Offline Signature Verification using Textural Descriptors

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Abstract. Offline signature verification has been the most commonly employed modality for authentication of an individual and, it enjoys global acceptance in legal, banking and official documents. Verifying the authenticity of a signature (genuine or forged) remains a challenging problem from the perspective of computerized solutions. This paper presents a signature verification technique that exploits the textural information of a signature image to discriminate between genuine and forged signatures. Signature images are characterized using two textural descriptors, the local ternary patterns (LTP) and the oriented basic image features (oBIFs). Signature images are projected in the feature space and the distances between pairs of genuine and forged signatures are used to train SVM classifiers (a separate SVM for each of the two descriptors). When presented with a questioned signature, the decision on its authenticity is made by combining the decisions of the two classifiers. The technique is evaluated on Dutch and Chinese signature images of the ICDAR 2011 benchmark dataset and high accuracies are reported.

Keywords: Offline Signature Verification · Local Ternary Patterns (LTP) · Oriented Basic Image Features (oBIFs) · Support Vector Machine (SVM)

1 Introduction

Biometric authentication [35, 33] represents a validation process that relies on the unique biological characteristics of an individual to verify the claimed identity. Typically, biometric systems compare the captured biometric data with the authentic data stored in the database. Among various biometric modalities, signatures represent one of the oldest and most commonly employed traits. Not only acquisition of signatures is simple and does not require any specialized hardware, they enjoy widespread social acceptability for authentication purposes in banking, legal and official documents. Signatures are produced as a result of complex elementary movements, or strokes, which are concatenated in such a way that their execution produces the desired trajectory with the minimal effort [3].

Two types of signatures are employed in the authentication systems, offline (static) and online (dynamic). Offline signatures are images of signatures digitized from paper versions using a camera or a scanner. Online signatures, on the other hand, are acquired on specialized devices which are capable of recording the signature trajectories (and other useful information like pressure etc.). While online signatures carry more information as compared to their offline counterparts [3, 2], a major factor limiting their widespread acceptability is the requirement of special hardware for acquisition purposes. This study focuses on the former of the two techniques, that is, offline signature verification. From the view point of technical contribution, the signature verification techniques reported in the literature either target the feature extraction [28, 29, 25] or the classification part of the system [15, 30, 26].

A number of International competitions have also been organized on offline signature verification [4, 18, 20, 19] in conjunction with the various editions of International Conference on Document Analysis and Recognition (ICDAR). Such competitions not only serve to provide an idea on the state-of-the-art performance on this problem but also allow an objective comparison of various techniques under the same experimental settings. The increasing number of participants in these competitions speaks off the research attention this problem has been attracting over the years.

In this study, we investigate the effectiveness of two textural measures in characterizing signatures, the oriented Basic Image Features (oBIFs) and Local Ternary Patterns (LTP). For classification, we employ the Support Vector Machine (SVM) classifier. Two separate classifiers are trained (using dissimilarity measures computed from each of the features) and each classifier aims to discriminate between genuine and forged signatures. The (partial) decisions of the two SVMs are then combined using the sum rule. Experiments on the benchmark ICDAR 2011 signature verification dataset report low error rates. More details are presented in the subsequent sections of the paper.

2 Related Works

Signature verification has been researched for many decades and the contributions have been summarized in a number of reviews on this problem [16, 17, 36]. As discussed earlier, the techniques reported in the literature focus either on enhancement of feature extraction or on proposition of classifiers to effectively discriminate between genuine and forged signatures. Among relatively recent contributions to verification of signatures, Guerbai et al. [13] propose a writer-independent framework that employs curvelet transform with the One-Class Support Vector Machine (OC-SVM) using only genuine signatures in the training. Experiments on CEDAR and GPDS signature datasets report low error rates. Likewise, Zois et al. [37] propose a grid-based template matching scheme with SVM classifier for verification of signatures and evaluate the technique on four different signature databases. In another work, Soleimani et al. [31] propose Histogram of Oriented Gradients (HOG) and Discrete Radon Transform (DRT) with Deep Multitask Metric Learning (DMML).

