Invariant Feature Extraction from Fingerprint Biometric Using Pseudo Zernike Moments

C.Lakshmi Deepika[1], Dr. A Kandaswamy[2], C. Vimal[3], and B. Sathish[4]

[1,2,3,4]*Department of Biomedical Engineering, PSG College of Technology, Coimbatore – 4.*
cldeepika@yahoo.com, hod@bme.psgtech.ac.in, vimalc@ieee.org, sathishb90@live.com

***Abstract*—To represent the large amount of data in the biometric images an efficient feature extraction method is needed. Further biometric image acquisition is subject to deforming processes such as rotation, translation and scaling. Hence it is also required that the image representation be invariant to the deformations and sustain the discriminating features. Considering the trade off between the discriminating power and the invariants, moments are a very qualifying object descriptor. In this paper, we have used Pseudo Zernike moments to create invariant feature vectors for the Finger print biometric. We have used the Bayesian classifier to validate our usage of moments. The accuracy of the system was found to be 96.89% on using lower order moments.**

***Index Terms*—Fingerprint, Biometrics, ROI Extraction, Zernike Moments, Pseudo Zernike Moments, Bayes Net Classifier**

I. INTRODUCTION

Biometric image acquisition is subject to various degradations during the acquisition process due to factors such as imaging geometry, lens aberration, wrong focus, motion of scene and other random and systematic errors. Biometric recognition involves recognition of biometric images that are deformed in any of the above said ways. Creating a template which includes representations of all these deformation classes would be impractical in terms of computational and time complexity. Therefore it is necessary to bring all the images to a standard form before classification. This standardization is also called normalization, which is also computationally complex. Another alternative is to represent the image with features that are invariant to deformations, especially the popular ones namely, scaling, translation and invariance. Moment invariant is a mathematical tool which is used for image representation by projecting a function onto a polynomial basis. Depending on the polynomial basis several types of moments are available. Orthogonal moments are found to capture image features efficiently even from low resolution images. In this paper we have chosen the fingerprint biometric to validate the efficiency of the moments in creating invariant templates.

There are several approaches to deal with Fingerprint Recognition. Because of their computational complexity it is an arduous job to create a global algorithm which could even deal with incomplete fingerprints. In Maltoni et al [1] the algorithms proposed mainly focus on image correlation, texture descriptor and filter banks or minutia points. Among these, minutia based techniques are the most widely used. The performance of a biometric depends to a large extent on the feature extraction or texture extraction. There are several approaches for the detection of singularity points in the literature, among these the most popular is the one proposed by Kawagoe et al [2]. In image enhancement, the most commonly used technique is Histogram equalization. It enhances the contrast of the image in spatial domain[3,4] In this paper we have used an adaptive method for enhancement . Herman et al [5] proposed wavelet transform to reduce the problems of illumination in the image recognition process. It is basically a flexible window Fourier transform which decomposes the image into different levels of resolution [6]. Moments and functions of moments [7,9,10,11] have been utilized as pattern features in a number of applications to achieve invariant recognition of two-dimensional image patterns. Prokop et al [8] have used several moments including the Cartesian moments. Yang et al [12] proposed image verification using invariant Moment Features. Hu [13] first introduced his seven moment based image invariants against rotation, scaling and translation. Calculation of Hu's moments of higher orders and image reconstruction from the moment invariants is a difficult task. To overcome this problem Teague [14] introduced Zernike moments which could recover the image using the concept of orthogonal moments. Zernike moments are superior to other moments because of their insensitivity towards information content and image noise [15]. Pokhriyal et al [16] proposed that Zernike and pseudo Zernike extract image features independently with less information redundancy in the moment set. These reasons make Pseudo Zernike moments more desirable for image recognition.

II. PROPOSED SYSTEM

In the system, we propose to develop a fingerprint authentication system using Pseudo Zernike moments. This system will enrol the users in a database by acquiring the fingerprints, processing them and then converting each fingerprint into the so-called template. At the time of authentication, the live fingerprint is captured from the user, processed, template created and then compared with stored template image. If it matches, then the user is authenticated and otherwise, not. When the fingerprint input image is captured, it cannot be used as a raw image.

