The Human Body Edge Detection of Infrared Image with IGA_CNN Algorithm

Gangyi Hu* and Sumeth Yuenyong
School of Information Technology, Shinawatra University
197 BBD Building Viphavadi-Rangsit Road,
Samsen Nai, Phayathai, Bangkok 10400, Thailand

Abstract

This paper presents an algorithm with improved genetic algorithm design template in cellular neural networks parameters and realizes the human body edge detection in infrared image. The algorithm uses population Cross generational elitist selection and the subgroups of parallel population that overcome the shortcomings of the simple genetic algorithm in solving for the optimal template in cellular neural networks, which is premature convergence. The improved genetic algorithm can converge quickly to the stable and optimal value. The simulation results show that this algorithm is more effective than traditional algorithms based on Particle Swarm Optimization and on a simple genetic algorithm. At the same time, compared with the traditional Canny algorithm, this algorithm can detect the human body more clearly and accurately in infrared images, with low miss-detection. This greatly improves the processing speed of the subsequent target tracking and provides a new method for body edge detection in an infrared image.

Keywords: human body edge detection; infrared image; Cellular Neural Network; improved genetic algorithm

1. Introduction

The edges of an image are basic and important information of the image. Edge detection is an important preliminary step for image tracking, recognition, and segmentation, and provide important information for further feature description.

1.1 Human body infrared image

With the rapid development of modern data acquisition technology, human body infrared image processing technology has also been widely used in security systems. In the infrared image processing system, the target acquisition, target recognition and tracking are not affected by light or darkness, nor by the influence of weather. So it has been widely used in various key sectors, special places, warehouses, small on-site monitoring and other fields. But compared to general images, human body detection with infrared imaging face challenges such as high background noise, edge information is fuzzy and low contrast. So the human body infrared image edge detection technology is a difficult

technology. To solve the edge detection of human body in infrared images will have significant contribution for infrared image processing, and has become the focus of many researchers.

1.2 The contribution of this paper

A. It's the first application of cellular neural network theory to the body edge detection in infrared image, which introduces a new method of human body edge detection in infrared image.

B. Unlike the traditional genetic algorithm, our algorithm uses population Cross generational elitist selection and the subgroups of parallel genetic thought, which can converge quickly to achieve a stable and global optimal value, and also avoid local optimal solutions.

C. The improved genetic algorithm was used to get the CNN template, which is then used for the human body edge detection in infrared image. It was found that it can quickly and accurately get the body image edge, and avoid false detection of buildings and cars and other objects. This provides the information needed for any follow-up processing.

D. The detection process of this algorithm uses fewer iterations, less operation time and has stable convergence, which can be referenced for future works.

2. Research background

2.1 Cellular Neural Network

A Cellular Neural Network (CNN) was proposed by L.O.Chua and L.Yang in 1988 for use in image, video signal processing, robotic, biological visions and high brain functions.

It consists of a large number of cellular components, and only adjacent cells can communicate directly. Each cell consists of a linear capacitor, a nonlinear voltage controlled current source and a small amount of linear circuit resistance. A group of cells are interconnected within a limited region. All state variables have continuous value, but the

time value doesn't need to be continuous. This allows for the realization of real-time signal processing in the digital domain [1].

2.2 The Cellular Neural Network structure model and the proof of stability

Figure 1 is a cellular neural network with 3 x 3 local interconnection model structure. In fact, the whole structure of CNN is composed of M x N cells component, and the cell in the i line and the j column will only be connected by the neighbor cell. The cells which is not directly connected communicate by acting through dynamic propagation [4].
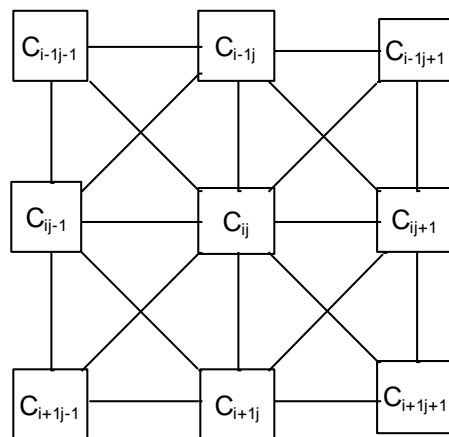

Fig.1. The model structure chart of C_{ij} cells in neural network.

