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IMAGE FUTURE EXTRACTON USING DYNAMIC NEURAL NETWORK

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ABSTRACT

Cellular Neural Network (CNN) is an analog parallel computing paradigm defined in space and characterized by the locality of connections between processing neurons. The behaviour of the CNN is defined by two template matrices and a template vector. CNN is designed by optimizing these weight coefficient for different applications. In this study, CNN was designed for corner detection by applying Back-propagation Algorithm.

Keywords: *Cellular neural network ,back propagation algorithm, image future extraction.*

I. INTRODUCTION

In Neural Network based filtering, the adaptive filter coefficients are optimized after training procedure for 1-Dimensional problems. In 2-Dimensional images, Cellular Neural Network (CNN) is one of the best case since in CNN, the neighbourhood of 2-D pixels and their stochastic properties are considered. Here, optimization of limited number of parameters of templates are sufficient for solving high order problems.

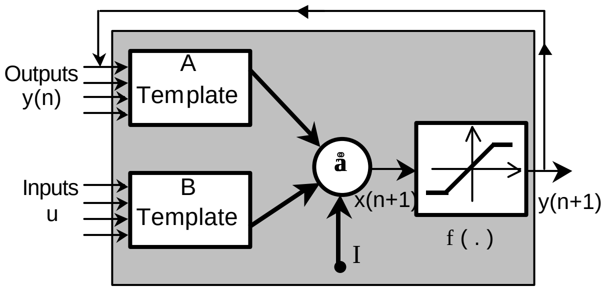

Fig. 1 CNN Architecture

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The mathematical equation of CNN shown in Figure 1 is as [1][5],

$$x_{ij}(n+1) = -x_{ij}(n) + \sum_{kl \in N_r(ij)} A_{(i-k)(j-l)}(n)\, y_{kl} + \sum_{kl \in N_r(ij)} B_{(i-k)(j-l)}(n)\, u_{kl} + I \tag{1}$$

$$y_{ij}(n) = f\left[x_{ij}(n)\right] = \frac{1}{2}\left(\left|x_{ij}(n)+1\right| - \left|x_{ij}(n)-1\right|\right) \tag{2}$$

Where $u_{i,j}$ is input image, $y_{i,j}(n)$ is the CNN output at stable condition of each pixel at n^{th} step. A, B, and I are feed forward, feedback and threshold matrices. We used BPA to adjust CNN templates A, B, and I. This algorithm does not depend on perceptron approach. The learning algorithm is repeated till the desired optimum A,B and I templates are formed for the image segmentation problem. Thus the desired outputs can be obtained. In the second step, CNN templates are tested for corner detection [4].

II. LEARNING FOR CORNER DETECTION

The supervised learning of the steady-state outputs of CNN attempts to approximate an unknown input-(steady-state) output map t=F(s) by minimizing an error function E(ω),where ω is defined by using A,B template matrices and 'I' threshold value defined as:

$$A = \begin{bmatrix} a_1 & a_2 & a_3 \\ a_4 & a_5 & a_6 \\ a_7 & a_8 & a_9 \end{bmatrix} \qquad B = \begin{bmatrix} b_1 & b_2 & b_3 \\ b_4 & b_5 & b_6 \\ b_7 & b_8 & b_9 \end{bmatrix}$$

$$w = [A\ B\ I] \tag{3}$$

The network is trained with the following set of pairs which are samples of the map t=F(s):

$$\left\{(s^1,t^1),(s^2,t^2),\ldots,(s^n,t^n)\right\} \tag{4}$$

where s^i and t^i represents the input and desired (steady-state) output for the i th sample ,respectively. The error function E (ω) to be minimized is a measure of the difference between the desired and actual (steady-state) output sets. E (ω) is defined by the following equation [2] .

$$E(\omega) = \frac{1}{2}\sum_{N}\sum_{i,j}\left(y^k_{i,j}(\infty) - t^k_{i,j}\right)^2 \tag{5}$$

The weight equation in algorithm of Steepest Descent which is used for minimizing the error, is given by [3]

$$\omega(k+1) = \omega(k) - \alpha \cdot \frac{\partial E(\omega)}{\partial \omega^k} \tag{6}$$

III. EXPERIMENTAL RESULTS

For estimation of ω values, we trained CNN structure. We used size of 16x16 image input data and the desired output is as corner image. Being the chosen image in a complex form, has an increasing effect on the success of the test.

