Offline Handwritten Signature Identification and Verification Using Contourlet Transform and Support Vector Machine

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Abstract: *In this paper, a new method for signature identification and verification based on contourlet transform (CT) is proposed. This method uses contourlet coefficient as the feature extractor and Support Vector Machine (SVM) as the classifier. In proposed method, first signature image is normalized based on size. After pre-processing, contourlet coefficients are computed on specified scale and direction. Next, all extracted coefficients are fed to a layer of SVM classifiers as feature vector. The number of SVM classifiers is equal to the number of classes. Each SVM classifier determines if the input image belongs to the corresponding class or not.*

The main characteristic of proposed method is independency to nation of signers. Two experiments on two signature sets are performed. The first is on a Persian signature set and the other is on Stellenbosch (Turkish) signature set.

Based on these experiments, we achieve a 100% recognition (identification) rate and more than 96.5% on Persian and Turkish signature sets respectively and 4.5% error in verification.

Keywords: Contourlet Transform, Signature Identification and Verification, Support Vector Machine.

1. Introduction

In recent years, while the popularization of computer and network makes interaction among people more and more convenient, security problem is becoming more and more serious.

Numerous credit cards, passwords and ID cards are filched and embezzled everyday, which makes tremendous loss to the country and individuals [1]. Handwritten signature is one of former biometrics; however, some researchers believe that handwritten signature is not a real biometric. Handwritten Signature identification is simple, inexpensive, non-intrusive and acceptable from society. Nevertheless, it has some drawbacks: lower identification rate with respect to other biometrics, non-linear changes with size changing and dependency to time and emotion [2], [3].

A signature recognition and verification system must provide two main tasks: to identify the owner of the signature and to decide whether the signature is genuine or forger. In general, we have two main kinds of handwritten Signature recognition systems: On-line recognition systems, where the computer is attached to special peripheral units capable of acquiring information about the way the human hand creates the pattern (velocities, pressures, etc.). Off-line recognition systems, where the only information the computer is acquired with, is usually the digitized image of the pattern [4].

During the last several years, many scientists have tried to solve the problem and several Signature Recognition Systems, both on-line and off-line, have been proposed.

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 have 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 are 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 [5].

The organization of this paper is as follows.

Section 2 presents the theory background of our method. In Section 3 deliberates how to get feature vector with Contourlet sub bands based on maximum direction. In section 4, we explain the experimental

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results. . Finally, in section 7, the summery and the future plans are presented.

2. Related Works

There have been many systems for handwritten Signature Identification (HSI). Sabourin and Drouhard [6] proposed an approach based on directional probability density function in combination with BP neural networks to detect random forgery. Bajaj and Chaudhury [7] proposed a system consisting of sub-classifiers based on three sets of global features. Sansone and vento[8] proposed a sequential three-stage multi-expert system, in which the first expert eliminates random and simple forgeries, the second isolates skilled forgeries, and the third gives the final decision by combining decisions of the previous stages together with reliability estimations. However, its performance relies greatly on the rejection criteria chosen for each expert. Ozgunduz et al have presented [9] an off-line signature verification and recognition system using the global, directional and grid features. SVM was used to verify and classify the signatures and a classification ratio of 95% was obtained. As the recognition of signatures represents a multi class problem, SVM's one-against-all method was used. In addition; the performance of this method was compared with MLP. This comparison shows that SVM has better performance than MLP.

Martinez et al [10] 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 to the problem were 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 set contains 228 signatures in 38 classes. In training phase, only one signature has been used for each class. Results show that SVM, which achieves up to 71% recognition rate, outperforms MLP with 47%recognition rate.

Kaewkongka et al [11] have described a method of off-line signature recognition by using Hough transform to detect stroke lines from signature image. The Hough transform is used to extract the parameterized Hough space from signature skeleton as unique characteristic feature of signatures. They have used a MLP neural network as classifier. The communication 283system has been tested with 70 test signatures from different persons. The experimental results reveal the recognition rate is 95.24%. Sigari et all [5] proposed Gabor wavelet transform (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. They also, proposed Contourlet transform as feature extractor and Euclidean distance as classifier in both identification and verification in another paper [20]. First, 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. They tested their system on two dataset. Identification rate resulted from first experiment (Persian signatures) is 100%. Rate of identification in second experiment (English signatures) is 93.2%. Kiani et all [21] proposed a new method for signature verification using local Radon Transform. The proposed method uses Radon Transform locally as feature extractor and Support Vector Machine as classifier.

3. Contourlet Transform

Contourlet, firstly proposed by Do and Vetterli [12], is a new image representation scheme which owns a powerful ability to efficiently capture the smooth contours of image.

Contourlets not only possess the main features of wavelets (namely, multi-scale and time-frequency localization), but also specially decomposes the sub band at each scale into different directional parts with flexible number [13].

The CT is also referred to as Pyramidal Directional Filter Bank (PDFB) [14]. PDFB is a double filter bank that consists of Laplacian pyramid (LP) and directional filter bank (DFB).

3.1 LP

One way of achieving a multi-scale decomposition is to use a Laplacian pyramid (LP), introduced by Burt and Adelson [15].

