LETTER

Feature Extraction of Postage Stamps Using an Iterative Approach of CNN

Jun KISHIDA†, *Student Member*, Csaba REKECZKY††, Yoshifumi NISHIO†, *and* Akio USHIDA†, *Members*

SUMMARY In this article, a new analogic CNN algorithm to extract features of postage stamps in gray-scale images is introduced. The Gradient Controlled Diffusion method plays an important role in the approach. In our algorithm, it is used for smoothing and separating Arabic figures drawn with a color which is similar to the background color. We extract Arabic figures in postage stamps by combining Gradient Controlled Diffusion with nearest neighbor linear CNN template and logic operations. Applying the feature extraction algorithm to different test images it has been verified that it is also effective in complex segmentation problems.

key words: *cellular neural networks, analogic algorithm, image processing, feature extraction, gradient controlled diffusion*

1. Introduction

Analogical neural networks have generally been developed on the basis of the experimental results obtained from studying the operation of the human nervous system in complex decisions and classification problems. In these networks asynchronous analog parallel signal processing in continuous-time is combined with local or global logical interaction of the network elements.

Cellular neural networks (CNNs) were introduced by Chua and Yang in 1988 [1], [2]. Since then the rapidly growing field of CNNs evolved to a general computational paradigm [3] and a universal hardware architecture has been designed, called the CNN Universal Machine (CNN UM) [4]. In cellular neural networks, nonlinear information-processing elements called cells are arranged regularly on a two or three-dimensional grid. Each cell is interconnected only to its neighbors and the cells that are not directly connected can affect each other indirectly through propagation effect. The connection pattern of all cells is translation-invariant throughout the network at any cell and is called cloning template. The operation of cellular neural networks is determined by the cloning templates. A cell consists of a linear capacitor, linear resistors and nonlinear voltage controlled current sources. Since the structure of cellular neural networks resembles the structure of the vertebrate retina, it has been widely recognized that are appropriate for solving various image processing tasks [5]–[9].

Applications in image processing using cellular neural networks have many varieties. Binary image processing has been researched for a long time. At present, gray-scale image processing has become important and is researched actively in various fields. Up to now, enhancement of X-ray mammograms [8], recognition of bank-notes [9], image compression and restoration [5] and others have been formulated as CNN analogic algorithms. Feature extraction is the process of finding a predefined "FEATURE" in input images, (e.g. whether they have junctions, concave forms, end points and so on,) and it is a significant task in image processing. In these problems, traditional feature extraction methods such as simple thresholding can be used to extract only a "dark part" above a given threshold. However, the dark part does not always contain the most important characteristics of images. For example, Arabic figures in postage stamps are the most important factors characterizing postage stamps. However, Arabic figures are sometimes drawn with a color which is similar to the background color, while the picture is drawn in a noticeable dark color in the center. This is one of the major difficulties in developing systems capable of classifying prices of postage stamps.

In this study, we synthesize an analogic CNN algorithm to extract Arabic figures in postage stamps drawn with a color which is similar to the background. The Gradient Controlled Diffusion method plays an important role in our approach. This method is discussed in [10], [11] and can be found in [12]. It simulates a simpler form of the anisotropic diffusion and has been reported to be effective for smoothing noise while preserving edges and the image structure. In our algorithm, it is used for smoothing and separating Arabic figures drawn with a color which is similar to the background. We extract Arabic figures in postage stamps by combining Gradient Controlled Diffusion with nearest neighbor linear CNN template and logic operations. This way we synthesize an analogic CNN algorithm that can operate in the environment of the first gray-scale input-output CNN Universal Chips. We apply the feature extraction algorithm to some test images and verify

Manuscript received February 2, 1996.
Manuscript revised June 7, 1996.

† The authors are with the Faculty of Engineering, Tokushima University, Tokushima-shi, 770 Japan.
†† The author is with Analogical and Neural Computing Systems Laboratory, Computer and Automation Institute, Hungarian Academy of Sciences, 27 H-1111 Budapest, Kende-u. 13–17, Hungary.

that the algorithm is effective even in the case of very complex problems. We consider that the proposed algorithm could be utilized to classify Arabic figures in postage stamps or to distinguish used stamps from unused ones.

