1.4-3

An Image Sharpening Algorithm for High Magnification Image Zooming

Ning Xu, *Member, IEEE* and Yeong-Taeg Kim, *Member, IEEE*
Digital Media Solutions Lab, Samsung Information Systems America, Inc., Irvine, CA 92612

***Abstract*-- Traditional image sharpening methods usually introduce over shootings along the edges, and do not perform well for sharpening an image resulting from high magnification zooming. In this paper, we present an image sharpening algorithm which is overshooting free and particularly suitable for high magnification zooming situation. Our algorithm modifies the pixel value based on the desired changes for its gradient profile, and the sharpening parameters can be learned for the particular zooming rate. Experimental results show that the proposed algorithm outperforms the conventional image sharpening methods.**

I. INTRODUCTION

High magnification zooming of digital images is getting more attentions nowadays as it is important for many applications in the consumer electronics industry. For example, the resolution of digital television is becoming higher and higher towards Ultra-high Definition (UDTV), which will require about five times zooming rate from the Standard Definition (SD) resources. A study of the image quality with respect to sharpness, contrast, and color fidelity, led to the conclusion that the dominant degradation in high magnification images results from image blur [1]. There are two major categories of algorithms towards image deblur, one is image sharpening and the other is image restoration. The image restoration method either requires a known PSF [2] or use blind deconvolution [3], and both have their limitations. In this paper we consider the first category of method, where a large number of algorithms have been designed such as Unsharp Masking [4] and Laplacian filtering [2].

Instead of de-blurring the scaled image, many researchers are tackling high magnification zooming problem with single frame super-resolution algorithms, which can further be divided to reconstruction algorithms and learning based algorithms. The reconstruction algorithms use the low resolution image as a reconstruction constraint, while the learning based algorithms uses training examples to infer the higher resolution images. A gradient profile prior is proposed in a recent reconstruction based algorithm for super resolution [5]. Our proposed algorithm is inspired by the usage of gradient profile prior, but we utilize it to sharpen an image directly instead of using it as regularization for reconstruction. Therefore, our algorithm can be computed locally like an adaptive filter while the method in [5] requires a global minimization over the entire image.

The main idea of our method is to find out the gradient profile of each pixel, and change the sharpness of the gradient profile accordingly. The differences between the integration of the tails of the two gradient profiles are compensated back to the pixel intensity. For high magnification zooming situation, the change rate of the sharpness of the profile can be learned from natural images [5]. As an image sharpening algorithm, we compare our method with the well-known Cubic Unsharp Masking [4] and provide both visual and numerical comparison.

II. APPROACH

For simplicity we focus on the processing of the luminance information of the input image *I*. For each pixel (*i*, *j*) in the input image *I*, the horizontal and vertical gradient $g_x(i,j)$ and $g_y(i,j)$ is computed as $g_x(i,j) = (I(i+1,j) - I(i-1,j))/2$ and $g_y(i,j) = (I(i,j+1) - I(i,j-1))/2$. The input image I is then sampled along the gradient direction to obtain a 1D array *intensity profile* $y_{i,j}$, which is centered at pixel (*i*, *j*) and has the length *2n+1*. Let *k* = -*n*,-*n+1*,...,*n-1*,*n*, where *n* is a tunable parameter of the algorithm, we have

$$Y_{i,j}(k) = I\left(i + \frac{g_x(i,j)}{\sqrt{g_x^2 + g_y^2}} \cdot k,\ j + \frac{g_y(i,j)}{\sqrt{g_x^2 + g_y^2}} \cdot k\right).$$

Bicubic interpolation is used to compute the intensity of those pixels whose locations are not aligned with the image grid. A gradient profile, named following Sun's paper [5], is computed as

$$p_{i,j}(k) = (Y_{i,j}(k+1) - Y_{i,j}(k-1))/2.$$

An example of intensity profile and gradient profile is shown as in Figure 1, where Figure 1(a) shows a pixel of interest and Figure 1(b) shows the intensity profile of this pixel, along the gradient direction, which is horizontal, and Figure 1 (c) shows the gradient profile.

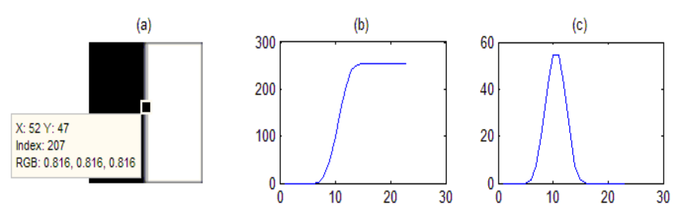

Fig. 1. Intensity profile and gradient profile. (a) A pixel of interest in the vicinity of an edge. (b) Intensity profile of the pixel. (c) Gradient Profile of the pixel.

The extracted gradient profile is then segmented to obtain a single mode that contains the center pixel. To achieve this, we search from the center pixel to the two opposite directions for the nearest zero-crossing pixel, until reaching the profile boundary. This is equivalently as finding out the nearest peak or valley point of the intensity profile. After segmentation, the gradient values within the segment are kept and those outside the segment are set to zero. The resulting gradient profile is denoted as $\widetilde{Y}$, which is parameterized to fit a Gaussian distribution, as $\widetilde{Y} \propto A \cdot Norm(\mu, \sigma^2)$. Here the parameters, i.e. A, μ, and σ, are estimated as $A = \sum_k \left|\widetilde{Y}(k)\right|$; $\mu = \sum_k \frac{1}{A}\left|\widetilde{Y}(k)\right|$ and $\sigma = \sqrt{\sum_k \frac{1}{A}\left|\widetilde{Y}(k)\right| \cdot (k-\mu)^2}$.

