Selected Problems of Intelligent Handwriting Recognition

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Abstract. We propose a new method for handwriting recognition that utilizes geometric features of letters. The paper deals with recognition of isolated handwritten characters using an artificial neural network. The characters are written on a regular sheet of paper using a pen, and then they are captured optically by a scanner and processed to a binary image which is analyzed by a computer. In this paper we present a new method for off-line handwriting recognition and also describe our research and tests performed on the neural network.

Keywords: Handwriting Recognition, Isolated Handwritten Characters, Artificial Neural Networks, Artificial Intelligence.

1 Introduction

Handwriting recognition has been studied for nearly forty years and there are many proposed approaches. The problem is quite complex, and even now there is no single approach that solves it both efficiently and completely in all settings. In the handwriting recognition process in Fig. 1, an image containing text must be appropriately supplied and preprocessed. Next, the text must either undergo segmentation or feature extraction. Small processed pieces of the text will be the result, and these must undergo recognition by the system. Finally, contextual information should be applied to the recognized symbols to verify the result. Artificial neural networks, applied in handwriting recognition, allow for high generalization ability and do not require deep background knowledge and formalization to be able to solve the written language recognition problem.

Handwriting recognition can be divided by its input method into two categories: off-line handwriting recognition and on-line handwriting recognition. For off-line recognition, the writing is usually captured optically by a scanner. For on-line recognition, a digitizer samples the handwriting to time-sequenced pixels as it is being written. Hence, the on-line handwriting signal contains additional time information which is not presented in the off-line signal.

P. Melin et al. (Eds.): Anal. and Des. of Intel. Sys. using SC Tech., ASC 41, pp. 298–305, 2007.
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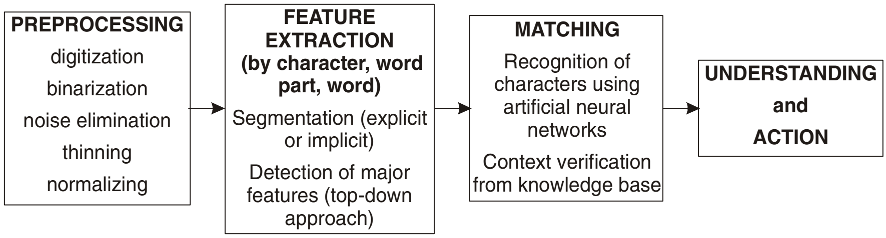

Fig. 1. Steps involved in handwriting recognition

2 The State of the Art

The state of the art of automatic recognition of handwriting at the beginning of the new millennium is that as a field it is no longer an esoteric topic on the fringes of information technology, but a mature discipline that has found many commercial uses. On-line systems for handwriting recognition are available in hand-held computers such as personal digital assistants. Their performance is acceptable for processing handprinted symbols, and, when combined with keyboard entry, a powerful method for data entry has been created.

Off-line systems are less accurate than on-line systems. However, they are now good enough that they have a significant economic impact on for specialized domains such as interpreting handwritten postal addresses on envelopes and reading courtesy amounts on bank checks [8,9,14,17].

The success of on-line systems makes it attractive to consider developing off-line systems that first estimate the trajectory of the writing from off-line data and then use on-line recognition algorithms [16]. However, the difficulty of recreating the temporal data [5,6] has led to few such feature extraction systems so far [1].

Research on automated written language recognition dates back several decades. Today, cleanly machine-printed text documents with simple layouts can be recognized reliably by OCR software. There is also some success with handwriting recognition, particularly for isolated handprinted characters and words. For example, in the on-line case, the recently introduced personal digital assistants have practical value. Similarly, some online signature verification systems have been marketed over the last few years and instructional tools to help children learn to write are beginning to emerge. Most of the off-line successes have come in constrained domains, such as postal addresses, bank checks, and census forms. The analysis of documents with complex layouts, recognition of degraded printed text, and the recognition of running handwriting continue to remain largely in the research arena. Some of the major research challenges in on-line or off-line processing of handwriting are in word and line separation, segmentation of words into characters, recognition of words when lexicons are large, and the use of language models in aiding preprocessing and recognition. In most applications, the machine performances are far from being acceptable, although potential users often forget that human subjects generally make reading mistakes [2,3,7].

The design of human-computer interfaces [10,11,12] based on handwriting is part of a tremendous research effort together with speech recognition [13], language processing and translation to facilitate communication of people with computers. From this perspective, any successes or failures in these fields will have a great impact on the evolution of languages [4,15].

