A NOVEL EFFICIENT MEDICAL IMAGE SEGMENTATION METHODOLOGY

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ABSTRACT

Image segmentation plays a crucial role in many medical applications. The threshold based medical image segmentation approach is the most common and effective method for medical image segmentation, but it has some shortcomings such as high complexity, poor real time capability and premature convergence, etc. To address above issues, an improved evolution strategies is proposed to use for medical image segmentation, there are 2 populations concurrently during evolution, one focuses on local search in order to search solutions near optimal solution, and the other population that implemented based on chaotic theory focuses on global search so as to keep the variety of individuals and jump out from the local maximum to overcome the problem of premature convergence. The encoding scheme, fitness function, and evolution operators are also designed. The experimental results validated the effectiveness and efficiency of the proposed approach.

KEYWORDS

Image segmentation, Evolutionary Algorithm, Chaotic Theory, Methodology

1. INTRODUCTION

Nowadays there are more and more image data in medical area[1-3]. It is significant to extract meaningful medical information such as volume, shape, motion of organs, to detect abnormalities by processing and analyzing medical images data. Medical image segmentation is a central technique used in clinics, it helps radiologists to improve the diagnostic accuracy[4].

Image segmentation refers to distinguish some certain regions and other regions in the image, so as to divide the image into a number of significant target regions. Image segmentation is a key procedure before analyzing and understanding the image. Successful segmentation contributes to successive recognition, target feature extraction, classification and understanding to image in higher level. Image segmentation is therefore extremely important and one of the crucial research issues in image processing and computer vision, and has increasingly wide range of applications, such as communications, military, remote sensing, medical diagnosis, intelligent transportation, smart agriculture and industrial automation, etc. Furthermore, image segmentation refers to many other research areas such as artificial intelligence, pattern recognition, machine learning, data mining, etc.

In recent years, there are many research results about image segmentation which can be used for medical image segmentation. Wen[4]proposed a lattice Boltzmann method based on integrated

edge and region information for medical image segmentation. Otsu[5] proposed a maximal variance based method and it is considered as a classical algorithm for image segmentation. Xiao[6] proposed an algorithm based on Otsu rule and image entropy, this algorithm combines the advantages of Information Entropy and Otsu methods. Vctor[7] proposed an improved Watershed algorithm, in this algorithm, it calculates watershed transform of grey digital image through simulating raining and using pixels instead of the rain. Parvati[8] proposed a modified Watershed algorithm using grayscale morphology and control tags. Liu[9] proposed an interactive image segmentation method based on Agent model. Qu[10] proposed a fast boundary tracking image segmentation method based on the rule of region-growth. Wei[11] proposed a clustering algorithm based on multiple color spaces, multiple measurement criteria, and region growing method, and used this algorithm for fragmented image region segmentation. Zhang[12] considered the characteristics of the different sensitivity to image information content region in human visual system, proposed an improved PCNN based adaptive image segmentation method. Berg[13] proposed a method based on pulse-coupled neurons, it first used neurons as the recursive function of ADATE system, and then used ADATE transformation to generate better neurons for image segmentation. Wei[14] proposed a fingerprint image segmentation method based on support vector machine. Liu[15] proposed a multi-scale remote sensing image segmentation method using support vector machine. Liu[16] proposed a method for remote-sensing image segmentation based on graph theory.

The threshold based medical image segmentation approach is the most common and effective method for medical image segmentation, but the disadvantage is its time complexity is high, especially in the situation of calculation for two-dimensional threshold, it usually takes a long time, so it has poor real-time capability. The procedure for selecting threshold using maximal variance is really a process of searching for optimal solution, so as to an optimization problem. So recently some researchers used evolutionary algorithms such as generic algorithm for image segmentation to enhance the efficiency. But traditional evolutionary algorithm could not converge to global optimal threshold, so it will be a meaningful way to improve existing evolutionary algorithm to enhance its ability of global search, and combining the improved evolutionary algorithm and Ostu method for image segmentation.

In order to overcome the shortcomings above, in this paper, an improved evolution strategy[17] is proposed to use for medical image segmentation . The threshold for image segmentation is obtained by modified evolution strategy, during evolution there are two populations concurrently to guarantee the algorithm has both strong abilities of global and local search. The encoding scheme, fitness function, and evolution operators are also designed. Experimental results show that the proposed method outperforms traditional ones.

This paper is organized as follows: The detailed algorithm is described in Section 2. Section 3 presents the experimental results. Finally, conclusions are summarized in Section 4.

2. OUR METHOD

Evolution Strategy (ES) is a branch of evolutionary algorithms, and it has strong parallel search ability[18-20]. There are 3 operators in ES: Recombination, Mutation and Selection. Recombination is equivalent to Crossover of GA, but different from GA, it is to produce only one offspring from two parent individuals, and Mutation strength can be governed by self-adaptation, Selection is strictly according to the fitness.

