A small scale fingerprint matching scheme using Digital Curvelet Transform

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Q. M. Jonathan Wu
University of Windsor

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Tanaya Mandal
Electrical and Computer Engineering
University of Windsor
Windsor, Ontario, Canada
mandalt@uwindsor.ca

Q. M. Jonathan Wu
Electrical and Computer Engineering
University of Windsor
Windsor, Ontario, Canada
jwu@uwindsor.ca

***Abstract*—This paper proposes a new method for fingerprint matching based on the features extracted using a new multiresolution analysis tool called Digital Curvelet Transform. The curvelet coefficients extracted from enhanced fingerprint images act as the feature-set for a k-nearest neighbor classifier. The performance of this scheme has been evaluated on a small database of 120 images. A comparative study between the wavelet-based and the curvelet-based techniques has also been included. The high recognition rate achieved by using this method suggests an efficient solution for a small scale fingerprint recognition system. Note that, this paper is the first documented attempt to explore the possibilities of a new multiresolution analysis tool called curvelet transform to address the problem of fingerprint identification.**

***Keywords*—fingerprint identification, curvelets, wavelets**

I. INTRODUCTION

Biometrics is the science of identifying an individual on the basis of physiological and behavioral features. Fingerprint is such a physiological biometric and is considered to be the oldest means of personal identification [1]. Fingerprint identification has gained immense popularity in the fields like social security, criminal investigation etc. due to its two very important characteristics: uniqueness (no two people in the world can have the same fingerprint; not even identical twins, where most of the biometrics fail) and permanence (fingerprints are developed at the fetal stage and remain unchanged through out our life).

The main problem with any fingerprint recognition system is that it has to deal with extremely noisy and poor quality images. Besides, these images vary in scale, position and orientation angle, further complicating the process of identification. Various automatic fingerprint matching techniques have been proposed, including minutiae based, image-based and texture-based approaches [1]. Minutiae based approach is most popular of the above and is used in most of the modern fingerprint recognition systems. In this method, fingerprint characteristics, called minutiae (e.g. code, delta, ridge, bifurcation etc.) are extracted and stored in order to perform identification. Image-based approach is also an effective one. Usually, this method requires the storage of the whole fingerprint image, as the entire image is used for template matching. Though this technique suffers from limited ability to deal with variations in scale, position or orientation angle [1], it can achieve high recognition rate as well as lower computational load compared to most of other fingerprint recognition techniques [2]. This method is sometimes the best option while dealing with low resolution images. The problem of variation in position can also be solved by registering the images with respect to a reference point. This reference point or core point can be detected using one of the standard methods [3-5]. However, accurate detection of reference point is difficult and prone to errors. Image based approaches include both optical correlation based [6] and transform based [7, 8] approaches.

Inspired by the success of wavelets, a number of new multiresolution analysis tools like contourlet, ridgelet and curvelet etc. have been developed. Researchers have used contourlets for fingerprint image compression [9] and for fingerprint identification [10]. In some recent works, curvelets have been used to address pattern recognition problems like OCR [11] and finger-vein pattern recognition [12]. Our paper suggests a new image-based method for fingerprint matching using curvelet transform. This is a new application of curvelet transform. Before the fingerprints are subjected to feature extraction, a standard image enhancement technique is employed in order to achieve better result. Locating the 'core point' or 'reference point' in a fingerprint image is very important. After it is located, a square area is cropped from each of the fingerprint images with the core point at the centre. The subimage thus obtained is then divided into four non-overlapping blocks. Thereafter, digital curvelet transform is applied on each of those blocks to extract the crucial features. These curvelet based features extracted from all four non-overlapping blocks act as the feature set to a simple distance based classifier (k-NN).

The rest of the paper is organized as follows. In section II, the procedure to enhance fingerprint images is described. The feature extraction and recognition method is discussed in section III; section IV lists the experimental results and finally, section V concludes and suggests the future prospect of this technique.

II. ENHANCEMENT OF FINGERPRINT IMAGES

Before performing extraction of features, a standard fingerprint image enhancement technique [13] has been applied in order to achieve better result; it may cause some loss of

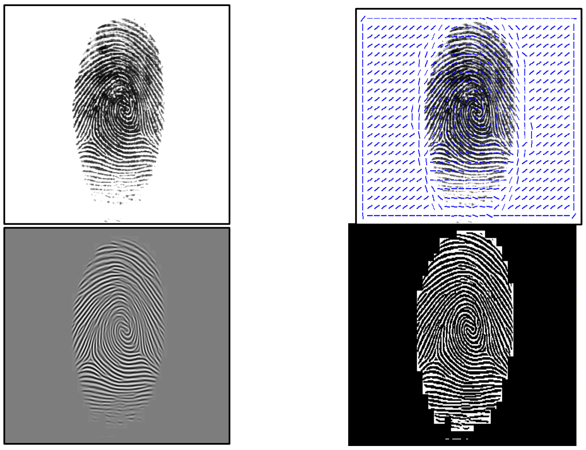

Figure 1. Top left: Original image, Top right: Ridge orientation detected image, Bottom left: Filtered image, Bottom right: Binarized image.