3 Method Description

The proposed system attempts to combine two methods for handwriting recognition, neural networks and preprocessing for geometric features extraction. The motivation behind that preprocessor is to reduce the dimensionality of the neural network input. The system consists of the preprocessing subsystem and the neural network subsystem, as shown in Fig. 2. However, another benefit given by the preprocessor is immunity against image translation, because all the information is relative to the image's center of mass in Fig. 3.

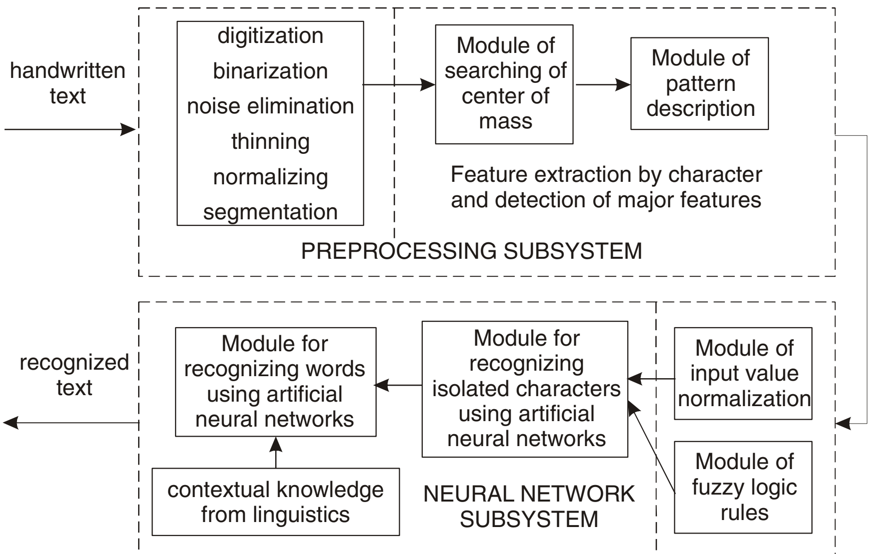

Fig. 2. The proposed system of handwriting recognition

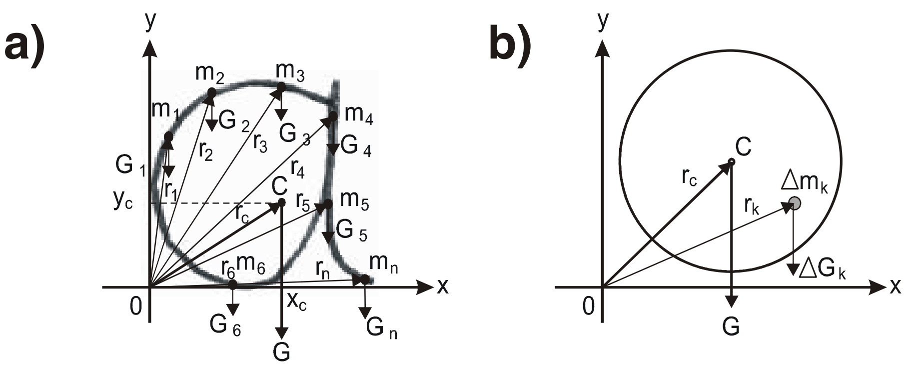

Fig. 3. a) Determining the center of mass of a character, b) determining the approximate position of the center of an optional letter

The handwritten text is made subject to the following preprocessing: digitization, binarization, noise elimination, thinning, normalizing and segmentation. The next step

