A Hybrid Two-Stage Fuzzy ARTMAP and LVQ Neuro-Fuzzy System for On-Line Handwriting Recognition

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Abstract. This paper presents a two-stage handwriting recognizer for classification of isolated characters that exploits explicit knowledge on characters' shapes and execution plans. The first stage performs prototype extraction of the training data using a Fuzzy ARTMAP based method. These prototypes are able to improve the performance of the second stage consisting of LVQ codebooks by means of providing the aforementioned explicit knowledge on shapes and execution plans. The proposed recognizer has been tested on the UNIPEN international database achieving an average recognition rate of 90.15%, comparable to that reached by humans and other recognizers found in literature.

1 Introduction

Handwriting recognition is widely regarded as one of the most difficult problems in the field of pattern recognition because of the great variations present in input patterns [9]. Three main sources of variation can be identified in handwriting generation: allograph variation, execution plan variation and instance variability.

Allograph variation refers to the large amount of different shapes (i.e. *allographs*) used by individuals to represent character concepts (e.g. the letter concept {a} can be written in different ways, such as an upper case, a block printed, or a cursive variant). The shapes used by the writer depend mainly on his education at primary school and personal preferences. *Execution plan variation* is related to the different possible ways (i.e. *execution plan*) of drawing a given shape (e.g. the shape of a zero can be drawn clockwise or counterclockwise). Again execution plans used by writers depend on education as well as on the context of neighboring letters. Finally, *instance variability* holds for a given writer, and refers to the noise (e.g. different slants and sizes, movement noise) introduced by the author when writing (i.e. instantiating) the character.

Handwriting recognition systems in general try to avoid instance variability while learning both allograph and execution plan variation. However, while most recognition systems found in literature do this by simply pouring large amounts of data into a single method, [10] remarks the need to provide explicit knowledge on handwriting shapes and execution plans in order to improve recognition performance.

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According to this idea, a Fuzzy ARTMAP based automatic prototype extraction method was presented and studied in [1]. This method is able to identify groups of character instances sharing the same allograph and execution plan, as well as to extract a prototype for them. Thus the extracted prototypes are intended to provide explicit knowledge about all the allographs and execution plans found in training data.

Within this framework, this paper presents a two-stage neuro-fuzzy system for handwriting recognition. In the first stage, the Fuzzy ARTMAP based method introduced in [1] is used to extract prototypes from the training data. The use of the explicit knowledge extracted by this method improves the performance of the system's second stage, consisting of a series of LVQ codebooks. This point may be shown by comparing the recognition rates yielded using prototypes extracted by the first stage of the recognizer with those achieved with other prototypes generated by two widely used LVQ initialization methods that are known to provide no explicit knowledge on shape and execution plans. The good performance of the proposed recognizer can also be realized when taking as a reference the rates achieved by other systems and human recognizers.

The organization of this paper is as follows. Section 2 briefly describes the neuro-fuzzy handwriting recognition system proposed in this paper. The UNIPEN data and the extracted prototypes used for the experiments are presented in section 3. Section 4 first shows that the explicit knowledge provided by the prototypes extracted using the first stage of our recognizer does improve performance. Next, the recognition results of our system are compared to those of some other systems from the literature. Finally, in section 5 conclusions and current research are discussed.

2 The Handwriting Recognition System

Since the prototypes extracted in [1] are computed as the mean of a cluster of vectors sharing the same allograph and execution plan, it seems reasonable to apply recognizers based on the comparison of distances between prototypes and test instances. For this purpose, Learning Vector Quantization (LVQ) codebooks [6] can be used.

LVQ is a supervised version of vector quantization that moves codevectors to define near-optimal decision borders between the classes, even in the sense of classical Bayesian decision theory [6]. Knowledge to LVQ codebooks is provided through the initial prototypes that are later refined by the LVQ algorithm.

The handwriting recognizer thus proposed consists of two stages. In the first one, knowledge on handwriting shapes and execution plans is obtained from the training data using the prototype extraction method described in [1]. This method employs Fuzzy ARTMAP neural networks to group character instances according to classification criteria. Next, a simple but effective algorithm finds clusters of instances within these groups having the same allograph and execution plan and computes a prototype for each of the clusters. One of the most outstanding properties of this extraction method is that the prototypes are extracted automatically (i.e. the number of prototypes is not fixed *a priori*).