information though. Figure 1 shows the step-by-step result of fingerprint image enhancement process. The image shown in figure 1 is a sample image from our database. Final binarized image obtained after enhancement has been used for feature extraction. The image enhancement process consists of the following steps [13]:

- Identification of ridge-like regions and normalization of intensity values
- Estimation of local orientation ridge
- Estimation of local ridge-frequency across the fingerprint
- Filtering of the image to enhance the ridge pattern
- Binarization i.e. conversion of a gray-scale fingerprint image to binary image

III. Feature Extraction and Recognition

This work is motivated by that of Tico et al [8]. Their fingerprint recognition scheme was based on features extracted using wavelet transform. However, the traditional wavelet transform has some inherent limitations. Wavelets rely on isotropic scaling and have limited abilities to resolve directional features; the standard orthogonal wavelet transform contains wavelets with primary vertical, primary horizontal and primary diagonal orientations only. Moreover, images do not always exhibit isotropic scaling. Though wavelets are good at representing point singularities in both 1D and 2D signals, they fail to detect curved singularities efficiently. These limitations of wavelet transform call for other improved multi-scale representations.

Curvelet Transform [14] is a recent entry in this category of multiscale multidirectional transform with better directional capabilities compared to wavelet transform. Conceptually, this mathematical tool is multiscale pyramid with many directions and positions at each length scale and needle-shaped elements at fine scales [15]. Curvelets present highly anisotropic behavior as it has both variable length and width. At fine scale the relationship between curvelets' width and length can be expressed as $width \approx length^2$; anisotropy increases with decreasing scale, in keeping with power law.

The second generation curvelet transform [15] has two different digital implementations: curvelets via USFFT (Unequally Spaced Fast Fourier Transform) and curvelets via Wrapping. These new discrete curvelet transforms are simpler, faster and less redundant compared to its first generation versions. Both the digital implementations use the same digital coronization but differ in the choice of spatial grid. Curvelets via wrapping has been used for this work; because this is the fastest curvelet transform currently available [15]. If $f[t_1, t_2]$, $0 \le t_1$, $0 \le t_2$ is taken to be a Cartesian array and $\hat{f}[n_1, n_2]$ to denote its 2D discrete Fourier transform, then the architecture of curvelets via wrapping is as follows [15]:

1. 2D FFT (Fast Fourier Transform) is applied to obtain Fourier samples $\hat{f}[n_1, n_2]$.
2. For each scale j and angle ℓ, the product $\tilde{U}_{j,\ell}[n_1, n_2]\hat{f}[n_1, n_2]$ is formed, where $\tilde{U}_{j,\ell}[n_1, n_2]$ is the discrete localizing window.
3. This product is wrapped around the origin to obtain $\hat{f}_{j,\ell}[n_1, n_2] = W(\tilde{U}_{j,\ell}\hat{f})[n_1, n_2]$, where the range for n_1 and n_2 is now $0 \le n_1 < L_{1,j}$ and $0 \le n_2 < L_{2,j}$; $L_{1,j} \sim 2^j$ and $L_{2,j} \sim 2^{j/2}$ are constants.
4. Inverse 2D FFT is applied to each $\tilde{f}_{j,\ell}$, hence generating the discrete curvelet coefficients.

Figure 2 shows the division of wedges of the Fourier Frequency plane in its left image; the right one represents curvelets in spatial Cartesian grid associated with a given scale and orientation [15].

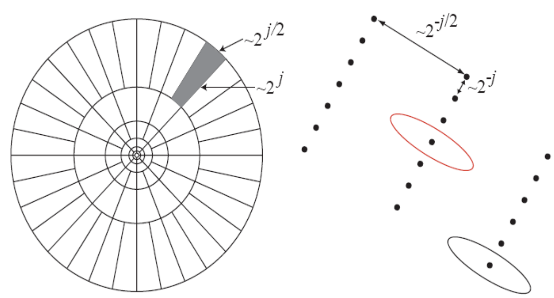

Figure 2. Curvelets in Fourier Frequency domain (left) and Spatial domain (right) [15]

