A Circular Grid-Based Rotation Invariant Feature Extraction Approach for Off-line Signature Verification

Marianela Parodi Juan C. Gómez
Laboratory for System Dynamics and Signal Processing
FCEIA, Universidad Nacional de Rosario
CIFASIS, CONICET
Rosario, Argentina
Email: {parodi,gomez}@cifasis-conicet.gov.ar

Abdel Belaïd
LORIA, Campus Scientifique, B.P. 236,
Vandoeuvre-Lès-Nancy, France
Email: abdel.belaid@loria.fr

***Abstract*—One of the main challenges in off-line signature verification systems is to make them robust against rotation of the signatures. A new technique for rotation invariant feature extraction based on a circular grid is proposed in this paper. Graphometric features for the circular grid are defined by adapting similar features available for rectangular grids, and the property of rotation invariance of the Discrete Fourier Transform (DFT) is used in order to achieve robustness against rotation. A Support Vector Machine (SVM) based classifier scheme is used for classification tasks. Experimental results on a public database show that the proposed verification system has a performance comparable to similar state-of-the-art signature verification systems with the additional advantage of being robust against rotation of the signatures.**

***Keywords*-Off-line Signature Verification; Support Vector Machine classifiers; Feature Extraction; Rotation Invariance Property.**

I. Introduction

Signature verification plays an important role in the field of personal authentication, being the most popular method of identity verification. Financial and administrative institutions recognize signatures as a legal means of verifying an individual's identity. In addition, signature verification is a noninvasive biometric technique, and people is familiar with the use of the signatures for identity verification in their everyday life. Two different categories of signature verification systems can be distinguished: off-line and on-line systems [1].

The aim of a signature verification system is to accurately distinguish between two categories of signatures, namely, genuine and forged signatures. Different types of classifiers have been applied to solve this classification problem, being those based on Hidden Markov Models (HMMs) ([2]–[5]), and Support Vector Machines (SVMs) ([4]–[7]), among the most frequently used. HMM-based classifiers have shown to be well suited for signature modeling since they are able to capture personal variability ([3], [4]). More recently, SVM-based classifiers have been successfully used in signature verification applications ([5]–[7]) since they have the ability to work with high-dimensional data, they provide high generalization performance without the need to add *a priori* knowledge and, in general, this generalization performance is better than that of other classification methods when the amount of data is small.

A fundamental step in a signature verification process is the feature extraction. Different methods have been proposed in the off-line signature verification literature to perform the extraction of the features from the signature image. Generally, the features can be classified into two categories, namely, global features and local features. Global features refer to those that are representative of the whole signature image, while local features are those extracted from particular parts of the signature image. Grid segmentation schemes have been frequently used to compute local features. In addition, features used in graphology, called graphometric features [8], have been adapted to compute them resorting to grid schemes. Different grid-segmentation schemes have been used in off-line signature verification systems for the purposes of graphometric feature extraction. In [2], [3], [5], [8] and [9], graphometric features are computed resorting to a rectangular grid scheme. In [10], a segmentation of the signature image using a circular grid is proposed, and graphometric features are adapted to this grid geometry. One of the motivations for using a circular grid is to avoid the problem of having empty sectors which appear when a rectangular grid is employed. The ideal gridding technique would be to compute a bounding ellipsoid of the signature and to divide it into sectors, but then no regular sectors would result. The bounding circular grid, instead, allows the division in regular sectors. A comparison between the circular and the rectangular grid approaches for feature extraction is performed in [10], showing the verification system based on circular grids better performance than the corresponding one based on rectangular grids. These gridding schemes, however, are not robust against rotation of the signatures. Robustness against rotation is one of the major challenges when dealing with off-line signature verification systems. This problem has not been extensively dealt with in the literature. In this paper, a representation of the signature that

1520-5363/11 $26.00 © 2011 IEEE
DOI 10.1109/ICDAR.2011.259

is robust against rotation is proposed. In this representation, graphometric features are extracted from a circular grid and mapped to the Fourier Transform domain in order to achieve robustness against rotation. Similar techniques have been proposed in [11] and [12].

