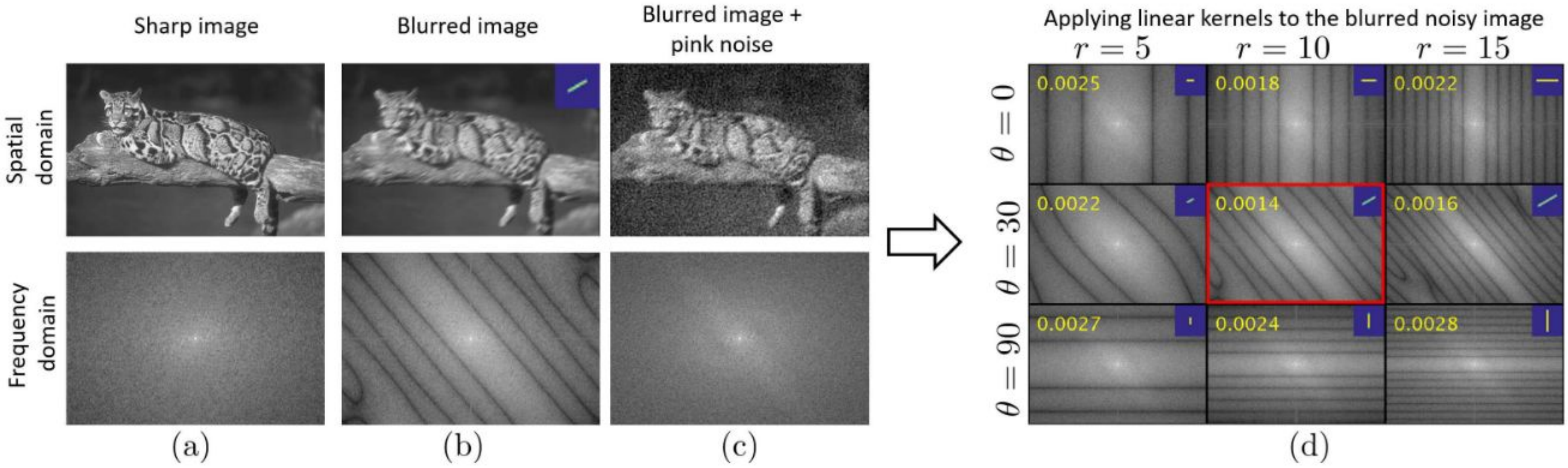
$$b(r^*, \theta^*) = \mathrm{argmin}_{r,\,\theta} \; \|(I_b+n)*b(r, \theta)-I_b\|_2$$

- As sharper images are recovered, I_s approaches the underlying sharp image I_s.

Adding Pink Noise (Blur Estimation)

- For non-ideal blurs, the blur kernel minimizing $\| I_b * b(r, \theta) - I_b \|_2$ will always be the trivial delta function (no blur), rather than the correct blur kernel.
- However, this changes once we add noise to I_b before Re-blurring.
- The kernel minimizing the $\|(I_b + n) * b(r, \theta) - I_b\|_2$
    - Removing as much of the added noise n
    - Harming as little the spectral content of I_b.

- The balance is best reached when the noise added is "pink-noise", whose Power Spectral Density(PSD)function $S(f) \propto 1/f^{\beta}$ resembles the PSD of natural images (we use $\beta = 2$)


