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ENHANCEMENT OF MEDICAL IMAGES USING BIDIMENSIONAL EMPIRICAL MODE DECOMPOSITION

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***Abstract*— Medical images are low contrast images with high noise and hence image enhancement is essential and aids to detect the abnormalities present in the images easily. In this work, a novel image enhancement method based on bi-dimensional empirical mode decomposition(BEMD) of images is proposed to improve the contrast of the image and to remove the noise from the image. In this work, first the medical images are decomposed using BEMD to intrinsic mode functions (IMFs). In the proposed enhancement algorithm, the decomposed IMFs are enhanced using histogram equalization individually and then enhanced IMFs are combined to produce over all enhanced image. The decomposed IMFs are also enhanced using Adaptive Histogram equalization and Median Filter separately. This is done to attain contrast enhancement and noise suppression. Then these IMF are enhanced using adaptive histogram equalization followed by median filtering. The enhanced IMFs are combined to reconstruct the enhanced medical image. The local contrast (C) and contrast improvement index (CII) of the enhanced images are computed for each of the enhancement algorithm. It is shown that BEMD based enhancement using adaptive histogram equalization yields better results than histogram equalization and Median filtering. The results are compared with the existing enhancement algorithms. The proposed work is applied for multi-modal medical images and better contrast and contrast improvement index is achieved in this work when compare to other algorithms.**

***Keywords*— Mat lab 2013 a Software, blurred medical image, histogram equalization, adaptive histogram equalization , median filter.**

I. INTRODUCTION

Image enhancement is considered as one of the most important techniques in image research. Image enhancement gives a vital task on feature identification. Medical images, real life photographs suffer from poor and bad contrast and noise. It is necessary to enhance the contrast and remove the noise to increase image quality. One of the most important stages in medical images detection and analysis is image enhancement techniques. It improves the clarity of images for human viewing, removing blurring and noise, increasing contrast, and revealing details. These are examples of enhancement operations. The enhancement technique differs from one field to another depending on its objective. The existing techniques of image enhancement can be classified into two categories: Spatial domain and frequency domain enhancement. In this paper, we present an overview of image enhancement processing techniques in spatial domain. More specifically, we categories processing methods based representative techniques of image enhancement. Thus, the contribution of this paper is to classify and review image enhancement processing techniques as well as various noises has been applied to the image. Also, we applied various filters to identify which filter is efficient in removing particular noises. From this we can get an idea about which filters is best for removing Once features have been detected, a local image patch around the feature can be extracted. This extraction may involve quite considerable amounts of image processing. The result is known as a feature descriptor or feature vector.

II. EXISTING SYSTEM

The quality of the image will not be achieved at decomposition Histogram cannot read exact values because data is grouped into categories. More difficult to compare two data sets. Uses only with continuous data. The median filter removes both the noise and the fine detail since it can't tell the difference between the two. Anything relatively small in size compared to the size of the neighbourhood will have minimal effect on the value of the median, and will be filtered out. The luminance histogram of a exemplary natural scene that has been linearly quantized is commonly highly skewed toward the darker levels; a majority of the pixels possess a luminance lower than the average.

In similar images, detail in the darker regions is often not visible. One means of enhancing these types of images is a method called histogram modification, in which the original image is rescaled so that the histogram of the intensified image follows some desired form. This method also assumes the detail carried by an image is related to the possibility of occurrence of each gray level.

To maximize the detail, the transformation should redistribute the possibilities of occurrence of the gray level to make it identical. In this way, the contrast at every gray level is

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proportional to the altitude of the image histogram. Several modifications of histogram equalization are also available which expansion its potential of contrast enhancement. Adaptive histogram equalization (AHE) and Contrast limited adaptive histogram equalization (CLAHE) belong to that classification which apply histogram. This is also as preparation of the next step where the histogram will be divided into two regions based on its average value.