The neighborhood of $N_{ij}(r)$ is defined as:

$$N_{ij}(r) = \left\{ C_{ab} \mid \max(|a-i|,|b-j|) \le r, 1 \le a \le M, 1 \le b \le N \right\}$$

, where r is the radius of the neighborhood of cellular C_{ij}, and C_{ab} is the cell of the neighborhood of cellular C_{ij}. In the M x N local interconnect model structure, any cell C_{ij}, is composed of linear circuit and non-linear circuit. Each cell of C_{ij} contains the input variables, output variables, state

variables and threshold. Using a first-order nonlinear differential equation the dynamic equation for cellular C_{ij} can be represented as[3]

$$C\frac{dx_{ij}(t)}{dt} = -\frac{x_{ij}(t)}{R_x} + \sum_{k,l\in N_{ij}(r)} A_{kl} y_{kl}(t)$$
$$+ \sum_{k,l\in N_{ij}(r)} B_{kl} u_{kl} + I_{ij}$$

where $1\leq i\leq M$, $1\leq i\leq N$, x_{ij} is a state variable, y_{kl} is an output variable, u_{kl} is an input variable, I_{ij} is the threshold, A is the feedback coefficient matrix and B is the control coefficient matrix.

The output equation of a standard for CNN is

$$y_{ij}(t) = \frac{1}{2}(|x_{ij}(t)+1| - |x_{ij}(t)-1|) = f(x)$$

where $1\leq i\leq M$, $1\leq i\leq N$, the output function of $f(x)$ is a piecewise linear function. Generally speaking, A, B and I define the CNN template. They decide the direction and the function of the dynamic changes of the cellular neural network. The design of A, B and I in CNN is to achieve the purpose of image processing.

In the application of human body edge detection in infrared image, the CNN in the process of image processing has to constantly update its state to finally reach a stable state. It also means that the CNN must be a completely stable network. Here we use the Lyapunov function method to analyze the dynamic nonlinear stability of CNN.

The Lyapunov function of cellular neural network is[7],

$$E(t) = -\frac{1}{2}\sum_{(i,j)}\sum_{(k,l)} A_{kl} y_{kl}(t) y_{ij}(t) + \frac{1}{2R_x}\sum_{(i,j)} y_{ij}^2(t)$$
$$- \sum_{(i,j)}\sum_{(k,l)} B_{kl} u_{kl} y_{ij}(t) - \sum_{(i,j)} I_{ij} y_{ij}(t)$$

According to the definition above, as long as $E(t)$ is bounded，and with the increasing time of t, $E(t)$ decreased monotonically, CNN is stable. On this basis and from the previous equation, we get that,

$$E(t) = -\frac{1}{2}\sum_{(i,j)}\sum_{(k,l)} A_{kl} y_{kl}(t) y_{ij}(t) + \frac{1}{2R_x}\sum_{(i,j)} y_{ij}^2(t) - \sum_{(i,j)}\sum_{(k,l)} B_{kl} u_{kl} y_{ij}(t) - \sum_{(i,j)} I_{ij} y_{ij}(t)$$

$$\leq \frac{1}{2}\sum_{(i,j)}\sum_{(k,l)} |A_{kl}|.|y_{kl}(t)|.|y_{ij}(t)| + \frac{1}{2R_x}\sum_{(i,j)} y_{ij}^2(t) +$$
$$\sum_{(i,j)}\sum_{(k,l)} |B_{kl}|.|u_{kl}|.|y_{ij}(t)| + \sum_{(i,j)} |I_{ij}|.|y_{ij}(t)|$$

Because of the state definition of cellular neural network, we know that

$$|u_{ij}|\leq 1, \quad |y_{ij}|\leq 1, \text{ so,}$$

$$E(t) \leq \frac{1}{2}\sum_{(i,j)}\sum_{(k,l)} |A_{kl}| + \frac{M.N}{2R_x} + \sum_{(i,j)}\sum_{(k,l)} |B_{kl}| + \sum_{(i,j)} |I_{ij}|$$

So $E(t)$ is bounded. On the other hand, we compute the time derivative of $E(t)$

$$\frac{dE(t)}{dt} = -\sum_{(i,j)}\sum_{(k,l)} A_{kl} \frac{dy_{ij}(t)}{dx_{ij}} \frac{dx_{ij}(t)}{dt} y_{kl}(t)$$
$$+ \frac{1}{R_x}\sum_{(i,j)} \frac{dy_{ij}(t)}{dx_{ij}} \frac{dx_{ij}(t)}{dt} y_{ij}(t)$$
$$- \sum_{(i,j)}\sum_{(k,l)} B_{kl} u_{kl} \frac{dy_{ij}(t)}{dx_{ij}} \frac{dx_{ij}(t)}{dt}$$
$$- \sum_{(i,j)} I_{ij} \frac{dy_{ij}(t)}{dx_{ij}} \frac{dx_{ij}(t)}{dt}$$

