Off-line Handwritten Signature Verification Using Contourlet Transform and Co-occurrence Matrix

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***Abstract*—We address, in this work, a new feature generation method for two different approaches of off-line handwritten signature verification (HSV), writer-dependent and writer-independent HSV. The proposed method uses conjointly the contourlet transform and the co-occurence matrix. The contourlet transform allows capturing contour segment directions of the handwritten signature, while the co-occurrence matrix allows describing the number of directions. Experiments are conducted on the well known CEDAR dataset and the classification through the support vector machines (SVM). The obtained results show the effective use of the Contourlet transform for handwritten signature verification comparatively to the state of the art.**

Keywords-off-line Handwritten Signature Verification; Contourlet transform; SVM; co-occurrence matrix; writer dependent; writer independent.

I. INTRODUCTION

The handwritten signature verification (HSV) is a discipline which aims to validate the identity of writers according to the handwriting styles [1]. It is one of the most widely used for being simple, inexpensive and acceptable from society. However, it also represents one of the easiest breakable security systems compared to the physiological biometric ones, since signatures can easily be imitated. Hence, the signature verification is still an open problem because a signature is judged to be genuine or a forgery only on the basis of a few reference specimens [2][3]. Furthermore, a same writer can sign differently depending on his or her state of emotion.

The design of a Handwritten Signature Verification System (HSVS) depends on the acquisition mode of the signature. The first mode, called on-line or dynamic acquisition, allows capturing some dynamic characteristics of the written style such as velocity, pressure and acceleration. The second mode, called off-line or static acquisition, allows generating an image, which represents a more difficult task due to the disappearance of dynamic features. However, this mode is still the most applicable in daily cases.

Two different approaches can be adopted for offline signatures verification [4]. The usual approach is the writer dependent HSV, where models for genuine and forgery signatures are constructed for each writer. Then, the questioned signature sample of a writer is compared to its own model. The disadvantage of this approach is the need to generate a model for each new writer to be verified.

The second approach called writer-independent HSV is used by forensic experts [4]. This approach is considered as the most practical cases, since it is not necessary to generate a model for each writer in order to verify its signature. In this case, a general model is built from some writers chosen randomly. However, the writer-independent HSV constitutes a more difficult task because of the important morphological variability inter-writers.

Generally, a HSV system is composed of three main stages: data acquisition and preprocessing, feature generation and classification. During the classification stage, personal features generated from an acquired signature are compared against features of the reference signatures stored in the database in order to judge its authenticity [3]. Hence, the feature generation stage plays an important role for the robustness of a HSVS.

Various methods have been developed for generating features from the signature image, which can be grouped into two categories: direct methods and transform methods. Direct methods allow generating features directly from image pixels such as grid-based information, pixel density, gray-level intensity, texture… etc. In contrast, transform methods need a transformation of the image into another domain in which features could be generated. Fourier, Wavelet, Radon transforms are the most popular methods for generating features [3][5].

The main drawback of these methods is that they don't allow capturing contours contained into an image. Hence, a sophisticated transform has been proposed more recently namely the contourlet transform (CT) [6].

The main advantage of the CT is the ability to capture significant information about an object. Furthermore, it offers a flexible multiresolution, local and directional image expansion [6]. These properties are interesting to exploit more specifically for the handwritten signature verification since the signature contains often special characters and flourishes [7].

The CT has successfully been used for many applications such as handwritten signature verification [1][2], vehicle recognition [8], noise reduction of biomedical images [9], face recognition [10] and image retrieval [11][12].

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When using the CT for signature verification, an important number of coefficients is generated from the signature image, which constitutes a serious drawback for forming the feature vector. Hence, various approaches have been developed for generating a reduced feature vector. For example, Yang et al [1] decomposed the image signature into two-level decompositions of CT from which each directional subband is divided into j equal blocks. Thus, the grid gray feature is computed for each block in order to get the statistical feature vector. Then, the KL transform is used for size reduction. In contrast, Pourshahabi et al [2] proposed to divide the signature image into four blocks. Then, the CT is applied on each block in order to generate a feature vector having two parts. The first part contains all of the coefficients in the approximation sub-band, while the second contains numbers of white pixels of binary detail information converted by Otsu's method. Thus, the four created feature vectors are concatenated in order to generate the whole feature vector of the signature image.

In this paper, we propose an alternative approach for generating features from the CT of the signature image. The main idea is to attribute to each signature segment its corresponding code representing its dominant direction. Then, the resulting coded image is characterized by the directions in terms of localization and occurrences of direction's signatures using co-occurrence matrix.

The remaining of the paper is organized as follows: the CT is presented in section 2. Then, a new feature generation method is defined in section 3. The experimental results are given in section 4. Finally, we conclude the whole paper and present some future works.

II. CONTOURLET TRANSFORM

The CT has been proposed by Do and Vetterli [6] in order to obtain sparse expansions of an image having smooth contours through a double filter bank structure. Hence, the Laplacian pyramid is firstly used to capture the point discontinuities and then followed by a directional filter bank to link point discontinuities into linear structures. The Laplacian Pyramid analyzes the two dimensional image into high pass and low pass sub-bands, the former is divided by the directional filter bank into directional subbands. The resulting image expansion uses basic elements like contour segments and supports different scales, directions and ratios [9].

