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PALMPRINT RECOGNITION SYSTEM BASED ON PROPOSED FEATURES EXTRACTION AND (C5.0) DECISION TREE, K-NEAREST NEIGHBOUR (KNN) CLASSIFICATION APPROACHES

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Abstract

In the biometrics research area, palmprint recognition system is gaining the most popularity. Significant performances have been achieved in the state-of-the-art palmprint recognition systems. However, only particular scenarios such as a features types and extraction methods are considered in the existing systems. However, these systems cannot meet complex application requirements due to the security challenges it terms of accuracy and reliability. Therefore, in this paper an accurate and reliable Palmprint Recognition System called (PRS) is proposed. The system used proposed features extraction and classification approaches using direction, Local Binary Pattern (LBP) features, C5.0 and K-Nearest Neighbour (KNN). The system used two palmprint images datasets which are College of Engineering Pune (COEP), Chinese Academy of Sciences (CASIA) and achieved very high recognition rate 99.7% with lower error matching rate 0.009%.

Keywords: Canny, C5.0, KNN, LBP, Palmprint.

1. Introduction

Today's the technology is grown rapidly in different fields of our lives. This growing makes people face several challenges. One of the most important challenge is the security issue. Previously, the security was provided through Identity Document (ID) cards, keys, passwords and Personal Identification Number (PIN). However, these techniques became not effective to face the current threats in the technology via hacking and also could be imitated and stolen by others. Therefore, biometric is taking place to face the security challenges. The biometrics recognition system is an active research work nowadays which includes palmprint, face, signature, iris, hand geometry, and fingerprint [1].

A convenient and stable solution could be provided by Biometrics due to the human characteristics in physiological and behavioural aspects [2]. It also has uniqueness, and distinctiveness features, which were employed to authenticate genuine person [3]. From the available biometric methods, palmprint is chosen for our research interest. In the common applications within high security, palmprint recognition has played the main role in such applications [4-6]. Palmprint biometrics provides a reliable and low-cost biometric system using the extracted features of low-resolution imaging. It has lot of features such as directional, texture, principal line features and minutiae feature which is a similar to fingerprint that make it more accurate and reliable [7].

Most of the researchers focused on the features stage of the palmprint and high recognition rate were achieved [8]. However, an improvement in the accuracy, error matching and computing time aspects is needed. Thus, in this paper a new palmprint recognition system is proposed for recognizing the palmprint images using an efficient segmentation, features extraction and classification approaches.

2. Related Works

Several researchers have introduced advances to palmprint recognition systems. Basically, most of the differences between these works are restricted to the nature of the preprocessing, feature extraction and classification methods. The most related to our work studies are briefly described below.

Fei et al. [9] proposed palmprint recognition system based on a double-layer direction extraction method. In their method, the apparent direction is extracted first from the surface layer of the palmprint. After that, the latent direction features are exploited from the energy map layer of the apparent direction. At last, a histogram feature descriptor for is built from the extracted palmprint recognition apparent and latent direction features using the multiplication and addition schemes. By using Polytechnic University (PolyU), Indian Institute of Technology Delhi (IITD), Digital Signal Processing Group (GPDS) and CASIA palmprint databases, the authors mentioned that, their method improve about 4.34%, 2.15%, 2.00% and 0.96% in the accuracies over state-of-the-art works.

Ma et al. [10] proposed a system for palmprint recognition based on Discriminant Orientation and Scale Features Learning (DOSFL). The authors prove that orientation and scale features can be extracted with more favourable discriminability by employing the idea of discriminant analysis into palmprint coding. After that, the orientation and scale features of palmprint are represented by DOSFL utilizes four code bits, and the Hamming distance is employed for matching. Besides that, a Multi-Orientation and multi-scale features Discriminant Learning (MOSDL) approach is proposed for better use of the orientation and scale information contained in palmprint samples. Experimental results show decreases in the Equal Error Rate (EER) at least by 0.108% compared to other methods and 96.3%, 97.6% using HK PolyU and UST database.

Zhao and Zhang [11] proposes a framework for palmprint recognition in multiple scenarios. The framework represents the high-level discriminative features with learned discriminative deep convolutional networks called Deep Discriminative Representation (DDR). The authors mentioned that, their system achieved a high recognition rate using the PolyU Multi-spectral database for contact-based palmprint. The obtained was 98.7% and 99.4% on the IITD and CASIA databases, respectively.

