Image Contrast Sharpening Using Adaptive Graylevel Transformation Functions

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ABSTRACT

This paper introduces the adaptive local graylevel transformation (ALGT) method as a new approach for contrast sharpening in grayscale images. This new approach is applicable for images with relatively high global contrast or those that have been processed by some global enhancement methods in order to increase the contrast sharpness. The new method is based on using local graylevel transformation functions that perform optimal graylevel stretching in terms of increasing the image contrast with reduced amplification of noise levels. The specification of the transformation functions is adaptive in the sense that it transforms the graylevel values in the image based on the content of their neighborhood. Our quantitative and qualitative experimental evaluations of the new method on a set of benchmark images, especially those with relatively smooth regions, prove this advantage.

Key Words: image enhancement, contrast, transformation function, image sharpening.

1. Introduction

The visual appearance of an image may be significantly improved by emphasizing its high frequency contents to enhance the fine details in the image. This is an essential task in many image processing and computer vision applications. One popular approach is the classical linear unsharp masking (UM) in which sharpening is achieved by adding the original image to a scaled highpass filtered version of itself. The highpass version of the original image is either computed in the spatial domain using derivative masks or in the frequency domain using highpass filters [1,2]. Although, the UM method is simple and works well in many applications, it suffers from two main drawbacks. i) It is extremely sensitive to noise, which in turn results in perceivable and undesirable distortions, particularly in uniform areas of even slightly noisy images. ii) It enhances high-contrast areas much more than areas that do not exhibit high image dynamics. Consequently, some unpleasant overshoot artifacts may appear in the output image. Although many approaches have been proposed to reduce the noise sensitivity of the linear unsharp masking technique [3,4], they still introduce some artifacts in smooth areas due to the amplification of the input disturbances. Furthermore, medium-contrast details are not enhanced as well as large-contrast details in these methods.

One interesting and relatively new approach for image sharpening is proposed by Matz and Figueriedo [5]. This method attempts to sharpen the contrast of an image that has sufficiently global contrast, i.e. it could be useful in increasing the contrast of images that have been processed by some global method, such as histogram equalization (HE) [1,2] or constrained variational histogram equalization (CVHE) [6]. Matz method approaches the problem of contrast sharpening by combining concepts from the direct and indirect contrast enhancement methods. This method is similar to the direct enhancement methods in the sense that it attempts to increase the value of local contrast defined by Beghdadi *et al.* [7]. However, the method does not operate on the contrast values directly. Instead, it uses the mean edge gray value, which is used in defining Beghdadi contrast, to partition one of the ten Munsell's Scale [8] intensity intervals based on the original graylevel value. Similar to the indirect enhancement methods their approach proceeds by utilizing a transformation function to map the original graylevel value.

Performance evaluation of this method shows its ability in contrast sharpening. However, it also results in noise amplification. This is because the transformation function depends only on the minimum and maximum intensity values of the pixel neighborhood and does not consider the local content around each pixel in the image, in addition to the fact that some of the intervals on the Munsell's scale are relatively wide which result in excessive stretching and accumulation of the graylevels near the intervals endpoints.

This paper presents the Adaptive Local Graylevel Transformation (ALGT) method for automatic image contrast sharpening. Similar to Matz method, the ALGT method borrows ideas from the direct and indirect approaches to achieve better sharpening results as a post-enhancement step. As in the indirect methods, the ALGT method uses a transformation function to modify the values. The similarity to direct methods in the ALGT method is based on the fact that it increases the local contrast based on the understanding of Gordon contrast [9]. The ALGT transformation function is derived by solving a variational optimization problem that provides the maximal graylevel stretching with minimal background noise amplification and image distortion. Additionally, the parameters of the ALGT transformation function are adaptive to the content of the pixel's neighborhood to reduce noise amplification and distorted edges. The performance comparison between the ALGT and Matz methods after processing the results of the CVHE method shows the ability of the ALGT method to produce images with better sharpness and less noise.

