43 Adaptive On-line Recognition of Handwritten Characters

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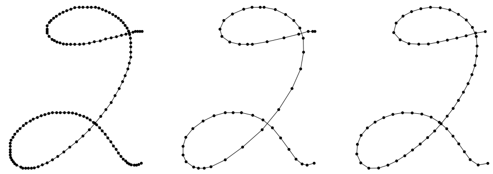
Automatic on-line recognition of handwritten text has been an on-going research problem for four decades. It has been gaining more interest lately due to the increasing popularity of hand-held computers, digital notebooks and advanced cellular phones. Traditionally, man-machine communication has been based on keyboard and pointing devices. These methods can be very inconvenient when the machine is only slightly bigger or same size as human palm. Therefore, handwriting recognition is a very attractive input method.

The most prominent problem in handwriting recognition is the vast variation in personal writing styles. There are also differences in one person's writing style depending on the context, mood of the writer and writing situation. The writing style may also evolve with time or practice. A recognition system should be insensitive to minor variations and still be able to distinguish different but sometimes very similar looking characters. Recognition systems should, at least in the beginning, be able to recognize many writing styles. Such multi-user systems usually have problems with recognition accuracy. One way to increase performance is adaptation, which means that the system learns its user's personal writing style.

The goal of the On-line Recognition of Handwritten Characters project is to develop adaptive methods for on-line recognition of handwritten characters. In this case, adaptation means that the system is able to learn new writing styles during its normal use. Due to the learning, the user can use his own natural style of writing instead of some constrained style. Our work concentrates on the recognition of isolated alphanumeric characters. The project is a part of the TEKES's technology programme Adaptive and Intelligent Systems Applications (AISA) and a subproject of the research project IMPRESS - Intelligent Methods for Processing and Exploration of Signal and Systems. The work is carried out in co-operation with Nokia Research Center.

The handwritten character recognition systems developed during this project are all based on template matching. They consist of a set of known characters (or prototypes), a similarity measure, and decision criteria. When a character is input to such a system, it is first preprocessed and normalized, then compared with all the prototypes, and finally classified according to its k nearest, or most similar, neighbors.

The preprocessing operations are very simple and they are used for altering the sampling of the characters. There were approximately 40 000 characters written by 46 subjects used in the experiments. The characters were collected with a system whose properties, such as sampling rate and resolution, are beyond the capabilities of the existing hand-held devices. Therefore, it was important to examine how sensitive the recognition methods are to the amount of data for each character. Prior to the matching, the characters are normalized by moving their centers, either mass or bounding box, onto each other. In addition, the characters can be rescaled



(a) (b) (c)

Figure 89: a) An original character and its two preprocessed versions when b) the sampling frequency is reduced to one third of the original frequency, and c) data points are sampled so that they are equidistant in space instead of time.

so that their bounding boxes are of equal size. In Figure 89, the original and two preprocessed versions of an example character are shown.
The prototype set is formed by clustering a large number of training samples and selecting one sample from each cluster to present all the samples in that cluster. The characters used for creating the prototype sets were written by different subjects than the character used for evaluating the performances of the recognizers. Therefore, all the experiments can be considered to be writer independent. The clustering algorithm applies the same similarity measure as the recognizer in the matching phase. Various similarity measures, all based on dynamic time warping (DTW) algorithm, have been suggested. DTW-algorithm enables nonlinear matching of curves or chain codes consisting of a variating number data points or items [7].
Adaptation of the recognition system is performed after each classification and it is based on the following ideas:

1. The prototype set is modified according to the recognition results of the new character samples. The prototype set is modified by by adding new prototypes, inactivating confusing prototypes, and reshaping existing prototypes with an algorithm based on Learning Vector Quantization (LVQ) [3]. These operations are carried out depending on how many of the k nearest prototypes belong to the correct class and their long term performances [8],[5],[6].

2. A set of classifiers is combined in a committee machine whose decision criteria are modified. The committee adaptation is based on the Dynamically Expanding Context (DEC) principle of Kohonen [1],[2]. The DEC principle adds new decision rules if the existing ones produce incorrect results. The new rules always strive to utilize more contextual information and are thus more specific than the old ones. In this case, the context is formed from the outputs of the committee members as is shown in Figure 90 [4].

