MEDICAL COLORED IMAGE ENHANCEMENT USING WAVELET TRANSFORM FOLLOWED BY IMAGE SHARPENING

Dr. Muna F. Al-Samaraie* and Dr. Nedhal Abdul Majied Al Saiyd**

*Management Information System Department
Faculty of Economics and Administrative Sciences
Al-Zaytoonah University, Amman, Jordan
Faik_muna@yahoo.com

**Computer Science Department
Faculty of Information Technology,
Applied Science University, Amman-Jordan
nedhal_alsaiyd@yahoo.com

ABSTRACT

This article proposes a novel method for enhancing and sharpening medical color digital images. Low contrast and poor quality are main problems in the production of medical images. By using the wavelet transforms and Haar transform followed by using the Sobel the Laplacian operator to obtain the sharpened image. First, a medical image was decomposed with wavelet transform. Secondly, all high-frequency sub-images were decomposed with Haar transform. Thirdly, noise in the frequency field was reduced by the soft-threshold method. Fourthly, high-frequency coefficients were enhanced by different weight values in different sub-images. Then, the enhanced image was obtained through the inverse wavelet transform and inverse Haar transform. Lastly, the filters are applied to sharpen the image; the resulting image is then subtracted from the original image. Experiments showed that this method can not only enhance an image's details but can also preserve its edge features effectively.

Keywords: Digital Color Imaging; Wavelet Transform, Haar Transform, Laplacian.

1 INTRODUCTION

Medical image enhancement technologies have attracted much attention since advanced medical equipments were put into use in the medical field. Enhanced medical images are desired by a surgeon to assist diagnosis and interpretation because medical image qualities are often deteriorated by noise and other data acquisition devices, illumination conditions, etc. Also targets of medical image enhancement are mainly to solve problems of low contrast and the high level noise of a medical image. Medical image enhancement technologies have attracted many studies, mainly on grayscale transform and frequency domain transform. Studies of frequency domain transform mainly concentrate on the wavelet transform, and histogram equalization is a quite typical method of image enhancement in the spatial field. The wavelet transform is a time-frequency analysis tool developed in the 1980s, which has been successfully applied in the image processing domain [1].

Image sharpening is one of several steps which enhances both the intensity and the edge of the images in order to obtain the perceive image. The step helps increase the resolution, the detail, as well as the sharpness of the image. In the early steps, before applying the data, image enhancement increases the difference between each object. As a consequence, the object and its edge were identical. In addition, image sharpening is eligible for emphasizing the individual location according to the scope of research [2,3]. The algorithm for sharpening and image segmentation is based on the information of color, color differences between neighbor pixels and geometry of the areas involved.

In this paper, methods of image enhancement based on wavelet transform were proposed. However, we cannot obtain more high-frequency information only through multi-scale wavelet transform. An image's different scale detail information can be obtained through wavelet transform, but there will be some high-frequency information hidden in high-frequency sub-images of wavelet transform. If we decompose these high-frequency sub-images, we can obtained more image high-frequency information which can help us to enhance a medical image effectively. Also, we can obtain a better enhancement image if we use both spatial field and transform field procession to enhance an image. In addition, we should remove or reduce noise for the reason that there are lots of

noises in high-frequency sub-images. Presented in this Letter is a novel approach which is used to enhance a medical image based on wavelet transform, Haar transform and nonlinear histogram equalization.
The structure of the paper is arranged as follows: section 1 included the introduction and section 2 included the methodology of the proposed scheme. The proposed method is explained with many details in Section 3. Section 4 included the results. Conclusions are shown in Section 5.

2 METHODOLOGY

2.1 Image Enhancement

Image enhancement is a process principally focuses on processing an image in such a way that the processed image is more suitable than the original one for the specific application. The word "specific" has significance. It gives a clue that the results of such an operation are highly application dependent. In other words, an image enhancement technique that works well for X-ray topographic images may not work well for MR images.

