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RESTORATION FOR WEAKLY BLURRED AND STRONGLY NOISY IMAGES ON THE BASIS OF NONHARMONIC ANALYSIS

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ABSTRACT

The restoration of images by nonharmonic analysis (NHA) algorithm is an active field of research and such algorithms are, in fact, now widely used. Conventional methods usually apply cannot handle strong noise well due to the inherent contradiction between sharpening and de-noising. To solve this issue here, we propose a NHA method to overcome this limitation by using signal prediction based on the NHA method proposed. In this paper we present NHA analysis algorithm for restoration of a picture which has been corrupted by mild blur, and strong noise. Experiments illustrate that compared with other sharpening approaches; our method can produce state of the art results under practical imaging conditions.

KEYWORDS: De-Noising, Signal Prediction, Nonharmonic, Sharpening

INTRODUCTION

Blur & noise are the common issues that exist in digital imaging. An important camera setting that strongly affects these distortions, & that needs to be carefully adjusted, is the aperture size. If the exposure time is fixed, a massive aperture will increase the signal to noise ratio (SNR), meanwhile reducing the depth of field (DOF) & thus increasing the out-of-focus blur, which eliminates high-frequency parts of the picture. On the other hand, a tiny aperture will alleviate the blur but increase the noise level [17, 4]. Noise may even be suppressed by using longer exposure time; but of work, this may cause motion (either camera motion or object motion) blur that is even more difficult to remove [3, 14, 1]. Simultaneously, limited accuracy of auto-focus systems & low light condition may add additional blur & noise in to the picture. So in actual applications, such as consumer digital imaging, it is common to record weakly blurred & comparatively noisy images. In general, there's feasible types of techniques that can enhance the sharpness of an picture under such conditions. group of methods is blind-deconvolution. In recent years, several blind-deconvolution algorithms have been proposed to restore images degraded by blur [3, 13, 5]. These algorithms are usually designed under the assumption that the point spread function (PSF) of blur is spatially invariant, & that noise is very weak or virtually absent. Regrettably, even when dealing with weakly blurred images, the presence of noise can be a significant issue for the state of the art deblurring algorithms. Think about the popular algorithms under the maximum a-posteriori (MAP) estimation framework, where total variation (TV) or other sparse picture priors are often used [8, 13]. These regularization terms concentrate on smoothing pixels with median or little gradient values, leaving high-value gradients preserved. They perform as smoothing filter assuming a worldwide model for the locally treated pixels without thinking about local picture characteristics. Although they can provide a nice balance between high frequency content restoration & noise suppression, the noise effect may still stay in the output knowledge, & corrupt the smoothness of latent object structure. On the other hand, space invariance of the PSF does not hold in general for out-of-focus blur since the scene depth varies spatially [7]. Besides, high computational cost is another significant shortcoming of deblurring approaches [2]. The algorithm proposed in [2] incorporates a denoising filter to smooth the input picture, & employs a clipping process to remove overshoot. However, this process smoothes mostly low-frequency parts of the input picture, and enhances unfiltered high-frequency part directly, which again amplifies noise. Meanwhile the clipping process may affect structure smoothness generating artifacts for heavily noisy regions. Another sharpening algorithm called adaptive bilateral filter (ABF) can accomplish lovely noise suppression [18]. ABF was designed by introducing an offset in to the bilateral filter, which switches the behavior of the filter from denoising to edge sharpening according to local picture structure. This method focuses on enhancing the slope of edges, but its sharpening strength for texture or other picture details is limited. In this paper a nonharmonic analysis (NHA) process is proposed for weakly blurred and strongly noisy images. The key idea behind this approach is to extract correct spectra, irrespective of the window function, and its frequency resolution is less than that of the discrete Fourier transform, so that denoising and sharpening processes can be effectively combined together[21].The remainder of this paper is organized as follows. Section II report the proposed algorithm, In this section is followed by Weakly Blurred and Strongly Noisy Images for Restoration In Section III, they show the restoration results for actual images, Finally, Section IV concludes the paper.

