International Journal of Scientific Research & Engineering Trends
Volume 7, Issue 3, May-June-2021, ISSN (Online): 2395-566X

Efficient Approach for Palm Line Extraction and Matching for Personal Authentication

Asst. Prof. N. Aravind, I. Rajkumar, D. Shalini, K. Pawankumar,R. Jhansi bai
Department of Electronics and Communication.
Gyan Ganga Institute of Technology and Sciences,
Jabalpur,MP,India

Abstract- **Palm print recognition has been reconnoitered over numerous years. During this instance of time, several different glitches related to palm print recognition have been addressed. Furthermost of the studies has been done in palmprint recognition due to its stability, reliability and exclusivity. Furthermore it has been used for law enforcement, civil applications and access control applications. Researchers have proposed a variety of palmprint preprocessing, feature extraction and matching approaches. This paper deliberates about the number of investigation works introduced to overcome the difficulties confronted in each stage of palm print verification. Our study on palm print recognition focuses on verifying the palm print in different types of schemes involved. In this thesis, we projected a novel framework to execute multi biometrics by broadly combining the left and right palmprint images. This framework integrated three kinds of scores generate from the left and right palmprint images to perform matching score-level fusion.**

Keywords- **Palmprint recognisation, knn classifier, multi biometrics, score level fusion, right palmprint.**

I. INTRODUCTION

The most widely used biometric feature is the finger print and the most reliable feature is the iris. However it is very difficult to extract small unique features such as minutiae from unclear finger prints and the iris input devices are very expensive. Other biometric features, such as the face and the voice, are as yet not sufficiently accurate.

Compared with all of these, the palm print, a relatively new biometric feature, has several advantages. Palm prints contain more information than fingerprints, so they are more distinctive. Biometric is the science of measuring human's characteristics for the purpose of authenticating or identifying the identity of an individual based on specific physiological or behavioral characteristics.

Several types of physiological characteristics used in biometric are appearance of face, hand geometry, fingerprint, iris and palm print. Palm print capture devices are much cheaper than iris devices. Further, palm prints contain additional distinctive features such as principal lines and wrinkles, which can be extracted from low-resolution images by combining all the features of palms, such as palm geometry, ridge and valley features, and principal lines and wrinkles, it is possible to build a highly accurate biometrics system.

The goal of the biometric system is to utilize physical and/or behavior characteristics to identify/verify the subject of interest. Biometric systems are widely used in access control and security-based applications.[1] There exist various kinds of biometric systems that are based on physical and/or behavioral cues such as the face, iris, speech, key-stroke, palmprint, retina, and so on. Among these, the palmprint-based biometric system that has been investigated for over 15 years has demonstrated its applicability as a successful biometric modality.

Further, recent work has demonstrated the anti-spoofing nature of palm prints that places the palmprint as a highly reliable biometric characteristic. Palm prints exhibit a unique characteristic that can be characterized using texture features that are contributed due to the presence of palm creases, wrinkles, and ridges. Furthermore, the palm prints can be captured using low-cost sensors with a very low-resolution imaging of 75 dots-per-inch (dpi).

The increasing popularity of the palmprint biometrics has resulted in various feature extraction techniques that have contributed to boosting the accuracy of palmprint verification.

The available techniques can be broadly classified into the following five types, namely:

- Local feature-based approaches,
- Statistical-based approaches,
- Appearance based approaches,
- Texture based approaches, and
- Hybrid approaches.

The local feature extraction techniques are based on extracting the feature such as ridges that include delta points, minutiae, and palm creases (or principle lines). The local features from the palmprint can be extracted using various techniques that include line segment approach,

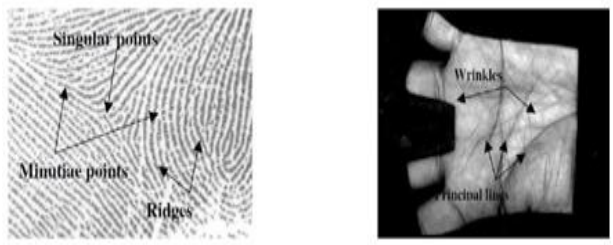
morphological median wavelet, Sobel operator, canny operators, Plessy operator, and wide-line detection operator. Even though the local features are proven to achieve the accurate performance, these methods demand very high-resolution palmprint images to be captured and thereby increases the cost of the sensor. The statistical-based approaches are based on extracting the features that correspond to mean, variance, moments, and energy.

