Score improvement using backpropagation in biometric recognition system

Gopal [1,*], Monika Gupta [2], Akshay Sahai [2], Shivam Verma[2], Vikramaditya Agarwal[2]
[1] Bharati Vidyapeeth's College of Engineering,
[2] Maharaja Agrasen Institute of Technology

Abstract. In this paper, a novel score improvement technique is proposed for person biometric authentication based on backpropagation. To obtain this, threshold values is optimized to reduce the Equal Error Rate (EER) and to trade off False Rejection Rate (FRR) with False Acceptance Rate (FAR). To validate the proposed method, palmprint recognition has been tested on IITD database of 230 persons and PolyU database of 386 persons. Experimental results show primacy of the proposed technique over the existing ones in the literature and achieved higher accuracy.

Keywords: k-Nearest Neighbor, palmprint, neural networks, biometrics.

1 Introduction

For the last few decades, biometrics have been a progressive field due to its cardinal contribution in the field of security, surveillance and banking. [1], [2], [3]. Biometric systems include measurement of various human physiological characteristics and traits such as, fingerprint scanning, facial recognition, palm print recognition, retinal and iris scanning. Many innovative and stout technologies have been seen in literature [4], [5]. It is noticeable from the existing literature that palm-print and face-print technologies are highly efficient and secure [6], [7], [8]. A typical biometric system is shown in Fig. 1.

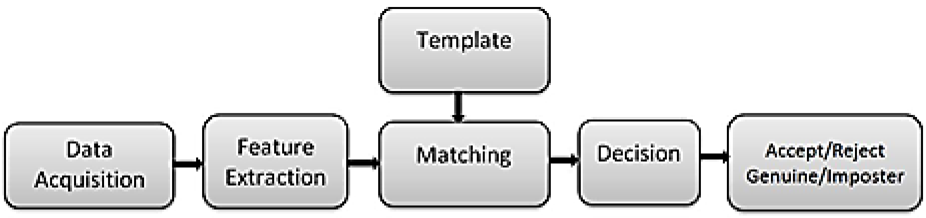

Fig. 1: A typical biometric system

Accuracy of Biometric Systems can be improved using several methods, some of them are image enhancement, feature extractions, better classifier, and fusions. Lots of research is done in image enhancements, feature extractions and fusions. In most of biometric systems, classifiers finally give scores to evaluate the performance of system. These scores are helpful in finding recognition rate, success rate, Genuine acceptance rate (GAR) etc. Euclidian Distance —to calculate the scores of training and testing samples —is obtained from features of each biometric process. Generally, Receiver Operating Characteristic (ROC) curves are employed to visually analyze the use of biometric systems in verification. To plot ROC, first threshold value *th* is selected. If the value of score is greater than threshold value *th* then this score is assumed to be a genuine score, that is, claimed identity is a true person. If the value of score is lesser than threshold value *th* then this score is assumed to be an imposter score, that is, claimed identity is a false person. Curve between the Genuine acceptance rate (GAR) and false acceptance rate (FAR) is usually referred to as ROC; GAR = 100 FRR. FAR is the rate of wrongly accepted person, whereas FRR is the rate of genuine subjects wrongly rejected.

Not a copious amount of research has been done on Score improvement methods. Cohort scores have been used in the literature before, such as, for normalization [11] in which ranking is used to distinguish the imposter and genuine. In [12], refined scores are used to improve the results. But in both the methods, score improvement has not taken place.

In this paper, a novel score improvement technique is proposed for person authentication based on backpropagation. To obtain this, threshold value is optimized to reduce the Equal Error Rate (EER) and to trade off False Rejection Rate (FRR) with False Acceptance Rate (FAR). To validate the proposed method, palmprint recognition has been tested on IITD database of 230 persons and PolyU database of 386 persons. Experimental results showed primacy of the proposed technique over the existing ones in the literature and achieved higher accuracy.

1.1 Novelties and Contributions of the paper

1. A novel score improvement technique is proposed for person authentication based on backpropagation.

2. Threshold value is optimized to reduce the Equal Error Rate (EER).

3. Score matrix is normalized.

4. Proposed technique is tested on IIT Delhi palmprint database of 230 persons and PolyU database of 386 persons.

The organization of the paper is as follows. Section 2 describes the method of pre-processing involved for ROI extraction from database. Section 3 presents the methodology. Section 4 demonstrated simulations and result analysis. Last section 5 concludes the suggested work.

