Research on Edge Detection Algorithm of Rotary Kiln Infrared Color Image

Jie-sheng Wang[1,2] and Yong Zhang[2]

[1] Hubei Province Key Laboratory of Systems Science in Metallurgical Process, Wuhan University of Science and Technology, Wuhan 430081, China
wang_jiesheng@126.com
[2] School of Electronic and Information Engineering, Liaoning University of Science & Technology, Anshan 114044, China
zy9091@163.com

Abstract. Shuffled frog leaping algorithm (SFLA) is a meta-heuristic optimization method that mimics the memetic evolution of a group of frogs in nature seeking for food, which has been very successful in a wide variety of optimization problems. A hybrid optimization method is proposed for self-tuning pulse coupled neural network (PCNN) parameters, a biologically inspired spiking neural network, based on SFLA and was used to detect rotary kiln infrared image edges automatically and successfully. The effective of the proposed method is verified by simulation results, that is to say, the quality of the rotary kiln grayscale image edge detection is much better and parameters are set automatically.

Keywords: Pulse-Coupled Neural Network, Shuffled Frog Leaping Algorithm, Edge Detection, Rotary Kiln Infrared Image.

1 Introduction

Edge detection is a terminology in image processing and computer vision, particularly in the areas of feature detection and feature extraction, to refer to algorithms which aim at identifying points in a digital image at which the image brightness changes sharply or more formally has discontinuities [1]. There are many ways to perform edge detection. However, the majority of different methods may be grouped into two categories: gradient and Laplacian. Recently, pulse coupled neural network (PCNN) originally presented to explain the synchronous burst of the neurons in the cat visual cortex by Eckhorn has been widely used in many digital image processing research fields, such as segmentation, edge extraction, texture extraction, object identification, object isolation, motion processing, noise suppression and image fusion effectively [2-3]. However, up to now the parameters of the PCNN model (such as amplified coefficient of creep age integrator, damply time constant and weighted coefficient) are always adjusted and confirmed manually for different images, which impede PCNN's application in image processing.

According to the maximal entropy of segmented binary image of PCNN output, iterative times is determined automatically [4]. However, the coupling coefficient,

H. Deng et al. (Eds.): AICI 2011, Part III, LNAI 7004, pp. 370–377, 2011.

threshold value and damply coefficient is determined by trial and error. Reference [5] 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. An automated PCNN system based on genetic algorithm was proposed in the image segmentation field [6]. A self-tuning optimized method for PCNN parameters based on PSO algorithm is proposed to be used to detect gray image edges [7]. However, the genetic algorithm has too many parameters to be set in advance and the local search ability of PSO algorithm is not strong.

In this paper, a new hybrid optimization method is proposed for self-tuning PCNN parameters based on SFLA was used to detect rotary kiln infrared image edges automatically and successfully. Simulation results show the effectiveness of the proposed method. The rest of the paper is organized as follows. In next section, the improved standard model of PCNN is introduced in short. Section 3 describes self-tuning method of PCNN parameters based on SFLA. Section 4 gives simulation results and contrasts with other approaches, and discusses the performance of our method. Conclusions are summarized in the end.

2 Improved Standard Model of PCNN

PCNN is a novel biological neural network developed by Elkhorn et al in 1990 and based on the experimental observations of synchronous pulse bursts in cat and monkey visual cortex [2]. The pulse coupled neuron (PCN) structure of such PCNN is exhibited in Fig.1 [7].

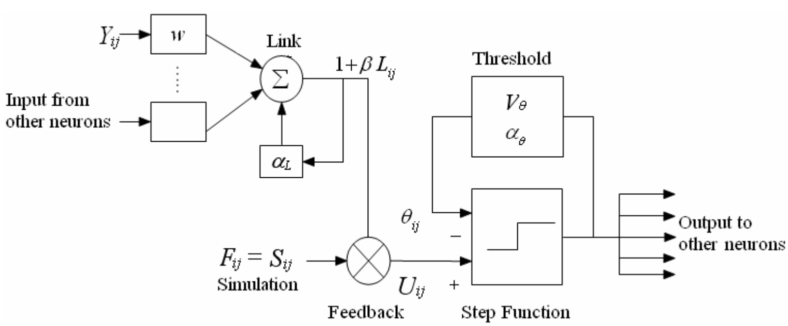


Fig. 1. Schematic representation of a PCNN processing element

The improved standard model of pulse coupled neural network [6] adopted in the paper is illustrated as follows:

$$F_{ij}[n] = S_{ij} \quad . \tag{1}$$

$$L_{ij}[n] = \sum w_{ijkl} Y_{kl}[n-1] \quad . \tag{2}$$

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

$$Y_{ij}[n] = 1 \ \ if \ \ U_{ij}[n] > \theta_{ij}[n] \ \ or \ \ 0 \ \ otherwise \ . \tag{4}$$

$$\theta_{ij}[n] = \exp(-\alpha_{\theta})\theta_{ij}[n-1] + V_{\theta}Y_{ij}[n-1] \ . \tag{5}$$

