Learn the Way We Write: Automatic Adjustment of Handwriting Neural Classifier to Individual Users

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Abstract

In this paper, we consider improving convolution neural network (CNN) classifier of offline handwritten text. We focus on the style of handwriting each of the individual users, causing of its great variability and huge impact on the ability to successfully recognize written characters. We present fast, scalable and a no-retrain method for improving CNNs classifier. Using only basic machine learning techniques, such as K nearest neighbor classifier and K means clustering, we achieve up to +2.7% improvement in neural classifier precision, and get state of the art results on the dataset we use. We evaluate our method on two dataset: NIST Special Database 19 and ETH Zurich Deepwriting dataset.

1 Introduction

The problem of automatic recognition of offline handwritten characters is a very practical problem, which is a part of the area of pattern recognition. Inspired by practical use, it develops both within academia as well as within the industrial sector. The industrial sector directly commercializes solutions of this problem by including them into devices like tablets, smartphones and the like. Cause of that it is very important to have precise classifiers that rarely make mistakes.

The pioneering attempt to automatically recognize handwritten characters dates back to the 1950s C.G. Leedham (1994). After this initial attempt a few a group of researchers worked independently on this problem Plamondon et al. (2000). Within the software and hardware limitations of that time, remarkable results were achieved. In the last ten years, the intensive development of neural networks has led to a shift in boundaries in many areas, including in the area of offline handwriting recognition. The results achieved by using convolutional neural networks exceeds the results of all methods developed up to then Srihari et al. (2006) Pavarez et al. (2013) Awaida et al. (2012).

Although convolutional neural networks have significantly increased offline handwriting classification accuracy, there is still plenty of room for progress. In this paper, we presented fast, alphabet-independent and scalable method which improves pretrained CNN without its retraining.

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The new approach is based on the idea of knowing the character writing style each of the individual users. Presented improvement of pretrained offline handwriting CNN classifier is based on the dynamic monitoring both of his mistakes and successful predictions. By this monitoring, we created the so-called user writing history. Based on user writing history, a set of several models of KNN classifiers is formed, for different values of K and the reliability of both the base classifier and these models is evaluated (in a principled way, which will be described later). Based on these ratings, method decide which one label to anticipate.

In this paper, Section 2 describes work related to this problem while the proposed method is fully described in Section 3. Section 4 provides experimental results, and conclusions are given in Section 5.

2 Related work

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2.1 Previous work in offline handwritten character recognition

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2.2 Previous work in improving offline handwriting classifiers

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3 Method

This section describe the proposed method for improving the CNN classifier of offline handwritten text. Note that while the idea behind the learning users handwriting style is rather simple, because of the complexity of the proposed method, we first give it an overview.

3.1 Method overview

The basic idea is to distinguish the reference modes of writing for each character. This is motivated by the intuition that each character can be written in finite significantly different ways. Separation the different writing styles of each character was achieved by clustering. Thus, for each of the characters, several clusters were obtained representing aggregated different writing styles of that character. This tends to separate the different writing styles each of them.

When proposed method is used, on application set, for each user a set of characters that he or she authored is divided into two sets: an adaptation set and test set. On adaptation set we detect the user's writing style by memorizing his individual characters writing patterns. On the test set, the proposed method makes predictions by taking into account the user's writing style.

A sketch of the proposed method, which will be explained in more detail in the following sections, is given with:

- Images from the training set for the base classifier and validation set for the base classifier are grouped by labels (characters) and clustered within each group. These clusters represent the main writing styles for each of the characters.
- For each author of the application set:
  - The set of his images is stratified into adaptation set and test set.
  - In the adaptation set, for each of the characters the most similar writing styles (from already defined writing styles) are being identified, which makes the author's writing history.
  - Alternative classifiers (K nearest neighbor method) and their confidence vectors are created on the adaptation set.
  - For every instance of test set (where proposed method is used):

* In addition to the base CNN prediction, alternative classifier predictions are also calculated.
* Based on the confidence vectors of all the classifiers, the prediction of the most reliable of them is selected.
* For each classifier, using the correct and its predicted labels, its confidence vector is updated.

A more detailed description of each step, as well as an explanation of terms such as writing history and the classifier confidence vector are given in more detail in the following sections.

3.2 Clustering individual character writing styles

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3.3 Creating a writing history

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3.4 Using writing history

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4 Evaluation

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4.1 Used datasets

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4.1.1 NIST Special Database 19

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4.1.2 ETH Zurich Deepwriting Database

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4.2 Images preprocessing

pass

4.3 Datasets split

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4.3.1 NIST Special Database 19 split

pass Patrick et al. (2016)

4.3.2 ETH Zurich Deepwriting Database split

pass Aksan et al. (2018)

4.4 Base CNN classificator

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4.4.1 Architecture

pass

4.4.2 Training and results

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4.5 Evaluation results

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4.6 Comparison with relevant papers

Ovo možda u related works?

5 Conclusion

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