Among other recent works, Hafemann et al. [14] present an interesting technique where features are extracted using deep convolutional neural networks in a writer-independent mode while classifiers are trained in a writer-dependent mode. Experimental study of the system is carried out on GPDS-960 and Brazilian PUC-PR datasets reporting promising results. A writer-independent approach based on deep metric learning is presented in [27]. The model learns signature embeddings in a high dimensional space. The technique relies on comparing triplets of two genuine and one forged signature for performance enhancement. Das et al. [7] propose to build multi-script signatures aggregating many single-script signatures. An analysis on nine different signature databases in five scripts conclude that Bhattacharyya distance can be employed to analyze multi-script against single-script scenarios. Diaz et al. [8] propose a set of linear and non-linear transformations which simulate the signing process. This allows duplicating the signatures. The duplicator is evaluated using four existing signature verification techniques on two public datasets resulting in an enhancement in the overall performance. In other recent studies, Bouamra et al. [5] exploit run-length features with a One-Class Support Vector Machine (OC-SVM) while Zois et al. [38] propose to compute transitions between asymmetrical arrangements of pixel structures.

We presented an overview of the recent works on offline signature verification. The discussion by no means is exhaustive and serves to provide an idea of the recent trends in this domain. Comprehensive surveys on verification of signatures can be found in [16, 17, 36].

3 Methods

This section presents the details of the proposed technique to validate the authenticity of a signature. An overview of the key steps involved in the methodology is presented in Figure 1. Like any pattern classification system, the technique comprises two key phases, training and evaluation. Training involves extracting features from images of signatures and training two separate SVM models using dissimilarity measures computed from the two features (LTP and oBIFs histograms). During classification, a questioned signature image is fed to the system, features are extracted and decisions of the two SVMs are combined to arrive at a final decision on the genuineness of the signature. Details on feature extraction, dissimilarity measure and classification are presented in the following.

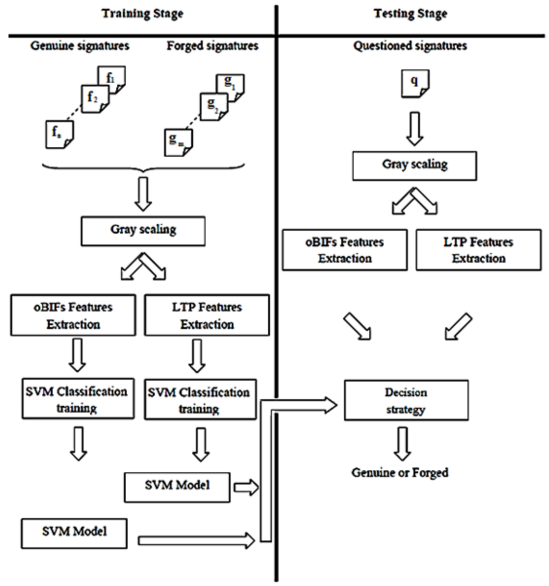

Fig. 1. An overview of the key steps in the proposed technique

3.1 Local Ternary Patterns

Local binary patterns (LBP) [24] and many of its variants [6] have been widely employed to characterize the textural information in an image and have reported promising performance on diverse problems. Among different variants of original LBP descriptor, Tan and Tiggs [32] proposed an extended version called Local Ternary Pattern (LTP). The key idea of the LTP descriptor is to extend the two valued $(0, 1)$ LBP codes to three values $(-1, 0, 1)$. LTP compute a representation based on the distribution of neighboring pixels into three values instead of thresholding values to 0 and 1, as summarized in Equation 1.

$$LTP_{P,R} = \sum_{p=0}^{P-1} 2^p (i_p - i_c); s(x) = \begin{cases} 1, x \geq t \\ 0, -t < x < t \\ -1, x \leq -t \end{cases} \quad (1)$$

Considering t to be the threshold value and x be the value of the central pixel, the upper and lower threshold values are set as $x+t$ and $x-t$ respectively. Neighboring pixels (with reference to the central pixel) taking values between these thresholds are assigned 0. A value 1 is assigned to the pixels with value greater than the upper threshold while the value -1 is assigned to the pixels with value less than the lower threshold.The generated ternary code is divided into two new codes; the upper pattern and the lower pattern. Finally, an LTP histogram is computed that is employed as feature to characterize the signature. Figure 2 illustrates the computation of LTP on a 3×3 block of an image.

