Normalised Local Naïve Bayes Nearest-Neighbour Classifier for Offline Writer Identification

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***Abstract*—Writer identification and verification can be viewed as a classification problem, where each writer represents a class. We propose a classifier for offline, text-independent, and segmentation-free writer identification based on the Local Naïve Bayes Nearest-Neighbour (Local NBNN) classification. Our proposed method takes into consideration the particularity of handwriting patterns by adding a constraint to prevent the matching of irrelevant keypoints. Furthermore, a normalisation factor is proposed to cope with the prevalent problem of unbalanced data. The method has been evaluated on several public datasets of different writing systems and state-of-the-art results are shown to be improved.**

1. Introduction

The task of writer identification can be defined as the process of assigning a writer with known reference handwriting samples to an unknown handwriting sample, while writer verification is the task of measuring the similarity between two samples of handwritings. Both tasks can be viewed as an image classification problem, where the images are samples of handwritings and all samples of the same writer represent a class. Given the task of writer identification, the number of samples per writer is usually rather small in most of the public datasets as well as practical scenarios; furthermore, a wide variation of handwriting patterns can be found within the same writer style. Therefore, we propose to use a learning-free algorithm that can cope both with a limited amount of training samples, and with intra-writer variations.

Since Local Naïve Bayes Nearest-Neighbour (Local NBNN) classification [1] has demonstrated state-of-the-art results for such a task of image classification, we propose an offline, text-independent, and segmentation-free writer identification method based on Local NBNN.

Boiman *et al.* [2] argued that two practices can lead to a significant degradation of the methods based on nearest-neighbour distance estimation; thus, these practices should be avoided:

- **Descriptor quantisation:** Quantisation of descriptors can cause a large loss of information for non-parametric classifiers; these classifiers do not have a training phase to compensate for this loss.
- **Image-to-image distance:** Measuring image-to-class distance will generalise the Nearest-Neighbour (NN) search to class-matching instead of image-matching; thus, non-parametric classifiers will cope better with intra-class variations. This is particularly important for handwriting patterns with variations even within the same style (writer).

An improvement of the Naïve Bayes Nearest-Neighbour (NBNN) classification has been proposed in [1], which increases the classification accuracy and better scaled to a large number of classes (viz., run-time of improved NBNN grows with the log of the number of classes rather than linearly).

Hence, the main contributions in this paper are: The application of Local NBNN with a novel matching constraint to the problem of writer identification, and the introduction of a normalisation factor in order to cope with the problem of unbalanced data.

This paper is organised as follows: In the next section, related work will be presented. In Section 3 the proposed method will be discussed, followed by the experimental results in Section 4 and conclusions in the final section.

2. Related work

Since the seventies, several writer identification and verification methods have been proposed and most are summarised in a survey by [3] until 1989. A comprehensive review of a large number of publications in the last 20 years can be found in ([4]–[6]).

A thorough evaluation of both texture-based and allograph-based features for writer identification is found in [4]. Features extracted from contours, contour-hinges, and run-length histograms are used as texture features, while writer-specific grapheme emission PDF (Probability Density Function) is used as an allographic feature, where the writer is characterised by a stochastic pattern generator producing graphemes. A detailed analysis of the performance of feature combinations is also included in [4].

As yet, a wide variety of features has been used for the task of writer identification, such as Quill features [7], run-length based features ([8]–[12]), contour-based features ([13], [14]), allographic features ([15]–[18]), as well as texture- and gradient-based features ([19]–[22]).

Working with cursive handwriting in contemporary documents reveals the difficulties of character/word segmentation, or even only reliable contour fragments extraction. On the other hand, texture- and gradient-based features showed very good results for the task of writer identification ([4], [20]–[23]). Therefore, we propose a segmentation-free method using Scale Invariant Feature Transform (SIFT) descriptors [24] as basis for our improved Local NBNN classification.

3. Proposed method

We propose an offline, text-independent, and segmentation-free writer identification method based on Local NBNN classification. First, both query and labelled images of handwritten pages are converted to grey scale using the weighted sum of RGB channels, whereas binary images are left without conversion. Then keypoints are detected and descriptors are calculated from all images. In order to match the calculated descriptors, a learning-free matching algorithm is used due to the fact that in many practical cases (as well as in many public datasets) the number of samples per writer is very small. A non-parametric learning-free classifier is proposed by Boiman *et al.* [2] and they demonstrated state-of-the-art results for image classification tasks. The two main limitations of this approach are: The need to search for a neighbour in each class, and the bias toward classes with more descriptors. While the first problem is tackled by McCann *et al.* [1], we propose a normalisation step in order to tackle the second problem. Details are presented in the following subsections.

