Image Segmentation with PCNN Model and Immune Algorithm

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***Abstract*—In the domain of image processing, PCNN (Pulse Coupled Neural Network) need to adjust parameters time after time to obtain the better performance. To this end, we propose a novel PCNN parameters automatic decision algorithm based on immune algorithm. The proposed method transforms PCNN parameters setting problem into parameters optimization based on immune algorithm. It takes image entropy as the evaluation basis of the best fitness of immune algorithm so that PCNN parameters can be adjusted adaptively. Meanwhile, in order to break the condition that population information fall into local optimum, the proposed method introduces gradient information to affect the evolution of antibody to keep the population activity. Experiment results show that the proposed method realizes the adaptive adjustment of PCNN parameters and yields the better segmentation performance than many existing methods.**

***Index Terms*—pulse couple neural network; Immune Algorithm; Image Segmentation; Parameter optimization; Image Entropy; Fitness function**

I. INTRODUCTION

PCNN (Pulse Coupled Neural Network) is bionic mathematical model proposed by Eckhorn based on Synchronous pulse release phenomenon of the cat's visual cortex neurons. Because the work mechanism of PCNN is similar to the activities of human visual cortex neurons, the model is widely used in image processing[1],image fusion[2], image denoising [3],target recognition[4],image compression[5].At present, this algorithm has two prominent problems:one is that in theory it is difficult to explain the exact relationship between the various parameters in PCNN mathematical model and the image processing performance so that the image processing performance is good or not depends on the continuous adjustment of parameters and the selection of many experiments; the other is that the model has lots of parameters and a complex calculation. Due to the above reason, many researchers devote to PCNN parameters optimization and self-adaption, there are three typical methods. The first method sets adjustment condition to stop PCNN algorithm through evaluating image processing results so that PCNN iterates automatically, e.g., Zhao Shijiang et al. [6] took the connected domain of the image segmentation results as the evaluation condition, Ma Yide et al. [7] proposed the stop criterion named as 2D-OTSU, Yao Chang et al. [8] used the cross entropy of segmentation results as PCNN stop criterion, Xin Guojiang et al. [9] took the maximum variance ratio of segmentation results as PCNN stop condition. The second method finds out the characteristics and changing trends of the parameters in different image processing tasks through analyzing the characteristics (mechanism) of PCNN parameters qualitatively and quantitatively, then given the specific calculation formula for each parameter[1],[10],[11]. The third method transforms parameter setting into multi-objective optimization problem. Concerning different image processing tasks, it searches optimal parameter combination by means of optimization algorithm to achieve PCNN self-adaption, e.g., Ma Yide etal. [12] use the genetic algorithm to optimize PCNN parameters, Xu Xinzheng et al. [13] use particle swarm optimization algorithm to optimize PCNN parameters, BI Xiaojun et al.[14] use immune algorithm to optimize PCNN parameters.

Although BI Xiao-jun et al. [14] successfully resolved the PCNN parameters self-adaption problems through the immune clone algorithm, as a intelligent algorithm, immune clone algorithm inevitably have to face some

doi:10.4304/jcp.8.9.2429-2436

problems such as precocity and stagnation. Based on the research work of predecessors we put forward a new idea that optimizes PCNN parameters combined with improved immune algorithm. The proposed method transforms PCNN parameters setting problem into parameters optimization based on immune algorithm by using the characteristic that immune algorithm has global optimization and fast convergence. In order to break the condition that group information fall into local optimum, the proposed method introduces gradient to affect the evolution of antibody to keep the group activity and takes Shannon entropy as the basis of evaluating immune algorithm is good or not. Finally, this method is applied to the specific image segmentation tasks. Experiment results show that introducing gradient information enhances the immune algorithm execution speed and PCNN can achieve parameters automatic optimization after optimized by immune algorithm, the optimized parameters are able to yield good image segmentation performance.

II. Related Works

A. PCNN Model

PCNN is two-dimensional network which is composed by $M \times N$ PCNs(pulsed coupled neural). The model has two characteristics: well imitating the fatigue and refractory period of visual cortex nerve cells; being good at classifying the pixels which their gray value is similar to each other. A single neuron is composed by three parts: the receiving domain, the modulation part and the pulse generator. The corresponding discrete mathematics equations are described below [15]:

$$F_{ij}(n) = \mathrm{e}^{-a_F} F_{ij}(n-1) + V_F \sum_{kl} M_{ijkl} Y_{kl}(n-1) + S_{ij} \quad (1)$$

$$L_{ij}(n) = \mathrm{e}^{-a_L} L_{ij}(n-1) + V_L \sum_{kl} W_{ijkl} Y_{kl}(n-1) \quad (2)$$

