IMPROVEMENT ON THE INDIVIDUAL RECOGNITION SYSTEM WITH WRITING PRESSURE BASED ON RBF

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Abstract: In our previous research work, an individual recognition system with writing pressure employing neuro-template of multiplayer feedforward network with sigmoid function has been developed. Although this system was effective on recognition for known registrant, its rejection capability for counterfeit signature was not good enough for commercial application. In this paper, a new activation function was proposed to improve the rejection performance of the system for counterfeit signature on the premise of ensuring the recognition performance for known signature. The experiment results showed that compared with original system the proposed activation function was seemed to be effective to improve the rejection capability of the system for counterfeit signature with keeping the recognition capability for known signature satisfied.

1 INTRODUCTION

In recently years, biometrics information such as fingerprint, iris is gradually applied into the individual recognition systems replacing the security material such as licence or security information such as personal identification number (PIN), password. Compared with conventional recognition systems, high security is one of superiority of recognition system with biometrics information because of difficulty of imitation or copy for biometrics information.

Every person's signature has unique character in terms of rhythm and force employed during signature. Writing pressure data detected dynamically from signature procedure can characterize individual signature if being properly processed. Being friendly biometrics information, writing pressure has little spirit resistance compared with other biometrics information such as fingerprint and iris. Furthermore, unlike handwriting, writing pressure data is dynamic signal and invisible to users, that contributes to more difficulties of imitation and copy, therefore writing pressure has higher security as personal information for individual recognition than handwriting. In our research work, writing pressure has been successfully employed to develop individual recognition system.

In our system, neuro-template of multiplayer feedforward neural network (MFNN) with sigmoid as activation function of hidden and output layer was used to construct kernel part of the system. The experiments showed that the system with sigmoid function was effective on recognition for the patterns having been learned (known registrant), but the rejection capability for counterfeit writing which is from imitating legitimate registrant's signature by intruders was not good. To solve the previous problem, Gaussian function, which is one of radial basic function (RBF), was proposed as activation function of the NN in this paper. In the experiment, both recognition and rejection performance of the system with Gaussian function were compared with that of original system with sigmoid function, and the results showed that the proposed method has effectively improved the rejection performance of the system for counterfeit signature with keeping recognition capability for known pattern satisfied.

2 BASIC STRUCTURE OF THE INDIVIDUAL RECOGNITION SYSTEM

The individual recognition system with writing pressure is composed of hardware section and software section.

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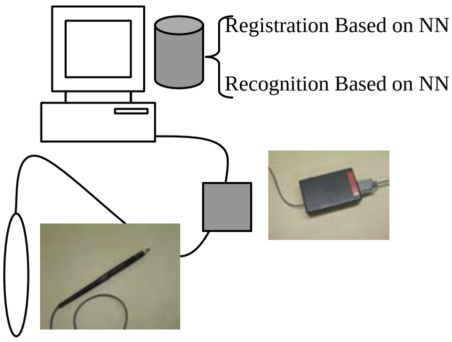

2.1 Hardware Construction of the System

The hardware section of system, which is constructed by the electronic pen, data collection box and personal computer, is in charge of data detection and transmission. Figure 1 illustrated the hardware structure of the system. In inner of electronic pen, there is a pressure sensor with 0.1g writing pressure resolution and 4ms time resolution, that makes high resolution of the extraction of writing pressure data possible. In the hardware section, writing pressure data are detected by the electronic pen, and then loaded to PC via the data collection box. After that, the registration and recognition procedure are executed on these data based on the Neuro-template.

2.2 Software Construction of the System

This section completes most function of the system such as data preprocess, new registration, registrant recognition and result display etc, It is composed of registration part and recognition part which are independent each other. Both of two parts are based on neural template of MFNNs. Registration subsystem is in charge of recruiting new legitimate registrant: generating and training one neuro-template for him (or her). Recognition subsystem has role of recognizing the identity of the user who entries the system from all the candidate registrants who have registered on the system legitimately by matching this user's signature with all of existing neuro-templates and then evaluating output of each template.

