High-efficiency Handwriting Recognition Online Shopping System by Mobile Devices

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***Abstract*—This paper proposed an innovational method and technology real-time to carry out remote recognition system by a mobile device. User draws a pattern in the local browser to transmit to remote server that will to do recognized task and database search immediately. The recognition system is bidirectional associative memory (BAM) employing artificial neural network technology. This study is based on the example of buying a dog house on the network. When users use the mouse to draw in the browser they want to buy a dog house outline map, the proposed system will instantly be recognized. The recognition result will display relevant dog house style on the web page and allows users to pick them. First, this study will be classified commercial dog house, and set the corresponding graphics stored in the system. These are specified graphics are also training sample patterns of the system. Currently in use on the network, people are almost always enter key words to search for relevant information. This paper presents an innovative approach that users can do hand-drawn graphics data recognition and search by mobile devices.Finally, this study for the accuracy of pattern recognition, and made some improvement analysis experiments.**

Keywords-component;recognition, BAM,associative memory, real-time)

I. INTRODUCTION

Network technology becomes more developed, people use mobile devices in the Internet has become an important part of life [1] [2] [3]. Internet shopping behavior has gradually become a routine habit. However, all shopping website design are all using text search approach [4] [5]. This paper presents hand-drawn pattern to search for information on the project want to purchase [6] [7].When the user Hand drawn outline local products, the remote server will perform pattern recognition, and instantly recognize relevant results will be presented one by one on the page. Bidirectional associative memory (BAM)technology utilizes cis and trans transmission of information in both directions, so that the output of the two neuron networks, in a recurring pattern reaches a steady state, thereby completing heteroassociation work [8].In this paper, mobile devices including smart phones, tablet PCs, notebook computers, and so on. Of course, the person computer also can be used as an input device, but our study can be more emphasis on online shopping anytime, anywhere.

The system remote database development using MySQL program architecture. This database system is used simultaneously connecting multiple distribute databases. So our pattern recognition processing system particularly efficient implementation of the work. Flowchart of the system described with reference to Figure 1, please.

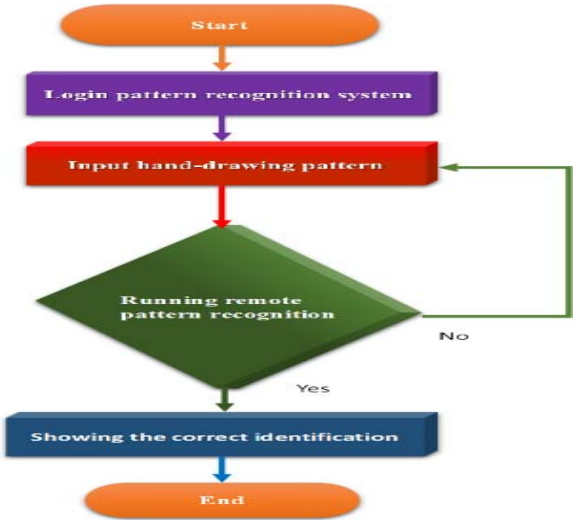


Figure 1. System flowchart illustrates recognition program

II. ESTABLISHING AND SPECIFYING THE TRAINING SAMPLE PATTERNS

In this research, the pattern database is built on a MySQL Server platform, and the platform integrates the whole recognition system to the web-based. The proposed technique employs a web assistant to increase interaction between the system and database. Our research shows that

the website of the recognition system uses apache web server. All web pages are located in the apache, facilitating convenient management by the administrator.

The functioning of the pattern database can be partitioned into two main parts pattern establishment and information management, both of which can be performed using the web-based browser. When these sample patterns are inputted into the pattern database, the approach presented here uses the web-based and real-time methods. After user input a pattern and clicks the submit button, the pattern is inputted into the database. Furthermore, simultaneously with inputting the patterns, users also input their relational properties information.

After users input a sample pattern, the administrator can monitored and manage the database with the help of web assistants. This work allows the administrator to observe the patterns most recently stored in the database by the browser. Furthermore, the administrator can also revise the database at any time.

In the system presented here, web assistants can sight the newest data in the pattern database. Besides, users can also watch the field data of pattern number and pattern builder, as illustrated in Figure 2. The pattern database designed here employs a relational mode to establish the data tables for viewing by users.

