2009 International Symposium on Nonlinear Theory and its Applications
NOLTA'09, Sapporo, Japan, October 18-21, 2009

# Rejection Judgment Method Using Neural Networks for Character Recognition

Yoshimasa Kimura†, Hiroyuki Nishi† and Eiichi Mukai†

† Faculty of Computer and Information Sciences, Sojo University
22-1, Ikeda 4-Chome, Kumamoto, 860-0082 Japan
Email: kimura@cis.sojo-u.ac.jp, nishi@cis.sojo-u.ac.jp, mukai@cis.sojo-u.ac.jp

**Abstract–** We propose a novel rejection judgment method using neural networks for character recognition. The neural networks take discriminant measures of an input pattern as input and learn so as to distinguish correct recognized and misrecognized patterns. This forms a nonlinear decision boundary which separates both patterns in a discriminant measure space, and enables the rejection of misrecognized patterns. Neural networks achieved higher performance for rejection judgment on similar shaped Kanji pattern recognition than the traditional method. Moreover, superior performance was obtained by transforming the discriminant measures in the form of the logarithm.

## 1. Introduction

Various character recognition techniques have been investigated and a high recognition rate was achieved for carefully written character patterns [1], [2]. However, when the quality of character pattern deteriorates, the rapid decline of recognition rate becomes to a problem. To solve this problem, feedback recognition, which performs recognition again by changing the parameter for the input pattern with low recognition reliability, is effective [3]. To realize this, the development of a judgment method which rejects the input pattern with low recognition reliability is needed.

The character recognition system initially extracts the feature from an input pattern, subsequently calculates the discriminant measures between the feature and that of the reference pattern for each category, then outputs the candidates and its discriminant measures from the discriminant module. A judgment module decides whether the recognition system accepts the candidates and its discriminant measures as a final result or rejects the same. Regarding rejection judgment, the correct recognized input pattern must be accepted as a final result and misrecognized input pattern must be rejected.

The distance between the feature of an input pattern and that of each reference pattern for each category is popularly used as a discriminant measure. A traditional rejection judgment method exists, which uses the candidates and their distances. Denoting $d_1$ and $d_2$ as the distances taken by the first and the second candidates, respectively, the traditional method performs rejection judgment by applying each threshold to the distances $d_1$ and $(d_2 - d_1)$, respectively. The traditional method is based on recognition reliability because $d_1$ and $(d_2 - d_1)$ relate to the permissible value and the room value in recognition, respectively.

As an idea from other viewpoints, suppose a two-dimensional plane exists, whose axes are $d_1$ and $(d_2 - d_1)$, and correct recognized and misrecognized pattern sets are distributed on this plane surface. Under this condition, the reject judgment becomes equivalent to solving the problem of separating two pattern sets. In the traditional method, two thresholds play the role of separating two pattern sets by horizontal and vertical lines. For rejection judgment, there is a need for misrecognized patterns to be firmly rejected. However, it is difficult to separate only the distribution of a misrecognized pattern accurately by horizontal and vertical lines. The reason is that the distribution of misrecognized patterns forms a complex shape, and it is not possible to separate it solely with horizontal and vertical lines. If horizontal and vertical lines separate the distribution of a misrecognized patterns and reject them, the correct recognized patterns also mixed in. This causes the problem of many correct recognized patterns being rejected.

Neural networks form a decision boundary represented by a nonlinear discriminant function, and can separate arbitrary distributions. Neural networks become a powerful tool to separate the pattern set. We propose a rejection method using neural networks and demonstrate how it provides efficient separation of two distributions compared with the traditional method. Moreover, we present an improved performance of neural networks by conducting variable transformation to the input [4].

## 2. Traditional Rejection Judgment

Discriminant measures are considered effective for judging the recognition reliability because they represent the degree of closeness to the reference pattern. This section describes the traditional rejection judgment method using discriminant measures.

### 2.1. Character Recognition System

Figure 1 shows a block diagram of the character recognition system. This system comprises a pre-processing module, which is not illustrated, a feature extraction module and a discrimination module. Firstly, the pre-processing module removes noise from the input pattern and implements normalization, e.g. expansion or reduction of the character size, etc. Next, the feature extraction module generates feature vectors. Subsequently, the discrimination module calculates the discriminant measure between the input and reference patterns for each category, permutes the category according to the discriminant measure, then finally outputs the candidates and its discriminant measure as a recognition result.

