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Threshold Optimization of Adaptive Template Filtering for MRI Based on Intelligent Optimization Algorithm

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Abstract—**Intelligent Optimization Algorithm (IOA) mainly includes Immune Algorithm (IA) and Genetic Algorithm (GA). One of the most important characteristics of MRI is the complicated changes of gray level. Traditional filtering algorithms are not fit for MRI. Adaptive Template Filtering Method (ATFM) is an appropriate denoising method for MRI. However, selecting threshold for ATFM is a complicated problem which directly affects the denoising result. Threshold selection has been based on experience. Thus, it was lack of solid theoretical foundation. In this paper, 2 kinds of IOA are proposed for threshold optimization respectively. As our experiment demonstrates, they can effectively solve the problem of threshold selection and perfect ATFM. Through algorithm analysis, the performance of IA surpasses the performance of GA. As a new kind of IOA, IA exhibits its great potential in image processing.**

I. Introduction

IMAGE processing and clinical diagnosis have been dependent on the high quality medical image. However, many factors directly affect its acquisition. For example, noise is introduced into MRI image due to inhomogeneity of magnetic field, excursion of temperature and motion of tissue and etc. [1]. So the denoising process is obligatory.

Many filtering methods are proposed to markedly improve Signal-Noise Ratio (SNR), but much high frequency information is lost at the same time.. In order to obtain high quality medical image, the preservation of useful information is more important than simple improvement of SNR [2]. One of the most important characteristics of MRI is the complicated changes of gray level, i.e., MRI is abundant in much high frequency information. Traditional filtering algorithms are not fit for MRI.

Adaptive Template Filtering Method (ATFM) can dynamically match the best template from the predetermined multi-templates based on local texture characteristics for each pixel. This method not only effectively suppresses noise, but best preserves useful information. So it is an appropriate denoising method for MRI. However, selecting threshold for ATFM is a complicated problem which directly affects the denoising result [3]. Threshold selection has been based on empirical formula and manual adjustment. It was lack of solid theoretical foundation [4]. Intelligent threshold optimization is a key problem for ATFM.

Intelligent Optimization Algorithm (IOA) mainly includes Immune Algorithm (IA) and Genetic Algorithm (GA). Biological Immune System (BIS) is a kind of highly evolved intelligent system. Simulating BIS, Artificial Immune System (AIS) has the abilities of learning, memorizing, recognizing and self-organized. Due to its powerful and robust information processing capabilities, many IAs based on AIS have emerged, and gradually applied to many engineering practices mainly involving classification and optimization [5]. Simulating biological principle of natural selection and mechanism of natural genetics, GA is randomized searching technique based on statistical theory. With the characteristics of colony searching strategy and information exchange among individuals in colony, GA is widely applied to complex and non-linear optimization problems [6]. In this paper, 2 kinds of IOA are proposed for threshold selection, and algorithm analysis is executed to explore their effects.

II. Adaptive Template Filtering Method

A MRI image is made up of a series of finite regions in which the gray levels are continuous or slow changed, and these regions are segmented by discontinuous edges. The main idea of ATFM is, from the predetermined templates, to find a template which is the best match for the finite continuous region including input pixel. Then the best denoising effect of input pixel can be obtained using this best matching template [7]. A set of templates is predetermined as figure 1 shown.

From figure 1, black point and gray point represent input pixel and non-background neighboring pixel respectively. The total number of templates is $\sum_{n=2}^{9} C_8^{n-1} = 255$. For each pixel, the best matching template is selected based on Standard Deviation (STD) of pixel values in a template:

$$\delta_j = \sqrt{\frac{1}{N_j - 1} \sum_{k=1}^{N_j} \left(I_k(x,y) - m_j \right)^2} \qquad (1)$$

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$$m_j = \frac{1}{N_j}\sum_{k=1}^{N_j} I_k(x,y) \quad (2)$$

