Comparison of ART-2 and SOFM Based Neural Network Verifiers ⋆

P. Mautner, V. Matousek, T. Marsalek, and O. Rohlik

University of West Bohemia,
Faculty of Applied Sciences,
Univerzitni 8,
CZ – 306 14 Plzen (Pilsen),
Czech Republic

Abstract. The Carpenter-Grosberg ART-2 and Kohonen Self-organizing Feature Map (SOFM) have been developed for the clustering of input vectors and have been commonly used as unsupervised learned classifiers. In this paper we describe the use of these neural network models for signature verification. The biometric data of all signatures were acquired by a special digital data acquisition pen and fast wavelet transformation was used for feature extraction. The part of genuine signature data was used for training both signature verifiers. The architecture of the verifiers and achieved results are discussed here and ideas for future research are also suggested.

1 Introduction

Commercial systems designed for handwritten text acquisition use as an input device a scanner, a pen with a tablet or a GPS-based pen with a (infrared or ultrasound) transmitter and several receivers (see [11], [13], [14]). Obvious disadvantage of these devices is the limited mobility of a system composed of two or more pen parts. System based on optical (OTM) technology require additional light sources (usually built-in inside the pen) in order to work properly which is intrusive an uncomfortable.

Under the BISP (Biometrical Smart Pen for Personal Identification) project several pen prototypes were constructed. These prototypes integrate all the electronic devices needed for the data acquisition inside the pen and are ergonomic and non-invasive as they do not emit light, sound, or electromagnetic radiation and provide a comfortable feeling while writing.

In our paper, we focused on two famous neural network architectures: the Carpenter-Grosberg ART-2 and Kohonen Self-organizing Feature Map (SOFM). These networks can be used as the signature verifiers for the data acquisition pen developed under BiSP project. The first experiments with these neural network verifiers were published in [1], the new feature set and results of new tests are presented here. The block scheme of the developed system using neural network verifier is shown in Figure 1. Short description

⋆ This work was supported by the Ministry of Education of the Czech Republic - Project No. MSM235200005 and the Bilateral Czech-German Research Project No. TSR 007/99

Mautner P., Matousek V., Marsalek T. and Rohlik O. (2004).
Comparison of ART-2 and SOFM Based Neural Network Verifiers.
In *Proceedings of the First International Workshop on Artificial Neural Networks: Data Preparation Techniques and Application Development*, pages 41-48
DOI: 10.5220/0001149300410048

of this pen can be found in Section 2, Section 3 deals with the pen output signal feature extraction method and Section 4 describes both neural network signature verifiers. Results of verification experiments, and possible future work are discussed in Section 5 and Section 6, respectively.

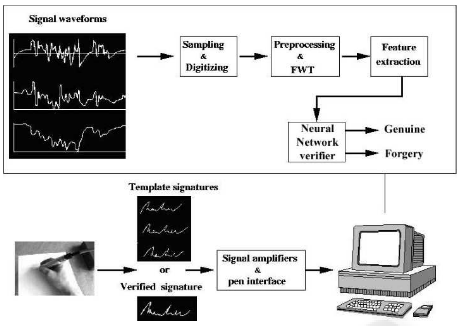

Fig. 1. Block Scheme of Signature Verification System

2 Data Acquisition Device

As mentioned above, data acquisition is performed by a special electronic pen which was built at the University of Applied Sciences in Regensburg during the spring 2002 (Figure 2). The pen consists of two pairs of mechanical sensors that measure the horizontal and vertical movements of the ballpoint nib and a pressure sensor that is placed in the top part of the pen. The pen produces a total of three signals (Figure 3). The upper signal corresponds to the pressure sensor and the other two correspond to the horizontal and vertical movements of the pen. The data were acquired while writing the signature ”Dobner” (Figure 3).

