Curvelet Transform-Based Features Extraction For Fingerprint Identification

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Abstract: The performance of the fingerprint identification process highly depends on its extractor of fingerprint features. So, to reduce the dimensionality of the fingerprint image and improve the identification rate, a fingerprint features extraction method based on Curvelet transform is proposed and presented in this paper. Thus, our paper focuses on presenting of our Curvelet-based fingerprint features extraction method. This method consists of two steps: decompose the fingerprint into set of sub-bands by the Curvelet transform and automatic extraction of the most discriminative statistical features of these sub-bands. An extensive experimental evaluation shows that the proposed method is effective and encouraging.

1. Introduction

Biometric is the science of person recognizing based on physical or behavioral characteristics/modalities. These modalities must be stable, distinctive and that you cannot lose or forget like the fingerprints, voiceprints, retinal blood vessel patterns, face, iris,.. . Among these biometric modalities, a fingerprint is the oldest biometric modality and the most public and reliable of these modalities. Modern fingerprint matching techniques were initiated in the late 16th century. In 1880, Henry Fauld was the first who, scientifically, suggested the individuality and uniqueness of fingerprints. At the same time, Herschel asserted that he had practiced fingerprint identification for about 20 years. This discovery established the foundation of modern fingerprint identification.

In a fingerprint-based biometric system, a fingerprint image will be represented by an extractor of relevant features. In the literature, two mainly and most important approaches was used to characterize a fingerprint image: an image-based approaches and a minutiae-based approach. The minutiae based approach is most popular of the above and is used in most of the modern fingerprint recognition systems. The main steps for minutiae extraction are smoothing, local ridge orientation estimation, ridge extraction, thinning, and minutia detection. For the low quality images, it is difficult to generate a reliable minutiae set. Whereas, the image-based approaches are more capable in dealing with low quality images [JPHP00]. In addition, the image-based approaches are able to represent a fingerprint by extracting of a fixed length feature vector in a multidimensionality space. The fixed length representation makes easier the application of multidimensional indexing techniques (e.g R-tree [Gu84]). Fingerprint indexing concerns the need of increasing the search speed for an unknown fingerprint in the identification problem, where the identification of a person may necessitate a comparison of his/her fingerprint with all the fingerprint templates stored in a database. Some researchers ([BT03]; [BBG01]; [LJK07]) have shown that an indexing technique based on image-based descriptors (i.e. FingerCode [JPHP00]) outperforms an approach based on the minutiae-triplets. Also, the representation with a fixed length vector makes image-based approach suitable to be coupled with a learning process, thus approaching the fingerprint verification problem as a two-class (genuine, imposter) pattern recognition problem ([NL06]). In addition to all those advantages, it has been experimentally demonstrated that even if the performance of a stand-alone image-based matcher is lower than that obtained by a good minutiae-based one, the fusion between these two approaches outperforms the best-stand alone approach ([NL07]; [MMJP03]). Moreover, in some works ([RJR03]) showed that using many fingerprint descriptors and several enhancement algorithms can considerably improves the performance of image-based matchers to become comparable to that obtained by a minutiae-based matchers. For all of the advantages of the image-based fingerprint, we have encouraged to propose a new image-based fingerprint features extraction method. So, in this paper we present our method which applies the curvelet transform to characterize the fingerprint image. Some curvelet Statistical descriptors were derived from the sub-bands generated by the curvelet decomposition of the ROI of fingerprint image. Then, Euclidian distance was used to calculate a dissemblance score between query fingerprint and all the templates.

So, the remainder of our paper is organized as follows: Section 2 describe the Curvelet transform approach. In Section 3, we present our fingerprint identification process which is based on the Curvelet transform which is used in our novel features fingerprint extraction method. Then we present the experiment results of the evaluation of our method in section 4. Finally, concluding remarks are given in Section 5.

2. Curvelet Transform

Curvelet transform is a geometric transform developed by Emmanuel Candes et al. [ED99] to overcome the inherent limitations of wavelet like transforms. Curvelet transform is a multi-scale and multi-directional transform with needle shaped basis functions. Basis functions of wavelet transform are isotropic and thus it requires large number of coefficients to represent the curve singularities. Curvelet transform basis functions are needle shaped and have high directional sensitivity and anisotropy. Curvelet obey parabolic scaling. Because of these properties, Curvelet transform allows almost optimal sparse representation of curve singularities [ED99]. The Curvelet transform at different scales and directions span the entire frequency space. So, Curvelet transform was designed to represent edges and other singularities along curves much more efficiently than traditional transforms, i.e., using fewer coefficients for a given accuracy of reconstruction.

