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Cellular Neural Network for Associative Memory and Its Application to Braille Image Recognition

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***Abstract*— Braille is widely used as communication tools for sight-impaired people. A recognition system of Braille characters is essential for those who can't read them. On the other hand, it is well-known that Cellular Neural Network for associative memory(CNN) is effective for pattern recognition, and various applications have been reported. This paper proposes an improved designing method of neighborhood, and use the Braille recognition system using CNN. We demonstrated an usefulness of the proposed system in recognition experiments. As a result, we could obtain a good recognition rate(87.9%).**

I. Introduction

Braille format invented by Louis Braille in 1829 is widely used as a communication method for sight-impaired people [1]. In Japan, about 300 thousands people are sight-impaired, but most of them(about 90%) can't read them. Especially, it is very difficult for sick and the aged to acquire Braille characters. Hence, the recognition system is essential for them.

Braille is composed of a rectangular six-dot cell on its end, with up to 63 possible combinations using one or more of six dots.

On the other hand, it is well-known that neural network is effective for classification problems. Some studies that neural networks was applied to Braille recognition have been reported. In [2], Braille documents read by tactile were considered as time series information, and a new SOM architecture with feedback connections was proposed. In [3], hierarchical neural network has been applied to Japanese Braille transcription, and its accuracy was improved. Thus, the hierarchical neural network with back-propagation method is widely used as network model. However, it requires a lot of time for learning. Furthermore, modifying, adding and deleting memory patterns are not easy.

Cellular Neural Network(CNN) proposed by Chua in 1988 which is one of interconnected neural networks [4], [5]. CNN has some remarkable features:(1) CNN can be arranged in matrix and implemented by a simple analog circuit called a cell. (2) Each cell in CNN is connected to its neighbors only. Hence, its computation efficiency is superior to that of full-connected neural network such as Hopfield model. (3) The dynamics of CNN are described by differential equations, and the input-output relation is described by a piecewise linear function. In fact, CNN is applied to various fields; for example, image processing [6], times series prediction [7], texture classification [8], and so on.

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Furthermore, it has been reported that CNN are effective for associative memory by Liu [9]. We proposed a CNN for associative memory system of diagnosing liver diseases, character recognition and abnormal sounds of automobiles, and so on [10], [11]. As mentioned above, dynamics of CNN are described by differential equations. And, memory patterns correspond to asymptotically stable equilibrium points. In case of classification problem, improvement of efficiency and verification of incorrect recognition are easy because information of the memory patterns are contained in the template which shows the connected state between each cell and its neighbors. Hence, designing neighborhood has a great influence on CNN's recall ability and efficiency. We have proposed a new designing method, and shown its effectiveness. In this paper, we propose an improved one, and use it in order to design CNN.

In this study, our final aim is to construct Braille image recognition system. CNN is effective for both image processing and associative memory. Hence, we adopt CNN as a constructing element of system. In this paper, we apply CNN for associative memory to Braille character recognition as the first step of system. Our recognition system contains preprocessing, feature extraction and recognition. We demonstrated an usefulness of the proposed system in recognition experiments. For comparison, we show a recognition result by hierarchical neural network with back-propagation method, too.

II. Cellular Neural Network for Associative Memory

A. Cellular Neural Network

CNN consists of simple analog circuits(cell) arranged in matrix. As shown in Fig.1, each cell is connected with neighbor ones only.

The cell C(i,j) (i-th row, j-th column cell) is described by Eq.(1). Note that we do not consider the control input for simplicity in this study.

$$\dot{x}_{ij} = -x_{ij} + T_{ij} * y_{ij} + I_{ij} \tag{1}$$

Here, x_{ij}, y_{ij} and I_{ij} represent a state variable, an output variable, and a threshold, respectively. T_{ij} is a template coefficient which represents the influence from the neighbor cells. Moreover, as shown in Fig.2, y_{ij} is a piecewise linear function of x_{ij}.

