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Fingerprints Identification Using Contourlet Transform

Abstract- This paper suggests the use of contourlet transform for efficient feature extraction of fingerprints for identification purposes. Back propagated neural network is then used as a classifier. Two fingerprints databases are used to test the system. These include fingerprints images with different positions, rotations and scales to test the robustness of the system. Computer simulation results show that the proposed contourlet transform outperforms the classical wavelet method. Where an identification rate of 94.4% was obtained using contourlet transform compare with 87% using wavelet transform for standard FVC2002 database.

Keywords- Back Prorogation Neural Network Classifier, Contourlet Fingerprint Identification, Contourlet Transform, Discrete Wavelet Transform.

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1. Introduction

Recently, human fingerprints have been widely used in various applications, such as electronic credit cards, authorized entry security systems, authentication, privilege of data access levels, etc. One of these varieties of applications is fingerprint identification systems [1]. Huge number of databases has been stored in many levels of networks servers. The main property of any identification system is the number of learning iterations to get the maximum reliable (correct) decision for identification. The use of image processing methods such as filters, transforms (DFT, DCT, DWT), LoG, Laplasian operators, gradient, sobel and canny methods and many other digital signal processing methods are used [2,3]. One of the main methods is the 2D wavelet transform, which represents an extension for 1D wavelet transform. It is used for edge detection depending on scalable levels and noise of image. The vulnerability of this method is that the detection is in three directions only, vertical, horizontal and diagonal [4].

In this paper, fingerprint identification is performed using contourlet transform as feature extractor then a back propagated neural network is used as a classifier. The remaining sections of this paper are organized as follows: Section 2 explains a brief theoretical background on contourlet transform. Section 3 gives the proposed system. Section 4 shows the computer

simulation results while section 5 concluded the paper.

2. Contourlet Transform

The features needed to detect in the application of fingerprint identification are, multiresolution, localization, critical sampling, directionality and anisotropy. The 2-D wavelet transform, satisfies the first three requirements. The curvelet is the first fixed transform used to capture contours and satisfy the fourth condition; however, it is defined only by the continuous domain [3], as shown in Figure 1. Capturing smoother contours and edges at any direction (orientation) can be derived directly from discrete domain. Contourlet transform can be implemented by using filter banks as shown in Figure 2.

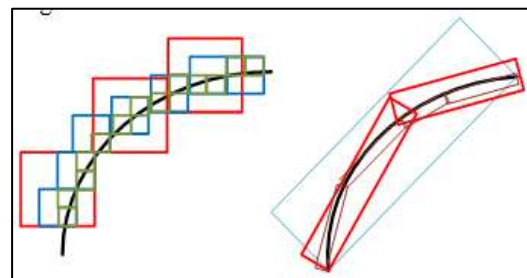


Figure 1: (a) Wavelet (b) New scheme (contourlet)

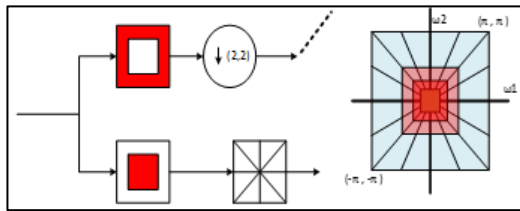


Figure 2: The contourlet transform decouples the multiscale and the directional decompositions. (a) Multi scale decomposition, (b) Directional decomposition

The contourlet transform decouples the multiscale and directional decomposition. The multiscale decomposition is handled by Laplacian pyramid [3], the direction description is handled by the directional filter bank. Thus, the contourlet transform is the new true two-dimensional transform that allows modeling of all visual parameters, scale, space and direction. Figure 3 shows the pyramid composition of the contourlet. Figure 4 shows the difference in processing procedure that results from wavelet transform and contourlet transform.

3. The Suggested Method (CLFI)

The contourlet fingerprint identification CLFI uses contourlet transform as feature extractor and neural network as a classifier. The feature vector is organized from the LL band of the contourlet transform with (16 x16) pixel size. It represents a smart key in complex vision system. It has been used widely in object recognition in many industrial and high-tech applications such as, vision-based industrial robots, autonomous flight vehicles [5,6]. While it is necessary to recognize the shape (fingerprint), regardless of position, rotation and scale. The curves in fingerprint should be distinguished from their background and additional objects once, isolated objects can then be extracted from the captured frame [7,8]. Unsupervised learning mechanism is used to place similar objects (fingerprints) into groups (data sets) as shown in Figure 5 (a,b). The database is used such that part of the images for each person are used for learning process, and the remaining images are used for testing process.

