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An Optimal Algorithm for Enhancing the Contrast of Chest Images Using the Frequency Filters Based on Fuzzy Logic

Choong-Ho Shin[1] and Chai-Yeoung Jung[2*], *Member, KIICE*

[1]Department of Computer Engineering, Chosun University, Gwangju 61452, Korea
[2]Department of Computer Statistics, Chosun University, Gwangju 61452, Korea

Abstract

Chest X-ray image cannot be focused in the same manner as optical lenses and the resultant image generally tends to be slightly blurred. Therefore, appropriate methods to improve the quality of chest X-ray image have been studied in this paper. As the frequency domain filters work well for slight blurring and moderate levels of additive noises, we propose an algorithm that is particularly suitable for enhancing chest image. First, the chest image using Gaussian high pass filter and the optimal high frequency emphasis filter shows improvements in the edges and contrast of the flat areas. Second, as compared to using histogram equalization where each pixel of chest image is characterized by a loss of detail and much noises, in using fuzzy logic, each pixel of chest image shows the detail preservation and little noise.

Index Terms: Fuzzy logic, Gaussian high-pass filter, High-frequency emphasis filter

I. INTRODUCTION

Early detection of lung tissue abnormalities can help lung patients getting early treatment for their illness. Lung tissue abnormalities that are roughly spherical with a round opacity and a diameter of up to approximately 30 mm are known as lung nodules [1]. To identify these abnormalities, it is essential to improve the visual quality of chest X-ray image. To this end, numerous enhancement methods have been proposed in the literature. Among them, histogram based techniques have been particularly developed to a high degree [2-4].

The histogram modification has many methods such as global histogram equalization (GHE), local histogram equalization (LHE), clipped histogram equalization (CHE), and edge-based histogram equalization [5]. However, these methods have the disadvantage of losing detail and requiring much longer processing time; hence, advanced methods of histogram modification focused on adaptive capabilities.

In this study, we describe two adaptive methods, namely, the gain-controllable clipped histogram equalization (GC-CHE) and the regionally adaptive histogram equalization of chest. The former works that it can avoid noise amplify-cation during the contrast process in that it sacrifices the amount of contrast for controlling noise and for preventing the original intensity level. The latter works that it divides into the three parts which consist of mediastinum, lung, and diaphragm to implement the histogram equalization [6, 7]. Then, these parts showed adaptive enhancements. However, these two adaptive methods have not been optimized as compared to the proposed algorithm (PA).

For one thing, the regionally adaptive method was not studied about the nodules of lung; furthermore, the GC-CHE was not applied to medical image.

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***Corresponding Author** Chai-Yeoung Jung (E-mail: cyjung@chosun.ac.kr, Tel: +82-62-230-6625)
Department of Computer statistics, Chosun University, 309 Pilmun-daero, Dong-gu, Gwangju 61452, Korea.

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Therefore, in this study, we propose the optimal algorithm based on fuzzy logic, which exhibits better contrast capability than many other more complicated filters.

In particular, the Gaussian high-pass filter, the optimal high-frequency emphasis filter, and fuzzy logic are used in this study. The experimental results demonstrate that an improved contrast has dark regions where the local contrast is darker and bright regions where the local contrast is brighter.

The remainder of the paper is organized as follows: Section II describes the high pass filter, the high-frequency emphasis filter, and the fuzzy logic used in this study. Experimental results and conclusions are presented in Sections III and IV, respectively.

