Particle Swarm Optimization with Time-Varying Acceleration Coefficients Based on Cellular Neural Network for Color Image Noise Cancellation

Te-Jen Su[1]
[1]College of Information Technology
Kun Shan University
Tainan 710, Taiwan, R.O.C.
[1]tejensu@mail.ksu.edu.tw

Jui-Chuan Cheng[2]
Yang-De Sun[3]
[2,3]Department of Electronic Engineering
National Kaohsiung University of Applied Sciences
Kaohsiung 807, Taiwan, R.O.C.
[2]eagle@cc.kuas.edu.tw
[3]1097305128@cc.kuas.edu.tw

***Abstract*—This paper proposes a novel method for designing templates of Cellular Neural Network (CNN) for color image noise removal. The control of CNN systems is achieved via Particle Swarm Optimization (PSO) with Time-Varying Acceleration Coefficients (PSO-TVAC). Based on PSO-TVAC method, the proposed approach can automatically update the parameters of the templates of CNN to optimize them for diminishing noise interference in polluted image. The demonstrated examples are compared favorably with other available methods, which illustrate the better performance of the proposed PSO-TVAC-CNN methodology.**

Keywords- Cellular Neural Network; Color Image Noise Removal; Particle Swarm Optimization with Time-Varying Acceleration Coefficients

I. INTRODUCTION

Particle swarm optimization is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995 [1, 2, 9–11], inspired by social behavior of bird flocking or fish schooling. It is easily implemented in most programming languages and has proven both very effective and quick for a diverse set of optimization problems. However, local convergence problem and slow later convergence problem are the two critical shortcomings of PSO that limit its applications [3]. A Particle Swarm Optimization with Time-Varying Acceleration Coefficients (PSO-TVAC) is presented in this paper, which allows to effectively overcome the two mentioned problems [12].

A novel class of information processing system called cellular neural networks was proposed by L.O. Chua and L. Yang in 1988 [6, 7]. CNN is characterized by the parallel computing of simple processing cells locally interconnected. It has been widely used for image processing, pattern recognition, signal processing, etc. In recent years, the problems of CNN templates design for image processing have received considerable attention [4, 5].

A new method that combines the discrete-time cellular neural network template learning method with an adaptive particle swarm optimization, and applies to gray image noise cancelation was developed [8]. The approach is able to find the template values easily without complex mathematic computing processes but also to obtain the balance of convergence speed and convergence accuracy. This work is extended from the previous study [8]; we attempt to apply the technique of gray image noise cancellation to color image noise cancellation by separating the color image into three Gray-Scale RGB elements.

The rest of this paper is organized as follows: in Section 2, the Particle Swarm Optimization techniques, while in Section 3, the Cellular Neural Network is discussed. In Section 4, the CNN based on PSO-TVAC template learning for images noise cancellation is presented. Examples are given in Section 5 to demonstrate the proposed methodology. Finally, conclusion is drawn in Section 6.

II. PARTICLE SWARM OPTIMIZATION WITH TIME-VARYING ACCELERATION COEFFICIENTS (PSO-TVAC)

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 equations 1 and 2. In its canonical form, Particle Swarm Optimization is modeled as follows [6-8]:

$$v_{id}(t+1) = wv_{id}(t) + c_1 rand(\,)_1 (p_{id} - x_{id}) + c_2 rand(\,)_2 (p_{gd} - x_{id}) \quad (1)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (2)$$

where

$v_{id}(t+1)$	: velocity of particle i at iteration $t+1$
$v_{id}(t)$	: velocity of particle i at iteration t
$x_{id}(t+1)$	: position of particle i at iteration $t+1$
$x_{id}(t)$	: position of particle i at iteration t
c_1	: cognitive parameter
c_2	: social parameter
$rand()_1$	: random number uniform distribution $U(0,1)$
$rand()_2$	: random number uniform distribution $U(0,1)$
p_{id}	: *pbest* position of particle i