The second stage of the handwriting recognizer comprises a series of LVQ codebooks initialized by the prototypes extracted in the previous stage. Different code-

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books are employed to classify the characters according to their number of strokes. Prior to training and test phases, raw handwriting data are first preprocessed and segmented into strokes according to the method presented in [4]. Feature vectors are built as described in [1].

3 UNIPEN Data and Prototypes Employed

UNIPEN versions 2 and 7 [5] have been used for the experiments in this paper. The use of the character database provided by UNIPEN ensures a large amount of data, author-independence and comparability to other systems.

Experiments have been carried out using three different sets of isolated characters of both versions: digits, upper-case letters and lower case letters. The number of labels found in each set is 10, 26 and 26 respectively, according to the English alphabet. Each of these sets was in turn divided in two subsets of the same size guaranteeing the presence of samples by any writer in both of them. The first subset was employed both to extract the prototypes that are used to initialize the LVQ codebooks and to further train the recognition system. The second subset was only used for recognition tests. Table 1 shows the distribution of employed data.

Table 1. Data distribution in subsets used for prototype extraction, learning and test of UNIPEN database and number of prototypes extracted from the training subsets

	Version 2			Version 7		
	Digits	Upper-c.	Lower-c.	Digits	Upper-c.	Lower-c.
Prot. Extraction / Learning	1916	2109	6100	7245	12105	23710
Test	1917	2109	6101	7242	12104	23714
Prototypes extracted	108	186	558	278	723	1577

Prototypes were extracted from the corresponding subsets using the extraction method and parameters described in [1]. The distribution of the extracted prototypes for each set is also shown in Table 1. A discussion on the performance of this prototype extraction method was held in [1] showing that a reasonable number of prototypes can be extracted from a large multi-writer amount of samples. Furthermore, the reconstructions of these prototypes are easily recognizable by humans.

4 Experiments and discussion

Once the recognition system has been introduced, in this section, we will first show that the prototypes extracted by the Fuzzy ARTMAP based method improve recognition performance by providing explicit knowledge on shapes and execution plans. Next, the recognition rates achieved are compared with those yielded by other relevant classifiers.

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4.1 Improving performance by providing explicit knowledge

Propinit and *eveninit*, are proposed in [7] as the standard initialization methods for LVQ codebooks. The *propinit* and *eveninit* initializations choose randomly the initial codebook entries (i.e. prototypes) from the training data set, making the number of entries allocated to each class be proportional or equal, respectively. Both methods try to assure that the chosen entries lay within the class edges, testing it automatically by *k-NN* classification. Thus, both *propinit* and *eveninit* can be said to provide no explicit knowledge of the allograph and execution plans found in the training data set.

Given this background, two experiments can be made to show that the explicit knowledge provided by character prototypes does improve performance. In the first experiment, the prototypes obtained with the three aforementioned methods (i.e. prototypes extracted in [1] and prototypes generated by *propinit* and *eveninit*) were used to classify the test data sets without any kind of LVQ training. In order to make comparisons as fair as possible, the number of prototypes generated by *propinit* and *eveninit* (which must be set *a priori*) was equal to the distribution of prototypes extracted by the Fuzzy ARTMAP based method. The results of the experiment is shown in the first 3 rows of Table 2.

It is noteworthy that the achieved recognition rates employing the extracted prototypes before training the system are significantly higher than using the *propinit* and *eveninit* methods in all cases. This is because the prototypes extracted by the Fuzzy ARTMAP based method are placed in the "middle" of every cluster in the training data, thus providing explicit knowledge of all the allographs and execution plans. On the contrary, the *propinit* and *eveninit* methods, given their random nature, do not assure the existence of a prototype in every cluster.

Table 2. Recognition rates achieved in experiment 1 using prototypes without LVQ training (first 3 rows) and in experiment 2 employing prototypes with LVQ training (last 3 rows)

	Version 2			Version 7		
	Digits	Upper-c.	Lower-c.	Digits	Upper-c.	Lower-c.
Extracted prot. / No training	92.80	86.96	83.87	91.12	87.28	83.53
Propinit / No training	75.85	70.65	67.30	83.97	75.78	75.50
Eveninit / No training	75.74	58.04	65.25	79.51	70.86	70.63
Extracted prot. / Training	93.84	87.81	86.76	95.04	89.68	87.76
Propinit / Training	88.47	78.38	76.71	89.23	80.92	83.49
Eveninit / Training	85.08	73.11	75.40	89.42	80.02	82.28

A second experiment can be carried out by training the three kind of prototypes with the LVQ algorithm. Actually, this training was made employing the OLVQ1 algorithm [7] using the parameter values recommended in the same paper.