3 PREPROCESSING

The writing pressure data detected by hardware section can not be fed into neural network directly because of too much redundant data. Therefore the preprocessing of writing pressure data is indispensable and crucial for system. There are three steps for the data preprocessing, and in each step different treatment is implemented and different data are obtained.

First, after three times of signature given by registrant, the writing pressure data set with more than 1000 data are transformed into normal data with number of about 300 by Moving Average method. During this process, the individual feature of pressure data is extracted and data scale is compressed greatly.

Second, validity check is implemented on normal data obtained in first step basing on two factors: correlation coefficient R and statistical distance D.

The correlation coefficient R between Data1 and Data2 is calculated as following equation:

$$R = \frac{\sum_{s=1}^{S}(Data1(s)*Data2(s)) - Ave(d1)*Ave(d2)}{\sqrt{\sum_{s=1}^{S}(\mathrm{Data1(s)})^2 - S*(Ave(d1))^2}\sqrt{\sum_{s=1}^{S}Data1(s)^2 - S*Ave(d2)^2}} \quad \text{—(1)}$$

Here, $Ave\ (d1)$ and $Ave(d2)$ are average of Data1 set and Data2 set respectively with assuming that there are S elements in each data set. The value of R varies between –1 and 1. More near 1 R is, more closely two data correlate.

Statistical distance (Euclidean distance) between Data1 and Data2 is calculated as following equation:

$$D = \sqrt{\sum_{s=1}^{S}(Data1(s) - Data2(s))^2} \quad \text{—(2)}$$

The deviation between each two of three writing pressure data are calculated according to their correlation coefficient and statistical distance, if deviation is more than upper limit, the corresponding signature data are treated as abnormal and registrant is asked for re-signature.

In this system, only three writing pressure data set as enforce data are not enough for purposive pattern learning of Neuro-template, furthermore the inhibit data for non-purposive pattern are also necessary. So not only purposive simulative data (enforce data) but also non-purposive simulative data (inhibit data) are constructed based on the detected writing pressure data and the corresponding normal data are then constructed.

Last, In order to obtain 50 slab data for Neuro-template from 300 normal data, mask data are made by comparison on distribution of standard error and average value between enforce normal data and inhibit data, then 50 slab data for the Neuro-template are obtained by filtering middle data with the mask data.

4 ALGORITHM

For traditional MFNN, when recruiting new pattern, the whole neural network will have to be restructured and retrained, that would lead to expensive cost of computation and time. In order to eliminate the restriction on the number of registrants in the recognition system and simplify the recruitment of new pattern, neural template matching method showed as Figure 2 was proposed and applied into this individual recognition system. In this method, one neural template corresponds to one pattern (registrant). When new registration is completed, a new neural template is constructed and trained for this new registrant, other neuro-templates generated previously will remain untouched unless mis-outputs are caused by signature of new registration in these templates. That is to say instead of training all of templates, only the training for new template and the retraining for the existing templates in which the mis-recognition occurred are involved in the procedure of new registration. Therefore the cost of calculation and time for new registration is greatly decreased and registration procedure is simplified.

In the neural template matching method, each neuro-template is constructed by three layers feedforward neural network with structure of 50×35 ×2 which is shown in Figure 3, one of two output layer units corresponds to purposive pattern (purposive registrant) and the other to non-purposive one (non-purposive registrant). The function of each neuro-template is evaluating whether the input data is the purposive pattern of this template or not rather than deciding which pattern the input data is from all of templates. Recognizing the pattern of input signature from existing templates is completed by template matching procedure. The experiment results showed that this strategy was effective for individual recognition system.