The technique falls in two categories on the basis of the domain they are applied on. These are the *frequency* and *spatial* domains. The frequency domain methods works with the Fourier Transforms of the image. The term spatial domain refers to the whole of pixels of which an image is composed of. Spatial domain methods are procedures that operate directly on the pixels. The process can be expressed as:

$$g(x, y) = T[\, f(x, y)]$$

Where *f(x, y)* is the input image, *g(x, y)* is the processed image, and *T* is an operator on *f* defined over some neighborhood of *(x, y)* [4]. A number of enhancement techniques exist in the spatial domain. Among these are histogram processing, enhancement using arithmetic, and logical operations and filters.

2.2 Wavelet Transform

The generic form for a one-dimensional (1-D) wavelet transform is shown in Fig. 1. Here a signal is passed through a low-pass and high-pass filter, h and g, respectively, then down sampled by a factor of two, constituting one level of transform. Multiple levels or "scales" of the wavelet transform are made by repeating the filtering and decimation process on the low-pass branch outputs only. The process is typically carried out for a finite number of levels K and the resulting coefficients, $d_{i1}(n)$, $i \in \{1,\ldots,K\}$ and $d_{K0}(n)$, are called wavelet coefficients.

Referring to Fig. 1, half of the output is obtained by filtering the input with filter H(z) and down-sampling by a factor of two, while the other half of the output is obtained by filtering the input with filter G(z) and down-sampling by a factor of two again. H(z) is a low pass filter, while filter G(z) is a high pass filter.

The 1-D wavelet transform can be extended to a two-dimensional (2-D) wavelet transform using separable wavelet filters. With separable filters the 2-D transform can be computed by applying a 1-D transform to all the rows of the input and then repeating on all of the columns. Using the Lena image in Fig. 2a shows an example of a one-level (K = 1), 2-D wavelet transform. The example is repeated for a two-level (K = 2) wavelet expansion in Fig. 2b.

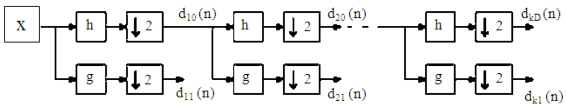
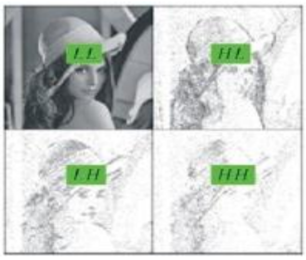
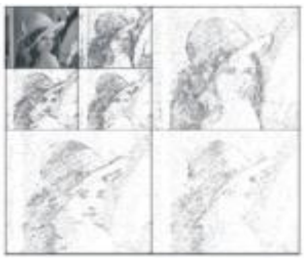


Figure 1: A K-level, 1-D wavelet decomposition.



(a)



(b)

Figure 2: (a) One level wavelet transform in both directions of a 2D signal; (b) Two levels of wavelet transform in both directions

From Fig. 2a subband LL is more important than the other 3 subbands, as it represents a coarse version of the original image. The multi-resolutional features of the wavelet transform have contributed to its popularity.

2.3 Medical Images

Medical images are a special kind of images. These images are used for the diagnostics of diseases in the patients [5, 6]. A number of modalities exist for obtaining these images. Among popular ones are Computed Topographic Imaging (CT), Magnetic Resonance Imaging (MRI), etc. Our focus here will be on the image obtained through Magnetic Resonance Imaging (MRI).

Biologic tissues are comparatively transparent to x-rays and opaque to radiation with intermediate wavelengths when proceeding from the shorter to the longer wavelengths of the electromagnetic spectrum. This is true for ultraviolet, visible, and, to some extent, infrared light and microwaves. However, there is a window in tissue absorption through with radio waves can be used to probe deep inside the human body. The benefits derived from low-energy radiation and unprecedented level of information available from nuclear signals combined to make imaging by magnetic resonance a valuable biomedical imaging modality [7].