The goal is to minimize the number of learning iterations to achieve minimum error by using real world fingerprints. The image format of bitmap (bmp) without compression is used, with

dimension of (128x128) pixels of gray scale level.

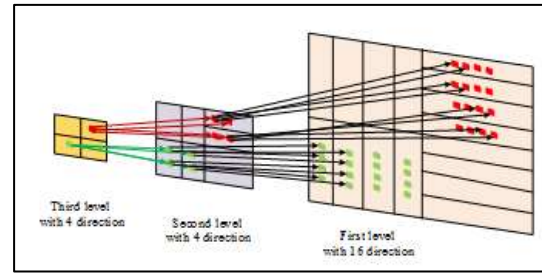


Figure 3: Three-level Pyramid (parent-son construction) for contourlet transform

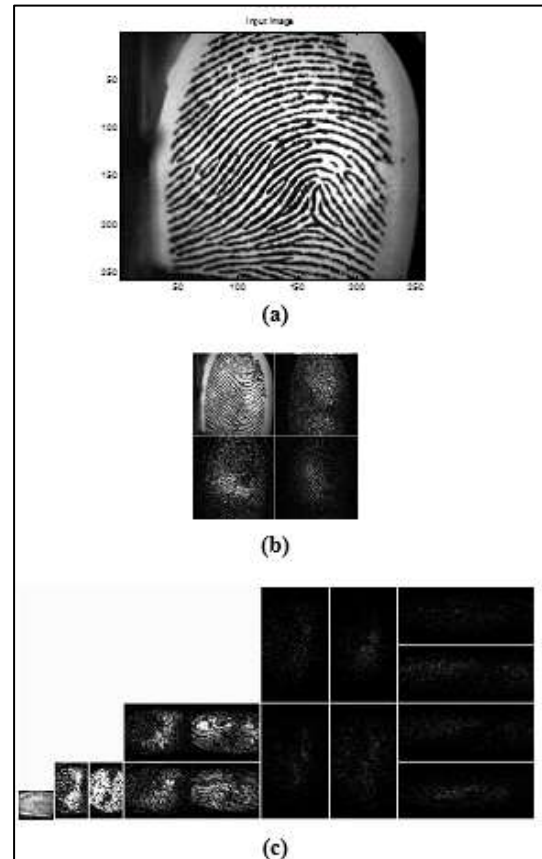
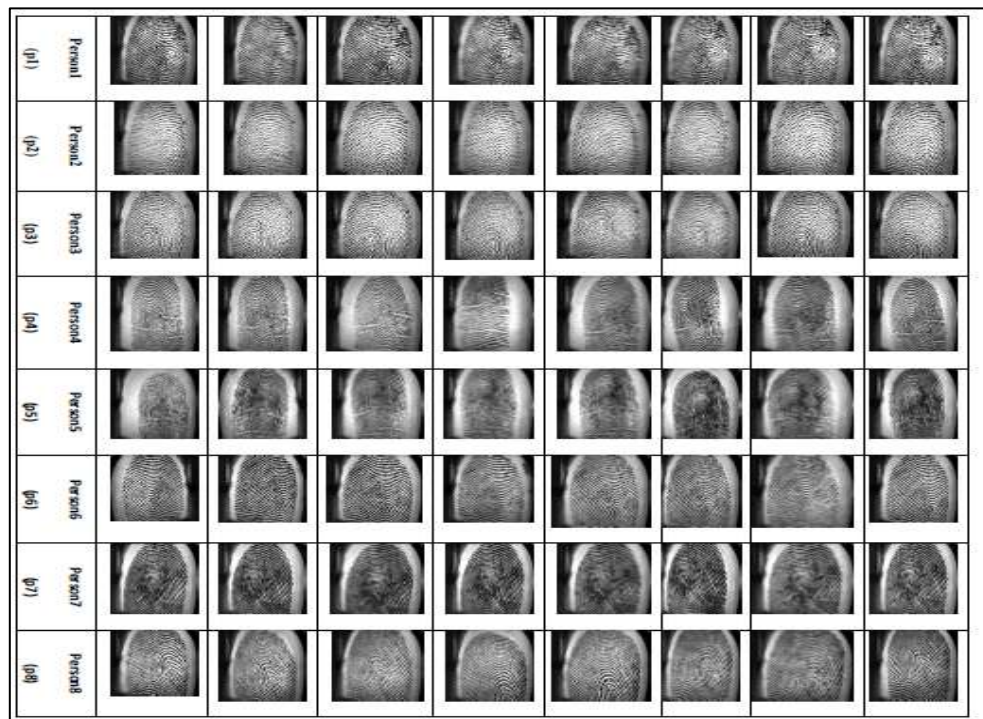
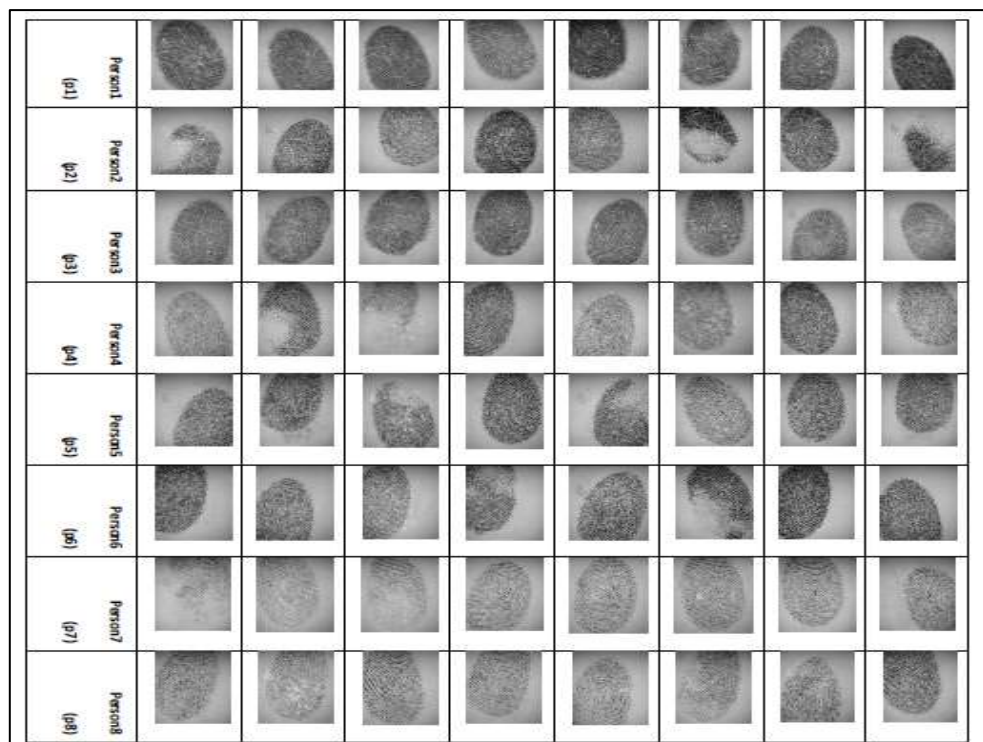


