

DWT based Adaptive Image Enhancement with Shrinkage Denoising

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ABSTRACT: Image enhancement is a pre-processing step to improve visual content or perception of image and provide better input for human or machine perception. In this paper, a new image enhancement algorithm that combines a multiscale image enhancement method with an adaptive enhancement is presented. The multiscale image enhancement method involves definition of a new contrast measure in terms of cumulative distribution function of image. It is implemented in discrete wavelet transform (DWT) domain. The adaptive enhancement is based on modification of image histogram and it provides a maximum contrast improvement. Since enhancement procedure may amplify noise, a noise suppression step is added. The new image enhancement algorithm has several advantages. First, the noise reduction step in this method can prevent noise amplification during enhancement and preserves original image information. Second, the wavelet based DWT can enhance image details in different scale representation of the image. Third, an adaptive enhancement procedure in this method can provide a maximum contrast improvement to image. Experimental results demonstrate that the advantage of proposed enhancement algorithm to achieve better visual quality for the enhanced images.

KEYWORDS: Image Enhancement, Denoising, Multiscale Transform, Discrete Wavelet Transform, Adaptive Enhancement, Cumulative Distribution Function

I. INTRODUCTION

The main goal of image enhancement is to improve images in such a way that visual content contained in the image is modified for human or machine perception [9]. Since there are no general criteria to uniquely define an ideal enhancement, many enhancement techniques with different criteria have been developed. Image enhancement methods are two types. They are Indirect and direct methods.

Indirect enhancement method enhances image without directly defining and measuring image contrast. Examples include basic pixel transformation, histogram equalization [1], [5] and its variants. These methods often cause inadequate detail preservation and over enhancement problems. Direct methods first define a contrast measure and achieve enhancement by magnifying the measured contrast. Examples include Unsharp Masking [3] and its multiscale extensions. The advantage of direct multiscale enhancement method is that it can measure image contrast at many different scales and then subsequently improve the contrast values. Multiscale transforms include pyramidal based [2] and wavelet based transforms. Tang [4] developed a direct image contrast enhancement algorithm in wavelet domain for mammogram enhancement and results showed that DWT can enhance both subtle details and large features simultaneously. Since wavelet transform can decompose image with directional properties, the wavelet based enhancement algorithm is better.

Contrast enhancement is process of increasing the difference in intensity between an object and its background relative to this background. In adaptive contrast enhancement techniques, the resulting intensity value at each pixel depends on its contextual region. Most of the existing contrast enhancement techniques use local statistics such as mean, standard deviation and histogram of pixel intensities in a contextual region to calculate new intensity value at a pixel. Since the enhancement procedure may also amplify noise, a noise suppression step is also required during enhancement. Denoising removes unwanted noise and restores original image [7]. Bivariate shrinkage denoising can be used for the remove of image noise.

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This paper is organized as follows. Section II deals with related work. Section III deals with bivariate shrinkage denoising. This is followed by Discrete Wavelet Transform in section IV. Section V illustrates the new Adaptive Multiscale Image Enhancement method. Section VI deals with Results and performance measures. Section VII draws Conclusions based on these experimental results.

