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Research Article

A New Image Enhancement Algorithm for Removing Artifacts

Vidhya R[Ȧ*] and Sifna N Shajahan[Ȧ]

[Ȧ]ECE department, University of Calicut, MES College of Engineering Kuttippuram Malappuram (dist) Kerala India

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Abstract

This paper proposed an efficient algorithm for image enhancement. The contrast of image is very important characteristics by which the quality of image can be judged as good or poor quality. HE-based algorithms concentrated on the contrast of an image. Most of the existing image enhancement techniques focus on improving the global contrast of an image and have paid little attention to the local information such as the local contrast and edges. This issue is considered to be the inherent limitation of HE methods. Another limitation occurs when a few adjacent luminance levels occupy dominant areas in an image; this leads to quantum jump in CDF so which produce unnatural resultant images. These two limitations are considered to be the major limitations of HE based enhancement technique. Although various methods have been proposed to overcome these limitations, they are still unsatisfactory from the viewpoint of robustness. Here proposing a new method to overcome these problems. In this method apply a wavelet image decomposition to separate an image into several frequency components in the spatial domain, to effectively reduce the quantum jump the proposed contrast enhancement algorithm has two key strategies of boosting noticeable minor areas and slantwise clipping bins in the histogram. And for preserving the local information here uses Laplacian pyramid decomposition. These strategies result in a well-balanced mapping function. The proposed method features robust enhancement without over-enhancement or severe failure.

Keywords: *Contrast Enhancement, Histogram Equalization, Laplacian Pyramid, Sigmoid Function, Wavelet Decomposition*

1. Introduction

Image enhancement is the process of Improving the interpretability or perception of information in images for human viewers and providing 'better' input for other automated image processing techniques. The objective of image enhancement is to modify attributes of an image to make it more suitable for a given task and a specific observer. According to the survey of available techniques, the commonly used techniques of image enhancement can be divided into two broad categories: spatial domain methods and frequency domain methods. The spatial domain methods operate on image pixels directly. The frequency domain methods directly operate on the frequency domain. In image processing technology, image enhancement means improving image quality through a broad range of techniques such as contrast enhancement, color enhancement, dynamic range expansion, edge emphasis, and so on. HVS is more sensitive to luminance than to other components such as color information so the critical technique affecting the human visual system (HVS) is improving the luminance of an image. Contrast is created by the difference in luminance reflectance from two adjacent surfaces. In our visual perception, contrast is determined by the difference in the color and brightness of an object with other objects. If the contrast of an image is highly concentrated on a specific range, the information may be lost in those areas which are excessively and uniformly concentrated. The problem is to enhance the contrast of an image in order to represent all the information in the input image. Contrast enhancement is an important area, is widely used for medical image processing and as a pre-processing step in speech recognition, texture synthesis and other image/video processing applications etc.

A very popular technique for contrast enhancement of image is histogram equalization technique (R.C. Gonzalez et *al*, 2008). A histogram equalization is a technique that generates gray map which change the histogram of image and redistributing all pixel values to be as close as possible to user specified desired histogram. This technique is useful for processing images that have little contrast with equal number of pixels to each the output gray levels. The HE technique is a global operation hence; it does not preserve the image brightness. HE usually introduces two types of artifacts into the equalized image namely over-enhancement of the image regions with more frequentgray levels, and the loss of contrast for the image regions with less frequent gray levels.

To overcome these drawbacks several HE-based techniques were proposed during past years, various researchers have also focused on improvement of

*Corresponding author: **Vidhya R**

histogram equalization based contrast enhancement techniques such as mean preserving bi-histogram equalization (BBHE) (C.K. Yeong-Taeg 1997), dualistic sub image histogram equalization (DSIHE) and minimum mean brightness error bi-histogram equalization (MMBEBHE). The BBHE separates the input image histogram into two parts based on input mean. After separation, each part is equalized independently. This method tries to overcome the brightness preservation problem. The DSIHE method uses entropy value for histogram separation. The MMBEBHE is the extension of BBHE method that provides maximal brightness preservation. Though these methods can perform good contrast enhancement, but they also cause more annoying side effects depending on the variation of gray level distribution in the histogram. Therefore, recursive mean separate histogram equalization (RMSHE) is proposed which provides better contrast results over. This algorithm is the improvement in BBHE. However, it has also some side effects (S. D. Chen et *al*, 2003).