Figure 4: The results of wavelet and contourlet transforms decomposition. (a) Source fingerprint, (b) Decomposed image as a wavelet Decomposed image as a contourlet with three levels, (c) The three levels image decomposition for contourlet transform



(a)



(b)

Figure 5: (a) Fingerprint database FVC2000 no 1 [9]
(b) Fingerprint database FVC2002 No. 2 [9]

4. Neural Network Classifier

Neural network of type BPNN (Back Propagation Neural network) has been chosen as a classifier, due to its simplicity and efficiency in computing. Training and testing for standard databases (FVC2000, FVC2002),

Figure 6 shows the BPNN used to train the resultant feature vectors from the third level contourlet processed images.

Where, N , is the feature vector, while, $A_1 \rightarrow A_N$ is the input vector (features), $B_1 \rightarrow B_N$, is the number of

person chosen. To train the network, it is possible to add hidden layers, but this will complicate the processing algorithm. The system will get the number of persons (M1), the number of training vectors (M2), then after choosing the required database, the system will begin to read images sequentially, then, preprocessing images by the third level contourlet transform, choosing its (LL) band only, with (16x16) pixels image size, then convert these images to feature vector (M2).

$$M2 = (X \times Y, 1) \quad (1)$$

While X, Y is the image dimensions, the vector will be used as a feature vector. Then feeding the necessary variables and setup the neural network as shown below:

- 1- Transfer function hidden layers filter used is (log sigmoid) for both.
- 2- Training parameter epochs = 100 (maximum)
- 3- Minimum performance gradient = 1.0×10^{-8}
- 4- learning rate = 0.01

Before processing any fingerprint for identification process, it's necessary to crop the edges of every image to eliminate the effect of black edges and empty regions that surround the fingerprint and causes in reduction the accuracy of decision made by the neural learning systems. This is done by using windows standard tool (paint) and taking the node of contours of each fingerprint, neglecting the regions outside these contours. The results of cropping are shown in Figure 7 (a, b). The simulation results are given for two sets of fingerprints, each has eight different persons, every person has eight fingerprint samples for the same finger hence there are 64 image samples for each data set of images.