 ISBN: 978-1-61208-127-4

p_{gd} : *gbest* position of swarm
w : inertia weight

The objective of PSO-TVAC is to enhance the global search in the early part of the optimization and to encourage the particles to converge toward the global optimum at the end of the search. With a large cognitive parameter and small social parameter at the beginning, particles are allowed to move around the search space, instead of moving toward the population best. However, a small cognitive parameter and a large social parameter allow the particles to converge to the global optimum in the latter part of the optimization. Under this development, the cognitive parameter c_1 starts with a high value c_{1max} and linearly decreases to c_{1min}. Whereas the social parameter c_2 starts with a low value c_{2min} and linearly increases to c_{2max}. This modification can be mathematically represented as follows:

$$c_1(t) = (c_{1\max} - c_{1\min})(\frac{T_{\max} - t}{T_{\max}}) + c_{1\min} \quad (3)$$

$$c_2(t) = (c_{2\min} - c_{2\max})(\frac{T_{\max} - t}{T_{\max}}) + c_{2\max} \quad (4)$$

where T_{max} is the maximal number of iterations and t is the current number of iterations.

III. CELLULAR NEURAL NETWORK

A two-dimensional CNN array is considered in which the cell dynamics are described by the following nonlinear ordinary differential equation with linear and nonlinear terms [13–16]:

$$\dot{x}_{ij}(t) = -x_{ij}(t) + \sum_{C(k,l)\in N_r(i,j)} A(i,j;k,l)y_{kl}(t) + \sum_{C(k,l)\in N_r(i,j)} B(i,j;k,l)u_{kl}(t) + \sum_{C(k,l)\in N_r(i,j)} D_{ij;kl}(\Delta v) + I_{ij} \quad (5)$$

$$y_{ij} = f(x_{ij}(t)) = \frac{1}{2}\left(\left|x_{ij}(t)+1\right| - \left|x_{ij}(t)-1\right|\right) \quad (6)$$

where

$$\Delta v = u,x,y_{kl}(t) - u,x,y_{ij}(t),\ \left|x_{ij}(t)\right| \le 1,\ \left|u_{ij}(t)\right| \le 1,\ 1 \le i \le M,\ 1 \le j \le N$$

x_{ij}, u_{ij}, y_{ij},, I_{ij} are the state, input, output and threshold voltage of the specified CNN cell, respectively. $A(i,j;k,1)$ is called the feedback cloning template, $B(i,j;k,1)$ is called the feedforward or input control template, $D_{ij;kl}$ are nonlinear terms applied for Δv (Δv is a generalized difference). The state and output vary in time, the input is static (time independent), and the CNN is single-layer with nearest neighbor linear.

In this paper, $D_{ij;kl}$ is the generalized nonlinear term applied to $\Delta v = u_{kl}(t) - x_{ij}(t)$, the voltage difference of either the input or state values. The nonlinear template D is as follows:

$$D = \begin{bmatrix} d_2 & d_1 & d_2 \\ d_1 & d_0 & d_1 \\ d_2 & d_1 & d_2 \end{bmatrix} d(\Delta v) \quad (7)$$

$$d(\Delta v) = (\Delta v)e^{-(\frac{\Delta v}{K})^2},\ \Delta v = u_{kl}(t) - x_{ij}(t)$$

where d_0, d_1, d_2 ,are the parameters in the nonlinear template *D*. *K* should be set very close to this value in an attempt to separate the noise effects and the image structure.

IV. CNN BASED ON PSO-TVAC TEMPLATE LEARNING

A digital image is composed of pixels which can be thought of as small dots on the screen and may be represented as *m*-by-*n* matrices. MATLAB is a matrix processing language for a wide range of applications. The color image in MATLAB is described as a two dimensional matrix in uint8 format. In order to apply the gray image noise cancellation from the precious study [8], we separate the color image into RGB elements. These three Gray-Scale images will be blend into a colorful image after finishing noise cancellation processes proposed. The process followed to perform noise cancellation is shown in Fig. 1

