Rotation Invariant Fingerprint Core-Point Detection using DWT

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ABSTRACT
The performance of majority of algorithms employed for fingerprint identification is strongly affected by the accuracy of detection of core-point. Unintentional finger rotation during acquisition process inspite of mounting a finger “guide” on the sensor results in rotation of fingerprint images. In order to tackle this rotational variance a Discrete Wavelet Transform (DWT) based approach for core-point detection has been presented in this paper. The approach does not involve computation of orientation field and is directly employed on the gray scale images. We use 2D-wavelet coefficients in horizontal, vertical and diagonal direction to locate the core. Experimental results on two different databases have shown that approach is robust and invariant to rotation.

General Terms
Digital Image Processing

Keywords
Biometrics, Fingerprint, core-point, Wavelet transform.

1. INTRODUCTION
Online shopping, e-banking and ATMs have become an integral part of our day to day life over the past one decade. This along with the increased threat perception has necessitated the need for reliable personal identification. Biometrics which deals with automatic recognition of humans based on their physiological and behavioral characteristics has emerged as a major player in this direction. Biometric based systems have greater reliability in comparison to the traditional token or password based systems. Fingerprint recognition [1, 2] belongs to the category of physiological biometrics which also includes face [3], iris [4,5], retina[6], ear[7] etc. while behavioral biometrics comprises of voice [8], signature[9] , gait[10], and keystroke dynamics[11]. In addition to these systems based on ECG [12, 13], EEG, lip-print [14], and mouse dynamics [15] are also being developed [16]. Fingerprints are probably the oldest biometric measure with evidence that Chinese employed it as early as 14th century. Moreover fingerprints have been traditionally employed by the forensic scientists for criminal identification and as a result have been the focus of research in biometrics. This has resulted in development of many commercial fingerprint based biometric systems and at present it has the largest revenue share among the various biometrics [17].

Fingerprint, shown in figure 1, is a pattern of interleaved ridges (dark) and valleys (bright). These are formed during the pre- natal stage and do not change during the life of an individual. Fingerprints pattern contain distinctive features which can be classified at global level (singularity points - loop and delta), local level (minutiae- ridge bifurcations, ridge endings etc.) and at very fine level (sweat pores). Automatic Fingerprint recognition systems extract and match these features and can be broadly categorized under two main headings minutiae based approaches [18] and image based approaches [19]. In most of these fingerprint patterns are pre-aligned according to a landmark or a centre point, called core.

Edward Henry has defined core as the north most point on the innermost ridge line. It is more appropriate to consider core point as the centre-point of north most ridge line of loop type singularity [2]. This definition is restricted to loop and whorl type singularities and does not cover arch singularity for which defining core is a difficult task. The success of majority of the fingerprint identification/verification algorithms is highly dependent on accurate detection of the core-point. In addition to this core-point also plays an important role in fingerprint classification and computation of ridge count. It is, therefore, pertinent to develop and employ a robust core-point detection algorithm.

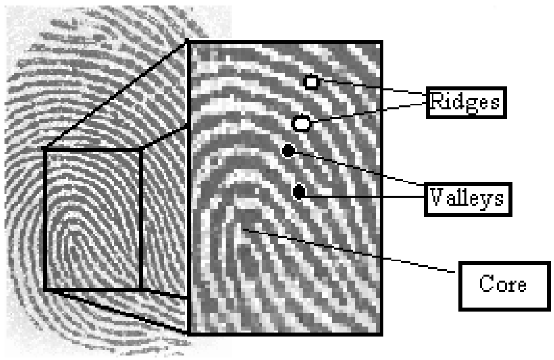

Fig 1. Fingerprint image showing ridges and valleys

In this paper we propose an approach for reliable core-point detection which exploits the directional properties of Discrete Wavelet Transform (DWT) and is applied directly on the image acquired from a fingerprint scanner.

The paper is organized as follows. This first section provides the introduction. Brief overview of other methods for core-point detection is presented in following section. The proposed method is described in section 3. Experimental results are shown in section 4 and finally paper is summarized with a brief conclusion.