Where n is the number of iteration and feeding input F_{ij} is simplified with the input impulse signal S_{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 4. 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 5 and damping coefficient is α_{θ}. Interaction value between current pixel and around pixels can be adjusted by connective coefficient 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. Apparently, the effectiveness of PCNN segmentation also relies on the parameters used in the network, such as 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 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 SFLA.

3 Self-tuning of PCNN Parameters Based on Shuffled Frog Leaping Algorithm

3.1 Shuffled Frog Leaping Algorithm

The SFLA is a meta-heuristic optimization method that mimics the memetic evolution of a group of frogs when seeking for the location that has the maximum amount of available food[8]. It is based on evolution of memes carried by the interactive individuals, and a global exchange of information among themselves [9]. Since its inception, SFLA has found several applications in a wide variety of practical optimization problems like the water distribution network design [8], scheduling problem [10-11] and clustering problem [12].

The SFLA is described in details as follows [13]. First, an initial population of N frogs $P=\{X_1, X_2, \cdots, X_N\}$ is created randomly. For S-dimensional problems (S variables), the position of a frog i in the search space is represented as $X_i=[x_{i1}, x_{i2}, \cdots, x_{iS}]$. After the initial population is created, the individuals are sorted in a descending order according to their fitness. Then, the entire population is divided into m memeplexes, each containing n frogs (i.e. $N=m\times n$), in such a way that the first frog belongs to the first memeplex, the second frog goes to the second memeplexe, the mth frog goes to the mth memeplexe, and the (m+1)th frog goes back to the first memeplex, etc. Let M^k is the set of frogs in the kth memeplex; this dividing process can be described by the following expression:

$$M^k=\{X_{k+m(l-1)}\in P \mid 1\le l\le n\},(1\le k\le m) \quad . \tag{6}$$

In the each memeplex, the frogs with the best fitness and worst fitness are identified as X_b and X_w. The frog with the global best fitness in the population is identified as X_g. Then the local searching is carried out in each memeplex, that is to say the worst frog X_w leaps towards to the best frog X_b according to the original frog leaping rules described as follows.

$$D=r\cdot(X_b-X_w) \quad . \tag{7}$$

$$\mathrm{X_w}'=X_w+D,(\|D\|\le D_{\max}) \quad . \tag{8}$$

Where r is a random number between 0 and 1 and $D_{\max}$ is the maximum allowed change of frog's position in one jump. If the new frog X_w' is better the original frog X_w, it replaces the worst frog. Otherwise, X_b is replaced by X_g and the local search is carried out again according to the formula (7-8). If no improvement is got in this case, the worst frog is deleted and a new frog is randomly generated to replace the worst frog X_w. The local search continues for a predefined number of memetic evolutionary steps $L_{\max}$ within each memeplex, and then the whole population is mixed together in the shuffling process. The local evolution and global shuffling continue until convergence iteration number $G_{\max}$ is arrived.

3.2 Coding and Fitness Function

In practice, the optimization of three parameters of the simplified PCNN model is multi-dimension function optimization problem. The SFLA adopts the real-number coding method and parameters are coded as (β, V_θ, α_θ). The fitness function the system adopts as performance criterion is the entropy function proposed in reference 4 and is represented as follows:

$$F(p)=-P_1*\log_2 P_1-P_0*\log_2 P_0 \quad . \tag{9}$$

Where P_1 and P_0 represents the probability of "1" or "0" for the pixel in the output image Y[n].

3.3 Algorithm Procedure

The arithmetic procedure for optimizing PCNN model parameters by means of the SFLA to detect rotary kiln infrared image is given as follows:

Step 1: Initialize the objective function and the SFLA algorithm parameters: The parameters include the frog population size N, the searching space dimension S, the number of memeplex n, the maximum allowed change of frog's position $D_{\max}$, the local searching number $L_{\max}$ and the global hybrid iteration number $G_{\max}$.

