Local Directional Strength Pattern for effective Offline Handwritten Signature Verification

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Abstract. Offline handwritten signature verification is one the oldest and widespread biometric identification tools. In various daily life applications, the handwritten signature is used for documents approval and identity verification. Systems that automatically achieve this task are mainly composed of feature generation and verification modules. The more features are robust the best the verification score is. Presently, we introduce the use of the Local Directional Strength Patterns (LDSP) for handwritten signature characterization. This descriptor is associated with SVM classifier to perform the signature verification. Experiments conducted on two public datasets reveal the effectiveness of the proposed descriptor which outperforms several state-of-the-art techniques.

Keywords: Signature Verification, Local Directional Strength Pattern, Support Vector machines, Local Directional Pattern.

1 Introduction

Biometric systems based on offline handwritten signatures analysis are widely required in applications using document papers such as official contracts, transactions, and bank checks. In addition to being well accepted by society as a biometric identification tool, another reason behind the wide use of signatures is the cheap cost of developing Signature Verification Systems (SVS), which benefit from a long experience in forensics domain. Roughly, the offline handwritten verification system can be developed according to the writer dependent approach or the writer-independent approach. In the first case, an SVS is developed for each writer, whereas the second approach consists of developing one SVS for all writers. This makes the writer-dependent verification more effective since learning the signatures of a specific writer is much simpler than learning the signatures of a set of writers. For both approaches, the SVS is composed of two modules which perform respectively, features generation and verification. The state of the art reports a huge variety of methods proposed for the two stages. Regarding the verification task, machine learning techniques such as convolutional neural networks and support vector machines which are the most qualified to detect the forged signatures from the original ones [1-8]. Furthermore, various kinds of descriptors were utilized to generate features over the past years. Among them one can note mathematical transforms such as Wavelets, Contourlets, Curvelets, and Ridgelets which provide static information depicting the signature shape [4-6, 9]. Experiments conducted on various datasets revealed the medium performance of these transforms. That is what led researchers to focus on gradient and texture descriptors to extract pseudo dynamic features. In this respect, Histogram of oriented gradients, Scale invariant features transforms Local Binary Patterns (LBP) and then, Local Directional Patterns showed interesting results on several offline signature datasets [10-14]. Besides, some shape descriptors such as the Histogram of templates and Run length features showed very attractive scores [10, 15-16]. On the other hand, some research works employed Convolutional Neural Networks (CNN) as writer-independent features generators [1-3]. However, a large amount of labeled data is required to derive robust features, whereas handwritten signature datasets contain few samples for each writer. Therefore, data augmentation techniques are commonly used to satisfy this training constraint. On the other hand, huge deep models such as VGG-Net and Res-Net induce a high computation cost, which doesn't automatically lead to higher performance than handcrafted features.

Roughly speaking, results collected on public datasets are sub-optimal and current SVS have not yet achieved the desirable performances. Therefore, researchers focus on combining multiple SVS or on developing more robust features, which can ensure the best tradeoff between intra-writer variability and inter-writer variability. In this respect, some new features were recently proposed such as the Local Difference Features [17-19]. Presently, we propose the Local Directional Strength Pattern (LDSP) as a new handcrafted descriptor for offline handwritten signature characterization. LDSP is an improved implementation of LDP that reduces the histogram size to only six bits highlighting the dominant orientation of the shape edges in the pixel vicinity [20-21]. To achieve the verification task, LDSP is associated with the Support Vector Machines (SVM classifier. Experiments are performed on two public datasets that are CEDAR, and MCYT-75.

The remaining of this paper is organized as follows: Section 2 presents the proposed SVS based on LDSP features. Section 3 details the experimental evaluation of the proposed system, and the last section gives the main conclusions.

2 Methodology

The proposed SVS is developed by associating LDSP features with SVM classifier. The training process is conducted according to the writer dependent protocol, where each writer enrolled in the system has its own SVM. So, the verification task is a binary classification in which, genuine signatures of the considered writer compose the first training class, while random forgeries (genuine signatures of other writers) compose the second training class. The signature verification stage is carried out by using all remaining genuine signatures and imitated signatures (That are called skilled forgeries) of the considered writer.

Recall that LDSP is an improved implementation of the LDP, which considers relative edge responses in eight directions [14].

2.1 Local Directional Strength Patterns

The key element in Local Directional Patterns (LDP) computation is the use of kirsch detector to highlight image edges. The, LDP calculation begins by applying the Kirsch edge detector to extract edge images in eight directions. Then, the maximal edge values for each pixel are considered to derive a single maxima edge image. Each pixel neighborhood undergoes a local binary coding by attributing 1 to the K highest values while putting the others to 0 (K is a user-defined parameter). Derived codes composed of height digits which are converted into decimal values to elaborate the LDP code.