The stretched-histogram will provide a better pixel distribution of the image channels and thus gives a more accurate average value of the channel which represents the average value of the channel for the whole dynamic range

III. PROPOSED SYSTEM

A . Block Diagram

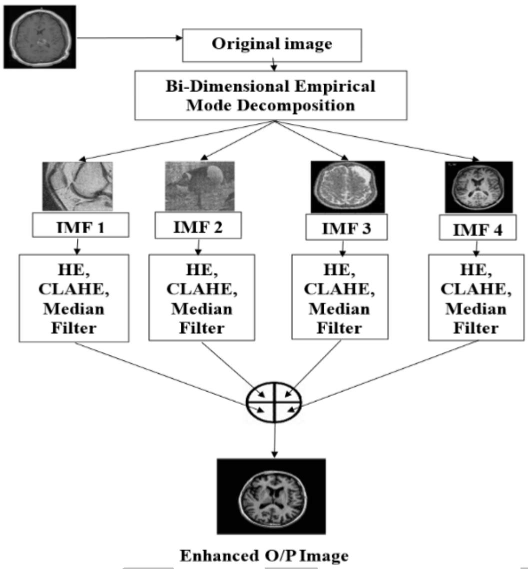

Figure 3.1 : Block diagram

B. Input Image

Medical images are often deteriorated by noise or blurring. Image processing techniques are used to eliminate these two factors. The de-noising process may improve image visibility with a trade-off of edge blurring and may introduce undesirable effects in an image. These effects also exist in images reconstructed using the lossy image compression technique. The proposed method can also be used to discern blurriness in an image using different image compression algorithms

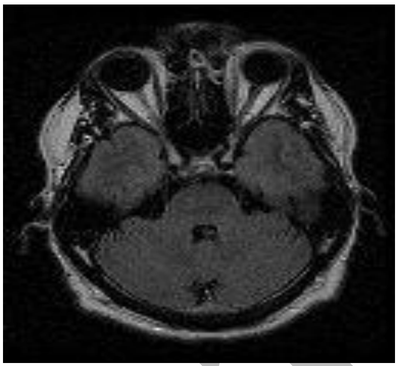

Figure 3.2 : Input Image

C . Bi-dimensional empirical mode decomposition

Bi-dimensional Empirical Mode Decomposition (BEMD), with high adaptive ability, provides a suitable tool for the noisy image processing, and, however, the edge effect involved in its operation gives rise to a problem—how to obtain reliable decomposition results to effectively remove noises from the image. Accordingly, we propose an approach to deal with the blurred images caused by BEMD in the decomposition of an image signal and then to enhance its de-noising performance. This approach includes two steps, in which the first one is an extrapolation operation through the regression model constructed by the support vector machine (SVM) method with high generalization ability, based on the information of the original signal, and the second is an expansion by the closed-end mirror expansion technique with respect to the extremes nearest to and beyond the edge of the data resulting from the first operation. Applications to remove the histogram, adaptive histogram (CLAHE), salt and pepper noise, from the noisy images show that the BEMD can be improved effectively by the proposed approach to meet requirement of the reliable decomposition results. They also illustrate a good de noising effect of he BEMD by improving the medical image on the basis of the proposed approach.

Similar to the EMD of the one-dimensional case, the BEMD uses the extrema that are found in the original image or obtained from the first derivative of the original or the higher-order derivative, to achieve the decomposition of the image signal. Distances between extrema may provide the information for characterizing the image on intrinsic length scales. For a two-dimensional image denoted by (m, n), the basic procedure of the BEMD may be summarized as follows. Initialize the image under consideration,

$$r0(m, n)=f(m, n),\ k=1, (m, n) \in [0, M-1]\times[0, N-1] \qquad ...(3.1)$$

where$M$ and N represent numbers of the rank on the discrete image plane Initialize the parameters,

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$k,0(m, n) = rk-l(m, n)$, and l=1 ….(3.2)

By cubic spline, interpolate between local maxima and between minima, respectively, to get two envelope surfaces

$e_{max}-1(m, n)$ and $e_{min}l-1(m, n)$ of $_{hk}l-1(m, n)$. ….(3.3)

Calculate the mean envelope surface in terms of these two envelope surfaces, given

$e_{mean}-1(m, n) = 1/2\ [e_{max}l-1(m, n) + e_{min}l-1(m, n)]$. …(3.4)