Four strain gauge sensors that measure the horizontal and vertical movements of the pen are located near the pen nib and are placed orthogonally to each other. The signal produced by the horizontal pair of sensors is called x and the one produced by the

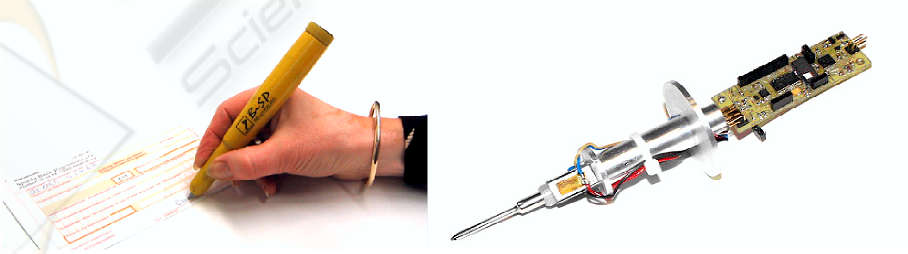

Fig. 2. Digital Data Acquisition Pen

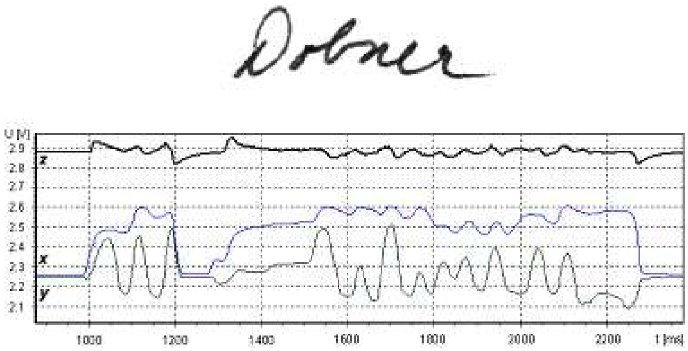

Fig. 3. Signature ”Dobner” and signals produced by the pen (reprinted from [1])

vertical sensors y. Each pair of sensors is connected to a Wheatstone bridge. Therefore there is only one output signal corresponding to the horizontal movement of the pen (x) and one corresponding to the vertical movement (y). We cannot provide more detailed description of the pen because of the patent pending status.

3 Feature Extraction

Before the feature vector is evaluated from the output signals, only the active part of the signature has to be determined. This is done from the first difference of output signal **z**. To determine the beginning (or the end) of the signature, the **z** signal is scanned from left to right (or conversely) and the first difference is evaluated. The beginning (or the end) of the signature is determined if the value of the first difference of signal **z** exceeds the threshold value Θ at the first occurrence and value of the signal is greater than the reference value σ. The threshold values Θ and σ are determined according to the type of the piezoelectric sensor used.

For the extraction of features from the signals, the fast wavelet transform (FWT) was used. At first, each signal of the signature was filtered by an average filter, afterwards it was decomposed by FWT and coefficients of $\mathbf{a_5}$ and $\mathbf{d_m}$, for $m = 1, 2, ..., 5$ were determined [6]. The Daubechies and the Coiflet wavelet families were tested for decomposition, the 5-th order Daubechies wavelet gave the best result. Using of this wavelet, the following features were evaluated:

- $\mathbf{W_{energy}}$ - energy values $\|\mathbf{d_m}\|^2$ and $\|\mathbf{a_5}\|^2$
- $\mathbf{W_{statistic}}$ - mean values and standard deviation of coefficients $\mathbf{d_m}$ and $\mathbf{a_5}$

where $\mathbf{d_m}$ and $\mathbf{a_5}$ are the detailed and the approximation coefficients of FWT in scale m and 5, respectively.

4 Neural Network Signature Verifiers

The neural network models are commonly used for processing classification problems. But signature verification differs from the general classification problem. The goal of the general classification problem is to choose one class from several classes, whereas the training data contain data from all classes. For our application all the training data are genuine signatures and we have no data for the class of forgery signatures. This is the reason why the frequently used supervised learned neural network model such as multi-layer perceptron are not suitable for the signature verification task.

