Fig. 9 Standardization of sizes applied to digit 5

6.2 Digit features

The characteristic matrices $(M_i^*)_i$ of the digit D according to the writers $(S_i)_i$ are all of the same size ($5 \times n^*$). Thus, the features of the digit D are:

1. The characteristic matrix M_D equal to the mean of the matrices $(M_i^*)_i$:

$$M_D = \frac{1}{n} \sum_{i=1}^{n} M_i^*$$

2. The class affiliation c of the digit D equal to the value c_k which is the most common in the sequence $(c_i)_{1 \leq i \leq n}$.

7. Recognition

By following the steps in the previous paragraph, we compute the features of each digit of classes LD and NLD. The recognition of an unknown digit D will occur in four steps.

7.1 Features of the digit D

We first compute the class affiliation and the characteristic matrix M_D of the digit D by following the steps developed in Paragraph 5. The next step consists to identify from characteristic matrices M_i of digits D_i belonging to the same class as D, the nearest matrix to M.

7.2 Distance between M_D and the characteristic matrix M_i of the digit D_i

Since the matrices M_D and M_i do not necessarily have the same size, we first standardize their sizes. For this, we distinguish three cases on their respective numbers of columns n_D and n_i.

7.2.1 First case: $n_D = n_i$

We ordain the columns of the matrix M_i so that the jth column of the obtained matrix is the closest to the jth column of the matrix M_D.

7.2.2 Second case: $n_D < n_i$

To complete the matrix M_D by $(n_i - n_D)$ additional dots, we proceed as in sub-paragraph 6.1.

7.2.3 Third case: $n_i < n_D$

We first ordain the columns of the matrix M_i so that the jth column, for $j \leq n_i$, of the obtained matrix is the closest to the jth column of the matrix M_D. As M_i is the characteristic matrix of D_i according to several writers (this is the mean of characteristic matrices $(M_{ij})_{1 \leq j \leq r}$ of the digit D_i according to the r writers $(w_j)_{1 \leq j \leq r}$ used in training phase), we first complete each matrix M_{ij} by $(n_D - n_i)$ additional dots by following the steps of the sub-paragraph 6.1. After, we substitute the matrix M_i by the matrix M_i^* mean of these matrices which is the same size as M_D.

After the standardization phase of matrix sizes, we denote M_i^* and M_D^* the obtained matrices, and we put $d_i = \| M_i^* - M_D^* \|$ where $\| \|$ is the Frobenius norm.

7.3 Identification of the digit D

The digit D will be identified with the digit D_i^* satisfying the following minimization equation:

$$d_{i^*} = \min_i d_i$$

The minimum is taken for all digits belonging to the same class as the digit D.

8. Recognition Results

The database DB consists of 360 digits. Each digit between 0 and 9 has been written by 36 different writers (see Fig. 10).

Fig. 10 Sample of handwritten digits.

One part of DB, denoted Tr_DB was used in the training phase, and the rest, denoted Te_DB was reserved to evaluate the system.
We sought to identify the best choice of the set Tr_DB giving the highest recognition accuracy in the test phase.

For this, we denote by S_r the rth writer and *RR* the recognition rate.

Given an integer $k \geq 1$, and for any combination of k writers among 36 writers, we first use these k writers as *Tr_DB* in the training phase, and after compute the corresponding recognition rate *RR*. Finally, we identify the combination of *k* writers giving the highest *RR*.

The results obtained for *k < 3* and *k > 8* are not interesting. So, we give in Table 1 only the results for *3 ≤ k ≤ 8*.

Table 1: Set *Tr_DB* of k writers giving the best recognition rate (RR)

K	Set Tr_DB of k writers giving the best RR	RR (%)
3	S_8 ; S_3 ; S_{16}	91.94
4	S_8 ; S_3 ; S_{16} ; S_{22}	94.44
5	S_8 ; S_3 ; S_{16} ; S_{22} ; S_{26}	96.39
6	S_8 ; S_3 ; S_{16} ; S_{22} ; S_{26} ; S_{14}	96.94
7	S_8 ; S_3 ; S_{16} ; S_{22} ; S_{26} ; S_{14}; S_{25}	90.00
8	S_8 ; S_3 ; S_{16} ; S_{22} ; S_{26} ; S_{14}; S_{25} ; S_{18}	86.67

The best performance has been achieved when we use the six writers S_8, S_3, S_{16}, S_{22}, S_{26} and S_{14} in the training phase. The explanation that we can advance on high performance obtained with this list is that the writing styles of these writers cover the different writing styles of all writers. Recognition errors are mainly due to writing styles of some writers. Indeed, the digits 1, 4, 7 and 9 are in some cases very confused, and even humans have difficulties to identify them (see Fig. 10).

For more details, we give in Table 2 the confusion matrix along with the recognition rate of each digit. These results are related to the use of the optimal list $(S_8, S_3, S_{16}, S_{22}, S_{26}, S_{14})$ in the training phase.