There exist various techniques to capture the statistics of the palmprint that includes wavelet transform, Fourier transform, Cepstrum energy, sub-block energy based on Gabor transform, micro-scale invariant Gabor, Zernike moments. However, the use of the statistics-based approaches are not robust against the sensor noise. The appearance-based approaches perform the data mapping from high dimension to low dimension to achieve high accuracy as well as speed in comparison.

The most popular appearance-based techniques includes Principal Component Analysis (PCA), 2DPCA, bidirectional PCA, (2D)2PCA, independent component analysis (ICA), linear discriminant analysis (LDA), kernel-based approaches like kernel discriminant analysis (KDA), kernel PCA (KPCA), and generative model-based approaches, namely: PCA mixture model(PCAMM) and ICA mixture model (ICAMM).

Even though the use of the appearance model can perform equally well with the statistics approach, it still lacks the robustness against variation in noise as well as variation in palmprint templates with time. The texture-based schemes normally extract the global patterns of lines, ridges, and wrinkles that constitute for the robust palmprint recognition.

Among the available texture extraction schemes, the use of local binary patterns (LBP), Gabor transform, palm code, ordinal code, fusion code, competitive code, and contour code have shown to perform accurately even on low-resolution palmprint images. The hybrid scheme combines more than one of the above-mentioned schemes so that it can address shortcomings of individual schemes. When compared to all five different types of schemes, the hybrid schemes appear to be more robust and accurate for the palmprint recognition.



(a) (b)

Fig 1. Palmprint features in (a) a high resolution image and (b) a low resolution image.

Palm-lines, including the principal lines and wrinkles, can describe a palmprint clearly. This paper presents a novel approach of palm-line extraction for the online palmprints. This approach is composed of two stages: coarse-level extraction stage and fine-level extraction stage.[3]

In the first stage, morphological operations are used to extract palm-lines in different directions. In the second stage, for each extracted line, a recursive process is devised to further extract and trace the palm-line using the local information of the extracted part. Experimental results show that the proposed approach is suitable for palm-line extraction.

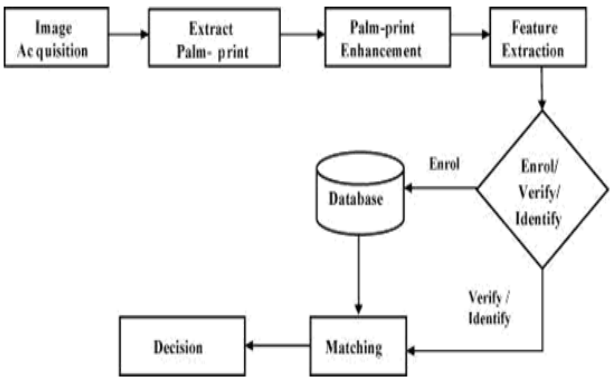


Fig 2. Basic steps for palm print verification.

II. LITERATURE SURVEY

Shalini Agarwal, Mohd Aamir, "An Optimized Palm Print Recognition Approach using Gabor filter," IEEE Trans. 8th ICCCNT 2017 July 3-5, 2017, IIT Delhi.
This paper proposed a method which first generates ROI of captured palm image then median filtering is applied to remove noise and increasing edge sharpness. Histogram equalization applied after that for contrast stretching for low resolution images. Enhanced image is then divided in sixteen equal part, texture feature is extracted from each part of image separately using different orientations of Gabor filter. The generated feature vectors of all sixteen images are then normalized to a single feature vector using n bin histogram process. This increase acceptance rate in case if palm is placed over scanner in slightly different angles because working on small areas of palm helps to extract detail features. This paper used SVM for classification of generated feature vector and Experiment performed on polyU palm print database.