II. EXPERIMENTAL SECTION

A. Frequency Domain Filter

First of all, to emphasize the edge of medical image, we have applied a high pass filter: Ideal, Butterworth, and Gaussian. Among them, the Gaussian has shown the most enhanced edge. The low frequency transfer function of Gaussian is:

$$H_{lp}(\mathrm{u,v}) = e^{-D^2(u,v)/2\delta^2}, \quad (1)$$

where δ is standard deviation (SD). The SD is replaced with the cutoff frequency (D_0), the equation is:

$$H_{lp}(\mathrm{u,v}) = e^{-D^2(u,v)/2{D_0}^2}. \quad (2)$$

If the low pass filter is given, the high pass filter is:

$$H_{hp}(\mathrm{u,v}) = 1 - H_{lp}(\mathrm{u,v}). \quad (3)$$

If an input image is applied with low cutoff frequency, the resulting image is degraded. Adversely, the resulting image takes noise. Empirically, we have acquired the optimized value, D_0=0.05 [8, 9].

The resulting image obtained through the high pass filter has an enhanced edge; however, the illumination of background is nearly deprived. To compensate for the shortcoming, we have applied the high frequency emphasis filter as follows:

$$H_{hfe} = a + bH_{hp}(\mathrm{u,v}), \quad (4)$$

where *a* is offset and *b* is constant multiplier. Empirically, as the constant is less than the offset, the enhancement of the low frequency is less than the high frequency [10]; hence, we have taken the optimized value: the offset=2.0, the constant >1.

B. Fuzzy Logic

The image process diagram is shown in Fig. 1. This figure shows the process of the optimal frequency domain filters. But, the resultant image of those filters is inclined to mist. To enhance the contrast of the image, the fuzzy logic is followed.

In fuzzy sets, the process of enhancing the contrast of a grayscale image can be considered to comply with the following rules:

IF a pixel is dark, then make it darker.
IF a pixel is gray, then make it gray.
IF a pixel is bright, then make it brighter.

Therefore, the areas of dark, gray, and bright can be expressed by the membership function (mf) [11]; hereby, the antecedent of the rule is an input and the consequent of the rule is an output. Because of dealing with fuzzy input (mf), so the mf of output has to be defined as well. In the process of inference, the three outputs are used for providing the result corresponding to that rule.

The parameters of mfs are optimized in three inputs (1-Sigma, Triangular, Sigma) and three outputs (Bell1, Bell2, Bell3), shown Fig. 1.

Fig. 2(a) is the mf of one input: the two inputs are adjusted to the only input; that is, the Sigma shape appears in the dark; reversely, the 1-Sigma shape does in the bright. Fig. 2(b) is the mf of the other input whose triangular shape appears in the gray. And Fig. 2(c) is the mf of output whose Bell shape appears in the each of areas (dark, gray, bright).

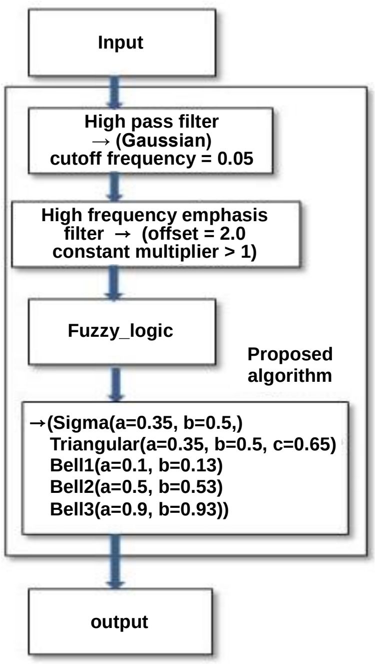

Fig. 1. Block diagram of image enhancement process.