The verification process is carried out resorting to a SVM-based classifier and the above mentioned graphometric features in the Fourier Transform domain. The system is tested on a public database containing genuine as well as forged signatures.

The paper is organized as follows. The proposed rotation invariant feature extraction approach based on a circular grid is described in Section II. Section III is devoted to the SVM-based classifier. Experimental results are reported in Section IV. Finally, some concluding remarks are given in Section V.

II. Feature Extraction

In this paper, a circular chart enclosing the signature is divided in N identical sectors, and graphometric features are computed for each sector. Since dimensions of signatures belonging to different writers, or even the same writer, may differ, a width normalization of the signature image is performed before gridding. This normalization maintains the original height-to-width ratio of the signature image. The circular grid is centered at the center of mass of the binary image of the signature as shown in Fig. 1(a). In this way, the probability of having empty grid sectors is reduced. In addition, this choice of the center of the grid guarantees invariance against translation of the signature.

Three static graphometric features are considered: pixel density distribution x_{PD}, gravity center distance x_{DGC} and gravity center angle x_{AGC}, defined as:

$$x_{PD_i} = \frac{\text{Num. of black pixels inside the sector}}{\text{total Num. of pixels inside the sector}}, \quad (1)$$

$$x_{DGC_i} = \frac{d_{GC_i}}{R}, \quad (2)$$

$$x_{AGC_i} = \frac{\alpha_{GC_i}}{\alpha_{max}}, \quad \text{being } \alpha_{max} = \frac{2\pi}{N}, \quad (3)$$

with $i = 0, \cdots, N-1$, respectively. Here d_{GC} is the distance between the gravity center (point A in Fig. 1(b)-(c)) and the center of the grid, R is the radius of the grid calculated as the major distance between extreme points of the signature, α_{GC} is the angle of the gravity center (as depicted in Fig. 1(c)) and α_{max} is the total angle of each sector. Note that due to the particular choice of the grid center and the grid radius, the features (1), (2) and (3) are translation and scaling invariant. Let the graphometric features for the ith sector of a signature S_0 be defined as in (1), (2) and (3). The ith sector of the grid is delimited by the angles $2i\pi/N$ and $2(i+1)\pi/N$. A generic feature calculated inside the ith sector of S_0 can be expressed as

$$x_{0_i} = f(S_0(\theta)), \qquad \frac{2i\pi}{N} < \theta < \frac{2(i+1)\pi}{N},$$

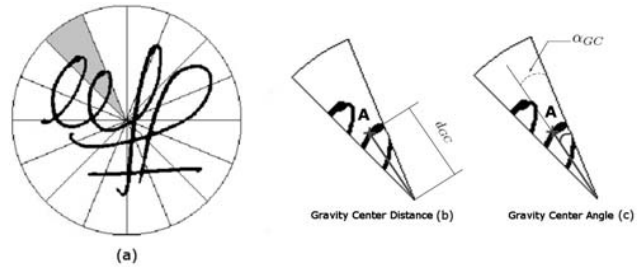

Figure 1. Features extracted from segmented sectors with the circular grid approach: (a) Segmented sector being analyzed; (b) Gravity Center Distance; (c) Gravity Center Angle.

with $i = 0, \cdots, N-1$.

Suppose now that the same features are calculated inside the same ith sector of a rotated version of S_0, namely, $S_\rho(\theta) = S_0(\theta - \rho)$ where the rotated angle is $\rho = k2\pi/N$ radians with $k = 1, 2, \cdots, N$ in counterclockwise direction. The corresponding feature is given by

$$\begin{aligned} x_{\rho_i} &= f(S_\rho(\theta)), & \frac{2i\pi}{N} < \theta < \frac{2(i+1)\pi}{N}, \\ &= f(S_0(\theta-\rho)), & \frac{2i\pi}{N} < \theta < \frac{2(i+1)\pi}{N}, \\ &= f(S_0(\theta)), & \frac{2(i-k)\pi}{N} < \theta < \frac{2(i+1-k)\pi}{N}, \\ &= x_{0_{i-k}}, & \end{aligned} \quad (4)$$

with $i = 0, \cdots, N-1$, $k = 1, \cdots, N$.