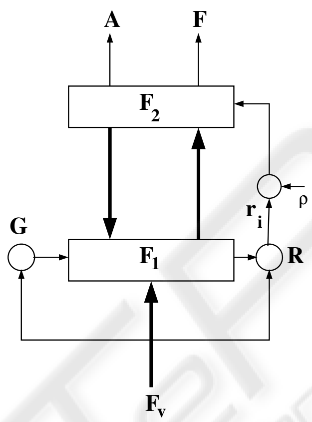

Fig. 4. ART-2 signature verifier (reprinted from [1])

4.1 Architecture of the ART-2 Neural Network Verifier

The adaptive resonance theory (ART), developed by Carpenter and Grossberg, was designed for clustering binary input vectors (ART-1) or continuous-valued input vectors (ART-2). With regards to the features what we used for description of signals, the ART-2 model is suitable for signature verification. The general architecture and description of the ART-2 network is not discussed here, for details see [7], [8].

The basic structure of the network verifier is illustrated in Figure 4. The network consists of two layers of processing elements labelled $\mathbf{F_1}$ (input and interface units) and $\mathbf{F_2}$ (cluster units), each fully interconnected with the others, and supplemental unit $\mathbf{G}$ and $\mathbf{R}$ (called *gain control unit* and *reset unit*), which are used to control the processing of the input data vector and creating of the clusters.

The input and interface layer $\mathbf{F_1}$ consists of six sub- layers (these are not illustrated in Figure 4); each sub-layer has the same number of processing units as is the size of the feature vector. The purpose of these sub-layers is to allow the ART-2 network to process continuously varying inputs. Moreover, they normalize the components of the feature vector and suppress the noise. The size of the $\mathbf{F_1}$ layer (and hidden sub-layers) was 18 in case of $\mathbf{W_{energy}}$ features and 36 for $\mathbf{W_{statistic}}$ features.

The clustering layer $\mathbf{F_2}$ consists of two processing units only, the former (labelled **A**) is active only if the feature vector corresponding to the genuine signature appears at the input of the network, the latter (labelled **F**) is active in other cases. More clusters are not enabled in our application.

4.2 Training and Verification

As was mentioned above, only the data for the genuine signature are known. Moreover, the number of template signatures cannot be too high because the acquisition of a large training set, e.g. at a bank counter could be boring and unpleasant for the customer. Hence only 5 signatures were used for the training of the ART neural network in our application. For these signatures corresponding feature vectors were evaluated and repeatedly presented to the input layer of the network (the slow learning mode was used for ART-2 network training). The parameters of the hidden sub-layers of $\mathbf{F_1}$ and vigilance parameter ρ were set so that only the unit labelled **A** of layer $\mathbf{F_2}$ was active during the whole training procedure (the network places the template signatures only in one cluster and adapts the corresponding weights between $\mathbf{F_1}$ and $\mathbf{F_2}$ layers). When the training is completed, the network is prepared for verification. The parameters of $\mathbf{F_1}$ sub-layers are not changed during the verification, only the vigilance parameter ρ have to be set properly to the genuine and the forgery signatures were set to right clusters. The three methods of setting the vigilance parameter were tested in our work:

- manual setting M: vigilance parameter ρ is set to the fixed value ($\rho = 0.98$) manually, for all verifications,
- automatic setting A_1: $\rho_{A1} = \min_i \{r_i\}\, i = 1 \cdots N_t$,
- automatic setting A_2: $\rho_{A2} = \frac{1}{N_t} \sum_i^{N_t} r_i \, i = 1 \cdots N_t$.

In the equations above, N_t is a number of training vectors and r_i is activation level of unit R (see Figure 4 and [7], [8] for detailed description and evaluation of r_i). The best results were achieved by automatic setting A_1.