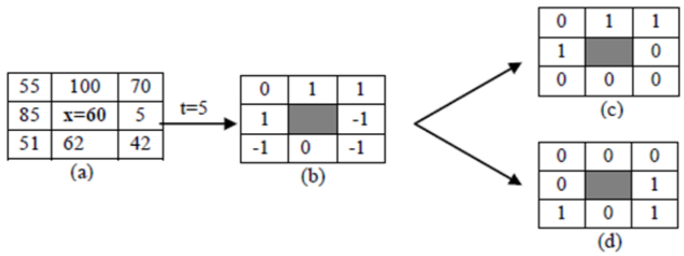

Fig. 2. Computation of LTP code (a): 3×3 Image Block (b):Ternary Pattern (c): Upper Pattern (d): Lower Pattern

3.2 oBIFs Histogram

Since its first appearance in [12, 11], the oriented Basic Image Features (oBIFs) have been employed as an effective textural descriptor for applications like digit recognition [9, 10], character recognition [21], classification of texture [23] and identification of writers from handwritten documents [22, 1]. The oriented Basic Image Features (oBIFs), an extending the Basic Image Features (BIFS) [12], combine local orientation with the local symmetry information. The computation of oBIFs involves classifying each pixel in the image into one of the local symmetry classes based on the response of a bank of six Derivative-of-Gaussian (DoG) filters. The computation of features is controlled by the scale parameter σ and the supplementary parameter ϵ. The defined classes include dark line on light, light line on dark, dark rotational, light rotational, slope, saddle-like or flat. In addition to the symmetry class, an orientation is also assigned to each pixel, orientations being quantized into n possible values. No orientation is assigned if the pixel is attributed to the dark rotational, light rotational or the flat class, n possible orientations can be assigned to the dark line on light, light line on dark and the saddle-like classes while $2n$ possible orientations can be assigned for the slope class. This gives a feature vector of dimension $5n+3$ for each image.

From the view point of signature verification problem, each signature image can be viewed as a unique texture that can be exploited to characterize the corresponding individuals. In our implementation, we fix the orientation quantization parameter to $n = 4$ resulting in a total of $(5 \times 4 + 3)$ 23 entries in the oBIFs dictionary. The number of pixels in each of the 23 classes is counted, the resulting histogram is normalized and is employed as the signature descriptor. Figure 3 illustrates a sample handwritten signature encoded using oBIFs.

3.3 Dissimilarity Measure

Unlike the typical classification framework where features extracted from classes under study are directly fed to the classifier, signature verification requires modeling of intra and inter class distances to authenticate the validity of a questioned

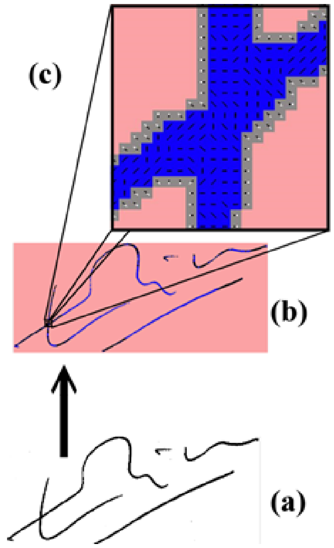

Fig. 3. Computation of oBIFs code (a): Original signature image (b): Signature encoded using the oBIFs (c): A segment of the encoded signature

signature. While the signatures of different individuals occupy different regions in the feature space, the dissimilarities between the signatures (feature vectors) of the same individuals are likely to be low. On the other hand, the inter-writer dissimilarities are likely to be high. Exploiting the same idea, we employ the L1 norm to compute the dissimilarity between two signatures, $Z = |V - Q|$, where V and Q represent the feature vectors of two signatures being compared. The dissimilarities are computed using pairs of signature images (genuine and forged pairs) and are fed to the training model as discussed in the following.

