Diyala Journal of Engineering Sciences

ISSN 1999-8716

Vol. 02, No. 01, pp. 109-127, June 2009

Low Vision X-Ray Images Contrast Enhancement Using Wavelet Transform and Non-Linear Mapping

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(Received:21/9/2008; Accepted:26/4/2009)

ABSTRACT - This paper proposes a new method for enhancing the contrast of medical images based on Wavelet Transform. Wavelet transforms offer an efficient representation of the signal, finely tuned to its intrinsic properties involves simple processing techniques in the transform domain, and multi-scale analysis can accomplish remarkable performance and efficiency for many image-processing problems.Wavelet transform is applied so that the intensity values of pixels in gray-level images are decomposed into the approximate component and detail components. The obtained coefficients of the approximate component are normalized before converted by a proposed non-linear grey-level contrast enhancement technique. The non-linearity, with its two degrees of freedom, is more versatile and can produce a more balanced contrast enhancement for low vision medical images. Then, denormalizing results before inverse Wavelet transform application on the converted coefficients, so that enhanced intensity values are obtained. Finally, we found that applying histogram equalization to the result of inverse Wavelet transform promotes the action done in transform domain. The effectiveness of the proposed method is demonstrated experimentally by measuring the contrast ratio and mean ratio for resulted images. The contrast enhancement ratio exceeds 100% of some low vision medical images.

Keywords: Image processing, Contrast enhancement, Human visual system, Wavelet transform.

1. INTRODUCTION

Image enhancement is a technology to improve the quality of an image in terms of visual perception of human beings.With the growing quality in image acquisition, image enhancement technologies are more and more needed for many applications.

Recent years, multi-scale technologies have been widely used in image processing. For example, Lu [1] proposed a contrast enhancement method based on multi-scale gradient transformation. Brown[2]proposed an adaptive strategy for wavelet based image enhancement. However, they hardly consider the features of human visual system. In all kinds of practical applications, most images are viewed by humans. Thereby, it is necessary to consider the human visual system in Medical image enhancement[3]. Numerous research works have proven that space-frequency and space-scale expansions with this family of analysis functions provided a very efficient framework for signal or image data. One of the most important features of wavelet transforms is their multi-resolution representation. Physiological analogies have suggested that wavelet transforms are similar to low level visual perception. Such multi-resolution analysis gives the possibility of investigating a particular problem at various spatial-frequency (scales). The wavelet transform is applied to decompose the Image information to approximate components and detail components. Then, a contrast enhancement technique for grey-level images based on the human visual system is applied to enhance approximate component. Then, inverse Wavelet transform is applied so that contrast enhanced color image is obtained.

2. BI - DIMENSIONAL DISCRETE WAVELET TRANSFORM

Wavelet transforms offer an efficient representation of the signal, finely tuned to its intrinsic properties. By combining such representations with simple processing techniques in the transform domain, multi-scale analysis can accomplish remarkable performance and efficiency for many image-processing problems. Multi-scale analysis has been found particularly successful for image enhancement problem given that a suitable separation of signal frequencies can be achieved in the transform domain (*i.e.* after projection of an observation signal) based on their distinct localization and distribution in the spatial-frequency domain. The DWT-2D corresponds to multi-resolution approximation expressions[4,5].

$$f(x,y)=\sum_{j=0}^{N_J-1} s_j \varphi_{jn}(x,y)+\sum_{j=0}^{N_J-1}\sum_{k=0}^{J} d_{jk}\psi_{jk}(x,y) \qquad \text{.....(1)}$$

Where J denotes the scale of the analysis, and scale j indicates the coarsest scale or lowest resolution of the analysis, N_J=N/2j, is the number of coefficients in scale j. As depicted in equation (2) the procedure of wavelet decomposition is as follows: wavelet has two functions “wavelet “and “scaling function”. They are such that there are half the frequencies between them. They act like a low pass filter and a high pass filter. φ_n is the scale function which can be defined by[6] as:

$$\varphi_n = \varphi(t-n) \qquad n \in Z, \varphi \in L^2 \qquad \text{.....(2)}$$

The subspace of $L^2(R)$ spanned by these functions is defined as:

$$V_0 = \overline{span\{\varphi_n(t)\}} \qquad \text{.....(3)}$$

This means that :

$$f(t) = \sum_n s_n \varphi_n(t) .... \forall .. f(t) \in V_0 \qquad \text{.....(4)}$$

One can generally increase the size of the subspace spanned by changing the time scale of the scaling functions. A two-dimensional family of functions is generated from the basic scaling function by scaling and translation by:

$$\varphi_{j,n}(t) = 2^{j/2} \varphi(2^j t - n) \qquad \text{.....(5)}$$

Whose span over k is:

$$V_j = \overline{span\{\varphi_{j,n}(t)\}} \qquad \text{.....(6)}$$

If $f(t) \in V_j$, it can be expressed as:

$$f(t) = \sum_n s_n \varphi(2^j t + n) \qquad \text{.....(7)}$$

If $\varphi(t)$ is in V_0 it is also in V_1, this means that $\varphi(t)$ can be expressed in terms of a weighted sum of shifted $\varphi(2t)$ as:

$$\varphi(t) = \sum_n h(n) \sqrt{2} \varphi(2t - n) \qquad n \in Z \qquad \text{.....(8)}$$

