Iterative Sharpening for Image Contrast Enhancement

Ali Alsam*†, Ivar Farup† and Hans Jakob Rivertz*
*Sør-Trøndelag University College, Norway
†Gjøvik University College, Norway

Abstract—In this paper, the problem of iterative sharpening for local contrast enhancement is addressed. We present a fast algorithm that spreads the high frequencies of an image to successively lower resolutions resulting in an improvement in sharpness and local contrast. The algorithm is similar to the well established unsharp masking with certain fundamental differences. The image is blurred with a Gaussian filter and a difference image representing the hight frequencies is calculated. This difference is then amplified and added back to the blurred image and the process is repeated without altering the original high frequencies. Our result demonstrate that up to 100 iterations can be applied without image artifacts.

Keywords—Image sharpening, local contrast, image enhancement.

I. INTRODUCTION

Smoothing and sharpening are two fundamental operations in image processing with the former receiving greater attention in the literature. The greater emphasis on solving the smoothing problem is due to its role in a vast number of applications such as image denoising [1], [2], segmentation [3] and edge preserving scale space decomposition [4], [5], [6], [7]. Sharpening on the other hand is typically regarded as a problem with well established solutions that include amplifying the high frequencies [8], [9].

Unsharp masking is one of the most established sharpening algorithms. It is implemented in every image processing library and commonly used in printers and cameras. In unsharp masking, an image is blurred using a gaussian filter and, as a second step, the difference between the original image and the blurred version is calculated. This difference image represents the high frequency elements at a scale defined by the size of the Gaussian filter. Finally, the difference image is added linearly to the original to arrive at the desired sharp image.

The process of sharpening can normally be repeated two or three times without noticeable image artifacts and in fact many photographers choose to sharpen their images more than once. If sharpening is repeated more than a limited number of times clear artifact appear in the image resulting in quality degradation.

In this paper, we tackle the problem of iterative sharpening and ask: how many times can we sharpen an image without degrading it? To answer this question, we present an algorithm that is similar to unsharp masking, i.e. we start by estimating the high frequencies and store them in a difference image, we then amplify the difference and add it to the blurred image rather than the original. We finally blur the result and repeat the process with the same original high frequency image. The image is blurred at each iteration to ensure that the result is always continuous. At every iteration, we add the high frequencies that we calculate in the first step, i.e. the difference image is calculated only once and the size of the Gaussian filter that we use is 3×3 .

By iteratively sharpening an image in the manner described, we have found that as many as 100 iterations can be applied without noticeable degradation. Further, the more we iterate, the more we spread the change to lower frequencies resulting in an improvement in the local contrast of the image. Finally, we note that if the high frequencies are not amplified then the algorithm can be repeated infinitely many times without any change to the original. Thus the number of allowable iterations is a function of the level of amplification.

II. ALGORTIHM

The starting point of our algorithm is a greyscale image I(x,y). This image is blurred by convolving it with a Gaussian filter D and the difference image H is calculated.

$$H = I - D * I \tag{1}$$

here \ast denotes convolution. The high frequency image H is then amplified using a gamma function and the result is added back to the blurred image which yields a result,

$$I_1 = H^{\gamma} + D * I \tag{2}$$

here we note that if γ is set to one the resultant image I_j is identical to I. The general iteration at any level j can be stated as:

$$I_{j+1} = H^{\gamma} + D * I_j \tag{3}$$

A. Implementation with FFT

Many iterations of this method can be done in one operation by using Fourier transforms. Let \mathcal{H}^* , \mathcal{I}_j , and \mathcal{D} denote the Fourier transforms of H^{λ} , I_j , and D respectively. In the Fourier domain, we have

$$\mathcal{I}_{j+1}(u,v) = \mathcal{H}^*(u,v) + \mathcal{D}(u,v)\mathcal{I}_j(u,v), \quad j = 0, 1, 2, .$$

If we expand the iterations we get

$$\mathcal{I}_n(u,v) = \left(\sum_{i=0}^{n-1} \mathcal{D}(u,v)^i\right) \mathcal{H}^*(u,v) + \mathcal{D}(u,v)^n \mathcal{I}(u,v).$$

