High Resolution Image Construction using Gradient Profile Prior

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Abstract

We employed the information in the gradient profile prior to construct high resolution images form the corresponding low resolution images. The reconstructed images are sharp while artifacts are minimal. For noisy images, we adopt the non local means algorithm to remove the noise and reuse the noise to recover denoising loss. Some reconstructed high resolution results are attached as example.

1 Introduction

Image resolution refers to the ability of a sensor to differentiate between two objects or pixels that are relatively close to each other. Compared to low-resolution images (LR), high-resolution (HR) images are often desirable especially in fields such as computer vision, video surveillance, medical imaging, etc. Despite the vast advancement in hardware technology, image resolution enhancement techniques are still significant in many applications. For example, digital surveillance products usually sacrifice not only frame rate but also resolution to ensure the long-term usability of the devices[1]. The purpose of super-resolution (SR) is to generate a HR image out of the LR image. In general, there are three different approaches, which are interpolation based methods, reconstruction based methods, and learning based methods, with their own advantages and disadvantages in the application[2]. Overall, many researches have been done on how to apply the prior or constraint of the HR images.

To solve this issue, the gradient profile prior[2] is adopted in this project. By enforcing both reconstruction constraint and the gradient field constraint, the HR images would be sharp with minimal artifacts along the edges. In this report, we show that the gradient profile prior could be used to enhance the sharpness and control the amount of artifacts in the image. One may expect that the model could be sensitive to noise such that the noise would be sharpened as well. Therefore, we also discuss how image denoising methods could be applied to better the HR image.

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2 Gradient Profile Prior for Image Super-Resolution

2.1 Gradient Profile Prior

Firstly, we define the image gradient as $\nabla I = (\partial_x I, \partial_y I) = \sqrt{(\partial_x I)^2 + (\partial_y I)^2} \cdot \vec{N} = m \cdot \vec{N}$ where m is the gradient magnitude and $\vec{N}$ is the gradient unit vector. To obtain the numerical derivatives, we adopts the central difference for both $\partial_x I$ and $\partial_y I$. For every pixel in the image, we denote the edge pixel as the local maximum along its gradient direction in the gradient field. In other words, if we trace the path along the gradient direction of a pixel until the gradient magnitude stops decreasing, we will eventually end up in the edge pixel for the particular pixel. The path from the pixel to the edge pixel is called the gradient profile. In implementation, piecewise linear interpolation is applied to estimate the gradient of the pixel when one of the spatial coordinates is non-integer (i.e. the gradient magnitude will be compared to the current gradient magnitude only when at least one of the spatial coordinates is an integer). The gradient magnitude and coordinate of the encountered is recorded for further usage.

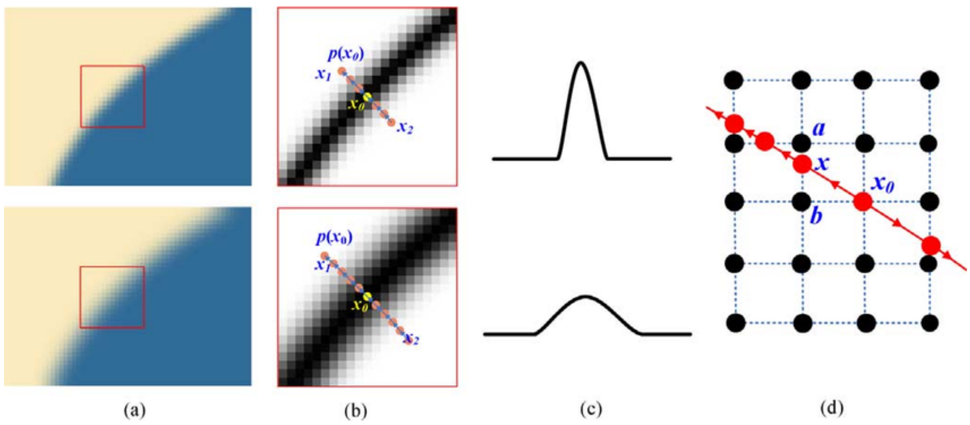

Figure 1: (a) two images with different sharpness where the top image is sharper than the bottom image. (b) inverted and normalized gradient magnitude for the corresponding region of the image in (a) and the gradient profile $p(x_0)$ is the path starting from x_1 and x_2 along the gradient direction and ending at the edge pixel x_0 where the gradient magnitude no longer increase. (c) graph of gradient magnitude along the path ($p(x_0)$) from x_1 to x_2. Note that sharp edge results in shorter gradient profile and greater change in gradient magnitude along the gradient profile. (d) encountered pixels are marked by red dots and, as an example, the gradient magnitude at x is interpolated from a and b.