Where h(n) is a sequence of real (or complex) numbers called the scaling function coefficients (or the scaling filter). In addition to the scaling function φ_n that has been discussed, another basic function called the wavelet function ψ_k is required. Dilations and translations of the “Mother function”, or “analyzing wavelet” $\psi(x)$, define an orthogonal basis, our wavelet basis:

$$\psi_{(s,l)}(x) = 2^{-\frac{s}{2}} \psi(2^{-s} x - l) \qquad \text{.....(9)}$$

The variables *s* and *l* are integers that scale and dilate the mother function to generate wavelets. The scale index *s* indicates the wavelet’s width, and the location index *l* gives its position. To span our data domain at different resolutions, the analyzing wavelet is used in a scaling equation:

$$W(x) = \sum_{k=-1}^{N-2} (-1)^k c_{k+1} \psi(2x+k) \quad \text{.....(10)}$$

Where W(x) is the scaling function for the mother function ψ, and c_k is the wavelet coefficients. There is an advantage in requiring orthogonal scaling functions and wavelets. Orthogonal basis functions allow simple calculation of expansion coefficients. The orthogonal complements of V_j in V_{j+1} are defined by W_j, this means that all members of V_j are orthogonal to all members of W_j [(4)].

$$\langle \varphi_{j,k}(t), \psi_{j,l}(t) \rangle = \int \varphi_{j,k}(t) \psi_{j,l}(t) dt = 0 \qquad j,k,l \in Z \quad \text{.....(11)}$$

Where $\langle , \rangle$ denotes the inner product. So, the wavelet can be represented by a weighted sum of shifted scaling function $\phi(2t)$ by:

$$\psi(t) = \sum g(n) \sqrt{2} \varphi(2t-n) \qquad n \in Z \quad \text{.....(12)}$$

The scaling coefficients are related to the wavelet coefficients by:

$$g(n) = (-1^n) h(1-n) \quad \text{.....(13)}$$

The function generated by equation (14) gives the prototype or mother wavelet $\psi(x)$ for a class of expansion functions of the form:

$$\psi_{j,k}(t) = 2^{j/2} \psi(2^j t - k) \quad \text{.....(14)}$$

There are no explicit expressions for Daubechies compact support orthogonal wavelets and corresponding scaling functions. Table (1) presents the low-pass wavelet filter coefficients for Daubechies 4 taps wavelet[(4)].

Table (1): Coefficients for the 4-tap Daubechies Low-pass Filter

Taps	Values
h0=	.4829629131445341
h1=	.8365163037378077
h2=	.2241438680420134
h3=	-.1294095225512603

The wavelet transform can be migrated to the matrix multiplication form(4). For D4 filter (4 elements), and a signal that's only 8 samples in length. The low pass and highpass sections as two 4-vectors combined to make one 8-vector:

[yl(0)] = [h3 h2 h1 h0 0 0 0 0][x(0)]
[yl(1)] = [0 0 h3 h2 h1 h0 0 0][x(1)]
[yl(2)] = [0 0 0 0 h3 h2 h1 h0][x(2)]
[yl(3)] = [h1 h0 0 0 0 0 h3 h2][x(3)]
[yh(0)] = [g3 g2 g1 g0 0 0 0 0][x(4)] **…..(15)**
[yh(1)] = [0 0 g3 g2 g1 g0 0 0][x(5)]
[yh(2)] = [0 0 0 0 g3 g2 g1 g0][x(6)]
[yh(3)] = [g1 g0 0 0 0 0 g3 g2][x(7)]

And for the inverse transform, we have something like this

[x(0)] = [h3 0 0 h1 g3 0 0 g1][yl(0)]
[x(1)] = [h2 0 0 h0 g2 0 0 g0][yl(1)]
[x(2)] = [h1 h3 0 0 g1 g3 0 0][yl(2)]
[x(3)] = [h0 h2 0 0 g0 g2 0 0][yl(3)]
[x(4)] = [0 h1 h3 0 0 g1 g3 0][yh(0)] **…..(16)**
[x(5)] = [0 h0 h2 0 0 g0 g2 0][yh(1)]
[x(6)] = [0 0 h1 h3 0 0 g1 g3][yh(2)]
[x(7)] = [0 0 h0 h2 0 0 g0 g2][yh(3)]

Where the matrices on equations (15) & (16) represent the transform (decomposition) matrix and reconstruction one respectively, both of these matrices derived in term of h[n] ,the low pass filter, and g[n] the high pass filter, for N filter length. 2D-DWT is a separable transform and it can be performed by first decomposing the image in one of the directions and then decomposing the transform coefficients in the other direction. The same is also applicable for 2D-IDWT[x-ray]. Note that (4) the DWT of an image consists of four frequency channels for each level of decomposition. For example, for j-level of decomposition one has:

$W_{\psi}^{D}(j,m,n)$: Coefficients of Diagonal Detail, speckled,

$W_{\psi}^{V}(j,m,n)$: Coefficients of Vertical Detail, speckled,

$W_{\psi}^{H}(j,m,n)$: Coefficients of Horizontal Detail, speckled, and

$W_{\phi}(j,m,n)$: Coefficients of Approximation. The $W_{\phi}(j,m,n)$ part at each scale is decomposed recursively, as illustrated in figure(1).

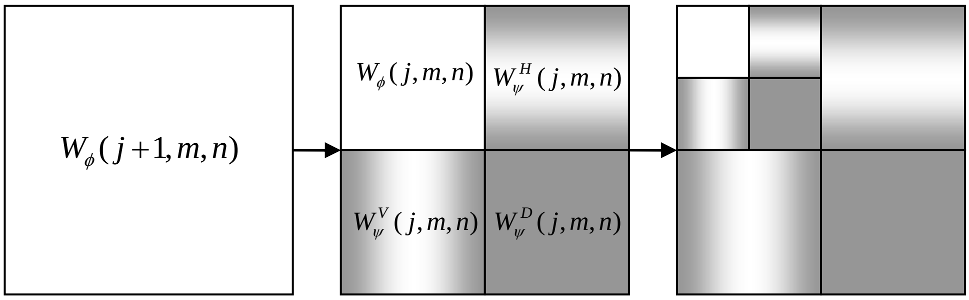


Fig. (1): Data preparation of the image. Recursive decomposition of W_ϕ parts

3. GENERAL GUIDELINES FOR DESIGNING A NON-LINEAR ENHANCEMENT FUNCTION

General guidelines for designing a non-linear enhancement function are $\lambda(u)$ [5] :

1. An area of low contrast should be enhanced more than an area of high contrast. This is equivalent to say that smaller values of wavelet coefficients should be assigned larger gains.
2. A sharp edge should not be blurred.