Magnetic Resonance Cholangiography (MRC) is an imaging method using a magnetic resonance imaging (MRI) scanner. Because MRC can acquire the pancreatic duct with a high MR signal, it has been widely used for diagnosing diseases of the pancreatic duct, such as calculi and pancreatitis [8]. However, there are some limitations for use of MRC: first MRC images often involve other tissues (e.g., fat, stomach) that have a high MR signal because MRC imaging method gives a high MR signal for water. Therefore, when we generate 2D projected images by means of maximum intensity projection (MIP), volume rendering (VR), or others, those tissues with high MR signal will overlap with the pancreatic duct and secondly, If we use a low-test MRI or a thick slice of imaging parameter to reduce the imaging cost or to be faster the imaging time, some parts of the pancreatic duct will disappear because of a partial volume effect (PVE). Such lacks may impede the physicians' observation, and might lead to a miss-diagnosis that is, the problem is that the MR signal of the pancreatic duct is lower than or equals MR signals of the other tissues. Therefore, use of image enhancement techniques will contribute to overcoming these limitations.

2.4 Sharpening Images

Sharpening techniques improve the clearness of digital images by enhancing the marks of the objects which are present in the scene. This improves their borders and their details, giving to the images greater neatness and depth. In general, the strategy of sharpening is to add to the original array a portion of its gradient [4]. This fraction is usually tuned by a coefficient α, which must be properly designed. If the coefficient is not selected adequately, then grain effect and noise are produced in flat regions also, where edges are absent. The coefficient α is usually selected according to rules of thumb or subjective evaluation of the grain side-effect.

Edge sharpening has been a commonly used approach [9, 10] for visual quality improvement in images. Edges are of primary importance in visual quality perception, because object boundaries are crucial information to the human visual system (HSV), and not surprisingly, the edge sharpness is one positive non-content-related attribute (content-related attributes include people, facial expression, action/fun and so on) towards the HSV. Apart from the dedicated edge-enhancement algorithms, it is desirable to incorporate appropriate contrast enhancement on edges in various image processing tasks (e.g. image reconstruction, post-processing for decompressed images/video). Edge sharpness can be evaluated via estimating local contrast and width/amplitude of lines and edges, based on subband decomposition. In [13], just-noticeable local contrast changes on edges and non-edge pixels have been distinguished in a gauge for visual quality; however, all contrast increase at edges was treated as a positive factor towards visual quality, and excessive edge sharpness and the influence of surroundings were not considered.

The algorithm deals with input images that have been transformed from the standard color space RGB to the device independent color representation HSV. The image is smoothed using the Laplacian filters that approximate the contrast sensitivity functions of the human vision system in the opponent color space. The viewing conditions of the output image displayed on a RGB monitor, i.e. resolution and viewing distance, are similarly taken into account in both works.

We use the Laplacian operator in each channel of the opponent space to obtain the sharpened image, the application of a second derivative or Laplacian operator to the spatially filtered components can be further simplified by introducing the Laplacian of Gaussian (*LoG*) operator. This operator takes advantage of the properties of convolution and derivatives and is widely used as an edge detector with reduced sensitivity to noise. After applying the *LoG* operator, the resulting image is subtracted from the original image component in each opponent channel and then back transformed to the device independent representation space HSV. The output color image appears sharpened. But, this sharpening operation is selective. Edges of big objects, which are preserved with distance, appear enhanced. On the other hand, small details, which are smoothed with distance, are not sharpened.

3 PROPOSED METHOD

Wavelet model: The idea is that we decompose a medical image with wavelet transform at first, and then we decompose high-frequency sub-images with

Haar transform. The nonlinear soft threshold filtering method is used to remove noise, different enhancement weight coefficients in different sub-images are used to enhance an image. The detailed process is as follows.

An image can be seen as a 2D signal, so an image's wavelet transform can be obtained by applying the matlab wavelet toolbox (wavemenu). In the wavelet frequency field, an image's edge feature information and detail information are distributed in high-frequency sub-images. When we decompose an image through wavelet transform of **k** scales, we can get 3k + 1 sub-images:

$$\{\mathbf{LL}_k, \mathbf{HL}_j, \mathbf{LH}_j, \mathbf{HH}_j\}$$

where j = 1, 2, ..., k, k denotes the image's decomposition scale levels of wavelet transform, LL_k denotes the kth scale level low-frequency subimage, and HL_j, LH_j, HH_j denote the jth scale level high-frequency sub-images.

