

## Medical Image Enhancement Algorithm Using Edge-Based Denoising and Adaptive Histogram Stretching

Seungjong Kim<sup>1</sup>, Byongseok Min<sup>2</sup>, Wongeun Oh<sup>3</sup> and Jooheung Lee<sup>\*</sup>

<sup>1</sup>*Department of Computer Science & Information Systems,  
Hanyang Women's University, Korea*

<sup>2</sup>*Department of Digital Electronic Communications, ChungCheong University, Korea*

<sup>3</sup>*Department of Multimedia Engineering, Sunchon National University, Korea*

<sup>\*</sup>*Department of Electronic & Electrical Engineering, Hongik University, Korea  
jkim@hywoman.ac.kr, min@ok.ac.kr, owg@sunchon.ac.kr, joolee@hongik.ac.kr*

### Abstract

*In the production of medical images, noise reduction and contrast enhancement are important methods to increase qualities of processing results. Wavelet transforms have shown promising results for localization in both time and frequency, and hence have been used for image processing applications including noise removal. By using the edge-based denoising and adaptive nonlinear histogram stretching, a novel medical image enhancement algorithm is proposed. First, a medical image is decomposed by wavelet transform, and then all high frequency sub-images are decomposed by Haar transform. At the same time, edge detection with Sobel operator is performed. Second, noises in all high frequency sub-images are reduced by edge-based soft-threshold method. Third, high frequency coefficients are further enhanced by adaptive weight values in different sub-images. Through the inverse Haar transform and the inverse wavelet transform, the enhanced image is obtained. Finally, the proposed adaptive nonlinear histogram stretching method is applied to increase the contrast of resultant image. Experimental results show that the proposed algorithm can enhance a low contrast medical image while preserving edges effectively without blurring the details.*

**Keywords:** *wavelet transform, denoising, soft-threshold, nonlinear histogram stretching*

### 1. Introduction

Medical imaging is related with the technique and process used to create images of the human body, parts, and function for clinical purposes or medical science. It plays a role in modern diagnosis, and is useful in helping radiologist or surgeons to detect pathologic or abnormal regions. Medical image enhancement techniques are important methods to increase qualities of image processing results. They often used to improve the useful information in an image for diagnosis purposes because medical image qualities are often deteriorated by noise and other data acquisition devices, illumination conditions, etc. The aims of medical image enhancement are mainly to increase low contrast and reduce the high level noises. Medical image enhancement algorithms have been studied mainly on grayscale transform and frequency domain transform. Histogram equalization is the most popular spatial approach for enhancing the contrast of image [1-2]. Histogram equalization may produce the worse quality of result image than that of the original image since the histogram of the result image becomes approximately uniform. Large peaks in the histogram can be caused by uninteresting area. Therefore, histogram equalization may lead to an increased visibility of unwanted image

noises [3]. This means that it does not adapt to local contrast requirement and minor contrast differences can be entirely missed especially when the number of pixels falling in a particular gray level range is relatively small. The image enhancement algorithms based on the wavelet transform are typical method in the frequency domain approaches. Wavelet transform is the improved version of Fourier transform. While Fourier transform is a powerful tool for analyzing the components of a stationary signal, it fails for analyzing the non-stationary signal whereas wavelet transform allows the components of a non-stationary signal to be analyzed. Wavelet transforms have shown promising results for localization in both time and frequency, and hence have been used for image processing applications including noise removal [4-5]. In the literature, many medical image enhancement methods based on wavelet transform have been proposed [6-11]. They have been widely used for the contrast enhancement algorithms by multi-scale edge representation and wavelet analysis together with image sharpening, soft-threshold filtering, histogram specification, nonlinear histogram stretching, *etc.*

In this paper, we propose a novel medical image enhancement algorithm using edge-based denoising and adaptive nonlinear histogram stretching. An image's different scale detail information is obtained by wavelet transform. However, some high frequency information is hidden in the high frequency sub-images. If these high frequency sub-images are decomposed by Haar transform, the more high frequency information can be obtained. If noises in all high frequency sub-images are reduced by edge-based threshold method, then the edges of the enhanced image will be preserving effectively without blurring the details. Since soft-threshold shrinks coefficients above the threshold in absolute value, high frequency coefficients should be further enhanced by adaptive weight values in different sub-images. Through the inverse Haar transform and the inverse wavelet transform, the enhanced image is obtained. However, it is observed that the pixel grayscale range of the enhanced image becomes narrower than that of the original image. To increase the contrast of resultant image, histogram stretching or equalization method is applied. The rest of the paper is organized in the following way. Section 2 provides brief review of the wavelet transform and the Haar transform. Section 3 describes the proposed algorithm while Section 4 presents the results of various experiments conducted. Section 5 concludes the work with future research directions.