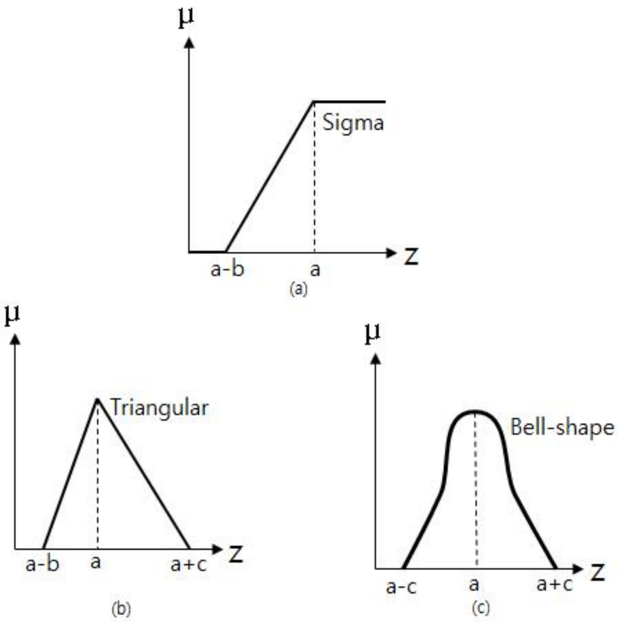

Fig. 2. The membership functions (mfs) of input/output fuzzy sets: (a,b) the mfs of inputs and (c) the mfs of outputs.

The mf of a fuzzy sets(μ(z)) maps all the elements of the set(z) into the real number in [0,1]. The nearer the value of mf is to unity, the higher the membership grade of *z*. The most commonly used mf for input fuzzy set is the sigma function. It is derived as:

$$\mu(z) = \begin{cases} 1-(a-z)/b & a-b \le z \le a \\ 1 & z > a \\ 0 & otherwise \end{cases} \quad (5)$$

where *a*, *b* are the parameters which determine the shape of Sigma function. The two points (*a*, *b*) of mf have to determine the optimized information of dark and bright region.

To improve low contrast, we used histogram equalization; Fig. 3(c) shows the histogram of this result, expanding the entire grayscale increases the contrast but introduces intensities that give the image an "overexposed" appearance. This appearance is so bright that the noises of the image appear. To compensate for the shortcoming, we have to explain the fuzzy logic histogram, shown Fig. 3(b). This histogram has kept the similar form of the histogram of the resultant image of frequency domain filter, shown Fig. 3(a). To the end, it means that the dark scales (peaks in the low end of the histogram) moved left, thus more darkening scales. The opposite was true for bright scales. The mid grey scales were spread slightly.

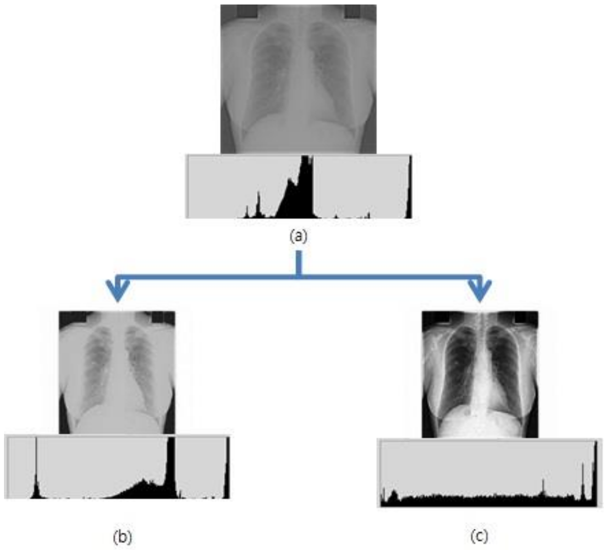

Fig. 3. The histogram comparison of fuzzy logic and histogram equalization: (a) the resultant image of frequency domain filters, (b) fuzzy logic of (a), and (c) histogram equalization of (a).

III. RESULTS AND DISCUSSION

A series of experiments have been performed using the images from the Standard Digital Image Database, Japan; here, nodule 154 and non-nodule 93 on the chest radiogram (CR) verify the PA.