$$U_{ij}(n) = F_{ij}(n)(1 + \beta L_{ij}(n)) \quad (3)$$

$$Y_{ij}(n) = \begin{cases} 1, U_{ij}(n) > E_{ij}(n-1) \\ 0, \text{other} \end{cases} \quad (4)$$

$$E_{ij}(n) = \mathrm{e}^{-a_E} E_{ij}(n-1) + V_E Y_{ij}(n) \quad (5)$$

In the formula(1)-(5), *F,L,U,E,Y,S* respectively stands for feedback input, link input, internal activity, dynamic threshold, pulse output, external stimulation; i and j are neuron labels; n is iterations; *W* and *M* are weight matrixes; W_{ikjl} and M_{ijkl} are neuron synaptic connection weights(generally, $W_{ikjl}=M_{ijkl}$); a_L,a_F,a_E and V_L,V_F,V_E respectively stand for time attenuation constants and amplitude coefficients;β is internal activity connection coefficient.

In image processing tasks, one pixel corresponds to one PCN, they constitute a two-dimensional network. First, external stimulation *S*(gray value of pixel in image processing) is input to receiving domain and fused with the output ***Y*** of the adjacent neurons, then the feedback input ***F*** is obtained, link input ***L*** receives ***Y***, internal activity multiplies ***F*** by ***L*** to get ***U,*** in pulse generator part, ***U*** is compared with dynamic threshold ***E***, if ***U***>***E***, the pulse generator starts neuron ignition, outputs $Y_i = 1$, else neuron misfires, outputs $Y_i = 0$. The above process is repeated, until it satisfies the conditions.

Due to lots of PCNN parameters, it is difficult to determine parameters artificially, and the calculation is large, the efficiency is low [15]. This paper uses the simplified PCNN model, the corresponding discrete mathematics equations are described below [16]:

$$F_{ij}(n) = S_{ij} \quad (6)$$

$$L_{ij}(n) = V_L \sum_{kl} W_{ijkl} Y_{kl}(n-1) \quad (7)$$

$$U_{ij}(n) = F_{ij}(n)(1 + \beta L_{ij}(n)) \quad (8)$$

$$Y_{ij}(n) = \begin{cases} 1, U_{ij}(n) > E_{ij}(n-1) \\ 0, \text{other} \end{cases} \quad (9)$$

$$E_{ij}(n) = \mathrm{e}^{-a_E} E_{ij}(n-1) + V_E Y_{ij}(n) \quad (10)$$

In the formula (6)-(10), the meaning of the parameters is as same as the above formula (1)-(5). Compared with original model, the improved model cuts down the number of the parameters from 9 to 5 and reduces the complexity of the parameters setting.

B. Immune Clone Selection Algorithm：ICSA

In 1999, based on biological immune clone selection principle, Dr. De Castro proposed the new intelligent algorithm: Immune Clone Selection Algorithm. This Algorithm shows excellent performance and efficiency in machine learning, anomaly and fault diagnosis, robot behaviour simulation and control, network intrusion detection and function optimization, etc. It transforms the problems and their corresponding solutions into the antibody and antigen of biological immune system, and uses the accessibility and proportion between antibody and antigen to select and clone antibody, and remembers the excellent antibody by constructing a memory unit, and realizes the diversity of population through generating new antibody to substitute old antibody, finally achieves the purpose of solving practical problems.

III. Optimizing the PCNN Model Combined with Gradient Information Immune Algorithm

Based on immune algorithm, this paper combines the excellent gene information of antibody and the characteristics of PCNN parameters to optimize PCNN parameters. In the optimization algorithm, it performs receptor editing to antibody gene and introduces gradient information to affect the evolution of partial antibody to keep the population activity.

A. Related Definition

Definition 1: Antigen. Image entropy is a kind of widespread evaluation index of image segmentation results, the bigger entropy value shows that the more information that the segmentation results obtain from original image. In this paper, the image entropy is defined as the antigen ($\max_{W \in \Omega} f(\boldsymbol{W})$, Ω is the feasible domain of W) of immune parameter optimization.

Definition 2: Antibody. Antibody is the optimization solution of immune algorithm. In this paper, the optimized PCNN parameters (amplitude coefficient V_L, internal connection coefficient β, time decay constant a_E and V_E) compose the vector (V_L, β, a_E, V_E) which is defined as antibody, then the antibody set corresponding to antibody population can be expressed as $\boldsymbol{W} = \{(V_L, \beta, a_E, V_E) | V_L, \beta, a_E, V_E \in [0,1]\}$.