In order to reduce the histogram size and allow a more consistent characterization, the Local Directional Strength Pattern has been introduced [20-21]. Specifically, LDSP modifies the coding of the maximal edge values image. First, a three-bit code is assigned for each edge orientation in the pixel surrounding. Then, codes of both maximal and minimal edge values are concatenated to compose a six-component sequence descriptor. More precisely, the LDSP calculation for negative image goes through the following steps:

1. Apply kirsch detector and generate the Maxima edge image.
2. Considering pixel vicinity, assign a three-bit binary code going from 000 to 111for each neighbor as shown in figure (1.c).
3. LDSP code corresponds to the concatenation of binary codes of both maximal and minimal values.
4. LDSP descriptor of the full image corresponds to the histogram of all LDSP codes.

Figure 2 illustrates the LDSP computed for a signature image.

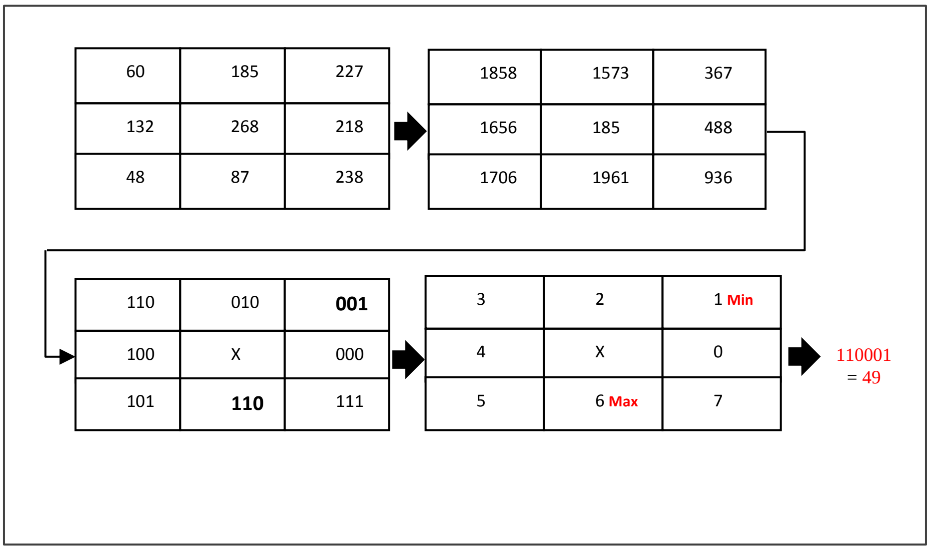

Fig. 1. LDSP computation for a central pixel

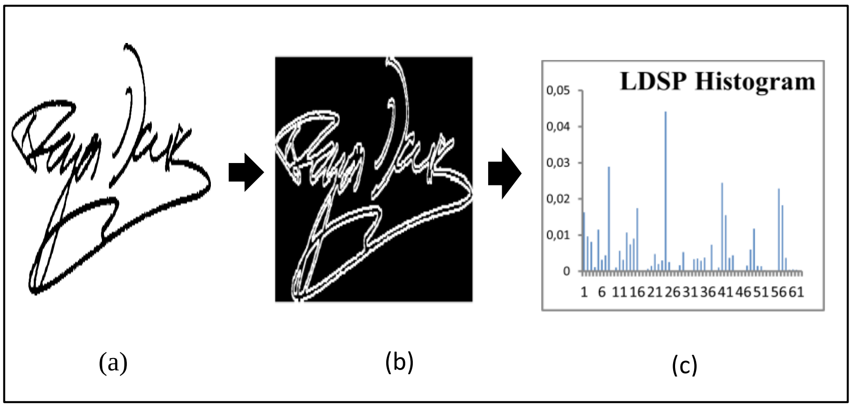

Fig. 2. LDSP histogram for a signature image: (a) Signature image, (b) Maxima edge image, (c) LDSP histogram.

2.2 Support Vector Machine

To achieve the verification task, which is a binary classification problem, Support Vector Machines classifier is utilized. This is a statistical learning theory method that is originally designed to solve binary classifications [22-23]. The training process aims to find the optimal linear separation between to classes. Let consider a learning set $\{(x_i, y_i)\}$, where: $i = 1, ..., n$. x_i represent the training samples, while $y_i \in \{-1, +1\}$ are the class labels.
The decision function is given by the following equation:

$$F(x) = sign\left(\sum_{i=1}^{Sv} \alpha_i K(x_i, x) + b\right) \quad (1)$$

α_i: Lagrange multiplier of x_i.
S_v: Number of support vectors that are x_i having non-zero α_i.
b: Bias of the decision function.
K: Kernel function.

In this work, the Radial Basis Function kernel is utilized. This kernel is depicted in equation (2).

$$RBF(x_i, x) = exp\left(\|x_i - x\| \; 2/\delta 2\right) \quad (2)$$

γ: User-defined parameter.

3 Experimental Results

To evaluate the performance of the LDSP-SVM verifier, two offline handwritten signature datasets were used in experiments:

- CEDAR corpus: it is containing 55 signers each of which has 24 genuine signatures and 24 skilled forgeries signatures.
- MCYT-75 corpus: it is composed of signatures belonging to 75 individuals. There are 15 genuine signatures and 15 skilled forgeries for each individual.

Figure (3) depicts some samples from adopted datasets.