Partially overlapped sub-block histogram equalization (POSHE), improves the computational complexity and speed of the block-overlapped HE. Though it significantly reduces the blocking effect, partially unnatural regions still exist. HE with bin underflow and bin overflow clips bins whose values are larger than an upper threshold or smaller than a lower threshold to suppress a sudden change in CDF (J. Y. Kim et al, 2001). Automatic and parameter-free piecewise linear transformation (APFPLT) (C. M. Tsai et al, 2008) smoothes the histogram where peaks and valleys are used as CDF inputs and outputs to provide the parameter-free scheme. The clipping technique of CLAHE was modified by the gain controllable clipped histogram equalization (GCCHE) (C.T. Kim et al, 2008). After a clipping step in the histogram, a portion of the residual is redistributed uniformly to all the bins and the rest is added locally to low and high intensity bins. However, its local process contributes less to the overall performance.

Hassan and Norio is proposed new approach for contrast enhancement using sigmoid function (Hassan N et al, 2008). The objective of this new contrast enhancer is to scale the input image by using sigmoid function. Another contrast enhancement approach is to decompose an image into spatial frequency bands. This decomposition enables manipulation of the individual bands. As one of the decomposition schemes, a Laplacian pyramid was primarily proposed for lossless image compression and has been applied to the multi-scale-based algorithms. Another method for image enhancement is the use of a fusion framework using histogram equalization and modified Laplacian pyramid. This method consists of a contrast enhancement and a full scale image pyramid decomposition scheme. This can be used to reduce the quantum jump as well as to preserve the local information (S. H Yun et al, 2010)

1.1 Proposed Method

In this proposed method apply a wavelet decomposition to the luminance extracted input image to separate an image into several frequency components in the spatial domain to achieve spar city and energy compaction. In order to effectively reduce the quantum jump the proposed contrast enhancement algorithm has two key strategies of boosting noticeable minor areas and slantwise clipping bins in the histogram (S. H Yun et al, 2010). And for preserving the local information here uses Laplacian pyramid decomposition to the LL1 component the wavelet decomposed image. These strategies result in a well-balanced mapping function

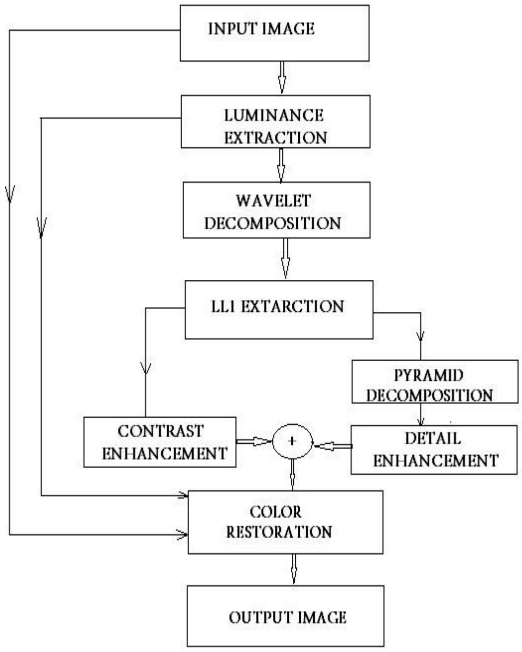


Fig.1 The block diagram of the proposed method

This method mainly includes four stages wavelet decomposition, contrast enhancement, detail enhancement and color restoration. For contrast enhancement a novel robust HE is proposed which is used to reduce the quantum jump. HE-based methods have inherent limitations on improving the local information of an image. To solve this problem, employ detail enhancement through the proposed framework which initially separates an image into band-pass images. With this framework, we can deal with the original details of high-pass images. For the decomposition, here use a Laplacian pyramid scheme. But do not down sample the pyramid images when the levels of the pyramid go up. This full-scale image pyramid scheme can prevent the halo effect generated during the reconstruction process.