Table 2: Confusion Matrix and the recognition rate (RR) of each digit

	0	1	2	3	4	5	6	7	8	9	RR (%)
0	36	0	0	0	0	0	0	0	0	0	100
1	0	34	0	0	0	0	0	2	0	0	94,44
2	0	0	36	0	0	0	0	0	0	0	100
3	0	0	0	36	0	0	0	0	0	0	100
4	0	4	0	0	30	0	0	0	0	2	83,33
5	0	0	0	0	0	36	0	0	0	0	100
6	0	0	0	0	0	0	36	0	0	0	100
7	0	0	0	0	0	0	0	36	0	0	100
8	0	0	0	0	0	0	0	0	36	0	100
9	0	0	0	0	3	0	0	0	0	33	91,66

9. Conclusion

We presented in this work a new approach of digit recognition. It is based on the extraction the Hermite data from the digit shape (dots with their derivatives). The choice of this approach was dictated by the possibility of recovering a close shape to that of the digit using the Bézier curve theory on these data.

The obtained results are very interesting, and we plan to improve them using other classifiers (the artificial neural networks, the hidden Markov models and the support vector machine) during both training and testing phases. Similarly, we will enrich our database in order to perform tests on a more consistent data base.

References

[1] C. L. Liu, K. Nakashima, H. Sako, and H. Fujisawa, "Handwritten digit recognition: benchmarking of state-of-the-art techniques", Pattern Recognition, Vol. 36, 2003, pp. 2271–2285.

[2] S. Impedovo, F.M. Mangini and D. Barbuzzi, "A novel prototype generation technique for handwriting digit recognition", Pattern Recognition, Available online 3 May 2013 http://dx.doi.org/10.1016/j.patcog.2013.04.016

[3] O. Rashnoodi, A. Rashnoodi and A. Rashnoodi", Off-line Recognition of Persian Handwritten Digits using Statistical Concepts", International Journal of Computer Applications, Vol. 53, No. 8, 2012, pp. 20–28.

[4] M. Shi, Y. Fujisawa, T. Wakabayashi and F. Kimura, "Handwritten numeral recognition using gradient and curvature of gray scale image", Pattern Recognition, Vol. 35, No. 10, 2002, pp. 2051–2059.

[5] A. Mazroui, Aissa Kerkour El Miad, "*Handwritten Arabic characters modeling by Bézier curves for recognition",* in proceeding of 4th International Conference on Approximation Methods and Numerical Modelling in Environment and Natural Resources, 2011, pp. 535-538.

[6] G. Farin, and P. Massart, Curves and Surfaces for Computer Aided Geometric Design, San Diego, CA, Academic Press, 1983.

[7] S. Arora, D. Bhattacharjee, M. Nasipuri, L. Malik, M. Kundu and D. K. Basu, "Performance Comparison of SVM and ANN for handwritten Devnagari Character Recognition", International Journal of Computer Science Issues, Vol. 7, No. 6, 2010, pp. 18-26.

[8] X. X. Niu, and C. Y. Suen "A novel hybrid CNN–SVM classifier for recognizing handwritten digits", Pattern Recognition, Vol. 45, No. 4, 2012, pp. 1318–1325.

[9] S. Mahmoud, "Recognition of writer-independent off-line handwritten Arabic (Indian) numerals using hidden Markov models", Signal Processing, Vol. 88, No. 4, 2008, pp. 844–857.

[10] D. Sharma, and D. Gupta, "Isolated Handwritten Digit Recognition using Adaptive Unsupervised Incremental Learning Technique", International Journal of Computer Applications, Vol. 7, No. 4, 2010, pp. 27-33.

[11] K. Mori, M. Matsugu, and T. Suzuki, "Face recognition using SVM fed with intermediate output of CNN for face detection", in Proc. of the IAPR Conf. on Machine Vision Applications (MVA), 2005, pp. 410–413.

[12] M. Szarvas et al., "Pedestrian detection with convolutional neural networks", in Proc. of the IEEE Symp. On Intell. Vehicles (IV), 2005, pp. 224–229.

[13] L.M. Lorigo, and V. Govindaraju, "Offline Arabic handwriting Recognition: A survey", IEEE Trans. Pattern Anal. Machine Intell., Vol. 28, 2006, pp.712-724.

[14] A.M. AL-Shatnawi, S. AL-Salaimeh, F. H. AL-Zawaideh, and O. Khairuddin, "Offline Arabic Text Recognition-An

Overview", World of Computer Science and Information Technology Journal (WCSIT), Vol. 1, No. 5, 2011, pp. 184-192.

[15] A. Mesleh, A. Sharadqh, A. Al-Azzeh, J. Abu-Zaher, M. Al-Zabin, N. Jaber,and T. Odeh, Hasn, "An optical character recognition", Contemporary Engineering Sciences, Vol. 5, No. 11, 2012, pp.521-529.

[16] Y. Y. Zhang, P. S. P. Wang, "A New Parallel Thinning Methodology", International Journal of Pattern Recognition and Artificial Intelligence, Vol. 8, 1994, pp 999-1011.