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A Novel approach for Enhancement of Image Contrast Using Adaptive Bilateral filter with Unsharp Masking Algorithm

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Abstract: In this project, Unsharp mask refers to a process used in both film and digital photographic processing to increase the apparent sharpness of an image. In this article we explain the working of both film and digital versions of the process, and discuss the meaning of the name. The article does not attempt to teach techniques for the effective use of the process. Enhancement of contrast and sharpness of an image is required in many applications. Unsharp masking is a classical tool for sharpness enhancement. We propose a generalized unsharp masking algorithm using the exploratory data model as a unified framework. The proposed algorithm is designed to address three issues: 1) simultaneously enhancing contrast and sharpness by means of individual treatment of the model component and the residual, 2) reducing the halo effect by means of an Bilateral filter, and 3) solving the out-of-range problem by means of log-ratio and tangent operations. We also present a study of the properties of the log-ratio operations and reveal a new connection between the Bregman divergence and the generalized linear systems. This connection not only provides a novel insight into the geometrical property of such systems, but also opens a new pathway for system development.

Keywords: image enhancement, unsharp masking, Bregman divergence, exploratory data model, generalized linear system.

I. INTRODUCTION

The unsharp mask process first emerged in the world of film photography, and its name comes from that practice. I'll discuss it briefly just for historical continuity. It is easiest to imagine a black-and-white context. We take our image negative and make a "contact print" of it on negative film stock, in such a way that the image there is slightly blurred. The usual way to do that is to put the receiving film against the face of the image negative opposite the emulsion. If the light source is diffuse, the spacing between the negative emulsion and the emulsion of the receiving film (owing to the thickness of the negative base material) causes the image to be slightly blurred.

We develop this film image, which will be a "positive" (more transparent where the actual scene was lighter, and thus the negative is more opaque). We then sandwich the positive image with the original negative in the negative carrier of our enlarger when we make a print. We can view this film positive as a mask, which of course has a range of transparencies (the complement of the transparencies of the negative proper). Rather than trying to show density profiles along a path across the "edge" (as we will do later in the digital application of the technique), we will look at the result of this in the spatial frequency domain.

There has been continuous research into the development of new algorithms. In this section, we first briefly review pre-vious works which are directly related to our work. These related works include unsharp masking and its variants, histogram equalization, retinex and dehazing algorithms, and generalized linear systems. We then describe the moti-vation and contribution of this paper.

II. EXPLORATORY DATA ANALYSIS MODEL FOR IMAGE ENHANCEMENT

A. Image Model and Generalized Unsharp Masking

A well known idea in exploratory data analysis is to decompose a signal into two parts. One part fits a particular model, while the other part is the residual. In Tukey's own words the data model is: "data = fit PLUS residuals" ([18]). From this point of view, the output of the filtering process, denoted ***y = f(x)***, can be regarded as the part of the image that fits the model. Thus, we can represent an image using the generalized operations (not limited to the log-ratio operations) as follows:

$$\boldsymbol{x} \oplus \boldsymbol{y} = \emptyset^{-1}[\emptyset(x) + \emptyset(y)] \quad (1)$$

$$\boldsymbol{\alpha} \otimes \boldsymbol{x} = \emptyset^{-1}[\alpha\emptyset(x)] \quad (2)$$

And

$$x = y \oplus d \quad (3)$$

where **d** is called the detail signal (the residual). The detail signal is defined as $\boldsymbol{d} = \boldsymbol{x} \ominus \boldsymbol{y}$ where $\ominus$ is the generalized subtraction operation. Although this model is simple, it provides us with a unified framework to study unsharp masking algorithms. A general form of the unsharp masking algorithm can be written as

$$v = h(y) \oplus g(d) \quad (4)$$

where ***v*** is output of the algorithm and both ***h(y)*** and ***g(d)*** could be linear or nonlinear functions. This model explicitly states that the part of the image being sharpened is the model residual. This will force the algorithm developer to carefully select an appropriate model and avoid models such as linear filters. In addition, this model permits the incorporation of contrast enhancement by means of a suitable processing function such as adaptive histogram equalization. As such, the generalized algorithm can enhance the overall contrast and sharpness the image.

