Offline Handwritten Signature Identification and Verification Using Contourlet Transform

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Abstract— **In this paper, a new offline handwritten signature identification and verification system based on Contourlet transform is proposed. Contourlet transform (CT) is used as feature extractor in proposed system. Signature image is enhanced by removing noise and then it is normalized by size. After preprocessing stage, by applying a special type of Contourlet transform on signature image, related Contourlet coefficients are computed and feature vector is created. Euclidean distance is used as classifier.**

One of the most important features of proposed system is its independency from signer's nationality. Experimental results show that proposed system has so reliable results for both Persian and English signatures.

Keywords-component; Offline signature, identification, verification, Contourlet transform, Euclidean distance

I. INTRODUCTION

Nowadays, person identification (recognition) and verification is very important in security and resource access control. For this purpose, the first and simple way is Personal Identification Number (PIN). But, PIN code may be forgotten. Now, an interesting method of identification and verification is biometric approach. Biometric is a measure for identification and verification that is unique for each person. Biometrics is together with persons always, and cannot be forgotten. In addition, biometrics usually cannot be misused. Handwritten signature can be considered as biometric; however, some researchers believe that handwritten signature is not a real biometric. Handwritten signature identification and verification are simple, inexpensive, non-intrusive and acceptable for society [1]. Nevertheless, it has some drawbacks: lower identification and verification precision in comparison with other biometrics, non-linear changes with size changing and dependency on time and emotion [1, 2]. Another problem of processing handwritten signature is that the signature of each nation is different with another nation. For example, European signature is the same as his/her name writing in a special style and Persian signature contains some curves and

symbols [3]. There are many applications for signature identification: in banking, user login in computer or Personal Digital Assistant (PDA) and access control. In [4] an intelligent signature processing system for banking environment has been presented named AutoSIG. More applications of signature identification and verification have been discussed in [3]. There are two modes for signature identification and verification: static or off-line and dynamic or on-line. In static mode, the input of system is a 2-dimensional image of signature. Contrary, in dynamic mode, the input is signature trace in time domain. In dynamic mode, a person sign on an electronic tablet by an electronic pen and his/her signature is sampled. Each sample has 3 attributes: x and y in 2-dimentions coordinates and t as time of sample occurrence.

Some electronic tablets in addition of time sampling, could digitize the pressure. Although the identification rate of dynamic mode is higher than static mode, but dynamic mode has a main disadvantage: it is on-line. So, it cannot be used in some important applications that the signer could not be presented in signing place.

In order to measure quality performance of designed system, FAR (False Acceptance Rate), FRR (False Rejection Rate), EER (Equal Error Rate) values related to verification has been computed. FAR is the rate of accepting forgery signature as genuine signature wrongly. FRR is the rate of rejecting genuine signature as forgery one wrongly. FAR and FRR is related to each other inversely. By setting and changing a threshold, when FAR is increasing, FRR is decreasing and vice versa. At specific threshold, FRR is equal to FAR. In this case this rate is named EER. Identification rate has also been computed.

II. RELATED WORKS

Automatic signature identification has received little attention in comparison with signature verification despite its potential applications for accessing security-sensitive facilities and for processing certain legal and historical documents. Cavalcanti et al [2] investigates the feature selection for signature identification that signature database contains different signature size. The size of signatures in each class is small, medium and big. Use of structural

features, pseudo-dynamic features and five moments and selected some classifier independent features have been described in this study. Normalizing signature images before identification has been advised finally. Mohamadi [5] has presented a Persian static signature identification system using Principle Component Analysis (PCA) and Multi Layered Perceptron (MLP) neural network. In training phase, PCA constructs some eigen vectors based on training database images. In test phase, PCA extracts the eigen value of each eigen vector from a new signature image. These eigen values are used as features and are fed to a MLP classifier. For experiment, 20 classes of Persian signatures comprising 10 signatures for training and 10 signatures for test per class have been used. Identification rate has been reported 91.5%.

Sigari and Pourshahabi [3] have investigated signature identification and verification using signal-processing approaches. In their thesis, they compared Discrete Cosine Transform (DCT), Hough transform, Radon transform and Gabor Wavelet Transform (GWT) and finally proposed GWT for feature extraction in signature identification and verification. They used GWT as feature extractor and Euclidean distance as classifier in both identification and verification. A virtual grid is placed on the image of signature and some coefficients are computed by GWT on each point of grid. A Persian signature database has been used for experiment. This signature database has been used in [5]. Identification rate and EER is reported 99.5% and 15% respectively.

Ozgunduz et al have presented [6] an off-line signature verification and recognition system using the global, directional and grid features. SVM has been used in order to verify and classify the signatures and a classification ratio of 95% has been obtained. For the recognition of signatures is accounted as a multi class problem type, one-against-all SVM method has been used. In addition, this method's performance has been compared with MLP. This comparison shows that SVM has better performance than MLP. Martinez et al [7] have presented an efficient offline human signature recognition system based on SVM and have compared its performance with a MLP. In both cases, two approaches have been used: (1) construction of each feature vector using a set of global geometric and moment-based characteristics from each signature and (2) construction of the feature vector using the bitmap of the corresponding signature. Signature database contains 228 signatures in 38 classes. In training phase, only one signature has been used for each class. Results show that SVM, with 71% recognition rate, outperforms MLP with 47% recognition rate.