## 2. Wavelet Transform

The imaging applications from a wavelet point of view include image matching, segmentation, denoising, restoration, enhancement, compression, and other medical image technologies, *etc.* Wavelets allow complex information such as music, speech, images, and patterns to be decomposed into elementary forms at different positions and scales and subsequently reconstructed with high precision. The term "wavelet" was introduced by Morlet [12]. Later, Mallat [13] proposed the fast wavelet transform. With the appearance of this fast algorithm, the wavelet transform had numerous applications in the signal processing fields. Wavelet denotes a function defined on  $\mathbb{R}$ , which, when subjected to the fundamental operations of shifts (*i.e.*, translation by integers) and dyadic dilation, yields an orthogonal basis of  $L^2(\mathbb{R})$ . That is, the wavelet series expansion of function  $f(x)$  relative to scaling function  $\varphi(x)$  and wavelet function  $\psi(x)$  are defined by Eq. (1).

$$f(x) = \sum_k c_{j_0}(k) \varphi_{j_0,k}(x) + \sum_{j=j_0}^{\infty} \sum_k d_j(k) \psi_{j,k}(x) \quad (1)$$

Where,  $j_0$  is an arbitrary starting scale. Also  $c_{j_0}(k)$  is called the scaling coefficients and  $d_j(k)$  is referred to as the detail or wavelet coefficients. The scaling function  $\varphi(x)$  and

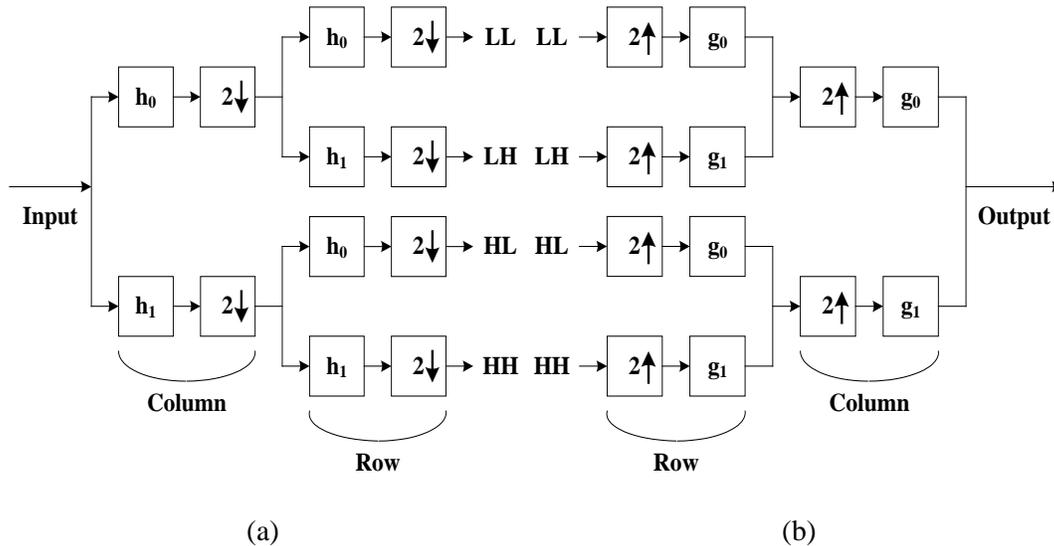
wavelet function  $\psi(x)$  are represented by Eq. (2), where  $k$  determines the position of  $\varphi_{j,k}(x)$  and  $j$  determines  $\varphi_{j,k}(x)$ 's width.

$$\varphi_{j,k}(x) = 2^{j/2} \varphi(2^j x - k), \quad \psi_{j,k}(x) = 2^{j/2} \psi(2^j x - k) \quad (2)$$

Haar wavelet is one of the simplest types of wavelet. The discrete wavelet transform uses the Haar functions in image coding, edge extraction, and binary logic design. Unfortunately, the Haar wavelet transform has poor energy compaction for image, therefore in practice, basic Haar wavelet transform is not used in image compression. The Haar mother wavelet is defined by Eq. (3).

$$\varphi(x) = \begin{cases} 1, & 0 \leq x < 1 \\ 0, & \text{otherwise} \end{cases}, \quad \psi(x) = \begin{cases} 1, & 0 \leq x < 1/2 \\ -1, & 1/2 \leq x < 1 \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

An obvious way to extend Discrete Wavelet Transform (DWT) to the 2-D case is to use separable wavelets obtained from 1-D wavelets. One-level 2-D DWT of an  $N \times N$  image can be implemented using 1-D DWT along the rows, leading to two sub-images of size  $N/2 \times N$ , followed by 1-D DWT along the columns of these two images, resulting in four sub-images of size  $N/2 \times N/2$ . Figure 1 shows this process. The first sub-image obtained by low-pass filtering and subsampling along rows and columns gives the low-pass approximation (LL), and the second one obtained by low-pass filtering and subsampling along rows and high-pass filtering and subsampling along columns gives the first added details corresponding to the vertical edge details (LH), and the third and fourth ones similarly give the horizontal (HL) and diagonal edge details (HH). Reconstruction from these sub-images can be done similar to the 1-D case. The process can be iterated on the low-pass approximation several times as in the 1-D case to obtain finer frequency resolution and perform multi-level 2-D DWT. Figure 2 shows three-level DWT of the Lena image.