The rest of this paper is organized as follows. In Section 2, the mathematical formulation and the derivation of the ALGT method transformation function is discussed. Section 3 discusses the experimental evaluation and Section 4 concludes our work.

2. ALGT Method

2.1 The Step Function for Contrast Enhancement

Let's start the discussion about the Automatic Local Graylevel Transformation (ALGT) method by considering the local contrast measure defined by Gordon *et al.* [9] in which the local contrast at any pixel in the image is defined as

$$GC = \frac{|r - \mu|}{r + \mu} \tag{1}$$

where **r** is the pixel's graylevel value and **μ** is the mean or the median graylevel of a small neighborhood around the pixel. Essentially, the numerator of the expression given in (1) reflects the deviation of the pixel's graylevel value from the mean value of the neighborhood **μ**. This deviation is normalized by the denominator **(r + μ)**, thus contrast values are between 0 and 1, with higher values indicating higher contrast.

Examining the Gordon definition for contrast implies that increasing the image contrast quantitatively requires pushing the pixel's graylevel values away from the neighborhood mean **μ**. If **a** and **b** represent the minimum and maximum graylevel values in the neighborhood around pixel (x,y), respectively, then one way to increase the contrast could be by using the step function

$$s = T_S(r) = \begin{cases} a \ , \ a \le r < \mu \\ b \ , \ \mu \le r \le b \end{cases} \qquad (2)$$

where **s** represents the new graylevel value.

Effectively, this function maps the pixel value to the minimum value in the neighborhood if it is less than the mean graylevel value. Similarly, the pixel value is set to the maximum value if it is greater than or equal to the mean graylevel value. It can be easily seen that the distance between the enhanced graylevel **s** is always greater than the distance between the original graylevel **r** and graylevel mean **μ**. This implies higher numerical contrast values in the processed image. However, using the step function $\mathbf{T_S(r)}$ to increase the image contrast is associated with a major problem. When the minimum and the maximum of the neighborhood are the only values used as the new graylevel values, this results in reduction in the number of graylevels that are available in the image. Consequently, this amplifies the noise and may distort the edges in the image [5].

2.2 Derivation of the ALGT Method

In order to take advantage of the simplicity of the step function in contrast enhancement and reduce the noise amplification and edge distortion, it is required to find a new smoother piecewise function that spans the entire interval **(a,b)**. If $\mathbf{T_D(r)}$ denotes such smooth function, then it should be simultaneously the closest to the step function $\mathbf{T_S(r)}$ given in (2) and the identity transformation

$$T_I(r) = r \qquad (3)$$

in order to provide graylevel stretching and at the same time reduces the change in the original image. Accordingly, the search is for a smooth function that has the optimal distance to both functions, $\mathbf{T_D(r)}$ and $\mathbf{T_I(r)}$, over the subintervals [a,μ] and [μ,b], separately. Mathematically, this can be formulated into a functional minimization problem with the objective function $\mathbf{J(T_D(r))}$ being defied as

$$J(T_D(r)) = \int_{l_1}^{l_2} \lambda_1 (T_D(r) - T_I(r))^2 + \lambda_2 (T_D'(r))^2 + (1-\lambda_1)(T_D(r) - T_S(r))^2 dr \qquad (4)$$

where $\mathbf{l_1}$ and $\mathbf{l_2}$ correspond to **a** and **μ**, respectively, in the case when the graylevel **r** is less than the mean value **μ**, and when the graylevel **r** is greater than or equal to the mean graylevel, $\mathbf{l_1}$ and $\mathbf{l_2}$ are set to **μ** and **b**, respectively. The constant $\boldsymbol{\lambda_1}$ is a weighting factor that shows the preference of preserving original pixel value over pushing it to one of the neighborhood extremes. The value of $\boldsymbol{\lambda_1}$ falls in the range [0,1]. The term $\lambda_2 (T_D'(r))^2$ with $T_D'(r)$ being the first derivative of the desired function and $\boldsymbol{\lambda_2}$ being a constant that is added to the functional in (4) to allow for smoother transition between the step and the identity functions. The specification for the parameters $\boldsymbol{\lambda_1}$ and $\boldsymbol{\lambda_2}$ is discussed in the following subsection.