The proposed frameworks transforms the RGB input image to luminance component I0 and then apply wavelet decomposition to I0, then extract its image approximation coefficients (LL1). Then take the LL1 as the new I0. The RGB input image and the original (before wavelet decomposition) I0 are reused in the final step of the color restoration. Figure1 shows the detailed block diagram of the proposed framework that transforms the RGB input image to I0 of the luminance and then decomposes I0 using wavelet method to get new I0. Then apply contrast enhancement and detail enhancement. Finally the color restoration to get the RGB output image.

2.1 Wavelet decomposition

Before applying the wavelet decomposition described in this method, the following steps are to be done.
1) Read the input image: Here different RGB color images are taken as the input images and applying the algorithm described in the following
2) Luminance extraction: The proposed framework transforms the RGB input image to I0 the luminance component. Here RGB to Luminance conversion is performed.
Wavelet decomposition: The proposed method decomposes the luminance component I0 in to its four sublevels using wavelet transform. And extract its approximation coefficients (LL1), and then take the LL1 Component as the new I0.

Wavelet analysis is a time frequency localization analysis method with changeable shape, time window and frequency, and unchangeable window size. It has good localization feature in time domain and frequency domain. After being separated by wavelet, the image will be divided into four sub-bands: LLI, LH1, HL1 and HH1. LL1 reflects the low-frequency information in horizontal and vertical directions. HH reflects the high-frequency information in horizontal and vertical directions. According to the above analysis, we can use histogram smoothing method only in low-frequency sections, which can strengthen the image as well as avoiding the vagueness of details and the increase of noises (S. Hua Zhang 2011). The first grade decomposition of image H with wavelet base system is shown in Fig.2

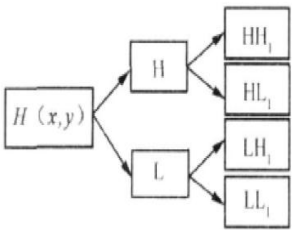


Fig.2 First Grade wavelet decomposition of an image

2.2 Contrast enhancement

This section mainly describe about the way to reduce the quantum jump, the proposed contrast enhancement algorithm has two key strategies for this, boosting noticeable minor areas and slantwise clipping bins in the histogram. These strategies result in a well-balanced mapping function.

1) Histogram generation*:* The histogram with luminance levels in the range K [0, L-1] is a discrete function described as

$$h(I_k) = n_k \tag{1}$$

Where l_k is the k^{th} luminance level in K and n_k represents the number of pixels having luminance level I_k.
2) Smoothing of histogram*:* Smoothing is mainly applied to globally distinguish between the peaks and valleys. Here smoothing is carried out by convolve the histogram with a Gaussian kernel

$$h_S(I_k) = h(I_k) * g(I_k) \tag{2}$$

Where g (I_k) is the Gaussian kernel

3) Boosting of minor areas: Boosting minor areas, i.e. small ridges, in the histogram is one of the key strategies of the proposed contrast enhancement to suppress the quantum jump. First, the peak value in the smoothed histogram $h_S(I_k)$ is found as

$$p(k) = \max_{k \in K} \{h_S(I_k)\} \tag{3}$$

Second, the ridges between valleys are searched and boosted. A ridge boundary is defined as the bins between the first point (L_{min1}) of the positive slope and the last point (L_{min2}) of the negative slope in a ridge. In the ridge boundary, after the local maximum value L_{max} and the local minimum value L_{min} (the higher value of two values, L_{min1} and L_{min2}) are found, the small ridge of a minor area is boosted up like the dashed line. This process is carried out in every single ridge boundary as

$$h_m(I_k) = \left\{\left(\frac{h_S(I_k) - L\min}{L\max - L\min}\right)(p(k) - L\min)\alpha + L\min, \right. \tag{4}$$