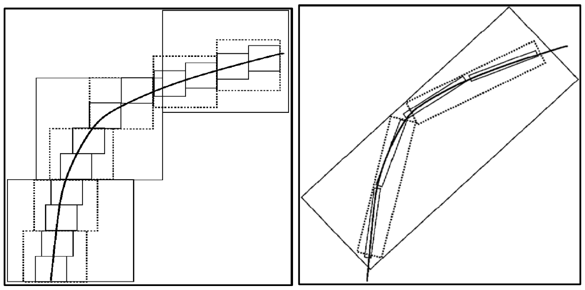

Figure 3. Edge representation using Wavelets (left) and Curvelets (right)

Like ridgelets, curvelets can occur at any scale, location and orientation [16]. But curvelets have variable length in addition to variable width (variable anisotropy), where as ridgelets have only variable width and global length. Curvelet transform has improved directional capability, better ability to represent edges and other singularities along curves as compared to other traditional multiscale transforms, e.g. wavelet transform. It requires less number of coefficients than that of wavelets to represent the same edge with the same given accuracy. For the square shape of wavelets at each scale, more wavelets are required for representing any edge, compared to elongated needle shaped curvelets. Roughly, to represent an edge of squared error *1/N*, we require *1/N* wavelets but only $1/\sqrt{N}$ curvelets [14]. This is illustrated in figure 3. Due to the limited scope of this paper, we are unable to delve into the mathematical details of digital curvelet transform. Interested readers may refer to the works of Candes and Donoho [15-17].

Curvelet transform has better ability to capture the edge information of an image. Images like fingerprints often have two nearby regions differing in pixel values. These variations in pixel values between two consecutive regions are likely to form such 'edges' and this edge information is eventually captured by digital curvelet transform. Our feature extraction method partly follows the steps mentioned in the work of Tico et al [8]. The feature extraction steps used for this work are as followed:

- Locate the reference point or core point in the fingerprint image.
- Crop an *N* x *M* subimage from the fingerprint pattern with core point at the center. This can be called 'central subimage' [8].
- Divide this central subimage into a number of non-overlapping blocks of size *W* x *W*.
- Take curvelet transform for each of the non-overlapping blocks at Scale = S and Angle = A.
- Take standard deviation of each of the curvelet coefficient sets for each scale and angle.
- The standard deviation thus obtained for each of the four blocks of a fingerprint image construct the global feature vector together.

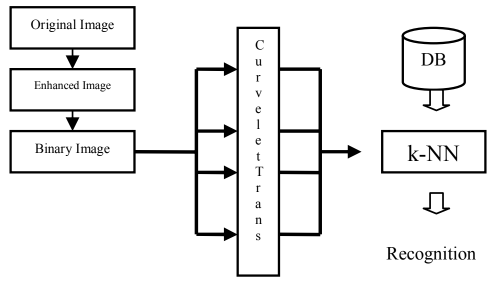

Figure 4. Fingerprint Recognition Scheme

No core point detection algorithm has been employed in order to avoid error. The core point for each image is located manually. The recognition procedure is simple. The images in the test set are subjected to similar treatment and the feature set of corresponding blocks are compared. A simple distance based classifier like k-NN classifier is used to identify the test sample. The distance between the query and the training sample is computed using L1 norm. A pictorial presentation of the entire recognition scheme is provided in figure 4.

IV. EXPERIMENTAL RESULT

Experiments have been carried out on a database of 120 images of size 640 x 480 including 8 images per finger of 15 individuals. The images have been selected from the FVC2004 database DB1 [18] on a random basis. FVC2004 database DB1, was collected using an optical sensor V300 by CrossMatch. It contains fingerprint impressions for 100 fingers, 8 impressions per finger; original image size being 640 x 480 (307 kpixels). A few sample images are shown in figure 5.

Curvelets, as mentioned before, are good at representing edge discontinuities. This property of curvelet transform to is exploited here to extract the features from fingerprint images. The parameters used for the experiments are: N = M = 64, W = 32; which means the central subimage is divided into four non-overlapping blocks. The parameters used for digital curvelet transform are: S = 2, 3 and A = 8, 16, 32, and 64. The experiments have been carried out using MatlabR2006 environment. For wavelet transform the inbuilt wavelet functions have been used and curvelet transform has been implemented using a curvelet toolbox called 'curvelab 2.0.2' [19].