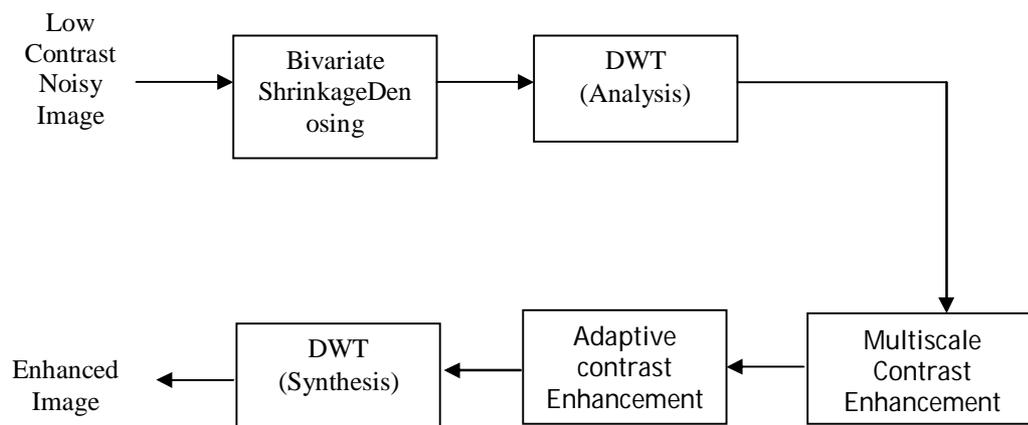


Fig. 1. Block diagram of the proposed image enhancement algorithm

The Figure 1 shows block diagram of proposed image enhancement method. The proposed image enhancement method is an integration of a multiscale contrast enhancement method with an adaptive enhancement method. It also includes a noise suppression step. Figure 1 is detailed in section V.

II. RELATED WORK

Many researchers in their work have prominently pointed out either indirect or direct methods for the enhancement of images. Omprakashpatel, Yogendra P. S et al. [1] have given a procedure of a technique called Recursively Separated and Weighted Histogram Equalization for Brightness Preservation and Contrast Enhancement (RSWHE) for a better contrast enhancement with brightness preservation. Sabine Dippel, Martin Stahl et al. [2] have found that LaplacianPyramis seem to be a more suitable decomposition method for multiscale image enhancement since it is free from artifacts and results in a balanced image impression. Giovanni Ramponi, Norbert Strobel et al. [3] have given a nonlinear unsharp masking technique for image enhancement. J. Tang, X. Liu et al. [4] have found a multiscale image enhancement procedure with a multiscale contrast measure which is implemented in DWT domain. Mr. Salem Saleh Al-amri, Dr. N. V. Kalyankar et al. [5] have found that nonlinear enhancement methods are better than linear methods since linear methods tend to enhance already strong edge structures. Shahan C. Nercessian, Karen A. Panetta et al. [6] in their publication studied the impact of luminance masking and contrast masking with a multiscale enhancement framework. PankajHedaoo and Swathi S. Godbole [7] gave a wavelet thresholding approach for image denoising. Levent S endur and Ivan W Selesnick [8] studied bivariate shrinkage image denoising with local variance estimation. M. Kumar and S. Dass [9] in their paper presented the effect of a total variation based algorithm for pixel level image fusion. Alexander Toet [10] gave the procedure of a nonlinear pyramid recombination in an adaptive multiscale contrast enhancement framework.

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III. BIVARIATE SHRINKAGE DENOISING

Image degradation comes from noise and blurring due to electronic and photometric sources. Noise is unwanted signal that interferes with original signal and degrades the visual quality of digital image. The principal sources of noise in digital images arise during image acquisition and transmission. So image denoising step is a preprocessing step for restoring the original image. Here denoising is done by local adaptive algorithm [8].

Let $y_k = w_k + n_k \dots$ (1)

Where $k= 1,2,\dots$ no. of wavelet coefficients, $w_k = (w_{1k}, w_{2k})$, $y_k = (y_{1k}, y_{2k})$ and $n_k = (n_{1k}, n_{2k})$. MAP estimator for w , given the corrupted observation

$$\hat{w}(y) = \arg \max [p_n(y - w) \cdot p_w(w)] \dots$$
 (2)

For the image coefficients and parents, the Non Gaussian bivariate pdf is evaluated by,

$$p_w(w) = \frac{3}{2\pi\sigma^2} \exp\left(-\frac{\sqrt{3}}{\sigma} \sqrt{w_1^2 + w_2^2}\right) \dots$$
 (3)

The marginal variance is dependent on wavelet coefficient index k. From (1) and (2,) the MAP estimator is derived to

$$\hat{w} = \frac{\sqrt{y_1^2 + y_2^2} - \frac{\sqrt{3}\sigma_n^2}{\sigma}}{\sqrt{y_1^2 + y_2^2}} + y_1 \dots$$
 (4)