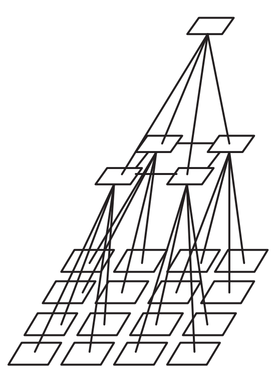

Figure 1. Laplacian Pyramid Structure.

We briefly review the main properties of the Laplacian pyramid and the directional filter bank.

A. Laplacian Pyramid

Laplacian Pyramid introduced by Burt and Adelson is a multi-scale decomposition [13], which provides a downsampled lowpass version of the original image at each level convolved with a Gaussian kernel. The difference between the original and the prediction allows generating details, which correspond to contours. The process is iterated by decomposing the coarse version repeatedly and the image size is halved at each scale. Figure 1 illustrates the Laplacian pyramid structure.

B. Directional Filter Bank

The Directional Filter Bank (DFB) has the ability to decompose images into any power of two's number of directions [14]. The DFB is efficiently implemented via a l-level tree-structured decomposition that leads to subbands. In fact, a DFB has the required ability to receive high frequencies of the input image which contains some information about directions. This is permitted by the Laplacian decomposition by removing low frequencies before DFB so that the directional information can be captured efficiently. Figure 2 illustrates an example of the image analysis for eight bands and corresponding positions in the Contourlet domain [1][6].

III. FEATURE GENERATION

In many HSV systems, the rotation of the image signature is required during preprocessing. In our case, we consider directions of the image features as a main characteristic of handwriting styles that allow separating more efficiently between writers.

Therefore, we propose a method that uses conjointly the CT and the co-occurrence matrix. The CT, being a structural characterization, allows capturing the smooth contours according directions. While, the co-occurrence matrix considered as a statistical feature allows describing the localization, organization and direction's occurrences. Hence, the proposed method involves four steps:

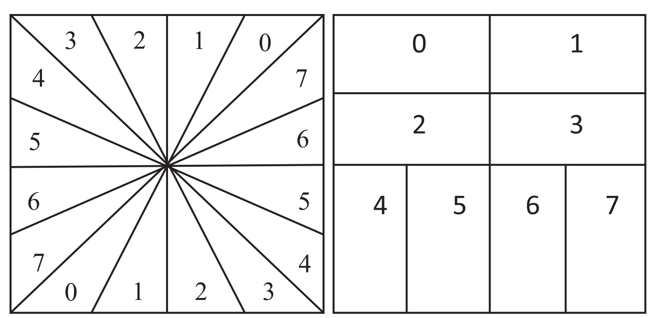

Figure 2. Frequency partition map for eight-band directional filter bank such that l=3 corresponding to directions. Sub-bands 0-3 correspond to the mostly horizontal directions, while sub-bands 4-7 correspond to the mostly vertical directions [9].

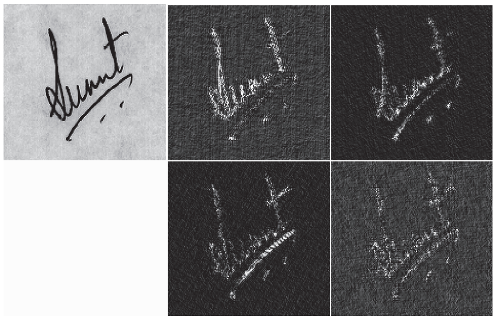

Figure 3. CT of a signature sample for the first level and four directions.

- **Step 1:** Compute the CT on the original signature image providing N directions at the first resolution level.
- **Step 2:** Construct an only contourlet coefficients image by selecting the dominant features through a comparison between directional sub-bands.
- **Step 3:** Code each dominant coefficient according to its direction.
- **Step 4:** Compute the co-occurrence matrix on the resulting code.

Another advantage of the proposed method is the considerable reduction of the feature vector. Indeed, each pixel takes the most important directional coefficient and thus the whole coefficient number is reduced by a factor of $1/N$, where N represents the number of directions.

Furthermore, computing the co-occurrence matrix on the coded image allows providing a feature vector of fixed size independently of the size of the signature image.

IV. EXPERIMENTAL RESULTS

A. Data set and evaluation criteria

The Center of Excellence for Document Analysis and Recognition (CEDAR) signature dataset [15] is a commonly used dataset for off-line signature verification.

The CEDAR signature dataset contains signatures from 55 signers. Each one signed 24 genuine signatures and simulated 24 forged signatures for other signers. Therefore, the dataset contains 1320 genuine and 1320 forged signatures, respectively.

In order to evaluate the performance of the proposed method, we use three standard evaluation criteria: False Acceptance Rate (FAR) allows taking into account only skilled forgeries; False Rejection Rate (FRR) allows taking into account only genuine signatures; and the Average Error Rate (AER) allows taking the average of both FAR and FRR. The AER constitutes a good criterion for evaluating the accuracy of a method. Hence, a method can be considered accurate when the AER is lower as much as possible.