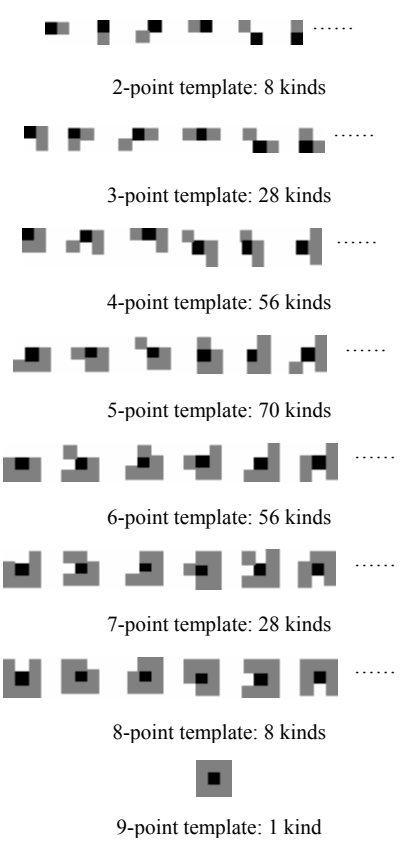

Fig. 1. A set of predetermined templates

In a template, $I(x,y)$ is the pixel value, N_j is the number of non-background neighboring pixels, m_j is the mean value of pixels and δ_j is STD of pixel values.

One kind of template is named smooth template in which the change of gray level is smooth, its STD is relatively small. So the best matching template T is the template which has the most non-background neighboring pixels in the finite continuous region.

$$T = \arg\max_{T_j} N_j\{T_j \mid \delta_j < t\} \quad j = 1,...,255 \quad (3)$$

Another kind of template is named edge template in which edge exists, its STD is relatively big since gray levels change markedly. So the best matching template T is the template in which STD is minimal:

$$T = \arg\min_{T_j} \delta_j\{T_j \mid \delta_j \geq t\} \quad j = 1,...,255 \quad (4)$$

Using which kind of template depends on the threshold t. Different t results in different denoising effect. In order to select optimal threshold intelligently, 2 kinds of IOA are proposed for ATFM in section III.

III. Threshold Optimization Based on IOA

A. Immune Algorithm

BIS is mainly made up of antibody and lymph. Lymphocyte includes B-lymphocyte and T-lymphocyte. B-lymphocyte originating from marrow can excrete antibody which can recognize and eliminate appropriate antigen. And through cell division, an antibody can clone many antibodies. In addition, some B-lymphocytes are differentiated to memory cell which can excrete a great deal of antibodies to eliminate antigens rapidly when the same kind of antigens inbreak next time. T-lymphocyte originating from thymus can enhance or suppress antibody excretion [8]. The response mechanism of BIS is shown in figure 2.

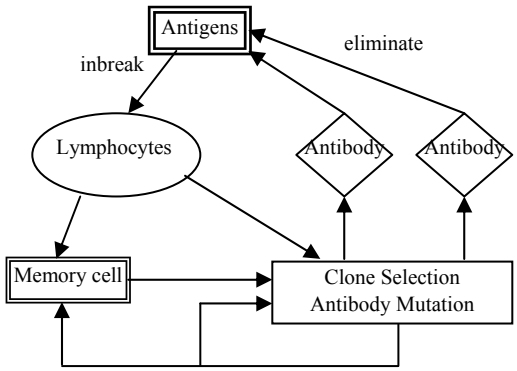

Fig. 2. The response mechanism of BIS

For IA, target function is regarded as antigen, and optimal solution is regarded as antibody. Then the matching degree of antigen and antibody is described as affinity which reflects the closeness between target function and potential solution. Resemblance among antibodies is described as similarity which reflects antibody diversification [9]. The schematic diagram of IA is shown as figure 3. The detail steps of IA for optimization are described as follows:

1) Define target function and subject condition of optimization problem as antigen.
2) Randomly choose N potential solutions from solution space as initial antibody generation.
3) Compute the similarity among antibodies. According to similarity, suppress high similarity antibodies.
4) Compute the affinity of antigen-antibody. According to affinity, execute clone selection including antibody removing for antibodies of low affinity and antibody cloning for antibodies of high affinity. By this way, the convergence speed of algorithm is expedited, and antibody diversification is maintained to avoid the degeneration and immaturity of algorithm.
5) Produce next antibody generation by antibody mutation to ensure that optimizing process evolves to global optimum.
6) Mutated antibodies are stored in immune memory matrix. We can get initial antibody generation from this matrix for next iteration or same problem encountered. By this

way, the convergence speed of algorithm is expedited and searching ability is enhanced.

