Personal Identification Using Palm Features Recognition

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Abstract

Personal recognition is meant for finding a way for establishment of connections between the person and his/her biometrical features. Such system is depending on various data types such as facial images, voice and limbs. Palm recognition is considered as the backbone of identification verification based on biometrical features recognition. Such biometrical identification system includes a complicated process to distinguish palm prints even if it belongs to the same person.

In this paper, palm print recognition is made using deep learning paradigms such as feed forward neural network (FFNN). The palm features are extracted by tracking the principal lines of palm skin. This involves performing of pixel to pixel analyses by comparing pixel value with its four sides neighbors. FFNN model is tuned up using ABC-KNN algorithm then used for classification. The proposed system has yielded good recognition accuracy score of 98.66%.

Keywords: FFNN, ROI, Score, Learning, Veins, NIR.

I. INTRODUCTION

The development in economic and society that could be witnessed over the last few years from posed new data security challenges as tons of confidential data like private/personal data, banking data, economic/financial planning data, etc. which have been exchanged over computer networks[1]. In order to prevent the none authorized access, traditional security methods stand unreliable in security enframement over current trend of challenges[2]. Password/security key protection is amongst those methods that prone to be forgotten or prone to be guessed. Biometrical recognition has paved the road to robust data security relying on human biometrical features that cannot be changed as well as requiring presence of the concern/authorized person at the time of verification. Among the biometrical recognition is face, iris print, and finger print recognitions. Each of these features has its own advantages and disadvantages as well. Face recognition is a vital recognition technology that relies on the features on human face to recognize the identity[3]. In spite of the user-friendly nature of face recognition approach; it is highly prone to errors[4]. Face image can be acquired without the concern of the owner (easily capture and misuse), and face features could vary according to the face expressions (e.g. smiles). Presence of hat, eye blinking, beard, etc. may degrade the recognition performance. On the other hand, finger print features are time variant since the finger print can be damaged due to internal and external factors and hence, it might be regenerated in other form[5]. Palm is enriched with plenty of time invariant and reliable features for constructing a robust identification system[6]. As a whole, palm recognition system is particularly limited to numbers of candidates/samples which were deployed during the features extraction. The remained sections of this paper included detailed problem statement of palm image-based recognition system along with proposed research methodology and objectives.

II. PROBLEM STATEMENT

Palm recognition is considered as corner stone for identity verification based biometrical features recognition [7].Such recognition system involves a complex process for differentiating palm prints even if it belongs to the same person. The challenges faced while implementing the palm recognition system can be illustrated under two categories; first is “features fusion and templates constructing challenges” and second is “templets matching challenges”. The templates constructing is preceded by several vital approaches such as: region of interest cropping/image segmentation and image enhancing for features extraction. According to [8] palm prints from different persons may not significantly vary which leads to a fact saying that palm recognition is a complicated task. First category challenges are more likely related to none uniformity of image illumination, size scales of the palm and image alignment[9]. The common problem in palm recognition system is their trade-of between recognition accuracy and computational cost measured during the features matching stage. On the other hand, features extraction stage is highly influenced by non-uniformity nature of samples/templates that lies on the variance in palms geometry and variance in sample alignment while image enquiry processes. The current trend of features extraction involves analytical approaches either in spatial domain or in frequency domain such as Gober filters. Furthermore, spatial-frequency analysis is feasible using wavelet transformation. Analytical analysis quality is limited to noise involvement and availability of computational power[10]. Features matching is usually performed by calculating minimum Euclidean distance; however, least attempts were seen in literature about deep learning deployment in palm recognition[11]. According to the literature, palm recognition is performed in either of two ways: first is deploying end to end deep learning approach such as convolutional neural network (CNN) for performing both features extraction and classification without intervention of standalone features extraction model. On the other hand, the second way involves both features extraction and classification more likely using principal component analysis for dimensionality reduction and features extraction and then support vector machine (SVM) for classification.