Tabejamaat et al. [12] present a supervised label learning framework called Manifold Supervised Label Prediction (MSLP). The framework is considering an effective learning strategy to incorporate intra-class relationships of the data through generalizing Minimum Squared Error Classification (MSEC) object function. The authors applied down-sampling process on the used images from the PolyU dataset by making the image resolution (16X16) for reducing the image size and computation time. Besides, they mentioned an improvement in the obtained results using the proposed work comparing to the existing state-of-the-art algorithms.

Dubey and Kanumuri [13] used oriented exponential wavelets to extract the aforementioned energy signatures. Moreover, oriented structural energy signature codes are generated using bi-directionally rotated oriented energy signatures. The authors use PolyU and IITD palm print images in order to test the proposed scheme and achieved a satisfied result.

Chandran and Verma [14] present a palmprint verification system using several methods such as Sobel Edge Detection for preprocessing, 2D Gabor Filter, and Principal Component Analysis (PCA) for features extraction. A 99.5% success rate and 0.5% error rate were achieved using the IIT Delhi palmprint database.

Zhao et al. [15] proposed a methodology for hyperspectral palmprint recognition called Joint Deep Convolutional Feature Representation (JDCFR). A joint convolutional feature is constructed for the hyperspectral palmprint image cube using a constructed Convolutional Neural Network (CNN) stack. Dozens of CCNs are included in the parameters within various parameter setting. These CCNs are using the palmprint images for local training in different spectrums. However, Collaborative Representation-based Classifier (CRC) is used for classification in order to avoid the obtained redundant features. The propose method achieved a good performance with 0.01% -EER and 99.62% - Accuracy of Recognition Rate (ARR) using 110.770 palmprint images with 53 spectral bands.

Bounneche et al. [16] proposed a novel multi-spectral palmprint recognition approach for enhancing the whole recognition process stages. The approach is based on oriented multiscale log-Gabor filters. The bitwise Hamming distance and Kullback-Leibler divergence are employed for matching. A high accuracy in mono-spectral and multi-spectral recognition is obtained using PolyU database.

Tamrakar and Khanna [17] present an efficient technique for recognizing the palmprint. ROI is extracted first then the computational is reduced using Haar wavelet for less noise and overhead. The authors used Gaussian derivative filter for quantization and Kernel Discriminant Analysis (KDA) for dimension reduction. The recognition rate was improved by the weighted score level fusion of spectral palmprints on Fisher criterion.

Fei et al. [18] address a double half-orientation-based method for extracting the required features from the palmprint image. The half-Gabor filters bank was employed for the half-orientation extraction of a palmprint in the proposed system. The obtained results show a higher accuracy for the double half-orientations than the single dominant orientation using three different palmprint databases.

3. Proposed System

The proposed system PRS recognize the input palmprint images using several effective methods. These methods are selected based on analysing the previous works and perform number of experimental. The output of the system is shows whether the input palmprint image belongs to the enrolled images in the dataset or not. In order to achieve a better recognition results, four essential stages are present in the proposed system. These stages are 1) preprocessing 2) segmentation 3) feature extraction and 4) classification. Figure 1 shows the main stages of the proposed system.

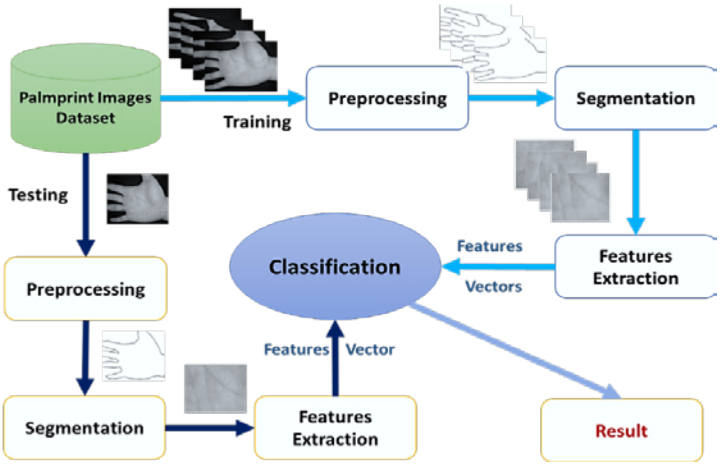

Fig. 1. The proposed palmprint recognition system.

