Enhancement of Sharpness and Contrast Using Adaptive Parameters

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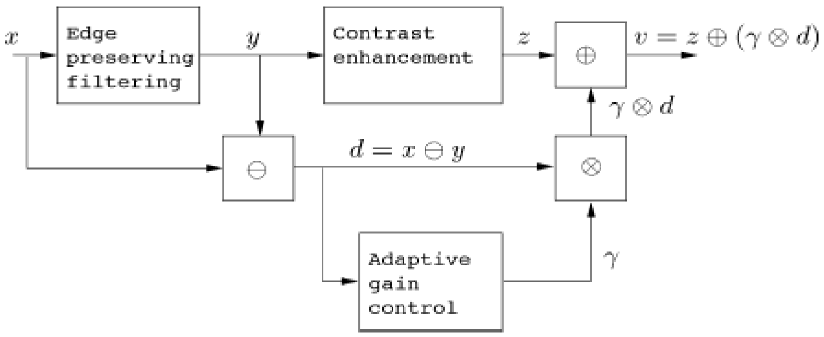
ABSTRACT

In the applications like medical radiography enhancing movie features and observing the planets it is necessary to enhance the contrast and sharpness of an image. 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 edge-preserving filter, and 3)solving the out of range problem by means of log ratio and tangent operations. We present a new system called the tangent system which is based upon a specific bregman divergence. Experimental results show that the proposed algorithm is able to significantly improve the contrast and sharpness of an image. Using this algorithm user can adjust the two parameters the contrast and sharpness to have desired output

INDEX TERMS: *Bregman divergence, exploratory data model, generalized linear system, image enhancement, unsharp masking.*

I. INTRODUCTION

Now a days in digital image processing applications requires an image that contains detailed information. So we need to convert a blurry image and undefined image into a sharper image. So in application orientation we need to enhance the contrast and sharpness of the image. While enhancing the qualities of the image, it is clear that noise components enhancement is undesirable. In this view the enhancement of undershoot and overshoot creates the effect called as halo effect. So ideally our algorithm should only enhance the image details. To overcome this problem we need to use filters that are not sensitive to noise and do not smooth sharp edges. In this paper we use log ratio approach to overcome the out of range problem. In this paper we proposed a generalized system which is used for general addition and multiplication which is shown in below figure.



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

And

$\alpha \otimes x = \varnothing^{-1}[\alpha\, \varnothing(x)]$ (2)

Where x and y are sample signals, α is a real scalar and ø is non-linear function. And the remarkable property of log ratio approach is that it is operable in the region (0, 1) gray scale and can overcome the out of range problem. The following are the main issues in contrast enhancement and sharpness enhancement in current existing systems. The existing systems dealt these processes as two tasks which will increase the complexity.

The contrast enhancement does not lead to the sharpness enhancement. Many of the existing systems facing the problem of halo effect. While enhancing the sharpness of an image, in parallel the noise of the image also is increased. Though all the systems have enhanced the sharpness and contrast of the image, this will give the best result only after careful rescaling process. This was not there in existing system. These issues can be solved through our approach using exploratory data model and log ratio approach.

II. EXPLORATORY DATA ANALYSIS MODEL FOR IMAGE ENHANCEMENT

A well known idea in exploratory data analysis is to decompose a signal into two parts. 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,

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

Where d is called as detail signal (the residual) and defined as $d = x \ominus y$ where $\ominus$ is generalized subtraction. The general form of unshaped masking algorithm is as follows.

$$V = h(y) \oplus g(d) \qquad (4)$$

Where v is the output and h(y) and g(d) are the linear or non-linear functions. Explicitly we can say that the image model that is being sharpened is the residual. In addition, this model permits the incorporation of contrast enhancement by means of a suitable processing function h(y) such as adaptive histogram equalization. As such, the generalized algorithm can enhance the overall contrast and sharpness of the image.

Fig 2. Generalized unsharp masking algorithm block diagram

The following is the comparison between classical unsharp masking algorithm and generalized unsharp masking algorithm.