2. RELATED WORK
A number of methods have been proposed for the detection of core point. A common step in most of them is the computation of the orientation field. The methodology of these approaches can be summarized as (i) pre-process the image by normalizing the image using its mean and variance, (ii) divide the normalized image into small non-overlapping blocks and compute the gradient in x and y-direction V_x and V_y respectively at the centre pixel of each block using gradient operator, (iii) estimate the values of local orientation by finding $\theta = \tan^{-1}(V_{y,}\ V_x)$, (iv) Smoothen the orientation field

and find the maximum curvature point in it . Assign the co-ordinates of this point as the core –point. Atipat and Samsak [20] have extended this method and proposed an algorithm in which they used a combination of Direction of Curvature (DC) and Geometry of Region (GR) approaches for optimal detection of the core-point. These methods work on the assumption that fingerprint images are vertically aligned which may not be the case in practical applications. In order to detect the core by the DC, GR method or their combination a scanning of the orientation image has to be carried out to locate the core-point. In [21] Alireza and Masoud have proposed a method in which instead of scanning the orientation image, wavelet coefficients of the orientation image in the horizontal, vertical and diagonal direction have been used to locate the core-point. The results presented by the authors show that proposed core-detection algorithm is robust to image rotation.

3. METHODOLOGY

The algorithm presented in this paper is an extension of method described in [21]. In our approach instead of finding the orientation image and computing its wavelet coefficients, we have worked directly on the gray scale images. As mentioned earlier fingerprint image comprises of alternative ridges and valleys. These ridges can be highlighted by using an edge detector. A binary image is obtained by using standard thresholding.

In order to extract the variations of the ridges and valleys in different directions the properties of two-dimensional wavelet transform are exploited. Two dimensional wavelet transform uses a two dimensional scaling function $\varphi(x, y)$ and three two-dimensional wavelets, $\psi^H(x,y)$, $\psi^V(x,y)$ and $\psi^D(x,y)$ [19,22]. The two-dimensional wavelet decomposition of an image $I_0(m,n)$ on J octaves results in $3J+1$ sub-images

$$[\, a_J ,\ \{d^{H}_{j},\ d^{V}_{j},\ d^{D}_{j}\}_{j=1 \text{ to } J}],$$

where a_J is the low resolution approximation of the original image and the d^{k}_{j} are the wavelet sub-images containing the image details at different scales (2^j) and orientations (k). Wavelet coefficients d^{H}_{j}, d^{V}_{j}, and d^{D}_{j} respectively provide a measure of intensity variations in horizontal, vertical and diagonal direction.

The algorithm uses the information obtained from these three coefficients for localization of core point and as such incorporates the direction information automatically.

3.1 Algorithm

Let I(x,y) be the input grey-level image obtained from a fingerprint sensor. The main steps of the proposed algorithm are mentioned below:

1. Perform an edge detection operation on the input image I(x,y) and obtain a binary image B(x,y).
2. Compute single level wavelet decomposition on the binary image B(x,y) to obtain the three wavelet coefficient subimages $I^H(x,y)$, $I^V(x,y)$ and $I^D(x,y)$; a sample result is shown in figure 2.
3. Smoothen the three wavelet subimages to remove noise by using an averaging filter.
4. Reconstruct three images using three smoothened wavelet images one at a time by employing inverse wavelet transform.
5. Find the locations of the pixels in each reconstructed image [23].
6. Find the intersection points of the three reconstructed images.
7. The coordinates of the pixels corresponding to minimum distance are selected. The mean value of these co-ordinates is the detected core-point.

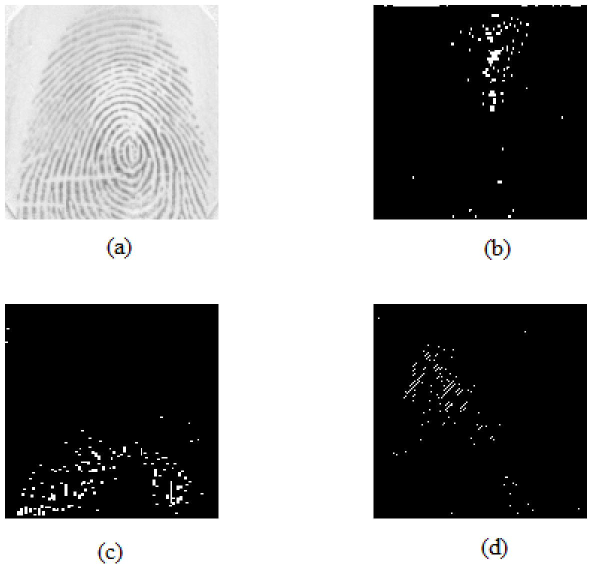

Fig 2. (a) Original Image (b) Horizontal Subimage (c) Vertical Subimage (d) Diagonal Subimage