To sharpen the input image, the sharpness of the gradient profile is changed to have a smaller σ, controlled by a sharpness ratio r, with range $0<r<1$. This ratio r can be learned based on the zooming ratio using natural images as training set. The new gradient profile will then become $\hat{Y} \propto A \cdot Norm(\mu, (r \cdot \sigma)^2)$.

To update the pixel intensity at the center, i.e. pixel (i, j) on the input image I, we calculate the difference between these two estimated Gaussian from $-\infty$ to $-\mu$ and add it back to the pixel intensity, as

$$\hat{I}(i,j) = I(i,j) + \int_{-\infty}^{-\mu} \hat{G}(x)dx - \int_{-\infty}^{-\mu} G(x)dx,$$

where $\hat{G}(x) \propto A \cdot Norm(\mu, (r \cdot \sigma)^2)$ and $G(x) \propto A \cdot Norm(\mu, \sigma^2)$.

However, some overshooting artifacts might occur as the pixel near the border of the segmentation might be corrected more than needed. In order to prevent overshooting, the intensity values at the two zero-crossing points of the gradient profile are used to limit the intensity change of the center pixel. Therefore the final pixel intensity will lie within the range that is defined by the two zero-crossing pixels.

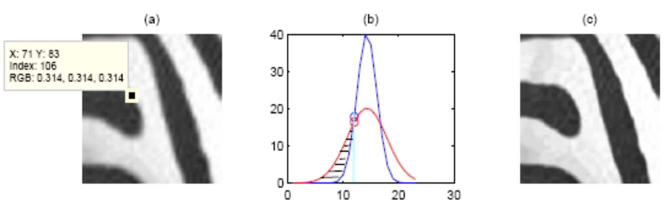

Fig. 2. Update of the gradient profile. (a) The input blurred image and a pixel of interest. (b) The red curve is the original gradient profile and the blue curve is updated one. The difference shown in the shadow is used to update the pixel intensity value. (c) Output image.

The above described our main algorithm of proposed image sharpening method, and is shown as in Figure 2. Figure 2(a) shows a pixel of interest in the input blurred image, and Figure 2(b) shows the original gradient profile in red, which is then updated in the sharper blue gradient profile. Figure 2 (c) shows the resulting image where the same procedure applied to every pixel, and the output image looks much sharper than the input image.

III. Experimental Results

We compared our algorithm with the well-known Cubic Unsharp Masking algorithm [4]. The input image is first zoomed in five times with bicubic interpolation before applying the sharpening algorithms. We measure the sharpness of the results with Tenengrad measure, as

$$S = \sum_{g(i,j) \geq T} (g_x(i,j)^2 + g_y(i,j)^2),$$

where T is a threshold. Figure 3 shows the resulting images and corresponding sharpness measures.

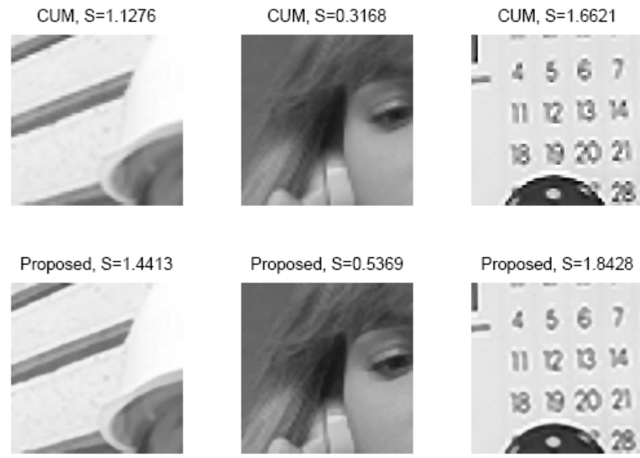

Fig. 3. Experimental results. The top row shows the output from Cubic Unsharp Masking algorithm, while the bottom row shows the output from our proposed method. The corresponding Tenengrad measure for sharpness is also shown on top of individual image..

IV. Discussion

In this paper, we presented a new image sharpening algorithm for high magnification image zooming. The proposed image sharpening algorithm is overshooting free and particularly suitable for high magnification zooming situation. The method shows better performance than the traditional ones both visually and in objective numerical measurements.

In practice, there are many improvements can be added, for example: 1. we approximate the gradient profile using Gaussian distribution for its simplicity and speed. A Generalized Gaussian Distribution can better approximate the gradient profile as described in [5], where a third parameter λ is used and fixed as $\lambda = 1.6$ for natural images. 2. We can improve the fitting procedure by using some iterative methods such as Mean Shift algorithm or even using Gaussian Mixture Model. 3. The only two parameters used for our algorithm can both be set based on the magnification rate.

References

[1] Yi Yao, Besma Abidi, and Mongi Abidi, "Digital imaging with extreme zoom: System design and image restoration," in *Proceedings of the Fourth IEEE International Conference on Comoputer Vision Systems*, 2006, pp. 52-59.

[2] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, Prentice Hall, Upper Saddle River, New Jersey, 2nd edition, 2002.

[3] D. Kundur and D. Hatzinakos, "Blind image deconvolution," *IEEE Signal Processing Magazine*, pp. 43-64, May 1996.

[4] Giovanni Ramponi, "A cubic unsharp masking technique for contrast enhancement," *Signal Process*, vol. 67, pp. 211-222, June 1998.

[5] Jian Sun, Jian Sun, Zongben Xu, and Heung-Yeung Shum, "Image super-resolution using gradient profile prior," in *2008 IEEE International Conference on Computer Vision and Pattern Recognition*, 2008, pp. 1-8.