By the output equation of the standard CNN which is

$$y_{ij}(t) = \frac{1}{2}(|x_{ij}(t)+1| - |x_{ij}(t)-1|) = f(x),$$

shows that,

$$\frac{dy_{ij}(t)}{dx_{ij}(t)} = \begin{cases} 1, |x_{ij}| < 1 \\ 0, |x_{ij}| \geq 1 \end{cases}$$

Because C_{ij} can only be connected with the adjacent cell element, we have

$$\frac{dE(t)}{dt} = -\sum_{(i,j)}\sum_{(k,l)} A_{kl} \frac{dx_{ij}(t)}{dt} y_{kl}(t)$$

$$+ \frac{1}{R_x} \sum_{(i,j)} \frac{dx_{ij}(t)}{dt} y_{ij}(t)$$

$$- \sum_{(i,j)}\sum_{(k,l)} B_{kl} u_{kl} \frac{dx_{ij}(t)}{dt} - \sum_{(i,j)} I_{ij} \frac{dx_{ij}(t)}{dt}$$

$$= \sum_{(i,j)} \frac{dx_{ij}(t)}{dt}\left[-\sum_{(k,j)} A_{kl} y_{kl}(t) + \frac{1}{R_x} y_{ij}(t) - \sum_{(k,j)} B_{kl} u_{kl} - I_{ij} \right]$$

$$= -\sum_{(i,j)} \left[\frac{dx_{ij}(t)}{dt} \right]^2 C \leq 0$$

We can be sure that $E(t)$ is monotonically decreasing. That is to say that CNN always reduces the energy in the direction of movement, and eventually achieves stable state.

2.3 The adjustment range of the CNN input value

If we use the CNN for image processing, in order to meet the CNN's constraints, we must adjust the range of input values as follows:

A. For the 8 bit gray image, the original pixel value is $g_{ij} \in \{0,1,...,255\}$, but the u_{ij} which is the external input of the CNN must satisfy $|u_{ij}| \leq 1$, so we must take the range of g_{ij} to be $[-1.0, 1.0]$ in a linear mapping as [6]

$$u_{ij} = (1 - 2g_{ij}/255) \in [-1.0, +1.0].$$

If the original gray image of the 0 (black) is mapped to the CNN 1.0 (black), and if the original gray image of the 255 (white) is mapped to the CNN -1.0 (white), the rest of the gray values from small to large are mapped to 1.0 until -1.0.

B. For binary images, because the original pixel value of it is $g_{ij} \in \{0,1\}$. The value 0 (black) is mapped to the CNN 1.0 (black), and the value 1 (white) is mapped to the CNN -1.0 (white).

The Cellular Neural Network has been widely applied in image processing. The key to applying CNN to image processing are the link weights which is also called the template. However some existing edge templates in the CNN template to the image detection can't achieve better effect than traditional methods. Therefore, edge detection based on CNN has become the research of coming up with a specific algorithm that can find the best template.

3. The improved genetic algorithm

The genetic algorithm is based on a population that evolves in generations. In every generation each individual must evaluate a fitness function and perform genetic operation to produce the offspring population. This will cause a problem when the population size is larger, more computation time is needed and convergence speed becomes slow. When the population size is large enough the genetic algorithm

becomes too slow and loses its original superiority. This paper combines the advantages of the genetic algorithm, and proposes an improved algorithm. This algorithm uses the cross generational elitist selection idea. The population is divided into parallel genetic treatment for N sub-populations and uses the multiple point crossover operation method. The proposed method can ensure robustness and improves the efficiency of search. This improved genetic algorithm was enhanced by the following 4 kinds of genetic operation. We contrast the improved genetic algorithm and traditional genetic algorithm in Table 1.

Table 1. The difference between the IGA and the GA.

algorithm	Population	Selection	Cross match	Variation
GA	One population	independent selection	Cross match	Variation
IGA	population is divided into n sub populations	First mix up Then selection	Cross match	First Variation Then migration operation

3.1 Population division

At first the population is divided into N sub populations with each sub population including n samples, and then running the genetic algorithm respectively for each sub population. Denoting them as $GA_i(i=1,2,...N)$, this can produce more excellent varieties for whole genetic algorithm for later.