The recognition rates using the extracted prototypes increase slightly after carrying out the training, as shown in Table 2. Since the prototypes are computed as the mean of the cluster vectors, the initial codebook vectors are already quite well placed from the classification point of view and the LVQ training just contributes to refine the prototypes' positions in order to minimize the classification error. The increase in recognition rates after training using *propinit* and *eveninit* initialization methods is

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much higher. In this case, the training phase moves the codebook entries towards more suitable positions in the feature space according to classification criteria. However, the obtained recognition rates using *propinit* and *eveninit* are still lower than using the prototype initialization. In addition, it must be also noticed that they are even lower than the achieved recognition rates using prototypes without any training. This is again because *propinit and eveninit* prototypes cannot be found in every cluster of characters sharing the same allograp and execution plan. These results support again the idea that the explicit knowledge provided by the prototypes extracted with the Fuzzy ARTMAP method improve recognition performance.

4.2 Comparison with other Handwriting Recognizers

In order to evaluate the performance of our system, recognition rates are compared in Table 3 with those achieved by some other relevant classifiers: the two neuro-fuzzy classifiers studied in [3]; a 1-NN classifier with prototypes computed using the unsupervised k-means algorithm, as described in [8] (again the number of prototypes is set according to the distribution shown in Table 1); a 1-NN classifier using all the training data as prototypes (this gives the asymptotic performance of the 1-NN rule, which was proved in [2] to be bounded by twice the Bayesian error rate); and human recognizers (results reported in [3]).

Table 3. Comparison of the proposed system's performance with other relevant classifiers

	Version 2			Version 7		
	Digits	Upper-c.	Lower-c.	Digits	Upper-c.	Lower-c.
Extracted prototypes	**93.84**	**87.81**	**86.76**	**95.04**	**89.68**	**87.76**
System 1 proposed in [3]	85.39	66.67	59.57	-	-	-
System 2 proposed in [3]	82.52	76.39	58.92	-	-	-
k-means + 1-nn	90.40	85.90	84.51	93.22	87.58	87.54
1-nn asymptotic performance	96.04	92.13	88.48	96.52	91.11	-
Human recognition	96.17	94.35	78.79	-	-	-

The proposed system exceeds the recognition rates achieved with the two systems proposed in [3] and the k-means with 1-NN classifier. It is also noticeable that the rates of our recognition system are quite near to the computed asymptotic performance. This is especially remarkable for version 7 digits and upper-case letters where the differences are under 1.5%.

The recognition rates achieved by humans give us an idea of the expected number of unrecognizable data for the different test sets. It is quite surprising to notice that the LVQ recognizer performs better than humans do in lower-case recognition. This can be due to different facts: first, humans did not spend too much time on studying the training data; second, humans get tired after some hours on the computer; and third, humans do not exploit movement information, while the recognizer does.

Finally, it can be said that the main sources of misclassification in the LVQ-based recognizer are erroneously labeled data, ambiguous data, segmentation errors and insufficient feature set. These problems affect the recognizer because of the appear-

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ance of incorrect prototypes. In addition, the presentation of erroneous patterns during the training phase may cause a deficient learning. The improvement of these aspects in the prototype extraction method should reduce the number of codebook vectors used and the increase of accuracy recognition.

4 Conclusions

In this paper, a two stage neuro-fuzzy system that exploits explicit knowledge on character's shape and execution plans was presented for on-line handwriting recognition. The first stage extracts prototypes using the Fuzzy ARTMAP based extraction method that was proposed and discussed in [1]. These prototypes provide the explicit knowledge about shapes and execution plans found in training data and are used to initialize the second stage of the recognizer consisting of a series of LVQ codebooks. It has been shown that the aforementioned explicit knowledge extracted by the first stage improves the rates of the handwriting recognizer according to the idea found in [10]. The comparison of our system's performance with other relevant recognizers showed interesting results that may foster further improvements.

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