Curvelet transform is a ridge transform added with binary square window, which means subdividing a curve into approximate straight enough to carry out ridge transform. However, there exists big data redundancy in the transform. Therefore, improving the first generation curvelet transform can obtain the 2nd generation, and the second takes on features of faster computation and less redundancy. First, define x as space position parameter, w as frequency domain parameter and (r, θ) as polar frequency domain in the 2-dimentional space R2. W(r) and V (r) are smooth non-negative “radius window” and “corner window” respectively, and they must satisfy:

$$\sum_{j=-\infty}^{\infty} W^2(2^j r) = 1, r \in \left(\frac{3}{4}, \frac{3}{2}\right) \tag{1}$$

$$\sum_{j=-\infty}^{\infty} V^2(2^j r) = 1, r \in \left(-\frac{1}{2}, \frac{1}{2}\right) \tag{2}$$

For all scales j>=j0, define its Fourrier frequency domain window:

$$U_j(r,\theta) = 2^{-\frac{3j}{4}} W(2^{-j} r) V\left(\frac{2^{\frac{j}{2}}\theta}{2\pi}\right) \tag{3}$$

Frequency domain curvelet transform is defined as product of $\varphi_{j,l,k}$ and $f \in L^2(R^2)$.

$$c(j,l,k) = \langle f, \varphi_{j,l,k}(x)\rangle = \int_{R^2} f(x)\, \overline{\varphi_{j,l,k}(x)}\, d(x) \tag{4}$$

$$c(j,l,k) := \frac{1}{(2\pi)^2}\int \hat{f}(w)\, \overline{\varphi_{j,l,k}(x)}\, d(w) = \frac{1}{(2\pi)^2}\int \hat{f}(w)\, U_j(R_{\theta_L} w) \exp[i\langle x_k^{(j,l)}, w\rangle]\, dw$$

Curvelet also include components on rough and fine scale, the same as wavelet theory. Introduce a low-pass window W0, which satisfies:

$$|W_0(r)|^1 + \sum_{j\geq 0} |W_0(r)|^2 = 1, (k1,k2) \in Z \tag{5}$$

Define curvelet on rough scale:

$$\varphi_{j_0,k}(x) = \varphi_{j_0}(x - 2^{-j_0}k) \tag{6}$$

$$\hat{\varphi}_{j_0,k}(x) = 2^{-j_0} W_0(2^{-j_0}|w|) \tag{7}$$

So, curvelet on rough scale is non-directional. The whole of curvelet transform is composed of directional components on fine scale and isotropic wavelet on rough scale. The implementation of Curvelet transform can be summarized by the following steps:

(a) *Sub-band Decomposition*: The image is decomposed into $\log_2 M$ (M is the size of the image) wavelet sub-bands. Then, the Curvelet Sub-bands are formed by performing partial reconstruction from these wavelet sub-bands at levels $j \in \{2^s, 2^{s+1}\}$. Thus the Curvelet Sub-band, s = 1 corresponds to wavelet sub-bands j = 0, 1, 2, 3, Curvelet Sub-band, s = 2 corresponds to wavelet sub-bands j = 4, 5 and so on.

(b) *Smooth Partitioning*: Each sub-band is subdivided into an array of overlapping blocks.

(c) *Renormalization*: Each square resulting in the previous stage is renormalized to unit scale.

(d) *Ridgelet Analysis*: Ridgelet transform [Ec98] is performed on each square resulting from the previous while being follow these steps:

- o Compute the 2-D Fast Fourrier Transform (FFT) of the image.
- o Perform cartesian to polar conversion. This is achieved by substituting the sampled values of the Fourier transform obtained on the square lattice with the sampled values on a polar lattice.
- o Compute the 1-D inverse FFT on each angular line.
- o Apply wavelet transform on the resulting angular lines in order to obtain the ridgelet coefficients.

The construction of curvelet basis obeys the anisotropic (parabolic) scaling relation between its length and width (length ≈ $2^{-j/2}$,width ≈ 2^{-j}) [ELD06]. In addition, the curvelet basis is oscillatory in one direction (x_1) and as low-pass filter in other direction (x_2). At fine scale 2^{-j}, a curvelet is a little needle shaped basis whose envelope is a specified ridge of effective length $2^{-j/2}$ and width 2^{-j} which display oscillatory behavior across the irregular main ridge [ELD06]. On the other hand, fingerprint image contains intrinsic geometrical structures and the ridges of fingerprint have a shape of a set of curvature. In effect, these features fingerprint will be represented effectively by the use of curvelet transform and due to parabolic scaling, curvelet transform extracts the aforementioned geometrical fingerprint structures and provide optimal sparse representation of curve singularities [ED99] with very high directional sensitivity and anisotropy for fingerprint features.

