

## Home Assignment 2 – Blind Super Resolution

In the first homework we dealt with correcting the motion blur occurring in images acquired through burst mode, where the motion of the camera is faster than the shutter speed of the lens. In this exercise, we will look at another instance of image blur called the *out-of-focus* blur, which is observed when the camera's focus is not properly adjusted by the user.

The point spread function (*PSF*) describes the distribution of light in the camera focal plane for a point source. This function strictly relates to the resolution and blur of the optical device. In the absence of any imaging noise, the action of the camera can be mathematically expressed as  $y(\mathbf{x}) = (f * p)(\mathbf{x})$ , where  $f(\mathbf{x})$  is the continuous scene,  $p(\mathbf{x})$  is the PSF of the camera and  $y(\mathbf{x})$  is the resulting continuous image.

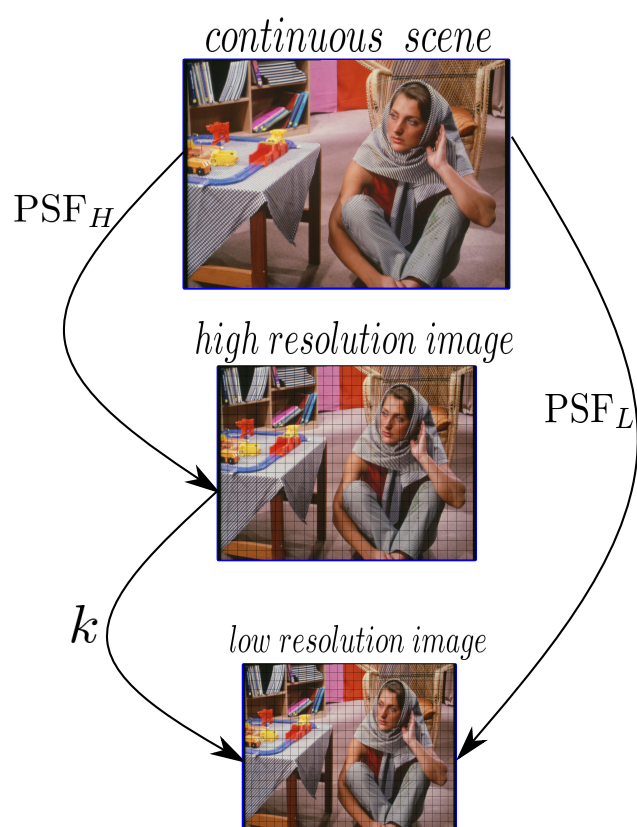
*Super resolution* is one of the cornerstone problems in image processing because it exemplifies the scenario of faithfully reconstructing a high-resolution image from an image captured out-of-focus. This can be modeled similarly to the above equation, where  $h(\mathbf{x}) = (f * p_H)(\mathbf{x})$  and  $l(\mathbf{x}) = (f * p_L)(\mathbf{x})$  correspond to capturing continuous high and low resolution images using two different PSFs, given  $p_H(\mathbf{x})$  is narrower than  $p_L(\mathbf{x})$  by  $\alpha \in \mathbb{N}$ , i.e.  $p_H(\mathbf{x}) = \alpha^2 p_L(\alpha \mathbf{x})$ . In practice, since  $l(\mathbf{x})$  contains less details than  $h(\mathbf{x})$ , their discrete counterparts,  $l[\mathbf{n}]$  and  $h[\mathbf{n}]$ , are sampled on different lattices,  $\mathbb{Z}^2$  and  $\frac{1}{\alpha}\mathbb{Z}^2$  respectively, resulting with different resolutions. Thus we will also assume  $l[\mathbf{n}]$  can be retrieved from  $h[\mathbf{n}]$  by decimation  $l[\mathbf{n}] = \downarrow_\alpha (h * k)[\mathbf{n}]$ , where  $k$  is a discrete low-pass filter (see the figure in the next page for an illustration).

Usually super resolution algorithms try to induce  $h[\mathbf{n}]$  given  $l[\mathbf{n}]$  and  $k[\mathbf{n}]$ . In this assignment, however, we will solve the blind super resolution problem, where  $k[\mathbf{n}]$  is unknown as well. Thus, we will first try to deduce  $k[\mathbf{n}]$  from  $l[\mathbf{n}]$ , and then use our estimation of  $k[\mathbf{n}]$  to retrieve  $h[\mathbf{n}]$ .

### 1 Theoretical questions

In the following questions you may ignore aliasing, i.e. assume every function  $g$  sampled on  $\mathcal{L}^*$  holds  $(III * G)(\xi) = G(\xi), \forall \xi \in \mathcal{L}_0$ .

1. Write expressions for  $l[\mathbf{n}]$  and  $h[\mathbf{n}]$  as integrals over  $f(\mathbf{x})$  and  $p_L(\mathbf{x}), p_H(\mathbf{x})$  respectively.