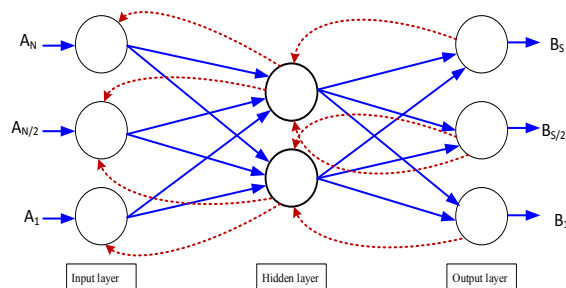


Figure 6: Neural network of type BPNN

A comparison is done in terms of the identification rates for the proposed contourlet method and wavelet method. It's necessary to mention that the execution time of wavelet learning is slower by 50-75% in the learning

process than contourlet method, equations (2) and (3) are used to find that the overall average identification rates.

$$S_c = \sum_{i=1}^M \frac{C_i}{M} \quad (2)$$

$$S_w = \sum_{i=1}^M \frac{W_i}{M} \quad (3)$$

Where C_i and W_i are the identification rates of person using contourlet or wavelet, M is the total number of persons in a database. Hence, S_c is the average value of identification rate by using contourlet transform and S_w is the average value of identification rate by using wavelet transform.

The Figure 8 (a,b) shows the relationship between identification rate and person number for contourlet transform, while (c,d) shows the relationship between identification rate and person number for wavelet transform. It should be noted that the differences between (a,b) and (c,d) are due to variations of images inside each database.

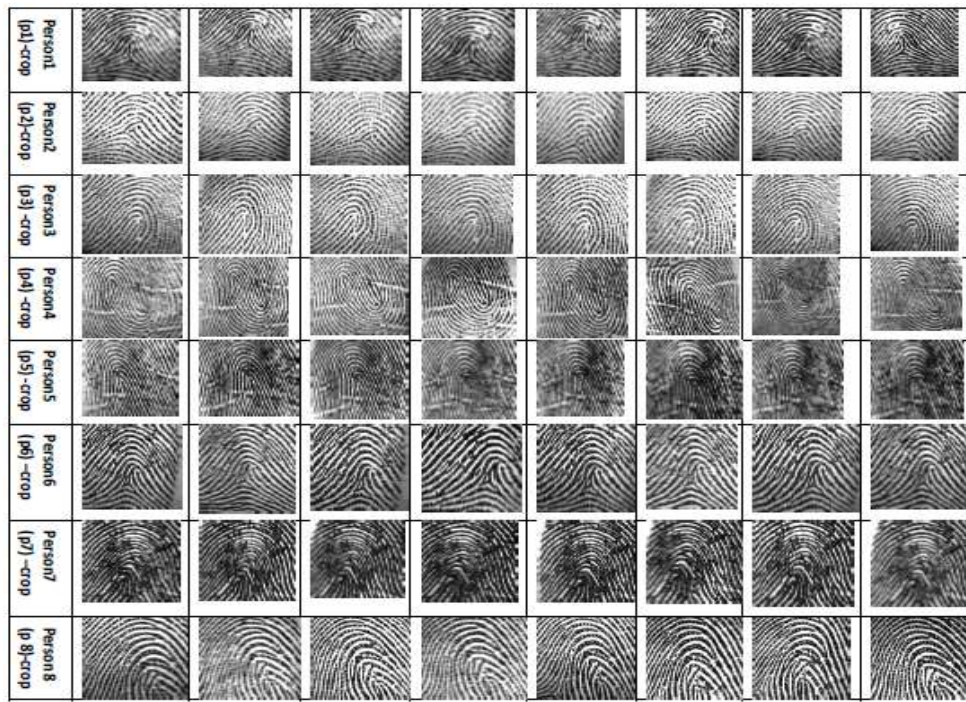
Table 1 and 2 show a comparison between contourlet and wavelet methods of the overall average identification rates for the two used data bases respectively. It is clear that contourlet method outperforms the wavelet method for both data bases.