In the previous research work, sigmoid function

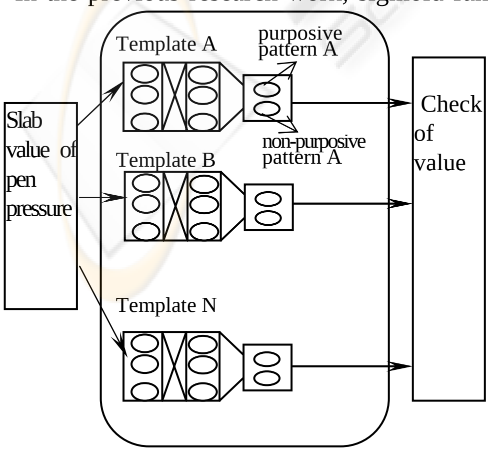

Figure 2: Construction of Neuro-template Matching Mechod

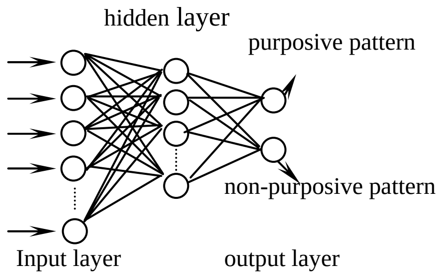

Figure 3: Structure of neuro-template

was employed as activation function of neuro-template in the individual recognition system. The simulation experiments have shown that the system was effective on classifying the signatures that belong to known patterns (the average recognition rate was over 95%), however rejection performance for counterfeit signature (always unknown pattern) was not satisfying. This problem caused by the limitation of the MFNNs: the pattern space is divided up into several areas corresponding to the patterns that have been learned in a specific case and the networks may be trained to have high accuracy in classifying patterns for a set of known categories, so it can successfully recognize the signature of registrant whose pattern have been learned. But for any pattern which is out of known categories, it is also very likely to be classified as one of known categories by MFNNs. That leads to the poor rejection capability for counterfeit signatures.

To improve the rejection performance of the system for counterfeit signature, Gaussian function, which is one of RBF, was proposed as activation function of neural unites in this paper. Instead of dividing up the pattern space as MFNNs do, neuro-template with Gaussian function learns the pattern probability density. Therefore, when an out-of-category pattern is evaluated, it is likely to be recognized as an unknown category by neuro-template with Gaussian function. Then the rejection performance of the system for counterfeit signature is expected to be improved. The expression of Gaussian activation function of hidden and output layers neuron is described as following equation:

$$f(x) = \exp(-\|x - x_c\|^2 / 2\sigma^2) \quad \text{— (3)}$$

Where x_c and σ are the centre vector and the width parameter of Gaussian function respectively. Both of them have direct effect on the convergence and recognition capability of the individual recognition system.

In the neuro-template training procedure, improved Back Propagation (BP) is employed to modify the weights between neighbour layer neurons and corresponding expression was described as following:

$$\Delta W(t) = -\eta \cdot \frac{\partial E}{\partial w(t)} + \alpha \cdot \Delta W(t-1) + \beta \cdot \Delta W(t-2) \quad \text{—} (4)$$

Where η, α, β are the learning rate, momentum coefficient, and oscillation coefficient respectively. The momentum item contributes to accelerating convergence and the oscillation item has function of escaping local minimum. The neuro-templates are trained with learning data set till the cost functions meet the requirements of minimal error.

5 EXPERIMENTS

In the research work of this paper, a series of simulation experiments were made on both of individual recognition system with Gaussian function and that with sigmoid function for the purpose of comparison. The conditions for neuro-template learning are listed in table 1.

Table 1: Conditions of neuro-template learning

Maximum iteration number	1000
Learning rate	0.05
Momentum coefficient	0.95
Oscillation coefficient	-0.1
Error threshold	0.0001
Value of σ (only for Gaussian)	0.3~1.0

Generally the registration and recognition of the system are operated on-line, but in order to ensure the identical writing pressure data for neuro-templates with different activation function, the registrant signs on the signature sheet under the same condition and off-line registration and evaluation is implemented with data file in the experiment. One of registrant signature and corresponding writing pressure data are shown as Figure 4.

