Cellular Neural Networks for Medical Image Noise Cancellation Based on Particle Swarm Optimization

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ABSTRACT

In this paper, a novel method for designing templates of cellular neural networks (CNNs) is discussed to cancel the image noise. The discrete-time cellular neural network (DTCNN) combining with particle swarm optimization (PSO) is applied to medical image noise cancellation. Computed tomography is familiar diagnosis in medical field, and it is often polluted by outside interference. Based on PSO method, the templates of cellular neural network is optimized to diminish noise interference in polluted medical computed tomography image. The demonstrated examples are presented to illustrate the effective results of the proposed methodology.

Categories and Subject Descriptors

G.1.6 [**Mathematics of Computing**]: Optimization –*Global optimization.*

General Terms

Algorithms.

Keywords

Particle swarm optimization, cellular neural network, stack smoother, medical computed tomography.

1. INTRODUCTION

A novel class of information processing system called cellular neural networks was proposed by L.O. Chua and L. Yang [1, 2] in 1988. Cellular neural networks (CNN) are characterized by the parallel computing of simple processing cells locally interconnected. Due to their local connectivity, cellular neural networks can be realized as image processing [3] and can allow operating at a very high speed in the real time. Therefore, cellular neural networks can apply to other areas, including signal processing, solving optimization problem [4], image compression [5], and VLSI implementation [6, 7], etc.

In a cellular neural network circuit, the data values of input image will always suffer from various kinds of noises. The sources of noise may come from external interference, e.g. atmospheric noise, man-made noise, that will cause the perturbations to the system. These perturbations can produce the wrong judgment in system operation. However, the CNN's configuration must be determined along with a template set, the parameters that describe such a nontrivial task.

Zeng (1994) [8,9] introduced a stack smoother design procedure that can preserve certain structural features of an image, such as straight lines or corners, the advantage of the stack smoother is noise reduction property. Zeng's algorithm leads to stack smoothers that compare favorably with other stack smoothers.

In this paper, we present a heuristic method – Particle Swarm Optimization (PSO) to optimal templates of cellular neural network apply to reduce the noise interference in medical computed tomography (CT) images. Different from traditional search algorithms, like genetic algorithm, particle

swarm optimization work on a population of potential solutions (points) of the search space.
In the next section, the CNN model is described and we review the particle swarm optimization in the section III, and our proposed algorithm introduced. In section V, the simulate results are demonstrated. Finally, the conclusion is presented in section VI.

2. CELLULAR NEURAL NETWORK

Cellular neural network constitute a class of non-linear, dynamic systems with local interaction. In this paper, two-dimensional (2-D) DTCNN are considered. These neurons are commonly called cells. The dynamics of each cell are described by the following set of nonlinear difference equations:

$$x_{ij}(k+1) = \sum_{C(g,l)\in N_y(i,j)} A_{ij;gl}\, y_{gl}(k) + \sum_{C(g,l)\in N_u(i,j)} B_{ij;gl}\, u_{gl}(k) + I \quad (1)$$

$$y_{ij}(k) = f\left(x_{ij}(k)\right) = \begin{cases} 1 & if \;\; x_{ij}(k) > 0 \\ -1 & f \;\; x_{ij}(k) < 0 \end{cases} \quad (2)$$

$$i = 1,\ldots,\overline{M}\,; \quad j = 1,\ldots,\overline{N}$$

where x_{ij} , u_{ij} and y_{ij} denote the state, input, and output of a cell, respectively. The parameters $A_{ij;gl}$ represent the feedback operators which described the interaction between the cell $C(i,j)$ and the output y_{gl} of each cell $C(g,l)$ that belongs to the neighborhood $N_y(i,j)$. Similarly, $B_{ij;gl}$ represent the control operators and the parameters Δ $B_{ij;gl}$ represent the uncertain feedback operators. They describe the interaction between the cell $C(i,j)$ and the input u_{gl} of each cell $C(g,l)$ within the neighborhood $N_u(i,j)$.
Then, equations (1) and (2) can be written in vector form by re-numbering the cells from 1 to n, with $n = \overline{M} \times \overline{N}$.
Therefore, the model of DTCNN can be described as follows:

$$x(k+1) = A\, y(k) + Bu(k)+I \quad (3)$$

$$y(k) = f(x(k)) \quad (4)$$

where $x(k) = [x_1(k),\ldots,x_n(k)]^T$ is the state vector, $y(x) = [y(x_1),\ldots,y(x_n)]^T$ is the output vector, $u = [u_1,\ldots,u_n]^T$ is a constant input vector and $f = [f(x_1),\ldots,f(x_n)]^T$ is the output functions, whereas the matrices A $\in \Re^{n\times n}$ and B $\in \Re^{n\times n}$ are known constant feedback matrix and control matrix.

Each CNN is uniquely defined by three terms of the cloning templates {A, B, I}, which consist of 19 real numbers for 3×3 neighborhood. In Fig.1, the signal flow structure of a CNN with a 3×3 neighborhood. The two shaded cones symbolize the weighted contributions of input and output values of cell $C(k,l) \in N_1(i,j)$ to the state value of the center cell $C(i,j)$. And then, the equivalent block diagram of a cell $C(i,j)$ is shown in Fig.2.