3.1. Preprocessing

The first stage of the proposed system is image preprocessing of palmprint. In order to prepare the input palmprint images for the next stages and enhance the system performance, several steps are considered. The preprocessing stage reduce the images dimensions and removes the unwanted pixels. Besides, it improves the image segmentation results to detect the Region of Interest (ROI) in the efficient manner. The main steps of the preprocessing are shown below:

- Read the input palmprint image.
- Remove the image background.
- Apply Gaussian filter on the input image.
- Convert image into binary.
- Detect the image edges using Canny filter.

The results of applying the preprocessing stage are illustrated in Fig. 2.

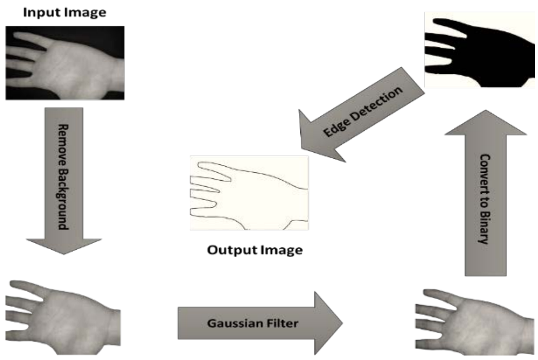

Fig. 2. Preprocessing stage.

After the system read the input palmprint image, the background is removed using fuzzy c-means clustering function in Matlab in order to limit the unwanted pixels in the input image. The fuzzy c-means clustering is depending on minimization the objective function of Eq. (1).

$$J_m = \sum_{i=1}^{N} \sum_{j=0}^{C} u_{ij}^{m} \left\| x_i - c_j \right\|^2 \tag{1}$$

The complete computation of fuzzy c-means is found in [19]. After that Gaussian filter is applied for image smoothing. By applying the Gaussian filter [20] the image will be blurred, and all the image noise are eliminated. Thus, the system results will be better for the input palmprint image. The 2d Gaussian can be defined in Eq. (2).

$$G(x,y) = \frac{1}{2\pi\partial^2} e^{-(x^2+y^2)/(2\partial^2)} \tag{2}$$

Binarization is the next step of the preprocessing stage. The image is converted to binary using Otsu method for reducing the image pixels and make the computation time less. The foreground pixels will set to (1) and the background pixels will set to (0). The Otsu method is defined as in Eq. (3).

$$\partial_w^2(t) = w_0(t)\partial_0^2(t) + w_1(t)\partial_1^2(t) \tag{3}$$

The last step in the preprosessing stage of the proposed system is the edge detection. Edge detection is an essential step in the most recognition system for detecting the edge of the image object. Detecting the edge in the proposed system make the segmentation process simpler and more accurate. Canny filter [21] that illustrated in Eq. (4) is used for detecting the palmprint edge in the image.

$$g_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad g_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \tag{4}$$

3.2. Segmentation

In the segmentation stage of the proposed system, several steps are applied in order to extract the Region of Interest (ROI) of the input palmprint image. These stages are listed below:

- Read the image from previous stage.

- Detect the image centroid.
- Find the valley point *v*1, *v*2 and *v*3 between the fingers (which are invariant to scaling and rotation).
- Draw line through the valley points and the centroid.
- Draw a square based on the distance between the valley points and the centroid in all centroid directions.
- Extract the detected ROI.

Figure 3 shows the result of applying the segmentation stage of the proposed system.

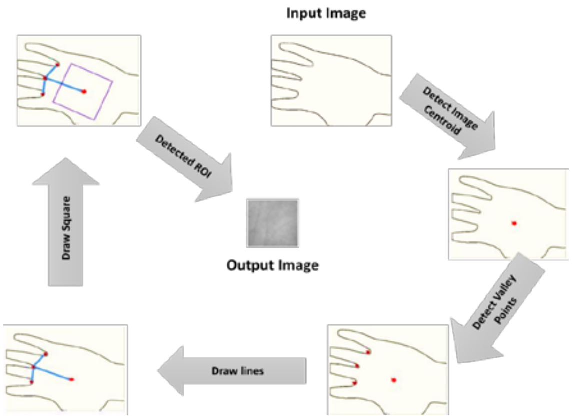

Fig. 3. Segmentation stage.