In order to find the desired function, the objective function defined above has to be minimized such that the boundary conditions

$$T_D(l_i) = l_i \ , \ \forall \ l_i \in \{l_1, l_2\} \qquad (5)$$

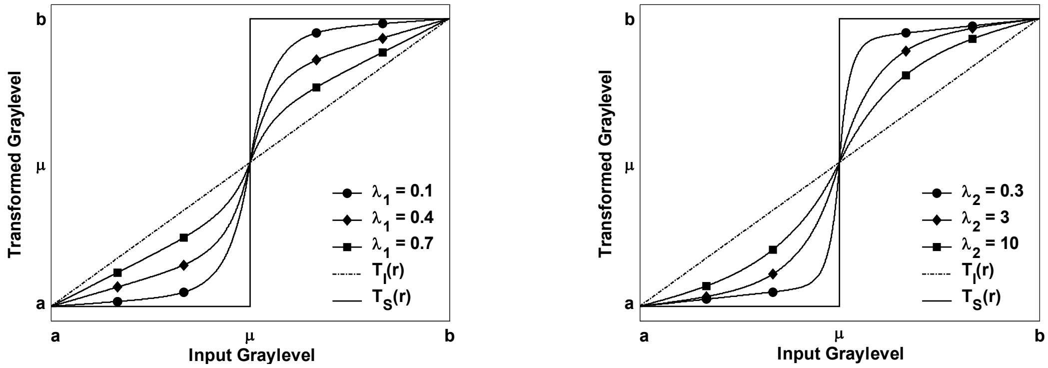
are satisfied for each subinterval. In calculus of variations, functional minimization can be carried out by utilizing the Euler-Lagrange equation

$$\frac{\partial J}{\partial T_D} - \frac{d}{dr}\left(\frac{\partial J}{\partial T_D'}\right) = 0 \qquad (6)$$

Substituting gives

$$T_D''(r) - \frac{1}{\lambda_2} T_D(r) = \frac{1}{\lambda_2}\left((1-\lambda_1)\, l_x - \lambda_1 r\right) \qquad (7)$$

with $\mathbf{l_x(r)}$ is substituted by **a** or **b** depending on what subinterval the solution is carried out. This is a second order linear nonhomogenous differential equation. Using the undetermined coefficient method to



(a) (b)

Figure 1: The effect of changing the parameters $\boldsymbol{\lambda_1}$ and $\boldsymbol{\lambda_2}$ on the ALGT transformation function.

solve the equation in (7) gives the desired transformation function as

$$T_D(r) = B_1 \exp\left(\frac{r}{\sqrt{\lambda_2}}\right) + B_2 \exp\left(-\frac{r}{\sqrt{\lambda_2}}\right) + (1-\lambda_1) l_x + \lambda_1 r \qquad (8)$$

The constraints given in (5) can be used to find the values of the constants $\mathbf{B_1}$ and $\mathbf{B_2}$ as

$$B_1 = \frac{(l_x - \mu)(1 - \lambda_1)\exp(2\lambda_2^{-0.5}(\mu - 2l_x))}{1 - \exp(2\lambda_2^{-0.5}(\mu - l_x))} \qquad (9)$$

and

$$B_2 = \frac{(\mu - l_x)(1 - \lambda_1)\exp(\lambda_2^{-0.5}\mu)}{1 - \exp(2\lambda_2^{-0.5}(\mu - l_x))} \qquad (10)$$

It can be easily verified that the function given in (8) with constants defined above satisfies the two essential requirements for graylevel transformation functions [1,2] in terms of being positive and monotonic. For example, in the subinterval **[a,μ]** the first derivative of transformation function is given by

$$T'_D(r) = \frac{B_1}{\sqrt{\lambda_2}} \exp\left(\frac{r}{\sqrt{\lambda_2}}\right) - \frac{B_1}{\sqrt{\lambda_2}} \exp\left(-\frac{r}{\sqrt{\lambda_2}}\right) + \lambda_1 \qquad (11)$$

