Signature Verifier Based on Self-Organizing Feature Map

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Abstract - *The Kohonen Self-organizing Feature Map (SOFM) has been developed for the clustering of input vectors and has been commonly used as unsupervised learned classifiers. In this paper we describe the use of the SOFM neural network model 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 authentic signature data was used for training the SOFM signature verifier. The architecture of the verifier and achieved results are discussed here and ideas for future research are also suggested.*

Key words - biometrics,signature verification, neural networks, SOM, BiSP, fast wavelet transform

1 Introduction

Automatic signature verification is an electronic analysis of a person's signature, which is used to determine if that person is who he/she claims to be. There are two types of signature verification - static and dynamic. The static verification methods are based on the limited information available solely from the basic shape and structural characteristic of the signature represented usually as a two-dimensional image (2-D image as input from a camera or scanner). A dynamic signature verification system gets its input from a digitizer or another one, usually pen-based dynamic input device. The signature is then represented as one or several time varying signals. Dynamic verification takes into account the features, which reflect the way of creating the signature and dynamics of writer's hand (e.g. pen motion, pen velocity, stroke sequencing, etc.). So they consequently are able to exploit information, which is not available in the image, but could characterize an individual signer. Many projects have been carried out on static and dynamic signature verification. Plamondon et al. summarized these work in [2], [6], [7]. The most of signature verification systems use conventional techniques for signature comparison (dynamic time warping [9], regional correlation, elastic matching tree matching or HMM [11]), but neural network have found their way into identity verification systems and they are also used now. Their primarily disadvantages are often the large number of specimens required for training process and long training time. The examples of application of neural networks for signature verification task are published in [1], [3], [4], [8]. In these applications usually 10 or more genuine signatures are needed for training.
In our paper, we focused on famous neural network architecture: the Kohonen Self-organizing Feature Map (SOFM). This network can be used as the signature verifiers for the data acquisition pen developed under BiSP project with the respect to small training set size

(only 5 genuine signatures were used for training the verifier). The block scheme of developed system using neural network verifier is shown in Figure 1. A short description of this pen can be found in Section 2, Section 3 deals with the pen output signal feature extraction method and Section 4 describes SOFM signature verifier. Results of verification experiments and possible future work are discussed in Section 5 and Section 6, respectively.

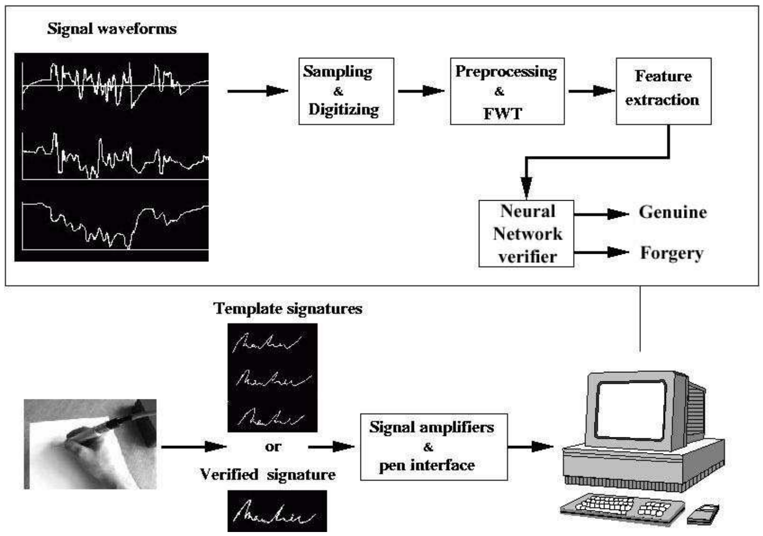

Figure 1: Block scheme of Signature Verification System

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 (see 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 (Figure 3) were acquired while writing the signature of "Dobner".

Four strain gauge sensors that measure the horizontal and vertical movements of the pen are located near the pen nib and are placed orthogonal to each other. The signal produced by the horizontal pair of sensors is called x and the one produced by the 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 (see [16] for more detailed description od the data acquisition pen).

Figure 2: Digital data acquisition pen

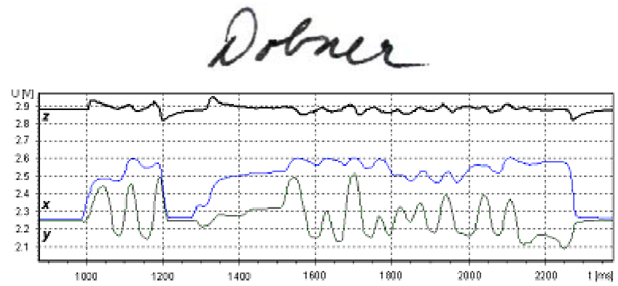

Figure 3: Signals produced by the pen while writing the signature "Dobner"

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 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 cA_5 and cD_m, for $m = 1, 2, ..., 5$ were determined [12]. The Daubechies and the Coiflet wavelet families were tested for decomposition, the 5-th order Daubechies wavelet gave the best result. Using this wavelet, the following feature vectors were evaluated:

- $\mathbf{W_{energy}}$ - energy of coefficients cD_m (m=1,...,5) and cA_5

$$F_v^{energy} = (D_m^x, D_m^y, D_m^z, A_m^x, A_m^y, A_m^z),$$

$$D_m^S = \sum_{j=1}^{N_m} d_{mj}^2, \quad m = 1, 2, ..., 5; \quad s = x, y, z, \tag{1}$$

$$A_5^S = \sum_{j=1}^{N_5} a_{5j}^2, \quad m = 1, 2, ..., 5; \quad s = x, y, z \tag{2}$$

- $\mathbf{W_{statistic}}$ - mean values and standard deviations of coefficients cD_m (m=1,...,5) and cA_5,

$$
\begin{aligned}
F_v^{statistic} &= (M_m^x, M_m^y, M_m^z, S_m^x, S_m^y, S_m^z), \\
M_m^s &= \frac{1}{N_m}\sum_{j=1}^{N_m}(C_{mj}^s), \qquad s = x, y, z \qquad (3) \\
S_m^s &= \sqrt{\frac{1}{N_m - 1}\sum(C_{mj}^s - M_m^s)^2}, \qquad s = x, y, z \qquad (4)
\end{aligned}
$$

where cD_{mj} and cA_{5j} are the detailed and the approximation coefficients of FWT in scale m and 5, respectively (Figure 4).

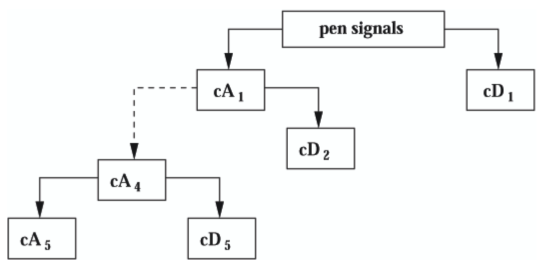

Figure 4: Decomposition of pen signals by FWT

4 Neural Network Signature Verifier

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 second class forgery signatures. This is the reason why the frequently used supervised learned neural network model such as multi-layer perceptron cannot be applied to the signature verification task.

4.1 Architecture of the 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 [5], [10], [13], [14]. 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 basic structure of the SOFM is illustrated in Figure 5. The map contains one layer of neurons, arranged to 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 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 winner-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.

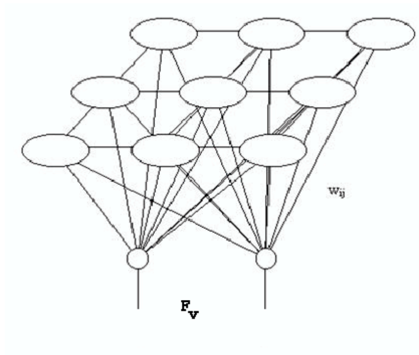

Figure 5: Kohonen's Self-organizing Feature Map

4.2 Training of the Signature Verifier

As was mentioned above, only the data of the genuine signatures 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 SOFM neural network in our application. For these signatures corresponding feature vectors were evaluated and repeatedly presented to the input layer of the network. For training, sequential traing algorithm was used (see [13]). During the training, the output layer of SOFM is ordering according to the training data and clusters corresponding to the genuine signatures are created. In most cases, the genuine signatures are projected to one part of the two-dimensional grid, the forgeries are then projected to other parts. After the training procedure the position of the BMU's for the genuine signature feature vectors are recorded and so called *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 correponding to the forgery signatures are maped to the location of genuines, i.e. distance between units signed as BMU's during the training process is smaller than *location threshold*. In this case, genuines and forgeries are separated according to the quantization error, i.e. euclidean distance betveen BMU's weight vector and input feature vector F_v. Quantization error threshold is also evaluated during the training procedure.

4.3 Verification Process

After the training of the SOFM and setting up corresponding parameters, i.e location threshols l_t, quantization error threshold Q_t, the neural network is ready for verification. The overall verification process can be done in 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 location and quantization error of BMU is evaluated
3. the signature is classified as genuine if the both following rules are true:

$$L_{err} = \min_{T_s} d(L_{G_i}, L_T) \leq l_t \quad (5)$$

$$Q_{err} \leq Q_t \quad (6)$$

where $T_s = \{G_i, i = 1, , 5\}$ is the set of feature vectors G_i of the signatures used for training, L_{G_i} and L_T are the locations of BMU of the i-th training signature and the unknown signature respectively (see Figure 6).