2. Image Processing Using Various CNN Templates

The operation of CNN is determined by a cloning template corresponding to the weight of cell interconnections. We can execute various image processing methods using translation-invariant CNN templates. The basic CNN equation is shown as follows.

$$C\frac{dv_{xij}(t)}{dt} = -\frac{1}{R}v_{xij}(t) + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r}\hat{A}_{(i,j;k,l)}(v_{ykl}(t), v_{yij}(t)) + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r}\hat{B}_{(i,j;k,l)}(v_{ukl}(t), v_{uij}(t)) + I \quad (1)$$

If the template is linear, Eq. (1) is rewritten as follows.

$$C\frac{dv_{xij}(t)}{dt} = -\frac{1}{R}v_{xij}(t) + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r}A_{(i,j;k,l)}v_{ykl}(t) + \sum_{k=i-r}^{i+r}\sum_{l=j-r}^{j+r}B_{(i,j;k,l)}v_{ukl}(t) + I \quad (2)$$

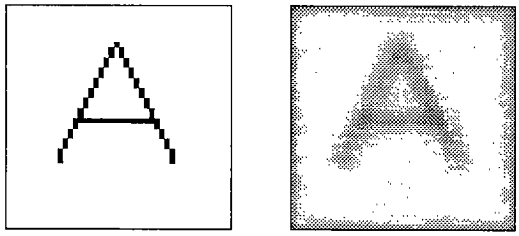
Where $R = 1\,[\Omega]$, and $C = 1\,[F]$ throughout this paper.

In this section, we introduce and analyze several templates proposed in Ref. [12] useful in image processing and show how they process different gray-scale images.

2.1 DIFFUSION Template

This template was obtained from the two-dimensional heat conduction equation and executes the heat-diffusion. The template is represented as Eq. (3). As the running time of this template is increased, the image becomes more and more blurred. An example of simulation results is shown in Fig. 1.

$$A = \begin{bmatrix} 0.1 & 0.15 & 0.1 \\ 0.15 & 0 & 0.15 \\ 0.1 & 0.15 & 0.1 \end{bmatrix}$$
$$B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$
$$I = 0. \quad (3)$$



(a) (b)

Fig. 1 Example of simulation results using the DIFFUSION template. Running time = 10. (a) Input image. (b) Output image.

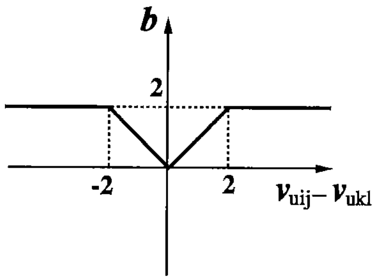


Fig. 2 Nonlinear characteristic of the $\hat{B}$ term in GRADIENT template.

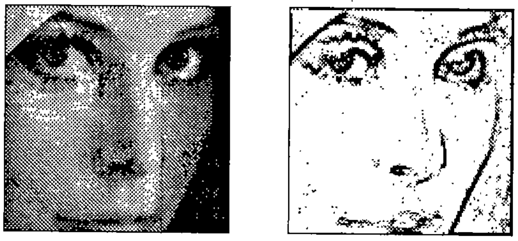
Remark 1: In analog CNNs, the diffusion template A in Eq. (3) has a very fast diffusion rate. Thus, we must control the diffusion for real applications. We are developing templates to solve the problem. For example, we have reported that the following template can control the diffused area for the image processing of X-ray images [13].

$$A = \begin{bmatrix} 0.1 & 0.15 & 0.1 \\ 0.15 & 0 & 0.15 \\ 0.1 & 0.15 & 0.1 \end{bmatrix}$$
$$B = \begin{bmatrix} 0.1 & 0.15 & 0.1 \\ 0.15 & 0 & 0.15 \\ 0.1 & 0.15 & 0.1 \end{bmatrix}$$
$$I = 0. \quad (4)$$

2.2 GRADIENT Template

This template finds the location where the gradient approximated by the sum of difference values of the field is higher than a given threshold value. This template is represented as Eq. (5) and has a $\hat{B}$ term with the nonlinear characteristic shown in Fig. 2. An example of simulation results is shown in Fig. 3.

