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# Identification and Authentication of Handwritten Signatures with a Connectionist Approach

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## Abstract—

TCSF/LER has developed an automatic system to identify or verify off-line handwritten signatures, using a connectionist approach. Our method combines image processing which consists in extracting significant parameters from the signature image and classification by a multi-layer perceptron which uses the previous parameters as input. In this paper, the image processing step is described according to the intrinsic features of handwriting. Then, the proposed neural networks are compared with others classifiers as pseudo-inverse, k-nearest-neighbours and k-means and the influence of pre-processing and bad segmentation is measured. On a base of around fifty signers (comprising english, french signatures and paraphes), many experimental results are given for identification and verification purposes.

**Keywords—** neural networks, image processing, classification, handwriting, off-line signatures

## I. INTRODUCTION

Handwritten signature recognition has been investigated for some years especially because of its potential application in access control. The main work has been driven with on-line acquisition (see [1]) where dynamic information is available to help the recognition. At the opposite, off-line recognition from digitized documents (bankchecks, official papers) is a more complex task and so is less studied. Here, we focus on two different problems in the off-line case: Identification and Verification. On one hand, Identification consists of recognizing a signer which belongs to a known group of possible scriptors. On the other hand, Verification occurs when a particular signer is supposed to be the scriptor and this supposition has to be checked.

In this paper, we focus only on the classification problem by using already segmented signatures which are issued mainly from european bankchecks which lead us to consider 3 different styles of writing: english, french signa-

tures and paraph (fig 1)



Figure 1: Signatures: english, french styles and paraph

To solve both tasks, identification and authentication, Thomson-CSF/LER applies the same method which combines image processing and connectionist classification. A system overview is depicted in fig 2 using Allegory environment (Thomson-CSF/LER product) which is a graphical software to develop image processing applications.

In the first section, we explain our signature description which is common for the two tasks. Then, we give, by application, the definition of the used neural network and experimental results.

## II. SIGNATURE DESCRIPTION

In our opinion, the recognition of the various european styles signatures on a pixel base implies such a large set of parameters (important and variable size of the image matrix) that the data will not be representative enough even with huge storage and computing capabilities. Consequently, we use image processing techniques to capture relevant characteristics and then get a reduced set of parameters. Such an approach is usual when the obtention of a large database is not easy and it permits to reduce complexity (free coefficients of the network) and learning time with good performances. Furthermore, the efficiency of a method combining image processing and connexionist classifier has been validated on a similar problem, the recognition of unconstrained handwritten ZIP codes (see [4]). So, the following features are extracted by image processing:

- **Height/width ratio** (fig 3), this ratio captures the global signature shape.

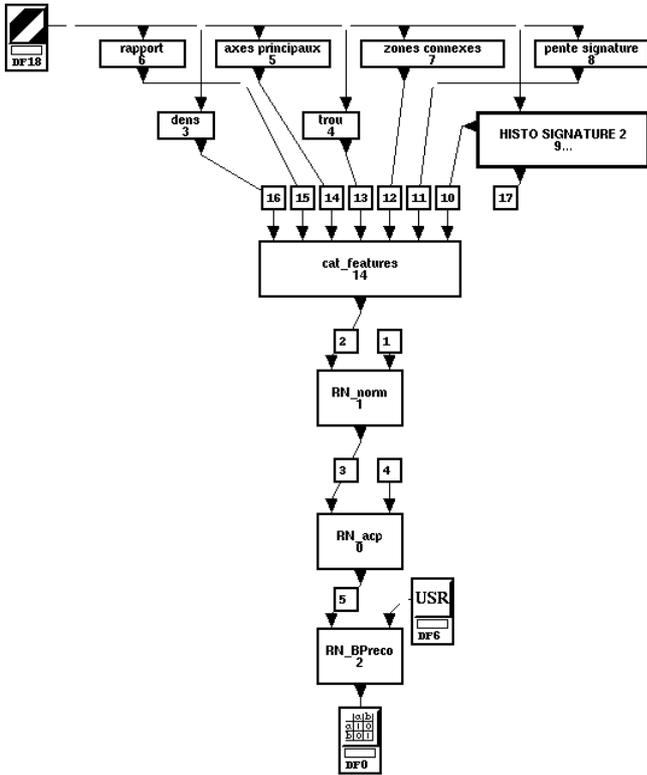


Figure 2: System over Allegory (TCSF trademark)