Definition 3: Memory Antibodies. Memory antibody set is composed by a certain number of highest-affinity antibodies selected from antibody set and the antibodies in the memory antibody set are defined as memory antibodies. These antibodies directly enter into the next generation of population evolution to ensure that the global convergence of population. The size of memory antibody set should be moderate, in this paper, it takes 10-20% of the size of antibody set.

Definition 4: Antibody Density. Antibody density means the percentage of the number of antibodies that are concentrated or have larger affinity currently in the antibody set. In this paper, it takes Euclidian distance between antibodies as the evaluation basis of antibody similarity. So the antibody density is defined as $DENSITY = V / N$, where V is the number of the antibodies that have large affinity with W_i, N is the total number of antibody. The calculation process first adopts formula (11) to acquire the Euclidian distance between antibodies, and then uses formula (12) to calculate antibody similarity, finally, calculates antibody density by use of formula (13). the corresponding calculation equations are described below:

$$D(Ab_i, Ab_j) = 1 - \sqrt{\sum_{k=1}^{4} (w_{i,k} - w_{j,k})^2} \quad (11)$$

$$s(Ab_i, Ab_j) = \begin{cases} 1, & D(Ab_i, Ab_j) \geq \theta \\ 0, & otherwise \end{cases} \quad (12)$$

$$DENSITY(Ab_i) = \sum_{k=1}^{N} s(Ab_i, Ab_k) \Big/ N \quad (13)$$

where θ represents the given threshold of antibody similarity, and N is the total number of antibodies in the antibody population.

B. Coding and Initialization

In this paper, antibody is encoded by a 11 bit binary number. Meanwhile, in order to increase the diversity of the initial population, the algorithm utilizes random initialization strategy, and then randomly generates M antibodies as initial population.

C. Immune Evolution

Immune evolution is realized through crossover, mutation, clonal variation, selection, etc.

- **Crossover Operator:** according to the coding characteristic, this paper adopts arithmetic crossover operation as the crossover operator. The algorithm randomly selects two antibodies on the basis of cross probability P_c to execute crossover operation. It concretely swaps the variables at each dimension in the two antibodies according to the certain probability. Take the variable at the first dimension for example, if the two antibodies before crossover are $W_1(w_{11}, w_{12}, w_{13}, w_{14})$、$W_2(w_{21}, w_{22}, w_{23}, w_{24})$, and after crossover they change into $W_1'(w_{21}, w_{12}, w_{13}, w_{14})$、$W_2'(w_{11}, w_{22}, w_{23}, w_{24})$. When the average affinity of the antibody set changes little or has no change for continuous generations, the algorithm again executes crossover operation on the basis of probability $P_c'=(1+a_c)P_c$, where $a_c=e^{-fa}$, f_a represents the change of average affinity before and after several generations.
- **Mutation Operator**:the algorithm randomly selects antibody to execute mutation operation on its binary bits according to the mutation probability P_b. When the average affinity of the antibody set changes little or has no change for continuous generations, in order to jump out local optimum and increase the degree of mutation, the algorithm increase mutation probability for the randomly selected antibodies. It concretely execute mutation operation for the binary bits according to the mutation probability $P_b'=(1+a_c)P_b$, *where* $a_c=e^{-fa}$, f_a represents the change of average affinity before and after several generations.
- **Clonal Variation**:clonal variation simulates the high frequency variation in biological immune process, it aims at ensuring the global convergence, enhancing local searching ability and making the algorithm quickly converge to global optimum. Concretely, it constructs temporary clone antibody set C* through cloning every antibody in the antibody set C which is acquired by immune algorithm, and then mutates every antibody in the set C*, where $C^* = N_C \times C$, N_C is the number of clone antibody of each parent antibody. In the antibody set C*, it respectively compares the antibodies after clonal variation with their parent antibodies according to affinity, and retains the better antibodies to construct a new antibody set C' which has a same size with C. Finally, it compares C' with the memory antibody set and substitutes the better antibodies in C' for antibodies which has low affinity in the memory antibody set, and then obtains a new memory antibody set.
- **Selection Operator**:according to immune memory mechanism, the selection operation in this paper includes two conditions. One is that the antibodies in memory antibody set directly enter into the evolutionary population of next generation. The other is that, aiming at a constant population size, it selects the remaining antibodies in the antibody set C' on the basis of affinity to enter into the evolutionary population of next generation.

When the evolution stops, according to the mechanism that immune system can dynamic randomly generate new antibodies, it randomly generates d_1 antibodies to substitute the antibodies which have low affinity in the previous antibody set and randomly generates d_2 antibodies to substitute the antibodies which have relatively high density, and then the diversity of the antibodies can be increased.

