International Journal of Fuzzy Logic and Intelligent Systems, vol. 9, no. 3, September 2009 pp. 172-177

Evolutionary Design of Morphology-Based Homomorphic Filter for Feature Enhancement of Medical Images

Heesoo Hwang and Jinsung Oh

School of Electrical Engineering, Halla University, 32, Halladai 1 gil, Wonju, Gangwon, 220-712, Korea

Abstract

In this paper, a new morphology-based homomorphic filtering technique is presented to enhance features in medical images. The homomorphic filtering is performed based on the morphological sub-bands, in which an image is morphologically decomposed. An evolutionary design is carried to find an optimal gain and structuring element of each sub-band. As a search algorithm, Differential Evolution scheme is utilized. Simulations show that the proposed filter improves the contrast of the interest feature in medical images.

Key Words : Morphological filter, homomorphic filter, medical image enhancement.

1. Introduction

The contrast enhancement among adjacent regions or features in medical images is aimed at supporting activities such as disease diagnosis and monitoring, and surgical planning. The wavelet and homomorphic filtering techniques have shown that they are capable of compressing the dynamic range and enhancing the contrast simultaneously[1]-[3]. They concentrate on reinforcing the details of the image to be enhanced in terms of the frequency domain. However, these linear approaches have drawback of not well solving problems involving geometrical components in the image. A mathematical morphology is widely used to enhance or detect the geometrical structure of the image object[4]. The mathematical morphology can decompose an image into different sub-bands through a multi-resolution analysis, where each sub-band contains the objects of a specific size. As a nonlinear methodology, the mathematical morphology is a new and powerful technique to solve the above-mentioned problems.

Concerning the feature extraction from the local information, another issue is to design the mapping gain. The conventional mapping gain used in the wavelet sub-bands for the noise suppression and the contrast enhancement is experimentally determined [1]-[3]. Since a feature of image object is very difficult to express mathematically, finding an optimal mapping gain for the feature extraction and a structuring element for the morphological filter is difficult and time-consuming task by trial and error. A GA(Genetic Algorithm)-based optimization of the structuring element is described[5]. Although many GA versions have been recently proposed[6], they are time-consuming since GAs require inherently large population and long evolution in order to prevent the wrong and early convergence of GA. In order to overcome the disadvantage DE(Differential Evolution) scheme is proposed[7], and has been applied to image processing areas[8], [9]. DE scheme has an advantage of the fast convergence, and it is due to the capability of finding global minimum with a small population size compared with other evolutionary algorithms.

For the nonlinear feature enhancement this paper presents the morphology-based homomorphic filtering method. Based on the well established concepts of wavelet approach[1] and the wavelet-based homomorphic-based filtering methods[2], [3], the proposed method decomposes an image into morphological sub-bands, and then performs the homomorphic filtering using the morphological sub-bands. The evolutionary design of an optimal mapping gain and a structuring element for each morphological sub-band is carried out by DE scheme with the fast convergence. Simulation results are given to verify the effectiveness of the proposed method.

2. Morphology-Based Homomorphic Filter

The morphology-based homomorphic filter of 3-level is shown in Fig. 1. The logarithm of the image is decomposed into several sub-bands through the morphological low and high pass filters with the different sized-structuring elements. The left and the right dotted boxes in Fig.1 indicate the part of the image decomposition and that of the reconstruction, respectively.

Let $f_L^0[n]$ be the logarithm of the original image. The morphological low and high pass filters uses the closing operator(●) for the dark feature enhancement. The operator is defined as in (1).

$$f_L^i[n] = \left(f_L^{i-1} \bullet B_i\right)[n],\ f_H^i[n] = f_L^i[n] - f_L^{i-1}[n] \qquad (1)$$

Here n denotes two dimensional variable and i denotes i-*th* level($i \geq 1$). The size of the structuring element B_i should be increased in the subsequent decomposition level, i.e. $B_i \leq B_{i+1}$. According to the extensity of closing, the following relationship holds: $f_L^i[n] \geq f_L^{i-1}[n]$. For 3-level an image is decomposed into three high passed sub-bands, $f_H^1[n], f_H^2[n], f_H^3[n]$ and one low passed sub-band, $f_L^3[n]$. The feature-enhanced image can be obtained from the

Manuscript received Dec. 24. 2008; revised Sep. 5. 2009.
This work has been supported by the 2009 research fund of Halla University.

reconstruction process: the summation of the weighted sub-bands, $K_1 f_H^1[n]$, $K_2 f_H^2[n]$, $K_3 f_H^3[n], K_4 f_L^3$ and then exponential operation.