- **Principal axis orientation** (fig 3), the principal axis matches approximately the base line. This measure is the angle with the horizontal axis.
- **Elongation**, this feature renders the shape compacity according to the principal axis.
- **Handwritten slope** (fig 5), the average slope with the base line may be discriminant when the signature is legible.
- **Amount of connected components**, this feature reflects the handwriting continuity and is rather stable for each writer.
- **Hole and cavity attributes** (fig 4), Holes are closed loops whereas cavities are different concavity orientations. They capture handwriting styles (propensity to draw loops, concavities on a specific orientation, etc).
- **point densities on different areas** (fig 6), these features reflect the spatial signature distribution and the graphic way of the signer (many or a few strokes).

- **Angular histogram**, it gives priveleged hand-writing orientations

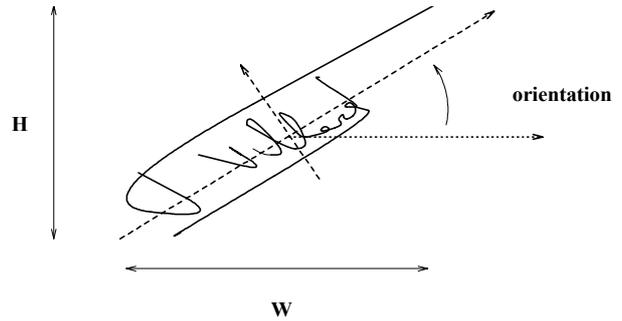


Figure 3: Features: axes

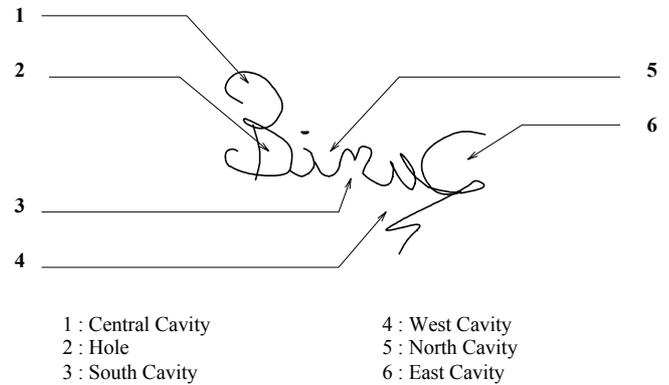


Figure 4: Features: morphological cavities

These metric, statistical and morphological features are concatenated to a vector of 41 parameters and constitute the inputs to neural nets.

### III. IDENTIFICATION

To deal with the identification task, a 2-layer perceptron for all signers is designed, knowing that the searched signer is known among a small group of signers (if not a clustering method such as Kohonen Topological Maps would be necessary to divide the space). The output class would be the number of the signer which is identified as the writer of the signature. The network is trained with an improved backpropagation algorithm (see [5]). To test feasibility, we use real data extracted from french bankchecks. The database comprises 912 samples from 48 signers (so there are about 20 signatures per writer). Random way of splitting in two sets provide 480 samples for learning, 432 for test.