B. Outline of the Proposed Algorithm

The proposed algorithm, shown in Figure1, is based upon the previous image model and generalizes the classical unsharp

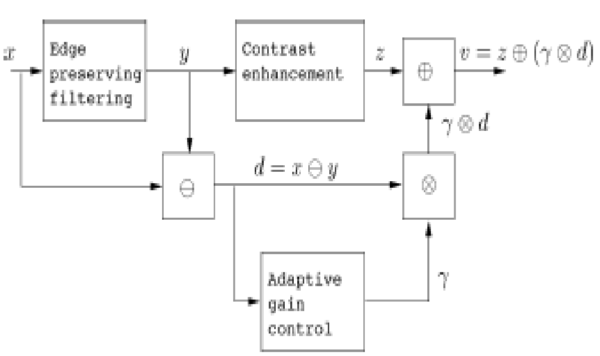

Figure1. Block diagram of the proposed generalized unsharp masking algorithm.

TABLE I

Comparision of The Classical Unsharp Masking (UM) Algorithm with the Proposed Generalized Unsharp Masking(GUM) Alorithm.

LPF: Low-Pass Filter.

EPF: Edge Preserving Filter.

ACE: Adaptive Contrast Enhancement

	y	d	$h(y)$	$g(d)$	output v	re-scale
UM	LPF	$x - y$	y	γd	$y + g(d)$	yes
GUM	EPF	$x \ominus y$	ACE	$\gamma(d) \otimes d$	$h(y) \oplus g(d)$	no

We address the issue of the halo effect by using an edge-preserving filter-the IMF to generate the signal . The choice of the IMF is due to its relative simplicity and well studied properties such as the root signals. Other more advanced edge preserving filters such as the nonlocal means filter and wavelet-based denoising filters can also be used.We address the issue of the need for a careful rescaling process by using new operations defined according to the log-ratio and new generalized linear system. Since the gray scale set is closed under these new operations on the out-of-range problem is systematically solved and no rescaling is needed. We address the issue of contrast enhancement and sharpening by using two different processes. The image is processed by adaptive histogram equalization and the output is called ***h(y).*** The detail image is processed by where is the adaptive gain $g(d) = \gamma(d) \otimes d$ and is $\gamma(d)$ a function of the amplitude of the detail signal **d**. The final output of the algorithm is then given by

$$v = h(y) \oplus [\gamma(d) \otimes d] \quad (5)$$

We can see that the proposed algorithm is a generalization of the classical unsharp masking algorithm in several ways which are summarized in Table I. In the following, we present details of the new operations and enhancement of the two images ***y*** and ***d***.

C. Bilateral Filter for Sharpness Enhancement

We present the adaptive bilateral filter (ABF) for sharpness enhancement and noise removal. The ABF sharpens an image by increasing the slope of the edges without producing overshoot or undershoot. It is an approach to sharpness enhancement that is fundamentally different from the unsharp mask (USM). This new approach to slope restoration also differs significantly from previous slope restoration algorithms in that the ABF does not involve detection of edges or their orientation, or extraction of edge profiles. In the ABF, the edge slope is enhanced by transforming the histogram via a range filter with adaptive offset and width. The ABF is able to smooth the noise, while enhancing edges and textures in the image. The parameters of the ABF are optimized with a training procedure. ABF restored images are significantly sharper than those restored by the bilateral filter. Compared with an USM based sharpening method the optimal unsharp mask (OUM), ABF restored edges are as sharp as those rendered by the OUM, but without the halo artifacts that appear in the OUM restored image. In terms of noise removal, ABF also outperforms the bilateral filter and the OUM. We demonstrate that ABF works well for both natural images and text images.

In this paper, we propose a new training-based approach to image restoration. Once the restoration algorithm has been fully developed, we are, however, free to apply it to images for which the degradation process is unknown. This puts us back in the domain of enhancement. The success of this broader application of the restoration algorithm will depend on how general is the degradation model under which the algorithm was developed, as well as how robust is the overall structure of the algorithm to deviations from the assumed degradation model. The scope of this paper is to deal with images that are appropriate for digital photography.