In addition, an enhancement function may be further subjected to the following constraints:

1. Monotonically increasing: Monoticity ensures the preservation of the relative strength of signal variations, and avoids changing location of local extreme, or creating new extreme.
2. Anti-symmetry: $\lambda(-u) = -\lambda(u)$. This property preserves the phase polarity for edge, a simple piecewise linear function[1]. Such enhancement is simple to implement, and was used successfully for contrast enhancement on mammograms and X-ray images [5,8]. A more careful design can provide more reliable enhancement procedures with a control of noise suppression.

3.1 Non-linear Contrast enhancement transform

In[9] analyzing the feature of human visual system result in a Reverse- S-Shape transform to enhance the grey-level image. To obtain the result, we generalize the method to medical image processing and applied the transform to the intensity of the image. Typically, high contrast images are visually more appealing. However a drawback of linear contrast enhancement is that it leads to saturation at both the low and high end of the intensity range.

This may be avoided by employing a non-linear contrast adjustment scheme, a sigmoidal non-linear symmetric with respect to mid level gray (0.5) transform is used for contrast enhancement, this transform takes the form:

$$g(u) = \frac{1}{1+e^{-\alpha u+\beta}} \qquad \text{.....(17)}$$

In which two degree of freedom are employed α and β, where α > 1 increases contrast, and α < 1 reduces contrast.

In order that *g(u)* be bound by the interval [0, 1], it must be scaled as follows:

$$\lambda(u) = \frac{g(u)-C_1}{C_2} \qquad \text{.....(18)}$$

where

$$C_1 = \frac{1}{(1+e^{\beta})} \qquad \text{.....(19)}$$

And

$$\mathbf{C_2 = \frac{1}{(1+e^{-\alpha+\beta})-C_1}} \qquad \text{.....(20)}$$

This non-linearity, with its two degrees of freedom, is more versatile and can produce a more balanced contrast enhancement. Example of proposed Sigmoidal enhancement functions, with two degree of freedom assuming that the input data was normalized to the range of [0,1]. (1) α=6, β=3 (2) α=12, β=6 (3) α=18, β=9 (4) α=24, β=12, is illustrated in figure(2).

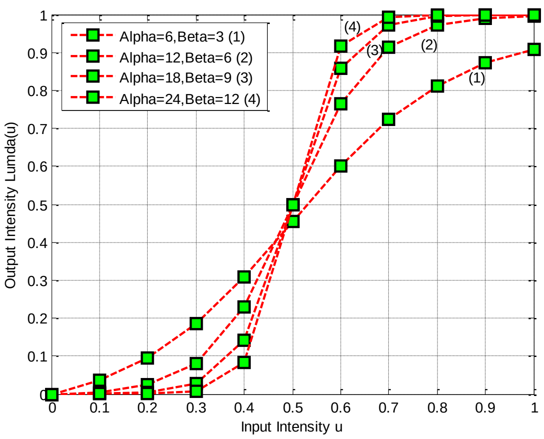


Fig. (2): Example of proposed sigmoidal enhancement function, with two degree of freedom assuming that the input data was normalized to the range of [0,1].
(1) α=6, β=3 (2) α=12, β=6 (3) α=18, β=9 (4) α=24, β=12.

Figure (3) shows the resulted images in transform domain of proposed Sigmoidal enhancement functions, by inspecting them it's clear that increasing α, and β results in enhancing and lightening the low low (LL) image in transform domain, but when we continue increasing the control values gray level saturation occurs[10]. Thus, we need to equalize the resulted image after two-dimensional wavelet reconstruction, hence the optimal selection control values for the image in figure (3) are α=18, β=9.

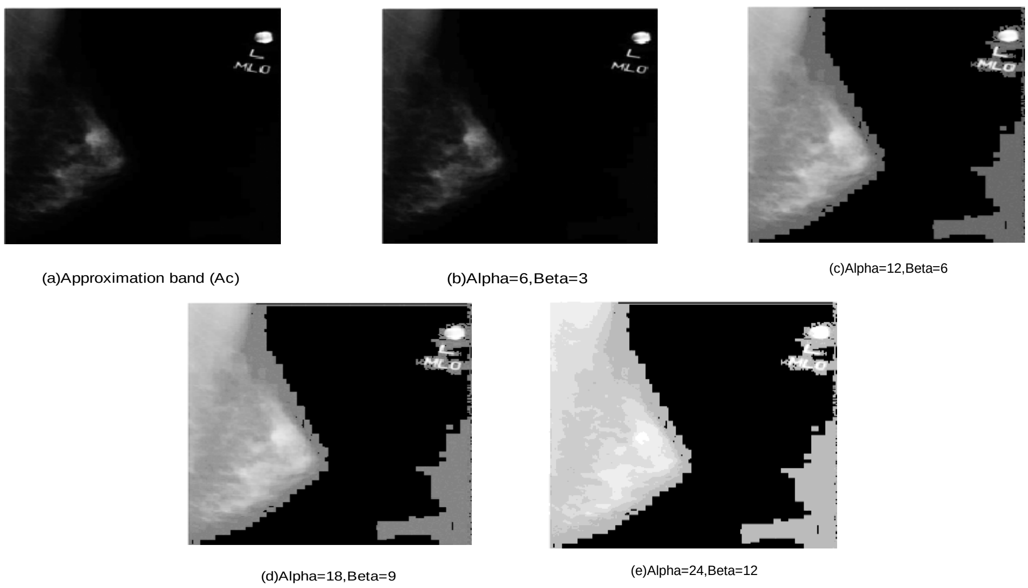


Fig. (3): Resulted images in transform domain for the proposed sigmoidal enhancement functions.

