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Hybrid generative/discriminative classifier for unconstrained character recognition

Lionel Prevost *, Loïc Oudot, Alvaro Moises, Christian Michel-Sendis, Maurice Milgram

Université Pierre et Marie Curie, Laboratoire des Instruments & Systèmes d'Ile de France, Groupe PARC 4 Pace Jussieu, Paris Cedex 75252, Case 252, France

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Abstract

Handwriting recognition for hand-held devices like PDAs requires very accurate and adaptive classifiers. It is such a complex classification problem that it is quite usual now to make co-operate several classification methods. In this paper, we present an original two stages recognizer. The first stage is a model-based classifier which store an exhaustive set of character models. The second stage is a pairwise classifier which separate the most ambiguous pairs of classes. This hybrid architecture is based on the idea that the correct class almost systematically belongs to the two more relevant classes found by the first classifier. Experiments on a 80,000 examples database show a 30% improvement on a 62 classes recognition problem. Moreover, we show experimentally that such an architecture suits perfectly for incremental classification.

Keywords: Handwriting recognition; Multiple classifier system; Pairwise neural networks; Confusion matrix; Adaptive classifier

1. Introduction

Recently, hand-held devices like PDAs, mobiles phones or e-books have became very popular. In opposition to classical personal computers, they are very small, keyboard-less and mouse-less. Therefore, electronic pen is very attractive as pointing and handwriting device. The first application belongs to man-machine interface and the second to handwriting recognition. Here, we focus on the second one.

For such an application, recognition rates should be very high otherwise it should discourage all the possible users. The major problem is the vast variation in personal writing style. This problem can be solved either by constraining the allowed style of writing (PDA's *grafiti* alphabet: Fig. 1a), trying to learn all personal writing styles

* Corresponding author. Tel.: +33 1 44 27 23 48; fax: +33 1 44 27 62 14.
E-mail address: lionel.prevost@lis.jussieu.fr (L. Prevost).

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(natural and script writing: Fig. 1b and c) to build an omni-writer recognizer or building a mono-writer recognizer by adapting the system to its user' style and habits (abbreviations, mathematical or chemical symbols for scientists...).

In dynamic handwriting recognition, signal is represented by sequences of (x, y) coordinates of the pen moving. Each handwriting style has got its typical allographs. This notion, particular to handwriting, includes on the one hand characters having the same image but presenting a very variable dynamics in term of the number of stroke composing the character, their senses and direction and on the other hand, the different handwriting model of a given character: cursive, hand-printed, mixed...

Focusing on classification errors, there are two situations which reduce the recognition rate.

- Pattern might be unrelated to the training data. As each user has his own way of writing, many dynamics can appear (Fig. 2a) This problem can be overcome by classifying both dynamic and static representations of the character and combining the classification results as shown in (Prevost and Milgram, 1997).
- Pattern might be ambiguous (Fig. 2b) and some specific pairs of classes constitute the majority of errors made by the classifier like (B, D) or (7, 1).

The idea of our hybrid combination method is based on the fact that a given classifier can achieve very good performances in terms of correct recognition rate when considering the two more relevant classes (see Table 2). This observation motivates the search for a suitable method which can detect

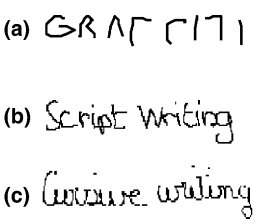

Fig. 1. Handwriting styles. (a) Constraint writing, (b) script writing, (c) natural writing.

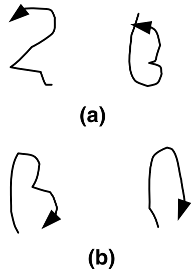

Fig. 2. Ambiguous characters. (a) Unknown dynamics, (b) ambiguous characters.

the correct classification among these two classes. This choice results in a two class (binary) problem. In this paper, we explore the following combination scheme. First stage generative classifier is used to detect ambiguous pairs of classes and the second stage is discriminative. It is composed of a set of pairwise neural networks, one for each ambiguous pair of classes.

The paper is organized as follows. Section 2 describes several standardized methods used for character classification and ways to build two stage classifier well-known for their accuracy. Section 3 details the first stage model-based classifier. Section 4 is devoted to the implementation of the second stage discriminative classifier used to improve performances. In Section 5, we show that this hybrid approach is adaptive. Finally, concluding remarks and future works are discussed in Section 6.

2. Review of classification methods

2.1. Model generation vs discrimination

There are two standard ways to perform handwriting classification: generate models (to build the so-called model-based classifier) or discriminate.

Generative classifiers train one (or several) model(s) for each character class with examples of this single class. During the test stage, the classification is performed according to similarity between the unknown pattern and the models. Neural models (Schwenk and Milgram, 1996), Markovian models (Connell and Jain, 1999) or prototype-based models (Anquetil and Lorette,