III. LITERATURE SURVEY

Gober filters are able to produce the frequency contents from different directions in the image, that is useful to tackle the inter samples discrimination due to scale/size or illumination problems, it was reported that Gober filters is coming with response sensitivity problems which influence the samples discrimination performance[12]. Another approach is proposed to tackle the response selectivity problem of Gober filter which is commenced by dividing the image resultant after Gober filters it into several none-overlapping blocks and subsequently evaluating of the binary pattern code (LBPC) for each block. Hereafter, it needs deploying another algorithm for determining the minimum hamming distance between the blocks in order to identify the similarity level between the samples/images [13]. This approach is running through a cost problem as more computational budget will be encountered. Some other attempts were found to detect the samples/images discrimination level which are performed at the fact that [14] it has proposed another method apart from the Gober filter for detecting the image edges and subsequently conducting a correlation approach in order to identify the similarity; such approach is not meeting the required performance in matching since no concern was given for the noise causes e.g. palm scale/size. Another method such as [15] what was proposed by Gober filter, it required Euclidean distance and fuzzy logic for performing the matching tasks. At [10] what author proposed as self-invariant features transform, angles from the particulars features vectors are calculated to detect the scale/size difference in the palm samples; however, this method lacks of the rest performance degradations elimination.

IV. METHODOLOGY

We proposed a novel hybrid palm recognition system based on smart features extraction and classification models in which both classification accuracy and processing time are expected to be enhanced. The proposed system is to be performed using PCOE dataset [16] in which the proposed system architecture is shown in Figure 1. In order to tackle the problems in the database such illumination, size/scale variation, rotation, existence of foreign objects (rings, bracelets, etc.) which are degrading the image region of interest (ROI) cropping as well as features extraction and classification, the proposed work is suggested in the following sequence.

A. Illumination adjustment

Illumination adjustment problem is realized as common/popular problem in palm print images; as a single user may provide multiple images of the same palm; the problem is raised as different lighting conditions of the image is producing a significant variation in the image.

Correlation approach is to be used for determining the similarity between any samples of the same palm under different light circumstances. However, it is proposed that the illumination adjustment is permissible approach to tackle the illumination variance.

This adjustment is usually performed by pixel intensity reduction by subtracting the average image intensity from each pixel intensity[17].

B. Region of Interest Cropping

In order to minimize the computational cost of palm image recognition, the regions other than principal lines region is to be neglected. It can be performed by cropping the required region in accurate fashion. The state of the art of palm region of interest (ROI) cropping is using the so-called global geometrical transformation which involves detecting the hand palm with reference to the palm size and structure [11].

Thus, gap between two fingers as demonstrated in Figure 3 has been used as reference for width of ROI. Image alignment is vital for accurate palm ROI detection. Hence, it is required to rotate the image (in-clock wise or anti clock wise) in accordance with alignment angle which can be obtained by determining the line slop (Figure 4). Slop angle can be determined in “Line 1” with reference to horizon angle “Line 2”.

