TEXT-INDEPENDENT OFF-LINE WRITER RECOGNITION USING NEURAL NETWORKS

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ABSTRACT

In this paper we present a text-independent off-line writer recognition system based on multi-layer perceptrons (MLPs). The system can be used for both identification and verification purposes. It was tested on a population of 20 writers with non-correlated training and test specimens. The mean error for identification was 3.5% while error rates as low as 0.5% were achieved on specimens with more than 25 characters. For verification the mean error was 1.2% (2.22% false rejection, 0.18% false acceptance) considering a minimum of 15 characters per test specimen. These error rates are comparable to those achieved by classical methods while the response of the system is substantially faster.

1 INTRODUCTION

The task of a writer recognition system is either to identify an unknown writer among several writers of known hand writing or to verify whether a writer is the person he claims to be. Writer recognition may be text-dependent using phrases or words from the same text for training and testing or text-independent using any phrase for testing.

Off-line writer recognition systems employ image processing and pattern recognition techniques to face the different types of problems encountered. Most of these problems are met also in handwritten character recognition tasks, where neural networks have been widely used giving satisfying results. Nevertheless, for writer recognition, the reported systems [2][3][4] are based on classical comparison methods.

In this work a novel neural network based writer recognition system with fast response is proposed. It uses a multilayer perceptron (MLP) trained on each writer included in the system, in order to verify whether a writing sample originates from a certain writer, or to identify its writer. It is assumed that a reference writing sample from each writer has been previously used for the construction of a writer-dependent reference database. This work can be considered as an extension of a previous work [1] where a similar approach has been used for speaker recognition.

2 SYSTEM DESCRIPTION

The basic modules of the system are shown in the block diagram of Figure 1. Every writer member is included in the system by delivering a reference writing sample which contains at least five occurrences of each one of the characters included in the character set. These reference data are used to train the writer MLP models. For testing the system a test sample is provided to the system and the writer name for the verification process or no writer name for the identification process is requested. For the verification procedure only the MLP of the specific writer is activated and its output is compared with a threshold to accept or reject the supposed writer. For the identification procedure the MLPs of all writers are activated and the unknown writer is classified to the MLP indicating maximum likelihood.

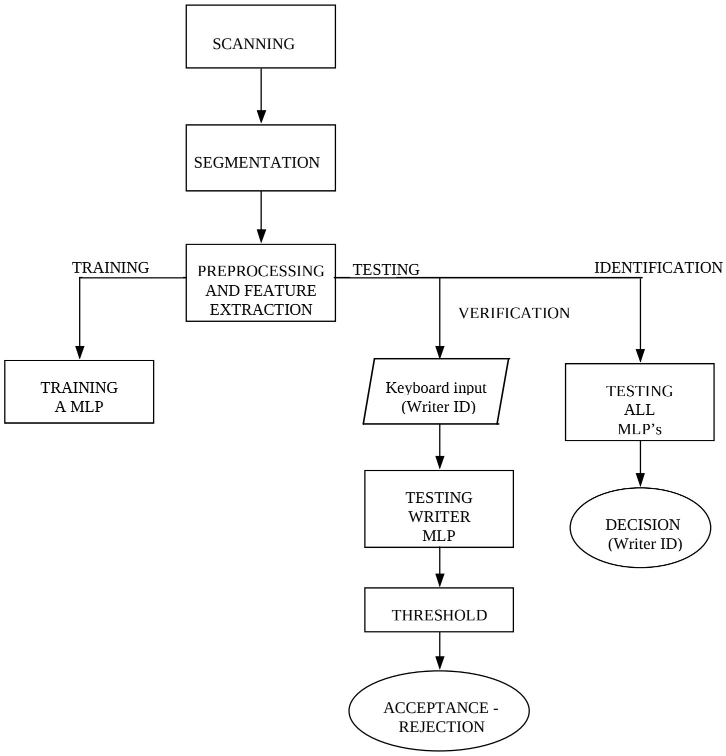

Figure 1. Block diagram of the proposed writer recognition system

2.1. Preprocessing and feature extraction.

The sheets with handwritten specimens are scanned at 300 dpi resolution, in 8 bits to produce one file per page. An automatic segmentation module is used to extract the character images either from the image blocks or from the continuous text. The isolated characters are stored initially as 32×32 binary patterns after resizing, giving a 1024 dimensional vector. Each one of the patterns needs to be parametrised in an appropriate way in order to be input to the MLP. A vector of the above size, it was difficult to be fed directly in to an MLP. On the other hand any compression or reduction of the original patterns could be critical for the performance of the system.