- **Introducing gradient information**:for function $f(x)$, where $x=(x_1,x_2,\cdots,x_n)$, the gradient of $f(x)$ is shown in the equation(14):

$$\nabla f(\boldsymbol{W})=(\frac{\partial f}{\partial W_1},\frac{\partial f}{\partial W_2},\frac{\partial f}{\partial W_3},\frac{\partial f}{\partial W_4}) \tag{14}$$

When immune algorithm stops evolving or evolves very slowly (the algorithm stops converging or converges slowly), in order to accelerate the convergence rate and improve searching performance, it randomly selects partial antibodies and searches along their gradient direction. Concretely, the proposed method randomly selects some antibodies to introduce the gradient information in the mutation process, and acquires acceleration step through linear searching along the negative gradient direction to make the algorithm search along the direction that antibody fitness fastest decline.

D. Calculating Affinity

The affinity between Antigen and antibody correspond to the matching degree between solution and objective function, the higher affinity means the better antibody. Image entropy reflects the amount of information that the segmented image acquires from original image, therefore this paper takes image entropy as the evaluation basis of the affinity of immune algorithm, and the formula is shown below:

$$fit=H=-\sum_{i=0}^{L-1}p_i\log_2 p_i \tag{15}$$

Where L is gray level, generally equals 256, $0\le i\le L$, p_i is the probability of gray value i appearing in image.

E. Algorithm Steps

Step1: The generation of the initial antibodies. It randomly generates N initial antibodies to construct antibody set $Ab(Ab_i \in Ab,\ i=1,2,\ldots,N)$, and randomly selects some antibodies to construct initial memory antibody set, in our experiments, *N = 50-150* is taken.

Step2: Affinity calculation. It calculates the affinity fit_i of antibody and the average affinity ($vmfit=(\sum_{i=1}^{N}fit_i)/N$) of the antibody set, where fit_i represents the affinity of the *i*th antibody.

Step3: For antibody set, it executes crossover operation according to Crossover Operator, and executes mutation operation according to Mutation Operator.

Step4: Clonal Variation. It executes clonal variation operation according to Clonal Variation. The number of the clone antibodies has a great impact on the convergence speed of the algorithm. When there are more clone antibodies, the evolution speed is faster, antibodies need fewer generations to move to the extremal point, but the time complexity of the algorithm will increase. In order to balance the convergence speed and the time complexity, in our experiments, clone control coefficient k=20 is taken.

Step5: It executes selection operation according to Selection Operator and selects the corresponding antibodies to enter into the next generation of population evolution.

Step6: If it satisfies the maximum generations *Ngen* of termination, the algorithm terminates; else goes to Step 2.

IV. EXPERIMENTS AND DISCUSSION

A. Using Test Function to Verify the Improved Immune Algorithm

We compared the method in this paper with the basic immune algorithm by use of the test function shown in formula (16). The characteristics of this test function includes multimodal, multi-variable and multi-extreme. Through test optimization algorithm, we can find out the number of maximum points and the number of extreme points and the run time of the test function to evaluate the global optimization ability, the stability and time efficiency of the optimization algorithm. In the formula, x、$y\in[-1,2]$.

$$x\times\sin(4\pi x)-y\times\sin(4\pi y+\pi+1) \tag{16}$$

The data in the table 1 shows that both the improved immune algorithm and the basic immune algorithm are able to find out the global optimal solution, they also find the same number of maximum points, but our method takes less time than the immune algorithm. The above comparison shows that the proposed method maintains the performance of the immune algorithm after introduced gradient information and has excellent global optimization ability and algorithm stability; meanwhile, it's better than the basic immune algorithm in run time.

TABLE 1
THE PERFORMANCE COMPARISON BETWEEN STANDARD IMMUNE ALGORITHM AND THE METHOD AFTER INTRODUCED GRADIENT

test times	Can find the optimal solution or not		The number of extreme points		Run time(S)	
	The proposed method	The basic immune algorithm	The proposed method	The basic immune algorithm	The proposed method	The basic immune algorithm
1	YES	YES	9	9	1.52	3.5
2	YES	YES	9	9	3.8	4.1
3	YES	YES	9	9	1.3	3.3
4	YES	YES	9	9	1.59	3.6
5	YES	YES	9	9	1.51	3.5

B. Comparison of Image Segmentation Performance

We picked original images from various field, such as medicine, mining, Marine life and real life . These images have low contrast and ununiformly distributed grayscale. Example images are shown in Fig.1:(1) Lena(2)bacterial image 1(3)bacterial image 2(4)chalk image (5)bubble image (6)fish image. Image segmentation algorithms used for comparison are PCNN, Maximum between-cluster variance(OTSU) , Particle swarm optimization-

PCNN(PSO-PCNN), maximum entropy, cross entropy, region uniformity, watershed algorithm.