3.1. Keypoints detection and feature extraction

Dense keypoints detection algorithms such as SIFT [24] or Features from Accelerated Segment Test (FAST) [25] are used for our proposed method in order to provide a sufficient number of keypoints for reliable nearest-neighbour search. We experimented with SIFT and FAST keypoints separately and the respective results for each type of keypoints are presented in Section 4. No combination of these two types of keypoints has been investigated in this work so far.

For SIFT keypoints we used the default parameters as proposed in the original publication [24].

For FAST keypoints, we used a circular neighbourhood of 16 pixels around every pixel p in the image as proposed in [25]; see Fig. 1.

p is classified as a keypoint if there are n contiguous pixels in the surrounding circle satisfying one of these conditions:

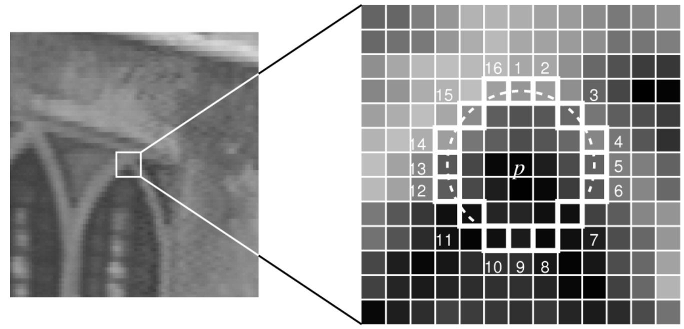

Figure 1: FAST keypoint detection (Reproduced from [25]).

- $\forall i \in n : I_i > I_p + t$
- $\forall i \in n : I_i < I_p - t$

I_p is the intensity of the candidate pixel and I_i is the intensity of any pixel that belongs to n. t is a threshold to be selected manually. We set $n = 9$ and $t = 0$ in all of our experiments

The corner strength is defined in [25] as the maximum value of t for which the segment test of that corner point is passed. We used the 70% of keypoints with highest strength value.

Vectorial SIFT descriptors are used for both SIFT and FAST keypoints representation.

3.2. Matching

A state-of-the-art Naïve Bayes Nearest-Neighbour (NBNN) classifier has been proposed by Boiman *et al.* [2]. They showed that conditional class probabilities can be well approximated by the squared Euclidean distance to the nearest feature vector belonging to the correct class:

$$\hat{C} = \underset{C}{\text{argmin}} \left[\sum_{i=1}^{n} \parallel d_i - \text{NN}_c(d_i) \parallel^2 \right], \qquad (1)$$

where $\hat{C}$ is the predicted class of the query image, C is the set of all classes, n is the number of query descriptors, d_i is a descriptor in the query image and $\text{NN}_c(d_i)$ is the nearest-neighbour of d_i in class c.

In other words, it suffices to find the class with the minimum sum of squared Euclidean distances of its feature vectors to those of the query image.

McCann *et al.* [1] presented the Local Naïve Bayes Nearest-Neighbour (Local NBNN) algorithm as an improvement to the NBNN algorithm. This improvement involved increasing both the classification accuracy and the classification speed; therefore it can also better scale to a large number of classes.

The basic idea of Local NBNN is eliminating the need to search for a nearest-neighbour match in all classes; instead, only the classes within a certain neighbourhood of the query descriptor in feature space are considered. Fig. 2 illustrates the main difference between NBNN and Local NBNN.

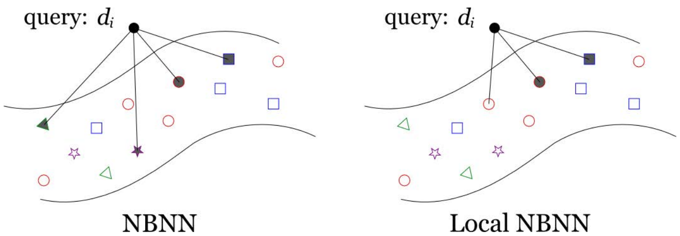

Figure 2: The difference between NBNN and Local NBNN. NBNN forces a query descriptor d_i to search for its closest neighbour in every class (given as filled icons). Local NBNN requires the query descriptor to only consider the closest neighbour in the closest classes. Reproduced from [1].