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

TABLE I
THE MATRIX $\boldsymbol{t}_{45}$

0	0	0	0	0	0	0
0	0	$t_{45(-2,-2)}$	$t_{45(-2,-1)}$	$t_{45(-2,0)}$	$t_{45(-2,1)}$	$t_{45(-2,2)}$
0	0	$t_{45(-1,-2)}$	$t_{45(-1,-1)}$	$t_{45(-1,0)}$	$t_{45(-1,1)}$	$t_{45(-1,2)}$
0	0	$t_{45(0,-2)}$	$t_{45(0,-1)}$	$t_{45(0,0)}$	$t_{45(0,1)}$	$t_{45(0,2)}$
0	0	$t_{45(1,-2)}$	$t_{45(1,-1)}$	$t_{45(1,0)}$	$t_{45(1,1)}$	$t_{45(1,2)}$
0	0	$t_{45(2,-2)}$	$t_{45(2,-1)}$	$t_{45(2,0)}$	$t_{45(2,1)}$	$t_{45(2,2)}$
0	0	0	0	0	0	0

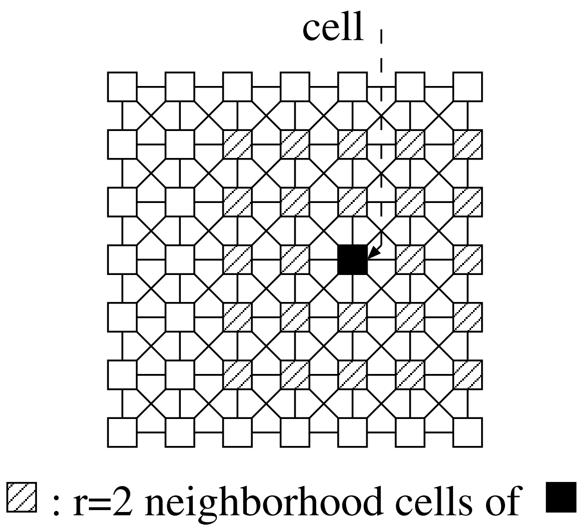

Fig. 1. 7×7 and $r = 2$ neighborhood CNN

$T_{ij} * y_{ij}$ is expressed as the following:

$$T_{ij} * y_{ij} = \sum_{k=-r}^{r} \sum_{l=-r}^{r} t_{ij(k,l)} y_{i+k,j+l}. \tag{3}$$

For example, the dynamics of cell C(4,5) in Fig.1 is represented as the following:

$$\dot{x}_{45} = -x_{45} + \sum_{k=-2}^{2} \sum_{l=-2}^{2} t_{45(k,l)} y_{4+k,5+l} + I_{45}, \tag{4}$$

and the matrix $\boldsymbol{t}_{45}$ is described as Table 1.

With vector notation, the differential equation of the whole CNN is expressed as

$$\dot{\boldsymbol{x}} = -\boldsymbol{x} + \boldsymbol{T}\boldsymbol{y} + \boldsymbol{I} \tag{5}$$

where $\boldsymbol{x}, \boldsymbol{y}$ and $\boldsymbol{I}$ represent a state vector, an output vector, and a threshold vector, respectively. $\boldsymbol{T}$ is a template matrix.

$$\left.\begin{array}{l} \boldsymbol{x} = (x_{11}, x_{12}, \cdots, x_{1n}, \cdots, x_{m1}, \cdots, x_{mn})^T \\ \boldsymbol{y} = (y_{11}, y_{12}, \cdots, y_{1n}, \cdots, y_{m1}, \cdots, y_{mn})^T \\ \boldsymbol{I} = (I_{11}, I_{12}, \cdots, I_{1n}, \cdots, I_{m1}, \cdots, I_{mn})^T \end{array}\right\}$$