After reading the palmprint image the obtained from the preprocessing stage the centroid of the palmprint is detected. Detecting the centroid will allow us to locate the required ROI in the image. Equations (5) and (6) show the computation of the image centroid ($\overline{x}, \overline{y}$).

$$\overline{x} = \frac{\sum\sum x\, f(x,y)}{f(x,y)} \quad (5)$$

$$\overline{y} = \frac{\sum\sum y\, f(x,y)}{f(x,y)} \quad (6)$$

Detecting the valley points is the next step of the segmentation stage of the proposed system. The method is inspired by Michael et al. [22] work. Euclidean distance in Eq. (7) is used to compute the distances between the centroid and the boundary pixels. Besides, the valley point's location is located using four local minima of the Euclidean distance distribution diagram.

$$D(x,y) = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2} \quad (7)$$

After detecting the valley points, a square based on the distance between the valley points and the centroid in all centroid directions using Matlab function. Then the required ROI is extracted.

3.3. Feature extraction

In the stage of features extraction, a proposed approach for extracting the most effective features is used. The procedure of the proposed approach depends on two methods, which are directional features and Local Binary Pattern (LBP). The main steps of the feature extraction approach are listed down:

- Read the ROI image.
- Divide the input ROI image into number of equal cells.
- Perform an overlapped-on ROI image starting from right to let.
- Compute image edge and magnitude for each scanned part.
- Apply the LBP method on the results.
- Build the histogram based on the LBP results.
- Convert the LBP results into vector.
- Return the features vector.

Figure 4 illustrate the complete steps of the features extraction approach in our system.

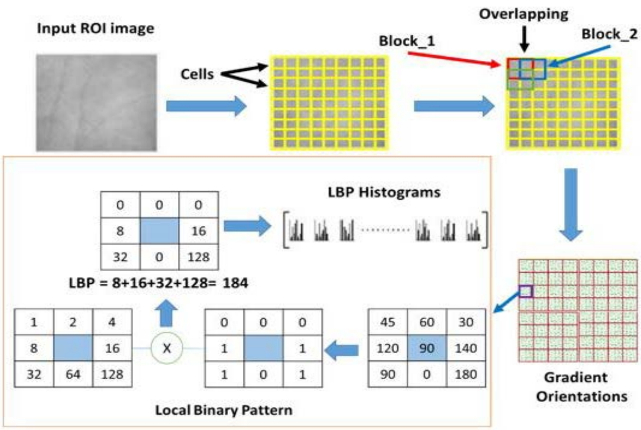

Fig. 4. Proposed features extraction approach.

In the directional features, canny filter is applied first to get the image edge. After that, the image gradient is computing using the following formulas [23]:

$$g = \sqrt{g_x^2 + g_y^2} \tag{8}$$

$$\theta = tan^{-1}(\frac{g_x}{g_y}) \tag{9}$$

The output gradient image then assigns to LBP to construct the histograms then the feature vector for each input image. In LBP, a 3×3 window is used first by comparing all the eight neighbours' pixel values with the centre value using the Eq. (10).

$$s(z) = \begin{cases} 0, & x < 0 \\ 1, & x \geq 0 \end{cases} \tag{10}$$

In addition, the LBP code is weighted using the binary relation of power of two to obtain the LBP code of the current selected centre pixel. In another hand, Eq. (11) is used to calculate the LBP code based on the I(xc, yc) which is represent the centre value of the used 3×3 window and the eight adjacent pixels which are: $g0$ …. $g7$.

$$LBP(x_c, y_c) = \sum_{i=0}^{7} s\,(g_i, g_c)2^i \tag{11}$$

The histograms then created using the LBP results and theses histograms represent the features of ROI images. The proposed approach reduces the features dimension by eliminate the small directions than the centre values. This technique ignores the unwanted directions and extract the only the most effective features that lead the system for better recognition results. Besides that, it reduces the computation time since it removes the undesired features.

3.4. Classification

The last stage of the proposed palmprint recognition system is classification. In classification, a matching process between the trained palmprint images and the test image is performed. In the proposed work an effective classification approach based on C5.0 Decision Tree (DT) and K-Nearest Neighbour (KNN) is used. A set of C5.0 decision trees are used for classification and KNN is used for voting process to obtain the final decision based on the trees results as shown in Fig. 5.