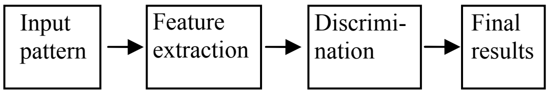


**Fig. 1**: Block diagram of character recognition system.

### 2.2. Rejection Judgment method

The rejection judgment module is set up in steps following the discrimination module in Fig. 1, and determines the destination of an input pattern. If the rejection judgment module judges the recognition reliability of the input pattern to be sufficient, the recognition result on discrimination module is output as a final result or otherwise rejected.

Although various measures exist such as distance and similarity degree, etc. as discriminant measures, we adopted the distance. Note that the aspect of generality is retained. The concept of reject processing on the traditional method is shown in Fig. 2. Here, the numerical straight line expresses the distance, $C_i$ indicates the $i$-th candidate and $d_i$ indicates its distance. The category is arranged in ascending order of distance, and the minimum and second minimum value of the distance among N categories are denoted as $d_1$ and $d_2$, respectively.

The traditional method employs the following two conditions:

$$d_1 \leqq \theta_1 \tag{1}$$

$$d_2 - d_1 \geqq \theta_2, \tag{2}$$

where $\theta_1$ and $\theta_2$ are predetermined thresholds [5]. If the two conditions are not satisfied, the current input pattern is rejected. $\theta_1$ and $\theta_2$ play the role of providing the permissible value of the minimum distance and the room value between the minimum and second minimum values, respectively. This method is based on to the principle of recognition, and is simple and suitable because judgment is possible only by comparison between the threshold and the distance and the physics meaning in processing is also

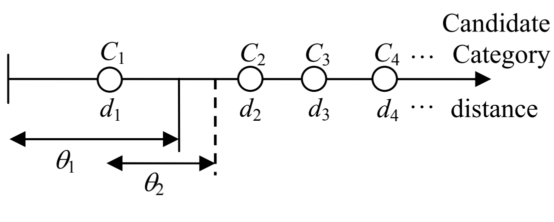


**Fig. 2** The rejection mechanism in the traditional method.

clear.

### 3. Neural Networks

Neural networks of the multi-layer perceptron type have the ability to learn the input-output relation. Therefore, neural networks can acquire the reject judgment function by learning of the relation between distances and correction information in recognition.

### 3.1. Learning Phase

The neural networks which learn the reject judgment mechanism are shown in Fig. 3. A three-layered feed forward neural network is adopted, and back-propagation [6] is used for the learning algorithm. The input of each unit on the input layer accepts two distances of $d_1$ and ($d_2 - d_1$). There are K units in the hidden layer, and two units, the outputs of which are $z_1$ and $z_2$ in the output layer. When the current input pattern shows correct recognition and misrecognition, the desired signal is set to $\boldsymbol{t}$=(1,0) and $\boldsymbol{t}$=(0,1), respectively. Training samples belonging to category $C_i$ consist of correct recognized and misrecognized patterns. These samples are presented sequentially, and neural networks are trained.

### 3.2. Rejection Judgment Phase

The neural networks learnt completely have acquired an internal mechanism, which leads $z_2 > z_1$ for the misrecognized pattern. By using this character, if a rule that the misrecognized pattern should be rejected is adopted, rejection judgment becomes possible. Namely, assume that the test pattern belonging to category $C_i$ is input to neural networks, and two outputs of $z_1$ and $z_2$ are obtained on output layer. If $z_2 > z_1$, the final result is rejected, otherwise, it is accepted.

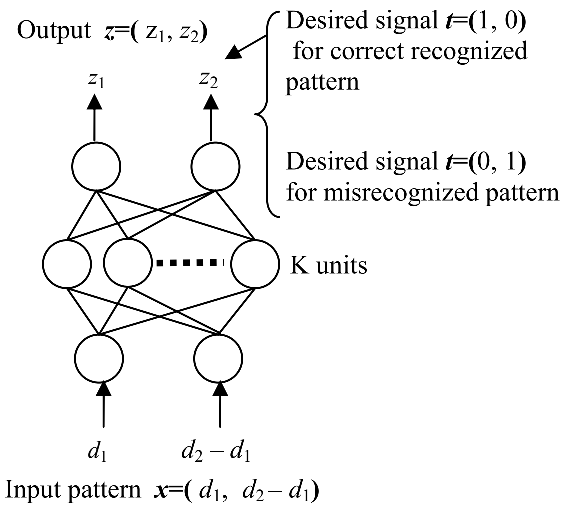


**Fig. 3** A neural network structure.

## 4. Difference of Judgment Mechanism in Both Methods

We consider the difference of judgment mechanism in both methods from a geometrical perspective. Let new $d_1$ and $d_2$ be the values $d_1$ and $d_2$ divided by the constant number and generate a point ($d_1$, ($d_2-d_1$)). Let $P(d_1, d_2 - d_1)$ be the point which is plotted on the two-dimensional plane; the axes of which are $d_1$ and ($d_2 - d_1$). Whenever one pattern is recognized, one $P$ is plotted. When many points are plotted on a two-dimensional plane, sets of $P$ form a region as shown in Fig. 4.