From (4) it can be concluded that the features of the rotated signature are circularly shifted with respect to the corresponding features for the original signature.

Finally, the features of the original and rotated signatures are obtained by taking the N-point Discrete Fourier Transform (DFT) of x_{0_i} and x_{ρ_i} respectively. That is

$$\begin{aligned} X_0(u) &= \frac{1}{N}\sum_{i=0}^{N-1} x_{0_i} e^{-j2\pi iu/N}, \\ X_\rho(u) &= \frac{1}{N}\sum_{i=0}^{N-1} x_{\rho_i} e^{-j2\pi iu/N}. \end{aligned} \quad (5)$$

Replacing x_{ρ_i} by $x_{0_{i-k}}$ in (5) yields

$$\begin{aligned} X_\rho(u) &= \frac{1}{N}\sum_{i=0}^{N-1} x_{0_{i-k}} e^{-j2\pi iu/N}, \\ &= \frac{1}{N}\sum_{i=-k}^{N-1-k} x_{0_i} e^{-j2\pi(i+k)u/N}, \\ &= e^{-j2\pi k/N} X_0(u), \end{aligned} \quad (6)$$

with $u = 0, \cdots, N-1$. It is clear then that $X_\rho(u)$ and $X_0(u)$ have the same absolute value, that is $|X_\rho(u)| = |X_0(u)|$, and then $[|X_0(0)|, \cdots, |X_0(N-1)|]^T$ is a feature vector which is invariant against rotation. In addition, since the spectrum

is symmetric at the central point, it is enough to keep the first $N/2+1$ values of the DFT for the representation of the signature.

Finally, the scaling, translation and rotation invariant feature vector X_{sign} is defined as

$$X_{sign} = [X_{PD}^T, X_{DGC}^T, X_{AGC}^T]^T, \tag{7}$$

where

$$\begin{aligned} X_{PD} &= [|X_{PD_0}|, |X_{PD_1}|, \cdots, |X_{PD_{N/2}}|]^T, \\ X_{DGC} &= [|X_{DGC_0}|, |X_{DGC_1}|, \cdots, |X_{DGC_{N/2}}|]^T, \\ X_{AGC} &= [|X_{AGC_0}|, |X_{AGC_1}|, \cdots, |X_{AGC_{N/2}}|]^T. \end{aligned}$$

III. Support Vector Machine Classifier

Support Vector Machine is a quite recent technique of statistical learning theory developed by Vapnik ([13], [14]). Given a set of samples belonging to two classes, a SVM classifier tries to find the hyperplane that maximizes the distance to either class, minimizing the misclassification error. Although in their basic form SVMs were developed for the purpose of learning linear threshold functions, they have been extended to the nonlinear case by means of the use of kernels. Several kernels have been proposed in the literature for SVM-based classifiers ([15], [16]). In this paper, the widespread-used linear, polynomial and Radial Basis Functions (RBF) kernels are considered.

Recently, SVM-based classifiers have been used in automatic signature verification showing a promising performance as pointed out in [5], [6] and [7], among others. In these works, comparisons between SVM-based classifiers and other classification methods like Artificial Neural Networks (ANNs) ([6] and [7]) and HMMs [5] have been carried out, showing the SVM-based classifiers several advantages with respect to the other techniques. The SVM-based classifiers in [5], [6] and [7] make use of different feature extraction techniques. Rectangular grid features are used in [5], global, mask and grid features are used in [6], while global and moment-based characteristics are employed in [7]. In this paper, the SVM-based classifier is used together with the rotation invariant features described in Section II.

The database used to test the performance of the proposed signature verification system, described in detail in Subsection IV-A, includes genuine as well as forged signatures. For the latter, random, simple and skilled forgeries are available. Random forgeries are usually represented as genuine signatures that belongs to anyone else but the writer under consideration. Simple forgeries are represented by signatures that have the same semantic of the writer's name without any knowledge about the original signature image. Skilled forgeries are represented by a trained imitation of the original signature. A SVM model was trained for each writer using a training set composed of genuine and false samples. The genuine samples were chosen as a subset of the available writer's genuine signatures. The corresponding false samples, were chosen as a subset of the genuine signatures (the ones separated for training purposes) of the remainder writers in the database. This set of signatures can be interpreted as random forgeries for the writer under consideration. Neither simple nor skilled forgeries were included in the training subset of false samples. For a real application, those types of forgeries are not available during the training phase. Then, avoiding their use for training results in a more realistic model.