To demonstrate average performance of the system for any template, three registrants (labelled as A, B, C) were selected randomly, 53 signature samples were extracted from each purposive registrant as purposive signatures and any three of these samples were employed for neuro-template learning and the left for evaluation. To evaluate counterfeit rejection performance of the system, 90 samples were extracted as counterfeit signatures from any five people (except A, B, C) with 18 samples per person for each registrants and the three groups of five people who give the counterfeit signatures were different each other.

The evaluation items in the experiments are recognition ratio and rejection ratio. Recognition ratio presents the percentage of signatures being successfully recognized to all purposive signatures

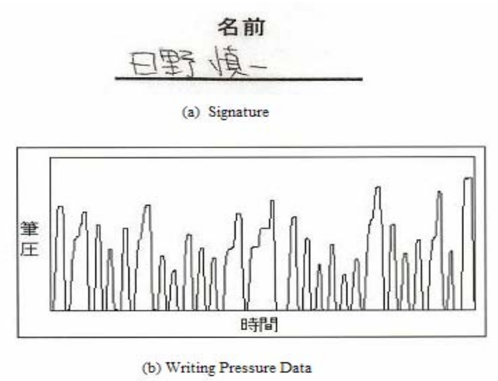

Figure 4: Registrant Signature and Corresponding Writing Pressure data

(50). Rejection ratio for counterfeit signatures presents the percentage of signatures being successfully rejected as unknown pattern to all counterfeit signatures (90). Assuming having three registrants (A, B and C) in the system, taking registrant A as purposive registrant for example, signature (purposive signatures of A or counterfeit signatures of A) is fed to each template and evaluated by respective template. All possible results of the system were illustrated in Table 2. Note that output of the system will be one of these three registrants or none of them (briefly N).

Table 2: All Possible Results of Experiments

Evaluated signature		Purposive signature	Counterfeit signature
Source of signature		A	Anyone except A, B and C
Ideal Results		A	N
Possible results of system	Success	A	N
	Failure	N	A
		B or C	B or C

In the previous table, the failure cases in which purposive signature of A is mis-recognized as B or C and the counterfeit signature for A is mis-recognized as B or C can easily be overcome by our system because of significant difference among the signatures of the respective registrant.

Based on the previous condition and the sampled data (including purposive and counterfeit), neuro-templates with Gaussian Function and that with sigmoid function are trained with the sequence of A, B, C and evaluated respectively, and the experiment results are presented in Table 3 and Table 4.

Table 3: Recognition ratio for purposive signatures (ideal value: 100%)

Registrant	Sigmoid	Gaussian	Difference
A	96%	96%	-0%
B	98%	96%	-2%
C	96%	92%	-4%
Average	96.67%	94.67%	-2%

Table 4: Rejection ratio for counterfeit signatures (ideal value: 100%)

Registrant	Sigmoid	Gaussian	Difference
A	64.44%	82.22%	+17.78%
B	85.56%	90.0%	+4.44%
C	71.33%	88.89 %	+17.56%
Average	73.77%	87.04%	+13.27%

The item of ‘Difference’ in above tables is for easy discrimination on the performance change between two systems. The minus sign (-) indicated deterioration of the performance of system with Gaussian function compared with that with sigmoid function and the positive sign meant the improvement. According to table 3 and table 4, though the recognition capability of system with Gaussian function decreased slightly (average –2%), its rejection capability for counterfeit signatures was improved greatly with average value of 13.27%. This result suggested that the neuro-template with Gaussian function proposed in this paper tended to be effective on improving the rejection capability of system for the counterfeit signatures and at the same time keeping the recognition capability for purposive registrant signatures satisfied.