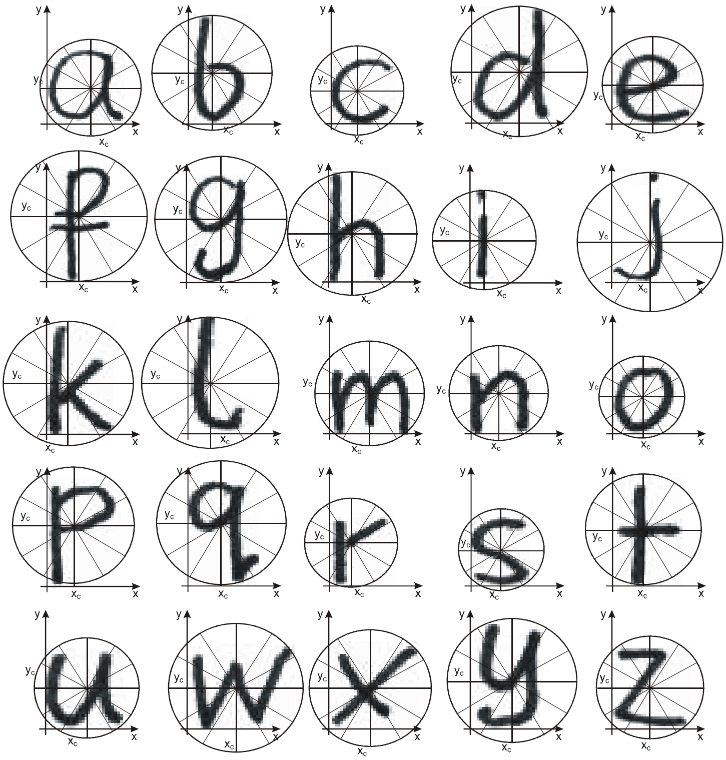

Fig. 4. Geometric analysis of letters for geometric feature extraction

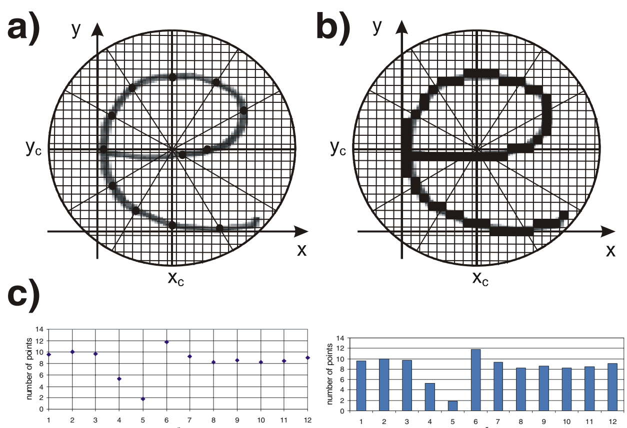

Fig. 5. Scheme of the preprocessing method for geometric feature extraction of characters: a) geometric analysis of letter e; b) pattern description by creating a binary image; c) histograms for letter e

is to find the center of mass of the character image. With the center of mass as a reference point, the vectors are drawn, creating a set of points describing the contour of the character so that its pattern description is made. The neural network training patterns are based on the geometric analysis of letters in Fig. 4. The description patterns of each isolated character in Fig. 5, after the normalization process, are inputs for an artificial neural network.

The letter can be considered as a set of points which mass m_k is constant, and have gravity forces $G_k=m_{k*}g$, and also vectors r_k (1):

$$r_c = \frac{\sum_{k=1}^{n} r_k \Delta G_k}{G} \tag{1}$$

The center of a letter i.e. the center of mass of the character image is found by determining gravity center coordinates (2):

$$x_c = \frac{\sum_{k=1}^{n} x_k \Delta G_k}{G} \qquad y_c = \frac{\sum_{k=1}^{n} y_k \Delta G_k}{G} \tag{2}$$

In (1) and (2) gravity force G is total weight of the set of points (**3**):

$$G = \sum_{k=1}^{n} \Delta G_k \tag{3}$$

4 Research Results

The data set for the system in Fig. 6 was the "Optical Recognition of Handwritten Digits" database, which was originally assembled by the National Institute of Standards and Technology (NIST) in 1994. It consists of handwritten numerals from a total of 43 people, 30 contributed to the training set database and 13 different people to the test set database.

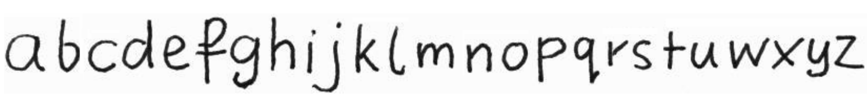

Fig. 6. The data set for this system

In the proposed hybrid system, the description patterns of each isolated character, after the process of input value normalization and application of letter description rules using fuzzy logic, are the input signals for the neural network as presented in Fig. 7.