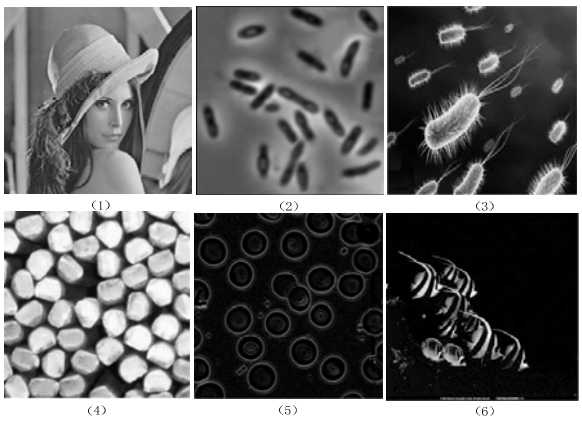

Figure 1. Some original images used in our experiments.

We compared performance of algorithms in terms of subjective visual preference and objective evaluation. Subjective visual preference is used to evaluate the visual preference of the segmentation. The better the visual effect is, the more the segmentation is in accordance with the actual human visual preference. Fig.2 to Fig.7 shows the segmentation result of our algorithm and other algorithms. In terms of subjective visual preference , better segmentation are obtained in lena image ,bacterial image2 ,chalk image ,bubble image and fish image due to no subjective goal was set . From the segmentation of these images , we can see more layers, complete region, obvious detail features were captured. As for the bacterial image 1, different segmentation produced by our algorithm and other algorithms. Our algorithm, PSO-PCNN、PCNN and cross entropy can distinguish the foreground and background properly, but the rest algorithms suffered from over-segmentation .

Figure 2. the actual segmentation results of OTSU, Maximum entropy, Cross entropy, Watershed, Region consistency, PCNN, PSO-PCNN and the proposed method for Lena image.

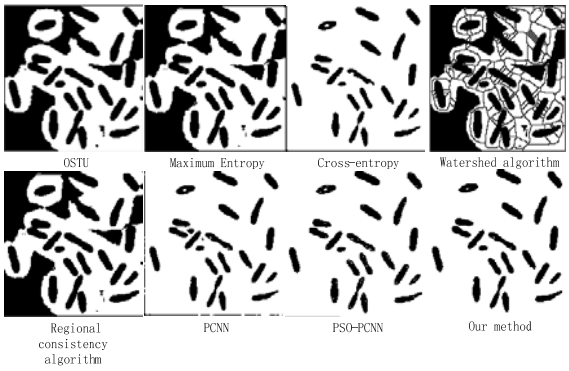

Figure 3. the actual segmentation results of OTSU, Maximum entropy, Cross entropy, Watershed, Region consistency, PCNN, PSO-PCNN and the proposed method for bacteria 1 image.

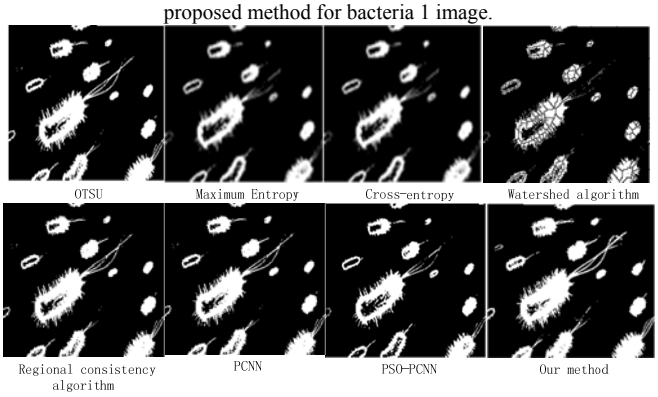

Figure 4. the actual segmentation results of OTSU, Maximum entropy, Cross entropy, Watershed, Region consistency, PCNN, PSO-PCNN and the proposed method for bacteria 2 image