We do not consider images that are severely degraded. The two most common forms of degradation an image suffers are loss of sharpness or blur, and noise. The degradation model we use consists of a linear, shift-invariant blur followed by additive noise, described in detail in [7]. The problem we are interested in is twofold. First we seek to develop a sharpening method that is fundamentally different from the unsharp mask filter (USM) [15], which sharpens an image by enhancing the high-frequency components of the image. In the spatial domain, the boosted high-frequency components lead to overshoot and undershoot around edges, which causes objectionable ringing or halo artifacts. Our goal is to develop a sharpening algorithm that increases the slope of edges without producing overshoot and undershoot, which renders clean, crisp, and artifact-free edges, thereby improving the overall appearance of the image.

The second aspect of the problem we wish to address is noise removal. We want to present a unified solution to both sharpness enhancement and noise removal. In most applications, the degraded image contains both noise and blur. A sharpening algorithm that works well only for noise-free images will not be applicable in these situations. In terms of noise removal, conventional linear filters work well for removing additive Gaussian noise, but they also significantly blur the edge structures of an image. Therefore, a great deal of research has been done on edge-preserving noise reduction. One of the major endeavors in this area has been to utilize rank order information [6]–[9]. Due to a lack of the sense of spatial ordering, rank order filters generally do not retain the frequency selective properties of the linear filters and do not suppress Gaussian noise optimally [10]. Hybrid schemes combining both rank order filtering and linear filtering have been proposed in order to take advantage of both approaches

III. LOG-RATIO, GENERALIZED LINEAR SYSTEMS AND BREGMAN DIVERGENCE

In this section, we first define the new operations using the generalized linear system approach. We use (1) and (2) to simplify presentation. Note that these operations can be defined from the vector space point of view which is similar to that of the development of the LIP model [6]. We then study properties of these new operations from an image processing perspective. We show the connection between the log-ratio, generalized linear systems and the Bregman divergence. As a result, we not only show novel interpretations of two existing generalized linear systems, but also develop a new system.

A. Definitions and Properties of Log-Ratio Operations

1) **Nonlinear Function**: We consider the pixel gray scale of an image $x \in (0,1)$. For an N-bit image, we can first add a very small positive constant to the pixel gray value then scale it by 2^{-N}, such that it is in the range (0,1). The nonlinear function is defined as follows:

$$\emptyset(x) = \log\frac{1-x}{x} \tag{6}$$

To simplify notation, we define the ratio of the negative image to the original image as follows:

$$X = \Psi(x) = \frac{1-x}{x} \tag{7}$$

2) **Addition and Scalar Multiplication**: Using (1), the addition of two gray scales and is defined as

$$x_1 \otimes x_2 = \frac{1}{1+\varphi(x_1)\varphi(x_2)} = \frac{1}{1+X_1X_2} \qquad (8)$$

where $X_1 = \varphi(x_1)$ and $X_2 = \varphi(x_2)$. The multiplication of a gray scale $\boldsymbol{x}$ by a real scalar $\alpha(-\infty < \alpha < \infty)$ is defined by using (2) as follows:

$$\alpha \oplus r = \frac{1}{1+X^{\alpha}} \qquad (9)$$

This operation is called scalar multiplication which is a terminology derived from a vector space point of view [9]. We can define a new zero gray scale, denoted , as follows:

$$e \oplus x = x \qquad (10)$$

It is easy to show that **e=1/2**. This definition is consistent with the definition of scalar multiplication in that $e \oplus x = x$. As a result, we can regard the intervals (0,(1/2)) and ((1/2),1) as the new definitions of negative and positive numbers, respectively. The absolute value, denoted by x, can be defined in a similar way as the absolute value of the real number as follows:

$$x_{\circ} = \begin{cases} x, & \frac{1}{2} \le x < 1 \\ 1-x, & 0 < x < \frac{1}{2} \end{cases} \qquad (11)$$