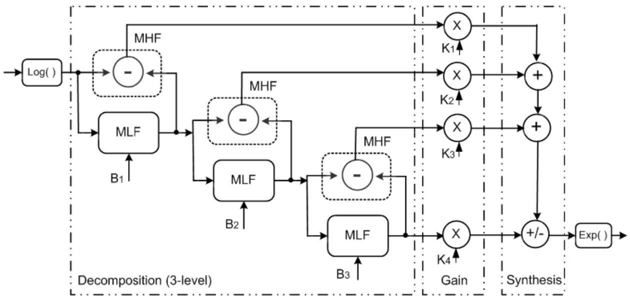


Fig. 1 Morplhology-based homomorphic filter structure(3-level)
MLF: Morphological low-pass filter
MHF: Morphological high-pass filter
B_i: Structuring element

Similarly, the morphological low and high pass filters using opening operator(O) for the bright feature enhancement are defined as in (2).

$$f_L^i[n] = \left(f_L^{i-1} \text{O } B_i\right)[n],\ f_H^i[n] = f_L^{i-1}[n] - f_L^i[n] \qquad (2)$$

Since the morphological filter can analyze the geometrical features of an image by locally comparing it with the structuring element, each high passed sub-band contains the objects of specific size and shape which are smaller than those of the structuring element. The mapping gain K_i and the structuring element B_i should be determined to enhance the interest feature. In the homomorphic and wavelet-based homomorphic filter the gains K_L, K_H for the low and high frequency components are experimentally decided by the guideline of $K_L < 1$ and $K_H > 1$[2], [3]. The experimental decision on the gains requires a repetitive task. The method of finding an optimal gain and the structuring element through the evolutionary search will be described in the next section.

3. Evolutionary Design of Optimal Gain and Structuring Element

DE scheme which is a simple, effective and powerful evolutionary algorithm with few control parameters, has been utilized for a stochastic optimization to minimize or maximize an fitness function that can model the objectives of the problem with constraints[7].

For the evolutionary design of the optimal gains and structuring elements in the proposed morphology-based homomorphic filter the fitness functions F_{MAE} and F_{MSE} are defined as in (3) and (4), respectively.

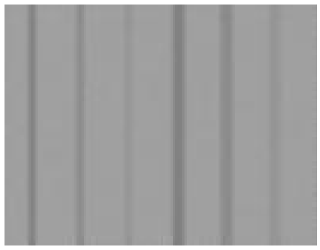
$$F_{MAE} = \frac{1}{N \times M} \sum_{n,m=1}^{N,M} |O(n,m) - T(n,m)| \qquad (3)$$

$$F_{MSE} = \frac{1}{N \times M} \sum_{n,m=1}^{N,M} \{O(n,m) - T(n,m)\}^2 \qquad (4)$$

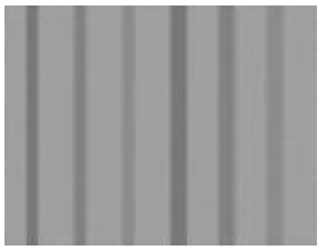
Here O(n,m) is the n-*th* row and m-*th* column pixel value of the output image O, and $T(n,m)$ is that of the target image T. N and M are the total numbers of row and column in the images.

Our goal is to minimize the dissimilarity between the output image $O(N \times M$ pixels) obtained from the morphology-based homomorphic filter and the corresponding synthetic target image $T(N \times M$ pixels). Under the conditions that the shape of the structuring element is symmetric disk-like and $B_i \le B_{i+1}$, the optimal size $\gamma(B_i)$ of the structuring element and the optimal gain K_i of each sub-band are searched through the differential evolution process.