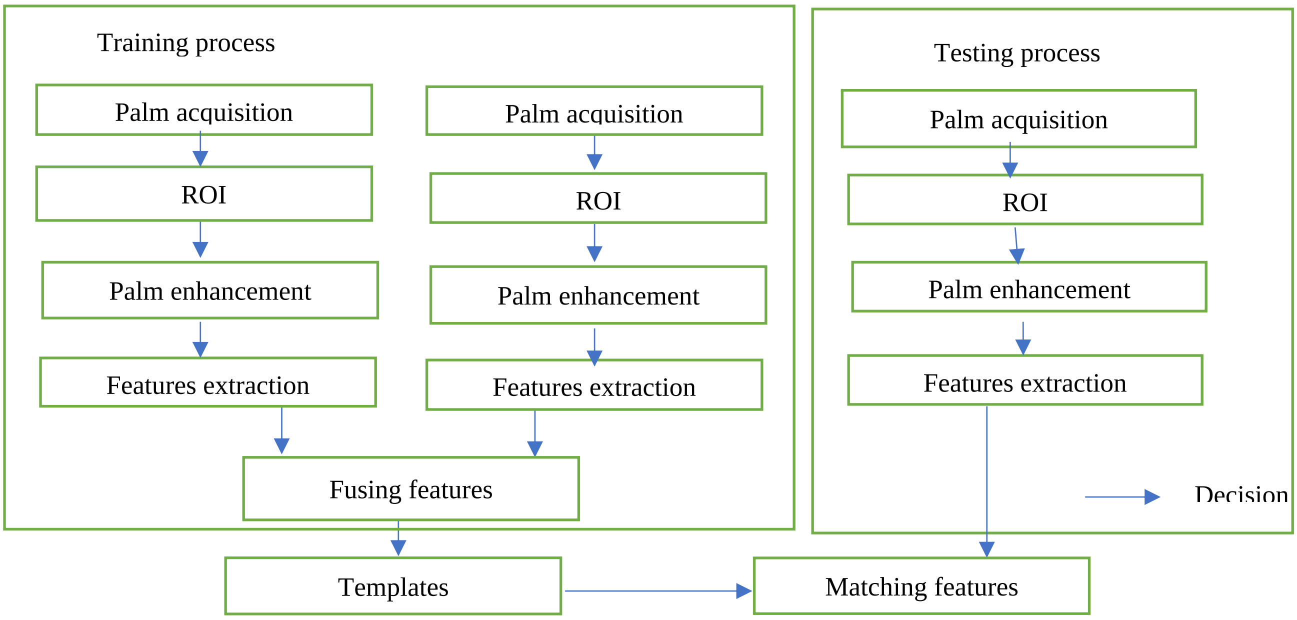

Figure 1: Project overall general structure

C. Features extraction

Since the feature extraction performing over spatial domain is highly influenced by the aforementioned noise sources impact (e.g. illumination) [18] and since the frequency domain features involves extra computation cost (e.g. intervention of Fourier transform)[19]; wavelet transform is best option which yields both spatial and frequency information. Hand palm is having three main lines called principal lines which are creating unique identity for the hand and cannot be repeated even in case of identical twins. From this point, it is proposed to extract the principal lines information from the palm image using discrete wavelet transformation (DWT)[20].

Palm veins tracking is another method that provides robust palm features, it is however includes tracking the principal lines located on the palm internal surface [18]; this involves performing pixel to pixel analysis by comparing pixel value with its four sides neighbors. One of those four corners is to be selected as next point in the tracking path of the principal line. The same process can be illustrated in Figure 2 with highlights of following points.

1. Each image with NIR band is then treated with edge detection in order to reduce the dimensionality. We propose using Radon transformation as edges detection method due to its lesser computation budget unlikely other methods e.g. [20], [21].

2. To define a radius and number of blocks and reference pixel location in order to begin the process. For demonstration purpose, let radius to be 2, number of blocks to be 8 and reference pixel is located is "PR" as in Figure 2.

3. The pixel "PR" is to be compared with each neighbor pixel (as number in Figure 2) in such way; if the PR > (neighbor pixel) of which the result is 1 and if otherwise then the result is 0. Eventually, each pixel in the image will be represented by array of 8 numbers i.e. [11010010].

4. Similarly, the veins network can be identified by tracking the local coordination of the similar pixels. This can be performed by calculating the Euclidean distance between the resulted arrays.