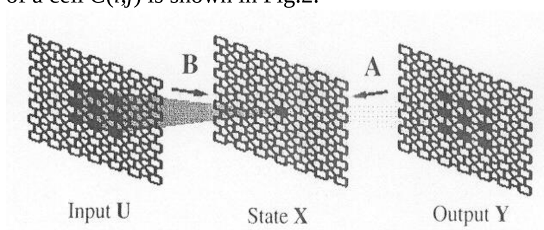


Fig.1 Signal flow structure of a CNN

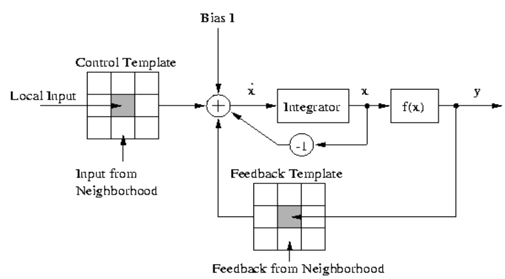


Fig.2 CNN System block diagram of a cell C(i,j)

3. Particle Swarm Optimization

Particle Swarm optimization (PSO) was first presented by Kennedy and Eberhart [10,11] in 1995, which was inspired by the social behavior of animals, such as bird flocking or fish schooling, when they search food. In PSO, particles denote a population or swarm of potential solutions, the behavior of each individual particle is affected by either the local best or global best particle to help it flies in the search space exploring for better solutions. As in a flock of birds, an individual can learn past experience to modify its flying speed and direction. Each particle can benefit from its explore the new regions of the search space. Therefore, each individual particle has a memory, remembering the best position of the search space that it has ever visited. In PSO, suppose that the search space is D-dimensional, and then the i -th particle is represented as $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$. The velocity (rate of the position change) of this particle is denoted as $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$. The best previous position of the i -th particle is represented as $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$. In other words, P_i involves the best previous position which X_i has visited (the best position called $pBest$). The index of the best particle among all the particles in the swarm is defined as the symbol g (called $gBest$). The particles are manipulated according to the following equations:

$$v_{id}(t+1) = w * v_{id}(t) + c_1 * rand() * (p_{id} - x_{id}) + c_2 * Rand() * (p_{gd} - x_{id}) \tag{5}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{6}$$

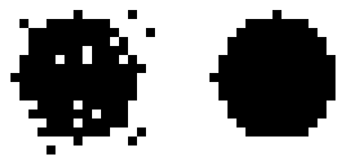
where $i = 1, 2, \ldots, N$, and N is the size of swarm; c_1 and c_2 called acceleration coefficients are bounded between 0 and 2. The $rand()$ and $Rand()$ are two random numbers, with uniform distribution $U(0,1)$. The use of the inertia weight w , is a factor used to control the balance of the search algorithm between exploration and exploitation. Equation (5) calculates a new velocity for each particle based on its previous $v_{id}(t)$. To avoid the $v_{id}(t)$ escaping from the search space, we set the range $[-X_{\max}, X_{\max}]$, $v_{id}(t)$ is limited by the range $[-V_{\max}, V_{\max}]$. Equation (6) updates each particle's position in search space. After the new position is updated for each particle, the particle will follow the new search direction to evaluate the best solution.

4. PSO BASED CNN TEMPLATE LEARNING

In the section, we used Particle Swarm Optimization (PSO) for the automatic templates optimization of DTCNN for canceling the noise interference in pictures. The templates of DTCNN distinguished into three arrays: the feedback matrix A , the control matrix B and bias I . We designed the scheme as following pattern structure:

$$A = \begin{bmatrix} a_2 & a_1 & a_2 \\ a_1 & a_0 & a_1 \\ a_2 & a_1 & a_2 \end{bmatrix}, \; B = \begin{bmatrix} b_1 & b_2 & b_1 \\ b_2 & b_0 & b_2 \\ b_1 & b_2 & b_1 \end{bmatrix}, \; I = i$$

where a_0, a_1, a_2 b_0, b_1, b_2, i are elements of the swarm, in order to satisfy output saturation effectively, we set $a_2 = 0$. The training image is corrupted by the salt and pepper noise shown in Fig.3.



(a) **(b)**

Fig.3: The training images (a) Input image to the CNN (b) Desired output image of CNN.

Next, the flow chart of CNN simulator is shown as Fig.5. And the process for implementing the PSO based on CNN is shown as Fig.4.

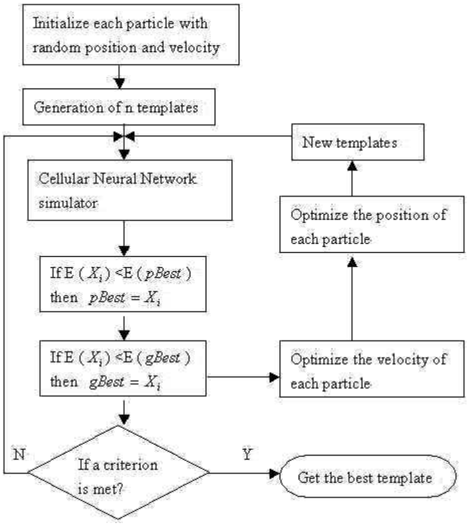


Fig.4: Flow chart of PSO-CNN.