Our proposed method is based on the Local NBNN Algorithm (2) in [1], which we reformulate in equations as follows:

$$Dist^c_{local} = \sum_{i=1}^{n} \Big[(\parallel d_i - \phi(\mathrm{NN}_c(d_i)) \parallel^2 - \parallel d_i - \mathrm{N}_{k+1}(d_i) \parallel^2) \Big], \tag{2}$$

$$\hat{C} = \underset{C}{\mathrm{argmin}} \left(Dist^c_{local} \right), \tag{3}$$

where

$$\phi(\mathrm{NN}_c(d_i)) = \begin{cases} \mathrm{NN}_c(d_i) & \text{if } \mathrm{NN}_c(d_i) \leq \mathrm{N}_{k+1}(d_i) \\ \mathrm{N}_{k+1}(d_i) & \text{if } \mathrm{NN}_c(d_i) > \mathrm{N}_{k+1}(d_i), \end{cases}$$

and $\mathrm{N}_{k+1}(d_i)$ is the neighbour $(k+1)$ of d_i.

One search index is created for all the classes using the kd-trees implementation provided by the FLANN (Fast Library for Approximate Nearest Neighbours) library [26] to have efficient nearest-neighbour search. Then the closest 10 neighbours (the parameter value is determined experimentally by [1] and confirmed by all of experiments with handwriting images) are retrieved for each descriptor in the query handwriting image.

As in [1], we used the distance to the $k+1$ nearest neighbours ($k = 10$) as a "background distance" to estimate the distances of classes which were not found in the k nearest neighbours.

In order to avoid the matching of descriptors with different keypoint-orientations, we neglected any match between descriptors with a keypoint-orientation difference larger than a pre-defined threshold by adding a matching condition; see Subsection 3.3. Then we normalise the total class distance by using the number of keypoints for each class in order to cope with the problem of unbalanced data; see Subsection 3.4.

3.3. Orientation threshold

Typically, handwriting patterns yield many keypoints with similar features but different orientations. As the keypoint orientation of certain features is a characteristic of the writing style of specific writers, the orientation is a discriminative property of these features. In order to match only features with similar orientation, we propose the following matching condition:

$$|Ort_{kpt1} - Ort_{kpt2}| \leq T_r, \tag{4}$$

where Ort_{kpt1} and Ort_{kpt2} are the orientations of keypoints (in degrees) which features to be matched, and T_r is the orientation-difference threshold.

In other words, features with orientation differences larger than a pre-defined threshold are not considered as valid for a match. The orientation-difference threshold can be estimated from the amount of rotation in handwriting due to line-skew or image rotation, which can be calculated automatically using run-length (or any other) skew-estimation method. From both considerations and the result of the test with a challenging dataset shown in Fig 3, where the best identification rate can be obtained from a 10 to 13 degrees difference, we were able to fix the value of this parameter to 10 degrees in all of our experiments. Note that this matching condition is not used for FAST keypoints, because no orientations were calculated by the original work in [25].

An orientation value is assigned to each keypoint by calculating the dominant directions of local gradients as proposed by Lowe [24]. The interpolated peak position by parabola fitting is used as an orientation estimate. The plot in Fig. 3 shows the impact of our matching condition in Eq. 4 on the identification rate. The identification rate is defined as the ratio of correctly identified samples over the total number of samples.

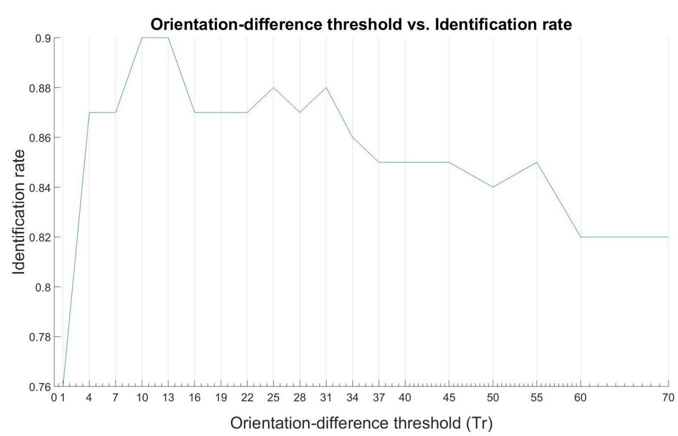

Figure 3: The identification rate versus orientation-difference threshold. the data is based on the validation set from ICFHR-2016 competition of writer identification, task 1A [27]

3.4. Class distance normalisation

Data sets are considered as unbalanced when at least one class is represented by only a small number of samples. Typically in the case of writer identification, the labelled (training) samples are not equally distributed among the writers (classes) in many practical scenarios. One of the main limitations of NBNN-based methods is the bias towards classes with a large number of keypoints; this limitation can reduce the identification rate significantly in the case of unbalanced data. Therefore, we normalise the final distance of each class in equation 3 by the number of keypoints in the respective class:

$$\hat{C} = \underset{C}{\operatorname{argmin}} \left(\frac{Dist^{c}_{local}}{K_c} \right), \tag{5}$$

where K_c is the number of keypoints for each class c.