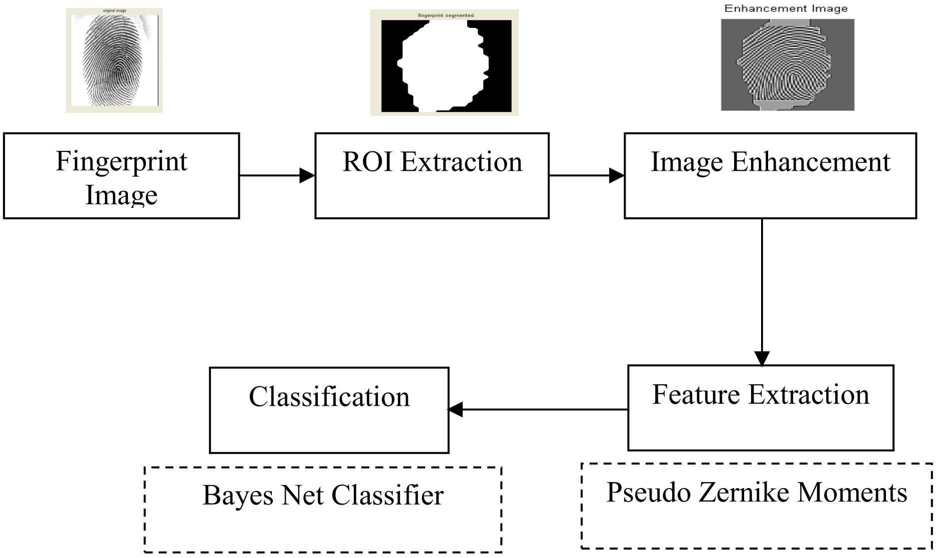

Figure 1. Proposed System

The region on the fingerprint which contains the maximum information has to be separated from the relatively less important regions. So, there is a need for extraction of the required region of interest. The extracted ROI contains many prominent features. However it is required to emphasise the details present in this region more, so that the features are extracted precisely. For this purpose image enhancement is performed. The steps involved in implementing the system are shown in Fig 1. The next stage is feature extraction which still reduces the space needed to save the biometric and the processing power needed to process the same further. The pseudo Zernike moments which are invariant to translation, scaling and rotation are used to extract the features from the enhanced image. These features are then used for classification using Bayes net classifier.

A. Data Soure

We have tested our fingerprint recognition system using one of the FVC 2002 databases [17]. The database all together contains fingerprint images of 31 participants with four different databases. The database consists of two different classes, set A for evaluation and set B for training. Among them, we have used set A of DB1. The size of fingerprint images of DB1 was 388×374 at 500dpi.

B. Binarisation and ROI Extraction

Binarization is an operation that converts a grayscale image into a binary image. We use an adaptive threshold based binarization method to binarize the fingerprint image [18]. This method involves transformation of the pixels value to 1 in case if the value of the pixel is larger than the mean intensity value of the current block in which the pixel is present.

$$I_{new}(n_1, n_2) = \begin{cases} 1 \text{ if } I_{old}(n_1, n_2) \geq Local\ Mean \\ 0 \qquad\qquad\qquad\qquad otherwise \end{cases} \tag{1}$$

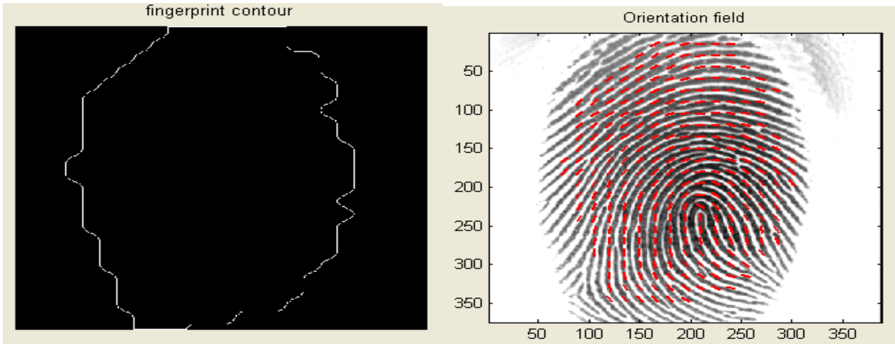

Figure 3: Fingerprint image after finding contour (left), Fingerprint image after finding Orientation Field (right)