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$
$$\hat{B} = \begin{bmatrix} b & b & b \\ b & 0 & b \\ b & b & b \end{bmatrix}$$



(a) (b)

Fig. 3 Example of simulation results using the GRADIENT template. I = −1.0. (a) Input image. (b) Output image.

(a) (b)

Fig. 4 Example of simulation results using the THRESHOLD template. I = −0.2. (a) Input image. (b) Output image.

$$I = -t. \tag{5}$$

2.3 THRESHOLD Template

This template executes a thresholding process. The template is represented as Eq. (6). Pixels with intensity greater than t will become black, while the others will become white. An example of simulation results is shown in Fig. 4.

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$
$$B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$
$$I = -t. \quad (-1 < t < 1) \tag{6}$$

3. Feature Extraction of Postage Stamps

First we will explain "Gradient Controlled Diffusion" proposed in Ref. [12] that plays an important role in this system. The flow-chart of the algorithm is shown in Fig. 5. This algorithm simulates a simpler form of anisotropic diffusion and it is used for smoothing noise while preserving edges and the image structure. Gradient Controlled Diffusion smooths regions of the image having little difference in shade from its neighborhood while preserving regions where the gradient is larger than a given threshold. The part drawn with a color which is similar to the background color is smoothed and separated in color from the background using this algorithm. So we expected that the feature can be extracted by subtracting the image smoothed by Gradient Controlled Diffusion from the original one.

According to this idea, we synthesized the algorithm for feature extraction shown in Fig. 6. Let us explain this algorithm according to the flow-chart. Template values and general parameters are shown in (Fig. 5) for the input image demonstrated in Fig. 7.

- The region with a color which is similar to the background color is significantly smoothed in the input image by the process of Gradient Controlled Diffusion and we obtain the smoothed image. The Arabic figure of the input image shown in Fig. 7 (a) is also smoothed (Fig. 7 (b)).
- The input image and the smoothed image are converted to black-and-white images 1 and 2 respectively by means of a thresholding process (Fig. 7 (c) and Fig 7(d)).
- Subtracting black-and-white image 1 from 2, we obtain an image whose feature are enhanced (Fig. 7 (e)). The pixel values of the output image must be +1 (black), −1 (white), or 0 (gray).
- Again we execute the thresholding template and obtain an image whose features are extracted. We see the Arabic figures in the output (Fig. 7 (f)).

We will demonstrate this algorithm for other examples. First we apply the algorithm to a stamp in which flowers are drawn. The result of the simulation is shown in Fig. 8. Although the Arabic figures lose their shape slightly, they are extracted.

The next example is a stamp in which a cat is drawn. The result of the simulation is shown in Fig. 9. In this case, not only Arabic figures but also the cat's paws and tail are extracted. The reason for that, is because their shade and thickness resemble the Arabic figures.

When we use the image shown in Fig. 10 (a) as an input, not only Arabic figures but also some black patches and dots are extracted as with example 3. In this case we can remove the black patches and dots by means of methods that are similar to those proposed in Ref. [9]. The algorithm finds the holes (e.g. in the number "0") using UNPEEL and HOLE-FILL templates and from the number "0" recalls the Arabic figures using PATCHMAKER and RECALL templates. UNPEEL, HOLE-FILL, PATCHMAKER and RECALL templates are represented as Eqs. (7), (8), (9) and (10), respectively. As a result we obtain the images shown in Figs. 11 and 12. The templates used in the classifying analogic CNN algorithm are as follows.

