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Off line signature recognition based on contourlet transform

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Abstract. In this paper, we propose new offline Persian signature recognition based on the contourlet transform (CT). We utilize Support vector machine (SVM) as a tool to evaluate the performance of the proposed method. In proposed method, first signature image is normalized by size then image is enhanced to remove noise. After pre-processing, signature image is divided into four regions, contourlet coefficients are computed on each region. Next the histogram of orientation and direction of each region are computed so we have four histograms that are fed to a layer of SVM classifiers as feature vector. Our Persian dataset include 400 genuine images and 200 forgery images. Recognition rate is 98%.

Keywords: contourlet transform, signature recognition, feature extraction

1. Introduction

The person identification system based on biometric measurement like voice, retina, fingerprints and signature is very active area of research[1] .The signatures are one of the most popular and reliable biometric features. There are two main research fields in this area are: signature verification and signature recognition (or identification). A signature verification system decides whether the signature is genuine or forger. A Signature recognition system identifies the owner of the signature [2]. There are two major methods of signature verification. One is an on-line method to measure the sequential data such as handwriting and pen pressure with a special device. The other is an off-line method that uses an optical scanner to obtain handwriting data written on paper [3]-[4].

In this paper, we utilize the global features, the Curvature and the orientation and use the contourlet transform as feature extractors. Support vector machine (SVM) evaluates the performance of the proposed method.

This paper is organized as follow. In section 2, we review the wavelet, curvelet and contourlet transforms. In section 3, we explain our proposed method that is included the preprocessing, feature extraction and classification stages. The experimental results are given in section 4. Section 5 presents the conclusion.

2. Wavelet, curvelet and contourlet transforms

2-D wavelet can decompose the image into subbands with different frequency and orientation. It can't capture directional information. Cand'es & donoho [5] introduced multiresolution transform, curvelet, that can capture the intrinsic geometrical structures such as smooth contours in natural images multiscale transform with frame elements indexed by location, curvature and orientation parameters, and have time-frequency localization properties of wavelets but also shows a very high degree of directionality and anisotropy [6]. Curvelets can represent a smooth contour with fewer coefficients compared with wavelets (Fig.1).

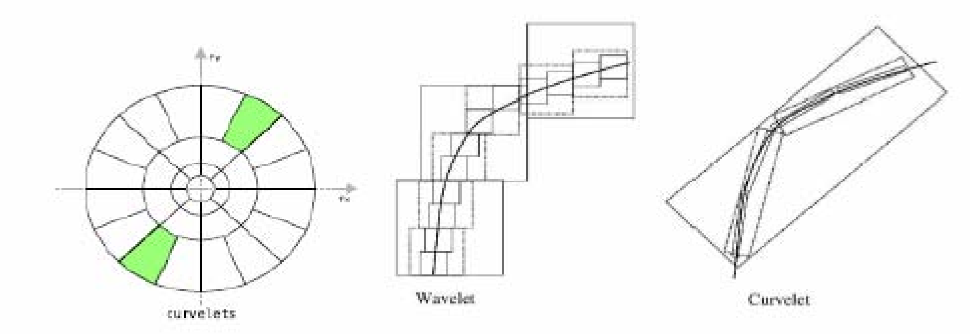


Fig. 1. Dyadic decomposition of the spectral domain. Wavelet and Curvelet decomposition obeying the scaling law width $\cong$ length ^{2} [8].

The curvelet transform is implemented by decomposing the image into a series of disjoint scales. Each scale is then analyzed by means of a local ridgelet transform. So, curvelet transform is based on multiscale ridgelet transform combined with a spatial bandpass filtering operation at different scales [7]-[8]-[15].

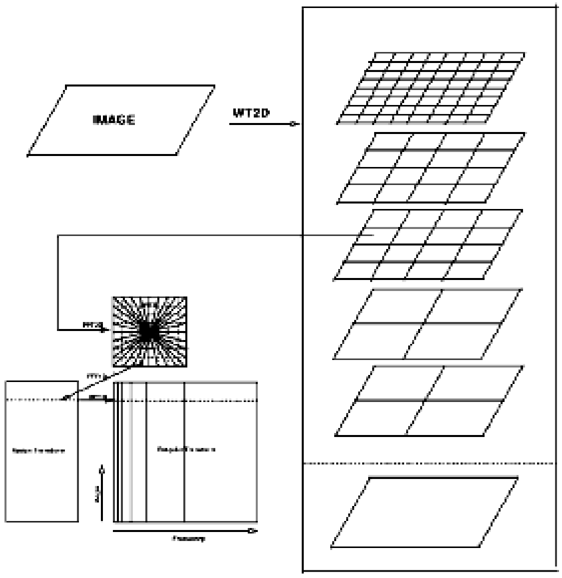


Fig. 2. curvelet transform flowgraph

The contourlet transform is represented by Do and Vetterli [9]. Contourlets not only possess the main features of wavelets (namely, multiscale and time-frequency localization), but also offer a high degree of directionality and anisotropy. The main difference between contourlets and other multiscale directional systems is that the contourlet transform allows for different and flexible number of directions at each scale, while achieving nearly critical sampling [10]. It is implemented by decomposing the image into multiscale with Laplacian Pyramid (LP) and then decomposing subbands at each scale into directional parts with Directional Filter Bank (DFB)[10]-[14].