To reduce the number of nodes in the input layer without losing significant information of the original patterns we apply the following method to extract parameters: We divide a binary pattern into a 4×4 grid with 16 sub-patterns. For every sub-pattern two attributes are estimated: the percentage of black pixels and the pixels center. For the later both coordinates X,Y are embedded in a unique X considering the two dimensional 4x4 matrix as an one dimension 16x1 matrix. The resulting pattern is represented by a 32 dimensional vector $\mathbf{v} = (P_1, X_1, \ldots, P_{16}, X_{16})$.

2.2 MLP classifier

For the experiments reported here we have trained and tested the system on the 24 uppercase Greek letters. For the training procedure we used a database with 20 writers. For each one of the writers we trained a simple feed forward MLP. The size of the net was experimentally derived to 32×32×1 (32 nodes for the input layer, 32 nodes for the hidden layer and 1 node for the output layer). The standard Back Propagation algorithm was used for training the net [5] . In order to train a MLP for each writer we used 640 sample letters. An amount of 160 letters belonged to the corresponding writer, the remaining 480 came from all the other writers, while each MLP had to decide whether a sample letter belonged to the corresponding writer. The criterion for the net to stop training, was to learn 100% of the training patterns. After the training procedure 20 MLPs were available, one for each writer.

3 TESTING AND RESULTS

To test the feasibility of the system we used a database of 40 A4 size manuscripts collected from all the member writers. It has to be noted that there was no correlation between training and test databases. From the test database we obtained a large number of specimens, varying in size from 5 to 80 characters in order to examine the sensitivity of the system in this range. It is noted that the system does not require to be informed by the user on the contents of the test specimens.

For the open set identification tests the resulting error rate is shown in Table 1 as a function of the specimen size. The maximum error rate is 10.5% (5-15 characters), the minimum one is 0.5 % (50-80 characters) and the mean error rate is 3.5%.

For the verification test we used as threshold the mean rejection rate ***R*** of the characters established in extensive tests of each MLP. For example, with specimens of 30 characters and R=50, a verification test fails if more than 15 characters are rejected by the corresponding MLP.

The verification error rates are shown in Table 2, false rejection, false acceptance and mean error, as a function of the decision threshold ***R***. The smallest mean error is achieved for R=50.

Specimen size (number of characters)	Identification mean error (%)
5-15	10.5
16-25	2.5
26-50	0.5
50-80	0.5
Total	3.5

Table 1. Identification accuracy versus specimen size.

R (%)	False rejection (%)	False acceptation (%)	Mean (%)
42.3	4.25	0.00	2.17
50.0	**2.22**	**0.18**	**1.20**
55.0	1.66	0.76	1.21
60.0	0.74	2.96	1.85
66.7	0.00	7.77	3.88

Table 2. Verification error rates, false rejection, false acceptance and mean, versus decision threshold R.

An advantage of the system is that we can achieve low error rates either for false rejection or false acceptance by simple adjustment of ***R***. The obtained mean response time was 0.4 seconds for verification on a 486-40MHz Personal Computer.

An additional experiment was to test how the increment of the member writers affects the performance of the system. To this end we kept intermediate results, while we updated the database from 5 to 20 writers. This experiment shows that for verification we can achieve satisfied results even for a large number of writers, while identification errors seem to be incremental.

4 CONCLUSIONS

A text independent writer recognition system based on multilayer perceptrons was presented. The open-set identification was measured to 99.5% for a specimen size of 50-80 characters. The accuracy decreased to 89.5% when the average length of the specimen decreased to 5-15 characters. The verification accuracy was measured to 98.8%.

The work is now continued with training and testing the system on the 24 freely written lowercase Greek letters. The group of the writers has been extended from 20 to 50. Preliminary results with specimens of the same size as the above mentioned for training and testing have given increased error rates but are encouraging. Therefore tests with larger reference specimens are carried out in order to better train the networks. For verification, the system gives promising results even for a larger number of member writers.

5 REFERENCES

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