Quantum particle swarm optimization based on chaotic mutation for automatic parameters determination of pulse coupled neural network

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Abstract: Pulse coupled neural network (PCNN), a well-known class of neural networks, has original advantages when applied to image segmentation because of its biological background. However, when PCNN is used, the main problem is that its parameters aren't self-adapting according to different image, which limits the application range of PCNN. Considering that, this paper proposed a new method based on quantum particle swarm optimization (QPSO) and chaotic mutation to determine automatically the parameters of PCNN. In this method, the chaotic mutation-quantum particle swarm optimization (CM-QPSO) is used to search automatically the optimal solution of the solution space of PCNN's parameters for image segmentation. Simulation results demonstrate that the proposed method is accurate and robust for image segmentation, and its performance is superior to the methods of GA and PSO when Shannon entropy is adopted as evaluation criteria.

Keywords: Quantum particle swarm optimization; image segmentation; pulse coupled neural network; chaotic mutation; parameters determination.

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1 Introduction

Image segmentation, which aims to divide the images into separate regions with certain distinctions, is one of the important fields of image analysis and processing. The threshold segmentation based on gray-scale is used validly and effectively. How to select the proper threshold to realize the correct segmentation is the crucial step of image segmentation, which makes binary image neither to produce under-segmentation, nor over-segmentation. Recently, the criterion of maximum Shannon entropy is applied to control information loss caused by segmentation (Ma and Dai, 2002). Because of the biological background, PCNN possesses a strong capability to solve image processing problems, e.g., image segmentation, image fusion and object detection (Xue and Zhang et al, 1999). The method makes neurons with similar pulse at the same time and can make up with the tiny changes of amplitude of inputting data. However, this model neither reflects the best objective estimation of segmentation result in the process of iteration nor controls the times of iteration, which would absolutely influence the results of segmentation.

Iterative times are determined automatically when the segmented binary image of PCNN outputs the maximal entropy (Ma et al, 2002). However, the coupling coefficient, threshold value and damply coefficient are determined by trial and error. Liu et al put forward a new method of improved PCNN image segmentation based on the criterion of minimum cross-entropy in order to determine the cyclic iterative times and also select the best threshold automatically (Liu et al, 2005). A PCNN system based on genetic algorithm was proposed in the image segmentation field (Ma and Qi, 2006). A self-tuning optimized method for PCNN parameters based on PSO algorithm is proposed to detect gray image edges (Wang and Cong, 2008). However, the genetic algorithm has too many parameters to be set in advance and the search ability of PSO algorithm is poor.

The PCNN's parameters can be determined by a combinatorial optimization problem, therefore, the genetic algorithm (GA) (Ma et al, 2002) and the particle swarm optimization (PSO) (Wang and Cong, 2008) can be used for PCNN parameters. However, both the GA and the PSO are slow convergence in searching near-optimal solution. Moreover, the natural system is one of the rich sources of inspiration for inventing new intelligence algorithms, inspiring intelligence algorithms are important scientific fields that are closely related to physical and biological phenomenon existing in nature. Lots of algorithms are widely used for engineering applications, such as particle swarm optimization (PSO) (Kennedy and Eberhart,1997; Gao, Wang and Pei, 2012), quantum particle swarm optimization (Gao , Cao and Diao, 2011), fuzzy adaptive weighted genetic algorithm(Ma et al,2012), quantum bacterial foraging algorithm (Gao, Cui and Li, 2013), social emotional optimization (Liu and Xu,2012) and membrane-inspired quantum shuffled frog leaping algorithm (Gao and Cao, 2012).The object is to design a MC-QPSO algorithm to improve QPSO algorithm by hybridizing swarm intelligence and quantum information theory to obtain the optimal system parameters. At last, simulation results demonstrate that the parameters determination of PCNN based on MC-QPSO is useful for the excellent performance with lower complexity.

This paper is organized as follows. In Section 2, we proposed a MC-QPSO algorithm using simulated quantum rotate gate and the particle swarm optimization principle. In Section 3, we provide the PCNN model and set up a PCNN optimization problem in an image segmentation environment, and an image segmentation based on the CM-QPSO is proposed. In Section4, we present simulation parameters, results, and an evaluation of the CM-QPSO. Finally, in Section 5, conclusions and future work are presented.