	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. 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 We address the issue of contrast enhancement and sharpening by using two different processes. The image y is processed by adaptive histogram equalization and the output is called h(y). The detail image is processed by g(d)= $\gamma(d) \otimes d$where $\gamma(d)$ is the adaptive gain and is a function of the amplitude of the detail signal d. The final output of the algorithm is then given by

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

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

The new generalized operations will be defined using the equations (1) and (2). Here these operations are defined based on the view vector space used logarithmic image processing.

A. definitions and properties of log-ratio operations:

Nonlinear Function: We consider the pixel gray scale $x \in (0, 1)$ of an image. 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:

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

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

$$X = \varphi(x) = \frac{1-x}{x} \qquad (7)$$

Using equation (1) the addition of two gray scales x_1 and x_2 can be defined as

$$x_1 \oplus x_2 = \frac{1}{(1+\varphi 1(x)\varphi 2(x))} = \frac{1}{1+x1x2} \qquad (8)$$

And the multiplication of the gray scale x by a real scalar α $(-\infty < \alpha < +\infty)$ is defined using (2) as follows

$$\alpha \otimes x = \frac{1}{1+X^{\alpha}} \qquad (9)$$

This operation is called as scalar multiplication and we define a new zero scale denoted by e as follows

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

The value of $|x|$ can be defined as follows.

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

Negative image and subtraction operation:

The negative of the gray scale, denoted by, is obtained by solving

$$x \oplus \bar{x} = 1/2 \qquad (12)$$

Now we can define the subtraction operation using the addition operation defined in (8) as follows.

$$x_1 \ominus x_2 = x_1 \oplus (\ominus x_2)$$

$$= \frac{1}{1+\varphi(x_1)\varphi(x_2)}$$

$$= \frac{1}{(1+X_1 X_2^{-1})} \qquad (13)$$

Properties:

Now when positive value a is added to the gray scale x then there will be fluctuations in output image y based on the values of a given below.

Order of reflections of the log-ratio addition.

	$0 < a < 1/2$	$1/2 < a < 1$
$0 < x < 1/2$	$0 < x \oplus a <$ min(x,a)	$x < x \oplus a < a$
$1/2 < x < 1$	$a < x \oplus a < x$	Min (x,a) $< x \oplus a < 1$

Order of reflections of the log-ratio multiplication.

	$0 < \alpha < 1$	$\alpha > 1$
$0 < x < ½$	$\alpha \otimes x > x$	$\alpha \otimes x < x$
$1/2 < x < 1$	$\alpha \otimes x < x$	$\alpha \otimes x > x$

In case of log-ratio addition, based on the value of the constant 'a' the variation of output gray value y is shown in the above table. The variations in y depends on the positive and negative nature of the gray scale x and the constant 'a'. While coming to log-ratio multiplication the result will be based on the gain value α and the polarity of the gray scale x.

Computation:

Computations can be directly performed using the new operations. For example, for any real numbers α_1 and α_2, the weighted summation is given by

$$(\alpha_1 \otimes x_1) \oplus (\alpha_2 \otimes x_2) = \frac{1}{1+X_1^{\alpha_1} X_2^{\alpha_2}} \qquad (14)$$

the generalized weighted averaging operation is defined as

$$y = (\alpha_1 \otimes x_1) \oplus (\alpha_2 \otimes x_2) \oplus (\alpha_3 \otimes x_3) \ldots\ldots\ldots \oplus (\alpha_n \otimes x_n)$$

$$= \frac{G}{G+\bar{G}} \qquad (15)$$

Where $G = (\prod x_n^{\alpha_n})^{1/N}$ and $\bar{G} = (\prod(1-x_n)^{\alpha_n})^{1/N}$ are the weighted geometric means of the original and the negative images, respectively.

An indirect computational method is through the nonlinear function (6).

$$y = \emptyset^{-1}\{\emptyset[(\alpha_1 \otimes x_1) \oplus (\alpha_2 \otimes x_2) \oplus \ldots\ldots.(\alpha_n \otimes x_n]\} \qquad (16)$$

B. Log-Ratio, the Generalized Linear System and the Bregman Divergence:

We study the connection between the log-ratio and the Bregman divergence.