A median estimator is used from the finest wavelet coefficients and estimate noise variance which is given by,

$$\sigma_n^2 = \frac{\text{median}(|y_i|)}{0.6745} \dots$$
 (5)

Here y_i belongs to subband HH. Also, where the marginal variance of noisy observation is estimated by

$$\hat{\sigma}_y^2 = \frac{1}{M} \sum y_i^2 \dots$$
 (6)

Here y_i belongs to $N(k)$. $N(k)$ is defined as all coefficients within a square shaped window is estimated as

$$\hat{\sigma} = \sqrt{\hat{\sigma}_y^2 + \sigma_n^2} \dots$$
 (7)

The algorithm first calculates noise variance using (5). Then for each wavelet coefficient $k=1,\dots$ number of wavelet coefficients, calculate $\hat{\sigma}$ using (7). Then calculate $\hat{\sigma}_y^2$ using (6). Then estimate each coefficient using $\hat{\sigma}$ and σ_n^2 in (4). This technique of denoising has an effective performance.

IV. DISCRETE WAVELET TRANSFORM

In this section DWT is briefly reviewed. DWT is a wavelet based multiscale transform. A wavelet transform can be used to decompose the image into different scales so that one can choose the appropriate scale in the wavelet transform domain, while reducing or ignoring the contribution of other scales. Thus different features can be selected to be enhanced in different scales. The 2D DWT uses a quadrature mirror set of 1D analysis filters g and synthesis filters \hat{g} and \hat{h} to provide a multi resolution representation of the image with added directionality. DWT is able to provide perfect reconstruction while using critical sampling [6]. Each analysis stage consists of filtering along rows, down sampling along columns, filtering along columns and down sampling along rows in order to generate approximation coefficient sub band $y_0^{(n)}$ and 3 detail coefficient sub bands $y_1^{(n)}$, $y_2^{(n)}$ and $y_3^{(n)}$ oriented horizontally, vertically and diagonally respectively of scale n [4]. The synthesis procedure begins from the wavelet coefficient sub bands at highest decomposition level. Filtering and up sampling steps are performed in order to perfectly reconstruct the approximation coefficients at the next highest level of decomposition and this is iterated until the image signal is perfectly reconstructed.

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V. ADAPTIVE MULTISCALE CONTRAST ENHANCEMENT

In this section, proposed Adaptive multiscale contrast enhancement with denoising algorithm is formulated. Firstly, a new multiscale contrast measure is presented in DWT domain. Secondly, image enhancement approach based on new contrast measure is developed. Thirdly, adaptive contrast enhancement is developed.

Many multiscale contrast measures have been developed in the past. Some of the contrast measures are only suitable for simple patterns and not suitable for measuring the contrast in complex images such as Michelson contrast measure and Weber contrast measure [6]. Some are especially designed for measuring the contrast in complex images. Histogram of a digital image with gray level in the range $[0, L-1]$ is a discrete function $h(r_k) = n_k$ where r_k is kth gray level and n_k is number of pixel in the image having gray level r_k . It is common practice to normalize a histogram by dividing each of its value by the total number of pixels in the image denoted by n [1]. Thus normalized histogram is given by,

$$p(r_k) = \frac{n_k}{n} \dots\dots \quad (8)$$

Where $k=0,1,\dots,L-1$. Loosely speaking, $p(r_k)$ or probability distribution function or pdf gives an estimate of probability of occurrence of gray level r_k . Cumulative distribution function or cdf is calculated from pdf. The cdf is given by

$$cdf(r_k) = \sum_{i=1}^k p(r_i) \dots\dots \quad (9)$$

In the spirit of pdf and cdf of image [1], the aim is to develop a new multiscale contrast measure with the parameter cdf. Given the approximation coefficient sub bands yielded using a DWT. The new contrast measure can improve the contrast value of the image based on the cdf value of the image obtained from its histogram. The new contrast enhancement equation for the i th approximation wavelet coefficient sub bands is given by

$$C = \text{maxvalue} * \left(\frac{i}{\text{maxvalue}} \right)^{(1.5-cdf)^4} \dots\dots \quad (10)$$