In order to enhance the dark features such as blood vessels in medical images, the synthetic input and target images sized of 100×130 pixels containing the patterns of blood vessels are constructed as in Fig. 2. The only blood vessel areas of the target image get darker than those of the input image.



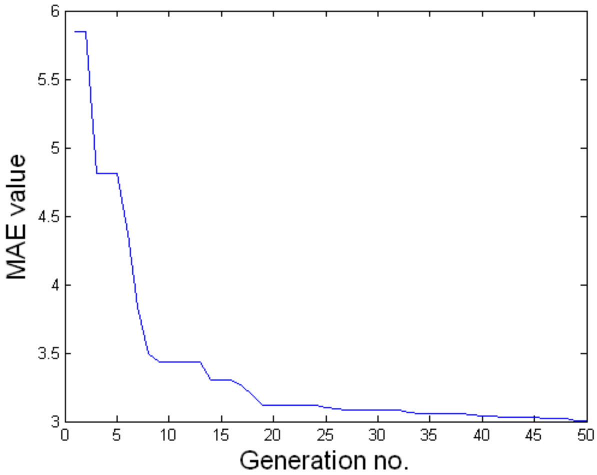
(a) Input image



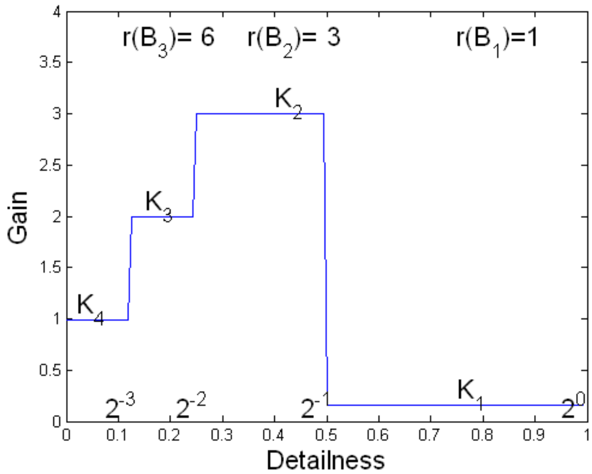
(b) Target image

Fig. 2 Syn thetic images for evolutionary design

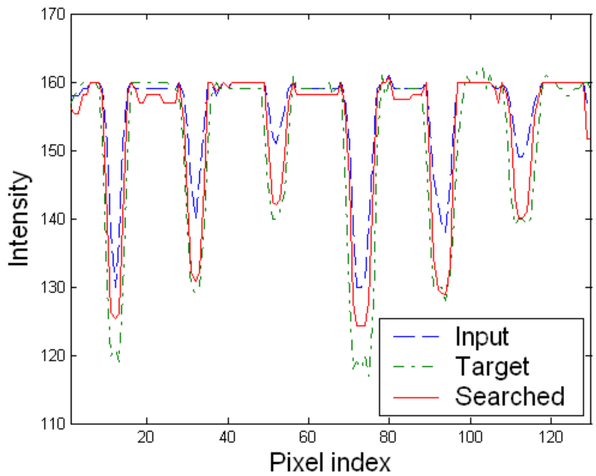
DE control parameters are as follows: population size = 5, maximum generation number = 50, differential amplification factor = 0.5, and crossover rate = 0.5. It is recommended that the population size be approximately equal to 10 times the number of the parameters in the search space. In our case the population size of 5 is enough to find the solution. The evolution results for the target image are shown in Fig. 3 and 4, where the fitness functions, F_{MAE} and F_{MSE} are utilized, respectively. The results demonstrate that the evolutionary design of the optimal gain and structuring element turns out to be practical with fast convergence and effective to find the optimal solution. Two fitness functions don’t make any noticeable difference in the intensity results as shown in (c)’s of Fig. 3 and Fig. 4. In the later sections, the gains and structuring elements identified by F_{MAE} are utilized.