The profile sharpness of an edge is defined as

$$\sigma_l(p(x_0)) = \sqrt{\sum_{x \epsilon p(x_0)} m'(x) d^2(x, x_0)} \tag{1}$$

where $m'(x) = \frac{m(x)}{\sum_{x \epsilon p(x_0)} m(x)}$ and $d(x, x_0)$ is the distance between x and x_0 along the gradient direction $p(x_0)$. Intuitively, sharp gradient profile has low σ value. Initially, the equation (1) is used to find the sharpness of the up-sampled image from the LR image. The sharpness σ_h in the HR image, which is to be constructed, could later be estimated from the sharpness σ_l based on the learning from natural images[2]. As a result of the findings from [2], the expected sharpness of the HR image could be computed using hardcoded data.

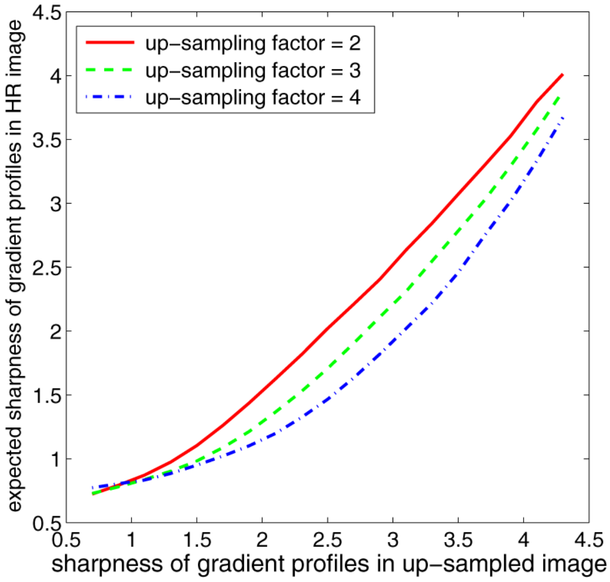

Figure 2: relationship between the sharpness of gradient profiles in up-sampled images and the sharpness of gradient profiles in the actual HR image.

2.2 Gradient Field Transformation

2.3 Super-Resolution Model

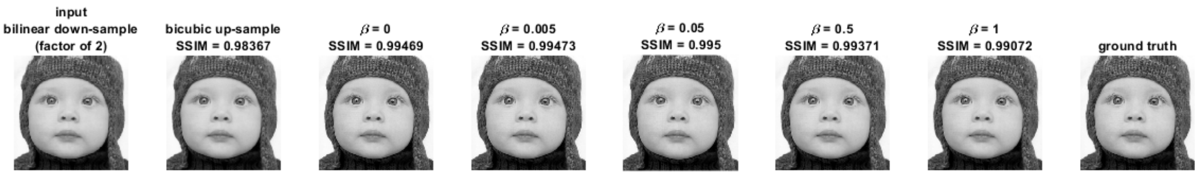

Figure 3: Effect of changing the value of the parameter β towards the SSIM between the reconstructed HR image and the ground truth. We set $\beta = 0.05$, by default, in the implementation. In experiment, the HR images are sharp and clear enough after 25 iterations (default number of iterations in the implementation).

Figure 4: HR image reconstruction with small and large value of parameter β. Setting $\beta = 0$ will produce HR image with ringing and jaggy artifacts. On the other hand, the artifacts are less visible when $\beta = 0.5$.

3 Gradient Profile Prior for Image Enhancement

3.1 Sharpness Enhancement Function

HR images are expected to have sharp edges as shown in the inverted gradient magnitude of the ground truth in Figure 5. This sharpness is identified by the σ_h value in the model. In addition to the gradient field transformation, the sharpness enhancement function could be applied to further enhance the sharpness of blurry edges. The sharpness enhancement function can be expressed as

$$F(\sigma_h) = (1 - e^{-\mu\sigma_h})\sigma_h \tag{2}$$

which is continuous and results in smaller σ_h values. As $\mu > 0$ is chosen to be closer to 0, the edge sharpness will be further enhanced.