**Figure 1. Discrete Wavelet Transform. (a) Decomposition (b) Reconstruction**

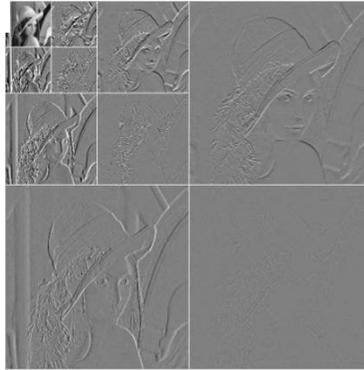


Figure 2. Three-level Discrete Wavelet Transform of the "Lena" Image

### 3. Proposed Algorithm

Block diagram of the proposed algorithm is shown in the Figure 3. First, a medical image is decomposed by wavelet transform, and then all high frequency sub-images are decomposed again by Haar transform. After the wavelet transform and the Haar transform, the signal energy is mostly concentrated in a small subset of the wavelet coefficients, usually along the edges in the image. This feature has been exploited in medical image enhancement algorithms. Therefore, a directional edge detection of the input image with Sobel masks is performed, and a binary edge map from the edge images is obtained. Second, noises in all high frequency sub-images are reduced by edge-based soft-threshold method. Threshold filtering is one of the simplest methods used for the image denoising. Mainly, hard-threshold and soft-threshold techniques are performed. Hard-threshold is a "keep or kill" procedure. However, soft-threshold shrinks coefficients above the threshold in absolute value [14]. Third, therefore, high frequency coefficients are further enhanced by the proposed adaptive weight values in each sub-image. Through the inverse Haar transform and the inverse wavelet transform, the enhanced image is obtained. However, the pixel grayscale range of the enhanced image becomes narrower than that of the original image. Finally, the proposed adaptive nonlinear histogram stretching method is applied to increase the contrast of the resultant image.

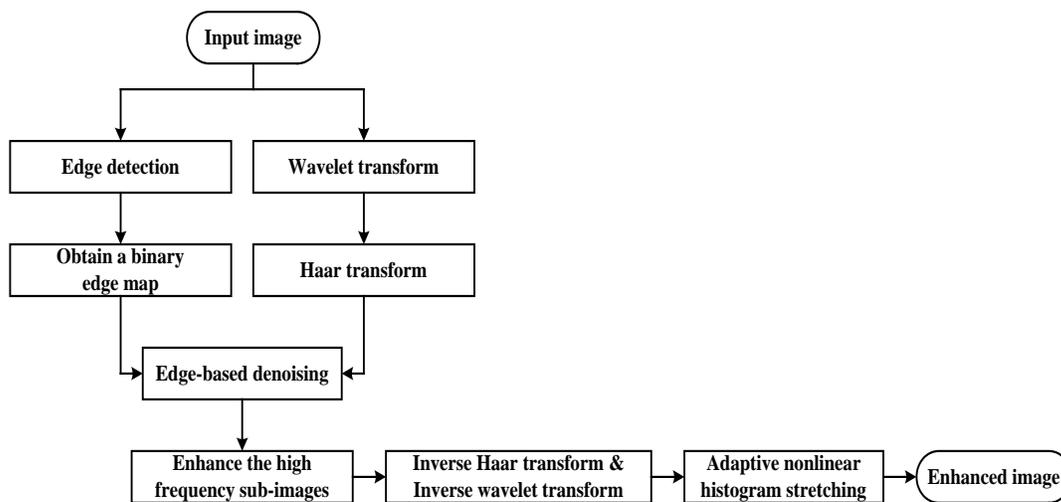


Figure 3. Block Diagram of the Proposed Algorithm

### 3.1. Image Wavelet Decomposition

In the wavelet frequency field, the edge feature of an image and detail information are distributed in high frequency sub-images. An image is decomposed by wavelet transform of  $k$  scales, and then  $3k + 1$  sub-images are produced as below:

$$\{LL_k, HL_j, LH_j, HH_j\} \quad (4)$$

where  $j = 1, 2, \dots, k$ ,  $k$  denotes the decomposition levels of wavelet transform,  $LL_k$  denotes the  $k_{th}$  scale level of low frequency sub-image, and  $HL_j, LH_j, HH_j$  represent the  $j_{th}$  level of the high frequency sub-images, respectively. The high frequency sub-images represent edge components, such as horizontal, vertical, and diagonal directions, and show the self-similarity inherent at different scales. To obtain finer details of an image information, all high frequency sub-images are decomposed again by Haar transform:

$$HL_{j1} = \{HL_{j11}, HL_{j12}, HL_{j13}, HL_{j14}\} \quad (5)$$

$$LH_{j2} = \{LH_{j21}, LH_{j22}, LH_{j23}, LH_{j24}\}$$

$$HH_{j3} = \{HH_{j31}, HH_{j32}, HH_{j33}, HH_{j34}\}$$

where  $j = 1, 2, \dots, k$ ,  $j_{11}, j_{12}, j_{13}$  and  $j_{14}$  denote the position of four sub-images that have been decomposed by Haar transform. Figure 4 shows the Haar transform of the high frequency sub-images.