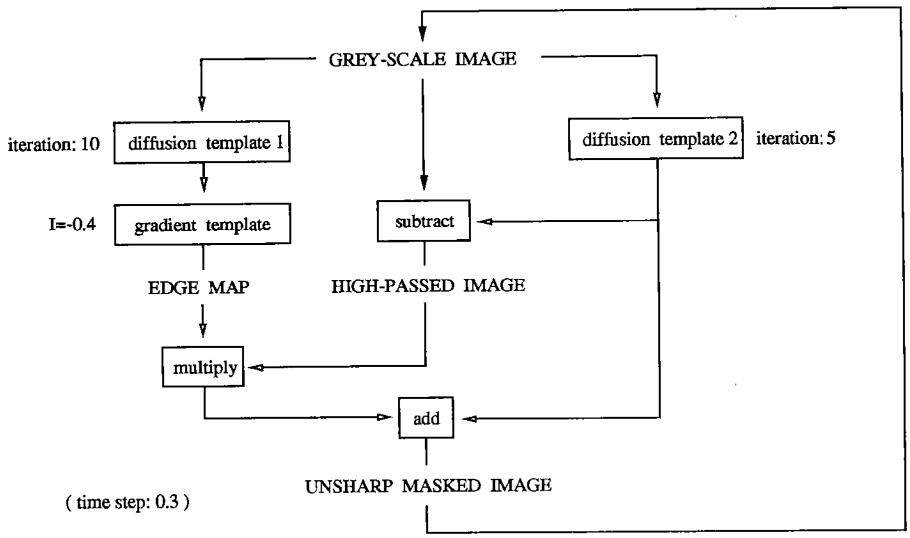


Fig. 5 Flow-chart of the Gradient Controlled Diffusion algorithm.

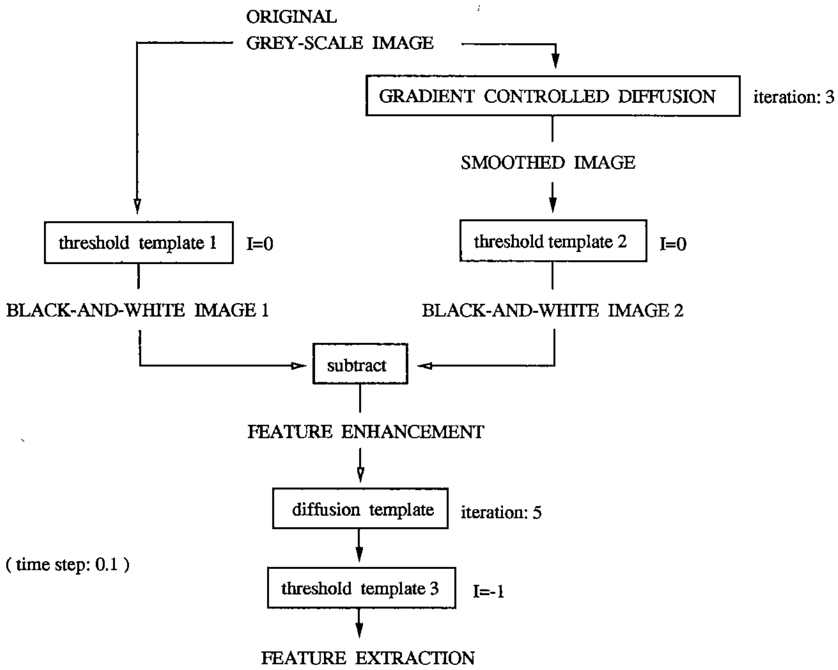


Fig. 6 Flow-chart of the feature extracting algorithm.