But there is still more detailed information in these sub-images. In order to obtain more image detail information, all high-frequency sub-images are decomposed with Haar transform. This method is simpler than the wavelet packet transform and the general multi-wavelet transform for that Haar transform is the simplest inverse symmetry orthogonal transform and is only used to decompose high-frequency sub-images. It can help us to obtain more detailed information in all level sub-images except low-frequency sub-images here. Also, it is used here to help us to obtain four new sub-images of every high-frequency sub-image of wavelet transform, and they are:

$$\{\mathbf{HL}_{j00}, \mathbf{HL}_{j01}, \mathbf{HL}_{j10}, \mathbf{HL}_{j11}\}$$
$$\{\mathbf{LH}_{j00}, \mathbf{LH}_{j01}, \mathbf{LH}_{j10}, \mathbf{LH}_{j11}\}$$
$$\{\mathbf{HH}_{j00}, \mathbf{HH}_{j01}, \mathbf{HH}_{j10}, \mathbf{HH}_{j11}\}$$

Where j = 1, 2, ..., k, j_{00}, j_{01}, j_{10} and j_{11} denote the position of four sub-images that have been derived from Haar transform. Fig.3 is the high-frequency sub-image's Haar transform.

Figure 3: Image wavelet decomposition and Haar transform of high-frequency sub-images

There is an abundance of image detail information in high-frequency sub-images. But there are also plenty of noises in these sub-images. The wavelet transform's smooth function can help us to reduce an image's noise, but it cannot meet our requirements. Haar transform can also help us to reduce some noise, but still there is much noise in high frequency sub-images. If we enhance high-frequency coefficients at this time, image detail information and noise are all enhanced. We reduce noises of high-frequency sub-images through the nonlinear method. Because the noise properties are different in different high frequency sub-images, different soft thresholds are used to reduce noise in different sub-images. To set the soft threshold

$$T_{jil} = \sigma_{jil}\sqrt{2\log N_{jil}}$$

Where

$$\sigma_{jil} = \sqrt{\frac{1}{N_{jil}}\sum_{k=1}^{N_{jil}}(x_{jil}^k - \bar{x}_{jil})^2}$$

j denotes scale levels, i (i = 1, 2, 3) denote HL, LH, HH high-frequency sub-bands, respectively, and l (l = 00, 01, 10, 11) denote Haar transform sub-images of high-frequency i. N_{jil} represents signal length, x_{ijl}^k are coefficients, and $\vec{x}_{ijl}$ denotes the mean value of the jil sub-image. The formula of reducing noise is

$$G(x,y) = \begin{cases} H(x,y) - T_{jil}, & H(x,y) \geq T_{jil} \\ 0, & -T_{jil} \leq H(x,y) \leq T_{jil} \\ H(x,y) + T_{jil}, & H(x,y) \leq -T_{jil} \end{cases}$$

Where T_{jil} are soft threshold values of the jil sub-image, values of j, i, l are represented in the preceding equation, H(x, y) denotes the high-frequency coefficient of the position (x, y) in the jil sub-image, and G(x, y) denotes the coefficient of the position (x, y) denoised.

After the soft-threshold filter, we enhance high-frequency sub-images by enhancement weight coefficients. Different high-frequency sub images denote different detailed information of an image, So we should enhance different sub-images through different enhancement weight values. Let set weight coefficients be W_{jil}, then we enhance all the high-frequency sub-image coefficients with the following formula:

$$M(G(x,y), W_{jil}) = W_{jil}G(x,y)$$

Where G(x, y) denotes denoised high-frequency coefficients of the ijl sub-image and $M(G(x, y), W_{jil})$ denote enhanced coefficients. Through the inverse wavelet transform and the inverse Haar transform, the enhanced image was generated.

Sharpening model: The new approach sharpening model in this research begins with brightness enhancement. Then follow by edge detection, using the equation below:

$$G_{sc}(x_i, y_i) = f(x_i, y_i) - \nabla^2\{T[f(x_i, y_i)]\}$$

Where:
$G_{sc}(x,y)$ = The new sharpened image
$f(x_i,y_i)$ = The original image
$T[.]$ = The function for contrast enhancement
∇^2 = Laplacian edge detection

The algorithm for this new sharpening technique from above equation was as shown in Fig. 4. We performed an edge detection process with Laplacian and Sobel. The algorithm of this technique was processed according to the sharpening model, which on the first stage, the color information of the digital image are transformed into grayscale image. Then, linear contrast stretch approaches to enhance the brightness of the image. The image is then edge detected by finding the second derivative of the Laplacian or Sobel method. Finally, increase the sharpness of the image by subtracting the result with the original image.