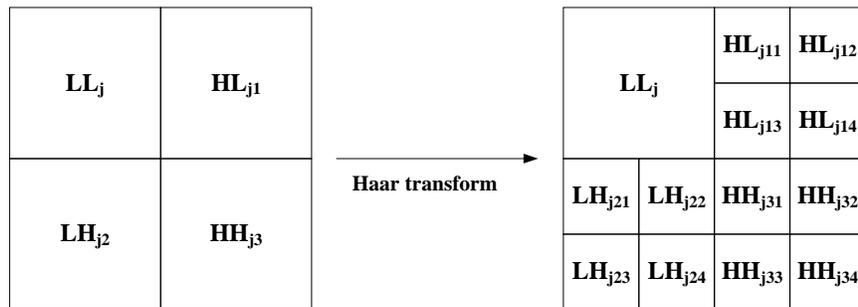
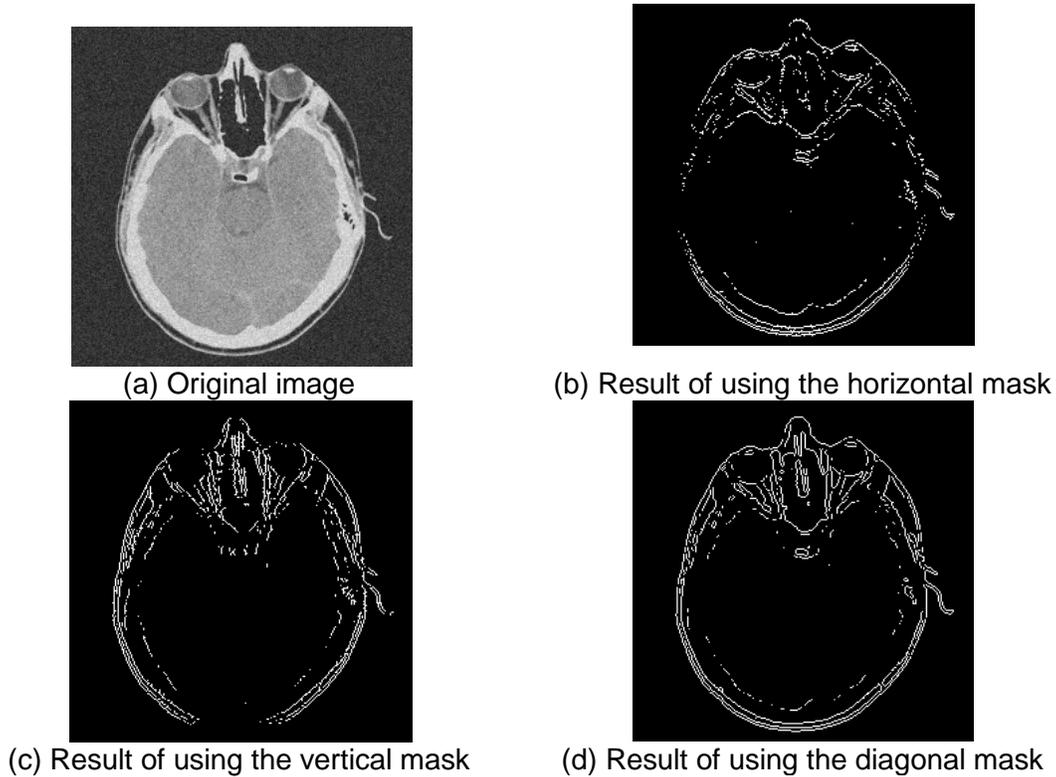


Figure 4. Haar Transform of the High Frequency Sub-images

### 3.2. Edge Detection

After the wavelet transform and the Haar transform, the signal energy is mostly concentrated in a small subset of the wavelet coefficients, usually along the edges in the image. This feature has been exploited in medical image enhancement algorithms. In this paper, therefore, the horizontal, vertical, and diagonal Sobel masks are applied to the original image, respectively, and then the binary edge patterns are obtained. Compared to other edge operators, Sobel has two main advantages: First, due to the introduction of the average factor, it has some smoothing effects to the random noise of the image. Second, because it is the differential of two rows or two columns, so the elements of the edges on both sides are enhanced so that the edge seems thick and bright. To apply denoising technique for the high frequency sub-images, we obtain each binary edge map from the detected edge images. Figure 5 shows binary edge images. In Figure 5, (a), (b) and (c) show the resultant images using horizontal, vertical, and diagonal Sobel masks, respectively. The binary edge map to reduce noise of the high frequency sub-images in level-1 scale is produced by investigating

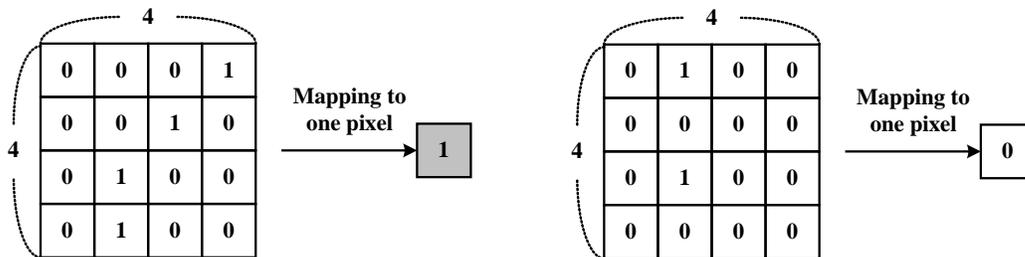
one or more consecutive 1's within  $4 \times 4$  block. If the  $4 \times 4$  block includes one or more consecutive 1's, it is set to 1 (considered as edge region) as shown in Figure 6. If there is no 1's within the  $4 \times 4$  block, it is set to 0 (considered as flat region). To iterate this approach for the high frequency sub-images in level-2 scale, we investigate one or more consecutive 1's within  $8 \times 8$  block, and so on.



**Figure 5. Edge Detection with Sobel Operators**

**3.3. Edge-based Denoising**

While there is much edge feature and detail information in high frequency sub-images, there are also plenty of noises in these sub-images. Wavelet transform can be used for denoising applications.