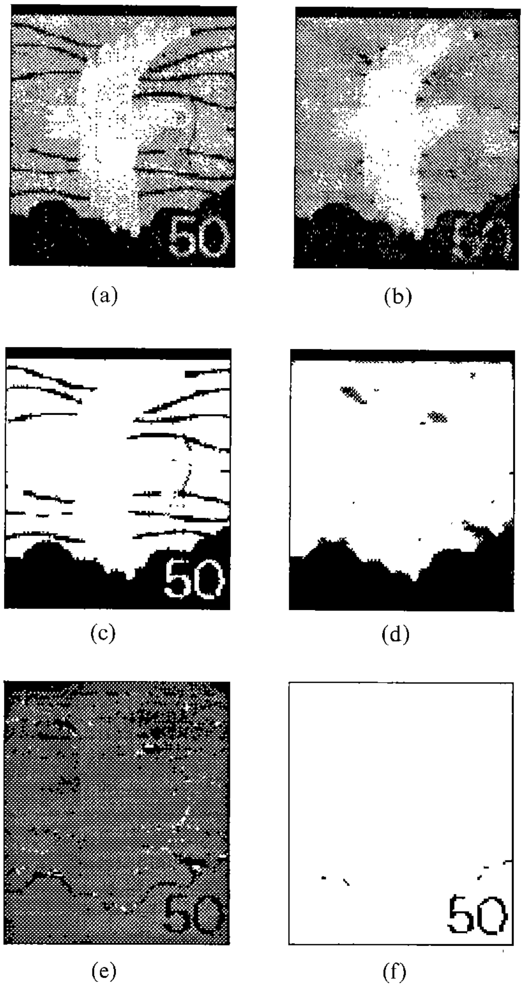


Fig. 7 Example 1. (a) Input image. (b) Smoothed image. (c) Black-and-white image 1. (d) Black-and-white image 2. (e) Enhancement of the features. (f) Extraction of the features.

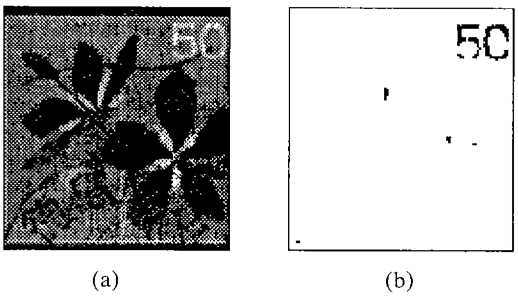


Fig. 8 Example 2. (a) Input image. (b) Output image.

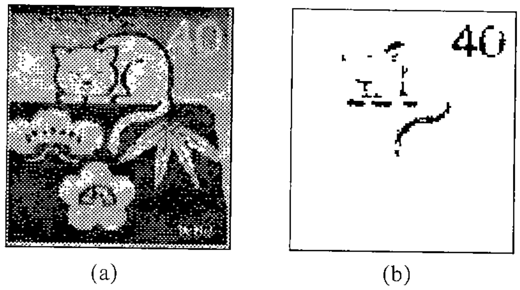


Fig. 9 Example 3. (a) Input image. (b) Output image.

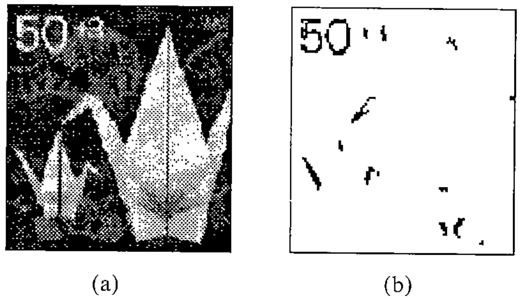


Fig. 10 Example 4. (a) Input image. (b) Output image.

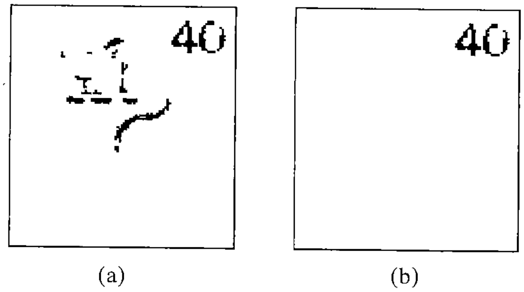


Fig. 11 Results when applying the "noise removal" algorithm to example 3. (a) Input image. (b) Output image.

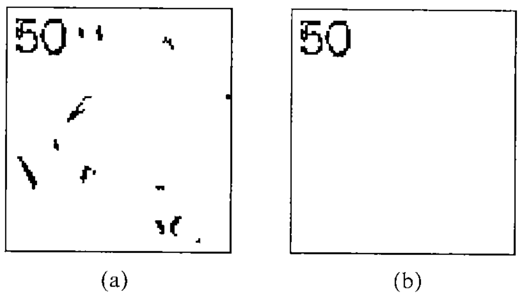


Fig. 12 Results when applying the "noise removal" algorithm to example 4. (a) Input image. (b) Output image.

