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Wavelet Decomposition on Histogram Based Medical Image Contrast Enhancement Using Homomorphic Filtering

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A Wavelet decomposition method that is being used in the system to increase more contrast of an image. A new image technique is based on the discrete wavelet transform (DWT) and singular value decomposition. This paper has been proposed based on the above techniques. The technique decomposes the input image into the four frequency sub bands by using DWT and estimates the filtering of the low–low sub band image, and, then, it reconstructs the enhanced image by applying inverse DWT. Then this technique is compared with the past image equalization techniques. They are as standard general histogram equalization and local histogram equalization. They are also composed of state-of-the-art techniques such as brightness preserving dynamic histogram equalization and singular value equalization.

Key words: Histogram equalization, wavelet decomposition, contrast enhancement, edge stretching

Contrast image enhancement techniques are many in number and all of them are applied to increase the contrast of the image. There are lot many techniques based on histogram. For example bi-he (BHE) is an algorithm that splits a histogram into two sub-histograms and they apply HE to each sub-histogram. Brightness preserving uses the mean intensity that is an important factor to split its histogram. Minimum mean brightness error BHE splits a histogram based on the absolute error. Brightness preserving dynamic HE (BPDHE) divides a histogram into several sub-histograms and applies HE to each sub-histogram separately, which is followed by the normalization that makes the contrast-enhanced image have the same mean intensity value as the input image[4]. These existing histogram-based CE methods tend to preserve global average intensity value with the contrast of the whole image improved. There are other well-known methods that improve HE. However, they are parameter-sensitive.

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Existing method

In this letter, a novel histogram-based CE method, which aims to preserve locality of the original histogram while enhancing the global contrast, is proposed. An optimization problem is formulated by combining proposed locality conditions of the histogram to achieve locality-preserving CE. The proposed method gives graceful CE on various images of different histogram profiles. While the existing histogram-based CE methods show excessive enhancement and unnatural artifacts, the proposed method gives better contrast-enhanced images with locality-preserved histograms. Future work will focus on extension of the proposed HBLPCE method to video sequences.

The proposed HBLPCE is tested on various color images with different statistical properties and compared to existing HE, BPDHE, BBHE, MBEBHE, and recursively separated and weighted HE (RSWHE) methods. The parameters of RSWHE method are chosen based on the authors' suggestion. The proposed method is compared with global CE methods only because local ones give very different tendency and are hard to compare with. In this letter, each CE method is realized in HSV color space, manipulating the V channel with the H and S channels unchanged[1].

CMBFHE is a local CE method, which implements well-known POSHE very efficiently with the identical results. CMBFHE takes much longer time than global CE methods, which increases drastically with the size of the input image. HBLPCE takes the longest time among the global CE methods for small images, while the execution times of global CE are similar for large images.

COMPARISON OF EXECUTION TIMES ON DIFFERENT SIZE IMAGES

Method	Execution time (ms)		
	768 × 512	2048 × 1080	4096 × 2160
HE [1]	11	61	349
BPDHE [4]	15	64	357
BBHE [2]	12	67	380
MMBEBHE [3]	26	123	626
RSWHE [7]	13	71	386
CMBFHE [10]	1013	1992	5596
HBLPCE	40	97	385

Proposed method

Histogram Equalization: In this method it usually increases the global contrast of many images, especially when the usable data of the image is often represented by many close contrast values. From this adjustment, the intensities can be distributed better on the histogram. This method allows for areas of lower local contrast to generate a higher contrast. Histogram equalization accomplishes this by spreading out the best frequent intensity values.

The method is useful for images having backgrounds and foregrounds that are both bright and both dark. This method can lead to better views of bone structure in images, and to better detail in photos that are over or under-exposed. A key advantage of the method is that it is a fairly forward technique and an invertible operator. If the histogram equalization function is known, then the fair original histogram can be recovered. Here calculation is not computationally intensive. A major disadvantage of the method is that it is indiscriminate. It is formulated to increase the contrast of background noise, while decreasing the usable signal.

In scientific imaging it's a technique where spatial correlation is more important than intensity of signal (such as separating DNA fragments of quantized length), the small signal to noise ratio usually damages the visual detection.