**Figure 6. Examples of Generating the Binary Edge Map. Left: In Case of the Edge Region. Right: In Case of the Flat Region**

The idea is that noises commonly manifest itself as fine-grained structure in an image, and the wavelet transform provides a scale-based decomposition, hence most of the noise tends to

be represented by wavelet coefficients at the finer scales [14]. However, there is still much noise in high frequency sub-images. If the high frequency coefficients are enhanced by any enhancement method, not only image detail but also noise are all enhanced. To reduce noises of high frequency sub-images, soft-threshold filtering method is proposed by Yang [15]. But the edge-related coefficients are also reduced in the input image with almost dark pixels. Because the noise properties are different in each high frequency sub-images, different soft-thresholds are needed to reduce noise. We, therefore, propose a new soft-threshold filtering method based on binary edge map. Let the threshold  $\lambda_{jil}$  is defined by Eq. (6).

$$\lambda_{jil} = m_{jil} \sqrt{2 \log N_{jil}} \quad (6)$$

where  $j$  denotes scale levels,  $i$  ( $i = 1, 2, 3$ ) denotes HL, LH, HH high frequency sub-images, respectively, and  $l$  ( $l = 1, 2, 3, 4$ ) denotes sub-images of high frequency  $i$  decomposed by Haar transform.  $N_{jil}$  represents number of high frequency coefficients in that sub-image.  $m_{jil}$  denotes median value defined by Eq. (7).

$$m_{jil} = \text{median}(x_{jil}^k), \quad k = 1, 2, \dots, N_{jil} \quad (7)$$

where  $x_{jil}^k$  denotes the high frequency coefficients. The proposed denoising method based on binary edge map is represented by Eq. (8). That is, if the position  $(x,y)$  in the  $jil$  sub-image belongs to an edge, denoising process is not performed. On the other hand, if the position  $(x,y)$  does not belong to an edge, different soft-thresholds are used to reduce noise in different sub-images.

$$\left[ \begin{array}{l} \text{if } b(x,y) \text{ is equal to } 1, \text{ then } g(x,y) = h(x,y) \\ \text{if } b(x,y) \text{ is equal to } 0, \text{ then } g(x,y) = \begin{cases} h(x,y) - \lambda_{jil}, & h(x,y) > \lambda_{jil} \\ 0, & -\lambda_{jil} \leq h(x,y) \leq \lambda_{jil} \\ h(x,y) + \lambda_{jil}, & h(x,y) < -\lambda_{jil} \end{cases} \end{array} \right. \quad (8)$$

Here,  $b(x,y)$  denotes binary edge map of the position  $(x,y)$  in the  $jil$  sub-image,  $h(x,y)$  denotes the high frequency coefficient of the position  $(x,y)$  in the  $jil$  sub-image, and  $g(x,y)$  represents the denoised coefficient of the position  $(x,y)$ .

### 3.4. Enhancement of the High Frequency Sub-images

Soft-threshold approach shrinks coefficients above the threshold in absolute value. High frequency coefficients should be further enhanced by different weight values in the  $jil$  sub-image. Let the weight value be  $w_{jil}$ , then all the high frequency coefficients are enhanced by Eq. (9).

$$e(x,y) = w_{jil} g(x,y) \quad (9)$$

where  $g(x,y)$  denotes denoised high frequency coefficients of the  $jil$  sub-image,  $e(x,y)$  represents enhanced coefficients, and  $w_{jil}$  is defined by Eq. (10).

$$w_{jil} = 1 + \frac{|\sigma_{jil} - \hat{\sigma}_{jil}|}{\sigma_{jil}} \quad (10)$$

where  $\sigma_{jil}$  denotes standard deviation before denoising of the high frequency coefficients in the  $jil$  sub-image and  $\hat{\sigma}_{jil}$  denotes standard deviation of the denoised high frequency

coefficients. If the difference of the standard deviation between denoised coefficients and coefficients before denoising is small, relatively small weight values are applied to enhance the high frequency coefficients in the *jil* sub-image.

### 3.5. Adaptive Nonlinear Histogram Stretching

Through the inverse Haar transform and inverse wavelet transform, the enhanced image is generated. However, the pixel grayscale range of the enhanced image becomes narrower than that of the original image. Moreover, due to the relatively low contrast in the enhanced image, it sometimes becomes visually unclear. To stretch the grayscale range, the nonlinear histogram stretching method is proposed by Yang [15]. However, the drawback of Yang's method is that poor quality of the image is generated especially when it is applied to the input image with almost low pixel values. To overcome this problem, we propose adaptive nonlinear histogram stretching method which depends on characteristics of the input image. If the maximum intensity of the image has less than 128, an image's pixel of the position  $(x,y)$  is transformed by Eq. (11). If, on the other hand, it has greater than 128, an image's pixel of the position  $(x,y)$  is transformed by Eq. (14). Therefore, the proposed nonlinear stretching method can be adaptively applied to enhance the image's new intensity range by changing parameters  $\alpha$  and  $\beta$  according to the actual requirements.

$$T_1(f(x, y)) = \begin{cases} f(x, y)M_1 / N_1, & f(x, y) \in [0, N_1] \\ (f(x, y) - N_1)(M_2 - M_1) / (N_2 - N_1) + M_1, & f(x, y) \in (N_1, N_2] \\ (f(x, y) - N_2)(255 - M_2) / (f_{\max} - N_2) + M_2, & f(x, y) \in (N_2, f_{\max}] \end{cases} \quad (11)$$