As mentioned in section four, the recruitment of new registrant in the system will lead to retraining on the exiting templates in which mis-outputs are caused by signatures for new register. That means the neuro-template in the system is likely to be influenced by the templates registered later. To investigate the mutual influence of different neuro-templates, more experiments were conducted on the system with different number and different sequence of templates. Registrant A and B in previous experiments were selected for the purpose of convenience. In these experiments, when registrant B registered after A, retraining on template A was induced by recruitment of B, however no retraining on template B in the case of registrant A registering after B. Note that any templates except A and B was not included in this system.

First, the performance of template A with sigmoid function and that with Gaussian function under different situation were investigated and the corresponding results were demonstrated in Table 5 and Table 6 respectively.

Table 5: Performance of template A with sigmoid function under different situation (ideal value: 100%)

Performance / Order of registrants	Recognition	Rejection
A only	96%	57.78%
A, B	96%	64.44%
B, A	96%	57.58 %

Table 6: Performance of template A with Gaussian function under different situation (ideal value: 100%)

Performance / Order of registrants	Recognition	Rejection
A only	96%	68.89%
A, B	96%	82.22%
B, A	96%	68.89 %

Table 7 and Table 8 showed the performance of template B with sigmoid function and that with Gaussian function under different cases respectively.

Table 7: Performance of template B with sigmoid function under different situation (ideal value: 100%)

Performance / Order of registrants	Recognition	Rejection
B only	98%	85.56%
B, A	98%	85.56%
A, B	98%	85.56 %

Table 8: Performance of Template B with Gaussian Function under Different Situation (Ideal Value: 100%)

Performance / Order of registrant	Recognition	Rejection
B only	96%	90.0%
B, A	96%	90.0%
A, B	96%	90.0 %

As can be seen from above tables, the recognition performance of both template A and B with different activation function were not influenced by the register sequence, that indicated that the recognition performance of the system was not affected by increase of templates. While for counterfeit rejection capability, there were two cases: one case was that new register led to retraining on the templates registered previously (Table 5 and Table 6); the other case was that no retraining was resulted by new register (Table 7 and Table 8). According to Table 5 and Table 6, in both two systems with different activation function, the rejection capability of template A was enhanced by new register of B and this improvement was especially remarkable with employment of Gaussian function. From Table 7 and Table 8, the rejection performance of template B kept untouched because no retraining was caused by recruitment of template A. these experiment results showed that recruitment of new templates was helpful to decreasing the possibility of mis-recognition on counterfeit signatures in one template.

The results in Table 3 and 4 involved the influence among templates. Excluding the influence among templates, the rejection performance of templates with different activation function was investigated and corresponding results were listed in Table 9. Note that in each case, only one registrant was involved in the system.

Table 9: Rejection performance of template with different activation function (ideal value: 100%)

Function / Registrant	Sigmoid	Gaussian	Difference
A only	57.78%	68.89%	+11.11%
B only	85.56%	90.0%	+4.44%
C only	73.77%	87.04 %	+13.27%
Average	72.37%	81.97%	+9.60%

It can be seen that even without the help of favourable influence of templates, Gaussian function was still effective on improving the rejection capability of template.

During experiments, the width parameter σ was found to have great influence on both recognition capability and counterfeit rejection capability of the system with Gaussian function. We are engaging in developing automatic optimisation method of σ for each registrant's neuro-template.

6 CONCLUSION

In this paper, both of the construction and algorithm of the individual recognition system with writing pressure were firstly described. Then, Gaussian function, which is one of RBF, was proposed as activation function of neuro-template to improve the rejection capability of the system for counterfeit signatures. Furthermore the influence among neuro-templates was investigated in this paper. The experiments results suggested that the influence among templates was favourable for rejection capability of the system, and more importantly the experiment results shown that Gaussian function combined with neuro-template was seemed to be very effective in improving rejection performance of the system for counterfeit signatures on premise of ensuring the recognition performance satisfied.

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