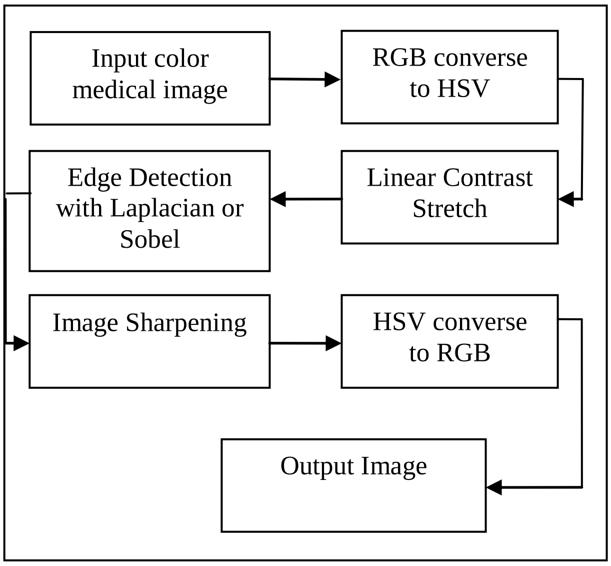


Figure 4: Algorithm diagram for medical image sharpening

RGB to HSV conversion: The obtainable HSV colors lie within a triangle whose vertices are defined by the three primary colors in RGB space (Fig. 5). The hue of the point P is the measured angle between the connecting P to the triangle center and line connecting RED point to the center of the triangle. The saturation of the point P is the distance between P and triangle center. The value (intensity) of the point P represents height on the line perpendicular to the triangle and passing through its center. The grayscale points are situated onto the same line. The conversion formula was as follows:

$$H = \cos^{-1}\left\{\frac{\frac{1}{2}[(R-g)+(R-b)]}{\sqrt{(R-g)^2+(R-b)(G-b)}}\right\}$$

$$S = 1 - \frac{3}{R+G+B}[\min(R,G,B)]$$

$$V = \frac{1}{3}(r+g+b)$$

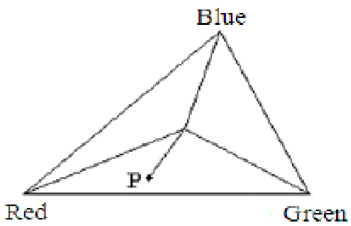


Figure 5: Obtainable HSV color from RGB color space

HSV to RGB conversion: Conversion from HSV space to RGB space is more complex. Particularly, given to the nature of the hue information, we obtained different formula for each sector of the color triangle.

Red-green sector: for $0° < H \le 120°$:

$$b = \frac{1}{3}(1-s),\ r = \frac{1}{3}\left[1 - \frac{S\cos H}{\cos(60° - H)}\right],\ g = 1 - (r-b)$$

Green-blue sector: for $120° < H \le 240°$:

$$r = \frac{1}{3}(1-s),\ g = \frac{1}{3}\left[1 + \frac{S\cos H}{\cos(60° + H)}\right],\ b = 1 - (r+g)$$

Blue-red sector: for $240° < H \le 360°$:

$$g = \frac{1}{3}(1-s),\ b = \frac{1}{3}\left[1 + \frac{S\cos H}{\cos(60° - H)}\right],\ r = 1 - (g+b)$$

Linear contrast stretch: This technique modifies the linear contrast stretch that was related to the value transformation of the brightness part of the image. It can be measured by the lowest value of the brightness contrast (grey level = 0) to the highest value of the brightness contrast (grey level = 255) to full the grey scale level. A brightness value of between 0-255 would be spread out and could be calculated with the equation below ([11]):

$$g(x,y) = T[f(x,y)]$$

If:
g(x,y) = A brightness value of the area in the image at the exit
f(x,y) = The brightness value of the area at the entrance
T = The function for the linear transformation

Edge detection: Edge detection is generally to define edges of the object inside the image. Edges can be found when the difference between luminance intensity from one point to the other appears. Practically, the more difference of light luminance, the edges are easier to define. In contrast, the lesser the difference the harder the edges can be define. Edge detection evaluates the brightness of each area with difference luminance.