The enhancement operation is also presented using the histogram representation of resulted images in transform domain for the proposed Sigmoidal enhancement function, is depicted in figure (4), so, if α, and β are increased the mean is shifted to the white regions with stretching the shape of histograms. Thus the contrast of image and its mean for example when α=6, β=3 the mean is 11 (histogram g) while when α=18, β=9 the mean becomes 129 (histogram i)

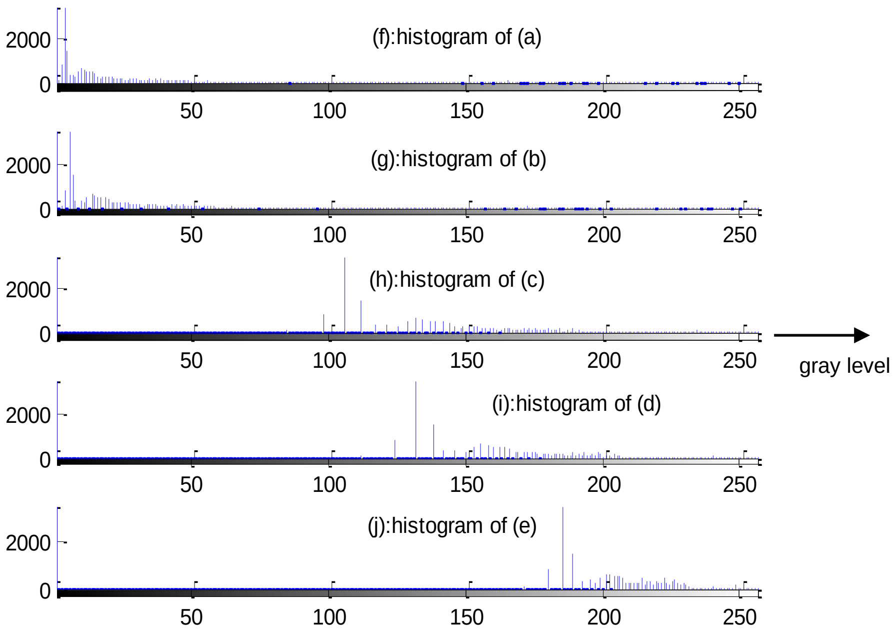


Fig. (4): Histogram representation of resulted images in transform domain for the proposed sigmoidal enhancement function.

3.1.1 Contrast Enhancement using wavelet transform

The intensity of medical X-ray images is enhanced, and then reconstruct the brightness information by applying inverse Wavelet transform[11]. Thus, the enhancement process consists of four steps: Wavelet Transform, contrast enhancement and Inverse Wavelet Transform. Histogram equalization. Figure (5) describes our proposed implementation of the contrast enhancement system to enhance the medical image with data matrix *f(x,y)* which is used as the first scale input, and output four quarter-size subimages W_ϕ, W_ψ^H, W_ψ^V, and W_ψ^D. Figure (5) shows the process in block diagram form.

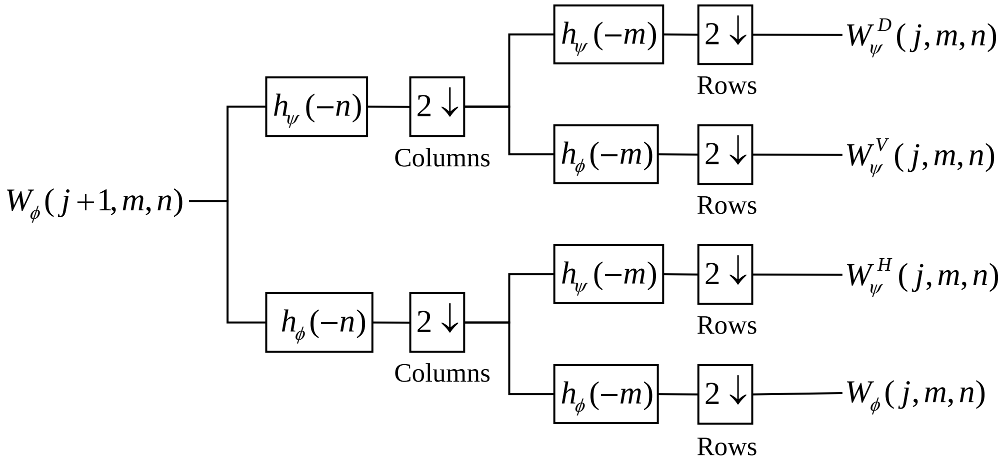


Fig. (5): The two-dimensional FWT — the analysis filter. bank

The reconstruction stage is shown in figure (6):