We notice that the sum is a geometric series. Therefore we have

$$\mathcal{I}_n(u,v) = \frac{(1 - \mathcal{D}(u,v)^n)\mathcal{H}^*(u,v)}{1 - \mathcal{D}(u,v)} + \mathcal{D}(u,v)^n \mathcal{I}(u,v).$$

III. RESULTS

In this section, we present results based on two images: Two women and a portrait. In Figure 1, an original photo of two women taken with a Fuji S2 camera is shown. This photo is then sharpened ten times with the proposed algorithm and the results are shown in Figure 2. In the resultant image, we notice that the result is sharper and that local contrast is enhanced. In Figures 3, 4 and 5 the same image is sharpened 20, 40 and 100 times respectively. In the images we notice that the results



Fig. 1. Two women photo.



Fig. 2. Two women photo sharpened 10 times with a $\gamma = 0.85$



Fig. 3. Two women photo sharpened 20 times with a $\gamma = 0.85$

exhibit successively more contrast that spreads in the image plane as the number of iteration increases. To



Fig. 4. Two women photo sharpened 40 times with a $\gamma = 0.85$



Fig. 5. Two women photo sharpened 100 times with a $\gamma=0.85$



Fig. 6. Two women photo sharpened 100 times with a $\gamma = 0.90$

arrive at these results we employed a γ of 0.85. As mentioned previously, the level of change is subject

to the chosen strength of the γ function where a $\gamma=1$ results in no change. To demonstrate the effect of the γ function, in Figure 6 we employed a $\gamma=0.9$. To allow for a side by side comparison with the results in Figure 5 we used a 100 iteration. We notice that the results in Figure 5 exhibit more contrast. The results in Figure 6, however, are more natural and the transition between dark and light regions is smoother.



Fig. 7. Original portrait image.



Fig. 8. Portrait image sharpened 100 times with a $\gamma = 0.85$.

Finally, in Figure 7 we present a portrait image taken with a Nikon D3s camera. This image is sharpened a 100 times with a $\gamma=0.85$ and the result

is shown in Figure 8. Here, we notice the change in sharpness, contrast and dynamic rage of the image.

IV. CONCLUSION

In this paper, we presented an algorithm to iteratively sharpen an image and successively improve the local contrast. The algorithm is fast and can be implemented as a direct solution in the Fourier domain or as an iterative solution in the spatial domain. Our results indicate that an image can be sharpened a hundred times without visible artifacts and that the more we sharpen the more the effect of the process spreads to the lower frequencies.

REFERENCES

- [1] Antoni Buades, Bartomeu Coll, and Jean-Michel Morel. A review of image denoising algorithms, with a new one. *Multiscale Modeling & Simulation*, 4(2):490–530, 2005.
- [2] Kostadin Dabov, Alessandro Foi, Vladimir Katkovnik, and Karen Egiazarian. Image denoising by sparse 3-d transform-domain collaborative filtering. *Image Processing, IEEE Transactions on*, 16(8):2080–2095, 2007.
- [3] Nikhil R Pal and Sankar K Pal. A review on image segmentation techniques. *Pattern recognition*, 26(9):1277–1294, 1993.
- [4] Pietro Perona and Jitendra Malik. Scale-space and edge detection using anisotropic diffusion. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 12(7):629–639, 1990.
- [5] Pietro Perona, Takahiro Shiota, and Jitendra Malik. Anisotropic diffusion. In *Geometry-driven diffusion in computer vision*, pages 73–92. Springer, 1994.
- [6] Michael J Black, Guillermo Sapiro, David H Marimont, and David Heeger. Robust anisotropic diffusion. *Image Processing*, *IEEE Transactions on*, 7(3):421–432, 1998.
- [7] Guo W Wei. Generalized perona-malik equation for image restoration. *Signal Processing Letters, IEEE*, 6(7):165–167, 1999.
- [8] Rafael C Gonzalez. *Digital image processing*. Pearson Education India, 2009.
- [9] Ali Alsam. Colour constant image sharpening. In Pattern Recognition (ICPR), 2010 20th International Conference on, pages 4545–4548. IEEE, 2010.