For a quality analysis, homomorphic (Homo), unsharp masking (Unsharp), Kuwahara (Ku), and Nagao (Na) have been compared; that is, two frequency domain filters [12] and two spatial mask filters (see the description below):

- Homo filter: Optical images consist of two primary components, lighting and reflectance. It provides us with the effect of boosting lighting component while reducing the reflectance component.
- Unsharp filter: It is representative of practical image sharpening methods. This process works because subtracting the low frequency image from the high frequency image has the effect of emphasizing the edges. And also, we show that as the low frequency is increased, the resulting image has a greater edge.
- Ku filter: There are the four mask areas where we find the mean and variance. Next, it replaces the mean of the least variance area with the center pixel. Having applied the average values of low frequency components, the resulting image tends to blur.
- Na filter: It is the same as Ku except for having 9 masks. Furthermore, it shows a better boundary preserving than Ku. Consequently, it has the edge preserving and smoothing effect.

As shown in Fig. 4, Homo, Unsharp, Ku, Na, and PA are used to improve the input blurred chest X-ray images.

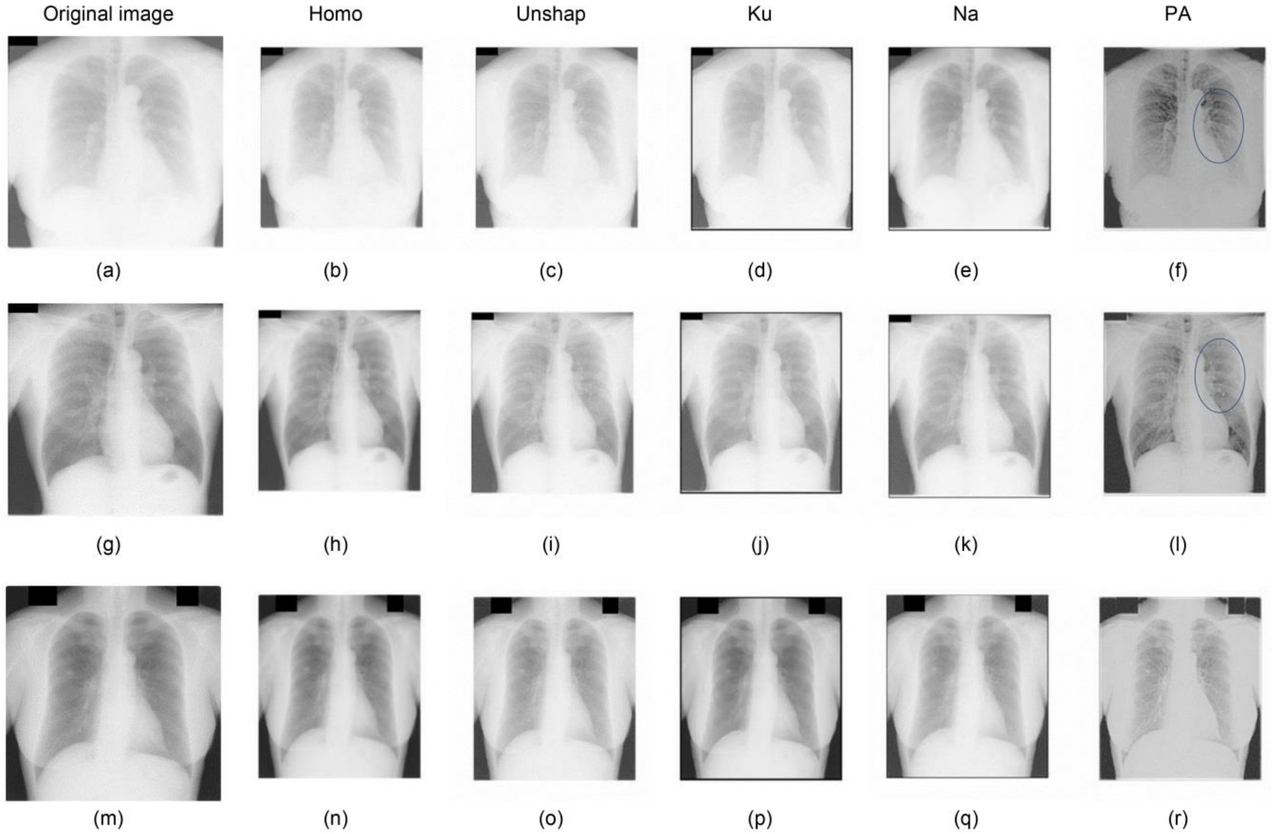

Fig. 4. Simulation results of the large nodule (a–f), the medium-sized nodule (g–l), and the small nodule (m–r).