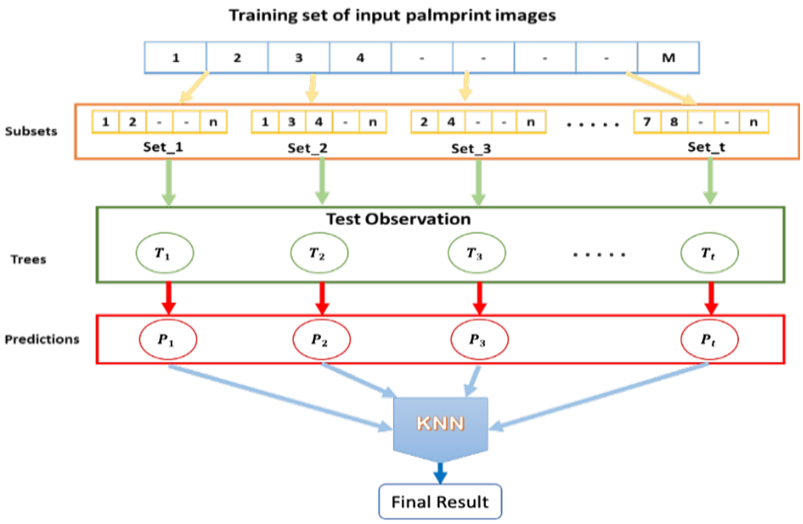

Fig. 5. Proposed classification approach.

C5.0 is a decision tree algorithm developed using ID3 and C4.5 algorithms [24]. The algorithm is faster than the previous algorithms in terms of making decisions and use low memory usage [25]. Furthermore, C5.0 builds an effective decision tree models based on calculating the Entropy value and information gain for each input attribute. The computing of the Entropy of the input dataset is shown in Eq. (12) :

$$H(S) = \sum_{i=1}^{n} -p(s_i)\, log_2\big(p(s_i)\big) \tag{12}$$

However, the root node is the attribute within largest value of the information gain which can be obtained using the following Eq. (13).

$$IG(S, A_i) = H(S) - \sum_{\propto \in A_i}^{n} \frac{S_\propto}{S}\, H(S_\propto) \tag{13}$$

After building the required subtrees and gain the prediction results for each set, KNN [26] is applied for voting by selecting the best possible solution of the classification stage. Euclidean distance in Eq. (7) is used for computing the KNN in the proposed system.

In the proposed system, the input features vector is divided into several subsets. These subsets cover all the features in the input vector. Also, some of the input futures could be used in more than one subset in order to get better classification results. The subsets are then assigning to several trees for classification and the results enter to the KNN for selecting the best result. The complete steps of the proposed classification approach showed below:

- Initialize the input training set $S \rightarrow 1 \ldots M$.
- Divide the input set into several subsets $1 \ldots n$.
- Build tree for each subset using C5.0 algorithm $1 \ldots t$.
- Collect the results of all trees included the most frequent results.
- Apply KNN on the collected results.
- Return the final predicted result.

4. Experiments

The proposed system implemented using Matlab 2016 under windows 10 (64-bit) environment, with 6 Giga Byte (GB) Random Access Memory (RAM), and core i5-2.50 GHs Central Process Unit (CPU). In addition, the used palmprint images datasets, evaluation and the obtained results are discussed below.

4.1. Palmprint images datasets

Two palmprint images datasets are used in the proposed system which are:

4.1.1. CASIA

Chinese Academy of Sciences (CASIA) palmprint images datasets [27] is a popular dataset that used for biometric system. The dataset has 5502 palmprint images that captures from 312 people (16 images for each person). CASIA has palmprint images for both left and right hands. Also, all the images are 8-bit grey-level JPEG. A sample images of the dataset are illustrated in Fig. 6.