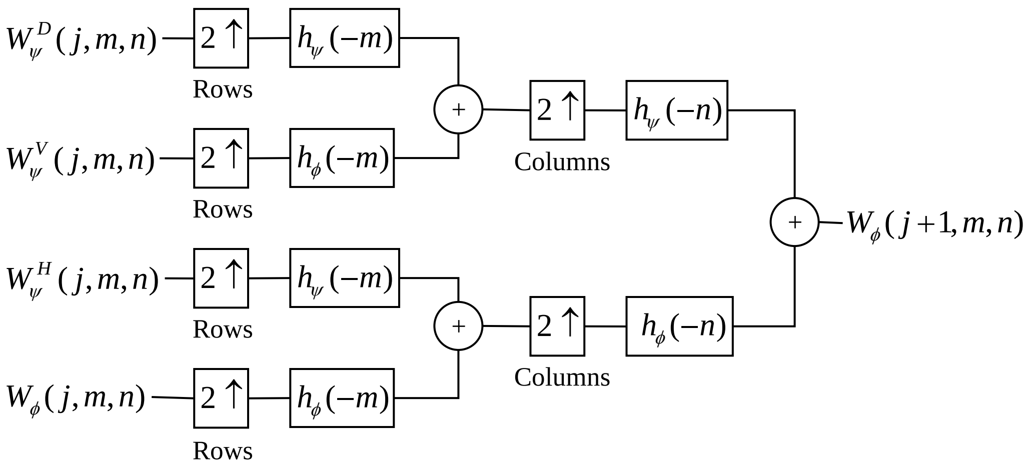


Fig. (6): The reconstruction two-dimensional FWT — the synthesis filter bank.

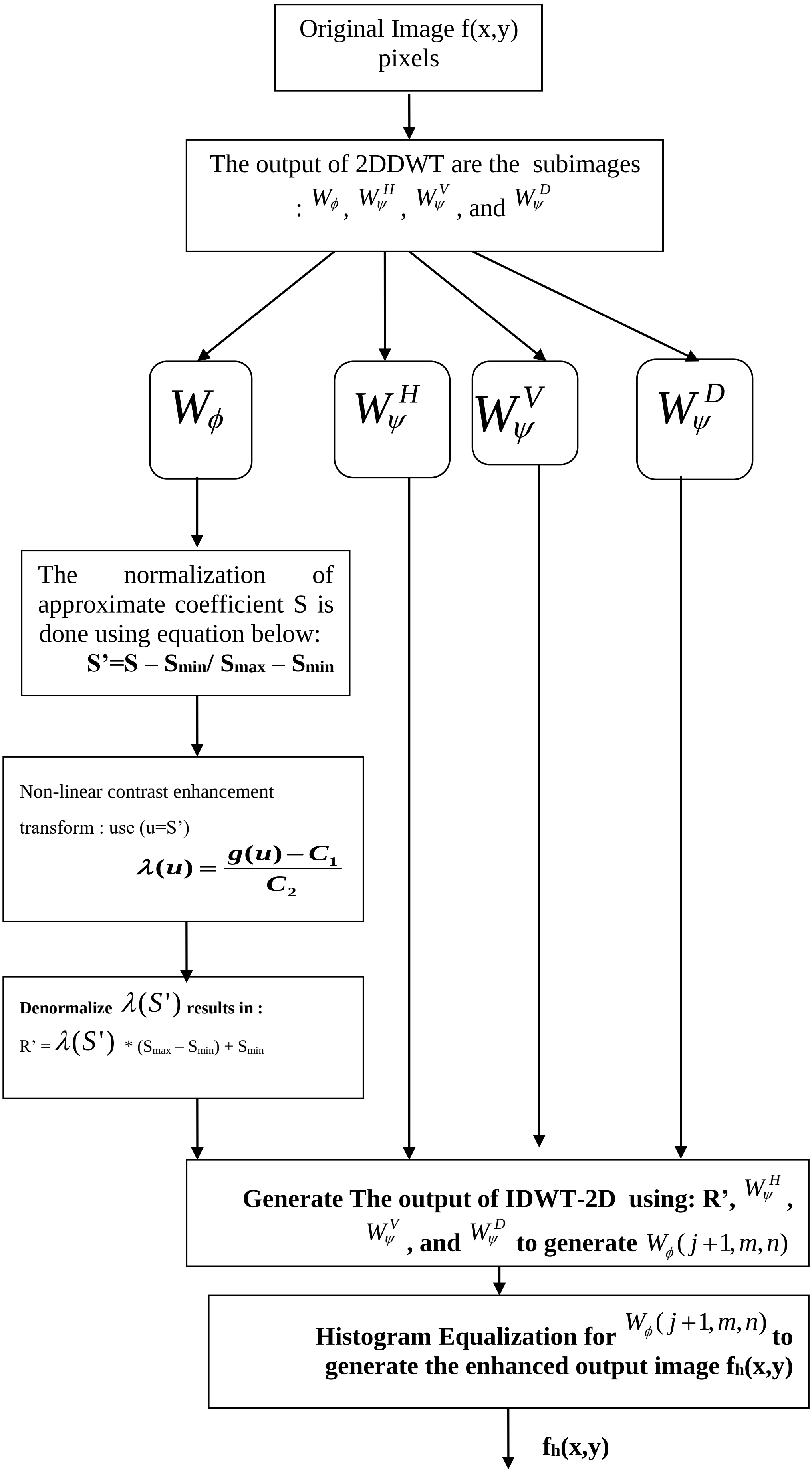


Figure (7): The stages of proposed system.

Figure (7) shows the block diagram stages of the proposed system .Thus As the transform used is an orthonormal transform, each is in the range [0,255] (same as the range of input image intensity value). We apply a contrast enhancement method for grey-level images to the approximate component. According to orthonormal wavelet transform, the intensity values of image of size N*N pixels are decomposed by Equation (1).