B. SVM Classification

To evaluate performances of our approach, we use the SVM classifier with a radial basis function (RBF kernel). Results are obtained using the cross-validation approach involving training, validation and testing steps [16] . The validation step is used to find the optimal parameters C (Regularization parameter) and σ (Kernel parameter) of the SVM. The optimal pair (C, σ) is selected when the AER is small as much as possible. These parameters are then used in test step in order to evaluate the robustness of the proposed method.

The dataset is divided into three equal subsets which are permuted successively. For each permutation, a subset is used for training while the remaining two subsets are used for validation and testing. Thus, 6 fold cross-validation are performed for the experiments using 8 genuine signature and 8 forgeries for each step in dependent writer approach. 440 genuine signatures and 440 forgeries for each step in independent approach.

C. Quantitative Results

The experiments are conducted by decomposing the signature onto one resolution and four directions. This leads to generate a feature vector having only 16 components that represent the only inputs of the SVM. Tables 1 and 2 report errors (min, mean and max) for writer-dependent and writer-independent, respectively.

In order to appreciate the effective use of the proposed method, various methods are selected for comparison, which are Word Shape [15] [18], Zernike moments [17][18], Graph Matching [18], and Adaptive Feature Thresholding [19]. These methods have been selected since experimental results have been conducted on the same CEDAR dataset.

Figure 4 shows the distribution of the obtained coded signatures images where the discrimination between direction occurrences in original signatures and forged ones is easily noticed. Moreover, the co-occurrence matrix provides the occurrences of passing from a direction to another one according to an inter-code and an orientation.

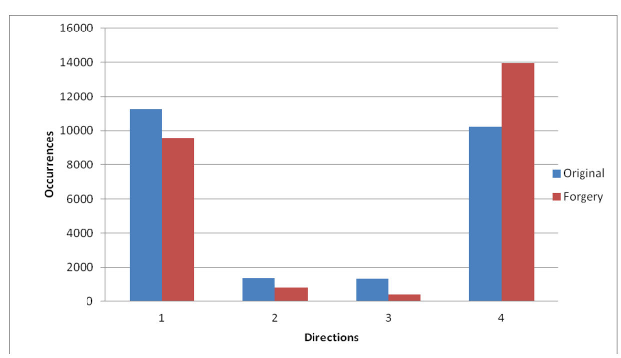

Figure 4. Histogram of directions of original signatures sample and forged ones for one writer.

TABLE I. RECOGNITION PERFORMANCES OBTAINED FOR THE DIFFERENT EXPERIMENTS ON CEDAR DATABASE FOR DEPENDENT WRITER HSV.

Errors	FAR (%)	FRR(%)	AER(%)
Min	0.00	0.00	0.00
Mean	0.03	0.11	0.07
Max	0.22	0.22	0.22

TABLE II. RECOGNITION PERFORMANCES OBTAINED FOR THE DIFFERENT EXPERIMENTS ON CEDAR DATABASE FOR WRITER INDEPENDENT HSV.

Errors	FAR (%)	FRR(%)	AER(%)
Min	0.00	0.00	0.00
Mean	0.09	0.27	0.18
Max	0.19	1.37	0.78

TABLE III. RECOGNITION PERFORMANCES OBTAINED FOR VARIOUS HSV SYSTEMS EXPERIMENTED ON CEDAR DATASET.

Method	NF	FAR (%)	FRR (%)	AER (%)
Word Shape [15] [18]	1024	19.50	22.45	21.50
Zernike moments [17][18]	640	16.30	16.60	16.40
Graph Matching	1032	8.20	7.70	7.90
Adaptive Feature Thresholding [19]	756	10.96	08.16	9.66
Proposed method (writer dependent)	16	0.11	0.03	0.07
Proposed method (writer independent)	16	0.09	0.27	0.18

Table 3 reports the Number of Features (NF) forming the feature vector, FAR, FRR and AER, respectively. We clearly can note that the best performance is reached by the proposed method (AER = 0.07%) which is lower by 7.83% compared to the smallest AER obtained by Graph Matching method (AER=7.90%). Further, the smallest number of feature obtained by the Zernike moment method contains 640 components whereas the proposed method generates only 16 components. Moreover, the proposed method uses a reduced number of references comparatively to the classical methods since only eight signatures are used for training whereas the classical ones used sixteen reference signatures. This constitutes an additional advantage comparatively to the state of the art.

The quantitative results prove that the proposed method provides the best performance in terms on both AER and dimensionality reduction.

V. CONCLUSION

In this work, we proposed a new handwritten signature verification method based on CT and co-occurrence matrix. Experimental results demonstrate that the proposed method effectively characterizes the writer style and gives a considerable improvement in terms of recognition rate for both writer-dependent and writer-independent approaches, respectively. Moreover, another contribution of this method is the reduced size of the feature vector which equals the square of direction's number compared to the state of the art. As future works, we propose to experiment the method on writer recognition and image retrieval.

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