Where C is new contrast value and maxvalue refers to the maximum value of i th wavelet coefficient sub band. Here i is in the range $[1, N]$ where N is the highest decomposition level of DWT. Since pdf of an image comes in range $[0, 1]$, cdf also is in same range. Then parameter γ value of the new contrast measure $(1.5 - cdf)^4$ varies from 5.0625 to 0.0625 according to the contrast level of the image. It is better compared to some of the existing contrast measures with fixed γ value. Since contrast enhancement means that change of image value distribution to cover a wider range. Thus for the contrast enhancement, the image values concentrated near a narrow range in low contrast image are changed to new image value distribution to cover a wider range. The new contrast measure in Eq. (10) improves the contrast value based on image value distribution or pdf of input image and gives effective results.

Figure 1 shows the new image enhancement algorithm. Here first module is denoising. Here noisy image undergoes a bivariate shrinkage denoising which is explained in section III. In the second module analysis stage of DWT, A forward DWT is applied to the input image and decomposed into several wavelet coefficient sub bands. Third module is multiscale contrast enhancement. Here approximation coefficients at each decomposition level i with $i=1,2,\dots,N$ are taken for enhancement. Evaluate histogram of the approximation coefficient at each level. From the histogram, calculate pdf and cdf values by Eq. (8) and Eq. (9) respectively. Improve contrast value of approximation coefficient sub bands at each level by new contrast measure in Eq. (10). After the new multiscale contrast enhancement, the image may still lack in contrast locally. Then fourth module is adaptive contrast enhancement. It develop an adaptive enhancement framework and integrate it into new multiscale contrast enhancement. One of the most common means of adaptive enhancement is by histogram modification [10]. After the contrast enhancement procedure, enhanced image sub bands are adaptively enhanced by modifying their histograms. For this, evaluate histogram of enhanced approximation coefficient sub bands at each decomposition level. For the histogram, calculate number of peak level in histogram and midpoint between each peak levels. Then iteratively smooth the histogram until number of peak levels in histogram is two or three. Similarly modify approximation coefficient sub bands at each decomposition level. Finally fifth module is synthesis stage of DWT. Here the enhanced image is reconstructed by inverse DWT. To summarize exact means by which an adaptive multiscale image enhancement with denoising is achieved, the proposed algorithm is described as follows.

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1. Observed low contrast image that contains noise is denoised using bivariate shrinkage denoising
2. Generate N level DWT of denoised image obtained by a forward DWT
3. Evaluate histogram of approximation coefficient sub bands at each decomposition level
4. Find pdf and cdf of histogram by Eq. (8) and Eq. (9) respectively.
5. Enhance the approximation coefficient sub bands at each decomposition level $i=1,2,..N$ by Eq. (10).
6. For the enhanced sub bands at each decomposition level $i=1,2,..N$, do steps from 7 to 9
7. Evaluate histogram of enhanced approximation coefficient sub bands
8. Find number of peak level in histogram and midpoint between each peak levels
9. Iteratively smooth the histogram until number of peak levels are two or three and number of pixels between each peak level are almost equal
10. Reconstruct enhanced image by synthesis procedure of DWT

VI. RESULTS AND PERFORMANCE MEASURES

The effectiveness of the presented image enhancement algorithm is validated through MATLAB simulations. The enhancement procedure can effectively enhance the image both locally and global in DWT domain. Quantitative and qualitative assessment is done using PSNR and MOS respectively. PSNR is used for quantitative evaluation. It is usually expressed in terms of logarithmic decibel scale. A low value of MSE denotes less error and improvement in PSNR denotes how effectively denoising is performed [7]. For peak signal to noise ratio PSNR, assume an input image is $X(i,j)$ which contains MXN pixels and processed image $Y(i,j)$. First compute the Mean Squared Error (MSE),

$$MSE = \frac{\sum_{i=1}^M \sum_{j=1}^N |X(i,j) - Y(i,j)|^2}{MXN} \dots \quad (11)$$

Now peak signal to noise ratio (PSNR) is given by,

$$PSNR = 10 \log_{10} \frac{MAX_X^2}{MSE} \dots (12)$$

Here MAX_X is maximum possible pixel value in image X.