In Fig. 4(b), (c), (h), (i), (n), and (o), the Homo and Unsharp image are sharpened , but have less contrast than PA, while in Fig. 4(d), (e), (j), (k), (p), and (q), the Ku and Na image are easily identified the nodule with blurring the image, but have less detail than PA. And also, the spatial mask filters require much processing time with computing convolution mask. To conclude, in Fig. 4(f), (l), and (r), the resultant PA image is superior to the resultant images of Homo, Unsharp, Ku, and Na.

Fig. 4(a), (g), and (m) show the original images with a large, medium-sized, and small nodule, respectively, which are blurred with a characteristic X-ray image; hence, the properties of the original images exhibit undesirable faults such as a low signal-to-noise ratio and a low contrast ratio. And so, these are too low quality to distinguish the nodules. In the PA simulation, the large, medium-sized, and small nodules can be clearly seen in the circle shown in Fig. 4(f), (l), and (r).

The mean values listed in Tables 1–3 denote the degree of symmetry of the histogram. The value for the PA image is the closest to 128 (the mid-gray level of a histogram) except for small nodule measure. As a result, the contrast of the PA image is improved with the histogram stretch. The frequency domain resultant image is nearly dark while losing the background contrast. Therefore, using the fuzzy logic, the dark region of it make darker; the bright make more. Consequently, the resultant histogram is symmetrically stretched.

Table 1. Big nodule measures based on histogram

	Mean	SD	Skew
Original	205	43	–2.027
Homo	173	50	–1.730
Unsharp	191	57	–1.753
Na	219	44	–2.040
Ku	218	49	–2.240
Proposed algorithm	171	66	–0.004

Table 2. Middle nodule measures based on histogram

	Mean	SD	Skew
Original	185	48	–1.156
Homo	208	51	–1.249
Unsharp	208	51	–1.275
Na	207	53	–1.250
Ku	205	56	–1.390
Proposed algorithm	178	65	–0.349

Table 3. Small nodule measures based on histogram

	Mean	SD	Skew
Original	171	56	–1.361
Homo	198	60	–1.300
Unsharp	200	60	–1.340
Na	197	64	–1.343
Ku	196	64	–1.343
Proposed algorithm	194	57	–1.050

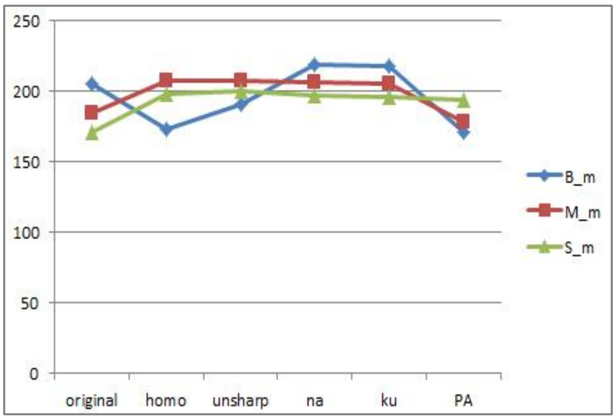

Fig. 5. Comparison of nodules (mean).

The values of the SD listed in Tables 1–3 show that the original image has significantly less variability in intensity levels (i.e., it is smoother) than the five images; hence, it is likely that the one has less contrast than the other five. Due to having the highest value of PA's SD except for the small nodule, it seems to have a high contrast.