Table 1: Comparison between contourlet and wavelet for database FVC2000 No. 1

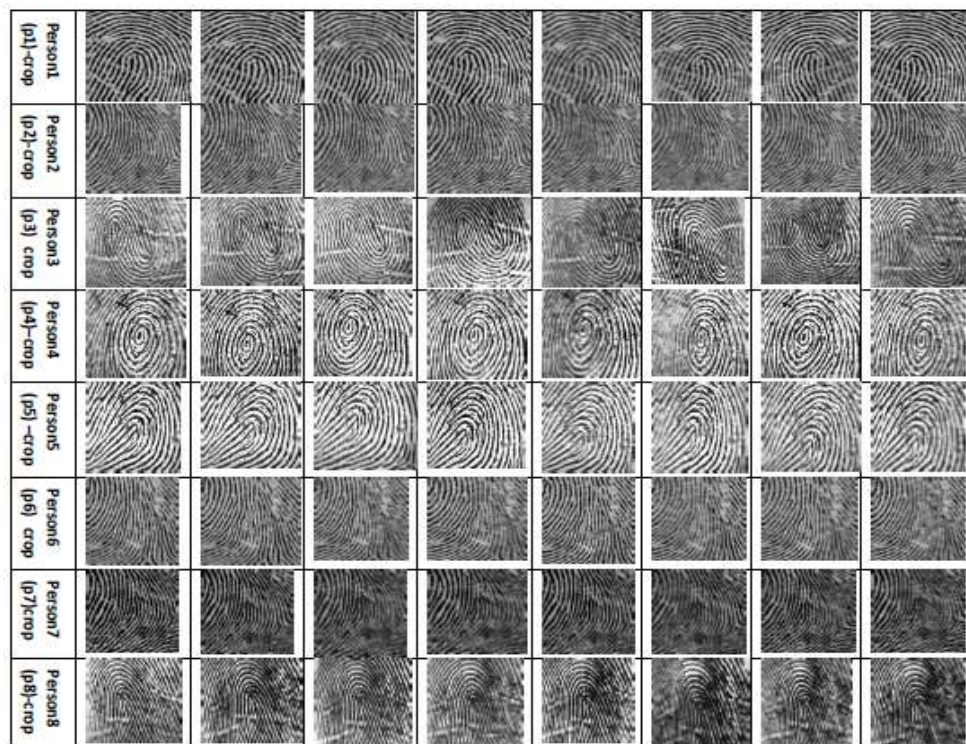
Average values of identification ratio using database FVC2002 No. 1		
Neural learning steps	Contourlet	Wavelet
6 learning, 2 testing	89.2872	77.8348
4 learning, 4 testing	82.4740	71.5737
2 learning, 6 testing	82.3562	57.3934

Table 2: Comparison between contourlet and wavelet for database FVC2002 No. 2

Average values of identification ratio using database FVC2002 No. 2		
Neural learning steps	Contourlet	Wavelet
6 learning, 2 testing	94.4717	87.5298
4 learning, 4 testing	79.3452	66.2178
2 learning, 6 testing	75.8371	62.4479

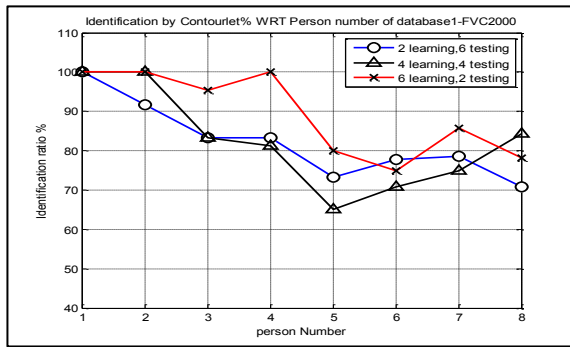


(a)

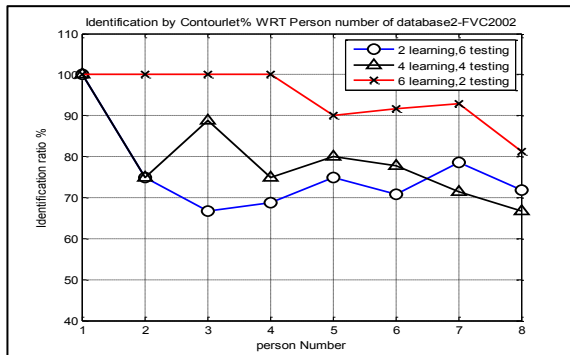


(b)