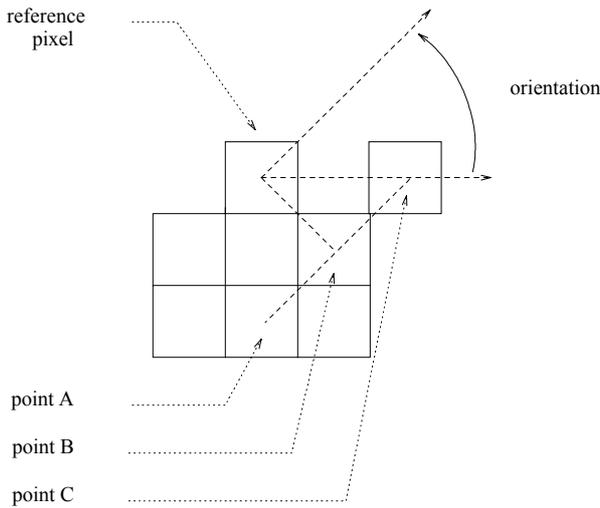


Figure 5: Features: slopes

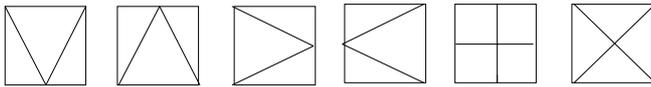


Figure 6: Features: statistical regions

We provide comparison of classifiers among the following list:

- 2-layer a full-connected perceptron with 2 layers
- 1-knn the 1-nearest-neighbour
- 3-knn the 3-nearest-neighbours
- 1-mean k-means with 1 centroid per class
- 3-means k-means with 3 centroids per class
- p-inv pseudo-inverse

Moreover, we apply 2 pre-processing steps on the input vector, normalisation (in mean and variance) and PCA. So, the measured recognition rates from raw data and preprocessed ones show that applying normalization and PCA before neural classification is useful for this application (98.1% versus 97.2%).

Classifier	Generalisation (raw)	Generalisation (pca)
2-layer	<b>97.2%</b>	<b>98.1%</b>
p-inv	94.2%	94.2%
1-knn	88.2%	96.3%
3-means	86.4%	97.0%
3-knn	84.5%	95.1%
1-mean	80.6%	92.6%

The figure 7 (case of raw data) shows that the error rate could be easily reduced if the concerned application accepts some rejected signatures according to a level of confidence.

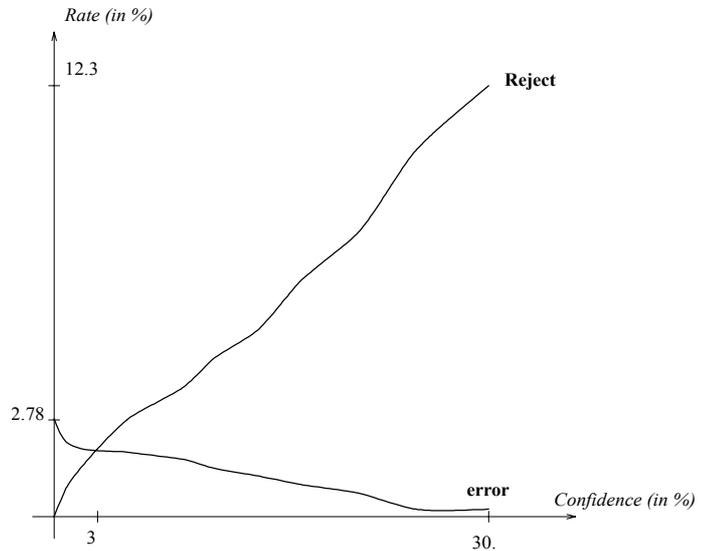


Figure 7: Error rates for the Identification task

To evaluate robustness of our method, we propagate through the 2-layers some poorly segmented signatures (full blocks of the signature are missing): the degradation of performances is only 0.5%, as shown in the table below.

Segmentation	Generalisation rate
accurate	97,22%
coarse	96,76%

To conclude, for the identification task, we obtain an error rate of 2.8% when there is no rejection, and an error rate of 0.2% when 10% of the signatures are rejected. Furthermore, the approach is robust with respect to bad segmentation.