The filtering technique in this research was performed by using Laplacian and Sobel technique, due to its evaluation capacity which filters the image constantly and spontaneously. This technique faces several limitations i.e., adding thick layers to the edges due to its slope from the result of first derivative computation at different grayscale level; from highest to lowest or conversely opposition. In addition, the result of the first derivative leads to the incorrect grayscale level from the original. By computing the second derivative we obtain Laplacian method which was proven to have a better filtering result than the first method. This method separates the thin layers of the area and determines the differences of each pixel accurately. Therefore, the benefits of the Laplacian method completely outweigh those of gradient edge detection the equation is as follows:

$$\nabla^2 f(x,y) = f(x+1,y) + f(x-1,y) + f(x,y+1) + f(x,y-1) - 4f(x,y)$$

Edge detection with Laplacian has limitations as well. The kernel is another important circumstance to determine the most suitable kernel for the pixels filtered. Sobel is considered a well replacement of Laplacian filter. According to the Sobel characteristics, the total factor of the filter equals to zero which in certain cases it can reduce the overflow problematic [12]. In digital images f(x,y), Sobel operator, S(x,y) in the convolution procedure and image were set to as the coefficients below:

$$A = [f(x-1,y+1) + 2f(x-1,y) + f(x-1,y-1)] - [f(x-1,y+1) + 2f(x+1,y) + f(x+1,y-1)]$$

$$B = [f(x-1,y-1) + 2f(x,y-1) + f(x,y-1)] + [f(x+1,y-1) + 2f(x,y+1) + f(x+1,y+1)]$$

$$S_m(x,y) = (A^2 + B^2)^{1/2}$$

Where:
A = The elements in the first and third column
B = The elements in the first and third row
After estimating above equation, we obtain:

$$S_m(x,y) \approx A+B$$

The Sobel kernel which filters the edge of the image is shown in Fig. 6. Each components placed in the kernel were the weighting factor of the output pixel.

$$\begin{matrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{matrix} \qquad \begin{matrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{matrix}$$

(a) (b)

Figure 6: Sobel operator mask (a) weight factor element in A (b) weight factor element in B

The edge detection evaluation S (x.y) and position (x,y) may need a suitable threshold level. However, specifying the threshold level may perform lost of edge in certain parts of the image which the level is lower than the threshold. Separating the overflow information would affect the value which we can reduce the results by dividing by the scale-factor. As a consequence, the grayscale evaluation obtains a better result than binary evaluation, as the equation expressed below, when; k refers to a constant of the scale-factor:

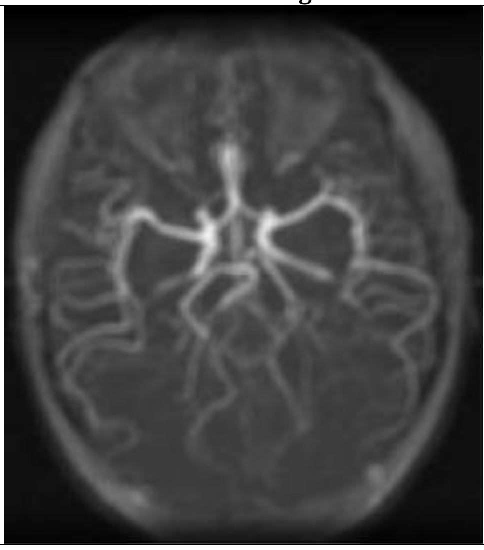
$$S_m(x,y) = (A^2 + B^2)^{1/2} / k$$

$$S_m(x,y) \approx (A+B)/ k$$

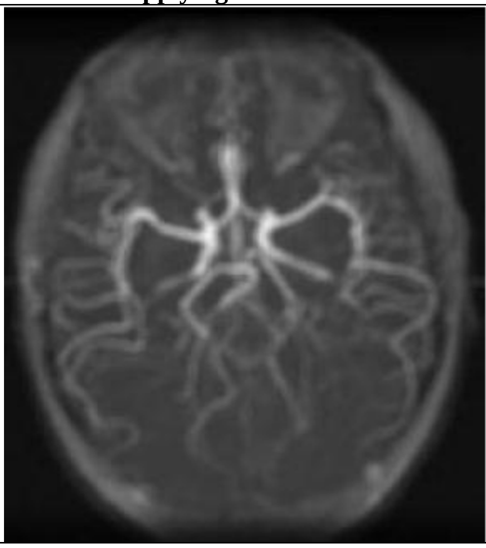
4 RESULTS

The proposed scheme is used to enhance the medical image. We use two level wavelet transform here. The enhancement weight coefficient is 1.8. Fig. 7 shows experiment results. Figs 7a is a main image, Figs. 7b is image after applying Wavelet transform via the proposed algorithm, Figs. 7c is the results of convert the image to gray, Fig. 6d is the result of applying linear contrast stretching, Fig 6e is the result of applying Laplacian filter and Fig 6f is the final result after edge sharpening. The PSNR value of Fig. 7b is 39.64, and of Fig. 7d 30.26, the PSNR value of Fig. 7e is 70.53, and that of Fig. 7f is 45.53. From the enhanced results, enhanced images with the method proposed are better than results with histogram equalization.