4.3 Architecture of the SOFM Neural Network Verifier

The self-organizing feature map (SOFM) has been developed by Theuvo Kohonen and it has been described in several research papers and books [3], [4]. The purpose of the self-organizing feature map is basically to map a continuous high-dimensional space into discrete space of lower dimension (usually 1 or 2). The principal architecture of the SOFM is illustrated in Figure 5. The map contains one layer of neurons, arranged in a two-dimensional grid, and two layers of connections. In the first layer of connections, each element is fully connected (through weights) to all feature vector components. Computations are feed-forward in the first layer of connection: the network computes the scalar product between the input vector F_{v_i} and each of the neuron weight vectors $w_{i,j}$. The second layer of connections acts as a recurrent excitatory/inhibitory network, the aim of which is to implement the winer-take-all strategy, e.g. only the neuron with the highest activation level is selected and labelled as the best matching unit (BMU). The weight vector of this neuron then corresponds to the vector which is the most similar to the input feature vector F_{v_i}.

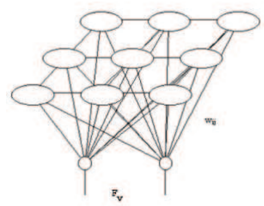

Fig. 5. Principal architecture of SOFM signature verifier

4.4 Training of the Signature Verifier

As in the case of ART-2 network, only 5 signatures were used for training of the SOFM. For these signatures the corresponding feature vectors were evaluated and repeatedly presented to the input layer of the network. To train the SOFM, the sequential training algorithm was used (see [3]). During the training, the output layer of SOFM is being arranged according to the training data and clusters corresponding to the genuine signatures are created. In the most cases, the genuine signatures are projected to one part of the two-dimensional grid, the forgeries are then projected to the other parts. After the training procedure the position of the BMU's for the genuine signature feature vectors are recorded and the *location threshold* l_t is evaluated. This threshold is used to decide whether the input feature vector corresponds to the genuine signature or forgery. In some cases the feature vectors corresponding to the forgery signatures are mapped to the location of genuine ones, i.e. distance between units signed as BMU's during the training process is smaller than *location threshold*. In this case, the genuine signatures and forgeries are separated according to the quantization error, i.e. euclidian distance between BMU's weight vector and input feature vector F_v. Quantization error threshold is also evaluated during the training procedure.

4.5 Verification Process

After the training of the SOFM and setting up corresponding parameters, i.e. location thresholds l_t, quantization error threshold Q_t, the neural network is ready for verification. The overall verification process consist of the following three steps:

1. the verified signature is scanned by the acquisition pen and corresponding feature vector is evaluated,
2. the feature vector is passed through the SOFM and the location and quantization error of BMU is evaluated,

3. the signature is classified as genuine if the both following rules are true:

$$\min_{L_{T_s}} d(L_{t_i}, L_{F_v}) \leq l_t \tag{1}$$

$$Q_{err} \leq Q_t \tag{2}$$

where $T_s = \{ t_i \mid i = 1, 2, 3\}$ is the set of feature vectors t_i of the signatures used for training, L_{t_i} and L_{F_v} are the locations of BMU of the i-th training signature and the unknown signature respectively.

5 Experimental Results

To test the verifier, signatures by 10 authors were taken. For each author, 20 genuine signatures and 36 skilled forgeries were recorded. The skilled forgeries were written by three different authors (12 forgeries for each person). Moreover, the signatures of other authors were used as the random forgeries. Both verifiers were also tested by these set of random forgeries (totally 5040 signatures).

Sometimes the author was not satisfied with his/her own signature. The quality of the signature depended on his/her physical and mental condition. In such a case the signatures were classified as forgery. For the evaluation of such cases, the authors marked their genuine signatures by a mark from a 1 - 4 scale (1 is the best form of signature). For the verifiers training, only the five signatures labelled by mark 1 or 2 were chosen.