(a) Fitness function value, F_{MAE}

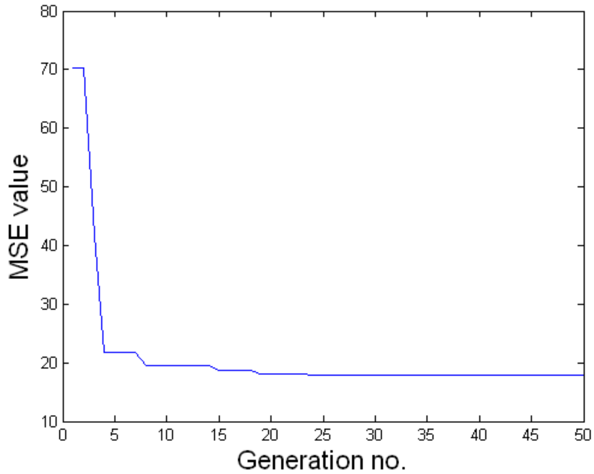


(b) Optimal gains(K_i's) and the sizes of structuring element($\gamma(B_i)$'s)

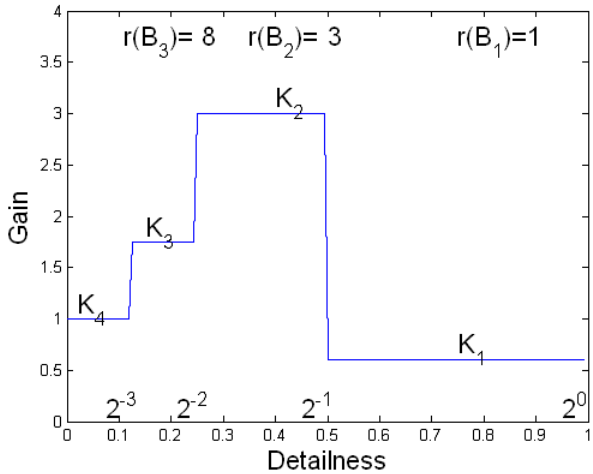


(c) A line sample

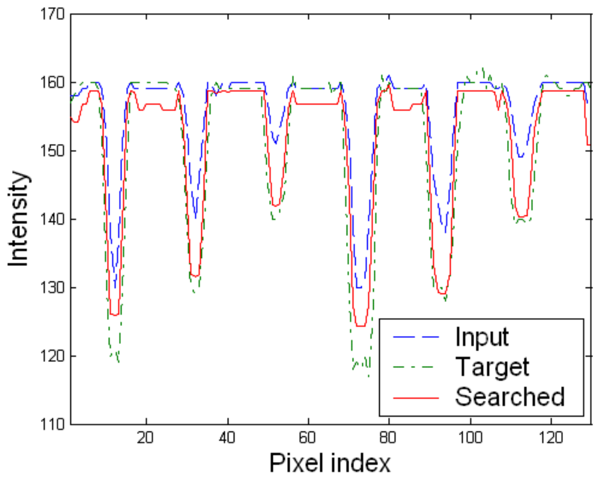
Fig. 3 Evolution result by fitness function, F_{MAE} for the target image



(a) Fitness function value, F_{MSE}



(b) Optimal gains(K_i's) and the sizes of structuring element($\gamma(B_i)$'s)



(c) A line sample

Fig. 4 Evolution result by fitness function, F_{MSE} for the target image

4. Simulation

To evaluate the performance of the proposed method, the contrast improvement index of our method is compared with that of the WHF(Wavelet-based Homomorphic Filter)[2]. The CII(Contrast Improvement Index) is defined as in (5).

$$\mathrm{CII} = \frac{C_p}{C_o} \qquad (5)$$

Here C_p and C_o are the contrast values for the region of interest in the processed and original image, respectively. The contrast C of an object is also defined as in (6).