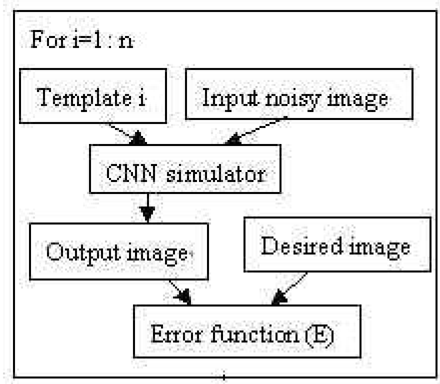


Fig.5: The flow chart of CNN simulator.

The criterion in Fig.5 is the following equation used as an objective function (error function).

$$Error = \sum_{i=1}^{k} \left(P_c(i) - P_d(i)\right)^2$$

where k denotes the total pixel of the picture, $P_c(i)$ is the value of the i th pixel of the input image and $P_d(i)$ stands for the pixel of the desired output image. Each resulting image is compared with the desired image which should be obtained in the end. The comparison is according to compute the value of the error function, and then the best template is obtained.

5. SIMULATION RESULTS

In order to demonstrate CNN with PSO approach for medical computed tomography (CT) image noise cancellation. Computed tomography is familiar diagnosis in medical field, and it is often polluted by outside interference. When it has noise interference, doctors may do the wrong diagnosis. We consider the 200*515 gray scale image which the fracture of finger was a noisy image and polluted by the salt and pepper noise. Because we use a bipolar CNN, a bipolar output filter, Eq. (2), preprocessed this image first shown in Fig.5. The fracture image is coded such that +1 corresponds to black pixels and -1 to white ones. This image was the input of the discrete-time CNN, through DTCNN processing, the result for the output image obtained in Fig.6.

By using our proposed method, we set the parameters of our algorithm as following Table 1:

Table 1. Parameters setting

The number of swarm size	10
The maximum position $X_{\max}$	1
The maximum velocity $V_{\max}$	10
Acceleration coefficient c_1	1.4
Acceleration coefficient c_2	1.2
Inertia weight w	0.8
Iterations	300

According to these parameters, the PSO found the consequences of approximated optimal templates A, B and bias item I after a few iterations as following:

$$A = \begin{bmatrix} 0 & 0.7658 & 0 \\ 0.7658 & 0.6874 & 0.7658 \\ 0 & 0.7658 & 0 \end{bmatrix}, \; B = \begin{bmatrix} 0.5805 & 0.1890 & 0.5805 \\ 0.1890 & 1.4733 & 0.1890 \\ 0.5805 & 0.1890 & 0.5805 \end{bmatrix}, I = 0.0285$$

By combining the above templates, the clearness of the result for the final output image can be obtained in Fig. 7.

Fig.6 Image preprocessed.

Fig.7 The contaminated image with 10% noise

Fig.8 The result using PSO-CNN algorithm

Fig.9 The result using Zeng's stack smoother

In order to demonstrate the optimal template has the same performance to process the computed tomography image of brain. Because the computed tomography image of brain contains many wrinkles, called sulcus. We consider the 181*217 gray scale brain computed tomography image which was also a noisy image and polluted by the salt and pepper noise in Fig.10. By the same method, the preprocessed image first shown in Fig.9. This image was also the input of the discrete-time CNN, through DTCNN processing, the result for the output image obtained in Fig.11.

Fig.10 Image preprocessed.

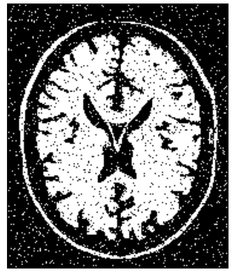


Fig.11 The contaminated image with 10% noise

Fig.12 The result using PSO-CNN algorithm

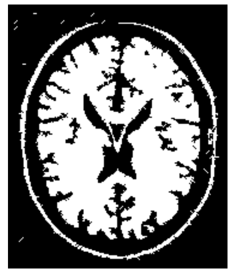


Fig.13 The result using Zeng's stack smoother

6. CONCLUSION

By comparing Fig.8 with Fig.9, and Fig.12 with Fig.13, our proposed method could restrain noise from the polluted medical computed tomography image more effectively than Zeng's stack smoother. Template learning is a crucial step in cellular neural network technology. A discrete-time cellular neural network's (CNN's) templates learning method combined particle swarm optimization (PSO) apply to image noise cancellation is proposed. From the demonstrated examples, we observe the better performance of noise cancellation can be obtained with designing the template of the CNN and corrupting image is recovered through CNN system. Simulation results show that proposed method and procedures are profitable to improve the polluted image quality in receiver, and can sustain different noise interference density.

Finally, this work does not include the noise cancellation of gray scale images and color images that are planned as future work.

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