Where α is a scaling factor

$$\alpha = \log(l\max - l\min)/\log(p(k) - l\min) \tag{5}$$

4) Global and local clipping of bins: In this method clipping is done by adding a luminance adaptive clipping. This method clips bins slantwise in $h_m(I_k)$, depending on the mean luminance of the input image, and performs the local clipping along with the global clipping. The global and local clipping is described in figure 3.The global clipping is done to the bins whose values are more than half of p(K), and the local clipping is done slantwise to the bins whose values are under half of p(K). Here define I_{max} as the maximum luminance value, I_{mid} as half of I_{max}, and I_{mean} as the mean luminance value in the histogram h (lk). The local clipping can be done as two cases which depend on both I_{mean} and I_{mid}. In Case 1, the bins with lower luminance values are more clipped. In Case 2, the bins with higher luminance values are more clipped. This characteristic is controlled by the variable point (0, y1) or (I_{max}, y2) at the slant line of the histogram according to each case. The graphs next to each histogram depict the positions of y1 and y2, depending on I_{mean}. The variable values y1 and y2 are as follows:

Technically, this local clipping buffers the excessive global clipping and has the effect of the contrast improvement while the global clipping more affects the quantum jump suppression.

$$y_1 = -0.5p(k).[I_{mean}/I_{mid}] + p(k) \tag{6}$$
$$y2 = 0.5p(k).[I_{mean}/I_{mid}]$$

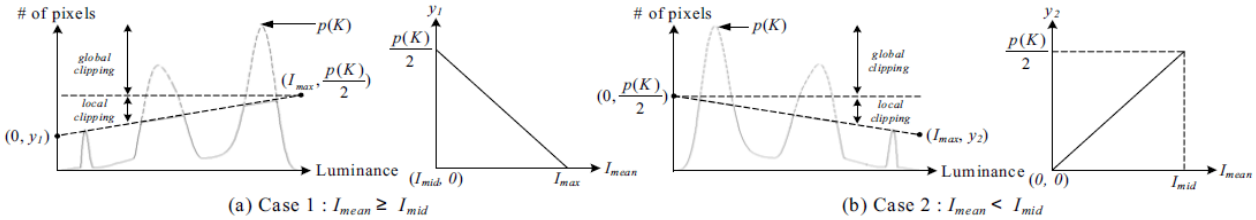


Fig.3 local and global clipping

5) Redistribute the residual: The proposed algorithm gathers the residual from the global and local clipping and redistributes them uniformly to the whole bins as follows

$$h_r(I_k) = h_c(I_k) + [R/(I_{\max} + 1)] \tag{7}$$

Where $h_c(I_k)$ is the result after $h_m(I_k)$ is clipped and R is the residual

6) Generate the luminance mapping function: The last step of the contrast enhancement is, the computation of the normalized luminance mapping function as

$$m(I_k) = \left[\sum_{x=0}^{k} h_r(Ix) \Big/ \sum_{t=0}^{p} h_r(It)\right].255 \tag{8}$$

The contrast enhanced image is obtained as

$$I_N^{'}(i,j) = m(I_N(i,j)) \tag{9}$$

2.3 Detail enhancement

This section gives a solution to reduce the inherent limitations of HE-based methods, here employ a detail enhancement by which improving the local information of an image is carried out. Through which, initially separates an image into its sublevels using wavelet decomposition. And then into band pass images. With this framework, we can deal with the original details of high-pass images. Two functions are used here, an adaptive gain function and a noise reduction function. For adaptive gains, we set the gain function whose concept is based on (Shyam Lal et al, 2012). We also use a noise reduction function which attenuates estimated noises and prevents them from being amplified due to the adaptive gain function. Thus, the proposed detail enhancement has the effect of distinctively emphasizing reliable details. The detail gain function of an image layer is as follows:

$$f^d(i.j) = [f^1(i.j) f^2(i.j)] * g(i,j) \tag{10}$$

Where f 1 is the adaptive gain function and f 2 is the noise reduction function, g is a Gaussian filter with a 5 × 5 mask. The gains are low-pass filtered to smoothly emphasize the details. The adaptive gain function can be derived from luminance values of new I_n

$$f_n^1(i,j) = 1\Big/\left\{q[I_n(i,j) + 1.0]^p\right\} \tag{11}$$

Where p is the gain parameter and q depends on p, $q = 1/(2^p)$. The maximum gain at the luminance zero is $2^{p.}$