Normalization step simply ensures that the input and the output ranges of the non-linear transformation are the same. The normalization of approximate coefficient S is done using equation below:

$$S' = S - S_{min} / (S_{max} - S_{min}) \qquad \text{.....(21)}$$

Where S_{max} and S_{min} are the maximum and minimum intensity level for approximation coefficient. Note that large wavelet coefficient magnitude occurs around strong edges. To enhance weak edges an enhancement function should be designed such that wavelet coefficients within certain magnitude range were to be amplified.

Thus compute R for each S' component using $R = \lambda(S')$. Then introduce the output to the denormalization stage, which remaps the output signal R to the original dynamic range of the input signal

$$R' = R * (S_{max} - S_{min}) + S_{min} \qquad \text{.....(22)}$$

The image is reconstructed by using the inverse wavelet transform as indicted by equation(23):

$$f'(x,y) = \sum_{j=0}^{N_J - 1} R'_j \varphi_{jn}(x,y) + \sum_{j=0}^{N_J - 1} \sum_{k=0}^{J} d_{jk} \psi_{jk}(x,y) \qquad \text{.....(23)}$$

Saturation adjustment is to make the resulted image soft. An analysis in[10] has shown that the saturation component often contains more high frequency spectral energy, i.e. image detail, than its intensity counterpart. In this paper, it is used a histogram equalization.

4. Experimental Result

To test the performance of the proposed method, this method is applied to a low contrast X-ray images. Figures (8), (9), (10), (11) and (12) respectively, shows the experimental result of the low contrast image. where (a) is the original image, (b) Wavelet decomposition to the original image (c) is the result obtained by proposed method in transform domain and (d) Histogram equalized Inverse Wavelet transform image. Figure (8) is the experimental result of the dark image, where the other figures represent less dark images to middle darkness images.

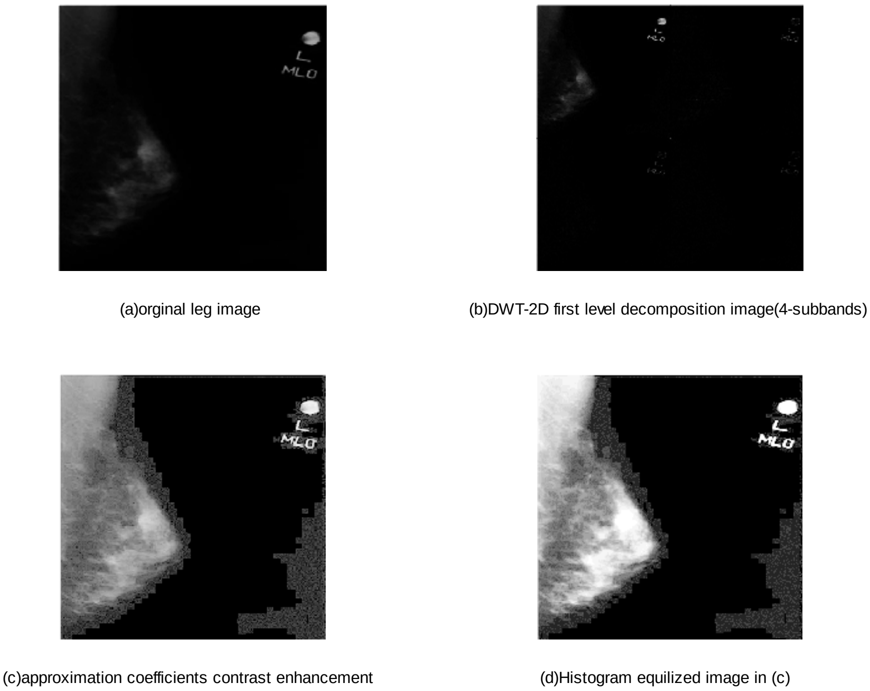


Fig. (8): Simulation result for image called Leg.

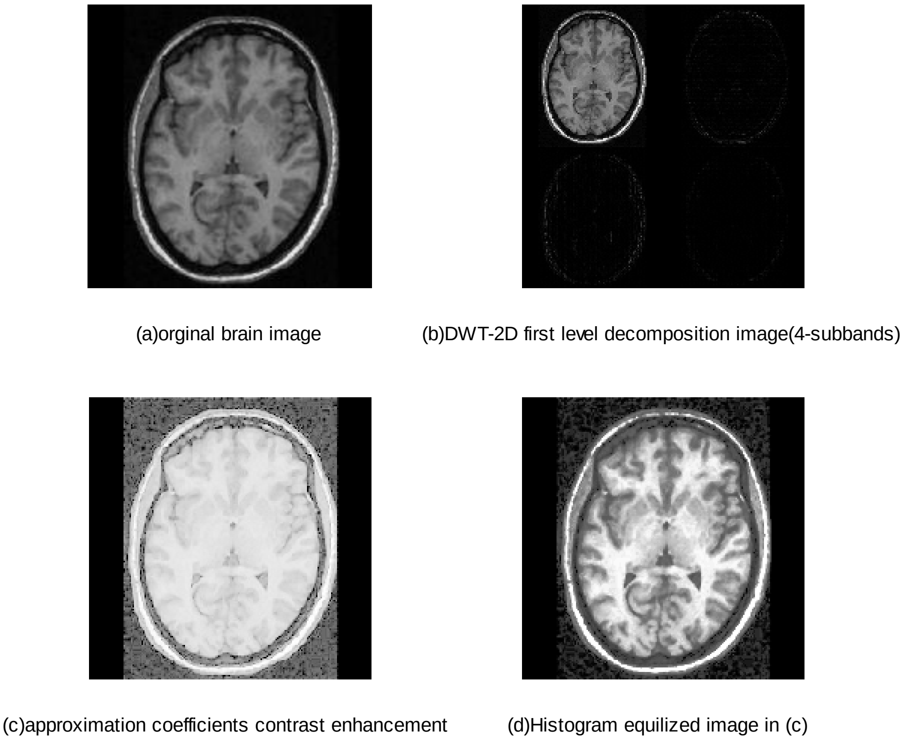


Fig. (9): Simulation result for image called Brain.