Since **0** < **a** < **μ**, then from (9) and (10), the constant **B1** is always positive while the constant **B2** is always negative. Since $\boldsymbol{\lambda_1}$ is in a positive number in the range [0,1] by definition, this implies that the first derivative of the transformation function is always positive; thus the transformation function is monotonically increasing over **[a,μ]** for all values **r**. Additionally, we know from the derivation that that **T(a) = a** and **T(μ) = μ**, where both a and μ are positive, thus it implies that $\mathbf{T_D(r)}$ is positive for all values of **r** in **[a, μ]** since it is monotonic. The same discussion applies for the transformation function defined over the subinterval **[μ,b]**.

2.3 Parameters Specification

An important issue in the ALGT transformation function is the specification of the parameters $\boldsymbol{\lambda_1}$ and $\boldsymbol{\lambda_2}$. One way to do so is to have the user input these two values based on prior knowledge of the image in hand. However, this specifies the same transformation function for each pixel in the image, regardless of its neighborhood, which in turn may amplify the noise and distort the edges in the image. Alternatively, the ALGT method defines these two parameters automatically such that the transformation function is adaptive to the content of the pixel's neighborhood. This adaptive nature of the transformation function allows for the reduction of noise amplification in the output image.

Let's first study the effect of changing the parameters $\boldsymbol{\lambda_1}$ and $\boldsymbol{\lambda_2}$, respectively, on the shape of the ALGT transformation function. In the following discussion and for illustrative purposes only, the values for **a** and **b** are set to 0 and 20, respectively, and the mean value is assumed to be at the middle of the interval **[a,b]**, thus the two parts of the transformation function are antisymmetric about the point (u,u). Figure 1.a shows the behavior of the transformation function when λ_2 is set to 1 and λ_1 takes the values 0.1, 0.4, and 0.7. It can be noticed that the transformation function approaches the identity transformation $\mathbf{T_I(r)}$ when λ_1 is increased. Conversely, when λ_1 is decreased, the transformation function is closer to the step function $\mathbf{T_s(r)}$. As seen in Figure 1.b, the same relation exists between the shape of the transformation and λ_2 when λ_1 is fixed to 0.15 and λ_2 takes the values 0.3, 3, and 10.

Now, to make the transformation function adaptive to the neighborhood content, we utilize the local standard deviation of the pixel's neighborhood in specifying λ_1 and λ_2. This is based on the fact that the standard deviation can be used as a measure of local contrast since it reflects the variations in the local graylevel values. Additionally, it is known that the details in the image correspond to low and medium values of standard deviation while high values may indicate noisy regions [10]. Thus in order to increase the image contrast with less noise amplification, the level of graylevel modification should be lower for regions with high standard deviation. Based on this and the understanding of the behavior of λ_1 and λ_2, the two parameters are defined as

$$\lambda_1 = \frac{\sigma}{\sigma_{max}} \tag{12}$$

and

$$\lambda_2 = \sigma \tag{13}$$

where $\boldsymbol{\sigma}$ is the standard deviation of pixel's neighborhood and $\boldsymbol{\sigma_{max}}$ is the maximum standard deviation of all neighborhoods in the original image. The two definitions of the parameters imply that they are directly proportional to local standard deviation. Consequently, the higher the local standard deviation, the closer is the transformation function to the identity transformation.

Accordingly, the graylevel values for the pixels in noisy neighborhoods are less stretched from their original values. This in turn produces less noise amplification especially in smooth regions and around the edges. When $\boldsymbol{\sigma}$ is zero, this implies that the neighborhood contains only one level; thus there is no need to apply the transformation function for the pixel at the center of the neighborhood. Instead, the pixel value is kept unchanged.