3.2 Selection

The algorithm will mix up the parent population and the crossover to generate new

individual groups. Then they are sorted according to the value of fitness, and the most fit individuals are selected as a new generation of population. This will accelerate the spread of outstanding individuals, and also can improve the speed of convergence.

3.3 Cross match

We used a certain probability of two parent individual chromosomes randomly paired with a cross pair, in order to produce two new individuals and at the same time to improve the global search ability of genetic algorithm.

3.4 Variation

We use a small probability for the individual chromosome mutation. And using the excellent individual of one sub population instead of poor individual in another sub population (we call it migration operation). This will improve the random search ability of the algorithm and ensure the population diversity of the individual.

4. The setting of the Cellular Neural Network algorithm with the improved genetic algorithm

This article uses the proposed improved genetic algorithm (IGA) to train the Cellular Neural Network. The global search ability and rapid convergence of the IGA algorithm makes it an appropriate algorithm to find the optimal template of CNN, which will improve its performance.

First of all, after the infrared image is acquired, we use the IGA algorithm to design the CNN's optimal template. The CNN then uses the IGA designed template for dynamic operation of the infrared image. Finally, after convergence the output is a binary edge image. Figure 2 is a flow chart of using the cellular neural network to produce the human body edge detection in an infrared image. Figure 3 is a flow chart showing design of the CNN template by the IGA algorithm.

4.1 Determine the population parameters

At present, the general CNN edge detection uses the following template format [5]. This paper will mainly use the IGA algorithm to optimize this template for human body edge detection.

$$A-template. A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & a_1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$B-template. B = \begin{bmatrix} b_1 & b_2 & b_1 \\ b_2 & b_3 & b_2 \\ b_1 & b_2 & b_1 \end{bmatrix} \quad I = i$$

By the above template format we can easily draw a conclusion that we only need to optimize the five parameters: a_1, b_1, b_2, b_3, i. In these templates, **B** is the control coefficient matrix, it is a spatial filter; through the spatial filter movement for processing the image, it can get the better effect for smoothing noise.

4.2 The steps to optimize the CNN's template parameters using the IGA algorithm

A. Selection

This algorithm first generates a new generation of population using crossover to generate new individuals and select excellent individuals from this new population. The specific approach is to use the fitness from the parent and offspring for sorting according to magnitude and choose the individuals with biggest fitness to form a new generation of population. This can speed up the spread of outstanding individuals, and can improve the convergence speed of the whole population. Assuming the previous generation and the current generation have population size M_1 and M_2, c'_{ij} is the location of an individual in order in the population and sp is the selection coefficient. The linear ranking after the fitness of individuals can be represented by this formula.
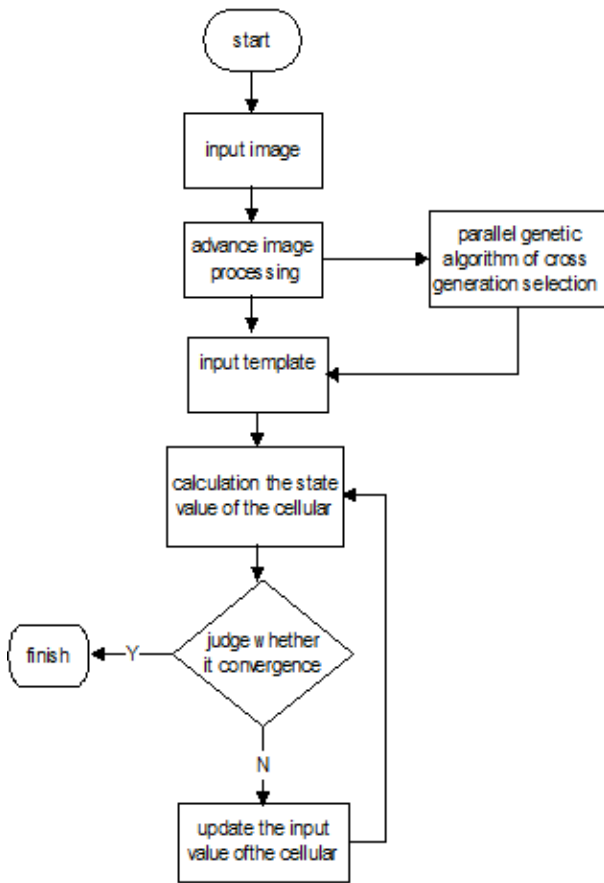
Fig.2. the flow chart which is used by
the cellular neural network for body
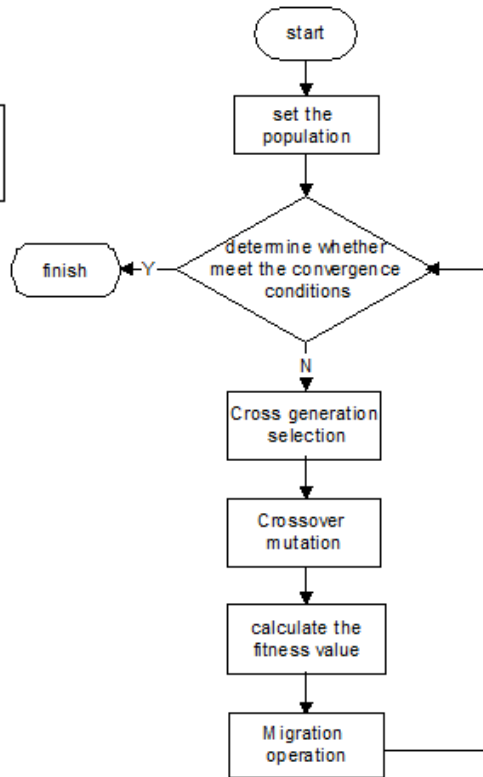edge detection in infrared image.