2.1. Encoding Scheme

In order to using evolution strategies to solve the problem, it is essential to encoding the solution space, so as to represent individuals of the algorithm. The code of the individuals contains 2 parts. For simplicity, the image for segmentation is assumed to consist of m grey levels without loss of generality. If genetic algorithm is used for this problem, the individual must be presented as an multi-bits binary byte. But evolution strategies can deal with real value directly, so we can directly use a decimal integer X which ranges from 0 to m to represent the individual of evolution strategies algorithm. The second part is a real float number representing adaptive mutation step size which describes mutation strength.

2.2. Encoding Scheme

According to traditional threshold based medical image segmentation approach, in general, the grey levels of a medical image is assumed to be 1-m, and the number of the pixels whose grey level is i is represented as ni, then the total number of the pixels of the image is as follows:

$$N = \sum_{i=1}^{m} n_i$$

The probabilities of each grey level are as follows:

$$P_i = \frac{n_i}{N}$$

Using variable k to divide them into two groups A_0=[1,…,k], A_1=[k+1,…,m], then the probability of A_0 is:

$$w_0 = \frac{\sum_{i=1}^{k} n_i}{N} = \sum_{i=1}^{k} p_i$$

The probability of A_1 is:

$$w_1 = \sum_{i=k+1}^{m} p_i = 1 - w_0$$

The average value of grey level of A_0 is :

$$u_0 = \frac{\sum_{i=1}^{m} P_i \times i}{w_0}$$

The average value of grey level of A_1 is :

$$u_1 = \frac{\sum_{i=k+1}^{m} P_i \times i}{w_1}$$

So the grey level of the whole image is :

$$u = \sum_{i=1}^{m} P_i \times i$$

The average value of grey scale whose threshold is k is as follows :

$$u(k) = \sum_{i=1}^{k} P_i \times i$$

The sampled average value is $\mu = w_0 u_0 + w_1 u_1$, the variance is:

$$d(k) = w_0(u_0 - u)^2 + w_1(u - u_1)^2$$

Therefore, the fitness function can be as follows:

$$d(k) = w_0 w_1 (u_1 - u_2)^2$$

The value of variable k ranges from 1 to m, and finding the k^* which can maximize $d(k)$,so k^* is the optimal threshold for image segmentation.

2.3. Evolutionary operators

2.3.1 Selection

According to Zhu's method[17], in the iteration of evolution, there are two populations in memory: the "local population" and the "global population". The former stores the best individuals, and focuses on local search in order to search good solutions near current optimal solution. On the contrary, the global population focuses on global search, it has more powerful mutation strength, and it can keep the variety of individuals and jump out from the local maximum, so it has strong ability to globally explore in solution space to overcome the problem of premature convergence.

Different from genetic algorithm, the evolution strategies using (μ+λ) selection strategy: μ parent individuals generate λ offspring individuals, and select μ individuals strictly according to the fitness from the μ+λ individuals as the next generation.

2.3.2 Recombination

If the two parent individuals are (X_1,σ_1) and (X_2,σ_2), then the offspring is $((X_1+X_2)/2, (\sigma_1+\sigma_2)/2)$.

2.3.3 Mutation

Mutation is to randomly make several modifications to the individual. In the local population, because of its focus on local search, we use traditional mutation method, that is:

$$\sigma^{t+1} = \sigma^t \cdot \exp(r_1 \cdot N(0,1) + r_2 \cdot N(0,1))$$
$$r_1 = (\sqrt{2\sqrt{n}})^{-1} \quad r_2 = (\sqrt{2n})^{-1}$$

$N(0,1)$ is standard normal distribution in which mean=0 and variance=1, n is the number of individuals in the population. X^{t+1} is generated by changing certain binary bit of X^t by $\sigma^{t+1} N(0,1)$ times randomly.

In the global population, in order to enhance the global search ability, we propose to adopt chaotic theory[21] which describe erratic behavior and reflect the randomness in nonlinear dynamical systems, the chaotic motion can traverse all the states un-repeatedly in the states space. One of the chaotic systems is Logistic mapping, it is written as following non-linear equation:

$$R_{i+1} = u \cdot R_i(1 - R_i); i = 0, 1, 2, ...$$

where $0<R_0<1$, and $R_0 \neq 0.5$, when $u=4$ the sequence generated by Logistic equation is complete chaotic. So we use $X^{t+1} = m \cdot R_{chaotic}$ to generate X^{t+1}, where $R_{chaotic}$ is chaotic sequence generated by Logistic equation, here the reason we use m·$R_{chaotic}$ is to make the chaotic values with the range of 0 to m.

2.3.4 Migration

The migration is realized by putting together the individuals of both two populations, then selecting the best μ individuals into local population, then putting the remaining μ individuals into global population.

The two populations evolve separately, after every once evolution, some individuals of the two populations are exchanged to balance the local search and global search by "migration" operator. Therefore, the algorithm has both abilities of local search and global search, it can enhance the searching accuracy.