2. Write an expression for  $l[\mathbf{n}]$  as a sum over  $h[\mathbf{n}]$  and  $k[\mathbf{n}]$ .
3. Write an equation relating  $f(\mathbf{x})$ ,  $p_H(\mathbf{x})$ ,  $p_L(\mathbf{x})$  and  $k[\mathbf{n}]$ . Assume it holds for every possible function  $f$ , and derive an expression for  $p_L[\mathbf{n}]$  as a sum over  $p_H[\mathbf{n}]$  and  $k[\mathbf{n}]$ , all of which sampled on the lattice  $\frac{1}{\alpha}\mathbb{Z}^2$ .
4. Assume  $k_c(\mathbf{x})$  is a continuous-domain filter which yields  $k[\mathbf{n}]$  when sampled on the lattice  $\frac{1}{\alpha}\mathbb{Z}^2$ . Further assume your expression for  $p_L[\mathbf{n}]$  as a sum over  $p_H[\mathbf{n}]$  and  $k[\mathbf{n}]$  holds true in the continuous case as well, i.e. as an integral expressing  $p_L(\mathbf{x})$  using  $p_H(\mathbf{x})$  and  $k_c(\mathbf{x})$ . Use this to express  $K_c(\boldsymbol{\xi})$  using  $P_L(\boldsymbol{\xi})$ , for  $\boldsymbol{\xi} \in \mathbb{R}^2$  such that  $P_H(\boldsymbol{\xi}) \neq 0$ .
5. Most non-blind super resolution algorithms assume  $k = p_L$ . Does this assumption holds when  $p_L = \text{sinc}$ ? What about when  $p_L$  is an isotropic Gaussian? Which PSF is more likely in real life? Base your answer on your estimated expression of  $K_c(\boldsymbol{\xi})$ .

From now on we will assume  $h$ ,  $p_L$ ,  $p_H$  and  $k$  are unknown.

6. Assume we have access to a collection of clean high-resolution patches  $\{p_1, \dots, p_N\}$ . Further assume every patch  $q_i$  in  $l$  is a noisy downsampled version of one of the high-resolution patches  $p_{j_i}$ , where  $j_i$  is uniformly distributed over  $\{1, \dots, N\}$ . Hence  $q_i = \downarrow_{\alpha} (p_{j_i} * k) + n_i$ , where  $n_i \sim \mathcal{N}(0, \sigma_N^2)$ . Derive an objective function whose minimum argument corresponds to the ML estimation of  $k$  given  $l$ , i.e. maximizes  $\mathbf{P}(l | k)$ . You can assume that  $\{p_i\}$ ,  $\{n_i\}$  and  $k$  are statistically independent.
7. Assume  $\mathcal{D}k \sim \mathcal{N}(0, \sigma_D^2)$ , where  $\mathcal{D}$  is some operator. Suggest a reasonable choice for  $\mathcal{D}$  and derive an objective function whose minimum argument corresponds to the MAP estimation of  $k$  given  $l$ , i.e. maximizes  $\mathbf{P}(k | l)$ . In your calculations, you can approximate  $\mathbf{P}(k)$  as  $\mathbf{P}(\mathcal{D}k)$ .
8. Write the derivative of the previous function and suggest an iterative algorithm to estimate  $k$ .
9. Let us look at a zoomed-in version of our scene  $f\left(\frac{\mathbf{x}}{\alpha}\right)$ , and assume it is being captured using  $p_L(\mathbf{x})$  on the lattice  $\mathbb{Z}^2$ . Write an expression describing the resulting image  $z[\mathbf{n}]$  as an integral over  $f\left(\frac{\mathbf{x}}{\alpha}\right)$  and  $p_H(\mathbf{x})$ .
10. Prove  $l[\mathbf{n}] = \downarrow_{\alpha} (z * k)[\mathbf{n}]$ .

11. Many natural images have recurring patches across scales, since small patterns tend to recur in the continuous scene at multiple sizes, i.e. some patterns in  $f(\mathbf{x})$  appear elsewhere in  $f\left(\frac{\mathbf{x}}{\alpha}\right)$ . Using this observation, suggest a way to obtain an approximation of the set  $\{p_1, \dots, p_N\}$  when only  $l$  is given, and explain why the algorithm you have suggested in question 8 can still recover the true  $k$ .
12. Suggest a way to recover  $h$  given  $l$  and  $k$ .

### Notes:

- Justify nontrivial mathematical transitions in your answers and especially point out whenever one the imaging assumptions listed above is being used. This aspect will be heavily examined when grading your submission.
- A variety of approaches are possible for tackling question 7,8,12. We encourage you to invest time thinking about the problem, and look up related papers online. You may especially benefit from reading "Nonparametric Blind Super-Resolution" by Michaeli and Irani. However, your answers should be stand-alone, explained thoroughly and correspond to the notation given here and not to any other paper. Please keep your answer concise and use the previous guiding questions and the material learned in class to establish a suitable method. Algorithms without an explanation will not get any points.

## 2 Practical questions

To do this exercise, please download the source image DIPSourceHW2.png from [here](#). We will treat this image as our continuous scene  $f(\mathbf{x})$ .

- Create two high-resolution and two low-resolution versions of the source image, once using a *sinc* filter and once using a Gaussian filter. You may choose any  $\alpha \in \mathbb{N}$ .
- Estimate the filters from the downsampled images using the algorithm you have designed. It is advisable to obtain the largest possible collection of high-resolution patches  $\{p_i\}$ , while adopting some of the implementation tricks from NLM in order to improve complexity. You may not use the high-resolution images in your algorithm.
- For each of the two recovered kernels, construct two high-resolution images, one from the low-resolution image the kernel was extracted from, and one from the other low-resolution image.
- Evaluate the PSNR for each of the high-resolution images you have obtained.

### 3 Deliverables

- **For Part I:** Write the answers for questions 1-12 in a digital file.
- **For Part II:**
  - The code
  - 2 low-resolution images
  - 6 high-resolution images (2 obtained using the true kernels, 2 using the estimated ones, and 2 using the wrong estimated ones)
  - 4 PSNR values for each of the high-resolution images obtained using the algorithm
  - A brief explanation discussing your results

Submit all the above mentioned deliverables by **22nd February, 11:55PM**.

Submission will soon be available [here](#).

Thanks and enjoy!  
Alex and Sanketh