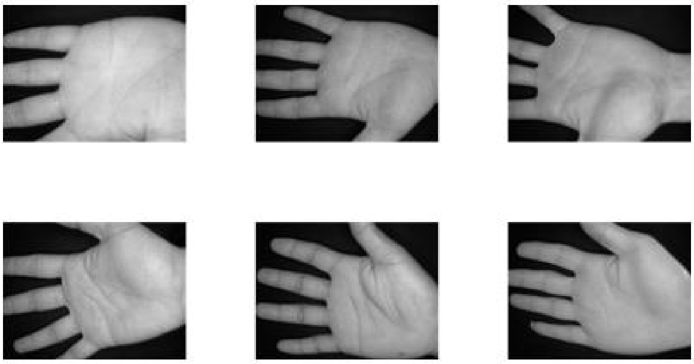

Fig. 6. CASIA palmprint images dataset.

4.1.2. COEP

COEP (College of Engineering Pune) palmprint images dataset is created by College of Engineering, Pune [28]. The dataset has 1344 palmprint images for 168 people (8 images for each person). The COEP images are captured using digital camera with 1600×1200 resolution. Figure 7 shows a sample of the COEP palmprint images.

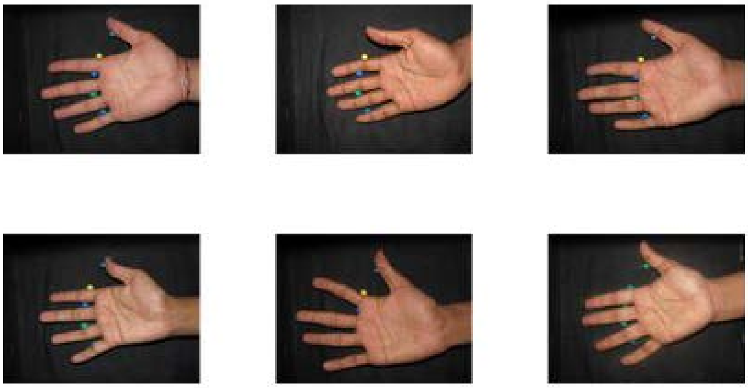

Fig. 7. COEP palmprint images dataset.

4.2. Recognition rate of the proposed system

In order to test the performance of the proposed palmprint images recognition system, number of metrics are used. These metrics are, Equal Error Rate (EER), and Accuracy of Recognition Rate (ARR) [29].

$$ARR = \frac{number\ of\ correctly\ classifised\ samples}{total\ number\ of\ samples} \tag{14}$$

$$EER = 1 - GAR \tag{15}$$

Genuine Acceptance Rate represent the palmprint images for the known users in the used database that classified correctly by the proposed system. By applying the proposed system on the extracted ROI images form CASIA and COEP dataset with 128x128 resolution, satisfied results are observed. Using the proposed approaches that starting from the preprocessing stage until the classification stage led the system to achieve a very high recognition rate as shown in Fig. 8.

Using effective preprocessing and segmentation with appropriate image resolution as shown in Fig. 8, lead to better recognition accuracy in the proposed palm print recognition system.

Furthermore, the features extraction method of the proposed system is an effective approach that made the system achieve better results within less computation time comparing to other methods. Tables 1 and 2 illustrate the obtained accuracy by PRS feature approach comparing with other methods.

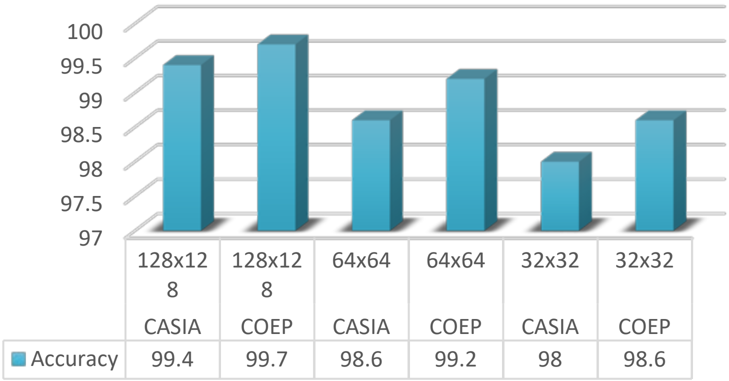

Fig. 8. The recognition rate of the proposed system.

Table 1. Comparison results of proposed method and existing methods.

Method	Accuracy %
LBP	92
Directional	94
Proposed	99.7

Table 2. Results of PRS feature extraction methods and other system methods.