To verify a signature, that is to verify the identity claimed by a writer, the feature vector (which is calculated as described in Section II) is used as the input of a SVM classifier trained for the writer under consideration. The SVM classification process will determine whether the signature belongs to the genuine class or to the false class. Then, the signature will be assumed as genuine and the writer's claimed identity will be true if it belongs to the first class, otherwise the signature will be considered as a forgery assuming the claimed identity to be false. The signature verification experiments were performed resorting to the SVM toolbox for Matlab described in [17].

IV. Evaluation Protocol

A. Signature Database

The database used is GPDS300Signature CORPUS [18] [1]. This is a freely distributed version of the database described in [4]. There are 160 writers enrolled in the database. For each writer, there are 24 genuine signatures and 30 forged signatures, taking into account simple and skilled forgeries. That is, a total of $160 \times 24 = 3840$ genuine and $160 \times 30 = 4800$ forged signatures. For a writer in the database, genuine signatures of all the other enrolled writers were used as random forgeries.

B. Experiments and Results

The database was organized as follows: First of all, a randomly selected subset of 30 out of the 160 writers was separated and used for parameter optimization purposes. This set of signatures was not used in the subsequent training and testing phases. The remainder 130 writers were organized as follows: The 30 forged signatures available per writer were used exclusively for testing, while the 24 genuine signatures available per writer were randomly divided into two groups. The first one, containing 13 signatures, was used for training purposes. The second one, consisting of 11 signatures, was used for testing. For each writer, the set of training samples was composed of 13 genuine signatures and 129 random forgeries (1 genuine signature randomly chosen from the 13 available for each of the 129 remainder writers).

[1] The authors, in the License Agreement for non-commercial research use of the database, required the database to be named as GPDS300Signature CORPUS and that any work made public based directly or indirectly on any part of the database has to include the reference [18].

The proportion of genuine samples to false samples used for training was optimized over the optimization subset.

In order to obtain reliable results, Monte Carlo techniques were used. The experiments were carried out randomly resampling the dataset into training and testing sets for each one of the 130 writers tested. The resampling process was repeated 100 times.

Experiments were specially focused on testing the rotation invariance property of the developed signature model. For that purpose, the signature model trained in each Monte Carlo instance, was tested over a dataset composed of the 11 original genuine signatures randomly chosen for testing, the 30 original forged signatures and rotated versions of both testing groups. Signatures used for testing were rotated 10, 20, 30, 40, 50 and 60 degrees in a counterclockwise direction. Experiments with different number of grid divisions $N = 8$, $N = 16$, $N = 32$, $N = 64$ and $N = 128$, and different types of kernels, namely, linear, polynomial and RBF, were carried out. The internal parameters of the SVM-based classifiers were optimized over the subset used for optimization purposes. The best results, which are presented in this section, were obtained with the polynomial kernel and $N = 16$ grid divisions.

In order to show the improvements achieved by mapping the features extracted from the circular grid to the Fourier Transform domain, the same experiments were also carried out with the features prior to the mapping. Fig. 2 shows the mean value of the False Rejection Rate (FRR) (top) and the False Acceptance Rate (FAR) for simple and skilled forgeries (bottom) calculated with the proposed rotation invariant features (red) and the features prior to the mapping to the Fourier Transform domain (blue), for the 130 writers tested. The rotation invariant property of the proposed features in the DFT domain can be clearly observed in Fig. 2. On the other hand, the verification errors of the features prior to the mapping to the DFT domain are strongly influenced by the rotation angle of the signature.

In Fig. 3 the FRR (top) and the FAR for simple and skilled forgeries (bottom) calculated with the proposed rotation invariant features, for each of the 130 writers tested are shown. From Fig. 3 it can be observed that the proposed method has a good performance in terms of the FAR except for only a few signatures while in terms of the FRR the performance is not that good for some of the signatures. Signatures for which the developed model is not well suited are those which present long thin lines underlying the signature which are too long with respect to the rest of the signature's body which, in these cases, is in an extreme of the underlying line. For this type of signatures, the center of mass of the signature is not a good choice for the circular grid center resulting in a poor verification performance.