3.4 Decision Strategy

For classification, we train separate Support Vector Machine (SVM) classifiers [34] for LTP and oBIF features. It is important to mention that we employ a write-independent approach where a single global classifier is designed rather than training separate models for each of the individuals (writer-dependent approach). For a questioned signature image, the dissimilarity measures computed from LTP and oBIF features are fed to the respective classifiers. Each classifier outputs the scores (probabilities) of the signature being genuine or forged. The scores of the two classifiers are added to arrive at the final decision about the genuineness of a given signature as summarized in Equation 2.

$$f = max(f_F(x_{LTP}) + f_F(x_{oBIF}), f_G(x_{LTP}) + f_G(x_{oBIF})) \quad (2)$$

f_F and f_G refer to genuine and forged scores respectively while x_{LTP} and x_{oBIF} refer to the dissimilarities computed using LTP and oBIF features. f is the maximum value selected from sum of genuine and forged scores provided by the two SVM classifiers. From the view point of implementation details, the training of the SVM requires selecting two parameters, the regularization parameter (C) and the Radial Basis Function (RBF) kernel parameter (σ). In our experiments, we investigated different values of σ and the soft margin parameter C in the interval $[1, 50]$ to empirically select the optimal combination.

4 Experiments and Results

This section presents the details of the database employed in our study along with the experimental protocol and the realized results. To evaluate the system performance standard metrics including accuracy, False Acceptance Rate (FAR) and False Rejection Rate (FRR) are used. To objectively compare the performance of our system with other techniques, we have employed the dataset from the International Competition on Signature Verification (ICDAR Sig-Comp2011) [18] that was held in conjunction with the International Conference on Document Analysis and Recognition (ICDAR 2011). The competition included both online and offline tasks and the offline datasets contained signatures of Chinese and Dutch signers. We employ the same dataset in our experimental study.

The Dutch training set includes signature images of 10 signers and for each contributor, there are, 24 genuine signatures and, on the average, 12 skilled forgeries. Likewise, for the Chinese signatures, there are 10 signers and for each signer there are 24 genuine samples and on the average 34 skilled forgeries. The test sets of both the subsets include a *'reference'* and a *'questioned'* set. The reference signatures are the known genuine signatures while the questioned signatures are either genuine or forged. The Dutch test set contains 648 reference signatures and 1286 questioned signature for 54 authors while the Chinese test set includes 116 reference and 487 questioned signatures provided by 10 authors. A summary of the these statistics is presented in Table 1.

Table 1. Number of Authors (A) and number of Genuine (G) (Reference (GR) and Questioned (GQ)) and Forged (F) (Questioned Forged (FQ)) Signatures in the ICDAR Sig-Comp2011 Dataset

Dataset	**Training Set**			**Test Set**			
	A	**G**	**F**	**A**	**GR**	**GQ**	**FQ**
Dutch	10	240	123	54	648	648	638
Chinese	10	235	340	10	116	120	367

We carried out a comprehensive series of experiments on the Sig-Comp2011 dataset. In case of LTP features, we investigated different combinations of the radius r and the number of neighbors n. The threshold t in computation of LTP features was fixed to $t = 0.3$ after empirical study in the range $t \in [0.1, 0.9]$ with steps of 0.1. The accuracies on the Dutch and Chinese test sets using different setting of LTP computation are summarized in Table 2.

Table 2. Accuracy on the Dutch Chinese Test Set with LTP Features

Descriptor	**LTP Parameters**			**Accuracy**	
	r	n	*Dim.*	Dutch	Chinese
LTP ($t = 0.3$)	1	8	118	91.53	74.74
	2	8	118	78.55	74.74
	4	8	118	76.38	74.54
	8	8	118	65.11	74.95
	1	16	486	**92.31**	**75.36**
	2	16	486	84.23	75.36
	4	16	486	75.91	75.36
	8	16	486	71.09	75.36
	16	16	486	72.03	75.36

Similar to LTP features, we also study the impact of scale parameter σ ($\sigma = 1, 2, 4, 8, 16$) while computing the oBIFs histogram on the overall accuracy. The accuracy values on Dutch and Chinese signatures on various values of σ are summarized in Table 3.