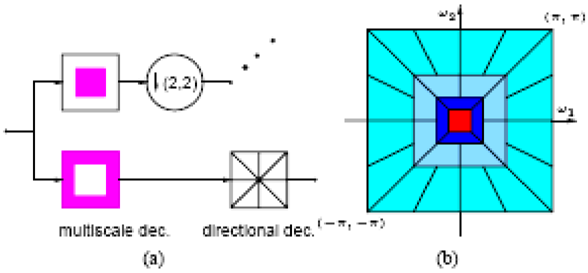


Fig. 3. The original contourlet transform. (a) Block diagram. (b) Resulting frequency division [11].

3. Proposed method

3.1. Preprocessing

Each signature is scanned into a gray level image .Grayscale images are converted to binary images by Otsu's thresholding method. Median filtering is applied to remove noise. Signature is then segmented by using a bounding box. Slant normalization is performed by extracting the axis of least inertia and rotating the curve until this axis coincides with the horizontal axis [12]. Then signature is segmented by using bounding box. A morphological closing operation with a 3 × 3 squared structuring element [13] is applied to filling the holes of signature image. At least, the signature image is converted to standard size 256*256.

3.2. Feature extraction

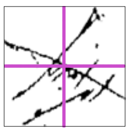
Feature extraction is very important stage in offline signature recognition system. We use the histogram of the curvature and orientation matrix of the signature image after using the multiresolution transforms. A histogram shows the frequency of data items in successive numerical intervals of equal size it is useful to represent the statistical information.

(a) (b)

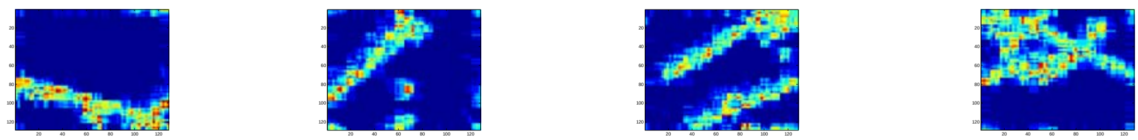
Fig. 4. Preprocessing steps: (a) before preprocessing, (b) after preprocessing

The image is divided into four regions. The contourlet transform is used on each region. After using the contourlet transform on a region to computing the orientation, we resize every orientation in every scale to 128*128. Then, they are converted to binary images by Otsu's thresholding method. The same orientations in all scale are added to each other. So obtained several matrix, 128*128, that each of them is showing a special orientation and each pixel of them shows the curvature of the corresponding pixel of a region in that orientation. As feature, we compute the frequency of occurrence of the curvature values in different orientations. Finally, we have four matrixes that each of them is a histogram (orientation, curvature) of a region of signature image.

Fig.5 shows curvatures of the four regions of a signature image. You can see in them, where a signature is curvier it has bigger value (red parts).



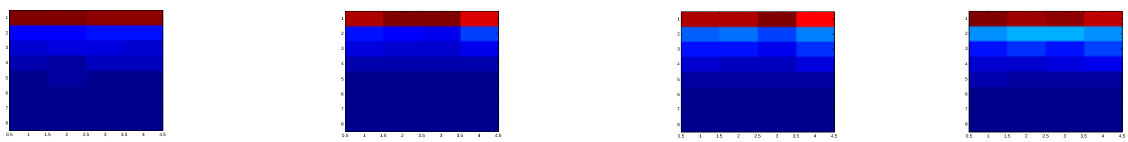
(a)



(b) (c) (d) (e)

Fig.5. a) a signature image is divided into four regions. b ,c ,d, e) curvature for each region of a signature image.

Fig.6 represents the histogram (orientation, curvature) for each region of a Fig.5.a.



(a) (b) (c) (d)

Fig.6 (a, b ,c ,d) histogram (orientation, curvature) for each region of a signature image.

3.3. Classification

After the feature extraction phase, the quality of features extracted is quantified to evaluate the accuracy of the classifier. An SVM is a classifier derived from statistical learning theory first presented by Boser. The main advantages of SVM when used for image classification problems are: (1) ability to work with high-dimensional data and (2) high generalization performance without the need to add a-priori knowledge, even when the dimension of the input space is very high.

4. Experimental Results

For testing the performance of our proposed method, we test 20 classes of signatures; our training data set include 200 genuine images. While our test data set include 200 genuine and 200 forgery images.

All experiments in this section use a contourlet transform with "9-7" pyramid filters and 4 decomposition level. In the DFB stage we use the "haar" directional filters and 8, 16, 32 and 64 directions. But, we just use 16 directions and 3 levels for building the histogram (orientation, curvature).

Table 1. The results of proposed method by different kernel for SVM

Kernel	Recognition rate (%)	False accept rate (%)
polynomial	98	15
RBF	91/83	22
Gaussian	96.5	15/51

5. Conclusions

We proposed new offline Persian signature recognition based on Contourlet transform. We used histogram (orientation, curvature) of signature shape as feature. SVM is used as classifier.

Unfortunately, there is not a standard Persian dataset. So, we used the dataset that is used by Sigari and Pourshahabi [18], they used Gabor transform and SVM classifier. They reported 96% for recognition rate. But our method could identify signatures with 98% true rate on same dataset.

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