3) **Negative Image and Subtraction Operation**: A natural extension is to define the negative of the gray scale. Although this can be defined in a similar way as those described in (8) and (9), we take another approach to gain deeper insights into the operation. The negative of the gray scale $\boldsymbol{x}$, denoted by x', is obtained by solving

$$x \oplus x' = 1/2. \qquad (12)$$

The result is $x' = 1 - x$ which is consistent with the classical definition of the negative image. Indeed, this definition is also consistent with the scalar multiplication in that $(-1) \otimes x = 1 - x$

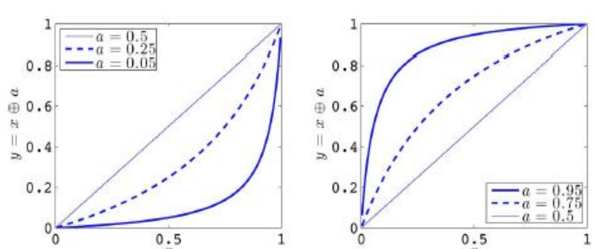

Figure2. Effects of the log-ratio addition $y = x \oplus \alpha$

and

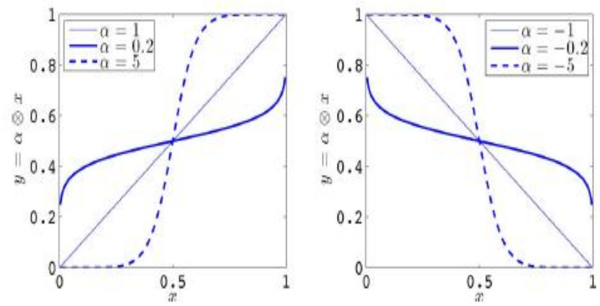

Figure3. scalar multiplication operations $y = \alpha \otimes x$.

Following the notation of the classical definition of negative numbers, We can now define the subtraction operation using the addition operation defined in (8) as follows:

$$\begin{aligned} x_1 \ominus x_2 &= x_1 \oplus (\ominus x_2) \\ &= \frac{1}{\psi(x_1)\psi(\ominus x_2)+1} \\ &= \frac{1}{X_1X_2^{-1}+1} \end{aligned} \qquad (13)$$

where we can easily see that $\psi(\ominus x_2) = 1/\psi(x_2) = X_2^{-1}$. Using the definition of the negative gray scale, we also have a clear understanding of the scalar multiplication for $\alpha < 0$

$$\begin{aligned} y &= \alpha \otimes x \\ &= (-1) \otimes (|\alpha| \otimes x) \\ &= 1 - \alpha \otimes x. \end{aligned} \qquad (14)$$

Here we have used $\alpha = (-1) \times |\alpha|$ and the distributive law for two real scalars α and β

$$(\alpha \times \beta) \otimes x = \alpha \otimes (\beta \otimes x).$$

The distributive law can be easily verified by using (9).

IV. PROPOSED ALGORITHM

A. Dealing With Color Images

We first convert a color image from the RGB color space to the HSI or the LAB color space. The chrominance components such as the H and S components are not processed. After the luminance component is processed, the inverse conversion is performed. An enhanced color image in its RGB color space is obtained. The rationale for only processing the luminance component is to avoid a potential problem of altering the white balance of the image when the RGB components are processed individually.

B. Enhancement of the Detail Signal

1) **The Root Signal and the Detail Signal**: Let us denote the median filtering operation as a function ***y = f(x)*** which maps the input ***x*** to the output ***y*** . An IMF operation can be represented as $y_{k+1} = f(y_k)$: where $k = 0, 1, 2, \ldots$ is the iteration index and $y_0 = x$. The signal y_n is usually called the root signal of the filtering process if $y_{n+1} = y_n$. It is convenient to define a number of iterations, the size and the shape of the filter mask have certain impacts on the root signal. The properties of the root signal has been extensively studied [13]. Here we use an example to illustrate the advantage of the proposed algorithm over the classical unsharp masking algorithm.

The signal is produced by a linear low-pass filter with a uniform mask of (3x3) and (5x5). The gain for both algorithms is three. Comparing the enhanced signals (last row in the figure), we can clearly see that while the result for the classical unsharp masking algorithm suffers from the out of range problem and halo effect (under-shoot and over-shoot), the result of the proposed algorithm is free of such problems.