Step 2: Frog population creation. Randomly initial the population of N frogs $P=\{X_1(t),\cdots,X_k(t)\cdots,X_N(t)\}$ $(k=1,\cdots,N)$. Set the iteration counter $t=0$. Then calculate the fitness (entropy of rotary kiln infrared image) $F_k(t)=F(X_k(t))$ based on formula (9) by means of decoding the frog individual solution vector $X_k(t)$ into the standard PCNN model (formula 1-5). Then the frogs are sorted in a descending order according to their fitness. The outcome is stored with the style $U_k(t)=\{X_k(t),F_k(t)\}$. The global best frog in the frog population is identified as $X_g(t)=U_1(t)$.

Step 3: Memeplex creation. The U is divided into the m memeplex $M^1(t),\cdots,M^j(t),\cdots,M^m(t)(j=1,\cdots,m)$ according to the formula (6). Each memeplex includes n frogs. The frogs with the best fitness and worst fitness in the memeplex are identified as $X_b^j(t)$ and $X_w^j(t)$.

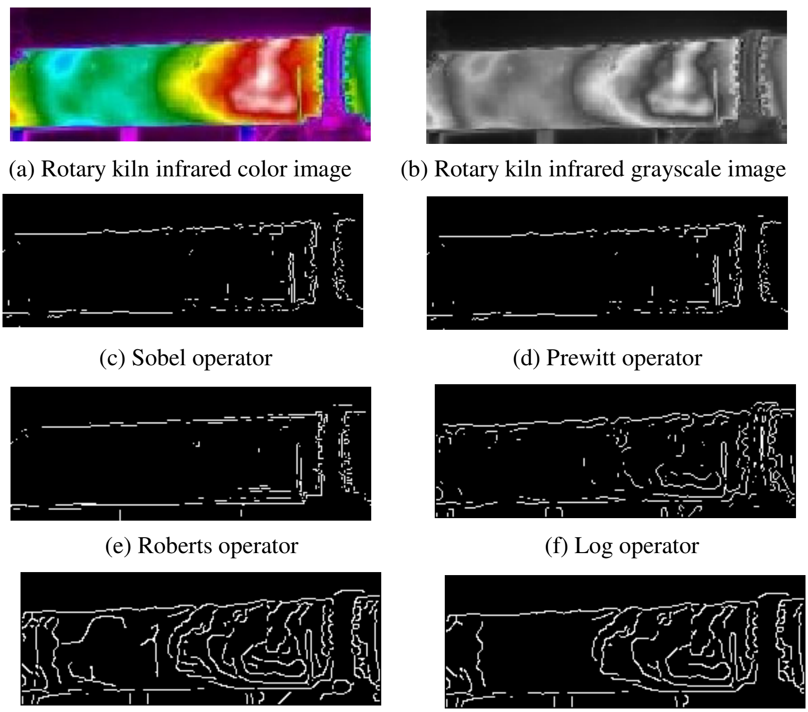
Step 4: Memeplex evolution. The worst frog $X_w^j(t)$ in the memeplex $M^j(t)$ is carried out the local search based on the frog leaping rules described in the formula (7-8). Then calculate the fitness (entropy of rotary kiln infrared image) based on formula (9) by means of decoding the frog individual solution vector into the standard PCNN model (formula 1-5). If the new frog is better the original frog, then the $X_w^j(t)$ is substituted. Otherwise, $X_b^j(t)$ is substituted by $X_g(t)$ to carry out the local search again. If no improvement is got, a new frog is created randomly to substitute the $X_w^j(t)$. The local search is gone on the $L_{\max}$ iteration to obtain the improved memeplex $M^1(t)',M^2(t)',\cdots,M^m(t)'$.

Step 5: Memeplex shuffled. The frogs in the iterated memeplex $M^1(t)',M^2(t)',\cdots,M^m(t)'$ is mixed together in the shuffling process and identified as $U(t+1)=\{M^1(t)',M^2(t)',\cdots,M^m(t)'\}$. Then the frogs in the $U(t+1)$ are sorted in a descending order according to their fitness. The new global best frog in the population is identified as $X_g(t+1) = U_1(t+1)$.

Step 6: Test the algorithm termination conditon. $t = t+1$, if $t < G_{max}$, go to then step 3. Otherwise output the best frog.