The lack of a standard international signature database makes it difficult to compare the performance of the different signature verification systems. For the sake of completeness,

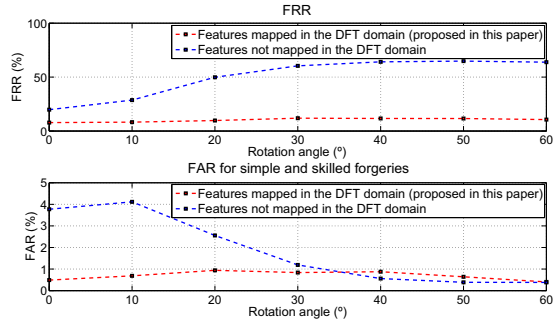

Figure 2. FRR (top) and FAR for simple and skilled forgeries (bottom) calculated with the proposed rotation invariant features (red) and with the features prior to the mapping to the DFT domain (blue).

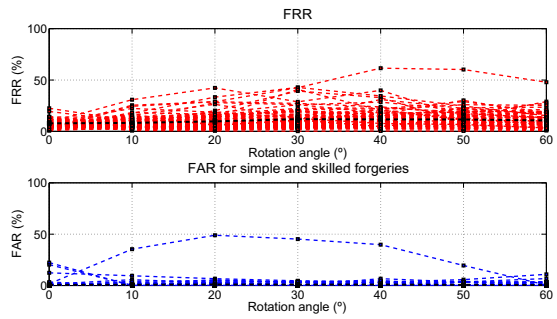

Figure 3. FRR (top) and FAR for simple and skilled forgeries (bottom) calculated for each of the 130 writers tested (rotation invariant features).

results published in some related works are presented in Table I, together with the corresponding results obtained with the approach proposed in this paper. In particular, Table I includes results from works that use a similar database (160 writers, 24 genuine signatures and 24 forged signatures) in which a polar representation of the image of the signature is used to compute the characteristic features ([4], [19]) and from [10] which uses the same database. Since no evaluation about the invariance property of the features are available for [4] and [19], the results included in Table I are the ones calculated for the original signatures (without any rotation).

It can be observed from Table I that the proposed method outperforms the methods of the state-of-the-art in [4], [10] and [19], for both the False Rejection and the False Acceptance Rates.

It is the intention of the authors to improve the obtained performance by introducing new features that take into account some other human factors as pen pressure and orientation. In addition, using unsupervised learning algorithms to perform an automatic pre-classification of the signatures according to their writing style and morphological aspect is being evaluated in order to adapt the feature extraction techniques to each identified signature class.

Table I
COMPARISON BETWEEN THE RESULTS OBTAINED WITH THE PROPOSED APPROACH AND OTHER APPROACHES PROPOSED IN THE LITERATURE.

	FRR	FAR	EER
Proposed approach	7.82%	0.49%	4.21%
Parodi and Gómez [10]	19.8%	3.77%	11.785%
Ferrer et al.[4]	14.1%	12.6%	13.35%
Vargas et al.[19]	10.01%	14.66%	12.33%

V. CONCLUSIONS

A new technique for rotation invariant feature extraction based on a circular grid has been proposed in this paper for off-line signature verification. A Support Vector Machine based classifier scheme was used for classification tasks. The classification results on a public database, quantified by the FRR and the FAR for simple and skilled forgeries, show that the proposed signature verification system has a performance comparable to similar ones of the state-of-the-art. In particular, the low FAR obtained indicates an improvement in the capability of the system to highlight the interpersonal variability. In addition, the proposed signature verification system has the advantage of being robust against the rotation of the signatures.

REFERENCES

[1] D. Impedovo and G. Pirlo, "Automatic signature verification: The state of the art," *IEEE Trans. Syst., Man, Cybern. C*, vol. 38, pp. 609–635, Sep. 2008.