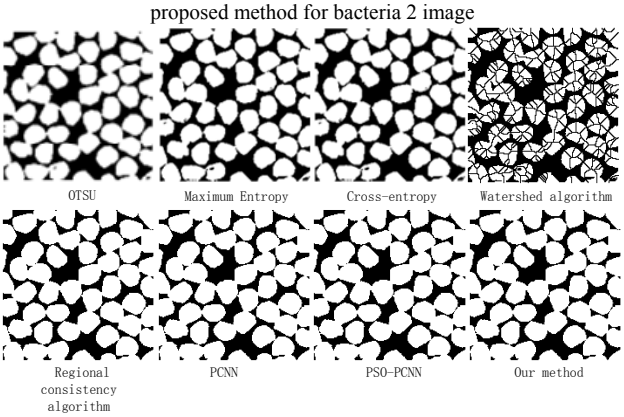

Figure 5. the actual segmentation results of OTSU, Maximum entropy, Cross entropy, Watershed, Region consistency, PCNN, PSO-PCNN and the proposed method for chalks image

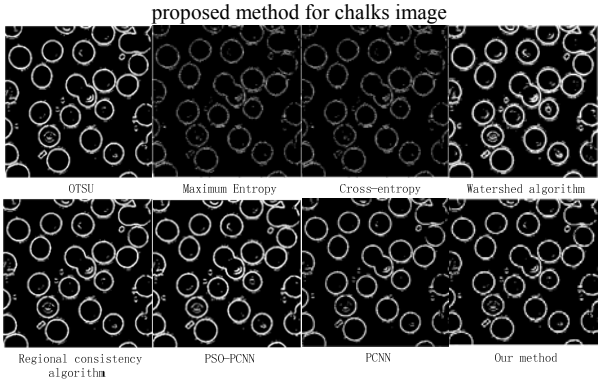

Figure 6. the actual segmentation results of OTSU, Maximum entropy, Cross entropy, Watershed, Region consistency, PCNN, PSO-PCNN and the proposed method for bubbles image .

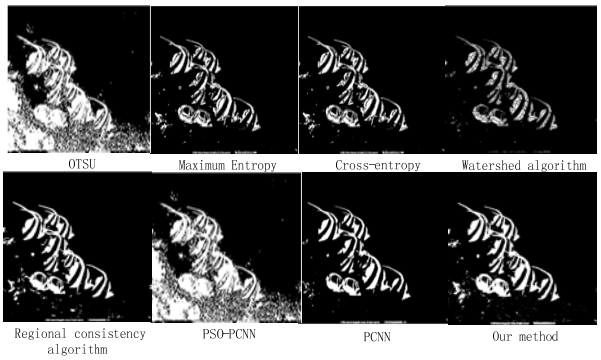

Figure 7. the actual segmentation results of OTSU, Maximum entropy, Cross entropy, Watershed, Region consistency, PCNN, PSO-PCNN and the proposed method for fish image.

As for objective evaluation, we used indices such as region uniformity(U), region shape(S),region contrast(C) and entropy(E) to compare the performance of our algorithm and other algorithms. The more the value obtained from the above indices is approached to 1 , the better the segmentation are. Figure 8 to figure 11 are the comparison result. Since different segmentation criteria reflect only certain aspect of the performance of algorithms. We use Eq.(17)to evaluate the compound performance of algorithms. The performance of algorithms compared in figure 12. From figure 8 to table 12, we can see that our algorithm excels at both the individual index comparison and the compound evaluation.

$$Z = U \times S \times C \times E \tag{17}$$

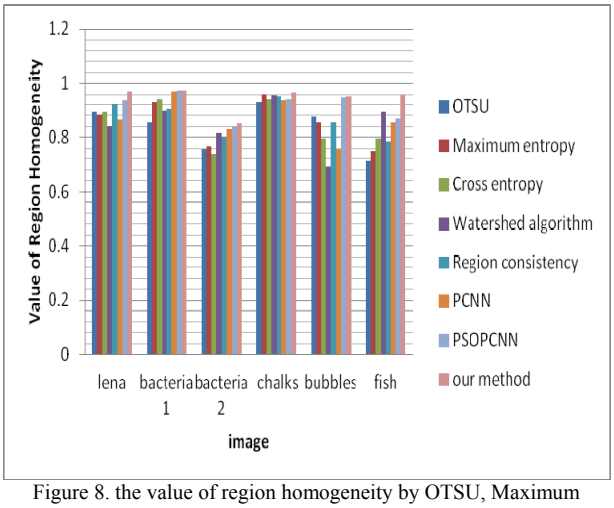

Figure 8. the value of region homogeneity by OTSU, Maximum entropy, Cross entropy, Watershed, Region consistency, PCNN, PSO-PCNN and the proposed method for test image.