2 Quantum particle swarm optimization based on chaotic mutation

Quantum particle swarm optimization is based on the consideration of that modifying the conventional algorithm to get a better performance. In quantum particle swarm optimization, a number of different representations can be used to encode the solutions onto particles. The QPSO uses quantum coding, called a quantum bit or Q-bit, for the probabilistic representation that is based on the concept of quantum bit, and a quantum velocity is defined as a string of quantum bits. And quantum velocity can be simplified as

$$\mathbf{v}_i = \begin{bmatrix} v_{i1} & v_{i2} & \cdots & v_{iD} \end{bmatrix} \tag{1}$$

where $0 \le v_{ij} \le 1$.

The evolutionary process of quantum velocity is mainly completed through quantum rotation gate (Gao, et.al, 2011). In our algorithm, for simplicity, the *j*th quantum bit v_{ij}^t with quantum rotation angle φ_{ij}^{t+1} is updated as

$$v_{ij}^{t+1} = | v_{ij}^t \cos\varphi_{ij}^{t+1} - \sqrt{1-(v_{ij}^t)^2}\sin\varphi_{ij}^{t+1} | \tag{2}$$

where $|\cdot|$ is an absolute function which makes quantum bit in the real domain [0, 1].

If $\varphi_{ij} = 0$, a quantum bit velocity v_{ij} is updated in a certain small probability by the chaotic mutation operator (Dos and Herrera, 2007) which is described below.

$$v_{ij}^{t+1} = 4v_{id}^t(1-v_{id}^t) \tag{3}$$

Quantum particle swarm optimization is a novel multi-agent optimization system inspired by social behavior metaphor of agents. Each agent, called quantum particle, flies in a *D*-dimensional space according to the historical experiences of its own and its colleagues'. There are h quantum particles that are in a space of *D* dimensions in a quantum swarm, the *i*th quantum particle's position in the space is $\mathbf{x}_i = [x_{i1}, x_{i2}, \cdots, x_{iD}], (i = 1, 2, \cdots, h)$, which is a latent solution. The *i*th particle's quantum velocity is $\mathbf{v}_i = [v_{i1}, v_{i2}, \cdots, v_{iD}]$ and until now the best position (the local optimal position) of the ith quantum particle is $\mathbf{q}_i = [q_{i1}, q_{i2}, \cdots, q_{iD}], (i = 1, 2, \cdots, h)$.

$\mathbf{q}_g = [q_{g1}, q_{g2}, \cdots, q_{gD}]$ is the global optimal position discovered by the whole quantum particle population until now. At each generation, the ith quantum particle is updated by the following quantum moving equations:

$$\varphi_{id}^{t+1} = e_1(q_{id}^t - x_{id}^t) + e_2(q_{gd}^t - x_{id}^t) \qquad (4)$$

$$v_{id}^{t+1} = \begin{cases} 4v_{id}^t(1-v_{id}^t), & \text{if} \quad (\varphi_{id}^{t+1}=0 \text{ and } r < c_1); \\ |v_{id}^t \cos\varphi_{id}^{t+1} - \sqrt{1-(v_{id}^t)^2}\sin\varphi_{id}^{t+1}|, & \text{if} \quad \varphi_{id}^{t+1} \neq 0. \\ v_{id}^t, & \text{else.} \end{cases} \qquad (5)$$

$$x_{id}^{t+1} = \begin{cases} 1, & \text{if} \quad \gamma_{id}^{t+1} > (v_{id}^{t+1})^2; \\ 0, & \text{if} \quad \gamma_{id}^{t+1} \le (v_{id}^{t+1})^2. \end{cases} \qquad (6)$$

where $(i = 1, 2, \cdots, h)$, $(d = 1, 2, \cdots, D)$, r is uniform random number between 0 and 1, c_1 is mutation probability which is a constant among $[0, 1/D]$, $\gamma_{id}^{t+1} \in [0,1]$ is uniform random number, superscript $t+1$ and t represent number of iterations (generations), $(v_{id}^{t+1})^2$ represents the selection probability of bit position state in the $(t+1)$th generation. The value of e_1 and e_2 expresses the relative important degree of $\mathbf{q}_i$ and $\mathbf{q}_g$ in the moving process.