3. Performance Evaluation

As discussed previously, the purpose of the ALGT and Matz methods is to sharpen the contrast of the image. Thus, it is assumed that either the image has a relatively good global contrast or it has been processed by some global enhancement method. For this reason, the performance evaluation of the ALGT and Matz methods assumes that the original images have been processed by the Constrained Variational Histogram Equalization (CVHE) method. The performance of the ALGT method is compared to the CVHE and Matz methods. The three methods are used to process 512x512 images on a PC with Pentium® 3GHz processor and 1 GB of RAM. The neighborhood size in the ALGT and Matz methods is set experimentally to 5x5. Choosing the size of the neighborhood is very important in the ALGT method since it determine the endpoint values for the interval [a,b]. Small neighborhoods may not capture the local variations, while large ones may introduce unnatural modification in the output image; though they may provide higher contrast values. For quantitative comparison, we use the Absolute Mean Brightness Error (AMBE)

$$\text{AMBE} = \left|\mu_o - \mu_p\right| \tag{14}$$

where $\boldsymbol{\mu_o}$ and $\boldsymbol{\mu_p}$ are the mean brightness of the original and processed images, respectively, to measure the change in the image brightness. The AMBE measure is usually used to measure the distortion in the processed image when compare to the original [11]. To measure contrast enhancement, we used the discrete entropy (H) which is defined by

Table I: Quantitative measures values for the test images *after* processing by the ALGT, CVHE, and Matz methods.

	Lena		*Bottle*		*Crowd*	
Algorithm	**ΔH %**	**AMBE**	**ΔH %**	**AMBE**	**ΔH %**	**AMBE**
ALGT	7.23	0.17	1.06	7.00	11.02	0.90
CVHE	1.29	0.016	-5.29	6.95	-3.77	0.50
Matz	5.40	0.94	0.22	8.46	5.20	2.13

(a) Original
(b) CVHE result
(c) ALGT result
(d) Matz result
(e) Close-up from CVHE result
(f) Close-up from ALGT result
(g) Close-up from Matz result

Figure 2: Results of the CVHE, ALGT, and Matz algorithms for image *Lena*.

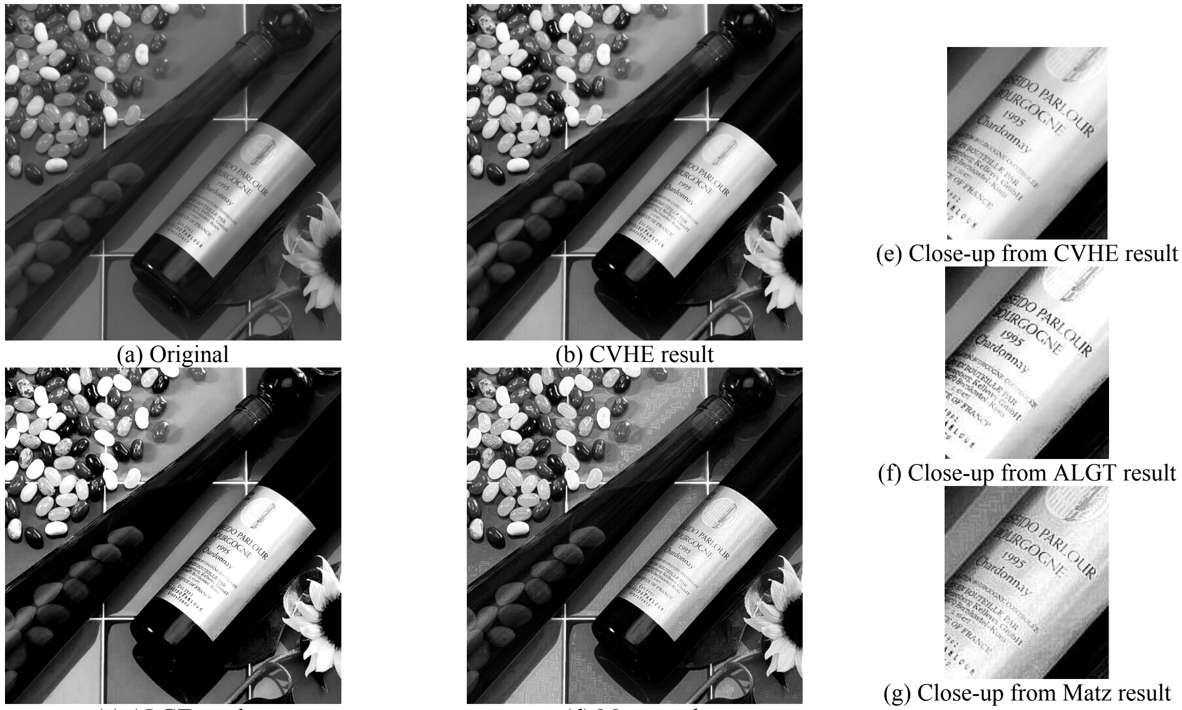
$$H = \sum_{k=0}^{255} h(r_k) \log h(r_k) \quad , \forall\ h(r_k) \neq 0 \qquad (15)$$