Table 3. Accuracy on the Chinese and Dutch Test Sets with oBIF histograms

Descriptor	**Parameters**		**Accuracy**	
	σ	*Dim.*	Dutch	Chinese
oBIFs	2	23	**96.19**	66.94
	4	23	78.79	72.69
	8	23	50.35	73.72
	16	23	50.27	**75.98**

It can be seen that LTP features with $r = 1$ and $n = 16$ outperform other configurations reporting the highest accuracies on both Dutch (92.31%) and Chinese (75.36%) signatures. In case of oBIF histograms accuracies of 95.19% and 75.98% are reported on the Dutch and Chinese signatures respectively. To study the effectiveness of combining the decisions of classifiers trained on LTP and oBIFs individually, we chose the best set of parameters for each of the features. The decisions are combined according to the fusion rule presented in Equation 2. Table 4 summarizes the combined accuracies on the two datasets where it can be seen that overall accuracies of 97.74% and 75.98% are reported on the Dutch and the Chinese signatures respectively.

We also compare the performance of the proposed technique with those of the systems submitted to the ICDAR 2011 competition [18]. A total of seven systems

Table 4. Accuracy on the Chinese and Dutch Test Sets by combining the decisions of individual classifiers

Descriptor	**Parameters**	**Dim.**	**Dutch**	**Chinese**
LTP	$r = 16$,$n = 1$,$t = 0.3$	486	92.31	75.37
oBIFs	$\sigma = 16$ $\epsilon = 0.001$	23	96.19	75.97
Combined	-	-	97.74	75.98

were submitted to the competition. The evaluation protocol in our experiments was kept similar to that of the competition to allow a meaningful comparison. The comparative results are summarized in Table 5 and Table 6 for Dutch and Chinese signatures respectively. It can be observed from the two tables that the proposed technique as well as the participating systems report high accuracies on the Dutch signatures as compared to the Chinese signatures. This may be attributed to the challenging images in the Chinese dataset as well as presence of noise in the signature images. Comparing the performance of our technique with the competition participants, it can be seen that the proposed technique outperforms the submitted systems on Dutch signatures (Table 5) while it is ranked second on the Chinese signatures (Table 6). These high accuracies validate the effectiveness of LTP and oBIFs in discriminating between genuine and forged signatures.

Table 5. Comparison of proposed technique with participants of ICDAR 2011 competition [18] - Dutch Signatures

Rank	**ID**	**Accuracy**	**FRR**	**FAR**
1	**Proposed Method**	**97.74**	**2.16**	**2.36**
2	Qatar-I	97.67	2.47	2.19
3	Qatar-II	95.57	4.48	4.38
4	HDU	87.80	12.35	12.05
5	Sabanci	82.91	17.93	16.41
6	Anonymous-I	77.99	22.22	21.75
7	DFKI	75.84	23.77	24.57
8	Anonymous-II	71.02	29.17	28.79

5 Conclusion

We presented an effective technique to characterize signature using textural descriptors. The textural information in a signature image is captured using two descriptors, the local ternary pattern and the oriented basic image features. Different configurations are investigated during the feature extraction step to find the optimal set of parameters for each of the features. Distances between the feature vectors (of genuine and forged signatures) are employed to train a separate

Table 6. Comparison of proposed technique with participants of ICDAR 2011 competition [18] - Chinese Signature

Rank	ID	Accuracy	FRR	FAR
1	Sabanci	80.04	21.01	19.62
2	**Proposed Method**	**75.98**	**24.07**	**20.00**
3	Anonymous-I	73.10	27.50	26.70
4	HDU	72.90	27.50	26.98
5	DFKI	62.01	37.50	38.15
6	Anonymous-II	61.81	38.33	38.15
7	Qatar-I	56.06	45.00	43.60
8	Qatar-II	51.95	50.00	47.41

SVM classifier for each of the two descriptors. During verification, the decisions of the two SVMs are combined to come to a final conclusion about the authenticity of a signature. The technique is evaluated on the ICDAR 2011 benchmark dataset containing Dutch and Chinese signatures and high accuracies comparable/superior to the state-of-the-art are reported.

In our further study on this problem, we intend to investigate other textural measures for signature verification and incorporate feature selection techniques to identify the most appropriate textural descriptors for this problem. With multiple features, sophisticated feature as well as classifier combination techniques can also be investigated. Another interesting direction could be to carry out a comprehensive series of experiments by varying the number of signatures in the training set to identify the minimum number of samples required for acceptable performance.

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