Here,  $f(x,y)$  denotes an image's pixel of the position  $(x,y)$ ,  $T_1(f(x,y))$  denotes the corresponding transformed pixel,  $f_{\max}$  is the maximum intensity of the image,  $N_1$  and  $N_2$  are defined by Eq. (12), and  $M_1$  and  $M_2$  are represented by Eq. (13).

$$N_1 = \frac{\bar{f}(x, y)}{2(\alpha - \beta)}, \quad N_2 = \bar{f}(x, y) + \frac{f_{\max} - \bar{f}(x, y)}{2(\alpha - \beta)} \quad (12)$$

$$M_1 = 1/\alpha, \quad M_2 = M_1 + (255 - M_1) / \beta \quad (13)$$

$\bar{f}(x, y)$  denotes mean value of the image, and  $\alpha$  and  $\beta$  denote control parameters for adaptive nonlinear histogram stretching.

$$T_2(f(x, y)) = \begin{cases} f(x, y)K_1 / N, & f(x, y) \in [0, N] \\ (f(x, y) - N)(K_2 - K_1) / (f_{\max} - 2N) + K_1, & f(x, y) \in (N, f_{\max} - N] \\ (f(x, y) - f_{\max} + N)(255 - K_2) / N + K_2, & f(x, y) \in (f_{\max} - N, f_{\max}] \end{cases} \quad (14)$$

In Eq. (14),  $T_2(f(x,y))$  denotes the corresponding transformed pixel,  $N$ ,  $K_1$  and  $K_2$  are represented by Eq. (15).

$$N = f_{\max} / 4, \quad K_1 = f_{\max} / \alpha, \quad K_2 = f_{\max} / \beta \quad (15)$$

## 4. Experimental Results

To demonstrate the performance of the contrast enhancement, we test the proposed scheme on low contrast medical images. Two level discrete wavelet transform is used. We set the control parameters  $1 < \alpha < 2$  and  $1 < \beta < 1.5$  for adaptive nonlinear histogram stretching. To evaluate performance of the proposed algorithm, we use the change rates of lightness and contrast instead of PSNR. The idea is that good visual representations seem to be based upon some combination of high regional visual lightness and contrast [10, 16]. To compute the regional parameters, the image is divided into non-overlapping blocks that are  $64 \times 64$  pixels. For each block, a mean  $m_f$  and a standard deviation  $\sigma_f$  are computed. The overall lightness is measured by the global mean  $\mu = \bar{m}_f$  which is also the ensemble measure for regional lightness. The overall contrast  $\bar{\sigma}_f$  is measured by taking the mean of regional standard deviations,  $\sigma_f$ . The global standard deviation of the image does not relate to the overall visual sense of contrast. The lightness change rate  $L$  and contrast change rate  $C$  are defined by Eq. (16).

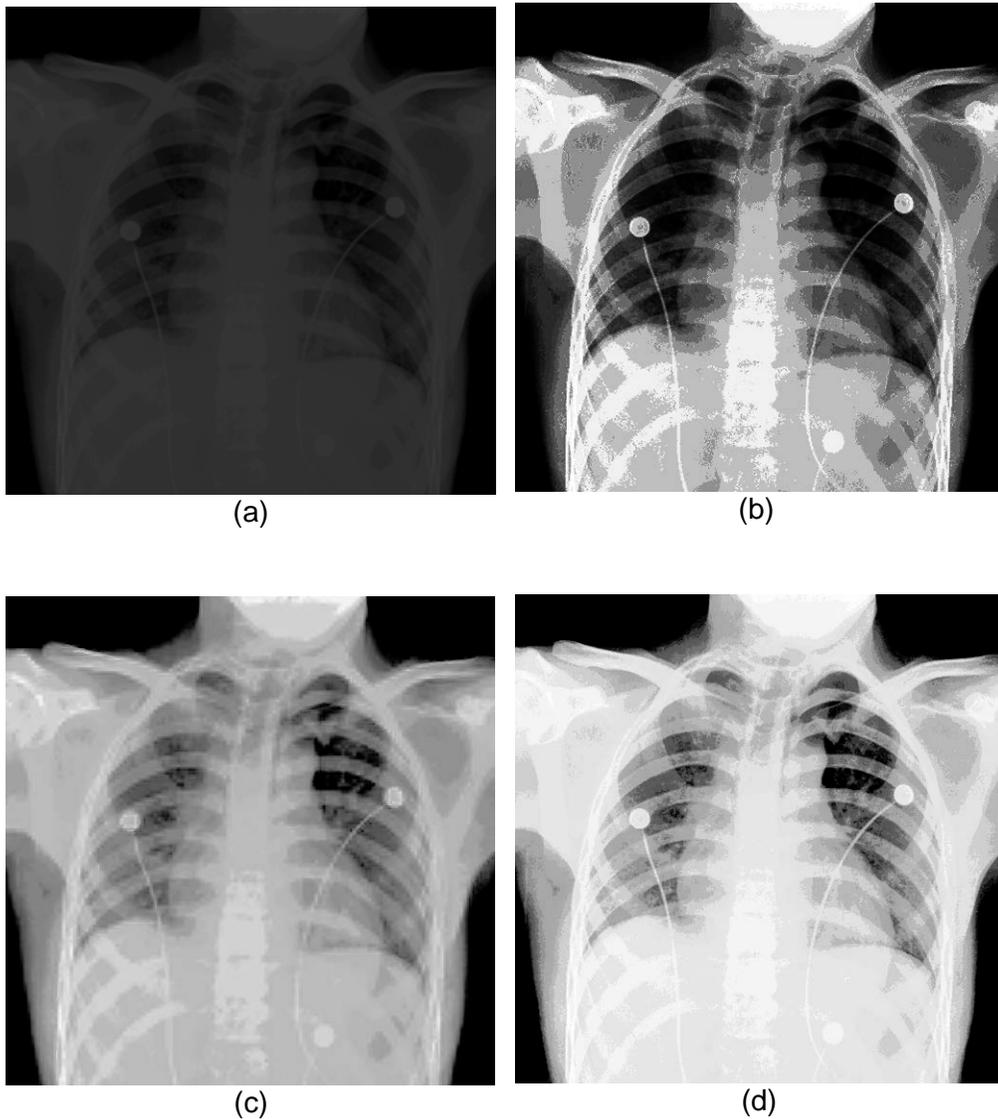
$$C = \frac{\bar{\sigma}_g - \bar{\sigma}_f}{\bar{\sigma}_f}, \quad L = \frac{\mu_g - \mu_f}{\mu_f} \quad (16)$$