3. Our fingerprint identification process

In preprocessing step, we proceed to enhance the fingerprint image, to improves its quality, using specific techniques (filtration, enhancement, ..). Then, we pass to detect a reference point (point core). The area within a certain radius around the detected reference point is then used as a region of interest (ROI) for feature extraction. Fingerprint features are extracted from the ROI using a curvelet transform, which decomposes the ROI into several directional subband outputs [ED99], [ELD06]. From the decomposed subband outputs, statistical descriptors values are calculated for each block. Thus, the ROI is represented by statistical descriptors in each block. As part of the matching process, an alignment between the input and all template of database is performed through a Euclidean distances.

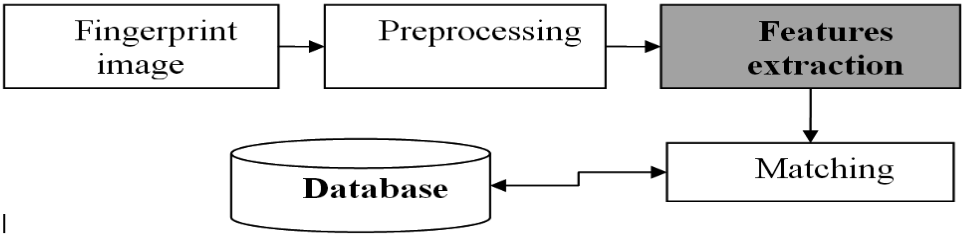


Figure 1. Chart Flow of our fingerprint identification process (Test phase)

3.1. Preprocessing & fingerprint

To ameliorate the quality of fingerprint image and to improve the clarity of the ridges and furrow structures, the input image has been enhanced using Fourier domain based block-wise contextual filter approach described in Chikkerur et al. [CG05]. The image is first divided into small overlapping windows, such that the signal can be assumed stationary and can be modeled approximately as a surface wave. Then short time Fourier transform (STFT) analysis is applied and the Fourier spectrum of each small region is analyzed to estimate the ridge frequency and ridge orientation. The resulting contextual information obtained from STFT analysis is used to filter each window in the Fourier domain. Then we pass to localize the reference point. This reference point was detected by the max concavity estimation [ELD06] and by the technique based on the Poincaré index analysis ([CG05];[JMMP03]). The enhancement method we used, generate an image with good quality thus we can correctly locate the reference point. In fig.3 we present a sample of enhanced fingerprint and the result of the localization of fingerprint ROI.

(a) The original image, (b) the enhanced image

Figure 2. Fingerprint enhancement

After enhancement of fingerprint image, we pass to binaries the image. Then, we took the squared ROI (175x175) which is around the reference point of the binary image. This binarized image will be skeletonise. This binarization is done by a simple thresholding of the gray scale image. In the Figure 3, we preset an example of the enhancement, binarization and localization of the ROI of the fingerprint.

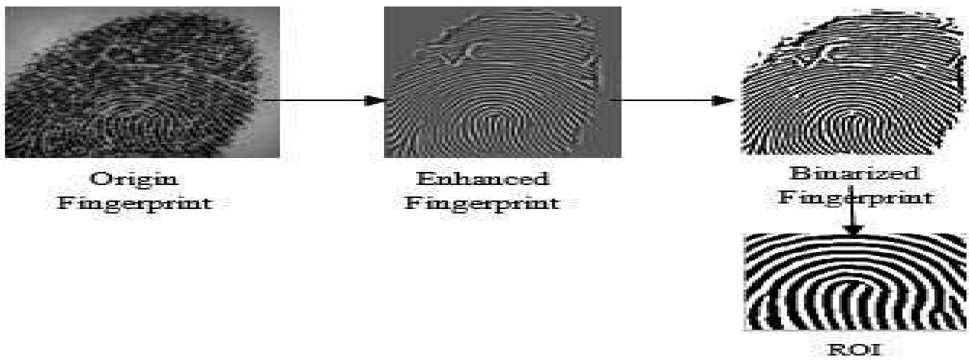
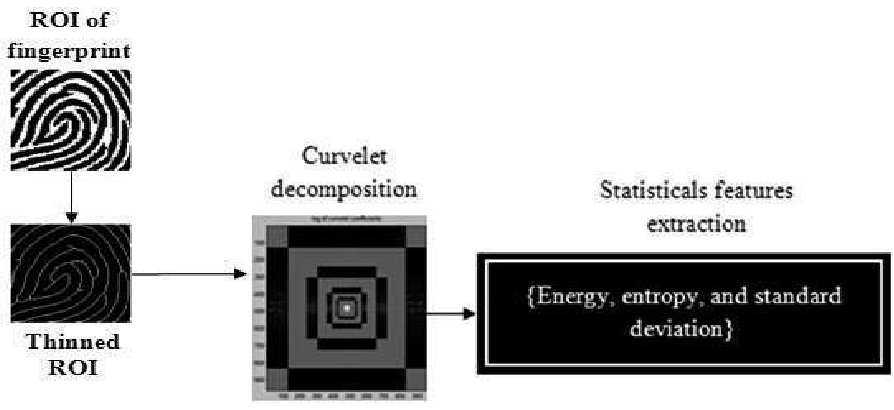