The LP decomposition at each level generates a down sampled low pass version of the original and the difference between the original and the prediction, resulting in a band pass image. Fig. 1(a) depicts this decomposition process, where H and G are called (low pass) analysis and synthesis filters, respectively, and M is the sampling matrix. The process can be iterated by decomposing the coarse version repeatedly. The original image is convolved with a Gaussian kernel [16]. The resulting image is a low pass filtered version of the original image. The Laplacian is then computed as the difference between the original image and the low pass filtered image.

This process is continued to obtain a set of band-pass filtered images (since each one is the difference between two levels of the Gaussian pyramid). Thus the Laplacian pyramid is a set of band pass filters.

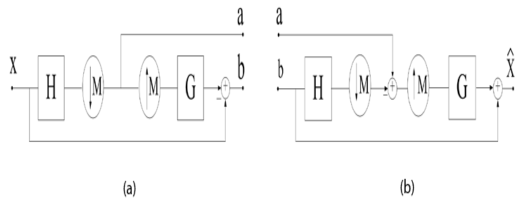

Fig. 1: LP. (a) One level of LP decomposition. The outputs are a coarse approximation a[n] and a difference b[n] between the original signal and the prediction. (b) The new reconstruction scheme for the LP [15].

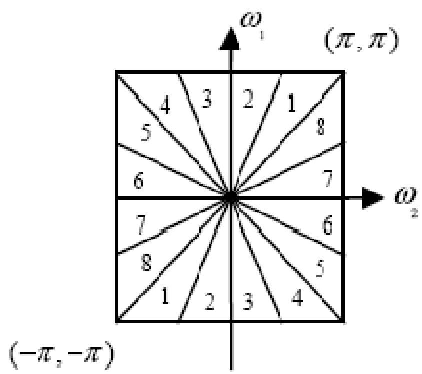

Fig. 2: An example of the directional filter bank frequency partitioning [15].

3.2 DFB

The directional filter bank is a critically sampled one that can decompose images into any power of two's number of directions. The DFB is efficiently implemented via a l-level tree-structured decomposition that leads to "2l" sub bands with wedge-shaped frequency partition as shown in Fig. 2. The original construction of the DFB in [17] involves modulating the input signal and using diamond-shaped filters. Furthermore, to obtain the desired frequency partition, an involved tree expanding rule has to be followed. The DFB is designed to capture the high frequency components (representing directionality) of images [18]. Therefore, low frequency components are handled poorly by the DFB. In fact, with the frequency partition shown in Fig. 2, low frequencies would leak into several directional sub bands, hence DFB does not provide a sparse representation for images. To improve the situation, low frequencies should be removed before the DFB. This provides another reason to combine the DFB with a multi-resolution scheme. Therefore, the LP permits further sub band decomposition to be applied on its band pass images. Those band pass images can be fed into a DFB so that direction information can be captured efficiently. The scheme can be iterated repeatedly on the coarse image. The final result is a double iterated filter bank structure, named pyramidal directional filter bank (PDFB), which decomposes images into directional sub bands at multiple scales. The scheme is flexible since it allows for a different number of directions at each scale.

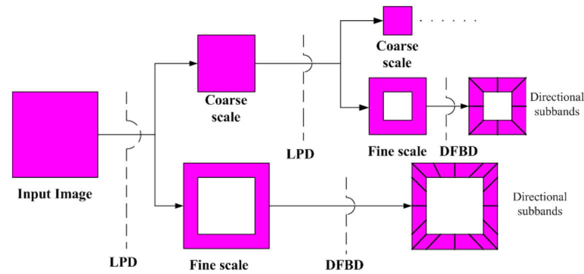

Fig. 3: The implement of CT via PDFB. LPD refers to Laplacian Pyramid Decomposition, DFBD refers to Directional Filter Bank Decomposition [14].

In CT, LP is first used to decompose images into multi-scale, followed by DFB to decompose sub bands at each scale into directional parts. This can be implemented iteratively with applying PDFB on the coarse scale of image, as is shown in Fig. 3.

4. The Proposed Method

4.1 Pre-processing

The origin handwriting image contains characters of different sizes and noises. Therefore before feature extraction, origin image should be processed to facilitate the feature extraction step followed. In our application, we do not design pre-processing phase but unified image size for identification from original handwritten signature image because the contourlet transform requires the size of image to be squared .(Fig4) Since some papers have discussed pre-processing [6-11], and this problem is not our focus in this paper, we do not introduce our methods on pre-processing in details.

4.2 Feature Extraction

Compared with feature extraction from the whole characters in identification, feature selection after direction decomposition can further reflect the structure composition of characters. Contourlet not only inherits the main traits of wavelet transform, such as multi-scale and time-frequency information, but also can capture direction characteristics. It can hold the geometrical structure of images, and implement a true sparse representation of images. Handwritten signature possesses abundant direction characteristics; so CT can seize the structural features of images effectively, which is in favor of the correct identification.

Fig. 4: Original Image

4-level decompositions of CT are carried out in our experiment, as shown in Fig. 5. The signature image is decomposed into a low pass sub band and 8 band pass directional sub bands. The multi-direction and multi-scale inherent of CT [14] enables it to effectively exploit the real image edges that are localized in both location and direction.