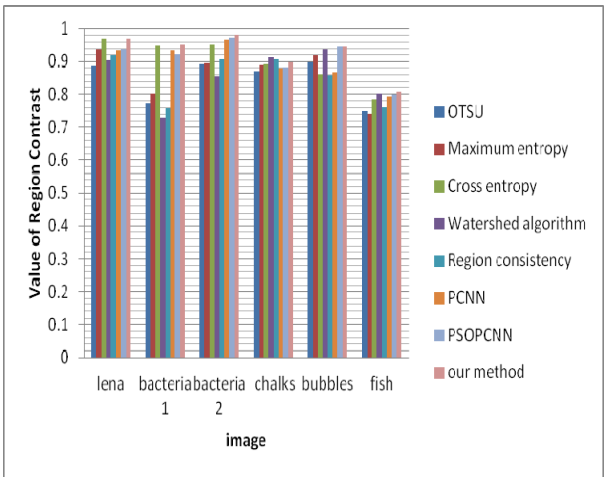

Figure 9. the value of region contrast by OTSU, Maximum entropy, Cross entropy, Watershed, Region consistency, PCNN, PSO-PCNN and the proposed method for test image.

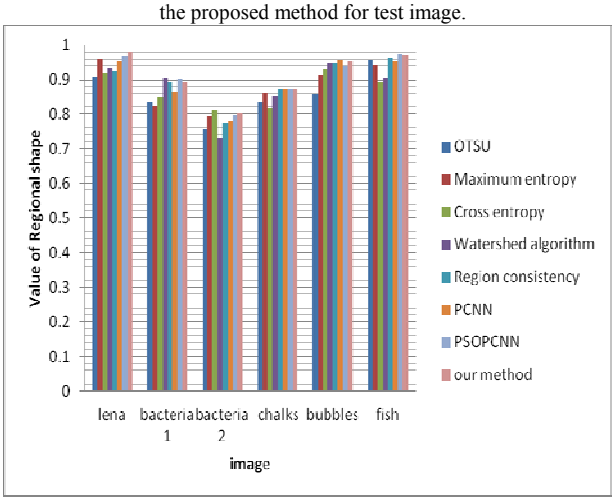

Figure 10. the value of regional shape by OTSU, Maximum entropy, Cross entropy, Watershed, Region consistency, PCNN, PSO-PCNN and the proposed method for test image.

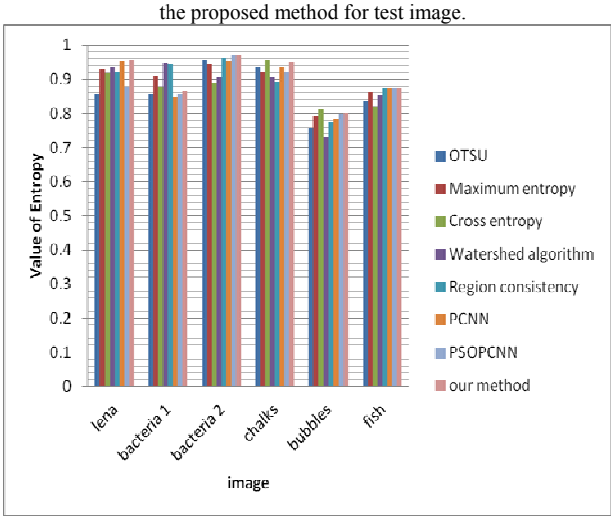

Figure 11. value of entropy by OTSU, Maximum entropy, Cross entropy, Watershed, Region consistency, PCNN, PSO-PCNN and the proposed method for test image.

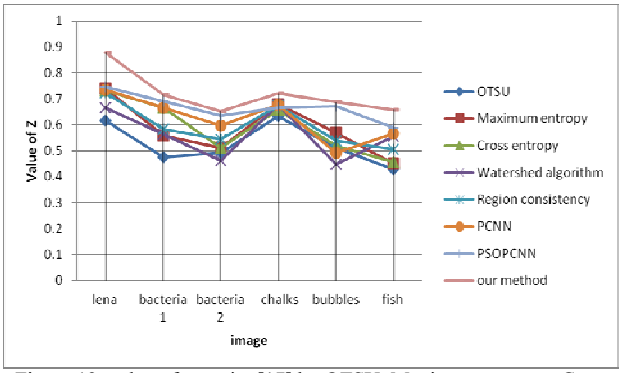

Figure 12. value of equation[17] by OTSU, Maximum entropy, Cross entropy, Watershed, Region consistency, PCNN, PSO-PCNN and the proposed method for test image.