Histogram equalization regularly produces effects those were unreal in photographs; however they are more useful for scientific images like thermal, satellite or x-ray images, often this same class of images to which one would apply false-color. Also here histogram equalization can produce undesirable effects (like visible image gradient) when applied with images of low color depth. For example, if applied to 8-bit image displayed with 8-bit gray-scale palette it will further reduce the color depth (number of unique shades of gray) of the original image. Histogram equalization will work the best when applied with images of much higher color depth than palette size, like continuous data or 16-bit gray-scale images.

There are only two ways to think about it and implement histogram equalization, either may be as image change or as well as palette change. This operation can be expressed as P (M (I)) where I am the original image, and M is histogram equalization mapping operation where P is a palette. If we define a new palette as P'=P (M) and leave image I unchanged as then histogram equalization is implemented as palette change. On the other hand if palette P remains unchanged and image is modified to I'=M (I) then the implementation is only by image change. In most cases here palette change is always better as it preserves the original data.

A modification in this method is made by using multiple histograms, also called as sub histograms, to emphasize local contrast of the image, rather than the overall contrast. Examples of such methods are included as adaptive histogram equalization, and a contrast limiting adaptive histogram equalization or CLAHE, or a multipeak histogram equalization (MPHE).

Consider a discrete grayscale image $\{x\}$ and then let it be n_i be the number of occurrences of gray level i. The probability of an occurrence of a pixel of level i in the image is

$$p_x(i) = p(x = i) = \frac{n_i}{n}, \quad 0 \le i < L$$

L being the total number of gray levels in the image (typically 256), n being the total number of pixels in the image, and $p_x(i)$ being in fact the image's histogram for pixel value i, normalized to [0,1].

$$cdf_x(i) = \sum_{j=0}^{i} p_x(j)$$

Which is also the image's accumulated normalized histogram?

We would like to create a transformation of the form $y = T(x)$ to produce a new image $\{y\}$, with a flat histogram. Such an image would have a linearized cumulative distribution function (CDF) across the value range, i.e.

$$cdf_y(i) = iK$$

for some constant K. The properties of the CDF allow us to perform such a transform (see Inverse distribution function); it is defined as

$$cdf_y(y') = cdf_y(T(k)) = cdf_x(k)$$

Where k is in the range [0, L). Notice that T maps the levels into the range [0, 1], since we used a normalized histogram of {x}. In order to map the values back into their original range, the following simple transformation needs to be applied on the result:

$$y' = y \cdot (\max\{x\} - \min\{x\}) + \min\{x\}$$

Discrete wavelet transform

The DWT of a signal x is calculated by passing it through a series of filters. First the samples are passed through a low pass filter with impulse response g resulting in a convolution of the two:

$$y[n] = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[k]g[n-k]$$

The signal is also decomposed simultaneously using a high-pass filter h. The outputs giving the detail coefficients (from the high-pass filter) and approximation coefficients (from the low-pass). It is important that the two filters are related to each other and they are known as a quadrature mirror filter.

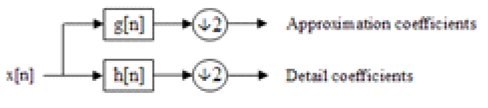


Fig. Block diagram of filter analysis

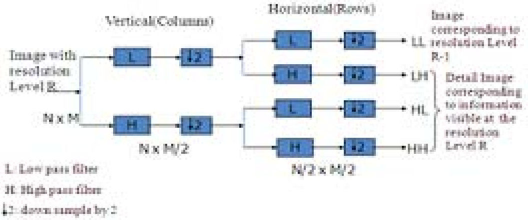


Fig: wavelet process flow

However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist's rule. The filter outputs are then subsample by 2. In the next two formulas, the notation is the opposite: g- denotes high pass and h- low pass as is Mallat's and the common notation.

$$y_{\mathrm{low}}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k]$$

$$y_{\mathrm{high}}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k]$$

This decomposition has halved the time resolution since only half of each filter output characterises the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled. With the sub sampling operator $\downarrow$

$$(y \downarrow k)[n] = y[kn]$$

The above summation can be written more concisely.