Update the original signal and designate a new one for iteration, given by

$_{k}(m, n)=k_{k,l-1}(m, n)-e_{mean,}l-1\ (m, n),\ l \Rightarrow l + 1$. …(3.5)

until the calculated standard deviation is less than a predetermined criterion (SD) (generally taken as 0.2–0.3) and stop the iteration. Right now, it is regarded that $k,(m, n)$ represents an intrinsic mode function (IMF); that is, imf$k(m, n) = k,l(m, n)$. Update this signal and obtain the residual signal

$rk\ (m, n) = rk-1\ (m, n)$ – imf$k\ (m, n)$. …(3.6)

over again, up to the Kth times, $K = (k + 1)$; when the residual $rK(m, n)$ is a monotonic signal, stop the process of BEMD and finally obtain all IMF components. Once the decomposition process has finished, the original image can be expressed as the sum of all IMFs and the residual rK, given by

$f\ (m, n) = K \sum k$=1 imf$k\ (m, n) + rK\ (m, n)$ …(3.7)

Stopping criterion directly decides the end of the decomposition process and also determines the corresponding final residual term. Therefore, the choice of the value of SD has a close relation with the number of the IMFs obtained by the BEMD. It is necessary to properly choose the value of SD on the basis of the actual situation. In decomposing a one-dimensional signal through the EMD, the residual presents a trend varying with time, which can be ignored in the following analyses. However, the residual resulting from the decomposition of a two-dimensional signal through the BEMD often contains some information of the original image characteristics. It cannot be ignored in the following works, and its influence must be considered for contributions to the original image.

Treatment of the Edge Effect It is an open problem that there is a certain edge effect in the process of the BEMD. Generally, an actual image signal is not so long or even very short, and serious edge effects can be seen sometimes for its decomposition. Such decomposition is a process screening one after another for many times. With the progression of this process, the edge effect will be more serious, leading to distortions of the IMFs of the image signal decomposed by the BEMD. To this end, some treatments should be taken to mitigate or eliminate edge effects occurring in the screening process of the BEMD operation. Combining advantages of the SVM method with those of the mirror expansion, a new approach to deal with the edge effect caused by BEMD in the decomposition of an image signal is proposed as follows. SVM Regression Model and Its Extrapolation Given training sampling data

$X = \{(x1, y1), \ldots, (xi, yi)\}$ ….(3.8)

where xi is an input vector of m columns, $xi \in Rm$, and yi is the output value corresponding to xi, $yi \in R$, may be transformed into a high dimensional feature space F by the SVM regression through a nonlinear mapping ϕ. In this feature space, one can operate a linear regression to get its regression function, expressed as

$y=f\ (x) = \{w, \phi\ (x)\} + b$ …. (3.9)

In this equation, {,} represents the inner product, w is the complexity of the function(x) described by the original data and transforming them into a high-dimensional space Rm, and b is a constant, as the bias term, $b \in R$. Equation (6) requires constraint conditions.

$yi - wT \cdot \phi\ (xi) - b \leq \varepsilon + \xi i\ (i = 1, 2, \ldots, l)$ ….(3.10)

$wT \cdot \phi\ (xi) + b \leq \varepsilon + \xi * i \xi * i\ ,\ \xi i \geq 0,\ (i = 1, 2, \ldots, l)$ ....(3.11)

where ξi and $\xi * i$ are the slack variables, denoting the upper and lower errors of the training $yi - wT \cdot \phi(xi) - b$ under the constraint of the error ε and C is a constant to control the penalty degree for the sampling data out of ε, C>0. Vapnik proposed that the risk is measured by the ε-insensitive loss function

D . Intrinsic mode decomposition

For a given time-series a(t), locate local maximum and minimum and interpolate to form au(t) and al(t) as upper and lower envelopes Work out the mean of upper and lower envelopes

am(t)=au(t)+al(t)2 …..(3.12)

Obtain a detailed component ad(t) by subtracting the mean component from the original time series as

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$$ad(t)=a(t)-am(t) \quad \text{….(3.13)}$$

Obtain first IMF and residue if am(t) and ad(t) full fill anyone of the stopping criteria. Stopping criteria: (i) mean envelope developed by maxima and minima should be zero, and (b) number of zero crossings and extrema should differ by one or zero Repeat the previous steps until you obtain the first IMF and residue.