Fig.3. the flow chart which is
designed for the CNN template by IGA
algorithm.

$$f(i) = 2 - sp + \frac{2(sp-1)(i-1)}{M_1 + M_2}$$

In the above formula, $sp \in [1.0, 2.0]$, the individual selection probability is P_{ij}, which can be calculated by the Michalewicz formula $p_i = c(1-c)^{i-1}$ where c is the selection probability of the first individual sort. In the specific practical application, we can use the threshold method for selection. Assuming that f_{avg} is the average fitness value of the whole population, the selection of the threshold can be set as $k f_{avg}$, $k \in [0,1]$. If an individual's fitness is larger than the threshold, then it will be selected. On the other hand, in the evolution process, if we use an optimal individual from the adjacent sub populations to replace one of the worst individuals from their sub population this can speed up the spread of outstanding individuals, and can improve the speed of convergence.

B. Cross

Using the chromosome of the two parent individuals randomly paired with a crossover probability, two new offspring will be generated. In order to prevent premature local convergence and loss of an optimal solution, the probability of crossover is calculated in accordance with the following formula.

$$p_{cross} = \begin{cases} k_1 \dfrac{f_{max} - f'}{f_{max} - f_{avg}}, & f' \geq f_{avg} \\ k_2, & f' < f_{avg} \end{cases}$$

In the above formula, f_{max} is the maximum value of the fitness of individuals, f' is the fitness value for the larger fitness value of the

two cross individuals, and f_{avg} is the average value of fitness of the individuals for the whole population.

C. Fitness function

After the transient process phase, all outputs will reach a stable equilibrium point. Therefore, the Lyapunov function below is used as the fitness function [7].

$$E(t) = -\frac{1}{2} \sum_{(i,j)} \sum_{(k,l)} A_{kl} y_{kl}(t) y_{ij}(t) + \frac{1}{2R_x} \sum_{(i,j)} y_{ij}^2(t)$$
$$- \sum_{(i,j)} \sum_{(k,l)} B_{kl} u_{kl} y_{ij}(t) - \sum_{(i,j)} I_{ij} y_{ij}(t)$$

In the above formula, A_{kl} is a feedback template of the cellular element, B_{kl} is a feedforward template of the cellular element, R_x is a linear resistance value, l is the threshold, u_{kl} is a input value of the cellular element, and y_{kl} is the output value of the cellular element.

D. Variation

Through the small probability of mutation for individual chromosome, the diversity of the population can be ensured. The following two equalities for a_{ij} were used for the mutation operation [6].

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{max}) * f(g) & r > 0.5 \\ a_{ij} + (a_{min} - a_{ij}) * f(g) & r \leq 0.5 \end{cases}$$

and $f(g) = r_1(1 - \dfrac{g}{G_{max}})^2$

In the above formula, a_{max} is the upper bound of chromosome decode for the individual which is a_{ij}, and a_{min} is the lower bound, r_1 is a random number, g is the current number of iterations, and G_{max} is the largest number of evolution, $r \in [0,1]$.