Sharp image
Blurred image
Blurred image + pink noise
Spatial domain
Frequency domain
(a)
(b)
(c)
Applying linear kernels to the blurred noisy image
$r = 5$
$r = 10$
$r = 15$
$\theta = 0$
$\theta = 30$
$\theta = 90$
0.0025
0.0018
0.0022
0.0022
0.0014
0.0016
0.0027
0.0024
0.0028
(d)

```
angle = 0 degrees --> count = 281
angle = 5 degrees --> count = 790
angle = 10 degrees --> count = 331
angle = 15 degrees --> count = 873
angle = 20 degrees --> count = 1138
angle = 25 degrees --> count = 1886
angle = 30 degrees --> count = 2627
angle = 35 degrees --> count = 3101
angle = 40 degrees --> count = 5911
angle = 45 degrees --> count = 8084
angle = 50 degrees --> count = 3614
angle = 55 degrees --> count = 3964
angle = 60 degrees --> count = 3532
angle = 65 degrees --> count = 2488
angle = 70 degrees --> count = 2310
angle = 75 degrees --> count = 4990
angle = 80 degrees --> count = 6066
angle = 85 degrees --> count = 6682
angle = 90 degrees --> count = 1765
angle = 95 degrees --> count = 1568
```

Non-Uniform Deblurring Given K

Patch Recurrence Property

According to *Glasner, D. et al*

approximately 90% of the 5×5 patches in a sharp natural image, recur “as is” 10 or more times in the image scaled-down to ¾ of the size

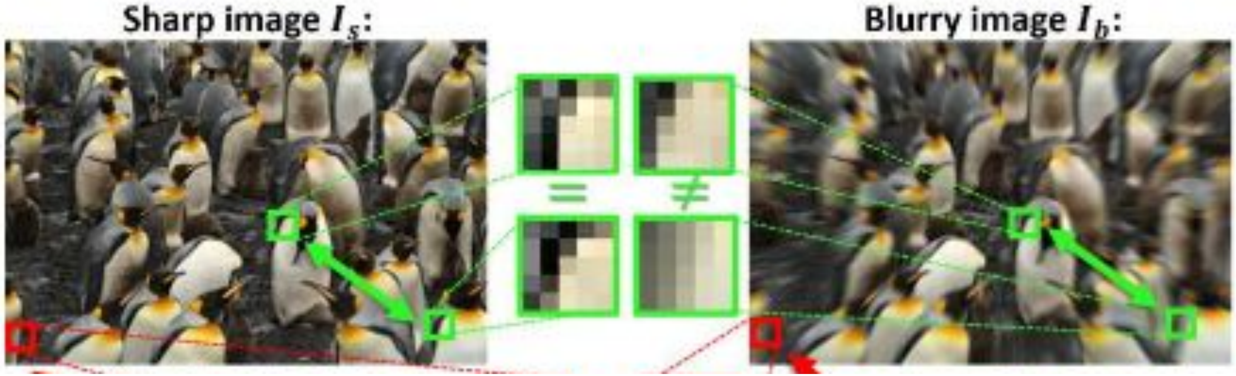
Patch Recurrence Property

- Seeking a blur kernel K, such that if its effect is undone(if y is deconvolved by K), the patch similarity across scales will be maximized.

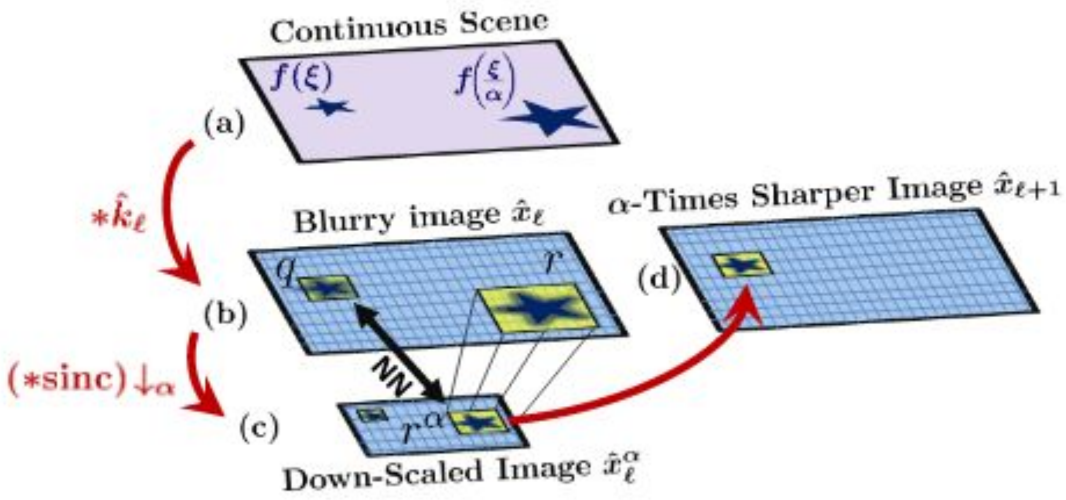
- Moreover, while the blur is strong in the original scale, the blur decreases at coarser scales of the image. Thus, sharper image patches “naturally emerge” in coarser scales of the blurry image.