After 352 iterations learning was completed and the following A,B,I values were found.

$$I = -0.4490$$

$$A = \begin{bmatrix} 0.3202 & -0.0284 & 0.3202 \\ -0.1024 & 3.5510 & -0.1024 \\ 0.3202 & -0.0284 & 0.3202 \end{bmatrix}$$

$$B = \begin{bmatrix} -0.3315 & -0.5153 & -0.3315 \\ -0.6047 & -0.4322 & -0.6047 \\ -0.3315 & -0.5153 & -0.3315 \end{bmatrix} \tag{7}$$

We applied these results to different test images (Fig 3.) In this applications network detected the corners without error.

IV. CONCLUSION

In this paper, for image future extraction problem, a corner detection is achieved by using a dynamic neural network.. Corner detection has been posed as an approximation to an unknown algebraic map from the input image space to the corresponding corner image space. Here, back propagation algorithm has been used in finding connection weights which define a CNN whose input-output relation approximates to the unknown map. The same approach can also be applied to other image processing tasks.

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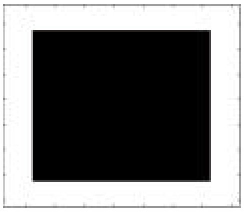
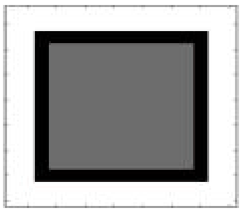

I-a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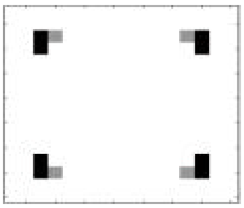
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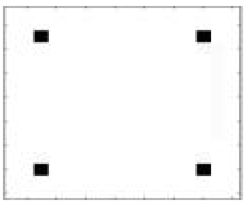
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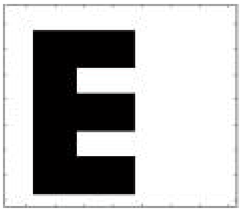
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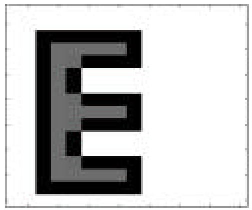
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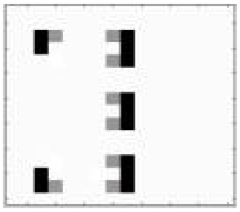
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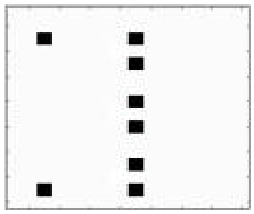
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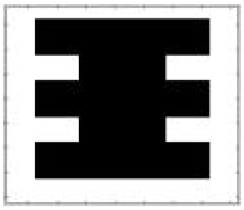
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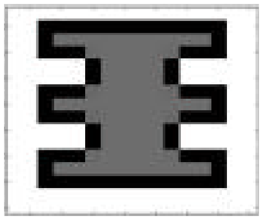
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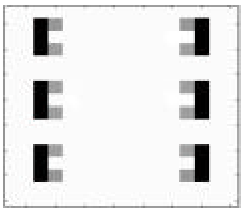
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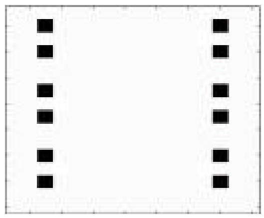
III-d

Figure 3- a) Input image, b) Second iteration result, c) Fourth iteration result d) Fifth iteration result e) Eighth iteration result

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