2 Pre-processing

For feature extraction, the orientation of data samples must be same to withdraw the same set of information. For any biometric system, first requirement is acquisition of enough databases for proper training and testing. After data acquisition, second step is to find out the region of interest (ROI) from the data sample. Most of the general biometric system are made to have inter-class variations to make the system more real time and includes those mistakes that can be added by users at the verification point, such as, in offices or banks. Hence orientation or rotational variations are made. In case where data acquisition is constrained by peg or pins, ROI can be easily extracted. If database has rotational variation, then hand samples are normalized before ROI extraction to make system robust to such variations. All the steps that align database samples for feature extraction are referred as Pre-processing. In most of the pre-processing methods, valley points between the fingers are extracted to crop the ROI. The basic steps are: binarizing to extract the boundary of hand which also helps in masking of hand on a background free image; finding the key-points; generating the coordinate system; cropping the ROI.

Generally, finding the fingertips and centroid is followed by masking of original bounded image. The ordering of fingertips is done by doing circular traversal with the centroid as the center of the hand in clockwise direction so that the first coordinates are that of small finger and last coordinates are of thumb. In this way, the coordinates of all the fingertips are obtained. A line is drawn joining the index and ring finger and rotated in such way that it becomes parallel to horizontal axis. After this, finger valleys are calculated indicating the rate of change of the slope of boundary. Then each palm is further straightened using the coordinates of finger valleys. Lastly, the ROI is cropped from the processed image.

3 Methodology

Feature extraction is performed on the preprocessed input. Matrices of dataset are then divided into grids, with each cell of size 5*5 and resultant matrices of size 30*30 were obtained. Mean value of each cell is calculated, and cell matrices 5*5 are replaced with their mean values and matrices of 30*30 are left. These matrices are then converted or resized into a single column matrix of size 1*900. There are 5 palmprint of 230 different people, therefore matrix of size 230*5 is created with each cell of size 1*900. The input is then provided to the classifier. Classifier is the algorithm that produces score matrix, which is used to evaluate performance of system.

K-NN is applied on the matrices i.e. first 4 columns are now considered for training and last column is considered for testing. Value of each cell of testing column is compared to each cell of all the training columns i.e. (testing-training). The values of each set of palmprint of each person – is considered separately. The minimum error value among the 4 values for each person are taken. This whole process is started again in clockwise direction, i.e., the testing and training columns are changed in clockwise direction. The minimum value, thus taken, corresponds to the genuine palmprint. What is being done above is training and testing palmprints of every single person with each other. Then these values are placed together in a matrix. We make a matrix of size 230*230, these minimum values are taken in the diagonal cells i.e. the diagonal cells become the genuine cells, and the rest becomes the imposter cells. This matrix of size 230*230 is known as Score matrix. Score matrix is the result matrix of k-NN, with ambiguous result. Score matrix is used to evaluate performance of system. It depends on one parameter known as Threshold value. Therefore, to increase the efficiency of system, score matrix must be optimized and to optimize score matrix, threshold value is optimized. Optimization of score matrix leads to reduction of Equal Error Rate(ERR) and trade off of False Rejection Rate (FRR) with False Acceptance Rate(FAR). The algorithm proposed to optimize the threshold value is shown in Algorithm 1. Architecture of proposed method used for backpropagation to update the threshold value is shown in Fig. 2.

Algorithm 1 Threshold optimization using backpropagation

procedure
    th 0.01
    total test score matrix=5
    target score matrix=diogonal matrix
    $s_{i=j} = 0$
    $s_{i\neq j} = 1$
    If
    number of$((s_{i=j} < th) < max(i; j)$
    $th \leftarrow th_{optimized}$
    Else
    Update th

;P

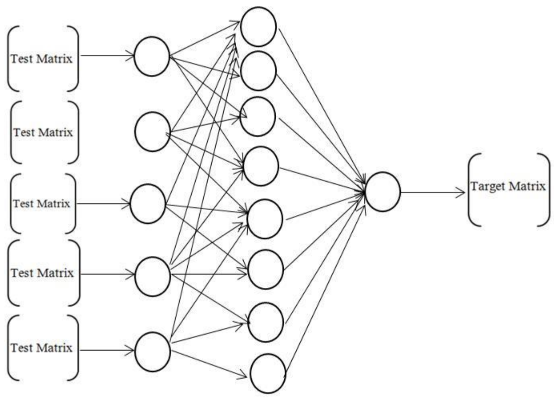

Fig. 2: Architecture of proposed method used for backpropagation to update the threshold value

4 Experimental Results

To judge the performance quantitatively, decidability index (DI Factor) [9] is used. Separation, and if required, overlap of similarity scores is given by the value of DI factor [10]. It is defined as

$$DI = \frac{|\mu_1 + \mu_2|}{\sqrt{\frac{\sigma_1^2 + \sigma_2^2}{2}}}$$

where μ_1 and μ_2 represent the mean of the genuine and imposter distributions, respectively, and σ_1^2 and σ_2^2 represent the variances of the genuine and imposter distributions. High value of DI Factor shows more separation of genuine and imposter distributions.
For verification, a performance measurement quantity in which its lower values show high performance of the system. In this paper, EER is chosen as the performance measurement quantity, where EER is calculated;
FAR equals FRR. FAR is False Acceptance Rate which shows the acceptance of imposters as genuine and FRR is False Rejection Rate which is rejection of true subjects.
It is clearly shown in Table 1 that EER is 1.686 for threshold *th=0.01* which is improved to 0.972 and 0.881 for th=0.015 and th=0.023 respectively, for IITD database and DI factor varied from 3.1684 to 4.544 and 4.888 for th=0.015 and th=0.023 respectively. It is seen that EER is reduced on optimizing threshold value of threshold *th*. Also DI Factor is also increased.