where  $\bar{\sigma}_f$  and  $\bar{\sigma}_g$  denote the mean of input and output image's local standard deviations, respectively, and  $\mu_f$  and  $\mu_g$  represent the global mean of input and output images. Figure 7 and Figure 8 show experimental results. We set the control parameters  $\alpha = 1.9$  and  $\beta = 1.1$  for the "chest X-ray" image, and use Eq. (11) to obtain the enhanced image. Also, we set the control parameters  $\alpha = 1.4$  and  $\beta = 1.1$  for the "brain MRI" image, and use Eq. (14) to enhance the low contrast medical image. The results are compared with the General Histogram Equalization (GHE) and existing wavelet-based methods including the proposed algorithm. Figure 7(a) is the original "chest X-ray" image, Figure 7(b) is the result of the GHE, Figure 7(c) is enhanced image of the proposed by Yang [15], and Figure 7(d) is enhanced image by the proposed algorithm. Figure 8(a) is the original "brain MRI" image, Figure 8(b) is the result of the GHE, Figure 8(c) is enhanced image of the proposed by Yang [15], and Figure 8(d) is enhanced image by the proposed algorithm. Experimental results show that the proposed algorithm produces visually better quality of images than the other methods. The proposed algorithm can enhance a low contrast medical image while preserving edges effectively without blurring the details. Table 1 and Table 2 represent results of the contrast and lightness change rates. If the maximum intensity of the image is less than 128 such as the "chest X-ray" image, our algorithm is superior in both contrast and lightness qualities when compared to the other methods. On the other hand, if the maximum intensity of the image is greater than 128 such as the "brain MRI" image, our algorithm outperforms the other methods in terms of the contrast. However, the lightness change rate is lower than the GHE.