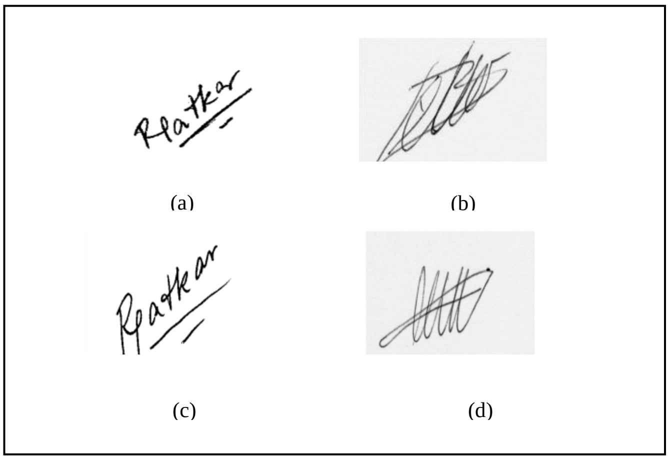

Fig. 3. Signature samples from adopted datasets. Genuine samples: (a) CEDAR, (b) MCYT 75. Forgeries: (c) CEDAR, (d) MCYT-75.

The performance assessment is based on three error types. The False Acceptance Rate (FAR) which is the percentage of skilled forgeries accepted as genuine by the system, the False Rejection Rate (FRR), which are genuine signatures considered as forgeries by the system, and the Average Error Rate (AER). Additionally, DET curves are utilized. For each writer, experiments were carried out by using two training sets. The first set contains 10 genuine signatures to train the SVM, while in the second test, a more challenging protocol is adopted since the number of training signatures is limited to 5 samples. In both experiments, all remaining genuine signatures as well as all skilled forgeries are used in the verification test. Error rates collected in these experiments are reported in table 1.

Table 1. Error rates (%) obtained using two training sets.

Dataset	**10 Genuine Signatures**			**5 Genuine Signatures**		
	FRR	**FAR**	**AER**	**FRR**	**FAR**	**AER**
CEDAR	10.25	05.07	07.66	10.33	10.15	10.24
MCYT-75	13.60	03.82	8.71	13.73	8.62	11.17

In overall, the number of training signatures has a substantial influence on the FAR score, which jumps to a difference of 5% when the number of training signatures is reduced to 5. This outcome reveals that using more training samples, leads to more robust modeling of the signer's traits, and helps the system to make a better detection of imitated signatures. On the contrary, quite similar FRR scores are collected for the two sets. So, as expected, better AER scores are obtained for the largest training set. The improvement varies between 2.46%, and 2.58 %, which indicates similar behavior for the two datasets.

Furthermore, DET curves highlight the effectiveness of the proposed SVS, since satisfactory Equal Error Rates (EER) calculated. These findings are proven when comparing the proposed system with the state-of-the-art results. As reported in table (2), the LDSP provides the best tradeoff between accuracy and data size.

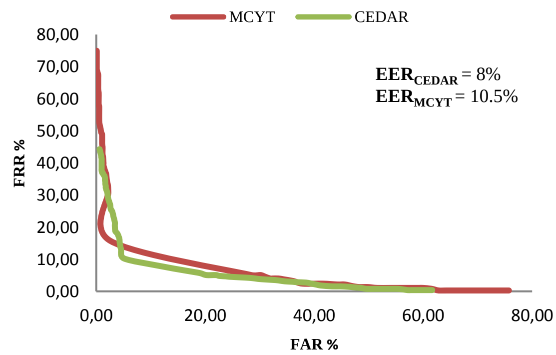

Fig. 4. DET curve obtained using 10 genuine signatures.

4 Conclusion

This work introduced the LDSP as a new descriptor edge descriptor for handwritten signature characterization. This descriptor was associated with SVM to develop the verification system according to the writer-dependent approach. The performance assessment was carried out on two public datasets, namely, CEDAR and MCYT. Compared to various state of the art features, the proposed LDSP can give similar and commonly better performance when it is associated with the same classification technique that is SVM. The AER is reduced by a gain of 0.94%, and 2.36% for CEDAR and MCYT, respectively. As future work, we are looking forward combining LDSP with other kinds of features to reinforce signature shape characterization.

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Table 2. state of the art results of adopted datasets

Dataset	Reference	Features	Classifier	Training Signatures	AER/ EER%
CEDAR	[24]	Surroundedness	SVM	24	11.59
	[26]	Zernike moments	Harmonic distance	16	16.4
	[25]	Quad-tree HOT	AIRSV	10	08.76
	[24]	Chain code histogram	SVM	12	8.6
	Proposed system	**LDSP**	**SVM**	**10**	**7.66**
MCYT	[29]	Geometriccentroids	Degree of authenticity	9	21.61
	[30]	Slantmeasure	Variability mesure	10	22.13
	[31]	LDP	LS-SVM	10	11.54
	[32]	HOT	AIRS-SVM	10	11.07
	[25]	HOT	SVM	10	11.47
	Proposed system	**LDSP**	**SVM**	**10**	**8.71**