The calculation of mutation probability uses the following formula [6]

$$P_{m} \quad _{u}= \begin{cases} k_3 \dfrac{f_m - f}{f_{ma} - f_{ta}} \underset{x_i v}{,} f \geq f_a \\ k_4 \qquad\qquad , f < f_a \end{cases}$$

In the above formula, f_{max} is the maximum value of the fitness of individuals, f is the value of the individual's fitness for variation, and f_{avg} is the average value of fitness of the individuals for the whole population.

5. The experimental results and analysis

In this experiment, we use two groups of images (shown in Figure 4 and Figure 5) as examples to evaluate the IGA_CNN algorithm. The parameters of IGA_CNN algorithm are set as follows: the population number is 30, the maximum number of iterations is 100, Rx=1,C=1, $x_{ij}(0)$ is the initial state value, and $y_{ij}(0)$ is the initial value of output; both of them were equal to 0 and the population takes initial values in range from -30 to 30.

This paper carried out the following simulations, comparing them with other algorithms. (1) Image sizes of 128 * 128, 256 * 256 and 512 * 512 were used (Figure 4) as test images. Using the PSO algorithm, GA algorithm and IGA algorithm in this paper to optimize the template parameters for CNN, Table 2 gives the convergence time of each algorithm. We can see from the data in Table 2 that the times for the Improved Genetic Algorithm in finding an optimal template was significantly shorter than that of the Genetic Algorithm and Particle Swarm Optimization algorithms. It is better than the other two algorithms in finding optimal solution efficiency.

Fig.4. the original image.

Fig.5. the original image.

Table 2. The convergence time for the three algorithms to process different images.

Image size	Convergence time based on PSO algorithm（s）	Convergence time based on GA（s）	Convergence time based on IGA（s））
128 * 128	107.48	74.26	49.83
256 * 256	395.30	294.56	226.63
512 * 512	1562.28	1169.35	862.32

(2) In order to compare different algorithms, we used the image of 256 * 256 shown in Figure 5 as the test images, and used the PSO algorithm, GA algorithm and IGA algorithm in this paper to optimize the template parameters for CNN. The resulting template from each algorithm is shown in Table 3. Then also by using this method, we can get the parameters of the template in Figure 4 which is also of 256 * 256. Template parameters were used with the CNN algorithm for human body edge detection in the infrared image shown in Figure 4 and Figure 5. We compare the result with the Canny edge detection algorithm which at present is the best algorithm for edge detection.

Table 3. The optimal value as using the three algorithms for optimized CNN edge extraction for Figure 5.

$$PSO\_CNN$$
$$A=\begin{bmatrix} 0 & 0 & 0 \\ 0 & -2.4530 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$
$$B=\begin{bmatrix} -11.2078 & -9.0538 & -11.2078 \\ -9.0538 & -5.2204 & -9.0538 \\ -11.2078 & -9.0538 & -11.2078 \end{bmatrix}$$
$$I=-14.5612$$

$$GA\_CNN$$
$$A=\begin{bmatrix} 0 & 0 & 0 \\ 0 & -2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$
$$B=\begin{bmatrix} -8.0202 & 7.5032 & -8.0202 \\ 7.5032 & 2.1252 & 7.5032 \\ -8.0202 & 7.5032 & -8.0202 \end{bmatrix}$$
$$I=-13.2488$$

$$IGA\_CNN$$
$$A=\begin{bmatrix} 0 & 0 & 0 \\ 0 & -2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$
$$B=\begin{bmatrix} -0.8754 & -4.7583 & -0.8754 \\ -4.7583 & -14.2706 & -4.7583 \\ -0.8754 & -4.7583 & -0.8754 \end{bmatrix}$$
$$I=-5.9617$$

The above templates are applied to the different algorithms to get the template parameters for Figure 5 in Cellular Neural Network. From the template we can see that, the template B consists of nine values which are called b_1, b_2, b_3, values. While b_3 is the center point of the corresponding local area, and gives the largest contribution for the image processing, b_1 is far from the center, and its contribution for the processing is the lowest. From the above three template values it can be seen that in the B parameter which is obtained by IGA_CNN, the b_3 is -14.2706, while the b_1 is -0.8754. It means that the center value is larger, and the one far from the center

is smaller. It conforms the characteristics of the Gauss filter, which has the best effect.