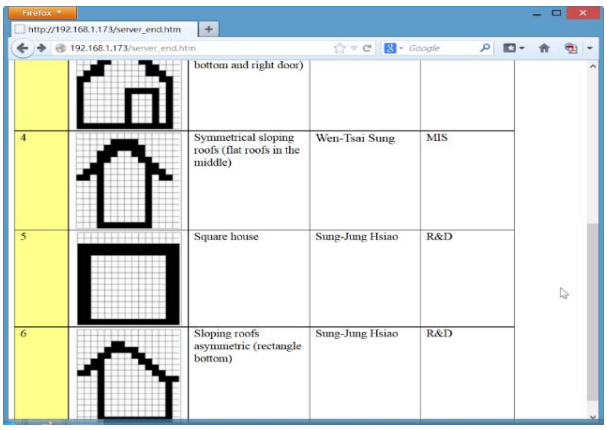


Figure 2 The system webpage presents the component pattern data and builder

III. RECOGNITION COMPUTING AND ALGORITHM ANALYSIS

Bidirectional associative memory (BAM) is a type of recurrent neural network.BAM is a kind of performing heteroassociation double neural network, which can be used to store the N input and output pairs of vectors, $\left(\underline{\chi_i}, \underline{y_i}\right), i = 1, \cdots, N$, $\underline{\chi_i}$ and $\underline{y_i}$ respectively, p and r-dimensional vector dimension, its basic structure shown in Figure 5.

BAM use forward and reverse transmission of information, so that the output neuron network of the two layer, in a recurring mode reaches a steady state, thereby completing heteroassociation work. Let Y output layer neuron at time $k$is$\underline{y}(k)$, this time $\underline{y}(k)$ that is regarded as the input neurons in layer X, and the neuron (X layer) will according to the following formula to update the output neuron:

$$\underline{x}(k+1) = \varphi\left(w_{\underline{y}}(k) - \underline{\theta}\right) \tag{1}$$

Oρ

$$\underline{x}(k+1) = \varphi\left(\sum_{j=1}^{r} w_{ij} y_j(k) - \theta_i\right), \quad i = 1, \cdots, p \tag{2}$$

$$= \begin{cases} +1 & if \sum_{j=1}^{r} w_{ij} y_j(k) > 0 \\ x_i(k-1) & if \sum_{j=1}^{r} w_{ij} y_j(k) = 0 \\ -1 & if \sum_{j=1}^{r} w_{ij} y_j(k) < 0 \end{cases}$$

Therefore,$\underline{x}(k+1) = \left[x_1(k+1), \cdots, x_p(k+1)\right]^r, \underline{y}(k) = [y_1(k), \cdots, y_r(k)]^r$, χ_i and y_i are bipolar binary valued, $W = \left[w_{ij}\right]$,w_{ij}represents weight values, Y layer the j-th neuron connected to the i-th neuron of X layer. The second term in the above formula and substituting a value which is equal to said x_i previous time, before the value without engraved, randomly select one or -1. Then $\underline{x}(k+1)$ as an input located on the Y layer neuron, and according to the following formula to calculate the neuron (Y layer) new output:

$$\underline{y}(k+2) = \varphi(W'\underline{x}(k+1) - \underline{\theta'}) \tag{3}$$

Oρ

$$y_j(k+2) = \varphi\left(\sum_{i=1}^{p} w'_{ij} x_i(k+1) - \theta'_j\right), \quad j = 1,2, \cdots, r \tag{4}$$

Which w'_{ij} representatives i-th neuron of X layer is connected to bond value j-th neuron of Y layer, and $W' = \left[w'_{ji}\right]$ Then, again $\underline{y}(k+2)$ as input to calculate $\underline{x}(k+3)$, this process has been repeated persist until convergence, the entire recall process can be summarized by the following steps.

1stfeedbacktransmit: $\underline{x}(1) = \varphi(W\underline{y}(0) - \underline{\theta})$

1stfeed forwardtransmit: $\underline{y}(2) = \varphi(W'\underline{x}(1) - \underline{\theta'})$

2stfeedbacktransmit: $\underline{x}(3) = \varphi\left(W\underline{y}(2) - \underline{\theta}\right)$

2stfeed forwardtransmit: $\underline{y}(4) = \varphi(W'\underline{x}(3) - \underline{\theta'})$

⋮

$(k/2)$-thfeedbacktransmit: $\underline{x}(k-1) = \varphi(W\underline{y}(k-2) - \underline{\theta})$

$(k/2)$-thfeedbacktransmit: $\underline{y}(k) = \varphi(W'\underline{x}(k-1) - \underline{\theta'})$

$\vdots$

Our studies employ learning rules the same as linear associative memory, and are based on Hebbian learning rule:

$$W = \sum_{k=1}^{N} \underline{w}_k \underline{y}_k{}^T$$

$$(\text{or } W_{ij} = \sum_{k=1}^{N} x_i(k) y_j(k) \quad i = 1, \cdots, p \quad j = 1, \cdots r) \quad (5)$$

$$W' = \sum_{k=1}^{N} \underline{y}_k \underline{x}_k{}^T$$

$$(\text{or } W'_{ji} = \sum_{k=1}^{N} \begin{matrix} y_j(k) x_i(k) \\ i = 1, \cdots, p \quad j = 1, \cdots r) \end{matrix} \quad (6)$$