The skew is positive if the tail of the histogram spreads to the right, and negative if the tail of the histogram spreads to the left. The values of the skew listed in Tables 1–3 show that the PA has the lowest value, As a result, the PA is the most spread out. Consequently, the distribution of the histogram is dispersed in a large number of different gray levels. Comparing the histogram of the original, the tail seems to be noise. The less is the value of the skew, the less noise is observed.

In Fig. 5, the mean of PA shows its bottom portion of the curve except for small nodule. Consequently, the contrast of these images (Big and Middle) has been increased.

In Fig. 6, the PA shows nearly the top portion of the curve.

In Fig. 7, it can be seen that in the portion of PA, the curve is abruptly very steep. The resultant image of PA has less noise.

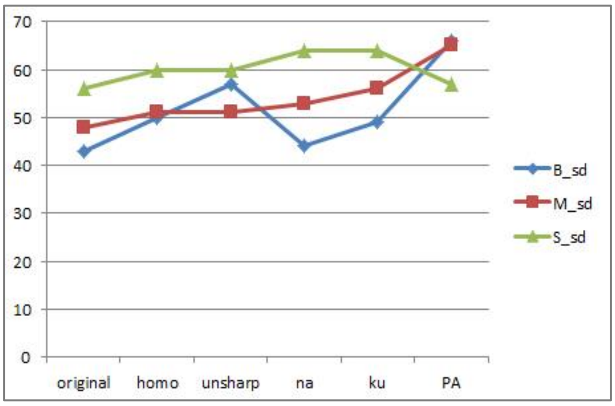

Fig. 6. Comparison of nodules (SD).

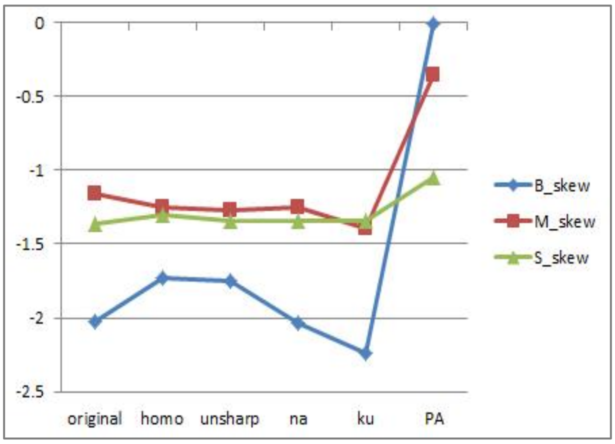

Fig. 7. Comparison of nodules (skew).

IV. CONCLUSION

In this paper, the Gaussian high pass filter and optimal high frequency emphasis filter were used for the X-ray CR image, which appropriates for enhancing with a frequency domain filter.

The Gaussian high pass filter became low in contrast to the background, while enhancing the detail of the image. Therefore, the high frequency emphasis filter which has well-regulated the offset and the multiply constant was followed; however, the resultant image showed the narrow range of histogram. To compensate for this shortcoming, we have applied the fuzzy logic to the resultant image. In conclusion, the use of fuzzy logic showed that the pixels were not lost, and that additional noises did not occur.

The three parameters (a, b, and c) of mfs have been optimized in this paper; for further optimization, statistical analysis should be performed in future research.

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Choong-Ho Shin
received his M.S. degree in 1991 from Department of Computer Applications, Hankuk University of Foreign Studies and his Ph.D. degree in 2004 from Department of Computer Engineering, Chosun University. Currently, he is a Guest Professor at the Department of Computer Engineering, Chosun University. His research interests include image processing and software engineering.

Chai-Yeoung Jung
received his M.S. and Ph.D. degrees from the Department of Computer Engineering, Chosun University, Gwangju, Korea, in 1987 and 1989, respectively. He is currently Professor at the Department of Computer Statistics, Chosun University. His research interests include artificial intelligence, information security, multimedia, multimedia content, and bioinformatics.