Feature Enhancement of Medical Images using Morphology-Based Homomorphic Filter and Differential Evolution Algorithm

Jinsung Oh and Heesoo Hwang

Abstract: In this paper, we present a new morphology-based homomorphic filtering technique for feature enhancement in medical images. The proposed method is based on decomposing an image into morphological subbands. The homomorphic filtering is performed using the morphological subbands. The differential evolution algorithm is applied to find an optimal gain and structuring element for each subband. Simulations show that the proposed filter improves the contrast of the features in medical images.

Keywords: Differential evolution algorithm, homomorphic filter, image enhancement, morphological filter.

1. INTRODUCTION

The goal of medical image enhancement is to enhance the contrast among adjacent regions or features in order to support activities such as disease diagnosis and monitoring, and surgical planning. Among the image enhancement techniques, it is shown that the wavelet and homomorphic filtering techniques proposed in [1-4] enable dynamic range compression and contrast enhancement simultaneously. All these approaches concentrate on reinforcing the details of the image to be enhanced in terms of frequency domain. However, these linear approaches are not suitable to solve problems involving geometrical components in the image. Mathematical morphology [5] is widely used to enhance or detect the geometrical structure of the image object. In mathematical morphology, a multi-resolution analysis decomposes an image into different subbands where each subband contains objects of a specific size. As described in [5], mathematical morphology is a powerful nonlinear methodology that can solve the above mentioned problems.

Another issue concerning the design of the mapping gain focuses on how to extract features from the local information. The conventional mapping gain [1-4] used in wavelet subbands for noise suppression and contrast enhancement is experimentally determined. Since a feature of image object is very difficult to express mathematically, finding an optimal mapping gain for the feature enhancement and structuring element for morphological filter is also a difficult task. In [6], an optimization method for structuring element by genetic algorithm is proposed. Although many genetic algorithm versions [7] have been developed, they are time consuming. In order to overcome this disadvantage, differential evolution has been recently proposed in [8]. It has been applied to the image processing area [9,10]. The differential evolution algorithm has three advantages: finding the true global minimum regardless of the initial parameter values, fast convergence, and using a few control parameters.

Based on the well established concepts of wavelet approach [1,2] and wavelet-based homomorphic filtering methods [3,4], we propose the morphology-based homomorphic filtering method for the nonlinear feature enhancement. The proposed method is based on decomposing an image into morphological subbands, and then the homomorphic filtering is performed using the morphological subbands. Since the differential evolution algorithm offers fast convergence rate with small population size, it is applied to find an optimal mapping gain and structuring element for each morphological subband. Simulation results are given to present the effectiveness of the proposed method.

2. MORPHOLOGY-BASED HOMOMORPHIC FILTER

Fig. 1 illustrates the morphology-based homomorphic filter for 3-level. The logarithm of the image is decomposed into several subbands through morphological low and high pass filters with different size of structuring elements. As shown in Fig. 1, the left and right dotted boxes show the part of image decomposition and reconstruction, respectively.

Letting $f_L^0[\underline{n}]$ be the logarithm of the original image, the morphological low and high pass filters using closing (•) operator for dark feature enhancement are given by

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

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Manuscript received November 18, 2008; accepted January 15, 2010. Recommended by Editorial Board member Sung-Kwun Oh under the direction of Editor Young-Hoon Joo.

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Fig. 1. Morphology-based homomorphic filter structure (3-level).

where \underline{n} denotes two-dimensional variables, and i denotes i-th level $(i \ge 1)$. The size of the structuring element B_i should be increased in the subsequent decomposition level, i.e., $B_i \le B_{i+1}$. According to the extensivity of closing, the following relationship holds: $f_L^i[\underline{n}] \ge f_L^{i-1}[\underline{n}]$. For 3-level, an image is decomposed into three high-passed subbands $(f_H^1[\underline{n}], f_H^2[\underline{n}], f_H^3[\underline{n}])$ and one low-passed subband $(f_L^3[\underline{n}])$. The feature-enhanced image can be obtained from the reconstruction process: the summation of weighted subbands $(K_1 f_H^1[\underline{n}], K_2 f_H^2[\underline{n}], K_3 f_H^3[\underline{n}], K_4 f_L^3[\underline{n}])$ and then using exponential operation.

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

$$f_L^i[\underline{n}] = (f_L^{i-1} \circ B_i)[\underline{n}], f_H^i[\underline{n}] = f_L^{i-1}[\underline{n}] - f_L^i[\underline{n}].$$
(2)

Since the morphological filter can analyze the geometrical features of an image by locally comparing it with the structuring element, each high-passed subband contains the objects of specific size and shape which are smaller than those of structuring element. For the enhancement of feature, the mapping gain K_i and structuring element B_i should be determined. In the homomorphic filter and wavelet-based homomorphic filters [3,4], the gains for the low- and high-frequency components, denoted as K_L and K_H , are experimentally determined by the guideline of $K_L < 1$ and $K_H > 1$. The experimental decision on the gains requires a repetitive task. The method for finding an optimal gain and structuring element will be described in the next section.