- UNPEEL template

$$A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$
$$B = \begin{bmatrix} 0 & 0.3 & 0 \\ 0.3 & 0 & 0.3 \\ 0 & 0.3 & 0 \end{bmatrix}$$
$$I = 2. \tag{7}$$

- HOLE-FILL template

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$
$$B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$
$$I = -1. \tag{8}$$

- PATCHMAKER template

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 2 & 1 \\ 0 & 1 & 0 \end{bmatrix}$$
$$B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$
$$I = 4.5. \tag{9}$$

- RECALL template

$$A = \begin{bmatrix} 0.5 & 0.5 & 0.5 \\ 0.5 & 4 & 0.5 \\ 0.5 & 0.5 & 0.5 \end{bmatrix}$$
$$B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$
$$I = 2.5. \tag{10}$$

4. Conclusions

In this study, we synthesized an analogic CNN algorithm capable of extracting information that is hard to be recognized in the images. The algorithm combines the Gradient Controlled Diffusion with simple CNN template operations and uses only nearest neighbor interactions. We have carried out tests using different intensity images. In the first and second examples, only Arabic figures were extracted. However, in the third and fourth examples, not only Arabic figures but also some black patches and dots remained. It has been shown that completing the main algorithm with additional templates a satisfactory segmentation and classification can be achieved even in the case of complex problems.

The main question of the future research is how to improve the algorithm to make it capable of distinguishing Arabic and other types of figures. Moreover, we intend to generalize the system to classify prices of postage stamps and distinguish used and unused stamps by means of examination for the presence of a postmark.

References

[1] L.O. Chua and L. Yang, "Cellular neural networks: Theory," IEEE Trans. Circuits & Syst., vol.35, pp.1257–1272, Oct. 1988.

[2] L.O. Chua and L. Yang, "Cellular neural networks: Applications," IEEE Trans. Circuits & Syst., vol.35, pp.1273–1290, Oct. 1988.

[3] L.O. Chua and T. Roska, "The CNN Paradigm," IEEE Trans. Circuits & Syst.-I, vol.40, pp.147–156, March 1993.

[4] T. Roska and L.O. Chua, "The CNN universal machine," IEEE Trans. Circuit & Syst., vol.41, pp.163–173, March 1993.

[5] P.L. Venetianer, F. Werblin, T. Roska, and L.O. Chua, "Analogic CNN algorithms for some image compression and restoration tasks," IEEE Trans. Circuits & Syst., vol.42, pp.278–284, May 1995.

[6] C. Rekeczky, Y. Nishio, A. Ushida, T. Roska, J. Ueno, I. Kasem, and H. Nishitani, "Analogic CNN algorithm in bronchogenic carcinoma analysis," Proc. of ECCTD'95, vol.2, pp.889–892, 1995.

[7] S. Jankowski and R. Wańczuk, "Improvement of echocardiograms by CNN program," Proc. of ECCTD'95, vol.2, pp.995–998, 1995.

[8] G. Liszka, T. Roska, Á. Zarándy, J. Hegyesi, and C. Rekeczky, "Enhancing X-ray mammograms by analogic CNN operations: Some experiments," Neuromorphic Information Technology, Graduate Center, pp.1–18, 1994.

[9] Á. Zarándy, F. Werblin, T. Roska, and L.O. Chua, "Novel Types of Analogic CNN Algorithms for Recognizing Bank-notes," Electronics Research Laboratory, U.C. Berkeley, pp.1–20, April 1994.

[10] T. Roska and T. Szirányi, "Classes of analogic algorithms and their practical use in complex image processing tasks," Proc. of NSIP'95, pp.767–770, June 1995.

[11] M. Csapodi and T. Roska, "Dynamic analogic algorithm for complex recognition task—A first step toward the bionic eyeglass," International Journal of Circuit Theory and Applications, vol.24, no.1, pp.127–145, 1995.

[12] T. Roska and L. Kék, "Analogic CNN Program Library Version 6.0, Analogical and Neural Computing Laboratory Computer and Automation Institute, Hungarian Academy of Sciences," pp.21, 1995

[13] S. Hirakawa, C. Rekeczky, Y. Nishio, A. Ushida, J. Ueno, I. Kasem, and H. Nishitani, "CNN application for medical image," IEICE Technical Report, CAS95-106, NLP95-97, Jan. 1996.