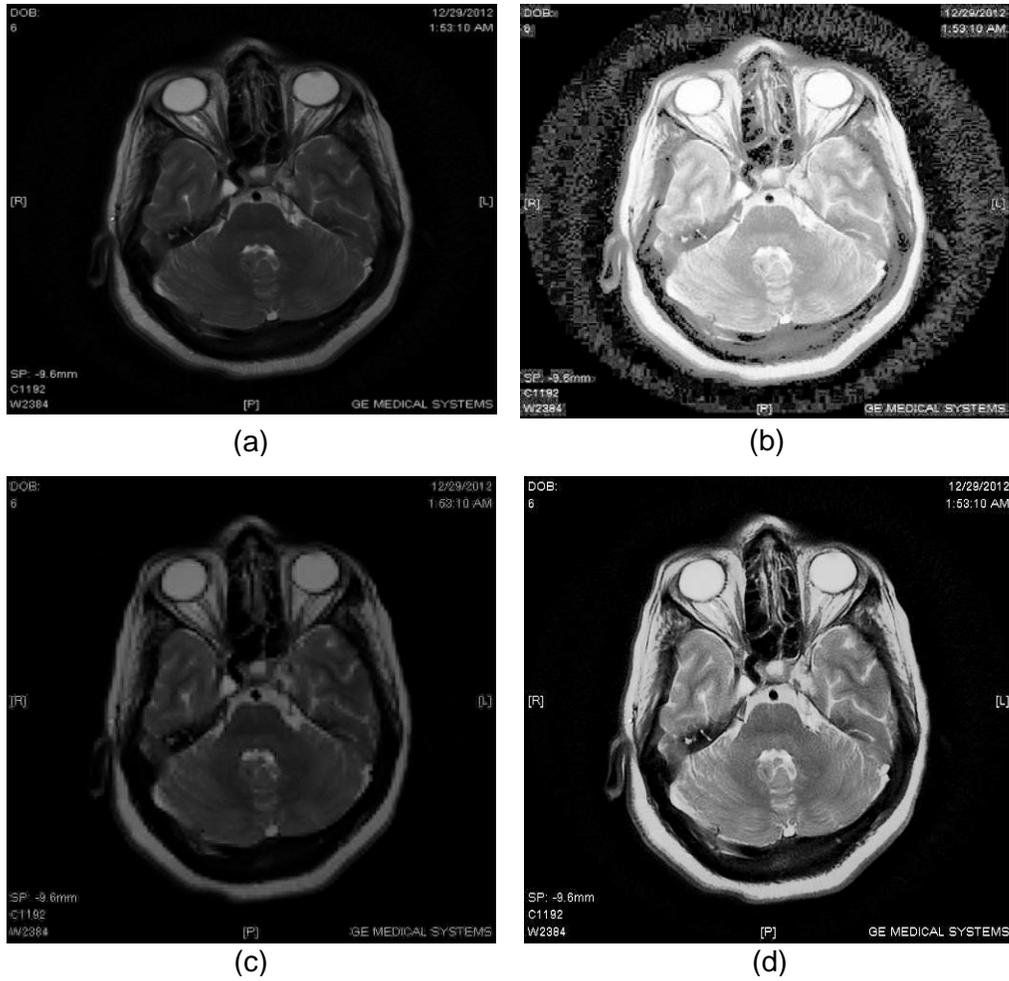
## 5. Conclusion

Medical image enhancement techniques are important methods to increase qualities of image processing results. It is to improve some useful information in an image for diagnosis purposes. The wavelet transform has been used to extract high frequency information effectively. In this paper, a new image enhancement algorithm using edge-based denoising and adaptive histogram stretching is proposed. First, a medical image is decomposed by wavelet transform, and then all high frequency sub-images are decomposed by Haar

transform. Second, noises in all high frequency sub-images are reduced by edge-based soft-threshold method. Third, high frequency coefficients are further enhanced by the proposed adaptive weight values in each sub-image. Finally, the proposed adaptive nonlinear histogram stretching method is applied to increase the contrast and lightness of the resultant image. Experimental results demonstrate that the proposed algorithm shows prominently better performance than the other methods, and can enhance a low contrast medical image while preserving edges effectively without blurring the details. While the proposed approach shows promising results, the current drawback is that the adjustment of the contrast control parameters for the given input image is a difficult process in increasing subjective and objective image qualities. This is the direction to be studied further in the proposed approach.



**Figure 7. Experimental Results of the “Chest X-ray” Image. (a) Original (b) GHE (c) Yang’s Method in [15] (d) Proposed Method**



**Figure 8. Experimental Results of the “Brain MRI” Image. (a) Original (b) GHE (c) Yang’s Method in [15] (d) Proposed Method**

**Table 1. Evaluation Data of the “Chest X-ray” Image**

<i>Method</i>	<i>Contrast change rate (C)</i>	<i>Lightness change rate (L)</i>
GHE	17.206	2.583
Yang’s method [15]	12.972	2.976
Proposed method	<b>20.914</b>	<b>3.971</b>

**Table 2. Evaluation Data of the “Brain MRI” Image**

<i>Method</i>	<i>Contrast change rate (C)</i>	<i>Lightness change rate (L)</i>
GHE	2.978	<b>5.593</b>
Yang’s method [15]	0.198	0.006
Proposed method	<b>3.371</b>	1.480

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## Authors



**Seungjong Kim** received the M.S. and Ph.D. degrees in Electronic Communications Engineering from Hanyang University, Seoul, Korea, in 1994 and 2000, respectively. Since 2000, he is a professor of the Department of Computer Science & Information Systems at Hanyang Women's University, Seoul, Korea. His research interests include digital signal processing, digital communication, and image processing for multimedia applications. He received the ETRI Journal paper award with the "Error Concealment Using Intra-Mode Information Included in H.264/AVC-Coded Bitstream" in January 2009. He received the "49th Annual Trade Day" award from the Prime Minister of Korea in December 2012.



**Byongseok Min** received the Ph.D. degree in Electronic Communications from Hanyang University in 2002, Republic of Korea. Currently, he is a professor of the Department of Digital Electronic Communications at Chung Cheong University, Republic of Korea. Also, His current research interests are image processing, pattern recognition, and multimedia communication.



**Wongeun Oh** received the M.S. and Ph.D. degrees in Electronic Communications Engineering from Hanyang University, Seoul, Korea, in 1992 and 1997, respectively. Since 1997, he has worked at the Sunchon National University, Korea, and currently he is a professor of the Department of Multimedia Engineering at the same university. His research interests include sound systems, audio signal processing, and multimedia systems. He was the recipient of the "Academic Award for Excellence" from the Acoustical Society of Korea in 2012.



**Jooheung Lee** has been working on various topics in the areas of multimedia signal processing algorithms and low power VLSI systems design including image and video coding algorithms, multimedia systems, power aware and reliable VLSI systems design. Previously, he worked at the Wireless Multimedia Communications Laboratory at the R&D Complex of LG Electronics in 1998, where he worked on low power video codec ASIC design for mobile applications. After completing his Ph.D. at the Pennsylvania State University in 2006, he joined the Department of Electrical Engineering and Computer Science at the University of Central Florida, Orlando, Florida, USA, where he was a full-time faculty member. Currently, he is an Associate Professor of the Department of Electronic and Electrical Engineering at Hongik University, Republic of Korea. (**Corresponding author of this paper**)