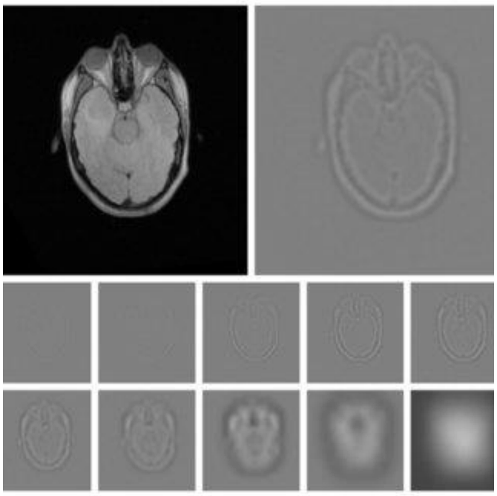

Figure 3.3 : Intrinsic mode decomposition

E . Histogram Enhancement techniques

The image histogram provides information about the intensity distribution of the pixels in the image. Images that are too light or too dark have a narrow histogram . Equalization of histogram has been widely applied and developed, multi-histogram equalization used to improve image contrast and brightness.

A dynamic equalization histogram can produce an image output with an average image intensity equal to the average intensity of the input image. Not only in the picture, histogram equalization method can also be applied to the video which can also produce a bright image output. Improved image quality is a process done to get certain conditions on the image . The process is carried out using a variety of methods depending on the expected conditions on the image, such as sharpening certain parts of the image, removing noise or interference, contrast manipulation and gray scale, etc. Noise is the points in the image that are not actually part of the image, but are mixed in the image for a reason. Noise arises usually as a result of poorly muted (noise sensors, photographic gain noise) .

The disorder is generally a variation in the intensity of a pixel that does not correlate with neighbouring pixels. Visually, the disorder is easily seen by the eye as it looks different from its neighbouring pixels. Pixels with disturbances generally have high frequency . image brightness, contrast stretching, histogram equalization, image smoothing, sharpening edge, pseudo colouring, , geometric changes. Generally, image quality improvement is done through image histogram representation through histogram equalization method. This method works by describing the distribution of pixels in a histogram by changing the gray level value of certain pixels regardless of its location in a picture.

F. Contrast Limited Adaptive Histogram(CLAHE)

Adaptive histogram equalization (AHE) is a computer image processing technique used to improve contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the lightness values of the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image. However, AHE has a tendency to over amplify noise in relatively homogeneous regions of an image. A variant of adaptive histogram equalization called contrast limited adaptive histogram equalization (CLAHE) prevents this by limiting the amplification.

Ordinary AHE tends to over amplify the contrast in near-constant regions of the image, since the histogram in such regions is highly concentrated. As a result, AHE may cause noise to be amplified in near-constant regions. Contrast Limited AHE (CLAHE) is a variant of adaptive histogram equalization in which the contrast amplification is limited, so as to reduce this problem of noise amplification. In CLAHE, the contrast amplification in the vicinity of a given pixel value is given by the slope of the transformation function.

This is proportional to the slope of the neighbourhood cumulative distribution function (CDF) and therefore to the value of the histogram at that pixel value. CLAHE limits the amplification by clipping the histogram at a predefined value before computing the CDF. This limits the slope of the CDF and therefore of the transformation function. The value at which the histogram is clipped, the so-called clip limit, depends on the normalization of the histogram and thereby on the size of the neighbourhood region. Common values limit the resulting amplification to between 3 and 4.

It is advantageous not to discard the part of the histogram that exceeds the clip limit but to redistribute it equally among all histogram bins. The redistribution will push some bins over the clip limit again (region shaded

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green in the figure), resulting in an effective clip limit that is larger than the prescribed limit and the exact value of which depends on the image. If this is undesirable, the redistribution procedure can be repeated recursively until the excess is negligible. the gray value of the pixel in the original image is r (0r1) and its probability density is p(r), the gray value of the pixel in the enhanced image is s (0s1) and its probability density is p(s), and the mapping function is s=T(r). According to the physics meaning of the histogram, it is clear that every bar on the equalized histogram is of the same height.