MOS or Mean Opinion Score (MOS) used for qualitative evaluation. The image enhancement results generated by the various algorithms were presented to participants who consider themselves image processing experts, and each enhancement result was ranked from 1 to 5, where 1 indicates the worst performance and 5 indicates the best performance. These opinion scores were then averaged yielding the MOS score for each result [6]. A higher MOS score indicates better performance. The adaptive multiscale image enhancement procedure with shrinkage denoising can effectively improve contrast value of image both locally and global. Results obtained using various images are shown in figure 2 and 3. The image in Figure 2(a), 3(a) has many visually poor elements. Overall, the image is dark. Figure 2(b) and 3(b) illustrates that the proposed enhancement algorithm can be effectively carried out in a wavelet transform domain. Table I and II illustrates the quantitative and qualitative image enhancement assessment via PSNR and MOS respectively. Table I gives high PSNR values indicating that noise is effectively removed in enhanced output results. Table II gives high MOS values indicating that enhanced output images have higher visual quality.

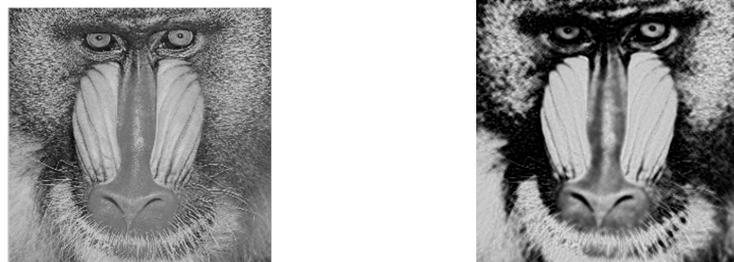


Fig 2.(a) original low contrast noisy 'baboon' image, (b) enhanced result using proposed method

The image in Figure 2(a) has many visually poor elements. It has low contrast level. Overall, the image is dark. Figure 2(b) is brighter and its contrast will be enhanced.

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Fig 3.(a) original low contrast noisy 'cameraman' image, (b) enhanced result using proposed method

The image in Figure 3(a) has many visually poor elements as in Figure 2(a). It has low contrast level. Overall, the image is dark. Figure 2(b) is brighter and its contrast will be enhanced. The Figure 2(b) and 3(b) illustrates that the proposed enhancement algorithm can be effectively carried out in a wavelet transform domain.

TABLE I
Quantitative Image Enhancement Assessment Via PSNR

Image	PSNR (db)
Baboon	29.3215
Cameraman	31.9461
House	33.6195
Lake	33.8175
Walk Bridge	28.4918

Table I illustrates the quantitative image enhancement assessment via PSNR. PSNR is expressed in decibel (db). Table I gives high PSNR values indicating that noise is effectively removed in enhanced output results.

TABLE II
Qualitative Image Enhancement Assessment Via MOS

Image	MOS
Baboon	4.7241
Cameraman	4.8436
House	4.5291
Lake	4.6402
Walk Bridge	4.3961

Table II illustrates the qualitative image enhancement assessment via MOS. Mean Opinion Score or MOS is the average of scores of enhanced results given by image processing experts. Table II gives high MOS values indicating that enhanced output images have higher visual quality.

VII. CONCLUSION

The new image enhancement algorithm is capable of providing contrast improvement with the prevention of noise amplification during enhancement. This image enhancement algorithm is a combination of multiscale contrast enhancement and adaptive enhancement methods. A denoising step in this method can maintain original image information during enhancement. The proposed image enhancement algorithm was able to achieve local and global enhancements simultaneously within a DWT based direct enhancement framework. Results illustrated the improved performance of the proposed method via quantitative and qualitative assessment. This can be extended to enhancement of medical images.

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