Figure 4. Example of ROI localisation

3.2. Our Curvelet transform-based fingerprint features extraction method

Previous research in multi-resolution texture analysis [JPH99] suggests some statistical descriptors: energy, entropy, and standard deviation to be applied on the Curvelet sub-bands in order to represent an image. Encouraging results were presented in these research works which have extracted these descriptors from texture which was decomposed by Curvelet transform. These results encouraged us to integrate this approach in our extractor of features fingerprint.

So, the structural activity extracted from the Curvelet transform of the image can be analyzed statistically to generate fingerprint features vector. Thus, we have applied the Curvelet transform on the ROI of the binarized & skeletonized fingerprint. The Curvelet decomposition generates several sub-bands images. Then, we calculate the statistical features from all these sub-bands to generate the fingerprint features vector. In the following figure (Figure 3.) we present our fingerprint encoding method.



Curvelet coefficients at varied angles (scale=5)

Figure 3. *Schematic diagram of a proposed fingerprint features extraction method.*

If a given ROI of fingerprint image resized to 512×512 and then decomposed into 5 scales, thus the number of the directional sub-bands images varies from scale to scale. So, we will have 32 sub-bands images at second scale and at scales 3 and 4 we will have 64 sub-bands images. So, extracting features from these sub-bands images and representing in a compact form is a major problem. To overcome this problem, we encode each sub-band image by three statistical features (Energy, entropy, standard deviation). Thus, in the totality, we have in the first scale one sub-band which is coded by three features values, in the second scale we have thirty two sub-bands which are coded by 32x3 features values. In the third scale, we get 64 sub-bands which are coded by 64x3 features values. Also, the follow scale, we get 64x3 features values. Finally, in the fifth scale, we get one sub-band which is coded by 1x3 features values. A result, we obtain 164x3 features values to encode the ROI of the binarized fingerprint. Thus, our features vector contains 3 rows. Each row contains 164 values of a feature (energy, entropy, or standard deviation) extracted from 164 sub-bands.

It is desirable to obtain a fingerprint representation invariant to translation, scale, and rotation. The rotation invariance is achieved by converting the ROI of fingerprint image with five initial angles $-20^{\circ};-10^{\circ};\ 0^{\circ};\ 10^{\circ};\ 20^{\circ}$. We thus define five templates which, respectively, denote the five rotation angles for each fingerprint class in the database. When matching the input feature vector with the templates of a class, the minimum of the five scores is taken as the final matching score.

3.3. Matching algorithm

In the matching algorithm, we calculate the Euclidian distances between the rows of features vectors of the both query fingerprints. We achieve three Euclidian distances. Then, we calculate the norm of these distances. We take this norm as a dissimilarity score. In our identification process, each test fingerprint image is compared with all the training fingerprint images.

For each of our databases used for the evaluation of our method of fingerprint identification, we have divided it into two subsets: one for training task and another for testing task. The subset includes 5*30 learning fingerprint from 30 people, so for each test image we will calculate 150 dissimilarity scores between the query fingerprint image and those of training. Then we order these score in descending order for that entry appears in the right image among the first positions. In the next section, we present what we have generated the experimental results

4. Experimental results

Our experiments were carried out on the FVC2004 DB1, DB2, DB3 and DB4 fingerprint databases [1]. Each subset of FVC2004 database contains 800 images of 100 different fingers with 8 impressions for each finger. More detailed characteristics of this database are summarized in Table 1.