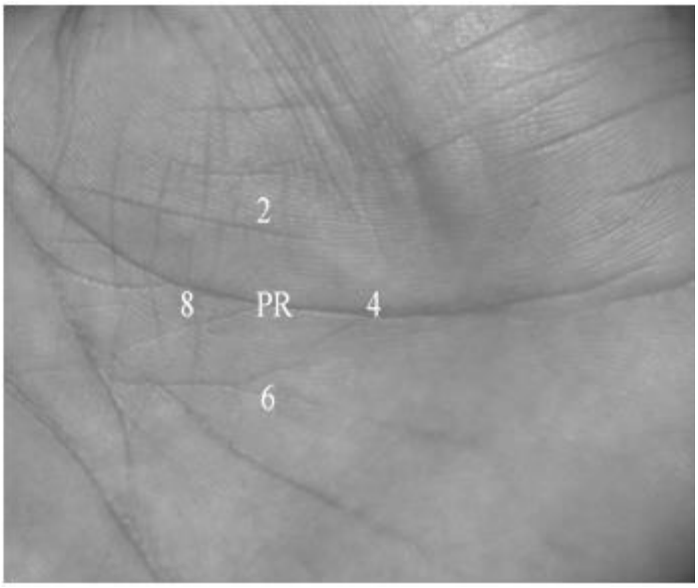

Figure 2: Principal lines features tracking demo.

V. *CLASSIFICATION*

As soon as palm ROI is extracted; the approach proposed at (a) is to be conducted for extraction of principle lines features. The following points are to be implemented in regards of features classification.

Our proposed state of the art is using artificial neural network (single hidden layer) with particle swarm algorithm-based k-nearest neighbor algorithm (KNN). Single hidden layer feed forward neural network is expected to provide good accuracy with lesser execution time as compared with points in 1 and 2, due to its simplest structure and simplified input dimensions. Input image fusion is required to reshape the featured image into a single dimensional array that is compatible with FFNN paradigm (Bernal Baró et al., 2020; Metz et al., 2020). In order to meet the high accuracy classification and to tackle the computational cost problem, FFNN model is tuned up using ABC-KNN algorithm.

We proposed seeded random search space generator based artificial bee colony (ABC)[22] using KNN algorithm [23]in order to reduce the computational cost and increase the classification accuracy.

Figure 3: Palm scale problem demonstration

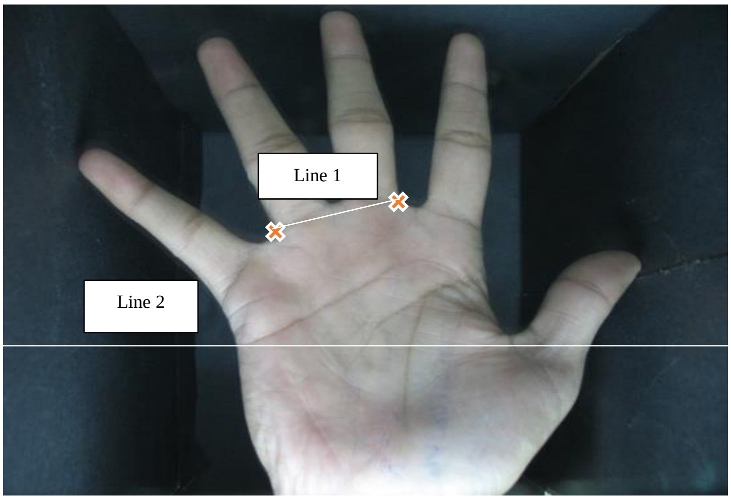

Figure 4: Illustration of line slop method in preprocessing

The first model is performed using the base line technology e.g. plain/standard feed forward neural network (P-FFNN). Thereafter, using freezing technique which freezes the model weights coefficients, the second model is made namely F-FFNN. Eventually, ABC state of the art is implemented for performance enhancement. Table 1 demonstrates the results.

Table 1. Numerical Results of the Proposed Approach

Algorithm	ACCUR	MSE	MAE	RMSE	Time (s)
P-FFNN	76.4247	0.2458	0.2458	0.49578221	0.1874
ABC-FFNN	81.6195	0.1938	0.1938	0.44022721	0.1359
F-FFNN	98.66	0.0004	0.0004	0.02	0.08157

VI. .RESULTS DISCUSSION

Palm recognition is performed using three stages of development using feed forward neural network. The baseline technology i.e. plain feed forward neural network (P-FFNN) is firstly trained using the palm images and 76.4247 % accuracy of palm recognition is achieved as shown in Table 1 and Figure 5. The algorithm is then optimized using artificial bee colony (ABC), this algorithm is used to provide the best weight values to the neural network; thus, the accuracy of palm recognition could be enhanced to 81.6195 %.