where $h(r_k)$ is the normalized image histogram at the k^{th} graylevel [12].

We present here three examples using the images *Lena*, *Bottle, and Crowd* images. The originals and the processing results for these images are shown in figures 2 through 4. Comparing the results of the ALGT and Matz methods reveals their capability of providing sharper images than the CVHE image. However, when Matz method is compared to the ALGT method, it is obvious that the sharpness of the ALGT images is better. Additionally, the ALGT method produces less noise amplification. This can be noticed by comparing the visual quality of images locally. The images in parts (e), (f), and (g) of each figure show a region that has been extracted from the CVHE, ALGT, and Matz images, respectively. It is apparent that the ALGT method has better contrast and edge quality than the CVHE and Matz methods and with less noise amplification in the smooth regions.

Quantitatively, the AMBE and the change in the entropy values for the two images are listed in Table I. In terms of contrast, Matz and ALGT methods have increased the entropy (H) which verifies the increase in the visual appearance of image details in both cases. However, the increase in entropy values in the ALGT method was larger. This was not the case for the CVHE method. This is because the CVHE method is applied globally, thus it results in mergence between the histogram bins, which in turn reduces the entropy.

For the distortion measure, the AMBE values for the ALGT method always fall between the values of CVHE and



(a) Original (b) CVHE result (c) ALGT result (d) Matz result (e) Close-up from CVHE result (f) Close-up from ALGT result (g) Close-up from Matz result

Figure 3: Results of the CVHE, ALGT, and Matz methods for image *Bottle*.

and Matz methods. This is acceptable since there is significant improvement in the perceived contrast. Matz method has the highest distortion values due to noise amplification and the absence of any mechanism to control the change in the image outlook. In the ALGT method, the parameter $\boldsymbol{\lambda_1}$ help reducing the change in the image.

On overall, combining the increase in the perceived contrast and the quantitative measures values for the ALGT method proves its ability of sharpening the image contrast with less noise amplification.

The average processing time for using the CVHE, Matz, and ALGT methods is 0.94, 9.33, and 16.29 seconds, respectively. The CVHE method has the lowest value since it is applied globally. Conversely, the other two methods are associated with an increase in the computation time since they are applied locally. The additional computation time required in the ALGT method is related to the computation of the minimum, maximum, and standard deviation for the neighborhood around each pixel in the image.

4. Conclusion

This paper discussed the development, implementation, and evaluation of the Adaptive Local Graylevel Transformation (ALGT) method. The rationale behind ALGT method is to sharpen the contrast of images that have relatively high global contrast or those images that have been processed by some global enhancement method. The ALGT method achieves this by stretching the local graylevel values using a transformation function that automatically adapts to the contents around each pixel in the image. This approach proves the ability of the ALGT method of sharpening the image contrast with less noise amplification and edge distortion. Generally, the ALGT method can be applied as a post enhancement step for images processed by some global methods in order to obtain sharper contrast.

(a) Original (b) CVHE Result (e) Close-up from CVHE result

(c) ALGT Result (d) Matz Result (f) Close-up from ALGT result (g) Close-up from Matz Result

Figure 4: Results of the CVHE, ALGT, and Matz methods for image *Crowd*.

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