Figure 5. Sample images from FVC2004, DB1 [18]

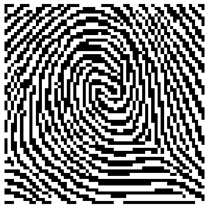

Figure 6. Central Subimage of a fingerprint image

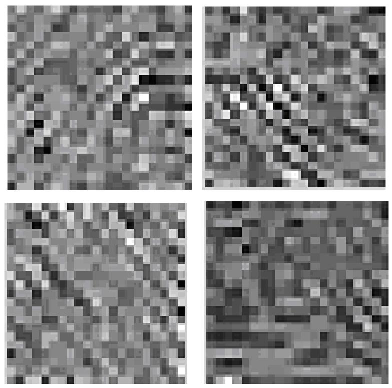

Figure 7. Curvelet coefficients of central subimage divided into four 32 x 32 non-overlapping blocks

In a small scale fingerprint matching system, the error induced by any core detection algorithm is not affordable. Hence the core points of the fingerprint images have been detected manually, instead of using any core-detection algorithm. For larger databases, core-point detection techniques can be employed though. An area of size N x M has been cropped from each image with the core point at the center, which is called 'central subimage'. The values of N and M are kept small so that the entire subimage can be located inside the fingerprint pattern in every case. Figure 6 shows a central subimage cropped from the original fingerprint image shown in figure 1 and figure 7 shows its curvelet coefficients for 4 non-overlapping blocks. The performance of this method using curvelet based feature extraction has been evaluated using a simple distance based k-NN classifier, with no rejection option. Entire dataset is divided into two parts. A number of X (= 5) images for each finger, i.e. 75 images in total have been used for training and the remaining 45 images have been used to construct the test set.

Table I lists the high recognition rate achieved by using curvelet based feature extraction technique. Five different wavelet basis have been used in order to carry out wavelet based feature extraction using the same training and test sets. The reason behind using only these five wavelet basis (Symmlet 4, 5, 6, 8, 9) is that in the work of Tico et al [8] best results were obtained with these five wavelet basis. This comparative study between wavelets and curvelets is presented in Table II.

TABLE I. CURVELET BASED RESULTS

Scale (*S*)	**Angle (*A*)**	**Fingerprint Matching Accuracy in %**				
		***1*-NN**	***2*-NN**	***3*-NN**	***4*-NN**	***5*-NN**
2	8	93.3	90	76.7	80	80
2	16	96.7	90	96.7	83.3	90
2	32	93.3	93.3	100	90	83.3
2	64	93.3	93.3	96.7	90	83.3
3	8	90	90	83.3	80	80
3	16	93.3	96.7	90	93.3	96.7
3	32	100	100	100	96.7	96.7
3	64	100	100	100	93.3	93.3

Though curvelet results are quite impressive, the results need to be compared to wavelets, curvelet's closest cousin, in order to establish its credibility. The best result achieved using curvelet transform is compared with aforesaid wavelet-based results on the same training and test sets. The recognition rates shown here are obtained by averaging the results of three different round of fingerprint matching. Each time the images are selected randomly to construct the training and test sets.

TABLE II. COMPARATIVE RESULTS OF CURVELETS AND WAVELETS

Feature Extraction by	**Fingerprint Matching Accuracy in %**				
	***1*-NN**	***2*-NN**	***3*-NN**	***4*-NN**	***5*-NN**
Curvelets ($S=3$, A=32)	100	100	100	97.77	97.77
Wavelets (Symmlet 9)	93.33	93.33	93.33	86.66	86.66
Wavelets (Symmlet 8)	93.33	93.33	93.33	82.22	82.22
Wavelets (Symmlet 6)	93.33	93.33	93.33	82.22	80.00
Wavelets (Symmlet 5)	93.33	93.33	93.33	91.11	86.66
Wavelets (Symmlet 4)	93.33	93.33	93.33	82.22	82.22

It is worth noticing that the best recognition rate achieved using curvelet based feature extraction is 100% for scale = 3, angle = 32 and 64, where as the highest recognition rate achieved by wavelets is 93.33 %. The experimental results in Table II evidently show superior performance of curvelet feature-based scheme over the wavelet-based one in terms of recognition accuracy; but wavelet-based method is computationally faster. So, there remains a trade off between accuracy and computational efficiency. It is a critical task to determine the optimum value of k. In practice, small value of k seems to work well for smaller size of training data, as in our case k = 1 seems to work most effectively.

V. Conclusion

A new method of fingerprint recognition using curvelet based feature extraction has been proposed. The technique is applied on the enhanced fingerprint images on a small database. This image based approach achieves comparatively low computational complexity compared to other minutiae based techniques; and the usage of curvelet transform for feature extraction instead of traditional multi-scale transforms like wavelet transform is justified by the higher accuracy of curvelets over the wavelets. The method works efficiently for a small scale fingerprint recognition system. The future work is suggested towards modifying this method to work for larger databases and to attain even lower computational complexity by applying the feature extraction technique directly on the gray scale images i.e. by avoiding image enhancement. The classification performance using other classifiers like neural network or support vector machines can also be explored and compared.

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