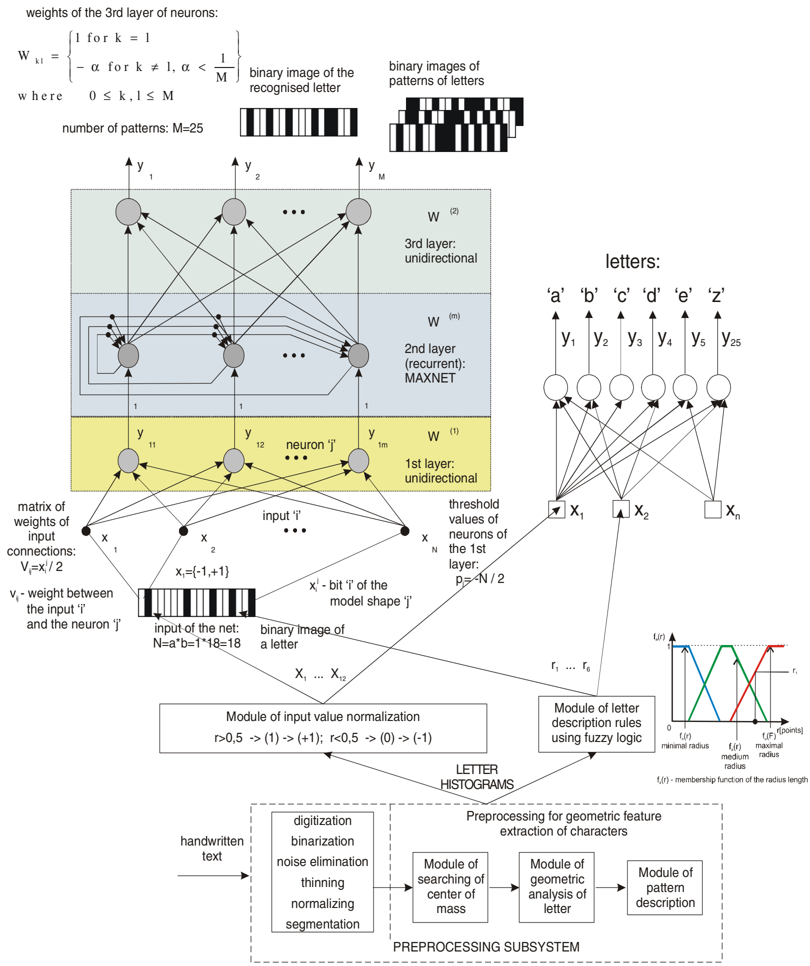

Fig. 7. Proposed hybrid system: input signals for the neural network

The simulation set of the recognition of isolated handwritten characters, built for creating and training artificial neural networks is shown in Fig. 8a. The neural networks are trained with the model of isolated written language characters. The applied neural network architecture is presented in Fig. 8b. The networks consist of two layers of neurons with the competitive mechanism. The ability of the neural network to learn to recognize specific letters depends on the number of learning epochs. The specified time of learning enables the network to minimize the error so that it could work more efficiently. Based on the research, the following conclusion has been reached as shown in Fig. 8c. Error rate is about 20% at learning time equals 50 epochs and 5% at 100 epochs. The error rate dropped by about 90% after training with 60 series of all patterns.

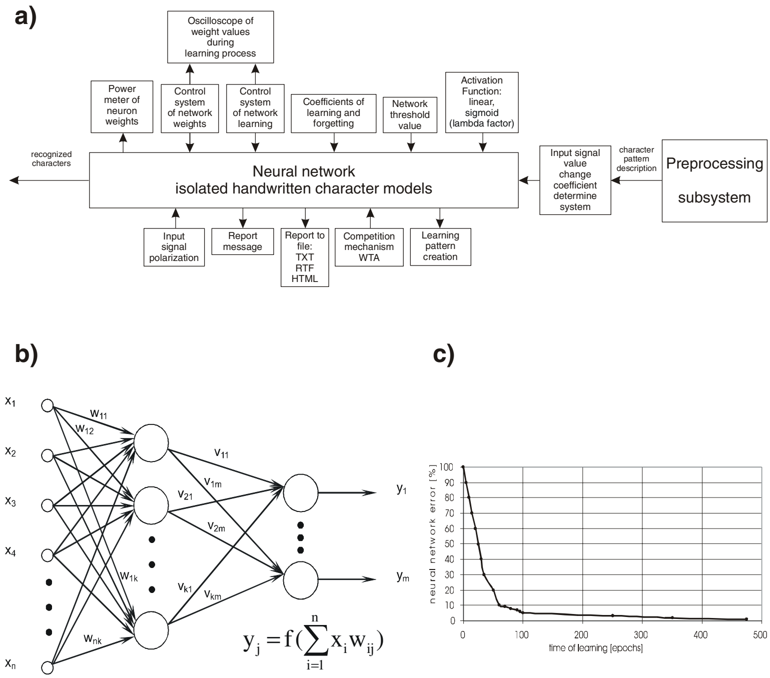

Fig. 8. Neural network simulations of isolated handwritten characters models, neural network architecture and error rate