Comparison of formula (5) and (6), the present study may be derived $W^T = W'$, i.e. $w'_{ji} = w_{ij}$. The threshold setting method, and discrete Hopfield network as there are two different ways:

$$\theta_i = \frac{1}{2} \sum_{j=1}^{r} W_{ij} \ (\text{or } \theta_i = 0) i = 1, \cdots, p \quad (7)$$

$$\theta'_j = \frac{1}{2} \sum_{i=1}^{p} W'_{ji} \left(\text{or } \theta'_j = 0\right) j = 1, \cdots, r \quad (8)$$

After the system network executed many times bidirectional iteration, weights presented bidirectional stable state, the following will happen: ： $\underline{x}(k) \longrightarrow \underline{y}(k+1) \longrightarrow \underline{x}(k+2) \longrightarrow \underline{y}(k+3) \longrightarrow \cdots \longrightarrow$， $\underline{x}(k) = \underline{x}(k+2)$ and $\underline{y}(k+1) = \underline{y}(k+3)$.Our research is still in use Hopfield network analysis methods to identify a network of Lyapunov function (To simplify the problem, so that the threshold entry $\underline{\theta} = \underline{\theta}' = \underline{0}$):

$$E\left(\underline{x}, \underline{y}\right) = -\tfrac{1}{2} \underline{x}^T W^T \underline{y} - \tfrac{1}{2} \underline{y}^T W \underline{x} = -\underline{y}^T W \underline{x} \quad (9)$$

BAM will go along with the evolution of time and move in the direction of low energy networks, convergence to the last few bi-stable state, and this state is a local minimum amount of energy mail function. It is worth mentioning that, BAM will have a so-called "fake state" appears.

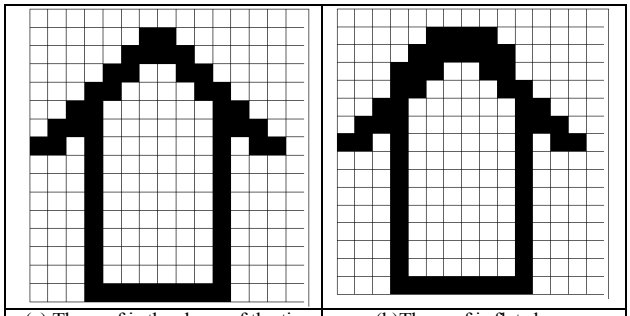
If discrete BAM with differential state change the rules, such as formula (2) and (4) into the following differential equation, it will become a so-called continuous BAM (continuous bidirectional associative memory):

$$\begin{cases} \dfrac{dx_i}{dt} = -x_i + \displaystyle\sum_{j=1}^{r} w_{ij} \varphi(y_j) + I_i \\ \dfrac{dy_j}{dt} = -y_j + \displaystyle\sum_{i=1}^{p} w'_{ji} \varphi(x_i) + I_j{}' \end{cases} \quad (10)$$

Which,I_i and $I_j{}'$ are positive constants

IV. PROBLEMS AND OVERCOMING

Our system planning many dog house pattern recognition, but some patterns similar to affect the accuracy of recognition.Figure 3 (a), Figure 3 (b) look very similar, only the differences between the shapes of the roof.Because the roof is a graphical feature points, so we have to find out for solutions to this problem. The solution is to first identify a similar pattern, and then to the feature point matching, find the correct graphics. Right graphic and recognition results subtraction, and then after subtracting the minimum valueis the system identification answers.



(a) The roof is the shape of the tip	(b)The roof is flat shape

Figure 3.Similar pattern recognition problems

In Figure 7 (a), (b), (c) and (d), the correct figure is displayed (on the right side of each graph), and is left incomplete recognition results. Although this study uses an asynchronization method to change network output, X converges on the stable state, and sometimes also on the incorrect recall [18]. The X state of final convergence is therefore used for matching with the original pattern database [20]. Computing each Hammer distance determines the minimum dH value [19]. Assume that a set of N-dimensional vectors (binary word), denoted by $\{\xi_\mu | \mu = 1, 2, ..., N\}$, and is to be stored. These N vectors are called fundamental memories and represent the patterns to be memorized by the network. Let ξ_μ denote the ith element of the fundamental memory, ξ_μ, where the class $\mu = 1, 2, ..., N$. Given n pattern records, the Hammer distance is calculated by

$$\text{dH} = \sum_{i=1}^{P} |X_i - \xi_i^u|, \quad u = 1,2, \ldots, n \quad (11)$$