We obtained the human body edge detection result as shown in Figure 6 and Figure 7 by using the CNN algorithm based on the IGA algorithm, the CNN algorithm based on the GA algorithm and the CNN algorithm based on the PSO algorithm. We find that IGA_CNN can greatly reduce the effect of high frequency noise because the control coefficient B has the filtering function, and it can detect the human edge information in an infrared image more accurately, while having low false detection of other objects such as roads, cars, trees and other redundant information which are not needed for subsequent processing. It also can greatly improve the processing speed of the subsequent target tracking. The convergence speed of the IGA_CNN algorithm is clearly faster than both PSO and standard GA.
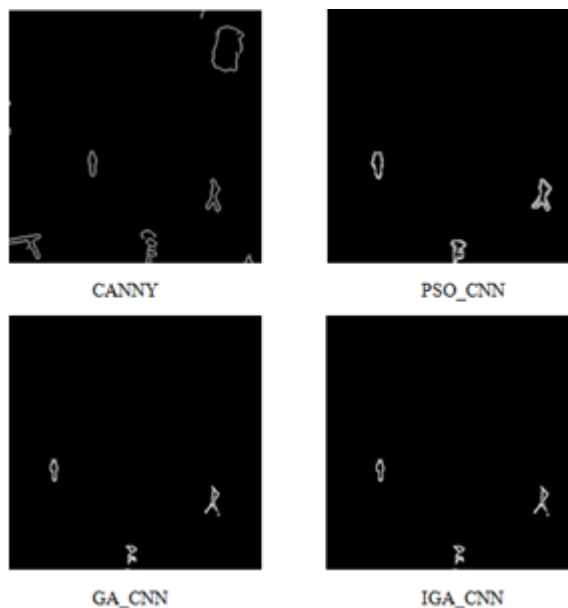

Fig.6. The body edge detection effect using different algorithms with the original image 4 as input.
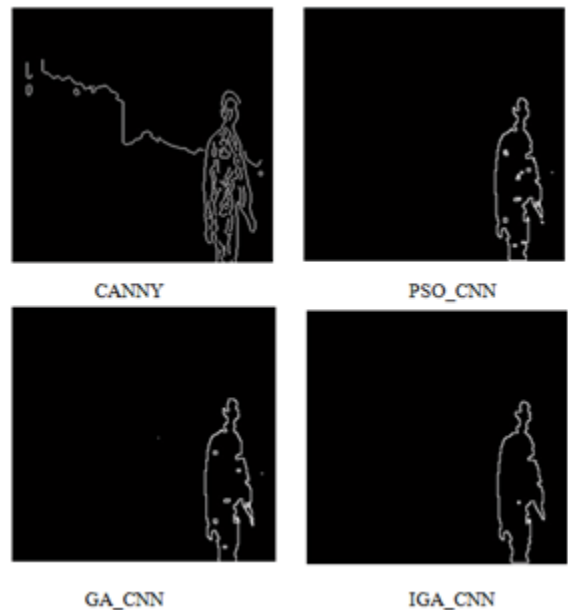

Fig.6. The body edge detection effect using different algorithms with the original image 5 as input.

6. Conclusion

This paper introduces in detail the use of sub populations across the generations of selection and parallel genetic idea, and sets up a method to design the template in cellular neural networks with the improved genetic algorithm. We applied this algorithm for edge detection in the infrared images. We found that this algorithm not only has faster convergence speed but also the search for the optimal solution is better than that of the traditional genetic algorithm and the PSO algorithm. It can greatly reduce the effect of high frequency noise because the control coefficient B has the filtering function; it also can more accurately detect the human edge information in infrared images, while having low false detection of other objects and other redundant information. This can greatly improve the processing speed of the subsequent target tracking. Therefore, the IGA algorithm provides a new way for cellular neural network parameter

optimization which also provides a new method for human body edge detection in infrared images.

7. References

[1] Wang Jianlai, Yang Chunling and Sun Chao, A Novel Algorithm for Edge Detection of Remote Sensing Image Based on CNN and PSO [C]. 2nd International Congress on Image and Signal Processing, CISP 2009, pp.17-19, 2009.

[2] Ahmed, S., and Dey S. Sarma, Image Texture Classification Using Artificial Neural Network[C]. 2011 2nd National Conference on Emerging Trends and Applications in Computer Science, NCETACS 2011, pp.1-4, 2011.