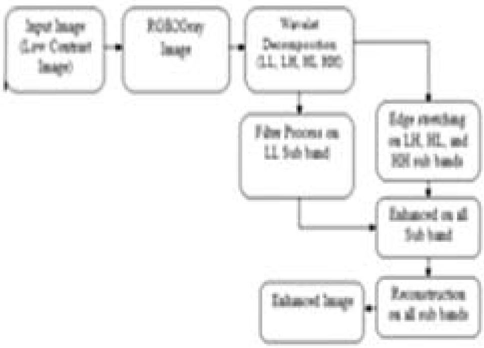
$$y_{\mathrm{low}} = (x * g) \downarrow 2$$

$$y_{\mathrm{high}} = (x * h) \downarrow 2$$

However computing a complete convolution x × gwith subsequent down sampling would waste computation time.

The Lifting scheme is an optimization where these two computations are interleaved.

The above mechanisms are brought together by following block diagram.



The performance parameters as shown above are also calculated. There is quite a considerable change in the parameters.

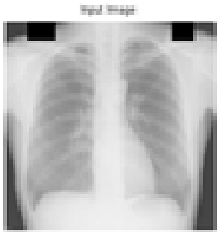


Fig. 1.

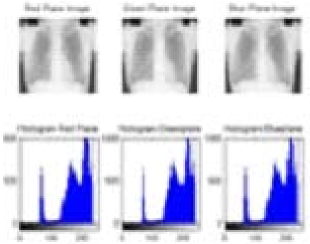


Fig. 2.

Fig. 3.

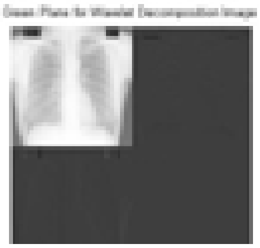


Fig. 4.

Fig. 5.

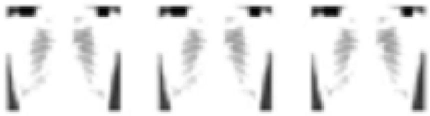


Fig. 6.

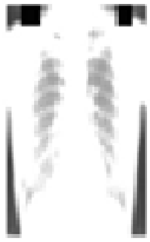


Fig. 7.

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Mean Square Error

Two other quantities that appear frequently when comparing original and reconstructed or approximated data are (root) mean square error.

$$MSE = \frac{\Sigma\Sigma[A(i,j) - B(i,j)]^2}{M X N}$$

Here, A (i.j) = Input Image.

B (i.j) =De-noised Image.

M X N=row and column of image intensity of pixel vales (255 255) image size.

Peak to Signal Noise Ratio

Peak signal-to-noise ratio has two definitions, the original more precise definition, and the second easier to compute and more commonly used. It is this second definition that we use throughout this report. This is the first metric mentioned so far where the results generally run proportional to image quality rather than the inverse.

$$\mathbf{PSNR = 10 \log_{10} [255 ^\wedge 2 / MSE]}$$

Generally when PSNR is 20 dB or greater, then the original and the reconstructed images are virtually in-distinguishable by human eyes.

Experimental results& caluclations

The proposed method has been tested on different images and their parameters are been noted. They have been compared with the previous method. An efficient increase of the PSNR and decrease of MSE shows the success of this method.

The input image is as shown below. It is an image of chest.

In fig.2 the plane separation into 3different planes namely red, green, blue and their respective histogram are been displayed in the figure.

In fig.3, 4, 5, the different planes are decomposed in their edge structures. All the 3planes are differentiated. The three planes have their own separate structures given all along.

In fig.6 the edge of all the structures are combined again with their regular intervals around them. These are later transformed using inverse discrete wavelet transform.

In the final fig. all the planes are again brought togher again into the single plain. These bring the output of the enhanced image. The input image is then used for more uses than the input image. It has more contrast change and it is perfect example for the user to view more clearly.

	Esisting Method	Proposed Method
MSE	2.75E+02	36.7203
	Esisting Method	Proposed Method
PSNR	54.6517	74.792

CONCLUSION

This paper has proposed a new resolution enhancement method using wavelet decomposition of the sub band images and edge stretching methods. The edge stretching method here provides a better contrast and makes it better to look through it. This technique enhances each edge individually and it makes for easy detection of problem. This technique is compared with conventional image equalization techniques such as standard general histogram equalization and local histogram equalization, as well as state-of-the-art techniques such as brightness preserving dynamic histogram equalization and singular value equalization.

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