Each D_n image is a noise corrupted image described by

$$D_n = d_n + Ni_n \tag{12}$$

Where d is an ideal band-pass image without noises and $N_i$is the additive noise. Although some noise estimation algorithms assume N_i *is* the additive Gaussian noise to calculate the noise variance, we simply regard N_i *as* the residual noise remaining from the processed or unprocessed image. The goal is not eliminating the Gaussian noise or impulse noise but suppressing the noise amplification caused by the adaptive gain function. In the same way as, the edge detection value $E_n$is set when the accumulated histogram of $|D_n|$ reaches the threshold T. Based on En, noises and edges with reliable details are distinguished. Here, we could set T to 10. But we revise T as follows:

$$T = 0.1[(2^p + 1)/2] \tag{13}$$

Where $(2^p+1)/2$ is the average gain of the adaptive gains. This can help compensate E_n because higher gains amplify noises more strongly.

To define the noise reduction function f 2, we adopt a sigmoid function through properly scaling and using an offset as

$$f_n^2(i,j) = NR_{offset} + \left\{NR_{band}\Big/\left[1 + e^{-(D_n(i,j)-E_n}\right]\right\} \tag{14}$$

Where $NR_{offset}$is a noise gain offset, $NR_{band}$is a noise gain band, and $D_n$and $E_n$are properly scaled. The noise reduction function performs a filter which cuts off small signals of Dn. In all experiments, we set NR_{offset} and, NR_{band} to 0.2 and 1.0 respectively. By accumulating the multiplications of detail gain function and detail image the enhanced image is constructed as D' (i.j)

$$D'(i,j) = \sum_{n=1}^{N} f_n^d(i,j)..D_n(i,j). \tag{15}$$

2.4 Color restoration

The enhanced luminance image is obtained as

$$I' = I_N^{'} + D' \tag{16}$$

To reflect the enhanced luminance image on color channels, we use a color restoration.

$$C' = (C/I_0)^S.I' \ \{R,G,B\} \in \mathrm{C} \tag{17}$$

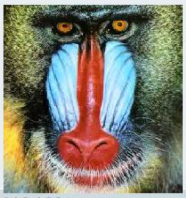
Where S is the saturation parameter and $I0$ is the original luminance image in Fig. 1. Although this equation is mostly used in high dynamic range compression techniques, it is also effective for other image processing methods that manipulate the luminance. We could achieve natural color images by automatically adjusting the parameter S pixel by pixel as

$$S(i, j) = S_{offset} + (1/3).\sum\left(I_0(i, j) - C(i, j)\right) \quad (18)$$

Where $S_{offset}$is computed as the mean luminance of the input image $I0$ divided by that of the output image I'.

Implementations & results

This enhancement method has been applied for various RGB color images. This produces a better result than the existing enhancement methods. The quality of the image measured here by an image quality matrix PSNR. The proposed method results in a better PSNR than the previously existing enhancement method, especially than (S. H Yun et al, 2010).The figure below shows the results of the proposedmethod and its comparison with the existing techniques.

	EXISTING METHOD	PROPOSED METHOD
INPUT IMAGE		
OUT PUT IMAGE		
MSE	111.5596	110.1886
PSNR	27.6897	27.7434

	EXISTING METHOD	PROPOSED METHOD
INPUT IMAGE		
OUT PUT IMAGE		
MSE	4.5682e+03	4.1088e+03
PSNR	7.5677	8.0577

Fig.4 Results for the proposed method

Conclusions

The proposed method shows better results than the existing method. The proposed enhancement method has been applied for various RGB color images. This produces a better result than the existing enhancement methods. It enhances the contrast, color as well as the colors of the images. And the decomposition uses wavelet transforms and extracted its approximation technique. Apply both the two enhancement techniques to the extracted images.

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