The results are more optimized using freezing technology where the weight values are freeze where the best recognition accuracy of 98.66 % is achieved see Table 1. The freeze feed forward neural network has achieved the best accuracy with the minimum mean square error of 4 e-3 as shown in Figure 6.

The proposed optimization has achieved accuracy enhancement of 22.53% from the baseline technology. From the other hand, the proposed model has achieved lesser processing time of 0.08157 seconds see Figure 9, which means that time is reduced by 56.4 % from the baseline technology.

Figure 7 shows that proposed optimization model has achieved the minimum Mean absolute error scores of the proposed models, furthermore Figure 8 illustrates the root mean square error scores where the F-FFNN of the proposed models achieved lesser error of 0.02.

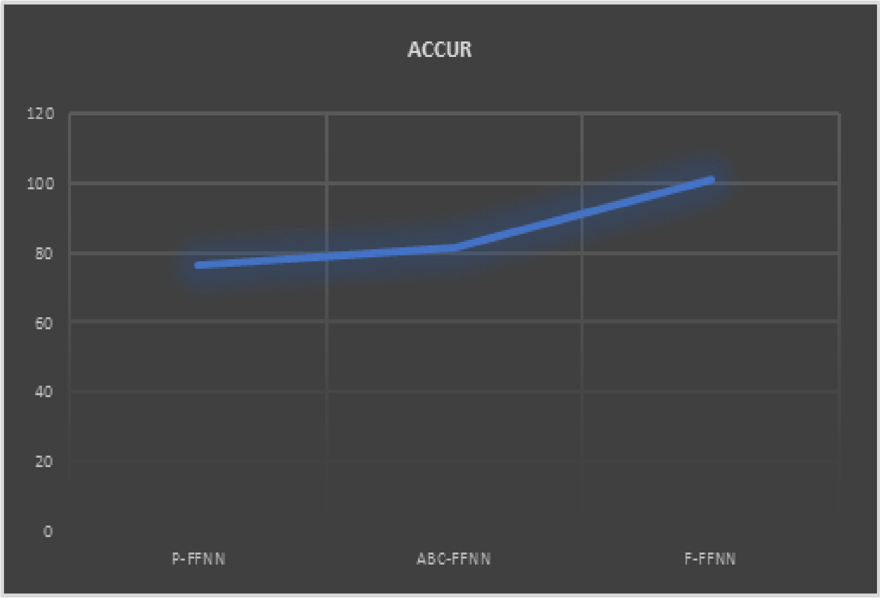

Figure 5: Accuracy scores of the proposed models

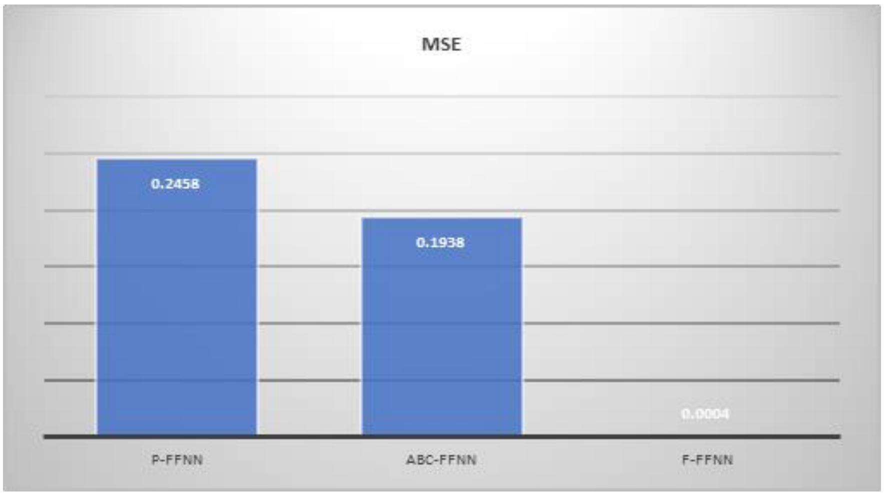

Figure 6: Mean square error scores of the proposed models.

