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

pass

2.2 Previous work in improving offline handwriting classifiers

pass

3 Method

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3.1 Method overview

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3.2 Clustering individual character writing styles

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3.3 Creating a writing history

Možda zaista usvojiti naziv 'dynamic writing history' za istoriju pisanja?

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

pass

4.1.2 ETH Zurich Deepwriting Database

pass

4.2 Images preprocessing

pass

4.3 Datasets split

pass

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

pass

4.5 Evaluation results

pass

4.6 Comparison with relevant papers

Ovo možda u related works?

5 Conclusion

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