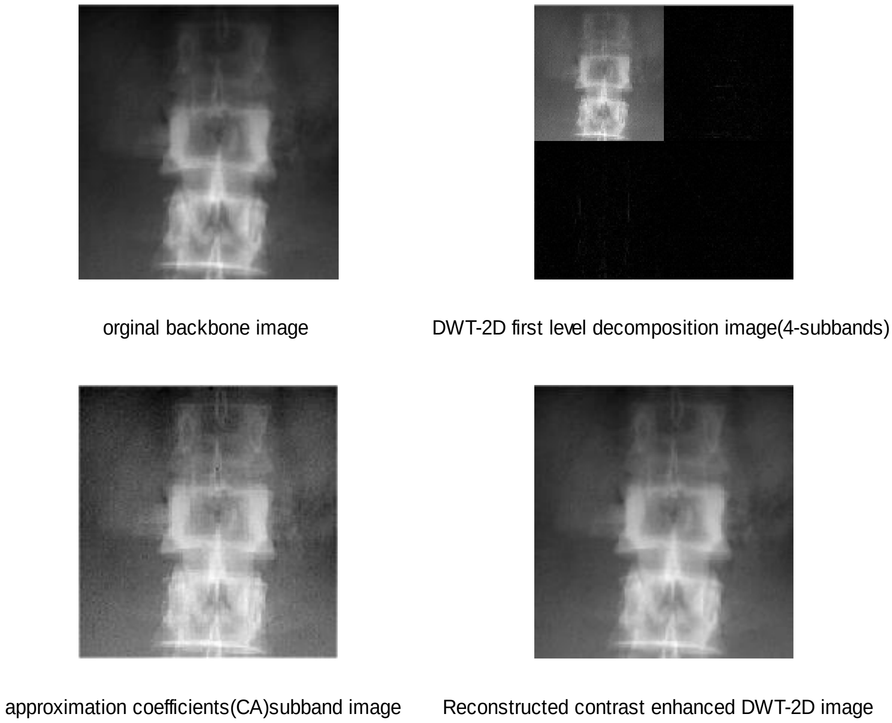


Fig. (10): Simulation result for image called Backbone.

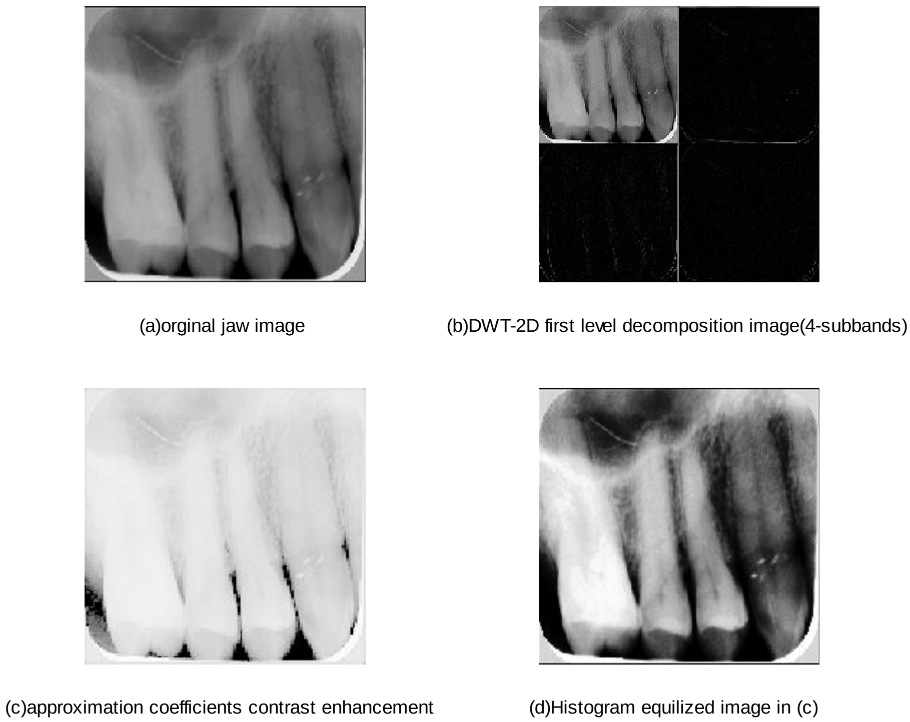
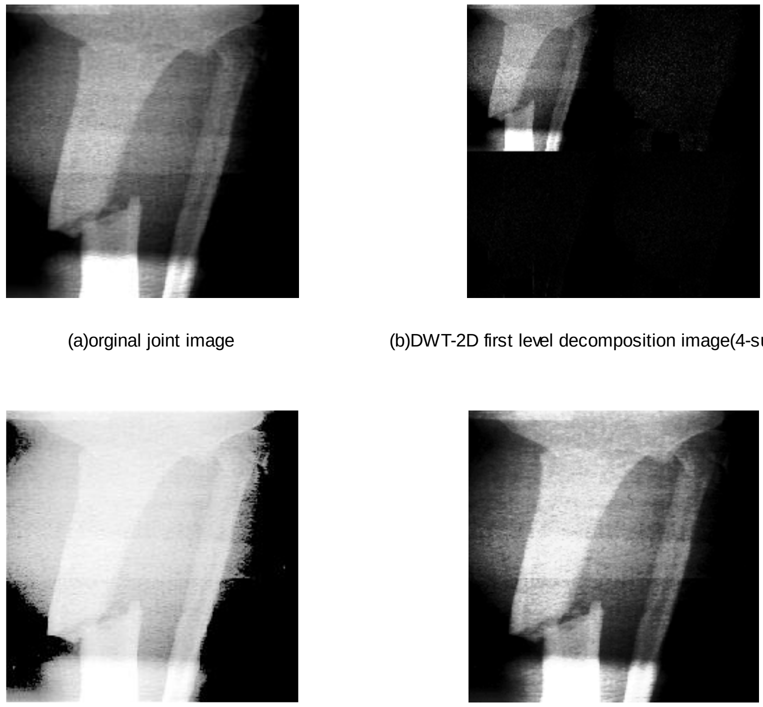


Fig. (11): Simulation result for image called Jaw.