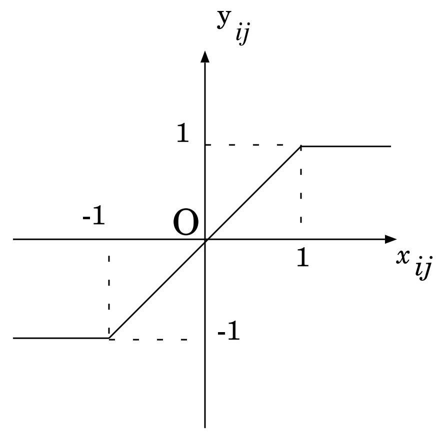

Fig. 2. Piecewise linear function

B. Cellular Neural Network for Associative Memory

In CNN, it is possible to store many patterns because they correspond to the asymptotically stable equilibrium points of the dynamics. We here assume q state vectors $\boldsymbol{\beta}_1, \boldsymbol{\beta}_2, \cdots, \boldsymbol{\beta}_q$ multiplied q memory $\boldsymbol{\alpha}_i$ whose element is $+1, -1$ by constant $K (K > 1)$. They are asymptotically stable equilibrium points in Eq.(6).

$$\boldsymbol{\beta}_i = K\boldsymbol{\alpha}_i \tag{6}$$

It is evident that $\boldsymbol{\alpha}_i, \boldsymbol{\beta}_i, \boldsymbol{T}$ and $\boldsymbol{I}$ can simultaneously satisfy the following equations:

$$\left.\begin{array}{l} -\boldsymbol{\beta}_1 + \boldsymbol{T}\boldsymbol{\alpha}_1 + \boldsymbol{I} = 0 \\ -\boldsymbol{\beta}_2 + \boldsymbol{T}\boldsymbol{\alpha}_2 + \boldsymbol{I} = 0 \\ \cdots \\ -\boldsymbol{\beta}_q + \boldsymbol{T}\boldsymbol{\alpha}_q + \boldsymbol{I} = 0 \end{array}\right\}. \tag{7}$$

Let matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ be

$$\left.\begin{array}{l} \boldsymbol{A} = (\boldsymbol{\alpha}_1 - \boldsymbol{\alpha}_q, \boldsymbol{\alpha}_2 - \boldsymbol{\alpha}_q, \cdots, \boldsymbol{\alpha}_{q-1} - \boldsymbol{\alpha}_q) \\ \boldsymbol{B} = (\boldsymbol{\beta}_1 - \boldsymbol{\beta}_q, \boldsymbol{\beta}_2 - \boldsymbol{\beta}_q, \cdots, \boldsymbol{\beta}_{q-1} - \boldsymbol{\beta}_q) \end{array}\right\}. \tag{8}$$

We can obtain the following equations:

$$\left.\begin{array}{l} \boldsymbol{B} = \boldsymbol{T}\boldsymbol{A} \\ \boldsymbol{I} = \boldsymbol{\beta}_q - \boldsymbol{T}\boldsymbol{\alpha}_q \end{array}\right\}. \tag{9}$$

In order for the CNN to have $\boldsymbol{\alpha}_i$ as memory vectors, it is necessary and sufficient to have $\boldsymbol{T}$ and $\boldsymbol{I}$ which satisfy these equations. We can easily obtain $\boldsymbol{T}$ and $\boldsymbol{I}$ by using the following method in spite of a large number of matrix.

If we focus on the computing at $k-$th cell in CNN($k = n(i-1) + j$), its conditional equation is given by

$$\boldsymbol{b}_k = \boldsymbol{t}_k \boldsymbol{A} \tag{10}$$

where $\boldsymbol{b}_k$ and $\boldsymbol{t}_k$ are the $k-$th row vector of matrix $\boldsymbol{B}$ and $\boldsymbol{T}$. A large number of null elements are included in the vector

$\boldsymbol{t}_k$. Using the property of the $r-$neighborhood, we obtain Eq.(11) by removing from $\boldsymbol{b}_k$,$\boldsymbol{t}_k$ and $\boldsymbol{A}$:

$$\boldsymbol{b}_k^r = \boldsymbol{t}_k^r \boldsymbol{A}^r \tag{11}$$

where $\boldsymbol{A}^r$ is a matrix having removed the elements not belonging to $r-$neighborhood of the $k-$th cell from matrix $\boldsymbol{A}$. $\boldsymbol{b}_k$ and $\boldsymbol{t}_k$ are the similar meaning vectors. The amount of computing can be decreased by these procedures. Generally, the matrix $\boldsymbol{A}^r$ is not a square matrix. Hence, we solve $\boldsymbol{t}_k^r$ by using a singular value decomposition as the following:

$$\boldsymbol{A}^r = \boldsymbol{U_k}[\boldsymbol{\lambda}]^{1/2}\boldsymbol{V_k}^T. \tag{12}$$