1) Log-Ratio and the Bregman divergence:

The Bregman divergence of two vectors x and y, denoted $D_F(X \| Y)$, is defined as follows:

$$D_F(X \| Y) = F(X) - F(Y) - (X-Y)^T \nabla F(Y) \qquad (17)$$

Where $F: \aleph \to \mathbb{R}$ is a strictly convex and differentiable function defined over an open convex domain $\aleph$ and ∇F is the gradient of F evaluated at point y. the weighted left-sided centroid is given by

$$C_L = \mathrm{argmin}_{c \in \aleph} \sum_{n=1}^{N} \alpha_n D_F(C \| X_n)$$
$$= \nabla F^{-1} \left(\sum_{n=1}^{N} \alpha_n \nabla F(X_n)\right) \qquad (18)$$

Comparing equations (17) and (19) we can see that x_n is scalar and we can conclude as follows.

$$F(x) = \int \emptyset(x)\, dx$$
$$= -x \log(x) - (1-x) \log(1-x) \qquad (19)$$

Where the constant of the indefinite integral is omitted. The previous function F(x) is called the bit entropy and the corresponding Bregman divergence is defined as

$$D_F(x \| y) = -x \log\left(\frac{x}{y}\right) - (1-x)\log(1-x)/(1-y) \qquad (20)$$

This is called as logistic loss. Therefore, the log-ratio has an intrinsic connection with the Bregman divergence through the generalized weighted average. This connection reveals a geometrical property of the log-ratio which uses a particular Bregman divergence to measure the generalized distance between two points. This can be compared with the classical weighted average which uses the Euclidean distance. In terms of the loss function, while the log-ratio approach uses the logistic loss function, the classical weighted average uses the squared loss function.

2) Generalized Linear Systems and the Bregman Divergence:

we can derive the connections between the bregman divergence with other established generalized linear systems such as the MHS with $\emptyset(s) = \log(x)$ where $x \in (0, \infty)$ and the LIP model $\emptyset(x) = -\log(1-x)$ where $x \in (-\infty, 1)$. the corresponding bregman divergences are the kullback-Leibler(KL) for MHS

$$D_F(x, y) = x log\left(\frac{x}{y}\right) - (x-y) \qquad (21)$$

And the LIP

$$D_F(x, y) = (1-x) log[(1-x)/(1-y)] - [(1-x) - (1-y)] \qquad (22)$$

Respectively.

3) A new generalized system:

We can define a new generalized system by letting $\emptyset(x) = \nabla F(x)$. This approach of defining a generalized linear system is based upon using the Bregman divergence as a measure of the distance of two signal samples. The measure can be related to the geometrical properties of the signal space. A new generalized linear system for solving the out-of-range problem can be developed by using the following Bregman divergence

$$D_F(x, y) = \frac{1-xy}{1-y^2} - \sqrt{1-x^2} \qquad (23)$$

Which is generated by the convex function $F(x) = -\sqrt{(1-x^2)}$ whose domain is (1,-1). The nonlinear unction for $\emptyset(x)$ the corresponding generalized linear system is as follows:

$$\emptyset(x) = \frac{dF(x)}{dx} = \frac{x}{\sqrt{1-x^2}} \qquad (24)$$

In this paper the generalized system is called as tangent system and the scalar addition and multiplication (equation (1) and (2)) is called as tangent operations.

In image processing applications the pixel values from the interval $[0, 2^N)$ is mapped into (1,-1).then the image is processed using tangent operations and then the image is mapped to $[0, 2^N)$ as reversible operation. The total signal set is confined to (-1,1) and hence using this the out-of –range problem can overcome using log-ratio. We can define the negative image and the subtraction operation, and study the order relations for the tangent operations.

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 to the output. An IMF operation can be represented as: $y_{k+1} = f(y_k)$ where $k = 0,1,2,3$ ....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 the root signal as follows.

n = min k, subject to $H(y_k, y_{k+1}) < \delta$

Where $H(y_k, y_{k+1})$ is the suitable measure between the two images and δ is a user defined threshold.