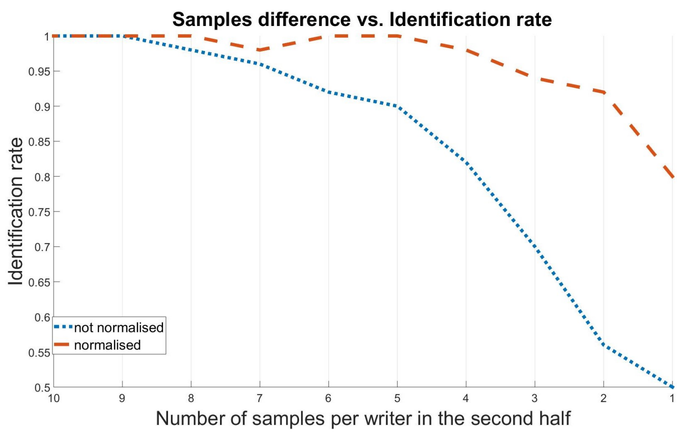

Figure 4: Comparison between the identification rate with and without normalisation. 10 samples for each of 50 writers are used for the test. The number of samples for the randomised half of the writers is fixed, while we decrement the number of samples for the other half from 10 to 1. The x-axis represents the number of samples per writer for the second half of writers.

In order to demonstrate the impact of the proposed normalisation, we measured the identification rate while we reduce the number of samples per writer for half of the dataset. We used the ICDAR-2011 dataset for musical scores [28] due to the fact that this dataset has a large number of samples (10 samples) per writer for testing. The graph of this experiment in Fig. 4 markedly shows the positive effect of the normalisation: The identification rate drops much slower with normalised class distance as the difference between the number of samples per writer increases.

4. Experimental results

We evaluated our method on several public datasets with different character sets, languages, and even musical scores to demonstrate the generality of the proposed approach. The images of ICDAR-2011 [29], ICDAR-2011 for musical scores [28], ICFHR-2012 [30] and ICDAR-2013 [31] datasets are binary, while the images in CVL [32] and ICFHR-2016 [27] datasets are given in RGB format. Important properties of these datasets are the variation of the number of writers (from 26 to 400), the variation of the number of pages per writer (from 2 to 20), and the variation of the amount of handwritten text per page.

A comparison with the state-of-the-art is presented for each dataset separately. The *identification rate* is the standard measure used in writer identification methods and is defined as the ratio of correctly identified samples over the total number of samples. In case of Top-N criterion, only Top-1 ranking is applied. It is important to note that all parameters were kept constant for all experiments.

We followed the exact evaluation criteria for each dataset. Results with different evaluation criteria are not considered; for example, SRS-LBP-11out method from [33] used the average performance of the cross-validation whereas contour-Zernike method from [34] partitions ICDAR-2013 and CVL datasets into training and test sets. Although we propose a segmentation-free method for robustness and reliability reasons, we considered segmentation-based methods for the comparison as well; see Tables 1, 2, 3, 4, 5 and 6. All the results we present in these tables are for the Normalised Local NBNN with orientation threshold, unless stated otherwise.

In Table 6, we present the official result of our participation in ICFHR-2016 competition [27] with SIFT keypoints but without normalisation; the results of SIFT keypoints and FAST keypoints with normalisation are presented as well.

Since a large number of keypoints is needed for reliable nearest neighbour search, it is expected that identifying writers (classes) with small number of samples will be less accurate. The existence of samples with different character sets but from the same class is not expected to enhance the performance in any way, because our method is not designed for a cross-character set identification.

Although the number of samples is the same for all writers in ICFHR-2016 competition, the amount of handwritten text varies significantly between the samples; see Fig. 5. The normalisation step has larger positive impact in such cases. Furthermore, a very high identification rate is obtained for the CVL dataset despite the large number of classes which clearly shows the scalability of our method.