Hence we have

$$\boldsymbol{t}_k^r = \boldsymbol{b}_k^r \boldsymbol{V_k}[\boldsymbol{\lambda}]^{-1/2}\boldsymbol{U_k}^T. \tag{13}$$

This solution is the minimal norm of Eq.(11), where $[\boldsymbol{\lambda}]^{1/2}$ is a diagonally dominant matrix consisting of square root of the eigenvalue of matrix $[\boldsymbol{A}^r]^T\boldsymbol{A}^r$. And $\boldsymbol{U_k}, \boldsymbol{V_k}$ are the orthogonal matrices, respectively.

In the CNN designed by the method described above, memory patterns correspond to each equilibrium point of dynamics theoretically. CNN can recall a pattern by solving Eq.(5) when an initial state $\boldsymbol{x}^0$ is given. That is, it will converge on the stable equilibrium point of the optimal solution of differential equations.

C. The Design of Neighborhood

In a conventional CNN, the neighborhood r of each cell is designed equally, and a larger value of r is generally used in order to maintain its recall capability. In other words, the neighborhood is not optimistically designed. From our experience, r is not important very much. As mentioned above, information of the memory patterns are contained in the template which shows connected states among cells. Hence, its amount has a great influence on CNN's ability and efficiency. Thereupon, we focus on it, and use a new method setting the optimal neighborhood for each cell. The new design rule can be shown as follows:

1) If a cell has the same state for every memory pattern, its neighborhood $r = 0$ will be determined. Because it isn't influenced by its neighbor cells.
2) The neighborhood r in other cells is determined so that N cells will be included in the range. Notice that N should be selected so that the classification capability can't be lowered.
3) However that the cells which satisfy Condition 1) are not included in N cells. Because their connection coefficients are zero.

Fig.3 shows six binary memory patterns in a 9×9 CNN. Black and white represent $+1$ and -1, respectively. For example, the cells C(2,2) are black in any memory pattern. Hence, it satisfies Condition 1). In this case, the differential equation of C(2,2) is expressed as the following:

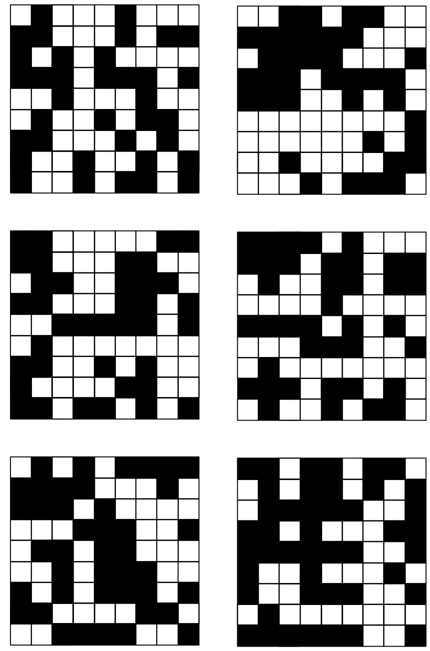

Fig. 3. 9×9 binary memory patterns(random)

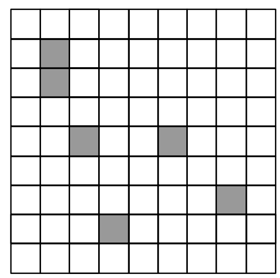

Fig. 4. The cells which satisfy the Condition 1.(Gray cells)

$$\dot{x}_{22} = -x_{22} + I_{22}. \tag{14}$$

From Eq.(14), we can know that the state of cell C(2,2) will surely converge on I_{12} when an initial state was given. This means that it is unrelated to its initial state and neighboring cells. Therefore, it is appropriate to determine $r = 0$. In this example, as shown in Fig.4 , six cells satisfy Condition 1). Determining $r = 0$ enables CNN to be improved efficiently.