It can be easily seen that the definition of the root signal depends upon the threshold.

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 c

$$c = 2d - 1 \qquad (30)$$

Such that the dynamic range of c is (-1, 1). A simple idea is to set the gain as a function of the signal c and to gradually decrease the gain from its maximum value γ_{MAX} when |c < T to its minimum γ_{MIN} value when |c|→1. More specifically, we propose the following adaptive gain control function

$$\gamma(c) = \alpha + \beta \exp(-|c|^{\eta}) \qquad (31)$$

Where η is a parameter that controls the rate of decreasing. The two parameters α and β are obtained by solving the equations:

γ (0) = γ_{MAX} and γ (1) = γ_{MIN} . For a fixed ή, we can easily determine the two parameters as follows:

$$\beta = (\gamma_{MAX} - \gamma_{MIN})/(1 - e^{-1}) \qquad (32)$$

And

$$\alpha = \gamma_{MAX} - \beta \qquad (33)$$

Although both γ_{MAX} and γ_{MIN} could be chosen based upon each individual image processing task, in general it is reasonable to set $\gamma_{MIN} = 1$. This setting follows the intuition that when the amplitude of the detailed signal is large enough, it does not need further amplification. For example, we can see that

$$\lim_{|d|_o \to 1} \gamma \otimes d = \lim_{|d|_o \to 1} \frac{1}{(1+\gamma(1-d)/d)} = 1 \qquad (34)$$

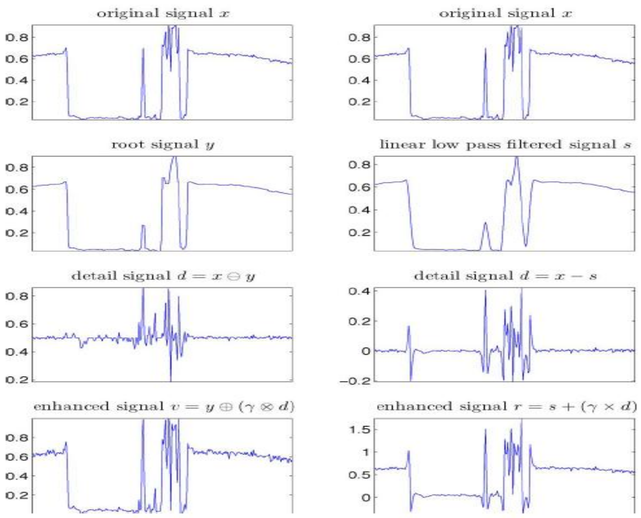
As such, the scalar multiplication has little effect. We now study the effect of γ and γ_{MAX} by setting $\gamma_{MIN} = 1$.

C. Contrast Enhancement of the Root Signal

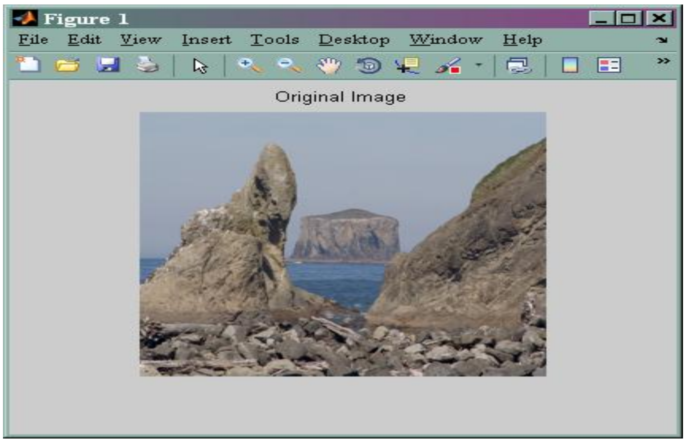
For contrast enhancement, we use adaptive histogram equalization implemented by a Matlab function in the Image Processing Toolbox. The function, called "adapthisteq," has a parameter controlling the contrast. This parameter is determined by the user through experiments to obtain the most visually pleasing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

V. RESULTS AND COMPARISON

We first show the effects of the two contributing parts: contrast enhancement and detail enhancement. 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. Next, we study the impact of the shape of the filter mask of the median filter. For comparison we also show the result of replacing the median filter with a linear filter having a 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 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. We have also performed experiments by replacing the log ratio operations with the tangent operations and keeping the same parameter settings. We observed that there is no visually significant difference between the results.