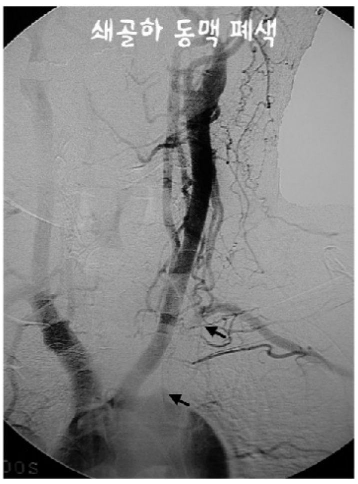
$$C = \frac{f-b}{f+b} \qquad (6)$$

Here f is the mean gray-level value of a particular object in the image and b is that of the surrounding region.

The processing results of the angiographic image are shown in Fig. 5. The original image, and the images processed by the histogram equalization, WHF method(3-level decomposition, $K_o = 3.5$, $K_1 = 2.5$, $K_2 = 1.5$ and $K_3 = 1.0$), and the proposed method with the optimal parameters of Fig. 3 (b). The near-infrared image is also considered, and its processing results are shown in Fig. 6. As in Fig. 5 and Fig. 6, it is noticeable that the dark features such as blood vessels and veins are all obviously enhanced without the distortion of the bright areas, on the other hand the images processed by the histogram equalization and WHF are too bright and considerably noisy. The proposed method seems to be very useful in the image enhancement in the fields of the vein authentication[10] and the catheter insertion[11].

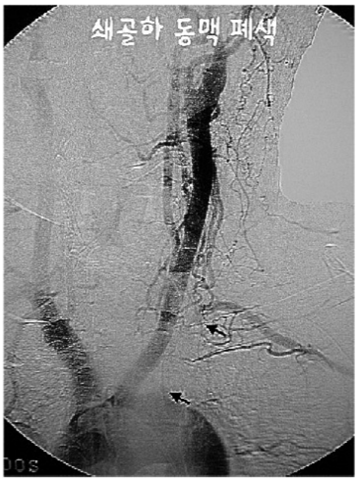
The contrast improvements for the original and enhanced features are summarized in Table 1, where the proposed method outperforms the conventional WHF method.

The effectiveness of the proposed method is verified by the intensity mapping results shown in Fig. 7, in which the proposed gives the contrast stretching for the dark features alone without overshooting the bright background.

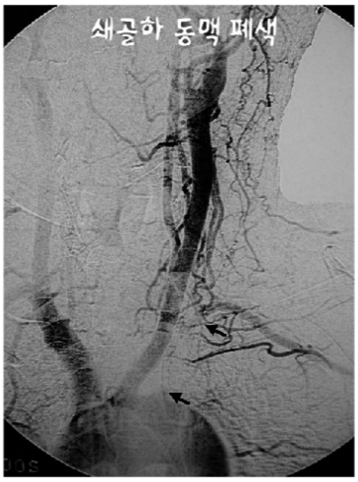


(a) Original image

(b) Histogram equalization



(c) WHF[2]

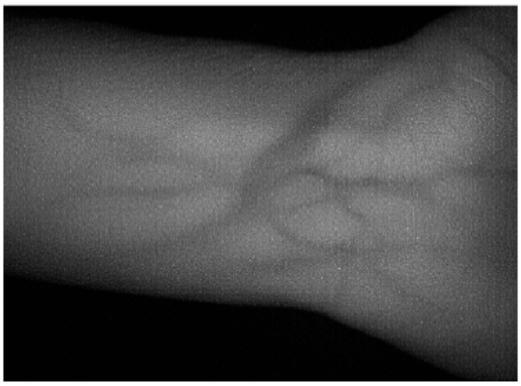


(d) Proposed

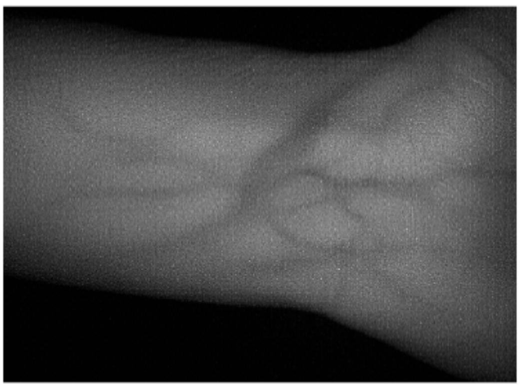
Fig. 5 Results of blood vessel enhancement in angiographic image