We took from each FVC2004 database the 240 first images of the four sub-databases to be the used in our evaluation of our identification process. We divided each set of images into two sub-sets: a test set containing 3 * 30 images and a training sub-set containing 5*30 images.

Table.1: Fingerprint DataBases

	Image size	Set A (wxd)	Set of images which are used to evaluate our method	Resolution
DB1	640x480 (307 Kpixels)	100x8	**30x8**	500 dpi
DB2	328x364 (119 Kpixels)	100x8	**30x8**	500 dpi
DB3	300x480 (144 Kpixels)	100x8	**30x8**	512 dpi
DB4	288x384 (108 Kpixels)	100x8	**30x8**	About 500 dpi

The experimental results were obtained on a PC running Windows OS with a 2.3 MHz clock speed and the implementations were carried out under MATLAB (R2008a) tools. The parameters of curvelet transform are: scale=5 and 32 angles.

In the following table, we present the rates for the test images appears in one of the first four positions (TOP1,TOP2, TOP3, TOP4) after having sorted the dissimilarity scores between the test images and all of the training images.

Table. 2: Experimental result of fingerprint identification (recognition and determination of appearance place of fingerprint)

Our iris fingerprint identification system				
%	**TOP1**	**TOP2**	**TOP3**	**TOP4**
DB1	95.56	96.67	97.78	100
DB2	88.89	92.22	93.33	97.78
DB3	87.78	93.33	98.89	100
DB4	94.44	96.67	100	100

From the point of view performance as shown in Table 2, our proposed method clearly made an encouraging result. The evaluation on the images token from the FVC2004 databases, for the fingerprint image appears in the first position; our recognition process has given a rate of 95.56% for all test images taken from the FVC2004_DB1 database and a rate of 88.89% for images of FVC2004_DB3 database. For the three databases DB1, DB2, DB4, the query fingerprint appears with a rate of 100% in the first four positions. But in the database DB2, the position of the fingerprint can exceed the fourth position among the learning fingerprints.

In order to examine and prove the performance of the proposed method, a number of experiments comparing performance with other renowned methods were carried out on the FVC2004 database. the method, proposed in reference [YP08], were selected for comparison.

(a) Method of Yang et al.[YP08]: the fingerprint features extraction method uses moments features invariant to characterize a fingerprint image.

For the experiments in the proposed method, the size of an ROI and the tessellated cells are identical with those used in the previous subsection. The Euclidian is used as the similarity measure in this experiment.
Table 3 illustrates the identification rate (%)of the methods of Yang, compared with the proposed method applied to the databases of FVC2004

Table. 3: Fingerprint identification rates obtained by FVC2004 databases

		DB1	**DB2**	**DB3**	**DB4**
TOP1	**Our method**	**95.56%**	**88.89%**	**87.78%**	**94.44%**
	Yang et al. [YP08]	90.00%	88.89%	86.67%	95.56%
TOP2	**Our method**	**96.67%**	**92.22%**	**93.33%**	**96.67%**
	Yang et al. [YP08]	92.22%	90.00%	91.11%	89.89%
TOP3	**Our method**	**97.78%**	**93.33%**	**98.89%**	**100%**
	Yang et al. [YP08]	95.56%	94.44%	94.44%	100%
TOP4	**Our method**	**100%**	**97.78%**	**100%**	**100%**
	Yang et al. [YP08]	97.78%	97.78%	96.67%	100%

The analysis of the figerprint identification rates presented table 3shows that the fingerprint hypotheses ranking obtained by the proposed method is more reliable than that obtained by the method of Yang (20]. The fingerprint identification rate is about 100% at top 4 for the proposed method (DB1, DB3 ad DB4). Whereas, just on the DB2, The fingerprint identification rate is about 100% at top 4 for the method of Yang and on the DB1, DB2 and DB4 the fingerprint identification rate is less then 100%.

Observing the presented results in the both table (table 1 and table2), we can conclude that the integration of curvelet transform in the features fingerprint extraction method can give good results for the identification of the fingerprint. Yet to prove the performance of this method, it's important to be evaluated on a larger fingerprint database.

5. Conclusion

Our proposed features fingerprint extraction method based on curvelet transform has demonstrated that can be promising for fingerprint identification. The method decomposes the fingerprint in a set of sub-bands images, and then calculates some statistical features of each sub-band to represent the binarized fingerprint image. Through various experiments, we have showed that our proposed fingerprint features extraction method can be used for personal identification systems in efficient way. On the fingerprint FVC2004 databases, the proposed method achieves encouraging results.

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