In this method, the determination of N influences the computation efficiency of CNN. In [12], we have examined the relation among N, MCT(Mean Convergence Time) and RCR(Right Cognition Rate) by using random three-values model patterns. As a result, CNN showed the best performance when $N = 16$ regardless of CNN's size. Hence, we determine $N = 16$ in this study.

Fig.5 shows each neighborhood r after applying the neighborhood design method described above. Each number denotes neighborhood r of each cell. Because Braille patterns are similar each other, there are many cells which satisfies Condition 1). Hence, the computation amount can be extremely decreased, compared with the conventional design

4	3	3	3	3	3	3	3	3
3	0	2	2	2	2	2	2	3
3	0	2	2	2	2	2	2	3
3	2	2	2	2	2	2	2	3
3	2	0	2	2	0	2	2	3
3	2	2	2	2	2	2	2	3
3	2	2	2	2	2	2	0	3
3	2	2	0	2	2	2	2	3
4	3	3	3	3	3	3	3	4

Fig. 5. Each r after applying the new neighborhood design method

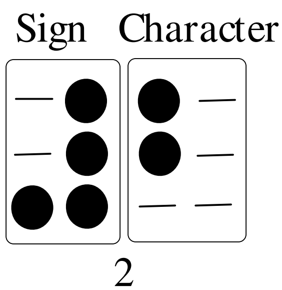

Fig. 6. A Braille character(numerical '2')

method.

III. CNN Braille Image Recognition System

We describe the procedure of CNN Braille image recognition system. As shown in Fig.6 and Fig.7, Braille character is composed of a rectangular six dot cell on its end, with up to 63 possible combinations using one or more of six dots. In this paper, we use their images composed of 12 dots only for simplicity. As shown in Fig.8, the procedure consists of preprocessing, feature extraction, and recognition.

A. Preprocessing

The preprocessing perform 1) gray-scale inversion, 2) binarization, 3) noise removal, 4) dilation 5) normalization in this order. All objective images are gray-scale.

1) **Gray-scale Inversion**
   If the image has white Braille characters and black background, the gray-scale inversion is performed.
2) **Binarization**
   The image is binarized based on the darkness of pixels.
3) **Dilation**
   We expand the edge of Braille character in order to emphasize itself.
4) **Normalization**
   The distances of two dots are modified so that they can correspond to size of CNN. Moreover, we transform all values as $(0 \rightarrow 1, 255 \rightarrow -1)$ in order to generate an input pattern of CNN.

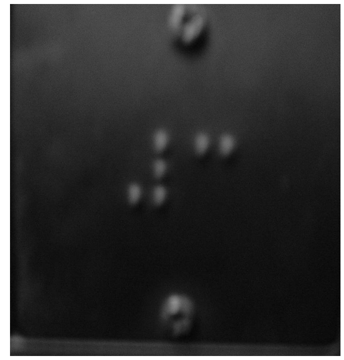

Fig. 7. An example of raw Braille image

B. Feature Extraction

At this stage, we perform 1) downsizing and 2) adjustment on the preprocessed image in this order.

1) **Downsizing**
   We downsize the preprocessed image in order to come close to size of memory pattern. In this paper, we transform a $M \times M$ small pattern into a white or black pattern as shown in Fig.9. When the $M \times M$ small pattern has a black pixel, we transform it into a black pattern. If not so, we do it into a white.
2) **Adjustment**
   Moreover we adjust it so that it can correspond to CNN's size.

Fig.10 shows an example of feature extraction. The 544×455 raw image is transformed into the 27×36 binary pattern. Thus, the obtained patterns here are initial pattern into CNN.

C. Recognition

CNN stores representative binary patterns(± 1) in advance. Based on an input pattern obtained by image processings, CNN self-recalls a pattern, which is considered as the final recognition result.

Fig.11 shows an example of recognized result by CNN. The left shows an input pattern, and the right shows a recalled one. In this case, CNN recognizes the pattern as '1'.

IV. Experimental Results

We demonstrated an usefulness of the proposed system in recognition experiments. 60 images whose sizes are 120×160 were taken by camera phones with two million pixels. The pictures can be classified into four categories by shooting mode. Table 2 shows the categories of pictures. "Fine" and "Economy" have the highest and lowest quality, respectively. Based on the procedures descrived in III, preprocessing and feature extraction were performed. As a result, two images could not be processed appropriately. Therefore, 58 images were used in this recognition experiment.