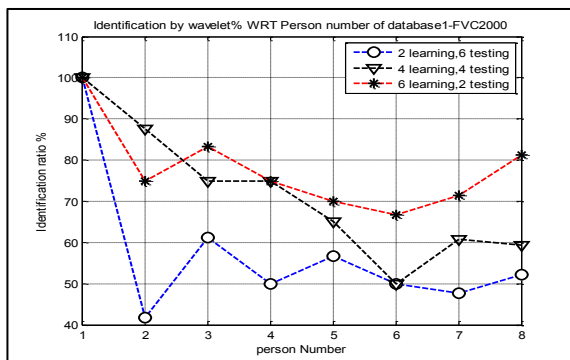
Figure 7: (a) Fingerprint database FVC2000 No 1 after cropping operation (128x128) pixel.
 (b) Fingerprint database FVC2002 No 2 after cropping operation (128xx128) pixel.



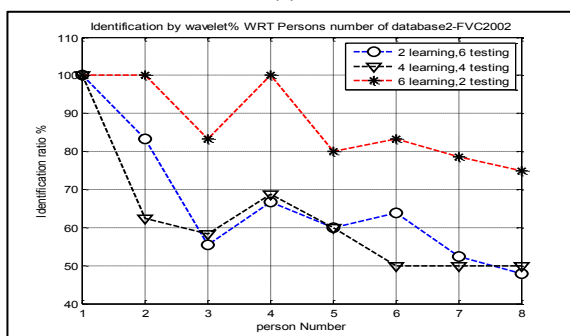
(a)



(b)



(c)



(d)

Figure 8: (a, b) The relationship between identification rate and person number for contourlet transform (c, d) The relationship between identification rate and person number for wavelet transform

5. Conclusion

Fingerprints identification is performed using the contourlet transform as feature extractor and back propagated neural network as a classifier. The

contourlet transform replaces the classical wavelet. Computer simulations in terms of average identification rates proved that the proposed system outperforms the wavelet method. This advantage can be utilized to reduce the number of learning iterations required by the neural network and hence make the identification system more reliable in many practical applications.

References

- [1] S. Bayram, H.T. Sencar and N. Memon, "Sensor Fingerprint Identification through Composite Fingerprints and Group Testing," *IEEE Transactions on Information Forensics and Security*, Vol. 10, No. 3, 597-612, 2015.
- [2] R. Sudhakar, R. Karthiga, S. Jayaraman, "Fingerprint Compression Using Contourlet Transform with Modified Spht Algorithm," *Iranian Journal of Electrical and Computer Engineering (IJECE)*, Vol. 5, No. 1, 3-10, 2006.
- [3] M.N. Do, M. Vetterli, "The Contourlet Transform: an Efficient Directional Multiresolution Image Representation," *IEEE Transactions on Image Processing*, Vol. 14, No. 12, 2091-2106, 2005.
- [4] A. Cohen; I. Daubechies; O.G. Guleryuz, "On the Importance of Combining Wavelet-Based Nonlinear Approximation with Coding Strategies," *IEEE Transactions on Information Theory*, vol. 48, no. 7, pp. 1895-1921, 2002.
- [5] T. Djara, M. K. Assogba, A. Naït-Ali and A.C. Vianou, "Fingerprint Registration Using Zernike Moments: An Approach for a Supervised Contactless Biometric System," *International Journal of Image Processing (IJIP)*, Vol. 9, No. 5, 254-271, 2015.
- [6] D. Peralta; I. Triguero; R. S. Reillo; F. Herrera; J.M. Benitez, "Fast Fingerprint Identification for Large Databases," *Pattern Recognition*, Vol. 47, No. 2, 588-602, 2014.
- [7] M.T. Leung; W.E. Engeler; P. Frank, "Fingerprint Image Processing Using Neural Networks," in *International Confrence on Computer and Communication Systems*, Hong Kong, 1990.
- [8] K.A. Nagaty; E. Hattab, "An Approach to a Fingerprints Multi-Agent Parallel Matching System," in *IEEE International Conference on Systems, Man and Cybernetics*, Netherlands, 2004.
- [9] D. Maltoni, D. Maio, A.K. Jain and S. Prabhakar, "FVC2004 Fingerprint Verification Competition," 2009. Available: <http://bias.csr.unibo.it/fvc2004/download.asp>. [Accessed 4 15 2017].

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