NHA Algorithm

In this section, we describe the NHA algorithm. The Fourier transform (FT), which has been used For frequency analysis can be represented as follows:

$$X(f) = \frac{1}{T}\int_0^T x(t)\, e^{-j2\pi f t} dt \tag{1}$$

Where T is analysis window length. Equation (1) is solved for determining the Fourier coefficients. This is because, FT assumes that a complex periodic signal model is the sum of sine waves, and ask for Fourier coefficients based on the product fellow sine wave and integral equation. In short FT is used for analyzing a completely periodic signal in an analysis window *T*. Therefore, analysis results depend on the window length, and errors frequently occur in the analysis of non-harmonic signal frequencies. Moreover, if the length of the analysis window is decreased to increase the time resolution, the frequency resolution also decreases. The discredited version of the FT is the DFT and the algorithm often used to compute the DFT is the fast Fourier transform (FFT). NHA estimates the Fourier coefficients by assuming a signal model similar to FT. However, the NHA estimates the Fourier coefficients by performing shape fitting of the target signal and signal model using the least squares method. In this way, NHA can reduce the effect of the shape or length of analysis window and can predict surrounding information from a part of the signal. The 2D basis sinusoidal model signal for 2D NHA can be expressed as follows:

$$\hat{I}(n_1, n_2) = \hat{A}\cos\left(2\pi\left(\frac{\widehat{f_x}}{f_{x_s}}n_1 + \frac{\widehat{f_y}}{f_{y_s}}n_2 + \hat{\phi}\right)\right) \tag{2}$$

Where n_1 and n_2 are the pixel numbers and f_{x_s} and f_{y_s} are the sampling frequencies, given as $f_{x_s} = 1/\Delta x$ and $f_{y_s} = 1/\Delta y$.Here, *x* and *y* are the two spatial dimensions. To minimize the sum of the squares of the differences between the original signal *I* and the 2D sinusoidal model signal $\hat{I}$, the spatial frequencies $\widehat{f_x}$ and$\widehat{f_y}$, amplitude $\hat{A}$, and initial phase $\hat{\phi}$ are calculated as follows

$$F(\hat{A}, \widehat{f_x}, \widehat{f_y}, \hat{\phi}) = \frac{1}{N_1 N_2}\sum_{n_1=0}^{N_1-1}\sum_{n_2=0}^{N_2-1}\left\{I(n_1, n_2) - \hat{I}(n_1, n_2)\right\}^2 \tag{3}$$

Where I is the original 2D signal and $N_1$and N_2 are the image dimension. By using the nonlinear equation, the 2D DFT converges to the appropriate initial values $\hat{A}, \hat{f_x}, \hat{f_y}\ and\ \hat{\phi}$, from which the optimal solution is obtained by using the steepest descent method for 2D NHA. By considering (3) as the function, this nonlinear problem is converted into a minimization problem and $\hat{f}_{x\,k}, \hat{f}_{y\,k}\, and\ \hat{\phi}_k$ are determined using the steepest descent method to obtain the following expressions:

$$\hat{f}_{x\,k+1} = \hat{f}_{x\,k} - \mu k \frac{\partial F}{\partial f_x} \tag{4}$$

$$\hat{f}_{y\,k+1} = \hat{f}_{y\,k} - \mu k \frac{\partial F}{\partial f_y} \tag{5}$$

$$\hat{\phi}_{k+1} = \hat{\phi}_k - \mu k \frac{\partial F}{\partial \phi}. \tag{6}$$

The above equations are expressed as follows:

$$\partial F = \partial F(\,\hat{A}_k, \hat{f}_{x\,k}\,, \hat{f}_{y\,k}\,, \hat{\phi}_k\,). \tag{7}$$

Equations (4)–(6) are used for the steepest descent method, where μk is a weighting coefficient obtained by the retardation method and takes a value between 0 and 1 when converting the cost functions calculated by recurrence formulas into amonotonically increasing sequence. Next, if $\hat{f}_{x\,k}\,, \hat{f}_{y\,k}\,, and\ \hat{\phi}_k$ are known, then $\hat{A}$ can be uniquely determined. The following formula is applied to cause $\hat{A}$ to converge:

$$\hat{A}_{k+1} = \hat{A} - \mu k \frac{\partial F}{\partial A}. \tag{8}$$

This series of calculations is repeated in order to cause $\hat{A}_k, \hat{f}_{x\,k}\,, \hat{f}_{y\,k}\,, and\ \hat{\phi}_k$ to converge with high accuracy. Although the steepest descent method causes values to converge over a comparatively wide range, performing a series of signal operations does not ensure sufficient accuracy and is, moreover, time consuming. Instead, NHA achieves highly accurate conversion by using Newton's method after the steepest descent method. The following recurrence formulas are used in Newton's method:

$$\hat{f}_{x\,k+1} = \hat{f}_{x\,k} - \frac{v_k}{J}\,|\,\alpha\ \beta_2\ \beta_3\,| \tag{9}$$

$$\hat{f}_{y\,k+1} = \hat{f}_{y\,k} - \frac{v_k}{J}\,|\,\beta_1\ \alpha\ \beta_3\,| \tag{10}$$

$$\hat{\phi}_{k+1} = \hat{\phi}_k - \frac{v_k}{J}\,|\,\beta_1\ \beta_2\ \alpha| \tag{11}$$

Where

$$\alpha^T = \left|\frac{\partial F}{\partial f_x}\ \frac{\partial F}{\partial f_y}\ \frac{\partial F}{\partial \phi}\right|$$

$$\beta_1^T = \left|\frac{\partial^2 F}{\partial f_x^2}\ \frac{\partial^2 F}{\partial f_x \partial f_y}\ \frac{\partial^2 F}{\partial f_x \partial \phi}\right|$$

$$\beta_2^T = \left|\frac{\partial^2 F}{\partial f_x \partial f_y}\ \frac{\partial^2 F}{\partial f_y^2}\ \frac{\partial^2 F}{\partial f_y \partial \phi}\right|$$

$$\beta_3^T = \left| \frac{\partial^2 F}{\partial f_x \partial \phi} \; \frac{\partial^2 F}{\partial f_y \partial \phi} \; \frac{\partial^2 F}{\partial \phi^2} \right|$$

$$J = |\, \beta_1 \, \beta_2 \, \beta_3 |$$

The above equations can be rewritten as follows:

$$\partial^2 F = \partial^2 F\left(\hat{A}_k, \hat{f}_{x\,k}, \hat{f}_{y\,k}, \hat{\phi}_k\right) \tag{12}$$

Here, v_k, like μk, is a weighting coefficient obtained by using the retardation method. Equations (9), (10) and (11) are constructed to converge by applying (8) in a manner similar to that used in the steepest descent method, and the series of calculations is repeated. In other words, the frequency parameters are rapidly estimated to a high degree of accuracy by using a hybrid process that combines the steepest descent method with Newton's method. Even when a signal comprises several sinusoidal waves, the spectral parameters can be approximated by sequential reduction. Here, let $I(n_1, n_2)$ be expressed as the sum of L sinusoidal waves as follows:

$$I(n_1, n_2) = \sum_{l=1}^{L} \hat{I}(n_1, n_2) \tag{13}$$

Where l is wave number. According to Parseval's theorem, the original signal frequencies, f_{xl} *and* f_{yl} , and the model signal frequencies, $\widehat{f_x}$ *and* $\widehat{f_y}$, do not match any of the f_{xl} *and* f_{yl} respectively. That is, if $(f_{xl} \neq \widehat{f_x}) \cap (f_{yl} \neq \widehat{f_y},)$ for any, then

$$F\left(\hat{A}, \hat{f}_x, \hat{f}_y, \hat{\phi}\right) = \hat{A}^2 + \sum_{l=1}^{L} A_l^2 \tag{14}$$

In addition, if $\hat{f}_x$, $\hat{f}_y$, *and* $\hat{\phi}$ match f_{xl} , f_{yl} , *and* ϕ_l, respectively, then

$$F\left(\hat{A}, \hat{f}_x, \hat{f}_y, \hat{\phi}\right) = \left(\hat{A} - A_n\right)^2 + \sum_{l=1, l\neq n}^{L} A_l^2 \tag{15}$$

If both A_n *and* A match, then the frequency component for the estimated spectrum can be completely removed from the original signal. Therefore, the possibility of obtaining an optimum solution is frequency-independent and the method can even be applied to a signal consisting of several sinusoidal waves by the process of sequential and individual estimation from the original signal *I*. In other words, even when the original signal *I* is a composite sinusoidal wave, several sinusoidal waves can be extracted using a similar processing approach similar to that for sequential residual signals. If the frequencies of two spectra are similar, then it is likely that an error will occur for the same reason that such errors occur. In general, the frequency spectrum that is included in the image is a predominantly low-frequency spectrum. In other words, it can be said that improvement of the low-frequency resolution is directly linked to efficient image representation. NHA has a very high frequency resolution, and it can represent the images by using very few spectral. The side lobes occur in FFT, but not in NHA [21]. Therefore, it is not necessary to consider the side lobes in NHA, and the influence of noise is suppressed. A representative example is given in Figure 1, where it can be seen that the proposed strategy successfully suppressed basically all the noise.