In case of ART-2 verifier, the some parameters of input sub-layers have to be set up (see [7]) before the training process. The FAR (**F**alse **A**ccept **R**atio) and FRR (**F**alse **R**eject **R**atio) strongly depends on the setting of these parameters. In our application we set up the parameters experimentally, but next tests have to be performed to find optimal setting.

For the SOFM, different sizes of the output layer, different topologies and different number of training steps were also tested. Finally the network size 30×30 units with rectangular topology was chosen as a good compromise between the length of the network training (100 training epochs) and the achieved results. The neural network weight vectors w_{ij} were initially set up linearly (see [3]).

The results of verification process for ART-2 and SOFM verifiers are presented in Table 1.

Table 1. Results of verification process

verifier	W_{energy}			$W_{statistic}$		
	FAR [%]		FRR [%]	FAR [%]		FRR [%]
	forgeries			forgeries		
	skilled	random		skilled	random	
ART-2	8	5	14	4	2	12
SOFM	9.5	4.5	11.5	6	4	10

6 Conclusion and Future Work

We have shown the application of two types of artificial neural networks for signature verification. It can be seen (Tab. 1) that classification of genuine and forgery signatures is reliable if the parameters of networks are trained by a sufficient number of dutifully prepared training patterns. The achieved FRR and FAR are fully comparable with the results obtained by standard statistical or structural methods, the wide range testing of both types of ANNs will be carried out in the future.

In our future work, we plan to focus on the following tasks which could improve the results of verification process:

– including the new valuable features to the feature vector describing signature,
– optimal setting of the parameters of the input and interface layer of ART-2,
– optimal setting of the thresholds l_t and Q_t of SOFM verifier,
– checking the possibility of the application of other neural networks (supervised or unsupervised learned).

References

1. Mautner, P., Matousek, V., Rohlik, O., Kempf, J.: *Signature Verification Using Unsupervised Learned Neural Networks*, Proceeding of the 1st IAPR-TC3 Workshop on Artificial Neural Network in Pattern Recognition, Florence, Italy, 2003
2. Plamondon, R., Lorrette, G.: *Automatic Signature Verifications and Writer Identification-The State of the ART*, Pattern Recognition, Vol 22, No. 2, 1989
3. Koivisto, L.: *Quinquennial Report 1994-1998*, Neural Network Research Centre and Laboratory of Computer and Information science,FIN-02015, Finland, 1999
4. Fiesler, E., Beale, R.:*Handbook of Neural computation*, Oxford University Press, New York, Oxford, 1997
5. Rohlik, O., et al.:*A New Approach to Signature Verification: Digital Data Acquisition Pen* , Neural Network World, Vol. 11, No. 5, pp. 493-501,2001
6. Pitnerr. S, Kamarthi, S. V.: *Feature Extraction from Wavelet coefficients for Pattern Recognition Tasks*, IEEE Transactions on PAMI, Vol. 21, No. 1, 1999
7. Fausett, L.: *Fundamentals of Neural Networks*, Prentice-Hall, New Jersey, 1994.
8. Carpenter, G. A., Grossberg, S.: *ART-2: Self-organization of Stable Category Recognition Codes for Analog Input Patterns*, Applied Optics, No. 26, pp. 4919-4930, 1987
9. Plamondon, R.: Progress in Automatic Signature Verification, World Scientific Publishing Co. Pte. Ltd., Singapore, 1994
10. Tseng, L. Y., Huang, T. H.: *An on-line Chinese Verification Scheme Based on the ART-1 Neural Network*, in Int. Joint Conf. on Neural Networks, Baltimore, Maryland, Jun. 1992, pp 624-630
11. *I-pen producer homepage*,
http://www.inductum.com/
12. *OTM technology overview*
http://www.omtech.com/
13. *E-pen documentation*
http://www.mediaforte.com.sg/products/graphic/epen/
14. *N-Scribe product documentation*
http://www.n-scribe.com/