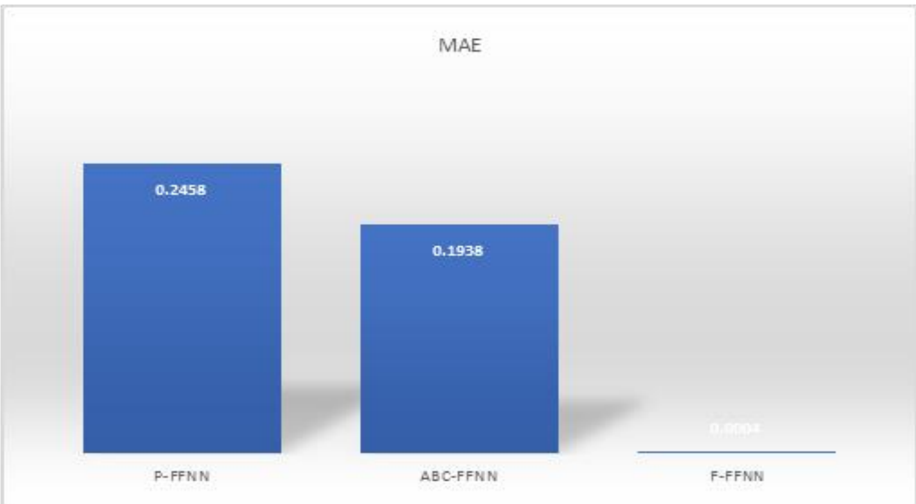

Figure 7: Mean absolute error scores of the proposed models.

Figure 8: Root mean square error scores of the proposed models.

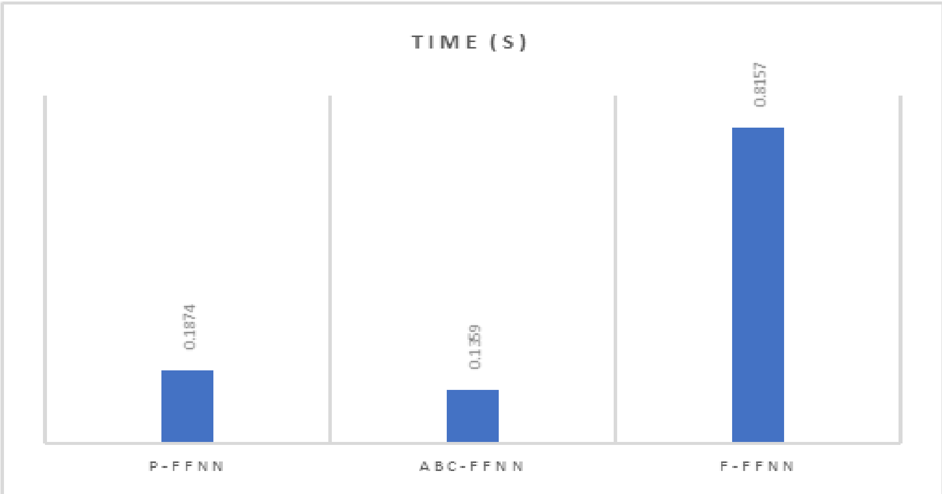

Figure 9: time delay of the proposed models.

VII. .CONCLUSION

a. The development of smart palm recognition system is capable of linking between the palm print and its features. Analytical methods and deep learning methods can be used for palm based personal identification and palm based age prediction.

b. The proposed approach had minimized the computational cost and enhance the recognition accuracy by deploying optimization approach based on linear feed forward learning approach e.g. (Feed forward neural network-based ABC optimization (ABC-PSO)).

c. It has been performed the palm recognition using deep learning feedback paradigms such as feed forward neural network (FFNN) and had monitored the accuracy-time trade off.

Ultimately, conducting statistical performance study using metrics alike means square error and means absolute error in all the proposed models for justifying the performance. The maximum recognition accuracy has reached to 98.66%.

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