7) Compute the affinity of antigen-antibody again. If the result satisfies the terminal condition, stop algorithm, otherwise, return step 2).

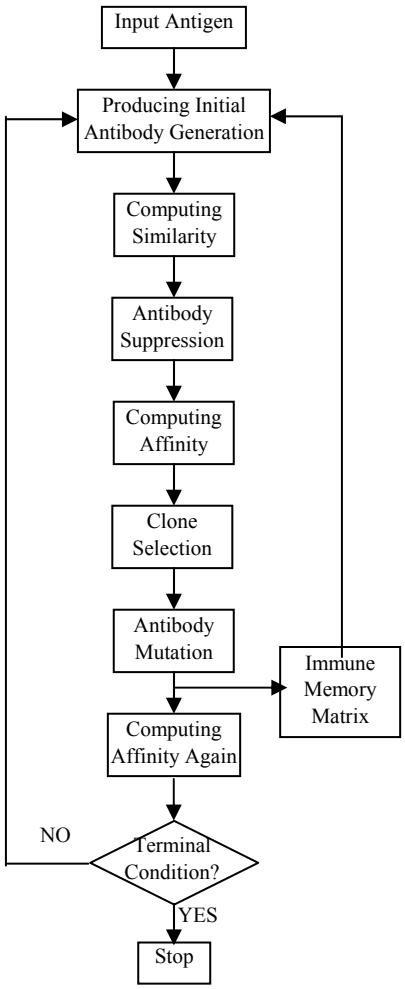

Fig. 3. The schematic diagram of IA

According to ATFM, in the surrounding finite region of an input pixel, if the change of gray level is smooth, use smooth template, if the change of gray level is drastic, use edge template. The selection of a template depends on the threshold t. By analyzing the change of gray level for MRI, we should search the pixel whose change rate of gray level is minimal among all the pixels whose change rate is drastic. Threshold t is the change rate of this pixel. So the target function is:

$$\min \left|\nabla^2 I(x,y)\right| = \left|\frac{\partial^2 I(x,y)}{\partial x^2} + \frac{\partial^2 I(x,y)}{\partial y^2}\right| =$$

$$\left|4I(x,y) - (I(x+1,y) + I(x-1,y) + I(x,y+1) + I(x,y-1))\right|$$

$$subject\ \text{to}\ \nabla I(x,y) = \frac{\partial I(x,y)}{\partial x} i + \frac{\partial I(x,y)}{\partial y} j =$$

$$2I(x,y) - (I(x,y+1) + I(x+1,y)) \neq 0 \qquad (5)$$

Consider optimization problem formula (5) as antigen, and consider solution space $I(x,y)$ as antibodies. The original problem is transformed to search the antibody which can best matches antigen. Randomly choose $N = 20$ antibodies from solution space as initial antibody generation. Compute antibody similarity as follows:

$$s_{ij} = 1 - \frac{\left\|Ab_i - Ab_j\right\|}{\max\limits_{1\le i,j\le N}\left\|Ab_i - Ab_j\right\|}, \quad i,j = 1,...,N \quad i \neq j \qquad (6)$$

According to similarity, suppress antibody whose similarity is high. Then compute the affinity of antigen-antibody using target function. According to affinity, remove antibodies of low affinity and clone antibodies of high affinity [10]. Then produce next antibody generation by antibody mutation according to following formula:

$$Ab_i^* = Ab_i - (1 - e^{-\left\|Ab_i - Ag_j\right\|})(Ab_i - Ag_j) \qquad (7)$$

Store Ab_i^* in immune memory matrix, and compute affinity of antigen-antibody again. If the result satisfies terminal condition, stop algorithm, otherwise, start next iteration.

B. Genetic Algorithm

GA is an iterative process of generate-and-test. The detail steps of GA for optimization are described as follows:

1) Coding: decimal code is adopted for GA.
2) Producing initial generation: initial generation of IA is used in order to analysis the performance of IA and GA.
3) Computing the fitness for each individual according to formula (5).
4) Selection: roulette wheel algorithm is used to copy better individuals and suppress worse individuals according to fitness.
5) Crossover: randomly partner among 20 individuals and cross each partner under the crossover probability of 0.9.
6) Mutation: mutate each individual under the mutation probability of 0.02.
7) Computing fitness again. If the result satisfies the terminal condition, stop algorithm, otherwise, return step 4).