4. EXPERIMENTAL RESULTS

We tested the proposed algorithm on the two different databases on Matlab environment. One of them is DB1 from FVC2000 database comprising of 880 fingerprints of 110 different fingers. Minor translational and rotational variation is inherently present in any two fingerprint images due to variation in placement of finger on the sensor during image acquisition. Even with sensors mounted with finger "guide", involuntary finger rotations of up to ± 20° with reference to vertical orientation has been observed in practice [2]. In order to verify the performance of proposed scheme for large rotational variations a second database was acquired using Digital Persona's optical sensor based U.are.U 4500 Reader. All subjects were asked to place finger vertically and horizontally (±90° with respect to vertical orientation). In total three images from 25 subjects each of size 355 x 320 with pixel resolution 512 dpi were acquired and tested.
Canny edge detector has been used for edge detection and global threshold has been used for obtaining the binary image. We have used the Haar wavelet function for obtaining the decomposed sub-images. For the case of the images rotated at an angle if the detected core is within a two ridge lines it is considered to be correct result.
Figure 3 provides the information regarding the performance of the algorithm on the in-house database at three different rotation angles for two different singularities (loop and whorl) ; while figure 4 shows the results of the experiments for four major classes of fingerprints (left loop, right loop, whorl and arch) from the Db1 database.

Fig 3. Core detection results for rotated images from the in-house database.

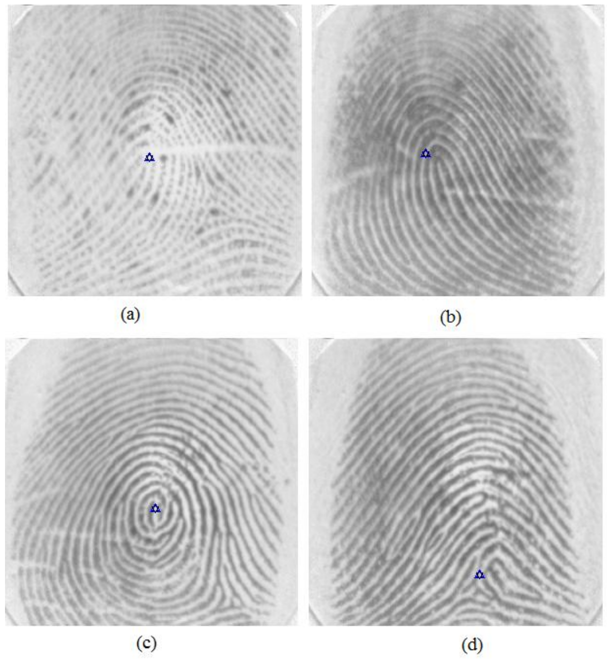

Fig 4. Core point detection results for (a) left loop (b) right loop (c) whorl and (d) arch type fingerprint

Figure 5 shows the sample cases in which the core was misclassified. It has been observed from experimentation that the algorithm fails to locate the core exactly in cases such when core has been occluded due to error during acquisition, when the delta and core type singularities are very close, a double loop exists, in arc type fingerprints and when the image is too noisy.

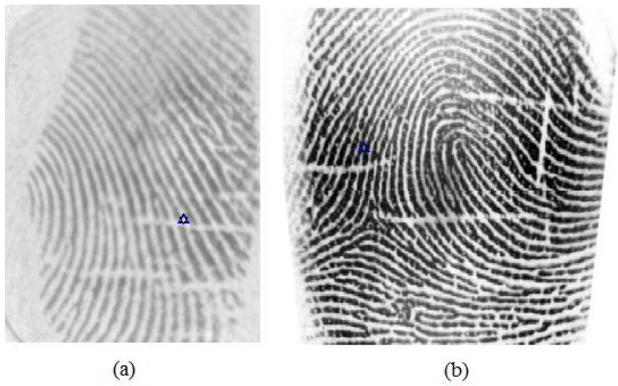

Fig 5. Failed cases (a) core absent (b) delta near to core.

The results are summarized below in table 1. The algorithm was tested for all 880 images in Db1 database and 25x3= 75 images of the in-house database.

Table 1. Table captions should be placed above the table

Database	Accepted Core-point	False core-point	% accuracy
Db1 (880)	829	51	94.2%
In-house database (75)	71	4	94.6%

5. CONCLUSIONS

The proposed approach gives results comparable with those reported in literature for Db1 database. In addition to this the algorithm was able to locate the core even on the rotated images for different types of fingerprints. Though the core point localization condition was relaxed for rotated images but in all cases algorithm assures to correctly locate the neighborhood of the core-point. The algorithm described in this paper also alleviates the need of computation of orientation field. The future work in this direction will involve verification of rotational invariance of the algorithm on a larger database and development of rotation invariant fingerprint recognition system.

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