We used a 27×36 CNN based on the similarity among memory patterns. Table 3 shows the recognition results by CNN. The good results were obtained in this experiment. The result shows that CNN has a high recall ability.

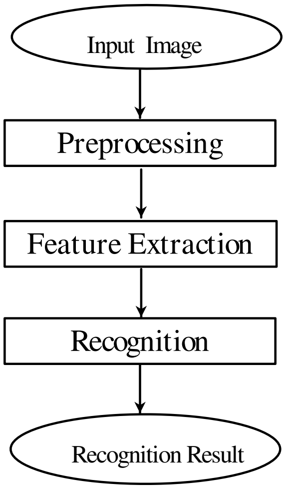

Fig. 8. CNN Braille Image Recognition System

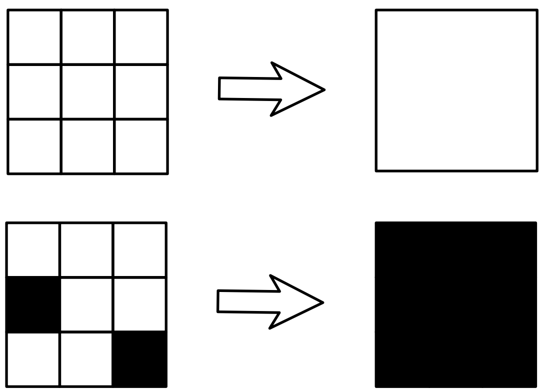

Fig. 9. Feature Extraction Algorithm ($M = 3$)

Moreover, for comparison, the same images were recognized by Multi-Layered Perceptron(MLP). The used MLP model has three layers(input,hidden,output), and each layer has 972(27×36),55, and 10 neurons, respectively(See Fig.13). The finishing condition of BP learning was $E < 0.01$(E:Mean Square Error). Table 4 shows the recognition result by MLP. The total recognition rate of BP was about 62.0%(CNN:87.9%). It is obvious that the classification ability of CNN is superior to that of MLP, and the usefulness of CNN in this study was shown.

V. Conclusion

In this paper, we proposed the Braille image recognition system by CNN for associative memory. The obtained results

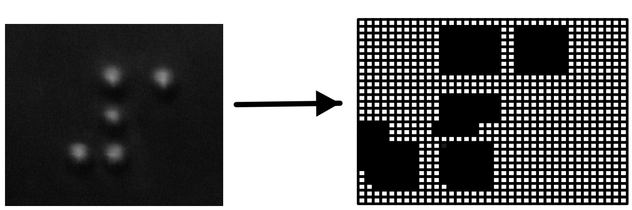

Fig. 10. Example of Feature Extraction

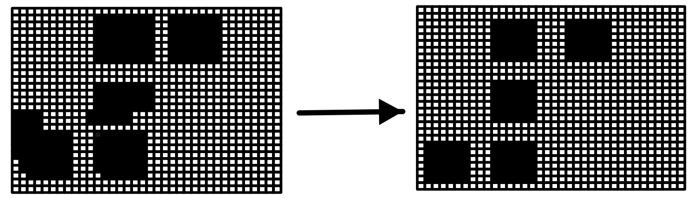

Fig. 11. Example of self-recall in CNN

TABLE II
CATEGORIES OF IMAGES USED IN THE EXPERIMENTS

Category	Raw Images	Input Images
Fine	15	14
Normal	15	14
Mail	15	15
Economy	15	15
Total	60	58

are as follows:

1) We constituted a part of Braille image recognition system with CNN. Our system contains "Preprocessing","Feature extraction", and "Recognition", and we have adopted CNN in "Recognition" part. For simplicity, we used a relatively simple algorithm as a preprocessing method.
2) We demonstrated an usefulness of the proposed system in recognition experiments. We used 58 images photographed by camera phone. As a result, a good recognition rate was obtained. For comparison, similar experiments have been performed by Multi Layered Perceptron(MLP). Compared them, it is obvious that the recognition ability of CNN(87.9%) is superior to that of MLP(62.0%). Consequently, the effectiveness of CNN for associative memory has been sufficiently shown. In future, we should improve the system by correcting the preprocessing and feature extraction algorithms.