4 Simulation Results

Rotary kiln pellets sintering is the most widely used agglomeration process for iron ores and is a very important chain of iron making. The paper adopts the SFLA to optimize the parameters of PCNN model to detect the rotary kiln infrared image edges. The parameters of the SFLA are: the frog population size N is 50. The searching space dimension S is 3. The number of memeplex n is 10. The maximum allowed change of frog's position D_{max} is 0.02. The local searching number L_{max} is 5. The global hybrid iteration number G_{max} is 100.



(a) Rotary kiln infrared color image (b) Rotary kiln infrared grayscale image

(c) Sobel operator (d) Prewitt operator

(e) Roberts operator (f) Log operator

(g) Canny operator (h) PCNN algorithm operator

Fig. 2. Edge detection results of rotary kiln infrared image

In order to validity the proposed method, the paper carries through the simulation tests to detect the edges of rotary kiln infrared image on the platform of MATLAB 7.0. The simulation results are illustrated in Fig.2. Fig.2 (a) and Fig.2 (b) is original rotary kiln infrared color image and the grayscale image, respectively. Fig.2 (c, d, e, f and g) is the edge detection results by means of Sobel operator, Prewitt operator, Roberts operator, Log operator and Canny operator. Fig. 2(h) is edge detection result by means of the proposed method. It is obvious that the detection result by the SFLA is finer and has better effect at the more blurry edge zones.

5 Conclusions

Pulse coupled neural network (PCNN) is a hot research in the intelligent field and has been widely used in denoising, segmentation, edge detection, object identification, and feature extraction effectively. The selection of PCNN model parameters is vital important to the performance. To solve this problem, based on the model of pulse coupled neural network, this paper brings forward a shuffled frog leaping algorithm in the rotary kiln infrared color image edge detection. The SFLA 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 proposed method.

Acknowledgments. This work is supported by the Hubei Province Key Laboratory of Systems Science in Metallurgical Process (Wuhan University of Science and Technology), China (Grant No. B201002) and the Program for the Innovative Research Team of Education Bureau of Liaoning Province, China (Grant No. 2008T091).

References

1. Ziou, D., Tabbone, S.A.: Multi-scale Edge Detector. Pattern Recognition 26, 1305–1314 (1993)
2. Johnson, J.L., Padgett, M.L.: PCNN Models and Applications. IEEE Trans. on Neural Networks 10, 480–498 (1999)
3. Kuntimad, G., Ranganath, H.S.: Perfect Image Segmentation Using Pulse Coupled Neural Networks. IEEE Trans. on Neural Networks 10, 591–598 (1999)
4. Ma, Y.D., Dai, R.L., Li, L.: Automated Image Segmentation Using Pulse Coupled Neural Networks and Images Entropy. Journal of China Institute of Communications 23, 46–51 (2002)
5. Liu, Q., Ma, Y.D., Qian, Z.B.: Automated Image Segmentation Using Improved PCNN Model Based on Cross-entropy. Journal of Image and Graphics 10, 579–584 (2005)
6. Ma, Y.D., Qi, C.L.: Study of Automated PCNN System Based on Genetic Algorithm. Journal of System Simulation 18, 722–725 (2006)
7. Wang, J.S., Cong, F.W.: Grayscale Image Edge Detection Based on Pulse-coupled Neural Network and Particle Swarm Optimization. In: 20th Chinese Control and Decision Conference, pp. 2492–2495. IEEE Press, New York (2008)
8. Eusuff, M.M., Lansey, K.E.: Optimization of Water Distribution Network Design Using the Shuffled Frog Leaping Algorithm. Journal of Water Resources Planning and Management 129, 210–225 (2003)

9. Elbeltagi, E., Hezagy, T., Grierson, D.: Comparison Among Five Evolutionary-based Optimization Algorithms. Advanced Engineering Informatics 19, 43–53 (2005)
10. Rahimi-Vahed, A., Mirzaei, A.H.: A Hybrid Multi-objective Shuffled Frog-leaping Algorithm for a Mixed-model Assembly Line Sequencing Problem. Computers and Industrial Engineering 53, 642–666 (2007)
11. Rahimi-Vahed, A., Dangchi, M., Rafiei, H.: A Novel Hybrid Multi-objective Shuffled Frog-leaping Algorithm for a Bi-criteria Permutation Flow Shop Scheduling Problem. International Journal of Advanced Manufacturing Technology 41, 1227–1239 (2009)
12. Amiri, B., Fathian, M., Maroosi, A.: Application of Shuffled Frog-leaping Algorithm on Clustering. International Journal of Advanced Manufacturing Technology 45, 199–209 (2009)