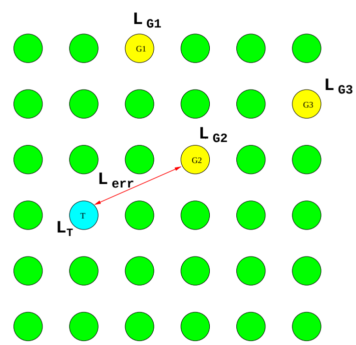

Figure 6: Location error L_{err} of BMU of tested signature

5 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). The forgeries (skilled and random) were used only for evaluation of the verifier. It would be difficult to obtain these forgeries in practical applications.
Sometimes the author is not satisfied with his/her own signature. The quality of signature depends on his/her physical and mental condition. In such a case the signatures can be classified as forgery. For the evaluation of such cases, the authors marked their authentic signatures by a mark from the scale $1-4$ (1 means a best form of the signature). For the verifier training, only the five signatures labelled by mark 1 or 2 were chosen. Different sizes of the output layer of the SOFM were also tested. Finally the network size 30×30 units was chosen as a good compromise between the length of the network training and the achieved results. The neural network weight vectors w_{ij} were initially set up linearly(see [13]). For these neural network parameters and training set size, the following results were achieved:

W_{energy}			$W_{statistic}$		
FAR [%]		FRR [%]	FAR [%]		FRR [%]
forgeries			forgeries		
skilled	random		skilled	random	
9.5	4.5	11.5	6	4	10

Table 1: Results of verification process

The table compares the results of verification for both types of input signal description methods ($W_{statistic}$ and W_{energy}) mentioned in Section 3. In this table FAR (**F**alse **A**ccept **R**ate) means the probability that forgeries were accepted by the verification system, FRR (**F**alse **R**eject **R**ate) means the probability that genuine signatures were rejected by the verification system. These values strongly depend on the setting of l_t and Q_t parameters (decrease of l_t and Q_t cause decrease of FAR and increase of FRR).

6 Conclusion and Future Work

We have shown the application of SOFM for signature verification. It can be seen (Table 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 SOFM 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 thresholds lt and Q_t of SOFM verifier,
- checking the possibility of the application of other neural networks (a supervised or unsupervised learned).

References

[1] Mighell, D. A., Wilkinson, T. S., Goodman, J. W., (1989): Back-propagation and its application to hand-written signature verification, in Advances in Neural In-formation Processing Systems I, pp. 340-347,

[2] Plamondon, R., Lorrette, G., (1989): *Automatic Signature Verifications and Writer Identification-The State of the ART*, Pattern Recognition, Vol 22, No. 2,

[3] Higashino, J., (1992):*Signature verification system on neuro-computer*, Proc. of 11th IAPR Int'l Conf. on Pattern Recognition, pp. 517-521,

[4] Chang, H.D., Wang, J.F., Suen, H.F., (1993):*Dynamic hand-written Chinese signature verification*, Proc. of ICDAR 93: Int. Conf on document analysis and recognition, pp. 258-261,

[5] Fausett, L., (1994): *Fundamentals of Neural Networks*, Prentice-Hall, New Jersey,

[6] Leclerc, F., Plamondon, R. (1994): *Automatic signature verification-the State of the art 1989-1993*, Int'l Journal of Pattern Recognition and Artificial Intelligence, Vol.8, No.3, pp. 643-660,

[7] Plamondon, R., (1994): Progress in Automatic Signature Verification, World Scientific Publishing Co. Pte. Ltd., Singapore,

[8] Lee, L.L., (1995):*Neural approaches for human signature verification*, 3rd Int'l Conf. on Document Analysis and Recognition, Vol.2, pp.1055-1058, Montreal,

[9] Martens, R., Claesen, L. (1996):*Online signature verificati-on by dynamic time-warping*, Proc. of 13th Int'l Conf. Pattern Recognition, pp. 38-42, Vienna,

[10] Fiesler, E., Beale, R., (1997):*Handbook of Neural computation*, Oxford University Press, New York, Oxford,

[11] Dolfing, J.G.A., Aarts, E.H.L., Van Oosterhout, J.J.G M. (1998):*Online Verification signature with hidden Markov models*, Proc. of 14th Int'l Conf. Pattern Recognition, pp.1309-1312,Brisbane, Australia,

[12] Pitnerr. S, Kamarthi, S. V., (1999): *Feature Extraction from Wavelet coefficients for Pattern Recognition Tasks*, IEEE Transactions on PAMI, Vol. 21, No. 1,

[13] Koivisto, L., (1999): *Quinquennial Report 1994-1998*, Neural Network Research Centre and Laboratory of Computer and Information science,FIN-02015, Finland,

[14] Kohonen, T., (2001):*Self-Organizing Map*, Springer-Verlag, Berlin Heidelberg,

[15] Rohlik, O., et al., (2001):*A New Approach to Signature Verification: Digital Data Acquisition Pen* , Neural Network World, Vol. 11, No. 5, pp. 493-501,

[16] Hook, Ch., Kempf, J., Scharfenberg, G., (2003): *New pen device for biometrical 3D pressure Analysis of handwritten characters, words and signatures*, Proceedings: ACM Multimedia 2003, Berkeley, USA,

[17] Mautner, P., Matousek, V., Rohlik, O., Kempf, J., (2003): *Signature Verification Using Unsupervised Learned Neural Networks*, Proceeding of the 1st IAPR-TC3 Workshop on Artificial Neural Network in Pattern Recognition, Florence, Italy,

[18] *I-pen producer homepage*,
http://www.inductum.com/

[19] *OTM technology overview*
http://www.omtech.com/

[20] *E-pen documentation*
http://www.mediaforte.com.sg/products/graphic/epen/

[21] *N-Scribe product documentation*
http://www.n-scribe.com/