Image Processing and Pattern Recognition

Assignment 1 - Guided Super-Resolution

October 21, 2019

Deadline: November 04, 2019 at 23:55h.
Submission: Upload your report and your implementation to the TeachCenter. Please do not zip your files. Please use the provided framework-file for your implementation.

1 Goal

The goal of the first assignment is to implement the Guided Image Filter He et al. (2013) as presented in the lecture. Guided image filtering is a lightweight and therefore very fast algorithm which can be used for e.g. edge-preserving image filtering, flash/no-flash denoising, guided super-resolution, etc. We will specifically focus on the task "guided super-resolution" in this assignment. Guided super-resolution is a process where a low resolution color image is upsampled with the help of a high resolution guidance image. In this assignment we have a high resolution gray-scale image which we can directly used for guidance. You can find a visualized example in fig. 1.

(a) Low res. RGB input (b) High res. grayscale guide (c) Output image

Figure 1: Guided super-resolution. A low resolution RGB input image (a) is used as the input, and a high resolution grayscale image (b) as the guide image. The output of the filter (c) captures the detailed edge information from the guide, while the color information is retained from the input image.

2 Method

The guided image filter is defined by a local linear model in the intensity space defined as

$$U_q = a_p I_q + b_p, \quad \forall q \in \omega_p, \tag{1}$$

where U_p are filtered pixels and a_p and b_p are the parameters of the linear model, I_q is the guidance image and

$$\omega_p = \{q : ||p - q||_\infty \leq r\}, \tag{2}$$

i.e. a window with size $(2r+1) \times (2r+1)$ centered at pixel p. Note that p and q are not the same: p denotes a pixel index, while q indicates a pixel in the window around p. Given an input image F we can find the local parameters a_p and b_p by minimizing

$$E(a_p, b_p) = \frac{1}{2} \sum_{q \in \omega_p} ((a_p I_q + b_p - F_q)^2 + \varepsilon a_p^2). \tag{3}$$

We can now compute the optimal values for a_p and b_p by setting the derivative of (3) *w.r.t.* the model parameters a_p and b_p to zero and solving the linear system of equations (this was already done in the lecture). The optimal values are then given by

$$a_p = \frac{\frac{1}{|\omega_p|}\sum_{q\in\omega_p} F_q I_q - m_p\mu_p}{\sigma_p^2 + \varepsilon} \tag{4}$$

$$b_p = m_p - a_p\mu_p, \tag{5}$$

where μ_p and σ_p^2 are the mean and variance of I in ω_p, $|\omega_p|$ is the number of pixels in ω_p and m_p is the mean of F in ω_p. After computing a_p and b_p for all patches ω_p in the image, we can compute the filter output by

$$U_q = \frac{1}{|\omega_p|}\sum_{p:q\in\omega_p}(a_p I_q + b_p) = \bar{a}_q I_q + \bar{b}_q, \tag{6}$$

where $\bar{a}_q$ is the mean of a in ω_p and $\bar{b}_q$ is the mean of b in ω_p.

3 Task

Your task is to implement the guided image filter as described in 2. Take a photo with your smartphone and apply the guided image filter to your image. We call the full-resolution smartphone image *reference image*. The name already indicates that this image is not an input to the guided filter, but only used during the evaluation.

We can compute the low resolution input image L by downsampling the reference image by a factor of d. The second input is the guidance image G. The guidance image can be obtained by converting the reference image to a gray-scale image. Note that the spatial resolution of L and G are not the same. G is d-times larger than L. The guided image filter requires the inputs to have the same spatial resolution. Thus, we have two possibilities to achieve this:

1. **Operate at guidance resolution**
   Compute the input image F_H by bilinearly upsampling the low-resolution input image L by a factor of d. The inputs to the guided filter are thus $F = F_H$ and $I = G$. This variant directly yields the high-resolution output image U.

2. **Operate at low-res input resolution**
   Compute the low-resolution guidance image G_L by bilinearly downsampling G by a factor of d. The inputs to the guided filter are thus $F = L$ and $I = G_L$. This approach yield only a low-resolution output-image U_L. To obtain the high-resolution output image we need to upsample the computed coefficients a and b and apply them to the high-resolution guidance image G using (6).

Implementation details

- Note that the result U will be a floating point image which can contain values outside the interval $[0, 1]$. Therefore we need to clip the result by applying equation (7) element-wise to the output of the guided image filter U_q.

$$U_q = \min(\max(U_q, 0.0), 1.0) \tag{7}$$

  This is necessesary for both a correct evaluation and correct plotting in Matplotlib.

- Because the color image has three channels you need to apply the filter for each channel, `R,G,B` separately and combine the individual results to get the filtered result. You should not use any for loop over all pixels in the image, because this makes the program very slow.

Evaluation Implement both approaches for guided super-resolution with the guided image filter. Evaluate your implementation with the provided image as well as with an image of your choice. Therefore, for both variants perform the following tasks:

- Use the downsampling factors $d = 4$ and $d = 8$.

- Vary the filter size and ε. You should use 3 suitable ε and 3 different filter-sizes.
- For all variants report the peak-signal-to-noise ratio (PSNR) between the reference image and your outputs at high resolution (the resolution of the reference image).

  The PSNR between two images color images I_1 and I_2 of size $(M \times N)$ with C channels is defined as

$$\mathrm{PSNR}(I_1, I_2) = 10 \log \frac{1}{\mathrm{MSE}(I_1, I_2)}, \tag{8}$$

  where

$$\mathrm{MSE}(I_1, I_2) = \frac{1}{CMN} \sum_{p=0}^{C-1} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \big(I_1(i,j,p) - I_2(i,j,p)\big)^2. \tag{9}$$

- Plot all your results in your report and describe them[1].
- What are the advantages/disadvantages of variant 1 and 2?
- If you do not use a loop in your guided super-resolution algorithm you will get 2 bonus points.

References

He, K., Sun, J., and Tang, X. (2013). Guided image filtering. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. http://ieeexplore.ieee.org/document/6319316/?reload=true.

[1] Only plotting the results without explaining the effect of what can be seen is not sufficient and will reduce your points.