(a)orginal joint image

(b)DWT-2D first level decomposition image(4-subbands)

(c)approximation coefficients contrast enhancement

(d)Histogram equilized image in (c)

Fig. (12): Simulation result for image called Joint.

To evaluate the contrast enhancement performance of proposed method, by count the following two evaluation parameters mentioned in[12]:

$$C = \frac{\sigma_{out} - \sigma_{in}}{\sigma_{in}} \qquad \text{.....(24)}$$

$$I = \frac{\bar{I}_{out} - \bar{I}_{in}}{\bar{I}_{in}} \qquad \text{.....(25)}$$

Where σ_{out}, $\bar{I}_{out}$ are the variance and average of the intensity value of the output image and σ_{in}, $\bar{I}_{in}$ are those of the input image.

$$\bar{I}_x = \sum_{g_x=0}^{L_g-1} g_x \, p(g_x) \qquad \text{.....(26)}$$

$$\sigma_x = \sqrt{\sum_{g_x=0}^{L_g-1} (g_x - \bar{I}_x)^2 \, p(g_x)} \qquad \text{.....(27)}$$

Where L_g= gray level range, g_x=gray level value in any region of interest in image, $p(g_x)$ =probability of occurrence of that gray level in region of interest, $\bar{I}_x$ =Mean value of gray levels in region of interest, finally σ_g= standard deviation of gray levels in region of interest.

Table (2): Simulation results.

Image	Leg	Brain	Backbone	Jaw	Joint
Contrast Increment Ratio	176.5%	17.59%	95.10%	76.49%	92.14%
Mean increment Ratio	341.9%	14.71%	21.48%	15.63%	64.48%
Beta (β)	9	3	6	6	9
Alpha (α)	18	6	12	12	18

From table (2) C = 1.765 and I = 3.419, which means the contrast is increased by 176.5% and the mean is increased by 341.9%, are obtained for the image called Leg. Similarly, the values for C and I for Brain image, backbone, Jaw and Joint are C = 0.1759 and I = 0.14, C = 0.95 and I = 0.21, and C = 0.76 and I = 0.15, C = 0.92 and I = 0.64 respectively. The experimental result shows that our contrast enhancement method can successfully enhance the X-ray images. According to simulation results for images, the results of proposed method conserve useful information.

5. Conclusion

This paper has proposed a contrast enhancement method that uses approximation component enhancement on wavelet transform domain: more specifically, proposed Sigmoidal contrast enhancement function, with two degree of freedom based on human visual system for the approximate component coefficients obtained by the Wavelet transform. Increasing α, and β results in enhancing and lightening the LL image in transform domain, but when increasing the control values α and β, saturation could occurs. The Saturation components are enhanced by histogram equalization. It turns out that the proposed wavelet based contrast enhancement method can achieve a successful enhancement of X-ray images, which are dark, or with low contrast.

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تحسين التباين للصور الطبية قليلة الوضوح باستخدام التحويل المويجي والتحويل اللاخطي

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جامعة صلاح الدين

الخلاصة

في هذا البحث تم اقتراح طريقة جديدة لتَحسين تباين الصورِ الطبيةِ مستندة على Wavelet Transform(DWT-2D).حيث يتيح تحويل المويجة تمثيلا كفوء للإشارة، بالاعتماد على خواصه الفريدة التي تشتمل على المعالجة البسيطةِ فيtransform domain ، والتحليل متعدّد الحزم يُمْكِنُ أَنْ يُحل الكثيرِ من مشاكلِ معالجة الصور بأداءَ وكفاءةَ رائعةَ .يتم تطبيق تحويل المويجة ذو البعدين لكل وحدة في الصور رمادية التدرج اللوني مما يؤدي إلى تجزاتها إلى المكوّنِ التقريبيِ ومكوّناتِ التفصيلِ. إنّ المعاملاتَ المكتسبةَ للمكوّنِ التقريبيِ تحول إلى الصيغة ال normalized قبل تحوَّيلِها مِن قِبل المحول اللاخطّي للمستويات الرمادية المُقتَرَح الذي يعمل بدرجتين مِنْ الحريةِ، إن اللاخطية يُمْكِنُ أَنْ تؤدي إلى تحسين تباين متوازنِ أكثرِ للصورِ الطبية منخفضةِ الرؤيةِ. تم إجراء Denormalizing للصورة معدلة التباين قبل اخذ ال(Inverse Wavelet transform(IDWT-2D أخيراً، وَجدنَا ان تطبيق ال histogram equalizationعلى نتيجةِ تحويل المويجة المعكوس قد عزز من فعالية الطريقةِ المُقتَرَحةِ التي تم حسابها بشكل تجريبي بقياس نسبةِ التباين والمتوسط للصورِ النَاتِجةِ. وقد كانت نسبة تحسينِ التباين قد تجاوزتُ ١٠٠ % لبَعْض الصورِ الطبية منخفضةِ الرؤيةِ.