There are two different regions in Fingerprint image, one with information regarding the fingerprint and the other without any information content. The areas in the image which does not contain this information are removed from the image since it contains only the background information which is of no use for the recognition process. This is basically known as the known as the extraction of the region of interest. We have followed a two step method to extract the region of interest from the binarized image. The first step involves estimation of the block direction along with direction variety check. The second step involves two morphological operations called 'OPEN' and 'CLOSE'. 'OPEN' expands the image eliminates the peaks due to background noise and the latter shrinks the images and removes minute cavities..

C. Image Enhancement

Wavelet-based normalization method is used in ROI extracted fingerprint images so as to normalize illuminations. [19]. In this method the contrast and edges of the fingerprint images are enhanced simultaneously using the wavelet transform. Wavelet-based image analysis decomposes an image into approximate coefficients and detail coefficients. Contrast enhancement can be done by histogram equalization of the approximation coefficients and meanwhile edge enhancement can be achieved by multiplying the detail coefficients with a scalar (>1). A normalized image is obtained from the modified coefficients by inverse wavelet transform. In this proposed model we used db10 1st level wavelet decomposition and 1.5 as the scalar value for multiplying the detail coefficient.

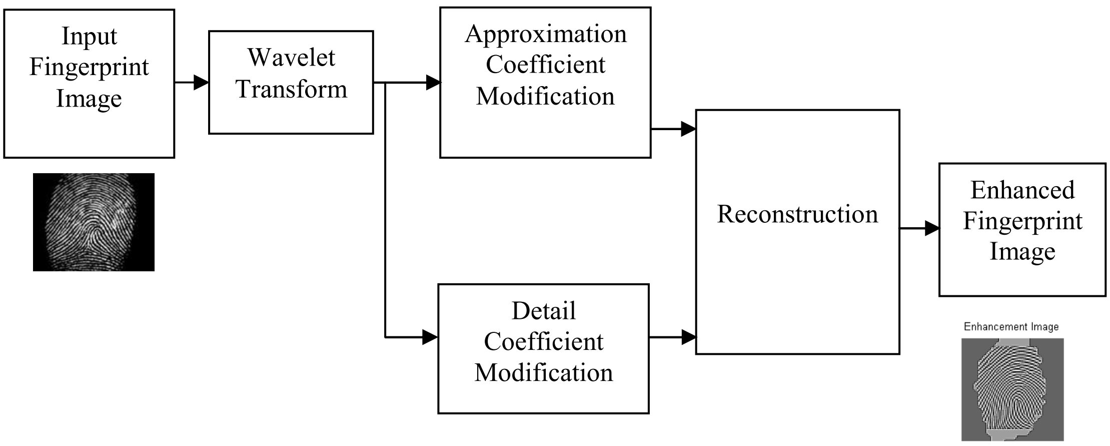

Figure 4. Image Enhancement

D. Feature Extraction Using Zernike Moments

The kernel of Zernike moments is a set of orthogonal Zernike polynomials defined over the polar coordinate space inside a unit circle [14]. The two dimensional Zernike moments of order p with repetition q of an image intensity function $f(r,\theta)$ are defined as:

$$Z_{pq} = \frac{p+1}{\pi} \int_0^{2\pi} \int_0^1 V_{pq}(r,\theta) f(r,\theta)\, r \, dr \, d\theta \; ; \; |r| \leq 1 \qquad (2)$$

where Zernike polynomials $V_{pq}(r,\theta)$ are defined as:

$$V_{pq}(r,\theta) = R_{pq}(r) e^{-jq\theta};$$
$$j = \sqrt{-1} \qquad (3)$$

and the real-valued radial polynomials, $R_{pq}(r)$, is defined as follows:

$$R_{pq}(r) = \sum_{k=0}^{\frac{p-|q|}{2}} (-1)^k \frac{(p-k)!}{k! \left(\frac{p-|q|}{2} - k\right)! \left(\frac{p+|q|}{2} - k\right)!} r^{p-2k} \qquad (4)$$

where $0 \leq |q| \leq p$ and $p - |q|$ is even

We can see that the Zernike moments in equation (2) become pseudo Zernike moments if the radial polynomials, R_{pq} , defined as in equation (4) with its condition p-|q|=even is eliminated. Therefore, pseudo Zernike moments offer more feature vectors than Zernike moments since pseudo Zernike polynomial contains (p+1)^2 linearly independent polynomials of order ≤p, whereas Zernike polynomial contains only $\frac{1}{2}(p+1)(p+2)$ linearly independent polynomials due to condition of p-$|q|$=*even.*

E. Classifier

Bayes Net or Bayesian Belief Networks (BBN) is a special type of "probabilistic graphical model". A BBN is a directed acyclic graph consisting of three elements: nodes representing random variables, arcs representing probabilistic dependencies among those variables, and a Conditional Probability-Distribution Table (CPT) for each variable [20]. The nodes can be either evidence variables or latent variables; an evidence variable is one with a known value (i.e. it is measured). Arcs specify the causal relation between variables [21,22]. Finally, each node has a CPT which includes the probabilities of outcomes of its variable given the values of its parents. The conditional probability is given by

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i | Parents(X_i)) \qquad (5)$$

We have used the Baye's classifier for the final decision making part of our authentication system. The classifier is trained with the fingerprint images of the enrolled users. Then whenever a user would to authenticate himself, the classifier approves him as an authorized user or dismisses him as an impostor. We have tested the classifier and obtained satisfactory results which prove that it is working well.

III. RESULTS AND DISCUSSION

This section describes the experimental protocol employed in our present work. Eight images per finger are considered for training the classifier and remaining eight images are used for testing the proposed algorithm. The experiments are conducted for moment orders ranging from 1 to 3, and portioning the fingerprint into (2×2); (3×3); (4×4); (5×5); (6×6); (7×7); (8×8); (9×9); (10×10);(11×11) ;(12×12) sub-images. The fingerprint image is now broken down into sub images for feature extraction to increase the quality and quantity of the moments extracted. The experiment is also conducted for moments of order 1 to 5 for the entire fingerprint image. Accuracy (ACC), True Positive (TP), False Positive (FP) are used for validating the proposed system. The results for fingerprint image of orders from 1 to 5 are presented in Table I.

TABLE I
OVERALL RESULT FOR ENTIRE FINGERPRINT IMAGE

	Order 1	Order 2	Order 3	Order 4	Order 5
Accuracy	62.3	71.1	82.7	84.5	**90.3**
TP	0.623	0.711	0.827	0.845	**0.903**
FP	0.035	0.026	0.017	0.015	**0.008**

From the above discussion we are able to infer that the features extracted from fingerprint images(sub-images-10×10) using the lower order 3 Pseudo Zernike moments outperform the features extracted from the entire image using higher order 5 Pseudo Zernike moments. The superior nature of Pseudo Zernike moments of lower order will help in ameliorating efficiency of Fingerprint Recognition.

IV. CONCLUSION

This paper has proposed fingerprint verification system using lower order Pseudo Zernike moments to extract features from fingerprint image after subdividing the fingerprint image into sub images. This method also performs better than the conventional method using the high order Pseudozernike moments for entire fingerprint. The proposed method also solves the major disadvantage of the fingerprint recognition system namely, making it invariant to translation, scaling and rotation.

Another important observation from this is the fact that, due to practical consideration and limitation, when multimodal biometric data is not available for improved verification one can uses single features of various sub images of an image of the unimodal biometric to obtain improved performance of verification. This also opens up area of research where multiple features can be obtained from sub images of an image may offer acceptable performance as against multimodal biometrics.

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