TABLE III
RECOGNITION RESULTS BY CNN

Category	Input Images	Correct	Recognition Rate(%)
Fine	14	14	100
Normal	14	13	92.9
Mail	15	11	73.3
Economy	15	13	86.7
Total	58	51	87.9

TABLE IV
RECOGNITION RESULTS BY MLP

Category	Input Images	Correct	Recognition Rate(%)
Fine	14	9	64.3
Normal	14	9	64.3
Mail	15	9	60.0
Economy	15	9	60.0
Total	58	36	62.0

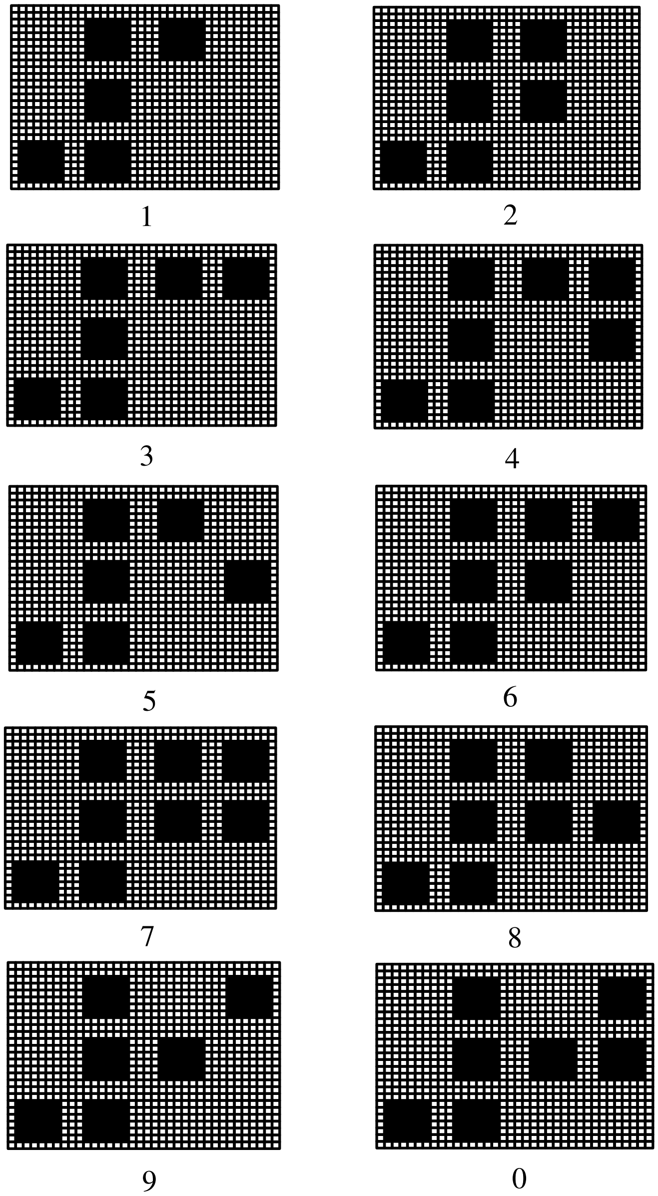

Fig. 12. Stored 10 patterns in CNN

CNN has an excellent ability for image processing. In this paper, though we have only used CNN for recognition tool, we would like to construct a synthesized Braille image recognition system by CNN in future.

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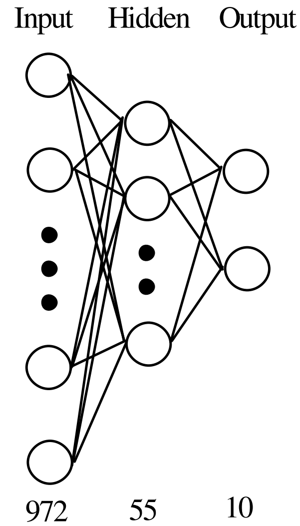

Fig. 13. Multi Layered Perceptron

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