Experiments performed with a recognition system which is able to adapt its prototype set have showed that a writer-independent classifier can be changed into a writer-dependent. Due to the adaptation, recognition accuracy high enough to be acceptable for a real-world application can be attained for most of the writers. An adaptation strategy which adds the input character into the prototype set if all the k nearest prototypes do not belong to the correct class was found to be the fastest

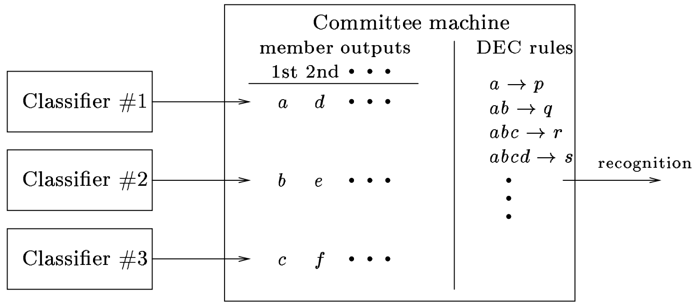


Figure 90: The basic setting of the DEC-based adaptive committee classifier.

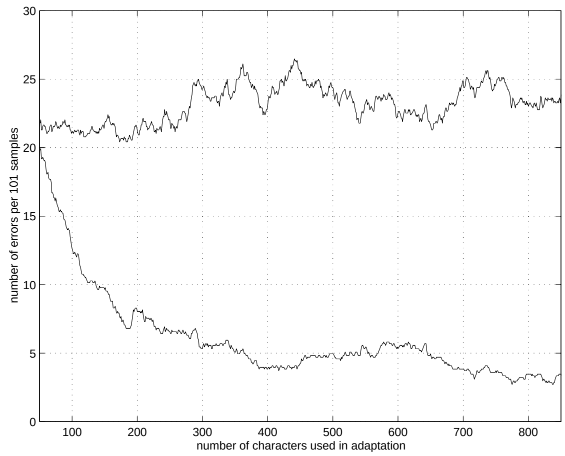


Figure 91: Evolution of the error rate during data collection in which the characters were recognized on-line. In the true data collection corresponding to the lower plot, input characters were added to the prototype set if one of the four nearest prototypes belonged to wrong class. The higher plot illustrates the nonadaptive simulation of the data collection. These result are obtained by averaging the result of eight writers.

way to decrease the error rate. However, the size on the prototype set increases considerably even if the recognition performance has ceased to improve.

Reshaping of the existing prototypes with a modified LVQ training rule nearly halves the error rate but is not sufficient when used alone as new writing styles fundamentally different from those represented by the initial prototypes cannot be learned. When these two adaptation strategies are combined so that new prototypes are added only if all the neighboring prototypes are incorrect and LVQ-learning is carried out otherwise, the growth of the prototype set is insignificant and the evolution of the recognition performance is nearly as good as with the pure adding strategy.

A part of the data was collected with a program that recognized the characters on-line and adapted itself to the writing style of the subject. The collected characters were both upper and lower case letters and digits. They were written in random order after the directions prompted by the program. The evolution of the error rate during the data collection and its nonadaptive simulation is illustrated in Figure 91 [8],[9].

A drawback of these adaptation strategies is that they all are supervised methods.

In practical applications, perfect supervision cannot be guaranteed. The recognition results are not necessarily correct even though they are accepted by the user, and, the user might change correctly recognized characters while correcting writing mistakes. In the future work, the recognition system's sensitivity to bad learning samples will be examined.

Several approaches to the DEC rules have been tested. Approaches for deciding the first result and order of the results taken by the system to form the context have been best classifier, majority voting, weighed majority voting, adjusting best classifier and adjusting majority voting. In the adjusting versions a measure of how well an individual classifier has performed has a direct contribution as to how decisive it is. As for the formation of the rules, examples of restrictions posed include requiring the output to belong to the context, predetermining the size of the context and various approaches to the situation where a new rule with the same context is created.

The use of the DEC rules has most notable effect when other adaptation is not used. Still, the use of the committee produces slight improvement in classification percentage when the members of the committee themselves are adaptive. Judging from the results available at this time, the most effective approach might be to at first have just the member classifiers adapt and begin using the DEC rules at a point when the error percentage of the individual classifiers has already reached a reasonably low level.

The main future goals of this project involve testing the sensitivity of the system in ambiguous situations and the development of a portable, hand-held testing and data gathering system.

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