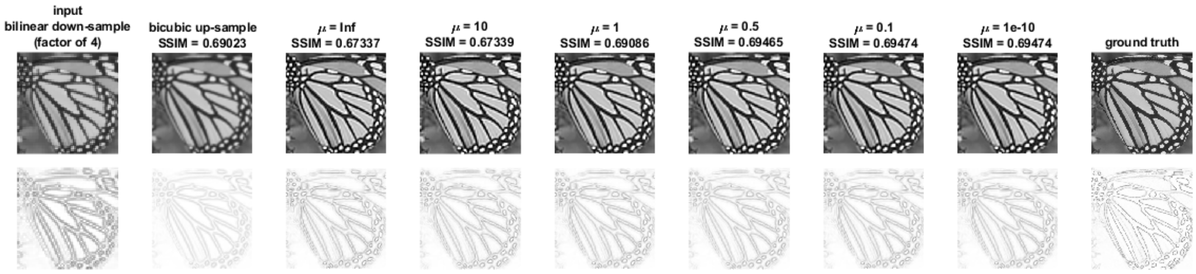

Figure 5: Image enhancement using the sharpness enhancement function: the reconstructed HR images (top) and inverted gradient magnitude map (bottom). The Structural SIMilarity (SSIM) [3] between the HR image and ground truth increases as μ gets closer to 0 since the sharpness gets closer to that of the ground truth.

3.2 Noisy Image Super-Resolution

The SR model using the gradient profile prior is incapable of differing between edge and noise in the image. In other words, the model will treat the noise in the same way as the edge, i.e. enhanced. As an implication, the noise might appear as local maximum in the gradient domain and, in turns, create unexpected gradient profiles. One straightforward solution is to firstly extract the noise layer through a denosing method before applying the HR reconstruction algorithm. This process would remove the unexpected gradient profiles in the image. Secondly, the noise layer is then upsampled and reapplied to the HR image constructed previously. In Figure 6, the LR image is denoised with the non-local means algorithm[4] to obtain a more pleasant result to our eye (bottom right) compared to the original result (top right).

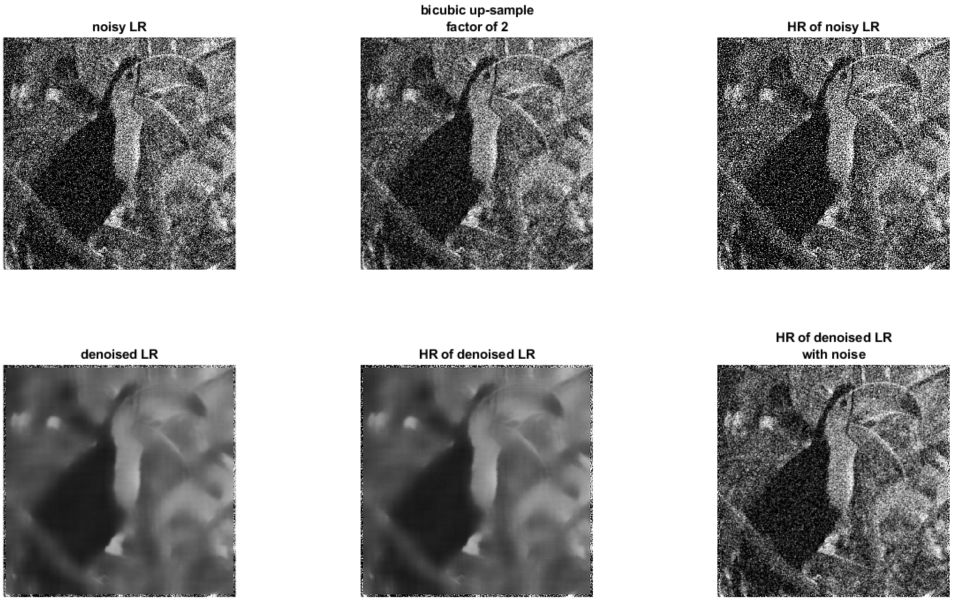

Figure 6: (top) HR image reconstruction from the noisy LR image. (bottom) HR image is reconstructed by adding back the up-sampled noise layer to the HR image generated from the denoised LR image

4 Conclusion

References

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