The above shown graphs are the main differnces between the classical and generalized unsharp masking algorithm. Here we show the clear difference between the addition and generalized addition. And at last we show that the enhancement is more in generalized unsharp masking algorithm rather than in classical unsharp masking algorithm.



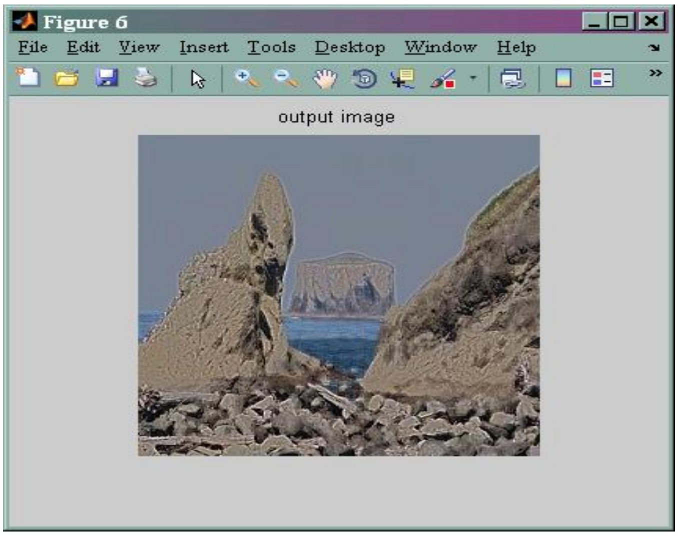


Figure 6
File Edit View Insert Tools Desktop Window Help
output image


Figure 1
File Edit View Insert Tools Desktop Window Help
Original Image

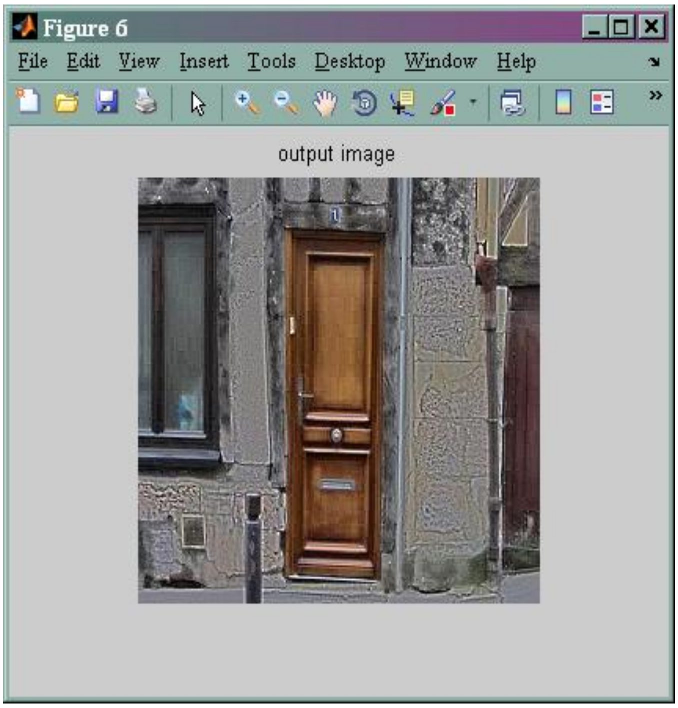


Figure 6
File Edit View Insert Tools Desktop Window Help
output image

The above are the two results which processed using generalized unsharp masking algorithm. These two output images show that the sharpness and contrast get enhanced in an exponential manner. No rescaling process is used here. And the out of range problem is not encountered here since the range of gray scale is (0, 1).

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