5. Conclusion

We present an improved Local NBNN classification method for the task of writer identification given small sets of unbalanced sample data. The orientations of keypoints are used to restrict the matching between descriptors to only those with similar orientation. Distances to classes are normalised by the number of keypoints for each class. The method has been tested with several public datasets of different writing systems including musical scores and state-

Method	Result % Full/Cropped	Dataset details
Our Method with SIFT keypoints	**100**/96.6	26-writer 208-pages 8-pages per writer (2-English, 2-French, 2-German, 2-Greek) Leave-one-out Top-1
Our Method with FAST keypoints	**100/98.6**	
TSINGHUA [29] 1st in competition	95.5/90.9	
CS-UMD [29] 2nd in competition	95.5/66.8	
TEBESSA [29] 2nd in competition	98.6/87.5	
Lehigh [35]	97.1/—	

TABLE 1: ICDAR-2011 [29], using full images / using only two lines per image.

Method	Result %	Dataset details
Our Method with SIFT keypoints	98.2	50-writer 1000-pages 20-pages per writer Musical scores Training and Test sets
Our Method with FAST keypoints	99.4	
PRIP02-combination [28]	77	
TUA03-SVMOAA [28]	76.6	
Fisher Vector [18]	**99.5** Segmentation-based	

TABLE 2: ICDAR-2011 for musical scores [28].

Method	Result %	Dataset details
Our Method with SIFT keypoints	96	100-writer 400-pages 4-pages per writer (2-English, 2-Greek) Leave-one-out Top-1
Our Method with FAST keypoints	**98.8**	
TEBESSA-c 1st in competition [30]	94.5	
TSINGHUA 2nd in competition [30]	92.8	
SIFT+Contour-directional [21]	96.8	

TABLE 3: ICFHR-2012 [30].

Method	Result %	Dataset details
Our Method with SIFT keypoints	92.4	250-writer 1000-pages 4-pages per writer (2-English, 2-Greek) Leave-one-out Top-1
Our Method with FAST keypoints	**97.9**	
CS-UMD-a 1st in competition [31]	95.1	
CS-UMD-b 2nd in competition [31]	95	
SIFT+Contour-directional [21]	96.2	
SRS-LBP metric [33]	96.9	

TABLE 4: ICDAR-2013 [31].

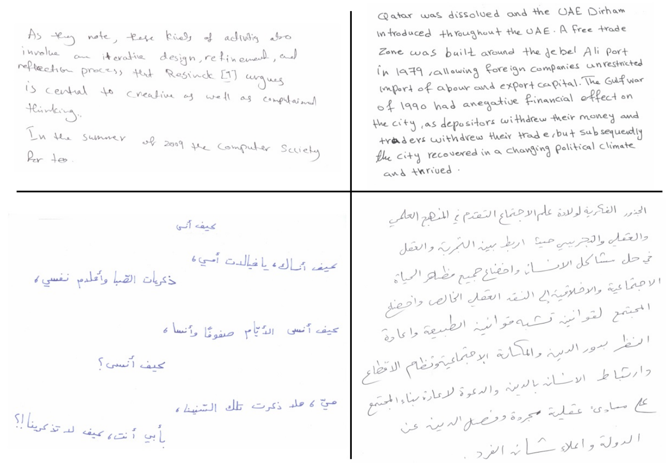

Figure 5: The amount of handwritten text varies significantly between the samples in ICFHR-2016 dataset.

Method	Result %	Dataset details
Our Method with SIFT keypoints	99.3	311-writer 1609-pages 7/5-pages per writer English Leave-one-out Top-1
Our Method with FAST keypoints	**99.8**	
CS-UMD 1st in competition [32]	97.9	
TSINGHUA 2nd in competition [32]	97.7	
SRS-LBP metric [33]	98.6	

TABLE 5: CVL [32].

of-the-art results were obtained in all experiments with a fixed parameter set..

Acknowledgement

This work has been funded by the German Research Foundation (DFG) within the scope of the Collaborative Research Centre (SFB 950) at the Centre for the Study of Manuscript Cultures (CSMC) at Universität Hamburg.

Method	Result % 1A/1B	Dataset details
Our Method with SIFT keypoints [27] without normalisation	90.33/87.67	400-writer 800-pages 2-pages per writer (2-Arabic / 2-English) Training and Test sets
Our Method with SIFT keypoints with normalisation	91.67/87.67	
Our Method with FAST keypoints	**99.7/97.7**	
Nuremberg [27]	89.33/84.67	
CVC [27]	80.67/80.33	

TABLE 6: ICFHR-2016 competition, tasks 1A and 1B [27].

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