3. OPTIMAL GAIN AND STRUCTURING ELEMENT BY DIFFERENTIAL EVOLUTION ALGORITHM

The differential evolution (DE) is a simple, effective and powerful evolutionary algorithm with few control parameters, and has been utilized for a stochastic optimization method minimizing a fitness function that can model the problem's objectives with constraints.

For the optimization of the gains and structuring elements, the fitness function F is defined as

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

That is, the dissimilarity between $N \times M$ output image, O, obtained from the morphology-based homomorphic filter and the corresponding synthetic target image, T, is minimized. The DE algorithm uses mutation operation as a search mechanism and selection operation to direct the search toward the prospective regions in the search space. As indicated in [6], however, the search for an optimal structuring element confronts potentially local minima. The DE search can overcome the problem. Under the conditions that the shape of structuring element is symmetric disk-like and $B_i \leq B_{i+1}$, the DE is applied to find the size of the structuring element $r(B_i)$ and optimal gain K_i for each subband.

For the enhancement of dark features such as blood vessels in medical images, a synthetic image (100×130) which contains patterns of blood vessels is used, and only the blood vessel areas of the target image are darker than those of input image. The DE control parameters are as follows: population size = 5, maximum generation number = 50, differential amplification factor = 0.5, and crossover probability = 0.5. It is recommended that



Fig. 2. Searching result for a synthetic image.

the population size be approximately equal to 10 times the number of parameters in the search space. In our case, however, a population size of 5 is enough to find the solution. The searching result for the synthetic image is shown in Fig. 2, which indicates that DE is practical and effective to find optimal solution with fast convergence.

4. SIMULATION RESULTS

The performance of the proposed method is evaluated and compared with the wavelet-based homomorphic filter (WHF) [3] in terms of contrast improvement index. The contrast improvement index (CII) [1] is defined by

$$CII = \frac{C_{processed}}{C_{original}},\tag{4}$$

where $C_{processed}$ and $C_{original}$ are the contrast values for a region of interest in the processed and original images, respectively. The contrast C of an object is also defined by $C = \frac{f-b}{f+b}$, where f was the mean gray-level value of a particular object in the image, and b was the mean gray-level value of a surrounding region.

Fig. 3 shows the processing result of the angiographic image with histogram equalization, WHF method (3-level decomposition, $K_0 = 3.5$, $K_1 = 2.5$, $K_2 = 1.5$, and $K_3 = 1.0$), and the proposed method with optimal parameters (see Fig. 2(b)). Fig. 4 also shows the processing result of the near-infrared image. As shown in

Table 1. Contrast improvement index.

	Angiographic original image	WHF [3]	Proposed
С	0.2325	0.5276	0.5594
CII		2.2692	2.4060
	Near-infrared original image	WHF [3]	Proposed
С	Near-infrared original image 0.0862	WHF [3] 0.1089	Proposed 0.1177
C CII	Near-infrared original image 0.0862	WHF [3] 0.1089 1.2633	Proposed 0.1177 1.3654





(a) Original image.



(c) WHF [3].



Fig. 3. Results of blood vessel enhancement in angiographic image. (a) Original image. (b) Histogram equalization. (c) WHF [3]. (d) Proposed. Fig. 4. Results of vein enhancement in near-infrared image. No. of pixels No. of pixels Level of veins Level of blood vessels Intensity Intensity (a) Histogram of angiographic and near-infrared subblock images. 8000 Mean-Intensity of enhanced pixel Mean-Intensity of enhanced pixel 12 080 Mean-Intensity of original pixel Mean-Intensity of original pixel (b) WHF [3] (•: matching point). Mean-Intensity of enhanced pixel Mean-Intensity of enhanced pixel Mean-Intensity of original pixel Mean-Intensity of original pixel

(c) Proposed.

Fig. 5. Intensity mapping results.

Fig. 3(d) and 4(d), it can be seen that the dark features such as blood vessel and vein are enhanced with less distortion on the bright areas. The proposed enhancement method will be very useful in the vein authentication [11] catheter insertion [12], and fingerprint verification [13] applications.

Table 1 shows the contrast values and contrast improvement indexes for the original and enhanced features. As shown in Table 1, the proposed method outperforms the conventional WHF method. Fig. 5 verifies the effectiveness of the proposed method. Intensity mapping results show that the proposed method gives nonlinearly contrast stretching only for the dark features.

5. CONCLUSIONS

In this paper, a new morphology-based homomorphic filtering technique for the feature enhancement in medical images is presented. The proposed method combines the morphological subband decomposition and homomorphic enhancement features. the The morphological subbands with the optimal gains are merged to reconstruct an enhanced image. To find an optimal gain and structuring element for each subband, the DE algorithm is applied. Simulation results show that the proposed method has improved the contrast of the feature in medical images. Therefore, the proposed method will be very helpful to support activities such as disease diagnosis and monitoring, surgical planning, and authentication.

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