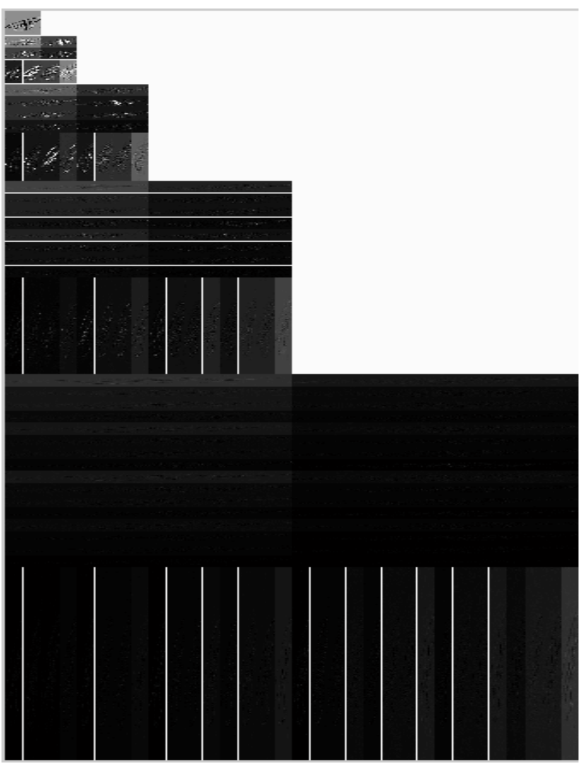

Fig.5: The Contourlet Coefficient in 4Scale and 8 Directions

For construction of feature vector of the signature, first in each direction of four different scales we find out in which scale the maximum value occurs and then increase the counter corresponding to the pair <scale, direction> in the feature matrix. This process in addition, these eight directions is produced by dividing of 180 degrees to 8 sub degrees. TABLE I shows this matrix which is extracted from the signature shown in Fig. 4.

TABLE I: Feature Vector

514122	7520	49561	9344	46737	19408	48793	3520
2144	49801	7840	49356	21616	49668	11920	51592
8032	11296	19152	9776	32160	3424	23792	1536
0	7456	1680	11600	3136	4768	640	3312

5. Classification

Classification is the last step of signature identification. For classification of signature classes, a layer of SVM classifier has been used.
The number of SVM classifiers in the classification layer is equal to number of signature classes. Vapnik [19] introduced the concept of SVM in late of 1970's. SVM, based on a solid mathematical foundation, which attempts to solve a universal problem of classification. The basic idea of SVM is deceptively simple. Given a set of vectors in R_n, labeled +1 or -1 that is separable by a hyper plane, SVM finds the hyper plane with the maximal margin. In this mode, the kernel of SVM classifier is a one order polynomial classifier. Sometimes, more complicated kernels such as higher order polynomial, MLP and Radial Basis Functions (RBF) are used.
Essentially, SVM is a binary classifier, i.e. SVM can categorize two classes. Therefore, for classification of *N* classes, *N* SVM classifiers are needed. For signature identification, number of SVM classifiers is equal with number of signers. A SVM classifier is used per class that classifier output is -1 or +1. When all classifier outputs except only one classifier are -1, the class of input signature will be the corresponding class of classifier that generates +1. When the output of all classifiers are -1 or two or more classifier outputs are +1, the input signature will not belong to any known class.

6. Experimental Result

In order to evaluate designed system's performance, two experiments are carried out as follows: The first experiment is performed on a Persian signature database. This signature database is the one used in [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 (Fig6).

TABLE II: Rates of Verification

Class number	FRR (%)	FAR (%)	Class number	FRR (%)	FAR (%)
1	0	0	11	0	10
2	10	10	12	0	0
3	0	0	13	0	0
4	0	0	14	0	10
5	0	10	15	20	0
6	0	10	16	0	20
7	0	20	17	0	0
8	10	0	18	10	20
9	0	10	19	0	10
10	0	0	20	0	0

The second experiment is performed on a Turkish signature set. This set is the one used by Ozgunduz et al in [9]. It contains 40 classes and 16 signatures per class. Eight signatures for training and eight signatures for test are used for each class. Identification rate resulted from the first experiment (Persian signatures) is 100%. Rate of identification in the second experiment (Turkish signatures) is 96.5%.

Fig. 6: one signature of each class.

Table II shows rates of verification for first experiment on Persian signature database.
Experimental results show that proposed system has very reliable results on both Persian and Turkish signatures. Therefore, this system can be used for signatures of many nations which is one of the most important features of such designed systems.

7. Conclusion

In this paper, a new signature identification and verification system using Contourlet transform was introduced. Evaluation and testing results showed excellent performance of designed system both in identification and verification. Two signature databases with different nationalities (Persian and Turkish) were used to evaluate system's independency from nationality.
Third order polynomial is selected as the kernel of SVM classifiers. Increasing or decreasing the order of polynomial kernel will eventuate to lower identification rate.
For the future works, we suggested other types of SVM or other learning machine for classification.

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