To summarize, the overall algorithm can be described as follows:

Algorithm

Algorithm for Color Image Restoration consist of following steps

- Given RGB image $I(n_1, n_2)$, transfer it into $\hat{I}(n_1, n_2)$, to minimize the sum of the square of the difference between the original image $I(n_1, n_2)$ and $\hat{I}(n_1, n_2)$.
- Obtain the NHA basis function depending on pixel values of input image (2).
- Subtract the basis function values from original image value (3).
- Again obtain basis function from modified image and follow step no. 3
- Perform step no 4 recursively to get the finer result.

EXPERIMENTAL RESULTS

To show the effectiveness of the proposed algorithm, we test it on several real images that suffer from mild blur and strong noise. Several leading adaptive sharpening approaches (Adaptive UM [11], Constrained UM [2] and ABF [18]) are also applied as comparison. One set of results are given in Figure 2, where (a) which contains strong shot noise and mild out of- focus blur. In (b) the Adaptive UM produced result with sharpened edges and detail, but the noise is also strongly amplified. A similar situation happens in Constrained UM in (c). Although it did not significantly raise the noise lever, the high-frequency noise artifacts can be easily observed especially in the flat areas. In (d), ABF provides an image with the noise sufficiently suppressed, since it incorporates bilateral filter. It sharpens edges well, but its sharpening effect in detail regions is limited. In (e), our proposed algorithm results are given in Figure 1, which suppressed both blur and noise. The surface of the doll and the background are very clean, while the restored details are at least as good as (b) and (c).

CONCLUSIONS

In this paper, we developed a nonharmonic analysis algorithm. This algorithm can capture local picture structure and thus effectively merge denoising and sharpening together. Experiments show that the proposed approach can effectively restore images distorted by weak blur and strong noise. Compared with other state of the art adaptive sharpening methods, it handles both denoising and sharpening tasks simultaneously well, and can remove noise. This algorithm is also computationally cheap, since it is not iterative.

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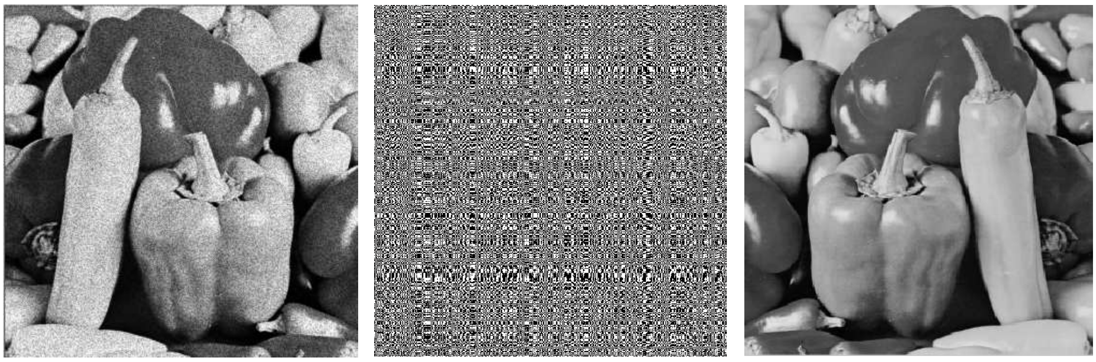
APPENDICES



(a) Original Image (b) Magnitude Image (c) Restored Image

Figure 1: Examples of Nonharmonic Restoration Using Our Proposed Method

(a) Original Image (b) Adaptive UM (c) Constrained UM (d) ABF (e) Proposed Method

Figure 2: Experimental Results: (a) Input Image; (b) Result of Adaptive UM [11]; (c) Result of Constrained UM [2]; (d) Result of ABF [18]; (e) Result of Proposed Method