[3] Basturk, A. and Gunay, E., Clonal Selection Algorithm Based Cloning Template Learning for Edge Detection in Digital Images with CNN[C], Signal Processing, Communication and Applications Conference, Aydin, April, 20-22, pp.1-4, 2008.

[4] Tukel, M. and Yalcin, M.E., A New Architecture for Cellular Neural Network on Reconfigurable Hardware with an Advance Memory Allocation Method[C], Cellular Nanoscale Networks and Their Applications, Cellular Nanoscale Networks and Their Applications, Berkeley, CA, Feb. 3-5, pp. 1-6, 2010.

[5] Osama Basil Gazi and Mohamed Belal, Edge Detection in Satellite Image Using Cellular Neural Network, International Journal of Advanced Computer Science and Applications, No. 10, 2014.

[6] Wei Wang, , Li-Jun Yang , Yu-Ting Xie and You-wei An, Edge Detection of Infrared Image with CNN_DGA Algorithm, Optik - International Journal for Light and Electron Optics, January, pp. 464-467, 2014.

[7] Huaqing Li, Xiaofeng Liao, Chuandong Li, Hongyu Huang and Chaojie Li, Edge Detection of Noisy Images Based on Cellular Neural Networks, Commun Nonlinear Sci Numer Simulat, vol. 16, pp. 3746-3759, 2011.

[8] Alper Basturk and Enis Gunay, Efficient Edge Detection in Digital Images Using a Cellular Neural Network Optimized by Differential Evolution Algorithm, Expert Systems with Applications, vol. 36, pp. 2645-2650, 2009.

[9] Ji-Zhao Hua, Jian-Guo Wang, He-Qiang Peng and Jing-Yu Yang, A Novel Edge Detection Method Based on PCA1, IJACT: International Journal of Advancements in Computing Technology, Vol. 3, No. 3, pp. 228 - 238, 2011.

[10] Azian Azamimi Abdullah, Bu Sze Chize, and Zulkarnay Zakaria，Design of Cellular Neural Network (CNN) Simulator Based on Matlab for Brain Tumor Detection，Journal of Medical Imaging and Health Informatics, Vol. 2, pp. 1-11, 2012.

[11] Biliana, S., Paskaleva and Majeed M. Hayat, Joint Spatio-spectral Based Edge Detection for Multispectral Infrared Imagery[C]. 2010 IEEE International on Geoscience and Remote Sensing Symposium, IGARSS 2010, pp. 2198-2201, 2010.

[12] Grassi, G. and Cafagna D., Dynamic Properties of a Class of Cellular Neural Networks: Model, Stability Analysis and Design Method[C]. Proceeding of the International Joint Conference on Neural Networks, IJCNN 2003, pp. 61-65, 2003.

[13] SanthoshKumar, S., Vignesh J., Rangarajan, L.R., Narayanan, V.S., Rangarajan, K.M. and Venkatkrishna, A.L., A Fast Time Scale Genetic Algorithm Based Image Segmentation using Cellular Neural Networks (CNN)

[C]. 2007 IEEE International Conference on Signal Processing and Communications, ICSPC 2007, pp. 24-27, 2007.

[14] Kiss, A. and Nagy, Z., Computational Fluid Flow Simulation on Body Fitted Mesh Geometry with FPGA Based Emulated Digital Cellular Neural Networks[C], Cellular Nanoscale Networks and Their Applications, Berkeley, CA, Feb. 3-5, 2010, pp. 1 - 6, 2010.

[15] Yuan-Hui Yu and Chin-Chen Chang, A New Edge Detection Approach Based on Image Context Analysis [J]. Image and Vision Computing, Vol.24, No. 10, pp. 1090-1102, 2006.

[16] Zhang Wenjuan and Kang Jiayin, A Modified CNN Algorithm for Contour Detection [J]，Journal of System Simulation, Vol. 24, pp. 141-144, 2012.

[17] Lijunshan, Maying, A Novel Arithmetic of Image Edge Detection of Canny Operator[J], Acta Photonica Sinica, Vol.40, pp.50-54, 2011.

[18] Srimat Chakradhar, Murugan Sankaradas and Venkata Jakkula, A Dynamically Configurable Coprocessor for Convolutional Neural Networks[C], International Symposium on Computer Architecture, Saint-Malo, France, June, 19–23, 2010, pp. 247-257, 2010.