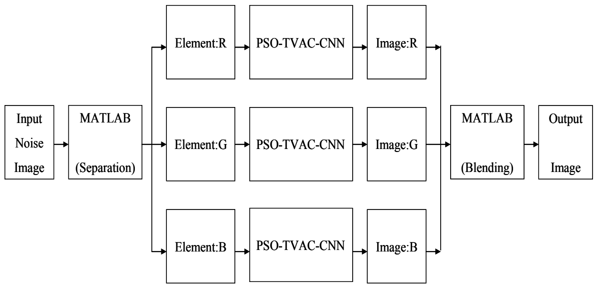


Figure 1. Block diagram of the image separation and blending

In this case, PSO-TVAC is employed to design templates of CNN for canceling the noise interference in Gray-Scale images. The templates are designed as following pattern structures, respectively:

$$A = \begin{bmatrix} a_2 & a_1 & a_2 \\ a_1 & a_0 & a_1 \\ a_2 & a_1 & a_2 \end{bmatrix}, B = \begin{bmatrix} b_2 & b_1 & b_2 \\ b_1 & b_0 & b_1 \\ b_2 & b_1 & b_2 \end{bmatrix}, D = \begin{bmatrix} d_2 & d_1 & d_2 \\ d_1 & d_0 & d_1 \\ d_2 & d_1 & d_2 \end{bmatrix}, I, K \quad (8)$$

where a_0, a_1, a_2 ,b_0, b_1, b_2 ,d_0, d_1, d_2, I, K are elements of the swarm, in order to satisfy output saturation effectively, we set a_2 =0 , b_0 =0, b_1 =0, b_2 =0, I=0, $x_{ij}(0)$= $u_{ij}(t)$. The training image is corrupted by the salt and pepper noise shown in Fig. 2.

 ISBN: 978-1-61208-127-4

(a) (b)

Figure 2. The training images (a) Input image to the CNN (b) Desired output image of CNN.

The following equation is used as an objective function (error function); the block diagram is shown in Fig. 3.

$$Error = \sum_{i=1}^{k} \left(P_c(i) - P_d(i)\right)^2 \tag{9}$$

where k denotes the total pixel of the picture, $P_c(i)$ is the value of the ith 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 allows to compute the value of the error function, and consequently obtain the best template.

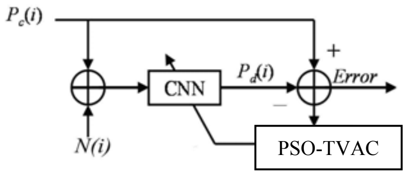


Figure 3. Block diagram of the objective function.

The process for implementing the PSO-TVAC based on CNN is shown as Fig. 4.

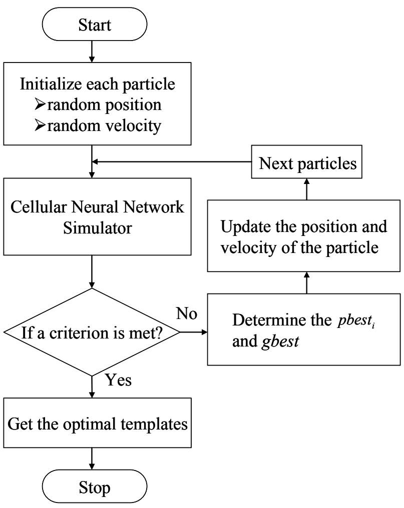


Figure 4. Flow chart of PSO-TVAC-CNN.

V. EXAMPLES AND RESULTS

In this section, we present the examples polluted by different percentage of noise density interference and using our proposed method PSO-TVAC-CNN compares with PSO-CNN [5] for gray and color image noise cancellation respectively.