Method	Accuracy %
PCA [30]	96.90
SIFT [31]	94.05
log-Gabor filter+KDA [32]	95
2-component partition [33]	90.25
DCT [34]	70.25
MLBP [35]	93.60
Proposed	99.7

In another hand, the proposed features extraction and classification approaches of the system is the powerful approaches that increased the system accuracy comparing to other palmprint recognition systems. The proposed approaches not only increased the accuracy of the system but also decreased the matching errors and achieved better results comparing to the existing systems as illustrated in Table 3.

Table 3. Results of proposed feature extraction methods and other system methods.

Method	EER %
Gabor filter [36]	1.50
Gabor filter [37]	1.70
log-Gabor filter+KDA [32]	0.1071
DOSFL [10]	0.306
Ridge Distance [38]	0.29
Proposed	0.009

In the above tables an improvement in terms of accuracy and matching error is achieved. All the existing palmprint recognition systems are focused on the features extraction stage and ignore the improvement that could be achieved in the others system stages.

In addition to the Obtained ARR and EER results by PRS, the execution time of the system also was better than the other systems that viewed in [39]. Table 4 shows execution time of the proposed system and the other recognition systems.

Table 4. Comparison results of the execution time of the proposed system and other systems.

System	Time (ms)
Systems present in [39]	12.5 - 749.9
Proposed	9.3

The last evaluation for the proposed system is the image sensitivity. A set of (50) palmprint images are randomly taken from the (IITD) dataset. These unknown images then used for testing the proposed system. The obtained sensitivity result was 97.1% using the following formula [38]:

$$sensitivity = \frac{TP}{TP+FN} \tag{16}$$

True Positive is represent the palmprint images which are correctly recognized. However, the False Negative represent the palmprint images which are recognized wrongly.

5. Conclusions

In this paper an accurate palmprint recognition system is proposed. The system achieved a high recognition accuracy which is 99.7% and less error matching rate 0.009%. Besides, using the proposed features extraction methods made the computation time reduced as well. The complete stages starting from the preprocessing, segmentation, features extraction and classification made the system more effective and accurate. The system used two public datasets for training, testing and to create a diversity in the achieved results. The comparison results showed that the system rise well than the existing systems and methods. With the efficient recognition stages especially the classification stage, the system can also perform accurately in online recognition manner by using a scanning device for reading the palmprint images directly then recognize the desired once as a future work. The system speed and its sensitivity to the unknown palmprint images, guarantee satisfied results for the future system.

Nomenclatures

A	The attribute
c	The number of clusters
cj	The d-dimension centre of the cluster
D	Euclidean distance
FN	False negative
g	The adjacent pixel
GAR	Genuine Acceptance Rate

m	Real number > 1
N	The number of data
N	The attributes A partition number
P_i	The Si to S proportion
S	The set of cases
TP	True positive
uij	The degree of membership of xi in the cluster j
w_0,w_1	Probabilities of the two classes separated by a threshold t
x	Training feature values
xi	The ith of d-dimensional measured data
y	Testing feature values
Z	LBP code

Greek Symbols

∂	The standard deviation of the distribution
$\|S\|$	The cases number in S
$\|S_\alpha\|$	The cases number
$\|\|*\|\|$	Any norm expressing for similarity measure

Abbreviations

AAR	Accuracy of Recognition Rate
CASIA	Academy of Sciences
CNN	Convolutional Neural Network
COEP	College of Engineering Pune
CPU	Central Process Unit
CRC	Collaborative Representation-based Classifier
DDR	Deep Discriminative Representation
DNN	Deep Neural Networks
DOSFL	Discriminant Orientation and Scale Features Learning
DT	Decision Tree
EER	Equal Error Rate
GB	Giga Byte
GPDS	Digital Signal Processing Group
ID	Identity Document
IITD	Indian Institute of Technology Delhi
JDCFR	Joint Deep Convolutional Feature Representation
KDA	Kernel Discriminant Analysis
KNN	K-Nearest Neighbour
LBP	Local Binary Pattern
MOSDL	Multi-Orientation multi-Scale features Discriminant Learning
MSEC	Minimum Squared Error Classification
MSLP	Manifold Supervised Label Prediction
PCA	Principal Component Analysis
PIN	Personal Identification Number
PolyU	Polytechnic University
PRS	Palmprint Recognition System called
RAM	Random Access Memory
ROI	Region of Interest

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