2) **Adaptive Gain Control**: We can see from Fig. 3 that to enhance the detail signal the gain must be greater than one. Using a universal gain for the whole image does not lead to good results, because to enhance the small details a relatively large gain is required. However, a large gain can lead to the saturation of the detailed signal whose values are larger than a certain threshold. Saturation is undesirable because different amplitudes of the detail signal are mapped to the same amplitude of either 1 or 0. This leads to loss of information. Therefore, the gain must be adaptively controlled.

In the following, we only describe the gain control algorithm for using with the log-ratio operations. Similar algorithm can be easily developed for using with the tangent operations. To control the gain, we first perform a linear mapping of the detail signal ***d*** to a new signal such that the dynamic range of c is (-1,1).

$$c = 2d - 1 \tag{30}$$

C. Contrast Enhancement of the Root Signal

For contrast enhancement, we use adaptive histogram equalization implemented by a Matlab function in the Image Processing Toolbox. The function, called “adapthisteq,” has a parameter controlling the contrast. This parameter is determined by the user through experiments to obtain the most visually pleasing result. In our simulations, we use default values for other parameters of the function.

V. RESULTS AND COMPARISON

We use the canyon image called: Hunt’s Mesa (shown in below top-left of figure) to study the proposed algorithms. We first show the effects of the two contributing parts: contrast enhancement and detail enhancement. As shown in Fig. 9, contrast enhancement by adaptive histogram equalization does remove the haze-like effect of the original image and contrast of the cloud is also greatly enhanced.

Figure4. Comparison of individual effects of contrast enhancement and detail enhancement. Images from left to right: original, only with contrast enhancement. using adaptive histogram equalization, only with detail enhancement, and with both enhancements.

Figure5. Results of the proposed algorithm using (3x3) mask with different shapes. Top left: square shape. Top right: diagonal cross. Bottom left: horizontalvertical cross. To illustrate the halo-effect, a linear filter with a (3x3) uniform mask is used to replace the median **filter** in the proposed algorithm. The result is shown in the bottom right. The halo-effects are marked by red ellipse.

However, the minute details on the rocks are not sharpened. On the other hand, only using detail enhancement does sharpen the image but does not improve the overall contrast. When we combine both operations both contrast and details are improved. Next, we study the impact of the shape of the filter mask of the median filter. In Fig. 10, we show results of the proposed algorithm using 3(x) 3 filter mask with shapes of square, diagonal cross(x) and horizontal-vertical cross (+) . For comparison, we also show the result of replacing the median filter with a linear filter having a (3x3) uniform mask. As we can observe from these results, the use of a linear filter leads to the halo effect which appears as a bright line surrounding the relatively dark mountains (for an example, see the bottom right figure in Figure5). Using a median filter, the halo effect is mostly avoided, although for the square and diagonal cross mask there are still a number of spots with very mild halo effects. However, the result from the horizontal-vertical cross mask is almost free of any halo effect. In order to completely remove the halo effect,

adaptive filter mask selection could be implemented: the horizontal-vertical cross mask for strong vertical/horizontal edge, the diagonal cross mask for strong diagonal edge and the square mask for the rest of the image. However, in practical application, it may be sufficient to use a fixed mask for the whole image to reduce the computational time.