Coetzer et al [8] have presented offline signature verification. Discrete Radon transform has been used as feature extractor and hidden Markov model has been used as classifier. A database containing 924 English signatures of 22 writers has been provided. In experimental results, EER 18% and 4.5% are reported for skilled forgery and casual forgery signatures respectively.

Fig. 1 shows an instance original signature before preprocessing stage.
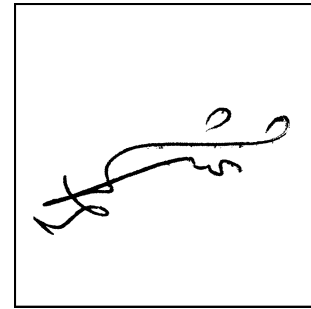

Figure 1.   An original instance signature image

A.   Finding The Outer Rectangle

Outer rectangle of signature is a rectangle with the least size that all pixels of signature are in it. The outer rectangle can be detected with multiplying horizontal by vertical projection of binary image (Fig. 2). Binarization of signature image is done using Otsu's method [9].

B.   Image Enhancement

Obtained threshold from Otsu binarization algorithm (T) is used in image enhancement. As background image is white, if the gray level of each pixel is more than T, its gray level will change to 255 (white pixel) else its gray level will not change (Fig. 3).

C.   Size Normalization

The last preprocessing step is size normalization. It plays an important role in preprocessing as it affects identification and verification rates directly [2]. In this paper if the width of image is more than its height, the normalization is based on width, and vice versa. All signature images are normalized in 256×256 pixels size. Therefore the image is resized based on its longer side and that side's long is changed to 256 pixels long. Other side of image is become larger with white line padding in each side symmetrically (Fig. 4).
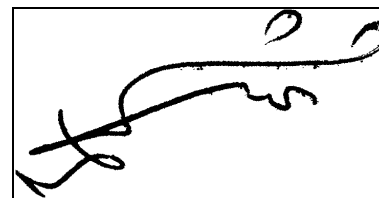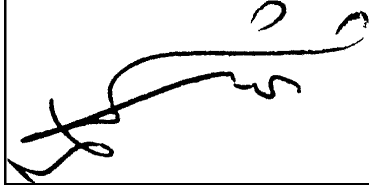

Figure 2.   Outer rectangle of signature
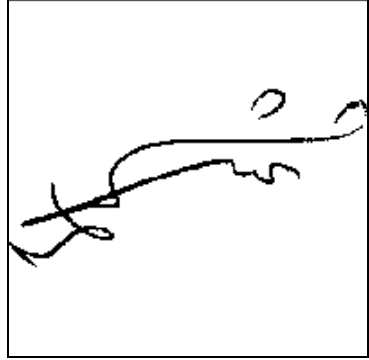
Figure 3.   Image enhancement

Figure 4.   Size normalization

IV.   FEATURE EXTRACTION

With consideration of type of signature images that contain a lot of contours like edges, Contourlet transform [10] is used as feature extractor.

A.   Contourlet Transform

Contourlet transform introduced by Do and Vetterli [10] is an efficient tool for capturing smooth contours. Contourlet transform as an effective and powerful image representation tool has five significant features: Multiresolution, localization, critical sampling, directionality and anisotropy. Contourlet transform is a double filter bank: Laplacian Pyramid (LP) followed by a Directional Filter Bank (DFB). So it is named pyramidal directional filter bank (PDFB). LP at each level decomposes input image into downsampled lowpass sub-band (coarse image) and one bandpass sub-band then DFB is applied to bandpass sub-band. By repeating this scheme iteratively on the coarse image resulted from LP at each level, a fine to coarse representation of input image will be obtained as shown in Fig. 5.

Considering $x = a_0[n]$ is the input image. The output after one level of the LP is a lowpass sub-band $a_1[n]$ and one bandpass sub-band $b_1[n]$. After J levels of the LP, there are J bandpass images $b_j[n]$, $j = 1, 2,..., J \psi$ (fine-to-coarse) and a lowpass image $a_J[n]$. Then each bandpass image $b_j[n]$ is decomposed by an l_j-level DFB into 2^{l_j} bandpass directional images $C_{j,k}[n]$, $k = 1, 2, ..., 2^{l_j} - 1$.
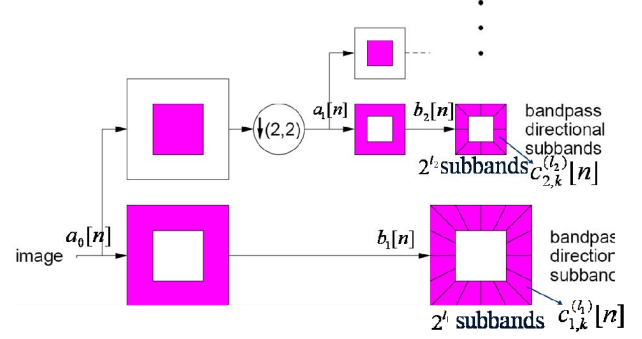