In this Figure, open circle and closed circle indicates a correct recognized and misrecognized pattern, respectively. Suppose all misrecognized patterns are rejected, the reject region $\Omega_1$ obtained by the traditional method is positioned outside in the region formed with vertical line $d_1=\theta_1$ and horizontal line $d_2$-$d_1=\theta_2$; derived by Eqs. (1) and (2), and is shown as a shaded region.

The reject region formed by the neural networks is considered to become the hatched region $\Omega_2$ located under the broken line in Fig. 4 because the neural networks separate the misrecognized patterns using a piecewise linear discriminant function [7].

When the error rate is 0%, part of the correct recognized patterns are rejected, as indicated by open circle in regions $\Omega_1$ and $\Omega_2$. The lower the number of open circle, the better the performance of the reject method. The trapezoid region $\Omega_3$ is rejected by the traditional method, but accepted by the neural networks. Conversely, the pentagonal region $\Omega_4$ is rejected by the neural networks, but accepted by the traditional method. The neural networks can accept the correct recognized patterns within the large region $\Omega_3$ instead of rejecting them in the small region $\Omega_4$. This was made possible by the action of the nonlinearity in the neural networks. These considerations show that the neural networks possess a promising mechanism.

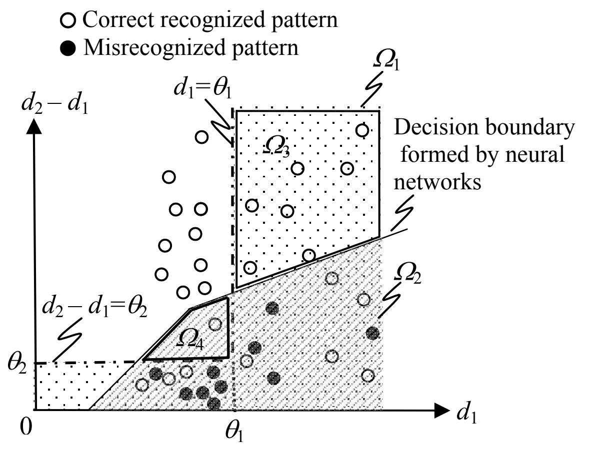


**Fig. 4** Geometric meaning of the judgment mechanism in both methods.

## 5. Input Representation Form

When the distances $d_1$ and $d_2$ are input into the neural networks, they are not used in their original form but in one that is changed based on a certain kind of transformation being conducted, since it is common knowledge that changing the input representation form improves the performance of the neural network. In this paper, consider the following three kinds of method as variable transformation methods:

[Method 1] Uniformly multiple transformation

The value obtained by multiplying a constant number $a_0$ by $d_1$ and ($d_2 - d_1$) is used as new $d_1$ and ($d_2 - d_1$). This method was described in Sect. 4.

[Method 2] Uniformly multiple transformation in each variable

The value obtained by multiplying a constant number $a_1$ and $a_2$ by $d_1$ and ($d_2 - d_1$), respectively, is used as new $d_1$ and ($d_2 - d_1$).

[Method 3] Logarithmic transformation

The value obtained by taking the logarithm of either or both $d_1$ and ($d_2 - d_1$) is used as new $d_1$ and ($d_2 - d_1$).

## 6. Experimental Results

To test the ability of the rejection judgment by the neural networks using the proposed method, experiments were made on handprinted Kanji pattern data.

### 6.1. Samples

Training data consisted of 97 samples of one category "間" (during) written in a square style. A subset of the training data is shown in Fig. 5. The category used in the experiment belongs to a similar shaped character and is hard to recognize. Here, $d_1$ and $d_2$ represent the projection distance obtained by using extended Peripheral Direction Contributivity (e-PDC) features. The e-PDC features are developed by enhancing the number of scanning directions of the original PDC features [8], and its effectiveness has been established [1], [9].

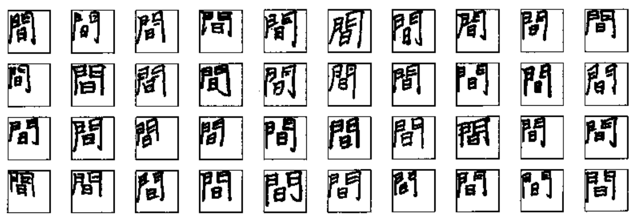

**Fig. 5** Subset of the training data.

### 6.2. Configuration of the neural networks

On neural networks, the input layer consisted of 2 units, each accepting transformed $d_1$ and ($d_2 - d_1$), and 2 units in the output layer, each corresponding to "accept" and "reject". The performance of the neural networks changes depending on the number of units K in the hidden layer. To simplify the confirmation of the neural networks' performance, we choose K=2. The neural networks are trained by back-propagation in order to separate the regions formed by correct recognized samples and those formed by misrecognized samples. 0.9 and 0.2 are set as the learning and momentum coefficients, respectively.