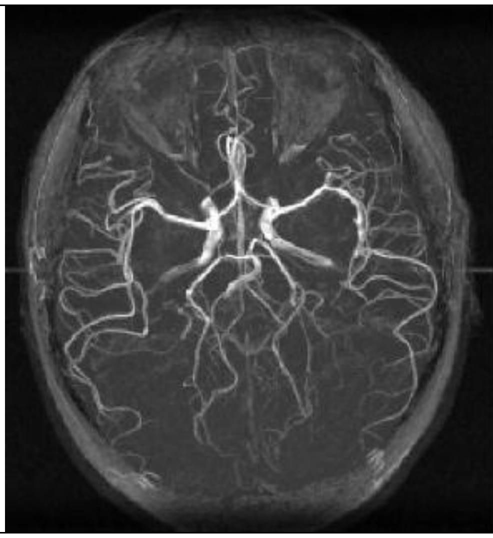
a. Main image



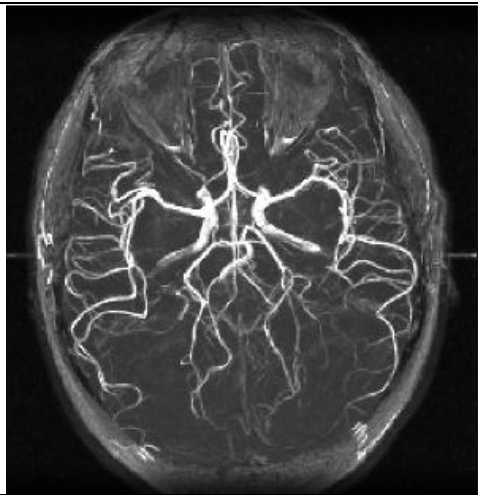
b. After applying Wavelet Transform



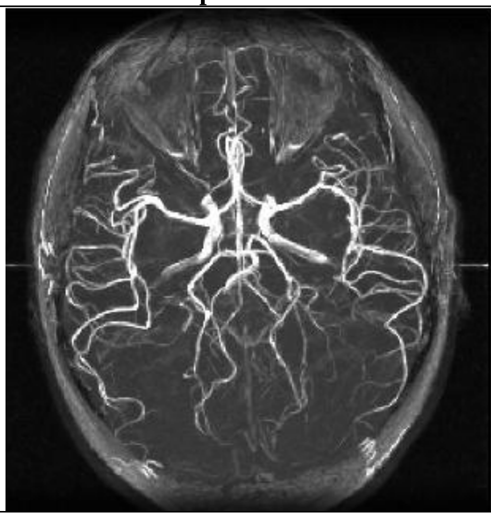
c. After convert to Gray



d. Linear contrast stretch



e. Laplacian Filter



f. Edge Sharpening

Figure 7: Medical image enhancement experiments

4 CONCLUSION

An important problem of medical image enhancement based on wavelet transform is how to extract high-frequency information. Haar transform is used to decompose the high-frequency sub-images of wavelets in this algorithm. This helps us to extract high-frequency information effectively. Different enhancement weight coefficients in different sub-images and Edge sharpening are used in the process of medical image enhancement. They can also help us to enhance a medical image effectively. Results of experiments show that the algorithm not only can enhance an image's contrast, but also can preserve the original image's edge property effectively. We use two level wavelet transform to decompose an image. The level of wavelet decomposition is preferably not more than four times for reasons of soft threshold filtering.

The sharpening method procedure was experimented with additional steps. We first transform the image from color image into grayscale, then begin edge detecting with Laplacian technique. The edge detected image is then subtracted from the original image. The result of the image was as expected; indicates its high quality after the enhancement process was performed. In the formal way, the final step which subtract the original image with the edge detected image benefits the scenery of the image and color is enhanced. In conclusion, the prototype enhancement procedure and the novel enhancement procedure indicates that proceeding with Laplacian filtering technique provide a more expedient result than of the Soble filtering technique

5 REFERENCES

[1] Mallat, S.G.: 'Multifrequency channel decompositions of image and wavelet models', IEEE Trans. Acoust. Speech Signal Process., 1989, 37, (12), pp. 2091–2110

[2] Alparone, L., L. Wald, J. Chanussot, C. Thomass and P. Gamba et al. Comparison of pansharpening algorithms: Outcome of the 2006 GRS-S data-fusion contest. IEEE Trans. Geosci. Remote Sens., 2007, 45: 3012-3021. DOI: 10.1109/TGRS.2007.904923

[3] Welsh, T., M. Ashikhmin and K. Mueller, Transferring color to greyscale images. ACM Trans. Graph., 2002, 21: 277-280. DOI: 10.1145/566570.566576

[4] Gonzalez, R. C. and Woods, R. E. Digital Image Processing. (2nd ed). Addison-Wesley Longman Publishing Co., Inc. 2001.

[5] He, Huiguang; Tian, Jie; Zhao, Mingchang; Xue, Jian; Lu, Ke, "3D Medical Imaging Computation and Analysis Platform", IEEE International Conference on Industrial Technology ICIT, Dec. 2006, Vol., Iss., 15-17, pp. 1160-1165.

[6] Latha Parthiban; R. Subramanian, "Medical Image Denoising using X-lets", Annual India Conference, Sept. 2006, Vol., Iss., pp. 1-6.

[7] D.Stark and W.Bradley Jr., Ed. Magnetic Resonance Imaging, St. Louis, MO: Mosby, 1992.

[8] Y. Watanabe, M. Dohke, T. Ishimori, Y. Amoh, K. Oda, A-Okumura, K. Mitsudo, and Y. Dodo, High-resolution MR cholangiopancreatography, Critical Rev Diagno Imaging, 39 (1998), 111–258.

[9] Michael J. Greaney, Douglas C. Hoffman, David F. Garway-Heath, Mamdouh Nakla, Anne L. Colemna, and Caprioli, "Comparison of Optic Nerve Imaging Methods to Distinguish Normal Eyes from Those with Glaucoma", IOVS, 2002, **43** (1), 140- 145

[10] Huiqi Li, and Opas Chutatape, "Automated Feature Extraction in Color Retinal Images by a Model Besed Approach", IEEE Transaction on Biomedical Engineering 2004, **51** (2), 246-254

[11] Xu, D. and R. Wang, An improved FoE model for image deblurring. Int.J. Comput. Vis., 2009, 81: 167-171. DOI: 10.1007/s11263-008-0155-3

[12] Yan, X., L. Kai-Yang, Y. Xuan-Dong, W.X. Fang and Z.X. Lin et al. The application of the edge sharpening operator to the breast near infrared. Wuhan Univ. J. Nat. Sci., 2002, 7: 421-425. DOI: 10.1007/BF02828241

[13] Zhang X, Wandell B A, "A spatial extensión to CIELAB for digital color image reproduction," Soc for Info Disp Symp Tech Digest 1996; 27:731-734.