#### IV. AUTHENTICATION

Here, the context of the Authentication application is that the expected signer is a-priori known. We accept the following limit: the forger has no model of the original signature (current case for stolen checks). So, the automatic system is able to detect anomaly but it is not accurate enough to detect specialist in forger.

The same database as described above is used for feasibility tests. For learning phasis, the examples of the right signer consists of 10 samples of his signature and the contre-examples comprise signatures of 47 false signers.

We train one neural network per signer. The output of such a network is yes or no to the question “is it the expected signer?”. We define two classes: true signature (i.e. issued from the expected signer) and false signature (i.e. issued from a forger).

To give results in authentication, 2 rates are usual:

- The average RTR (Rate of True signatures Rejected) is given by:

$$RTR_{av} = \sum_i P(C_i)RTR_i$$

where  $P(C_i)$  is the fraction of signatures from signer  $i$  in the test set, and  $RTR_i$  is the RTR for signer  $i$ .

- The average RFA (Rate of False signatures Accepted) is given by:

$$RFA_{av} = \sum_i P(C_i)RFA_i$$

The table below indicates the values of these rates for 10 signers.

signer	RFA		RTR	
0	1,1%	(1/94)	14,3%	(1/7)
1	0%	(0/94)	0%	(0/7)
2	0%	(0/88)	0%	(0/13)
3	1,4%	(1/74)	0%	(0/27)
4	0%	(0/88)	0%	(0/13)
5	4,4%	(4/91)	0%	(0/10)
6	3,2%	(3/95)	0%	(0/6)
7	0%	(0/96)	0%	(0/5)
8	0%	(0/95)	0%	(0/6)
9	0%	(0/94)	0%	(0/7)

The average RFA is 1%, and the average RTR is also 1%. As for identification, one can reduce the error rate if one accepts rejection. Figure 8 shows the evolution of the errors and reject according to the threshold on the confidence.

To conclude, for the authentication task, we obtain an error rate of 1% when there is no rejection and an error rate of 0.1% when 17% of the signatures are rejected.

## V. CONCLUSION

An approach for off-line signature identification and authentication has been proposed. It combines image processing techniques and a connexionist network. Image processing is used to extract significant characteristics on the image of the signature. Then, a connexionist network uses this information to identify or authenticate the

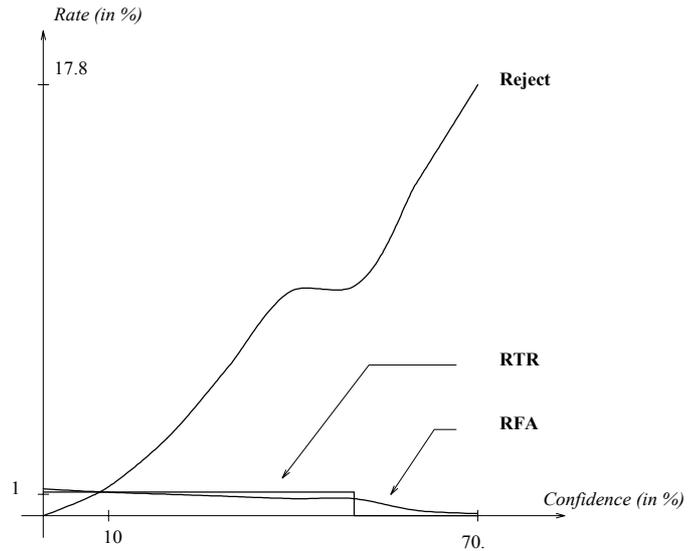


Figure 8: Error rates for the Authentication task

signature.

The interest of this approach is its ability to provide good results despite quite a small training set (because the information provided to the connexionist network is pertinent), and, as far as the classifier is concerned, its superiority with respect to other classifiers. The confidence measure provided by the connexionist network allows to reduce the error rate by increasing rejection.

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