[2] E. Justino, A. El Yacoubi, F. Bortolozzi, and R. Sabourin, "An off-line signature verification system using HMM and graphometric features," in *Proc. 4th IAPR International Workshop on Document Analysis Systems*, Rio de Janeiro, Brazil, Dec. 2000, pp. 211–222.

[3] E. Justino, J. Edson, F. Bortolozzi, and R. Sabourin, "Off-line signature verification using HMM for random, simple and skilled forgeries," in *Proc. International Conference on Document Analysis and Recognition*, Seattle, USA, Sep. 2001, pp. 105–110.

[4] M. Ferrer, J. Alonso, and C. Travieso, "Offline geometric parameters for automatic signature verification using fixed-point arithmetic," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, pp. 993–997, Jun. 2005.

[5] E. Justino, J. Edson, F. Bortolozzi, and R. Sabourin, "A comparison of SVM and HMM classifiers in the offline signature verification," *Pattern Recognition Letters*, vol. 26, pp. 1377–1385, Jul. 2005.

[6] E. Özgündüz, T. Sentürk, and M. E. Karsligil, "Off-line signature verification and recognition by support vector machine," in *Proc. European Signal Processing Conference*, Antalya, Turkey, Sep. 2005.

[7] E. Frias-Martinez, A. Sanchez, and J. Velez, "Support vector machines versus multi-layer perceptrons for efficient off-line signature recognition," *Engineering Applications of Artificial Intelligence*, vol. 19, pp. 693–704, 2006.

[8] L. S. Oliveira, E. Justino, C. Freitas, and R. Sabourin, "The graphology applied to signature verification," in *Proc. 12th Conference of the International Graphonomics Society*, Salerno, Italy, Jun. 2005, pp. 286–290.

[9] C. Santos, E. Justino, F. Bortolozzi, and R. Sabourin, "An off-line signature verification method based on the questioned document experts approach and a neural network classifier," in *Proc. 9th International Workshop on Frontiers in Handwriting Recognition (IWFHR-9)*, Tokyo, Japan, Oct. 2004.

[10] M. Parodi and J. Gómez, "Off-line signature verification: A circular grid-based feature extraction approach," in *Proc. 36th Latinamerican Conference on Informatics (CLEI 2010)*, Asunción, Paraguay, Oct. 2010.

[11] J. Wen, B. Fang, Y. Tang, and T. Zhang;, "Offline signature verification:a new rotation invariant approach," in *Proc. IEEE International Conference on Systems, Man and Cybernetics (ISIC 2007)*, Montreal, Canada, Oct. 2007, pp. 3583–3587.

[12] A. Chalechale, G. Naghdy, P. Premaretne, and A. Mertins, "Cursive signature extraction and verification," in *Proc. 2nd International Workshop on Information Technology & Its Disciplines (WITID 2004)*, Kish Island, Iran, Feb. 2004, pp. 109–113.

[13] V. Vapnik, *The nature of statistical learning theory*. NY: Springer-Verlag, 1995.

[14] V. Vapnik, *Statistical learning theory*. NY: Wiley, 1998.

[15] C. Burges, "A tutorial on support vector machines for pattern recognition," *Data Mining and Knowledge Discovery*, vol. 2, pp. 121–167, Jun. 1998.

[16] B. Schölkopf and A. Smola, *Learning with kernels: Support vector machines, regularization, optimization, and beyond.* MIT Press, 2001.

[17] S. Canu, Y. G. V., Guigue, and A. Rakotomamonjy, *SVM and kernel methods Matlab toolbox*, Perception Systèmes et Information, INSA de Rouen, Rouen, France, 2005.

[18] F. Vargas, M. Ferrer, C. Travieso, and J. Alonso, "Off-line handwritten signature gpds-960 corpus," in *Proc. 9th International Conference on Document Analysis and Recognition (IAPR)*, Curitiba, Brazil, Sep. 2007, pp. 764–768.

[19] F. Vargas, M. Ferrer, C. Travieso, and J. Alonso, "Off-line signature verification based on high pressure polar distribution," in *Proc. 11th International Conference on Frontiers in Handwriting Recognition (ICFHR08)*, Montreal, Canada, Aug. 2008.