### 6.3. Rejection Judgment Results

Benchmarking studies for the traditional method and neural networks using input representation forms as described in Method 1 were made under the condition of a 0% error rate. The correct recognition rate achieved by the neural networks using Method 1 was 83.1%, superior to the traditional method at 77.3%. Here, a constant number $a_0$ was experimentally determined. These results lead us to conclude that neural networks have the ability to relieve patterns rejected by the traditional method and it is confirmed that they play the role shown in Fig. 4, as expected.

### 6.4. Result of Transformation of the Input Representation Form

Experiments which change the input data form were conducted under the same condition as Sect. 6. 3. The results are shown in Table 1.

(1) In Method 2, the correct recognition rate is improved to 84.3% when $a_1$ and $a_2$ are set in the ratio 1:10. This ratio adjusts so that $d_1$ and $(d_2 - d_1)$ may become almost the same sizes; hence the neural networks can easily separate correct recognized samples from misrecognized samples on the two dimensional plane.

(2) In Method 3, the correct recognition rate is improved to 86.5% when the logarithm of $(d_2 - d_1)$ is used. This logarithm has the character to expand a small value. Even if the value of $(d_2 - d_1)$ is overcrowded within a small range, the logarithmic transformation expands a slight difference, which facilitates recognition by the neural networks. This is thought to be a cause of the improvement of the recognition rate.

These results show that change of input representation form leads to an improvement in the correct recognition rate. We have confirmed that adjusting the level of the input is an effective way to facilitate the separation of distribution.

**Table 1** Comparison of the correct recognition rates of each technique.

| Method | Correct recognition rate (%) |
|---|---|
| Traditional Method | 77.3 |
| Method 1 | 83.1 |
| Method 2 | 84.3 |
| Method 3 | 86.5 |

## 7. Conclusions

We have presented a new rejection judgment method using neural networks. This method performs rejection judgment using a function which separates the region formed by a correct recognized pattern set and the region misrecognized pattern set by learned neural networks.

The mechanism of the proposed method is differs from that of the traditional method. Neural networks have more advantages than the traditional method because they form a decision boundary, which is represented by a nonlinear discriminant function while the traditional method uses the horizontal and vertical lines. The proposed method shows great promise to develop a new area of rejection judgment.

Moreover, we have presented the variable transformation of input used for neural networks. Logarithmic transformation achieved the highest improvement of recognition rate among the three trial methods. It is confirmed that the variable transformation of input is also effective in the field of rejection judgment.

## References


[1] M. Umeda, "Advances in recognition methods for handwritten Kanji characters," IEICE Trans. Inf. & Syst., vol.E79-D, no.5, pp.401-410, 1996.

[2] J. Tsukumo, "Handprinted Kanji OCR development – What was solved in handprinted Kanji character recognition?," IEICE Trans. Inf. & Syst., vol.E79-D, no.5, pp.411-416, 1996.

[3] K. Yamada, "Adaptive Processing Parameter Adjustment by Feedback Recognition Method with Inverse Recall Neural Network Model." IEICE Trans. Inf. & Syst., vol. E77-D, no. 7, pp.794 – 800, July 1994.

[4] Y. Kimura, "Input representation form in reject judgment using neural networks," Proc. of the IIEEJ Annual Conf., 05-76, 2005.

[5] Y. Kimura and K. Ishii, "Chinese character recognition by feature distribution method," Int. Conf. on Text Processing with a Large Character Set, pp.181-185, Oct. 1983.

[6] D. E. Rumelhart, J. L. McCelland and The PDP Research Group, "Parallel Distributed Processing," The MIT Press, 1986.

[7] R. P. Lippmann, "An introduction to computing with neural nets," IEEE ASSP Magazine, pp.4-22, April, 1987.

[8] T. Akiyama and N. Hagita, "Automated entry system for printed documents," Pattern Recognition, vol.23, no.11, pp.1141-1154, 1990.

[9] A. F. Arif, H. Takahashi, A. Iwata and T. Tsutsumida, "Handwritten Postalcode Recognition by Neural Network – A Comparative Study –," IEICE Trans. Inf. & Syst., vol.E79-D, no.5, pp.443-449, 1996.