(a) Original image

(b) Histogram equalization



(c) WHF[2]

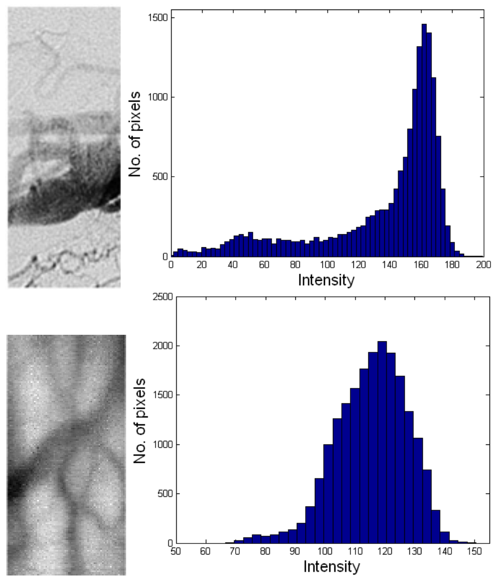


(d) Proposed

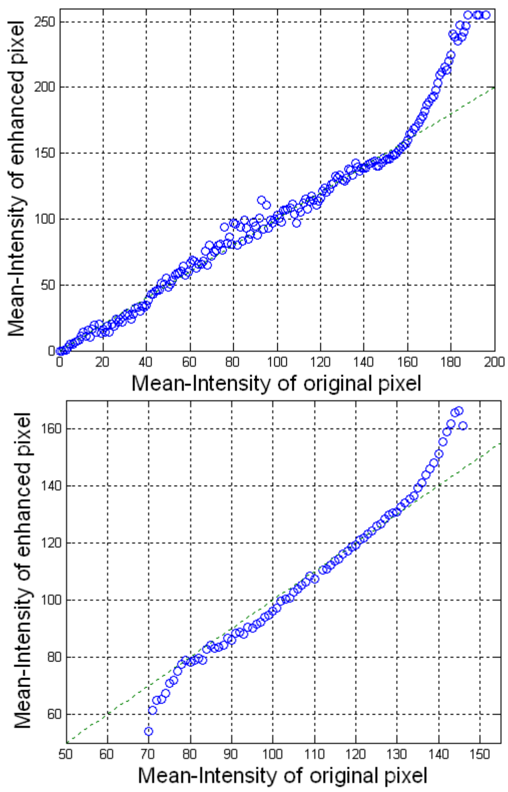
Fig. 6 Results of vein enhancement in near-infrared image

Table 1 Contrast improvement

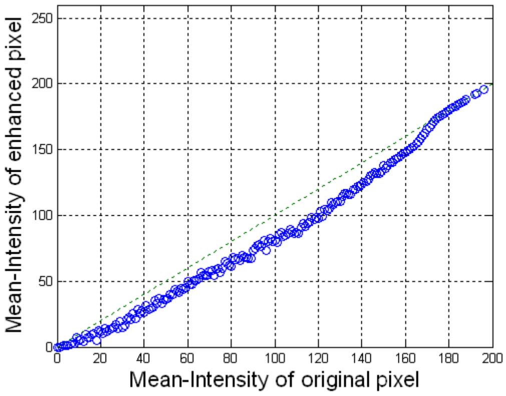
Index	Angiographic original image	WHF[2]	Proposed
C	0.2325	0.5276	0.5594
CII		2.2692	2.4060
	Near-infrared original image	WHF[2]	Proposed
C	0.0862	0.1089	0.1177
CII		1.2633	1.3654

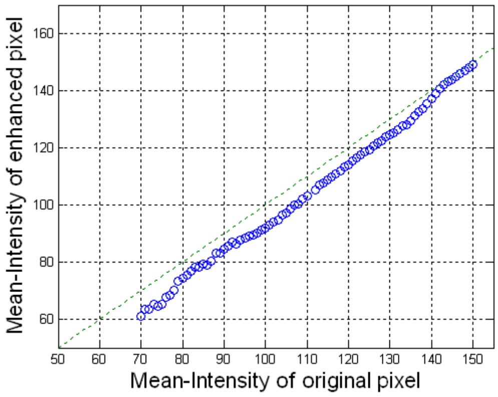


(a) Histogram of angiographic and near-infrared sub-block images



(b) WHF[2]