Figure 5.   Contourlet transform: Laplacian Pyramid (LP) followed by a Directional Filter Bank (DFB)[10]

In Fig. 6, the analysis part of contourlet transform is shown as a block diagram.
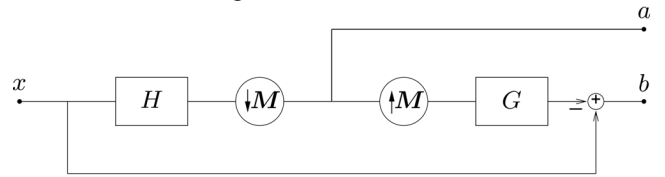

Figure 6.   The analysis part of contourlet transform

Feature vector has two parts. As approximation sub-band ($a_J[n]$) contains overall information of the image, all of the coefficients in this sub-band are considered as one part of feature vector. Moreover the need for detail information is also necessary. Thus all other sub-bands ($C_{j,k}[n]$) convert to binary ones using Otsu's method and number of white pixels in each of these binary sub-bands is computed. The second part of feature vector is including these numbers. As stated before all signature images are 256×256 pixels size. For achieving better results each image divided into 4 blocks (128×128 pixels size). Contourlet transform is applied on each block separately and feature vector is created for that block. With putting the 4 created feature vectors together, final feature vector is obtained.

B.   System Parameters

Pyramidal filter type, directional filter type, number of scales and directions per scales are system parameters. 8 different cases have been tested. It was found from the test results that using 'Burt' filter as pyramidal filter type, 'pkva' filter as directional filter type, considering 3 scales with 16, 8 and 4 directions in each scale (fine to coarse) are the best selective system parameters' types in verification process. But in identification, using '9-7' filter instead of 'pkva' filter for directional filtering is achieved better identification rates.

V.   CLASSIFIER

In order to compare feature vectors with each other, Euclidean distance has been used. Euclidean distance is accounted as one of the most favorite method for measuring the distance between vectors. In identification process, the least distance between feature vector of input image and

stored feature vectors, using Euclidean distance is obtained and its related signature class is specified. In verification process for each signature class a reference point is considered, if the distance between feature vector of input image and this reference point is less than a specific threshold, input image belongs to that signature class, otherwise it doesn't belong to that signature class. Reference point can be considered as a vector containing mean of corresponding elements of feature vectors of each class.

VI. EXPERIMENTAL RESULTS

In order to evaluate designed system's performance, two experiments have been carried out as follows: The first experiment has been performed on a Persian signature database. This signature database has been used in [3, 5]. It contains 20 classes and 30 signatures per class. Each class comprises 10 genuine signatures for training, 10 genuine signatures for testing and 10 skilled forgery signatures. Other experiment has been carried out on an English signature database. This signature database has been used by Coetzer et al in [8]. It contains 22 classes. Each class contains 42 signatures (10 genuine signatures for training, 20 genuine signatures for testing, 6 casual forgery signatures and 6 skilled forgery signatures).

Identification rate resulted from first experiment (Persian signatures) is 100%. Rate of identification in second experiment (English signatures) is 93.2%.

Table I, shows rates of verification. FAR and FRR are 14.5% and 12.5% for Persian skilled forgery set, 22.72% and 23.18%, for English skilled forgery set and 2.27% and 23.18% for English casual forgery set. FRR is the same in both English skilled and casual forgery database, as the genuine signature database is not changed. The related EERs are also computed and shown in Table I. The low rates of EER show the reliability of designed system.

TABLE I.   RATES OF VERIFICATION

Signature Type	FAR (%)	FRR (%)	EER (%)
Skilled Persian	14.50	12.50	14.00
Skilled English	22.72	23.18	23.00
Casual English	2.27	23.18	9.77

VII. CONCLUSION

In this paper, a new signature identification and verification system using Contourlet transform was introduced. Evaluation and testing results show excellent performance of designed system both in identification and verification. Two signature databases with different nationalities (Persian and English) were used to evaluate system's independency from nationality. English signatures are very like to other European signatures, because of using the signer's name as signature. Experimental results show that proposed system has so reliable results on both Persian and English signatures. Therefore, this system can be used for signatures of many nations and this feature is one of the most important features of such designed systems.

The software of this system has been written in MATLAB version 7.6.0.324(R2008a) environment and has been run on an AMD Athlon(tm) 64 X2 Dual Core processor 5600+, 2.9 GHz, 2048 MB of RAM system. The mean processing time needed for each signature identification or verification is about 5 seconds that is an acceptable run time.

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