- The patches in coarser image scales can thus serve as a good patch prior (sharper examples) for deblurring the input scale.

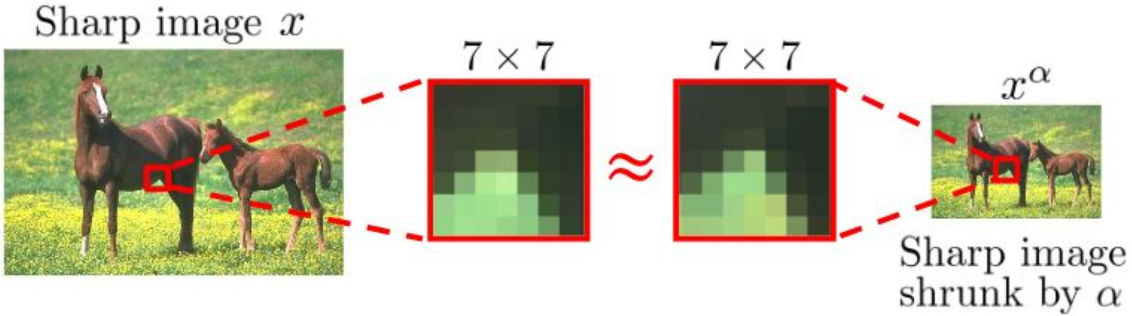
Patch Recurrence Property
(across scales)



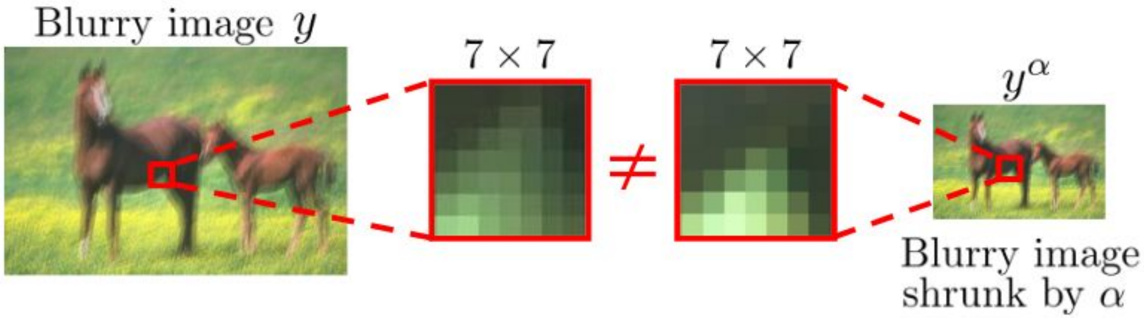
Patch Recurrence Property
(across scales)



(a) **Patch recurrence across scales in a sharp image:**



(b) **In a blurry image, cross-scale patch recurrence deminishes:**



Non-Uniform Deblurring

We deblur an image corrupted by non-uniform blur **given the blur field K.**

Optimizing in this case reduces to,

$$E(I_s) = E_{data}(I_s,K) + E_{image}(I_s)$$

E_{image} : **internal patch recurrence prior** + **gradient sparsity prior**.

E_{data} : is an **image specific prior**

Optimisation Problem (Non-Uniform Deblurring)

- Objective Function:

$$E(I_s) = E_{data}(I_s, K) + E_{image}(I_s)$$

- Direct optimization of objective is intractable since prior is not convex.