IV. Experimental Result and Analysis

MRI data were provided by Brigham & Women's Hospital, Harvard Medical School. It is T2 weighted image. 256*256 pixels for one slice, the thickness of each slice is 1mm, no gap between the slices, the gray level is 2^{16}, the total number of slices is 150 from left ear to right ear. The original images of 112th slice and 116th slice are shown in figure 5.

Using IA and GA, almost the same optimal threshold is obtained for each slice. For example, threshold $t = 0.004$ for 112th slice; threshold $t = 0.0001$ for 116th slice. Using ATFM for 2 images, the denoising results are shown in figure 6.

In the process of denoising, we have to optimize thresholds for 150 slices of MRI and the change of the thresholds for all

slices is small. The iterative numbers of IA with immune memory (IM IA), IA without immune memory (Non-IM IA) and GA from 111th slices to 115th slices are shown in Table I. For IA, Immune memory is an important function of IA. Experiment indicates that, after processing the previous image, the initial antibody generation of subsequent images can be directly produced from immune memory matrix of previous slice, i.e., vaccination. So it can markedly reduce the iterative number and expedite searching speed.

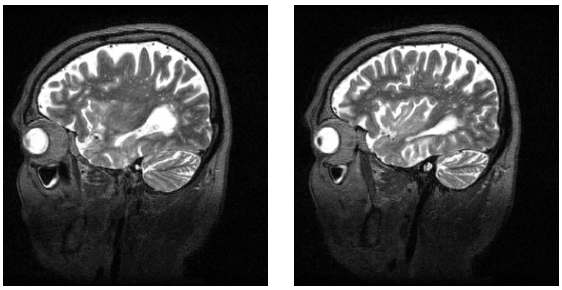

Fig. 5. Original 112th slice and 116th slice

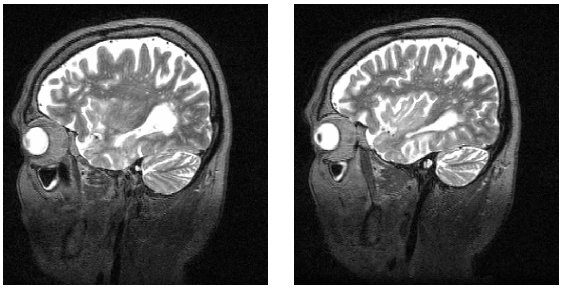

Fig. 6. Adaptive template filtered 112th slice and 116th slice

TABLE I
ITERATIVE NUMBERS OF IM IA, NON-IM IA AND GA

Iterative Number	Slice 111	Slice 112	Slice 113	Slice 114	Slice 115
IM IA	3	2	6	4	4
Non-IM IA	9	9	14	27	4
GA	28	32	47	38	14

Table I also manifests that the performance of IA surpasses the performance of GA. Although GA can obtain the same optimal threshold, its 2 main operators i.e., crossover and mutation, randomly search without direction under the probability condition. So GA cannot avoid the possibility of degeneration when its 2 main operators provide evolution chance for individuals at the same time. The mutation of IA is described as formula (7) which has been proved that recognizing antigen ability of new antibody is better than that of old antibody. It ensures that optimizing process evolves to global optimum.

V. CONCLUSION

IOA mainly includes IA and GA. In this paper, MRI images are denoised using ATFM. In this method, optimal threshold is intelligently searched by 2 kinds of IOA which can avoids the blindness of using empirical formula and manual adjustment for threshold selection. IOA provides solid theoretical foundation to threshold selection and makes ATFM more intelligent and effective. Hence it perfects ATFM. Compared to GA, IA has powerful and robust information processing capabilities due to its characteristics of learning, memory, identification, diversification and self-adaptive adjustment. Its inherent mechanism can overcome the phenomenon of degeneration and immaturity. AIS and its applications have been a new research area, and paid more attention by scientists of intelligent computation. As a new intelligent computing method, IA exhibits its great potential in image processing.

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