Table 1: Performance of proposed technique

	IITD database		PolyU database	
	EER	DI Factor	EER	DI Factor
Th=0.01	1.686	3.1684	0.3464	4.0426
Th=0.015	0.972	4.544	0.271	4.898
Th=0.023	0.881	4.888	0.182	6.668

Table 2: Identification results of different values of threshold for IITD database

	Genuine Acceptance Rate (GAR %)		Identification results
	FAR=0.1	FAR=1	
Th=0.1	79.82	84.18	91.1
Th=0.015	81.96	87.09	93
Th= 0.023	93.95	96.05	96

Table 2: Identification results of different values of threshold for PolyU database

	Genuine Acceptance Rate (GAR %)		Identification results
	FAR=0.1	FAR=1	
Th=0.1	97.6	98.5	99
Th=0.015	97.5	99.2	100
Th= 0.023	98.2	99.4	100

From Table 2 and 3, it can be seen that recognition rate is also dependent on threshold value. It is also seen that convergence of proposed method is faster.

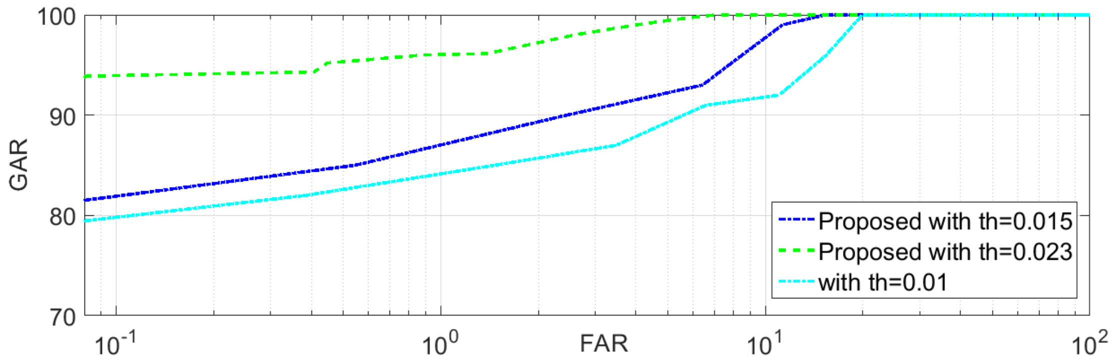

Fig. 3: Results for IITD database

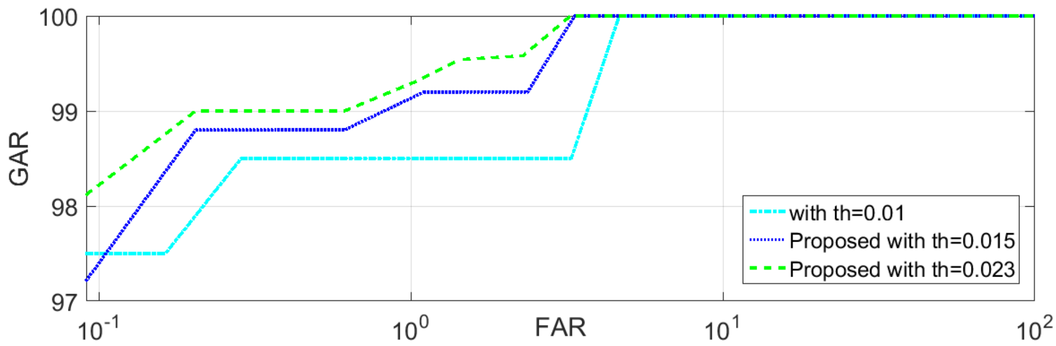

Fig. 4: Results for PolyU database

In Fig. 3 and 4, it is clear that the proposed result covers the maximum area under the curve and reaches 100% GAR at faster rate as compared to ROC's of other technique.

5 Conclusion

In this paper, a novel score improvement technique is proposed for person authentication based on backpropagation. To obtain this, threshold value is optimized to reduce the Equal Error Rate (EER) using backpropagation. The ROC plots have shown improvement by using improved threshold value. It is clear that optimized value of threshold can clearly distinguish the genuine score to imposter score. In future, score optimization can be done using bio-inspired optimization algorithm also.

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