Meanwhile, the minimum value is calculated by

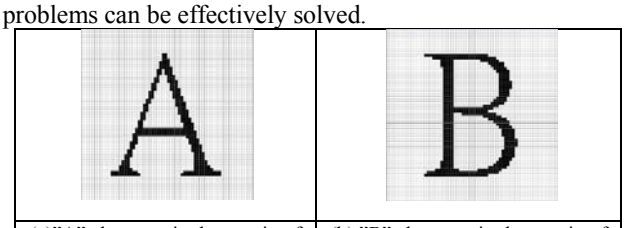
$$\mathrm{dH}_{min} = \min\left\{\sum_{i=1}^{P}|X_i - \xi_i^1|, \sum_{i=1}^{P}|X_i - \xi_i^2|, \ldots, \sum_{i=1}^{P}|X_i - \xi_i^n|\right\} \quad (12)$$

Capacity problem of the BAM is a challenging issue. According to Kosko estimated that about BAM memory capacity up to min (p, r). However, Kosko in depth analyzed BAM capacity no greater than $\sqrt{\min(\mathrm{p},\mathrm{r})}$.

$$\mathrm{W} = [w_{ji}] = \begin{bmatrix} w_{11} & \cdots & w_{1p} \\ \vdots & \ddots & \vdots \\ w_{r1} & \cdots & w_{rp} \end{bmatrix} = \sum_{k=1}^{N} \underline{y}_k \underline{x}_K^T \quad (13)$$

W is the weight matrix of r × p. Our experiments are r = 16, p = 15, so the min (p, r) = min (15, 16) = 15, and $\sqrt{\min(\mathrm{p},\mathrm{r})} = \sqrt{15} \cong 4$.

Next, the experiment will 16x15 matrix becomes 64x64 matrix, as figure 4(a) (b). Further experiments can be calculated min (p, r) = 64, $\sqrt{\min(\mathrm{p},\mathrm{r})}$ = 8. Research shows that the larger the available recognition matrix pattern, the pattern capacity of their training is increased. If the investigation employed distributed computing, the capacity problems can be effectively solved.



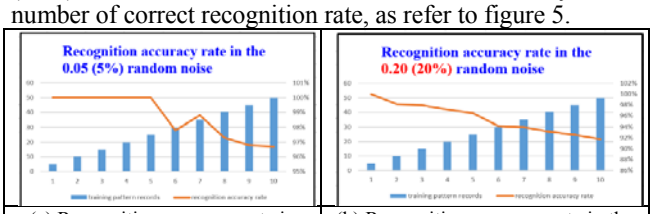
(a)"A" character in the matrix of 64x64	(b) "B" character in the matrix of 64x64

Figure 4.Showing greater recognition matrix graphics.

V. Implementing the Web-Based Pattern Recognition System

This section begins with an introduction to the content of the experiment. First, patterns are inputted at the cloud-device and displayed at the cloud-server, please refer to figure 9. Operator input pattern recognition in Cloud-device, when the submit button is pressed the system will do the recognition work. This experiment first adds 5% random number noise in the correct recognition pattern. A selected pattern is distorted by randomly and independently reversing each point of the input pattern from -1 to 1 and vice versa, with a probability of 0.05(5%), and then testing the network employing the corrupted pattern.The patterns produced by the TCP/IP network after 80, 120, 200, and 212 iterations reveal a steady increase the resemblance of the TCP/IP network output to the component pattern. Indeed, after 212 iterations, the network converges onto the correct form of the pattern.

The proposed recognition system has already overcome many of the problems of previous systems. For example, the proposed system has substantially better capacity and accuracy than existing systems, and the neural network with distributed computation is highly efficient. Next, we use the study were 0.05 (% 5), 0.10 (% 10), 0.15 (15%) and 0.20 (20%) of the random noise interference to analyze the number of correct recognition rate, as refer to figure 5.



(a) Recognition accuracy rate in the 0.05 (5%) random noise	(b) Recognition accuracy rate in the 0.20 (20%) random noise

Figure 5 Recognition accuracy rate in the different random noise

VI. Conclusion

The utilization of hand-drawn recognition on the Internet is still immature. This work applies a real-time, web-based method to recognize network patterns on the Internet. The development of a dog house pattern database can solve numerous problems in recognition technology. This work has reached some new solutions of improved recognition, as follows:

Using the Minimum Hamming Distance technology of a pattern database to determine the patterns that are most similar to one another reduces spurious states of BAM and increases neural network recognition rate.

Utilizing the parallel computing approach to overcoming the problem of limited BAM capacity.

The web-based method uses Internet, and any user can use a mobile device to connect to the cloud-server via the Internet. Furthermore, users can recognize the source pattern immediately after inputting the training pattern.

Continue with further development, the proposed recognition system will be able to be widely applied to electronic commerce and network shopping.

Acknowledgment

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