3. EXPERIMENT AND RESULTS

The experiments are conducted on an Intel Xeon 1.8 GHz workstation with 8 GB of RAM running under Windows 7 SP1. In the experiment, some medical images are tested using the proposed method, and the segmentation results of two typical medical images (an X-ray image of a vessel and a brain MRI) are selected to be shown in Figure 1 and Figure 2.(The following is Fig1~Fig3)

(a) X-ray image of a vessel before segmentation

(b) X-ray image of a vessel after segmentation

(a) Brain MRI before segmentation

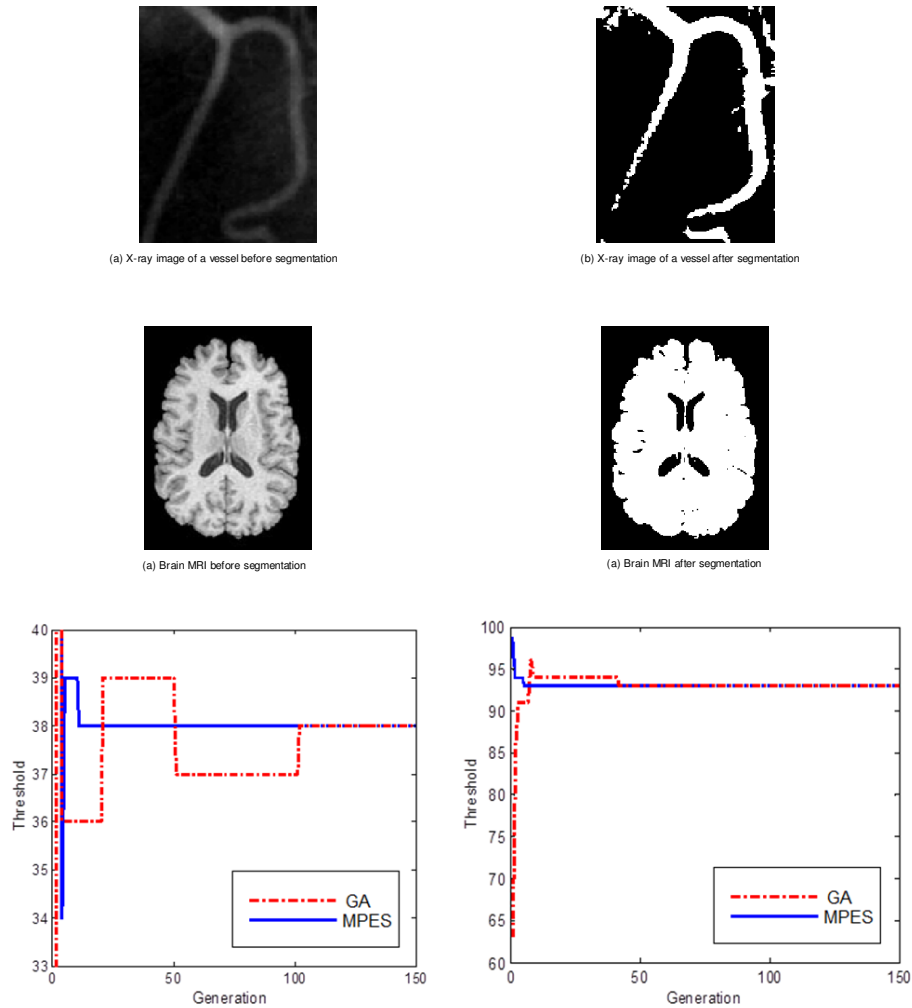(a) Brain MRI after segmentation

Figure 3 illustrated the converge process of the threshold for image segmentation, in which GA represents genetic algorithm, and MPES represents the proposed multiple population evolution strategies. As shown in Figure 3, because the medical image for experiment is simple that the grey level is from 0 to 255, the GA method and proposed method can both find the optimal threshold, but the proposed method converge faster than GA.

4. CONCLUSION AND FUTURE WORK

In order to overcome the shortcomings of traditional threshold-based medical image segmentation approaches such as high complexity and premature convergence, in this paper, an efficient medical image segmentation based on multiple population Evolution Strategies is proposed. In the method, the threshold for image segmentation is obtained through multiple population Evolution Strategies, in iteration of evolution, there are two populations: the "local population" and the "global population". The former focuses on local search, the global population which is implemented based on chaotic systems focuses on global search, so it has strong ability to globally explore in solution space to overcome the problem of premature convergence. The

experimental results show that the proposed method outperforms traditional genetic algorithm based method. In the future, we would like to optimize our proposed algorithm in the following ways: (1) add image denoising technique[22-26] to preprocessing step; (2) enhance the mathematical background of the proposed method, using more complex machine learning methods such as fuzzy clustering[27-31] and machine learning traditional algorithms[32-38] to improve our method.

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