C. Medical Image Segmentation

We took a further comparison between the proposed method and other methods through medical image segmentation which has explicit segmentation purpose and practical significance. Medical image segmentation aims at extracting the regions which have practical significance from organs and organizations, but it is difficult to obtain a ideal segmentation results because of the noise, the texture of organs and organizations, etc. The above situation results in that medical image segmentation is still a worldwide problem so far, and therefore it has certain significance to evaluate the performance of segmentation algorithms through medical image segmentation. The first image in Figure 13 is a nuclear magnetic resonance imaging (NMRI) without any preprocessing for typical cerebral hemorrhage, where red-line marked region is the actual position of bleeding. Although doctor can make a definite diagnosis of cerebral hemorrhage, it is necessary to segment this region precisely to calculate the amount of bleeding and the size of bleeding region. Figure 13 shows the segmentation results of the proposed method and other algorithms.

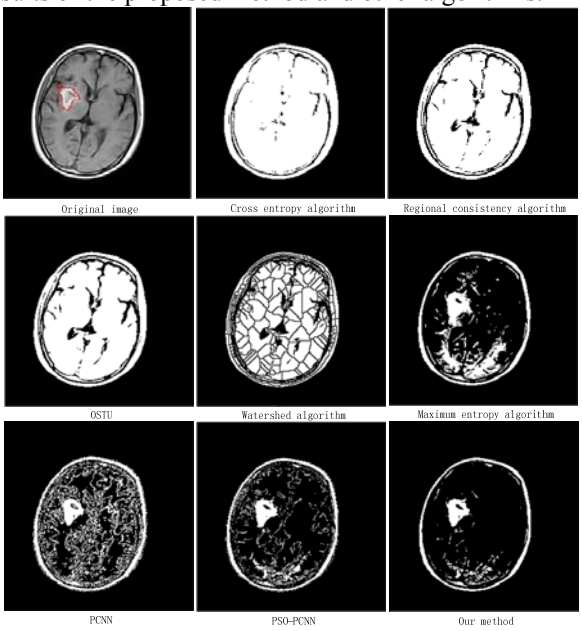

Figure 13. The comparison between the proposed method and other algorithms by brain image segmentation results.

Figure 13 shows that the proposed method, PSO-PCNN, PCNN and Maximum entropy can mainly extract the accurate bleeding region, but the segmented region of the proposed method satisfies the actual demand better, meanwhile PSO-PCNN, PCNN and Maximum entropy exist more serious over-segmentation phenomenon so that some organizations irrelevant to lesion region also are extracted. Although Watershed, OTSU, Cross entropy and Region consistency can obtain the better visual segmentation results, the results can not reflect the bleeding region precisely.

D. Analysis of Experimental Results

(1) Analysis of algorithm integrated performance. According to the subjective results of figure 2 and figure 3 and the objective evaluation of figure 4, the proposed method as a whole has a better performance among the algorithms. Besides, according to the medical image segmentation results of figure 5 and figure 6, the proposed method is superior to other algorithms, PCNN combined with human visual characteristics can obtain the better results in image segmentation tasks to satisfy the subjective perception of human vision.

(2) Comparison among the same-type algorithms. In different segmentation tasks, the results of the proposed method is superior to PCNN and PSO-PCNN in both subjective vision and objective evaluation. This is because the parameters of the PCNN completely dependent on artificial regulation in the image segmentation tasks, there is no rules to follow for artificial setting pattern of parameters, and the mechanism of various parameters and the law between each other still do not get a good proof, the good segmentation results completely rely on experience and a lot of experiments, therefore, the optimal parameter combination can not be found in the finite experiments. PSO-PCNN optimizes PCNN parameters depending on PSO while the proposed method optimizes PCNN parameters through combining with immune algorithm. LI Linyi et al. [17] indicate that immune algorithm compared with PSO has the higher global optimization ability and the ability of jumping out of local optimal solution. Therefore, the proposed method combined with immune algorithm can obtain the more reasonable parameters than PSO-PCNN.

V. CONCLUSIONS

This paper uses the gradient information based immune algorithm to optimize PCNN parameters and applies this method to image segmentation. The algorithm combines with the automatic optimization characteristic of immune algorithm and fuse PCNN parameters into the optimization tasks of immune algorithm, so that it better solves the problem that PCNN parameters need artificial adjusting. Experiments verify that immune algorithm can be used to optimize PCNN parameters and it can obtain a better image segmentation performance with this optimized parameters.

ACKNOWLEDGMENT

This work was supported by the National Natural Foundation of China under Grant No. 61262032,61173122;Hunan province science and technology project NO.2012FJ3100, Colleges and universities in Hunan Province scientific research project -- Youth Project NO.12B103;Hunan Province Research Learning and innovative experiment project NO.2012227.

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