- Adopted the “Half Quadratic Splitting” method[1], which solves the problem iteratively.

[1] Zoran, D., Weiss, Y.: From learning models of natural image patches to whole image restoration. In: IEEE International Conference on Computer Vision (ICCV). pp. 479–486 (2011)

Optimisation Problem (Non-Uniform Deblurring)

- In each iteration the current estimate I_s is constructed from patches in $DB(I_s,\alpha)$ to produce an intermediate sharper image z.

- The data term is then enforced using the constraint that the recovered image should be close to z.

- This gives a new estimate I_s, used to construct an updated database $DB(I_s, \alpha)$. In the latter internal step (enforcing the data term), we add the sparse gradient prior, which minimizes $\sum_i |\nabla I_s|^\gamma$ where $\gamma < 1$.

- The sparse gradient term helps reduce ringing artifacts, especially in cases of overestimation errors in K.

Optimisation Problem (Non-Uniform Deblurring)

- Objective Function:

$$E(I_s) = E_{data}(I_s, K) + E_{image}(I_s)$$

- The given objective can be reduced to solving for:

$$(K^TK + \beta I)x = K^Ty + \beta z$$

Here, x = deblurred image
y = blurred image
z = image formed by replacing patches in y with their NN in patches of downscaled image

- No closed form solution as z non-linearly dependent on x.
- Used bicg/bicgstab/gmres as solver

ALGORITHM

Input: Blurry image I_b
Output: Sharp image $\hat{I}_s$ and motion blur field $\hat{\mathbf{u}}$
Initialize: $\hat{I}_s = I_b$
for $t = 1, \ldots, T$ **do**

1. **Estimate motion blur field** (Sec. 3):
   (a) **Add pink noise** to $\hat{I}_s$, yielding $\hat{I}_s^{noised}$
   (b) **Re-blur** $\hat{I}_s^{noised}$ to estimate $\hat{\mathbf{u}}$, yielding $\hat{K}(\mathbf{u})$.
   (c) **Impose smoothness on** $\hat{\mathbf{u}}$**:** Fix $\hat{I}_s$ and minimize 13 w.r.t $\hat{K}(\mathbf{u})$, using $\hat{K}(\mathbf{u})$ from step **(b)** as an initial guess.
2. **Deblur image** (Sec. 4):
   (a) **Construct** $DB(\hat{I}_s, \alpha)$ from patches of $\hat{I}_s$ and its α-times downscaled version $\hat{I}_s^{\alpha}$.
   (b) **Deblur image**: Fix $\hat{K}$ and $DB(\hat{I}_s, \alpha)$, and minimize 14 w.r.t $\hat{I}_s$.

end

Summary

- Objective Function:

$$E(I_s, K) = E_{data}(I_s, K) + E_{image}(I_s) + E_{blur}(K)$$

- Objective is not convex (due to the nature of the patch-recurrence prior and the matrix K), hence has no closed-form solution => Minimize it using an alternating iterative minimization procedure.

- The initial estimate of the non-uniform blur-field u is computed directly from the blurry image I_b , using the Re-blurring method and used to generate our initial blur matrix K(u).

- The algorithm then proceeds to alternate between estimating a sharper image I_s and refining the blur field estimate u.

Related Works

- T. Michaeli and M. Irani. Blind deblurring using internal patch recurrence. In ECCV, 2014.
  - Worked on uniform blurs

- Zoran, D., Weiss, Y.: From learning models of natural image patches to whole image restoration. In: IEEE International Conference on Computer Vision (ICCV). pp. 479–486 (2011)
  - Worked on Expected Patch Log Likelihood (EPLL)

Division of Work

Kartik (20171018) : Optimisation, Deblurring

Sankalp (20171161): Blur Estimation, Multiscale, Utilities

Sawar (20171013) : Pink Noise, Nearest Neighbour

THANK YOU