(c) Proposed

Fig. 7 Intensity mapping results

5. Conclusions

In this paper a new morphology-based homomorphic filtering method for the feature enhancement in medical images is presented. The method combines the morphological sub-band decomposition and the homomorphic enhancement features. The morphological sub-bands with the optimal gains are merged to reconstruct an enhanced image. The optimal gain and structuring element of each sub-band are searched in the process of differential evolution. Simulation results shows that the proposed method has improved the contrast of the interest feature without deteriorating the bright areas in medical images. Therefore, the method is considered to be of great use in supporting activities such as disease diagnosis and monitoring, surgical planning, and authentication.

References

[1] A. Laine, J. Fan, and W. Yang, “Wavelets for contrast enhancement of digital mammography,” *IEEE Eng. Med. & Biol. Mag*., vo. 145, pp. 536-550, 1995.

[2] J. H. Yoon, and Y. M. Y. M., “Enhancement of the contrast in mammographic images using the homomorphic filter method,” *IEICE Trans. Inf. & Syst*., vol. 85-D, no. 1, pp. 298-303, 2002.

[3] H. I. Ashiba, K. H. Awadallah, S. M. El-Halfway, and F. E. El-Samie, “Homomorphic enhancement of infrared images using the additive wavelet transform,” *Progress In Electromagnetics Research*, vol. 1, pp. 123-130, 2008.

[4] P. Maragos, “Morphological filtering for image enhancement and feature detection,” in ‘*The Image and Video Processing Handbook*’, Elsevier Academic Press, pp. 135-156, 2005.

[5] N. Harvey, and S. Marshall, “The use of genetic algorithms in morphological filter design,” *Elsevier Signal Processing: Image Communication* , vol. 8, no. 1, pp. 55-72, 1996.

[6] M. Paulinas, and A. Usinska, “A survey of genetic algorithms applications for image enhancement and segmentation,” *Inform. Tech. & Control*, vol. 36, no. 3, pp. 278-284, 2007.

[7] R. Storn, “Differential evolution, a simple and efficient heuristic strategy for global optimization over continuous spaces,” *Journal of Global Optimization*, vol. 11, no. 4, pp. 341-359, 1997.

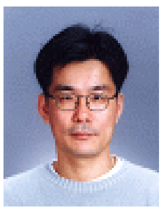
[8] P. Thomas, and D. Vernon, “Image registration by differential evolution,” *Proc. Int. Conf. Machine Vision & Image Processing*, pp. 221-225, 1997.

[9] S. Rahnamayan, H. R. Tizhoosh, and M. M. A. Salama, “Image thresholding using differential evolution,” *Proc. Int. Conf. Image Processing, Computer Vision & Pattern Recognition*, pp. 244-249, 2006.

[10] M. Watanabe, T. Endoh, M. Shiohara, and S. Sasaki, “Palm vein authentication technology and its applications,” *Proc. Conf. Biometric Consortium*, pp. 37-38, 2005.

[11] V. Paquit, et. al., “Near-infrared imaging and structured light ranging for automatic catheter insertion,” in *Visualization, Image-Guided Procedures, and Display*, pp. 61411T-1~9, 2006.

Heesoo Hwang received the B.S., M.S. and Ph.D. degrees in Electrical Engineering from Yonsei University in 1986, 1988 and 1993, respectively. He is currently an associate Professor in the School of Electrical Engineering at Halla University, Korea. His research interests include data based modeling, prediction, and diagnosis.



Jinsung Oh received B.S. and M.S. degrees in Electrical Engineering from Yonsei University, Korea in 1987, 1989, and the Ph.D. degree in Electrical Engineering at University of Pittsburgh, U.S.A. in 1998. He is currently an assistant Professor in the School of Electrical Engineering at Halla University, Korea. His research interests include signal and image processing.