A. Examples 1

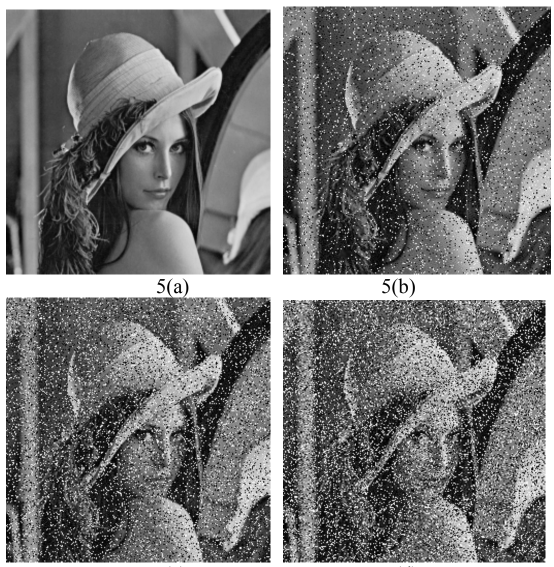
Consider a 256×256 LENA Gary-Scale image Fig. 5(a) which is polluted by the salt and pepper noise 10%, 20%, 30% in Fig. 5(b) - Fig. 5(d), respectively. The parameters of the proposed method PSO-TVAC-CNN and PSO-CNN are set as indicated in Table 1 and Table 2, respectively. The self-adapting inertia weight w is defined in [17].

TABLE I. PSO-TVAC PARAMETERS SETTING

The number of swarm size	12
The maximum position X_{max}	10
The maximum velocity V_{max}	1
Acceleration coefficient c_{1max}	2.5
Acceleration coefficient c_{1min}	0.5
Acceleration coefficient c_{2max}	2.5
Acceleration coefficient c_{2min}	0.5
Inertia weight W	0.8
Iterations	500

TABLE II. PSO PARAMETERS SETTING

The number of swarm size	12
The maximum position X_{max}	10
The maximum velocity V_{max}	1
Acceleration coefficient c_1	2.05
Acceleration coefficient c_2	2.05
Inertia weight W	0.8
Iterations	500



5(a) 5(b) 5(c) 5(d)

Figure 5. (a) Original LENA gray-Scale image (b) The contaminated image with 10% noise (c) The contaminated image with 20% noise (d) The contaminated image with 30% noise.

According to these parameters, the consequences of approximated optimal templates A, D, and threshold K were found by the PSO-TVAC after a few iterations.

The contaminated image with 10% noise:

$$A=\begin{bmatrix}0 & 0.3698 & 0\\ 0.3698 & -0.6665 & 0.3698\\ 0 & 0.3698 & 0\end{bmatrix}, D=\begin{bmatrix}0.2810 & 0.6154 & 0.2810\\ 0.6154 & 5.5066 & 0.6154\\ 0.2810 & 0.6154 & 0.2810\end{bmatrix}, K=0.2495$$

The contaminated image with 20% noise:

$$A=\begin{bmatrix}0 & 0.4256 & 0\\ 0.4256 & -0.8792 & 0.4256\\ 0 & 0.4256 & 0\end{bmatrix}, D=\begin{bmatrix}0.2881 & 0.7562 & 0.2881\\ 0.7562 & 4.9813 & 0.7562\\ 0.2881 & 0.7562 & 0.2881\end{bmatrix}, K=0.2488$$

The contaminated image with 30% noise:

$$A=\begin{bmatrix}0 & 0.4144 & 0\\ 0.4144 & -0.8347 & 0.4144\\ 0 & 0.4144 & 0\end{bmatrix}, D=\begin{bmatrix}0.2475 & 0.6196 & 0.2475\\ 0.6196 & 3.6130 & 0.6196\\ 0.2475 & 0.6196 & 0.2475\end{bmatrix}, K=-0.2721$$

Similarly according to above parameters setting, the PSO found the consequences of approximated optimal templates A, D and threshold K as following:

The contaminated image with 10% noise:

$$A=\begin{bmatrix}0 & 0.2732 & 0\\ 0.2732 & -0.1733 & 0.2732\\ 0 & 0.2732 & 0\end{bmatrix}, D=\begin{bmatrix}0.2824 & -0.0459 & 0.2824\\ -0.0459 & 3.4591 & -0.0459\\ 0.2824 & -0.0459 & 0.2824\end{bmatrix}, K=-0.2460$$