3 Automatic parameters determination of PCNN based on CM-QPSO

3.1 Pulse coupled neural network

The improved standard model of pulse coupled neural network adopted in the paper is illustrated as follows:

$$F_{ij}[n] = I_{ij} \qquad (7)$$

$$L_{ij}[n] = \sum w_{ijkl} Y_{kl}[n-1] \qquad (8)$$

$$U_{ij}[n] = F_{ij}[n](1 + \beta L_{ij}[n]) \qquad (9)$$

$$Y_{ij}[n] = \begin{cases} 1, U_{ij}[n] > \theta_{ij}[n]; \\ 0, \text{othewise} \end{cases} \qquad (10)$$

$$\theta_{ij}[n] = \exp(-\alpha_\theta)\theta_{ij}[n-1] + V_\theta Y_{ij}[n] \qquad (11)$$

where n is the number of iteration and feeding input $F_{ij}[n]$ is simplified with the input impulse signal I_{ij}, the gray scale of pixel corresponding to neurons. L_{ij} is the link input. U_{ij} is the internal activity of corresponding neurons and decided by the feedback input F_{ij} and the link input L_{ij}, which means the state of the neuron is affected by the state of its neighborhood. Y_{ij} is the output and θ_{ij} is the dynamic threshold of the neurons. The weight matrix w_{ij} is the local interconnection. The output of neurons is only 1 or 0 based on the formula 10. When the internal activity U_{ij} is larger then the temporal dynamic threshold θ_{ij}, the neuron output is “1” or “pulsing”, otherwise, it is “0” or “not pulsing”. The threshold θ_{ij} corresponding to each neuron is exponential damping according to formula 11 and damping coefficient is α_θ. Interaction value between current pixel and around pixels can be adjusted by connective co-efficient β.

For a two-dimensional image of $M \times N$, the PCNN can have $M \times N$ input neurons, each corresponding to a pixel in the image and taking its grayscale as the external stimulus. Neurons pulsing at the same time (which is called synchronous pulsing) have the same external stimulus, and neurons pulsing at different times (which are called asynchronous pulsing) have different external stimuli. This leads to a binary segmentation of the processed image.

The studies of human visual system (HVS) show, being apperceived by visual neuron, that object outline are superior to object detail. Internal activity not only includes pixel gray-scale information corresponding neuron, but also incarnates fully pixel neighborhood information, because this neuron input is weighted and modulated by using the outputs of neighborhood neurons. Matrix composed by internal activity (matrix **U)** is further more abundant than information of original image gray-scale matrix, processing of the former.

Apparently, the effectiveness of PCNN segmentation also relies on the parameters used in the network, such as $\mathbf{w}$, β, α_θ and V_θ. The selections and adjustments of these parameters often make proper image segmentation unreliable. The local interconnection weight matrix $\mathbf{w}$ is easily to be set the reciprocal of distance square between pixels at nine tenths occasions. The other three parameters are adjusted in the solution space by means of a hybrid optimization method based on quantum particle swarm optimization and chaotic mutation.

3.2 Automatic parameters determination of PCNN using CM-QPSO

The initial position population of quantum particle swarm optimization is randomly chosen from the solution space. All quantum bit velocity should be initialized as $1/\sqrt{2}$. In practice, the optimization of three parameters of the simplified PCNN model is multi-dimension function optimization problem. The CM-QPSO algorithm adopts the discrete coding method and parameters are coded as $(\beta, V_\theta, \alpha_\theta)$. The fitness function of the system adopts as performance criterion is the entropy function and is represented as follows:

$$H(P_0, P_1) = -P_1 \log_2 P_1 - P_0 \log_2 P_0 \qquad (12)$$

Where P_1 and P_0 represents the probability of “1” or “0” for the pixel in the output image $Y[n]$. The goal of the objective function is to evaluate the status of each quantum particle. In the image segmentation of PCNN, the target of position optimization is the maximization of entropy function.

According to the above introduction, the work processes of CM-QPSO for image segmentation of PCNN are shown below:

Step1: To initialize the quantum particle swarm, it includes the quantum particle's position, the quantum particle's quantum position, the quantum particle's local optimal position and the global optimal position.

Step2: To calculate the fitness of each quantum particle position based on entropy formula by means of decoding each image into the standard PCNN model.

Step3: Update quantum velocity and position of each quantum particle.