VI SIMULATION RESULTS

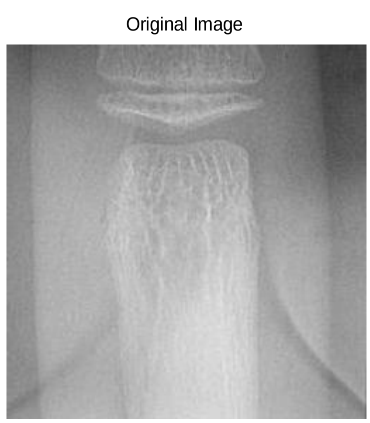

Figure6: Input Image

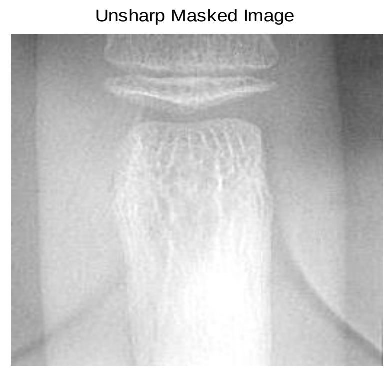

Figure7: Unsharp Masked Image for input image

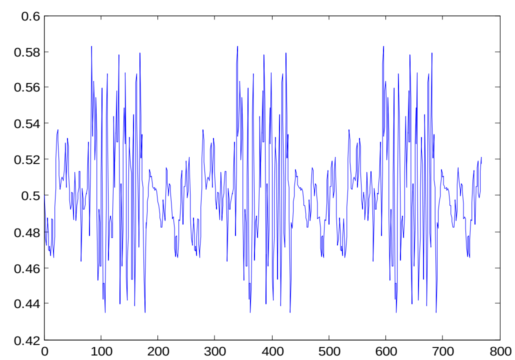

Figure8: Adaptive Histogram Equalization for input image.

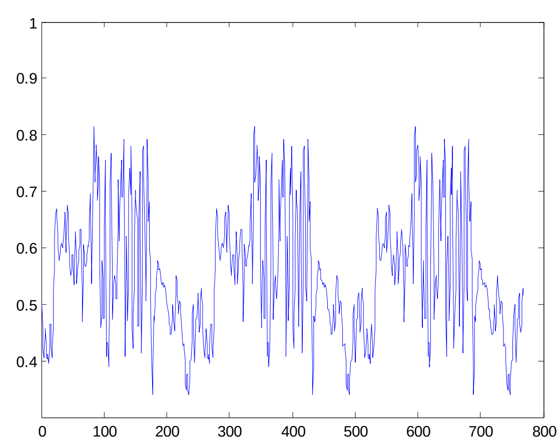

Figure9: Adaptive Histogram Equalization for Unsharpe Masked Image.

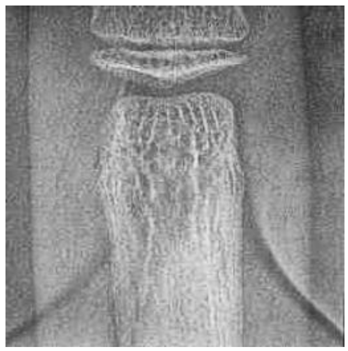

Figure10: Enhancement image output using Proposed Method with Contrast Factor 0.001

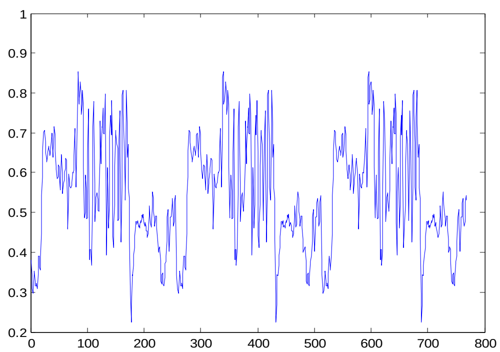

Figure11: Adaptive Histogram Response for Proposed output image.

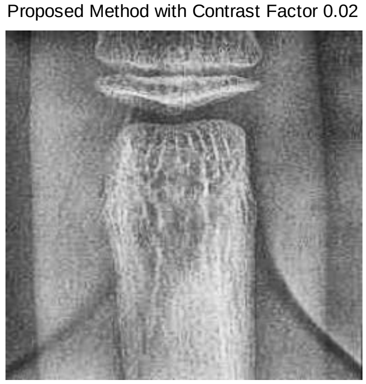

Figure12: Enhancement image output using Proposed Method with Contrast Factor 0.02

VII. CONCLUSION

In this paper, we use an exploratory data model as a unified framework for developing generalized unsharp masking algorithms Using this framework. Experimental results, which are comparable to recently published results, show that the proposed algorithm is able to significantly improve the contrast and sharpness of an image. In the proposed algorithm, the user can adjust the two parameters controlling the contrast and sharpness to produce the desired results. This makes the proposed algorithm practically useful.

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