The contaminated image with 20% noise:

$$A=\begin{bmatrix}0 & 0.6230 & 0\\ 0.6230 & -1.5564 & 0.6230\\ 0 & 0.6230 & 0\end{bmatrix}, D=\begin{bmatrix}0.0928 & 1.1943 & 0.0928\\ 1.1943 & 4.4690 & 1.1943\\ 0.0928 & 1.1943 & 0.0928\end{bmatrix}, K=0.1440$$

The contaminated image with 30% noise:

$$A=\begin{bmatrix}0 & 0.3224 & 0\\ 0.3224 & -1.0504 & 0.3224\\ 0 & 0.3224 & 0\end{bmatrix}, D=\begin{bmatrix}0.1076 & 0.6847 & 0.1076\\ 0.6847 & 3.9886 & 0.6847\\ 0.1076 & 0.6847 & 0.1076\end{bmatrix}, K=0.4617$$

The error after a few iterations for PSO-TVAC-CNN and PSO-CNN are shown in Fig. 6-8. Table 3 shows the PSNR [18] of the image noise cancellation with both cases.

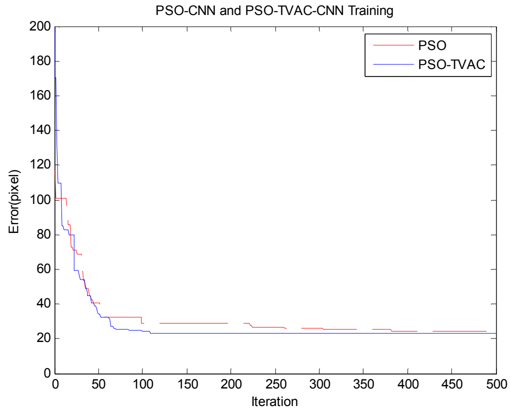


Figure 6. PSO-TVAC-CNN and PSO-CNN Training for Gray image with 10% noise

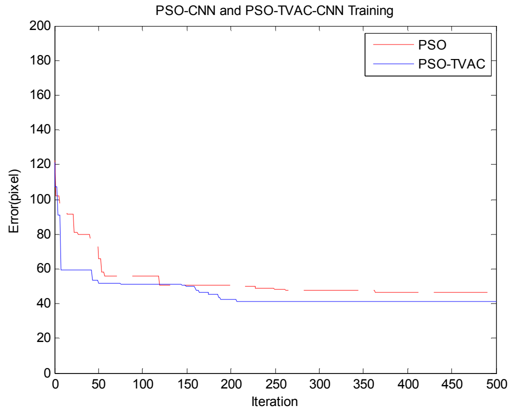


Figure 7. PSO-TVAC-CNN and PSO-CNN Training for Gray image with 20% noise

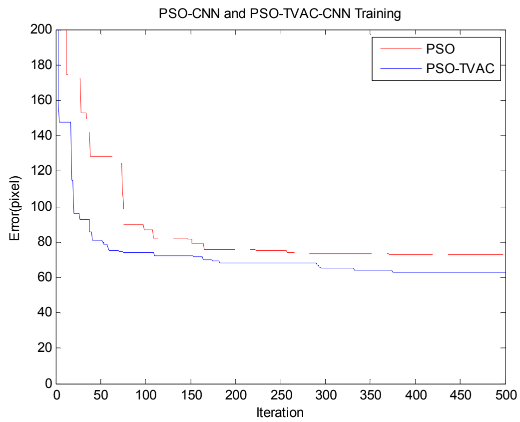


Figure 8. PSO-TVAC-CNN and PSO-CNN Training for Gray image with 30% noise

TABLE III. PSNR OF THE GRAY IMAGE (256×256 LENA) NOISE CANCELLATION

Salt and Pepper	Contaminated Image	PSO-TVAC-CNN	PSO-CNN
10% Noise	15.1659 dB	34.3663 dB	33.3802 dB
20% Noise	12.0989 dB	31.9834 dB	27.3987 dB
30% Noise	10.3124 dB	29.8721 dB	26.9026 dB