Step4: For new position of each quantum particle, to calculate the fitness of each quantum particle position based on entropy formula by means of decoding each image into the PCNN model.

Setp5: Update quantum particle's local optimal position. Update the global optimal position.

Step6: If the algorithm hasn't got the stop condition (the stop condition is set as maximum iteration times in generally), then back to step 3, else the algorithm stops.

4 Experiment and simulation result

In this paper, initial population and maximum generation of the three evolutionary algorithms are set as same. For GA (Ma and Qi, 2006) and PSO (Wang and Cong,2008), the parameters are set according to corresponding references. For CM-QPSO, we set $e_1 = 0.06\pi$, $e_2 = 0.015\pi$, $c_1 = 0.01/D$. All intelligence algorithms will be terminated at the same maximal iteration number which is set as 20. As for GA, the crossover probability and the mutation probability are set to 0.8 and 0.01, respectively. For comparison, the population size and the initial individuals of GA, PSO and CM-QPSO are supposed to be identical. The population size of 3 intelligence algorithms was set to 10. In the following simulations, we use binary-encoding, and the length of parameter is 50 bits.

Lena image and cameraman image are adapted to make sure the novel algorithm validity, maximal entropy criterion is used to judge whether iteration stop or not for each image. The foundation of Shannon entropy criterion is the information content after the image is segmented, which also can be considered as criterion of judging segmented result, it only relies on proportion of 0 and 1 possessed in the result when segmented result is a binary image. Obviously, if 0 and 1 of segmented result are occupied by 50 percent respectively, Shannon entropy is maximum value. It can be seen from Table 1 and Table 2, it is clear that CM-QPSO is superior to the GA and PSO. To segmented binary image, optimal segmented effect doesn't satisfy certainly maximum Shannon entropy when area difference of segmented objects and backgrounds is distinctive in the image. Compared Figure 2(b) with 2(a) and 1(b), it shows that MC-QPSO is more adaptive than GA and PSO as optimization algorithm of segmentation results. . Object regions are less than background regions by observing original image in Figure 3(a), some pixels that should have belonged to the background are divided into the object in Figure 3(b), Figure 4(a) and Figure 4(b) segmented results, it is irrelevant certainly to stop network iteration and export final outcome. Compared Figure 4(b) with 4(a) and 3(b), it shows that MC-QPSO is more adaptive than GA and PSO as optimization algorithm of segmentation results.

Table 1 *Parameters and entropy value for Lena*

Algorithm	β	V_θ	α_θ	H
GA	0.2826	205.92	0.7655	0.9985
PSO	0.08612	170.11	0.56217	0.9994
CM-QPSO	0.50054	243.64	0.90812	1

(a) Original Lena image (b) Segmented image based on GA

Figure 1 Original Lena image and segmented image based on GA

(a) Segmented image based on PSO (b) Segmented image based on CM-QPSO

Figure 2 Segmented image based on PSO and CM-QPSO for Lena image

Table2 *Parameters and entropy value for cameraman*

Algorithm	β	V_θ	α_θ	H
GA	0.2812	188.46	0.6217	0.8477
PSO	0.3826	245.98	0.7855	0.8961
CM-QPSO	0.2504	250.37	0.7818	0.9063

(a) Original cameraman image (b) Segmented image based on GA

Figure 3 Original cameraman image and segmented image based on GA

(a) Segmented image based on PSO (b) Segmented image based on CM-QPSO

Figure 4 Segmented image based on PSO and CM-QPSO for cameraman image

5 Conclusion and future work

This paper has proposed a CM-QPSO algorithm which is a novel algorithm for discrete optimization problems. Based on CM-QPSO, we have proposed a robust multiuser detection method. Experimental results show that our method not only improves the performance of BER, but also has better convergence rate.

Pulse coupled neural network (PCNN) is a hot research in the intelligent field and has been widely used in image segmentation, edge detection, object identification, and feature extraction effectively. The selection of PCNN model parameters is vital important to the performance of segmentation. To solve this problem, based on the model of pulse coupled neural network, this paper brings forward a CM-QPSO algorithm in the image segmentation. The CM-QPSO algorithm is simple in concept, few in parameters, easy in implementation, and does not require any derivative information. The experiment results show the good effect of the new optimization method.

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