5 Conclusions and Perspectives

Many advances and changes have occurred in the field of automated written language recognition, over the last decade. The different sources of variability of various psychophysical aspects of the generation and perception of written language make handwriting processing so difficult.

Considerable progress has been made in handwriting recognition technology particularly over the last few years. Handwriting recognition systems have been limited to small and medium vocabulary applications, since most of them often rely on a lexicon during the recognition process. The capability of dealing with large lexicons, however, opens up many more applications.

References

1. Artieres, T., Gauthier, N., Gallinari, P., Dorizzi, B.: A Hidden Markov Models combination framework for handwriting recognition. International Journal on Document Analysis and Recognition, 5(4) (2003). Springer Berlin Heidelberg. 233-243
2. Besner, D., Humphreys, G. W.: Basic Processes in Reading: Visual Word Recognition. Lawrence Erlbaum Associates. Hillsdale, New Jersey (1991)

3. Bishop, C. M.: Neural Networks for Pattern Recognition. Oxford University Press Inc., New York (2004)
4. Bradford, R., Bradford R. B.: An Introduction to Handwriting Examination and Identification. Nelson-Hall Publishers. Chicago (1992)
5. Boccignone, G., Chianese, A., Cordella, L. P., Marcelli, A.: Recovering Dynamic Information from Static Handwriting. Pattern Recognition, 26(3) (1993). Elsevier Science (1993) 409-418
6. Doermann, D. S., Rosenfeld, A.: Recovery of Temporal Information from Static Images of Handwriting. Computer Vision, 15(1-2) (1995). Springer Netherlands. 143-164
7. Dori, D., Bruckstein, A.: Shape, Structure and Pattern Recognition. World Scientific Publishing Co., New Jersey (1995)
8. Kavallieratou, E., Fakotakis, N., Kokkinakis, G.: An unconstrained handwriting recognition system. International Journal on Document Analysis and Recognition, 4(4) 2002. Springer Berlin Heidelberg. 226-242
9. Li, Z. C., Suen, C. Y.: The partition-combination method for recognition of handwritten characters. Pattern Recognition Letters, 21(8) 2000. Elsevier Science. 701-720
10. Majewski, M., Kacalak, W.: Automatic recognition and evaluation of natural language commands. International Symposium on Neural Networks ISNN 2006. Chengdu, China. Lecture Notes in Computer Science 3973: Springer (2006) 1155-1160
11. Majewski, M., Kacalak, W.: Natural language human-machine interface using artificial neural networks. International Symposium on Neural Networks ISNN 2006. Chengdu, China. Lecture Notes in Computer Science 3973: Springer (2006) 1161-1166
12. Majewski, M., Kacalak, W.: Intelligent Layer of Two-Way Voice Communication of the Technological Device with the Operator. International Conference KES 2005. Melbourne, Australia. Lectures Notes in Artificial Intelligence 3683, Springer (2005) 930-936
13. Kacalak, W., Douglas Stuart, K., Majewski, M.: Intelligent Natural Language Processing. International Conference on Natural Computation ICNC2006. Xi'an, China. Lectures Notes in Artificial Intelligence 4221, Springer (2006) 584-587
14. Mitiche, A., Lebidoff, M.: Pattern Classification by a Condensed Neural Network. Neural Networks, 14(4-5) (2001). Elsevier Science. 575-580
15. Mori, S., Nishida, H., Yamada, H.: Optical Character Recognition. John Wiley & Sons, Inc., New York, New Jersey (1999)
16. Nishida, H.: An Approach to Integration of Off-Line and On-Line Recognition of Handwriting. Pattern Recognition Letters, 16(11) 1995. Elsevier Science. 1213-1219
17. Zhou, J., Krzyzak, A., Suen, C. Y.: Verification-a Method of Enhancing the Recognizers of Isolated and Touching Handwritten Numerals. Pattern Recognition, 35(5) 2002. Elsevier Science. 1179-1189