9(a) 9(b)

9(c)

Figure 9. Results by using PSO-TVAC-CNN algorithm for the Gary-Scale image with noise of (a) 10%, (b)20%, (c)30%

10(a) 10(b)

10(c)

Figure 10. Results by using PSO-CNN algorithm for the Gary-Scale image with noise of (a) 10%, (b)20%, (c)30%

Using the above templates, the output images processing by PSO-TVAC-CNN and PSO-CNN are shown in Fig. 9(a) - 9(c) and Fig. 10(a) - 10(c) respectively. By comparing Fig. 6 - 8, Table 3 and Fig. 9(a) – 9(c) with Fig. 10(a) – 10(c) respectively, our proposed method PSO-TVAC-CNN could restrain from noise of the polluted image more effectively than PSO-CNN.

Next we apply the same optimal templates found by PSO-TVAC-CNN to the Color images to prove the better performance.

B. *Examples 2*

In order to demonstrate that the optimal template has the same performance when processing color images, we have performed similar tests with the color version of the Lean image (Fig. 11(a)). The 256×256 LENA color image in Fig. 11(b) - 11(d) which is polluted by the salt and pepper noise 10%, 20%, 30%, respectively.

11(a) 11(b)

11(c) 11(d)

Figure 11. (a) Original LENA color image (b) The contaminated image with 10% noise (c) The contaminated image with 20% noise (d) The contaminated image with 30% noise.

By using the proposed method PSO-TVAC-CNN and median filter, the results for the output images obtained in Fig. 12(a) - 12(c) and 13(a) - 13(c). Table 4 show the PSNR of the color image noise cancellation with both cases.

TABLE IV. PSNR OF THE COLOR IMAGE (256×256 LENA) NOISE CANCELLATION

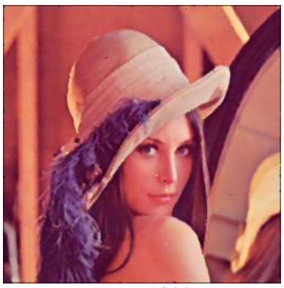
Salt and Pepper	Contaminated Image	PSO-TVAC-CNN	Median filter
10% Noise	15.1767 dB	34.0704 dB	30.6477 dB
20% Noise	12.1143 dB	30.9633 dB	27.4666 dB

30% Noise	10.3164 dB	28.3820 dB	22.9037 dB


12(a) 12(b)

12(c)

Figure 12. Results by using PSO-TVAC-CNN algorithm for the color image with noise of (a) 10%, (b)20%, (c)30%.




13(a) 13(b)

13(c)

Figure 13. Results by using median filter algorithm for the color image with noise of (a) 10%, (b)20%, (c)30%.

By comparing Fig. 12(a) - 12(c) with Fig. 13(a) - 13(c), and Table 4, our proposed method (PSO-TVAC-CNN) could restrain from noise of the polluted image more effectively than PSO-CNN.

VI. CONCLUSION

In this paper, we have presented a Cellular Neural Network templates learning method that combined Particle Swarm Optimization with Time-Varying Acceleration Coefficients, applied to color image noise cancellation. Template learning is a crucial step in cellular neural network technology. The implementation of PSO-TVAC-CNN is a contribution to the modern heuristics research in the image processing area. From the demonstrated examples, the proposed algorithm shows the better performance of the noise cancellation for color image than PSO-CNN.

In the future research, we hope to improve the adaptive templates training to repair the color images that are polluted by the higher density of miscellaneous noises. For real applications, the proposed method may be implemented and fabricated on FPGA or VLSI technology.

REFERENCES

[1] J. Kennedy and R. C. Eberhart, “Particle Swarm Optimization”, *Proceedings of IEEE International Conference on Neural Networks*, Perth, Australia, pp. 1942–1948, 1995.

[2] J. Kennedy and R. C. Eberhart, “A New Optimizer Using Particle Swarm Theory”, *Proceedings of the Sixth International Symposium on Micromachine and Human Science*, Nagoya, Japan, pp. 39–43, 1995.