G. Median Filter

The median filter is the one type of nonlinear filters. It is very effective at removing impulse noise, the "salt and pepper" noise, in the image. The principle of the median filter is to replace the gray level of each pixel by the median of the gray levels in a neighborhood of the pixels, instead of using the average operation. For median filtering, we specify the kernel size, list the pixel values, covered by the kernel, and determine the median level. If the kernel covers an even number of pixels, the average of two median values is used. Before beginning median filtering, zeros must be padded around the row edge and the column.

MEDIAN [A(x) +B(x)] =! MEDIAN [A(x)] + [B (x)]⋯(3.14)

H. Enhancement Image

The output will be restored image which can be obtained from the computer using MATLAB software.

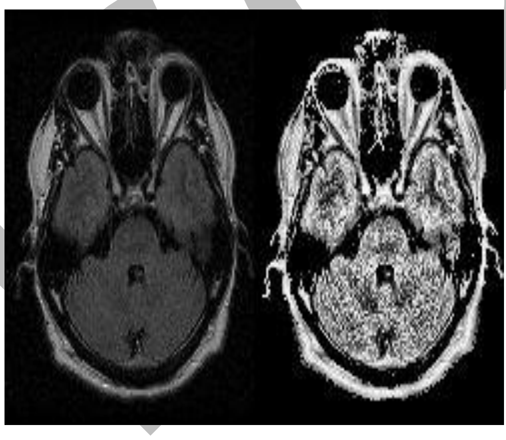

Figure 3.4 : Enhanced Image

IV. FUTURE ENHANCEMENT

Fast And Adaptive (Bi-Dimensional Empirical Mode Decomposition) A novel approach for bi dimensional empirical mode decomposition (BEMD) is proposed in this paper. BEMD decomposes an image into multiple hierarchical components known as bi dimensional intrinsic mode functions (BIMFs). In each iteration of the process, two-dimensional (2D) interpolation is applied to a set of local maxima (minima) points to form the upper (lower) envelope. But, 2D scattered data interpolation methods cause huge computation time and other artefacts in the decomposition. This paper suggests a simple, but effective, method of envelope estimation that replaces the surface interpolation. In this method, order statistics filters are used to get the upper and lower envelopes, where filter size is derived from the data. Based on the properties of the proposed approach, it is considered as fast and adaptive BEMD (FABEMD). Simulation results demonstrate that FABEMD is not only faster and adaptive, but also outperforms the original BEMD in terms of the quality of the BIMFs.

The bi dimensional empirical mode decomposition (BEMD) has taken its place among the most known decomposition methods as Fourier transform and wavelet, but the enormous execution time that it requires represents a real obstacle for its application. Hence the fast and adaptive bi dimensional empirical mode decomposition (FABEMD) is proposed basically to overcome this obstacle by decreasing the execution time of the BEMD; its principle is based on the use of statistical filters to generate the upper and the lower envelopes instead of the interpolation functions used in the BEMD. In this work we propose a 3d extension of the FABEMD denoted fast and adaptive tri dimensional empirical mode decomposition which can decompose a volume into a set of tri dimensional intrinsic mode functions (TIMFs), the first TIMFs belong to the high frequencies and the last ones to the low frequencies.

The proposed approach takes an efficient runtime compared with the considerable one required by the multidimensional ensemble empirical mode decomposition, and it ensures a good quality of the decomposition in term of orthogonality and reconstruction. The obtained results are encouraging and will open a new road to three dimensional extensions of many applications.

IV. CONCLUSIONS

This paper presented a new BEMD-based image enhancement method for reducing the vignetting and noise effects in the demodulated medical images for enhancing Medical image detection. With the new BEMD method, a sequence of Adaptive histogram, histogram, median filters were predefine for envelope estimation. The performance of the BEMD, along with the three other BEMDs, was evaluated both visually and by using quantitative metrics in computer simulations. Results showed that the BEMD method effectively isolated the vignetting and noise contributions in the medical images . This produced enhanced images through selective reconstruction.

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The BEMD method showed significant improvements in the image decomposition speed, compared to the other three methods. The BEMD method can be used for enhancing medical image, and it also looks promising as a general image enhancement technique for medical images enhances with other imaging techniques.

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