[3] D.X. Zhang, Z. Hong Guan, X.Z. Liu, “An adaptive particle swarm optimization algorithm and simulation”, *Proceedings of the IEEE International Conference on Automation and Logistics*, pp. 2399–2402, 2007.

[4] M. Nakagawa, T. Inoue and Y. Nishio, “CNN Template Learning To Obtain Desired Images Using Back Propagation Algorithm”, *IEEE Workshop on Nonlinear Circuit Networks*, pp. 93-95, 2009.

[5] T. J. Su, T. H. Lin, J. and, W. Liu “Particle Swarm Optimization for Gray-Scale Image Noise Cancellation”, *International Conference on Intelligent Information Hiding and Multimedia Signal Processing*, pp.1459-1462, 2008.

[6] L. O. Chua and L. Yang, “Cellular Neural Networks: Theory”, *IEEE Trans. Circuits Syst.*, vol. 35, pp.1257–1272, Oct. 1988.

[7] L. O. Chua and L. Yang, “Cellular Neural Networks: Applications”, *IEEE Trans. Circuits Syst.*, vol. 35, pp.1273–1290, Oct. 1988.

[8] T. J. Su, J. C. Cheng, M. Y. Huang, T. H. Lin, and, C. W. Chen “Applications of Cellular Neural Networks to Noise Cancelation in Gray Images Based on Adaptive Particle-swarm Optimization”, *Circ. Syst. Signal*, Jan. 2011, doi: 10.1007/s00034-011-9269-x.

[9] F. Heppner and U. Grenander: “A Stochastic Nonlinear Model for Coordinated Bird Flocks”, *The Ubiquity of Chaos*, *AAAS Publications*, Washington DC, 1990.

[10] Y. Shi and R. Eberhart, “A Modified Particle Optimizer”, *Proceedings of the 1998 IEEE World Congress on Computational Intelligence*, pp. 69–73, May 1998.

[11] Y. Shi and R. Eberhart, “Parameter Selection in Particle Swarm Optimization”, *Proceedings of the 7th International Conference on Evolutionary Programming VII*, Lecture Notes In Computer Science, pp. 591—600, 1998.

[12] A. Ratnaweera, Saman K. Halgamuge and Harry C. Watson, “Self-Organizing Hierarchical Particle Swarm Optimizer with Time-

Varying Acceleration Coefficients", *IEEE Transactions on Evolutionary Computation,* Vol. 8, No. 3, pp. 240–255, 2004.

[13] P. L. Venetianer, T. Roska and L. O. Chua, "Analogic CNN Algorithms for Some Image Compression, Decompression and Restoration Tasks", *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications,* Vol. 42, No. 5, pp. 278–284, 1995.

[14] A. Zarandy, F. Werblin, T. Roska and L. O. Chua, "Novel Types of Analogic CNN Algorithms for Recognizing Bank-Notes", *CNNA-94 Third IEEE International Workshop on Cellular Neural Networks and their Applications*, pp. 273–278, Dec. 8–21, 1994.

[15] A. Zarandy, A. Stoffels, T. Roska and L. O. Chua, "Implementation of Binary and Gray-Scale Mathematical on the CNN Universal Machine", *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications,* Vol. 45, No. 2, pp. 163–168, 1998.

[16] C. Rekeczky, T. Roska and A. Ushida, "CNN-Based Difference-Controlled Adaptive Nonlinear Image Filters", *International Journal of Circuit Theory and Applications,* Vol. 26, pp. 375–423, 1998.

[17] M. Zhang, C. J Li, X.H. Yuan, Y.C. Zhang, "An improved PSO and its application in research on reservoir operation function of long-term", *Third International Conference on Natural Computation*, vol. 4, pp. 118–122, 2007.

[18] R. Lukac and K. N. Plataniotis, "A Taxonomy of Color Image Filtering and Enhancement Solutions", *Advances in Imaging and Electron Physics,* Vol. 140, pp. 187–264, 2006.