Yassir Aberni, Larbi Boubchir, "Multispectral Palmprint Recognition: A State-of-the-Art Review", 978-1-5090-3982-1 ©2017 IEEE.
This paper presents an overview of recent advanced palmprint recognition methods using multispectral palmprint images providing various discriminate features. The methods surveyed are discussed, and their recognition performances are also compared and analyzed. The

similarity of two Fusion Codes is measured by their normalized hamming distance. A dynamic threshold is used for the final decisions. A database containing 9599 palmprint images from 488 different palms is used to validate the performance of the proposed method. Comparing our previous non-fusion approach and the proposed method, improvement in verification and identification are ensured. Our palm print identification system consists of two parts: a palm print scanner for on-line palm print image acquisition and an algorithm for real-time palm print identification.

Amit Chauhan, " Latent Palm Prints- an Appraisal of Concealed individualize Evidence and Its Aspect in Forensic Investigation," J Forensic Sci & Criminal Inves Volume-6 Issue 5 - December 2017.
The palm print verification in this method was carried out based the principal lines in the palm. In feature extraction stage, the modified finite Radon transform is proposed, which can extract principal lines effectively and efficiently even in the case that the palmprint images contain many long and strong wrinkles. In matching stage, a matching algorithm based on pixel-to-area comparison is devised to calculate the similarity between two palmprints, which has shown good robustness for slight rotations and translations of palmprints. The experimental results for the verification on Hong Kong Polytechnic University Palmprint Database show that the discriminability of principal lines is also strong.

III. PROPOSED METHODOLOGY

In this process, we propose a novel framework of combining the left with right palmprint at the matching score level. The palm prints are matched by using multi biometrics for this the recognition rate will be better than the existing system and computation cost for that system will be reduced. In the framework, three types of matching scores, which are respectively obtained by the left palmprint matching, right palmprint matching and crossing matching between the left query and right training palmprint, are fused to make the final decision. The framework not only combines the left and right palmprint images for identification, but also properly exploits the similarity between the left and right palmprint of the same subject.

Extensive experiments show that the proposed framework can integrate most conventional palmprint identification methods for performing identification and can achieve higher accuracy than conventional methods. This work has the following notable contributions. First, it for the first time shows that the left and right palmprint of the same subject are somewhat correlated, and it demonstrates the feasibility of exploiting the crossing matching score of the left and right palmprint for improving the accuracy of identity identification.

Second, it proposes an elaborated framework to integrate the left palmprint, right palmprint, and crossing matching of the left and right palmprint for identity identification.

Third, it conducts extensive experiments on both touch-based and contactless palmprint databases to verify the proposed framework.Pre-processing is to setup a coordinate system to align palmprint images and to segment a part of palmprint image for feature extraction. Feature extraction is to obtain effective features from the pre-processed palm prints.

Finally, a matcher compares two palmprint features that the left palmprint images and uses a palmprint identification method to calculate the scores of the test sample with respect to each class. Then it applies the palmprint identification method to the right palmprint images to calculate the score of the test sample with respect to each class. After the crossing matching score of the left palmprint image for testing with respect to the reverse right.

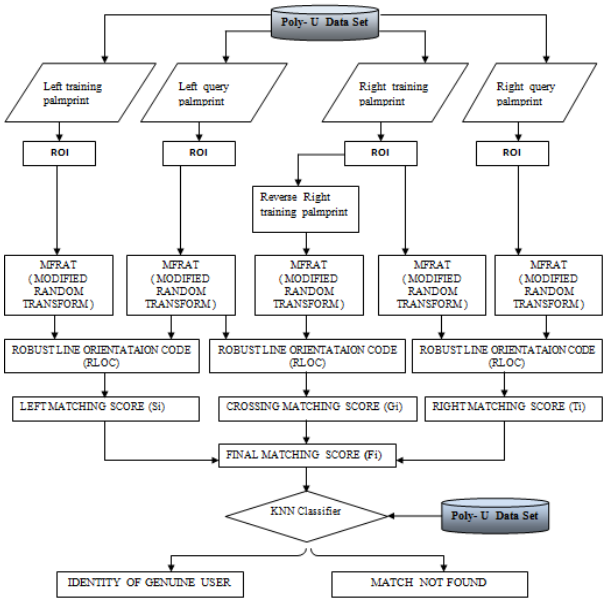


Fig 3. Flow Diagram of proposed Palm print identification.

IV. KNN CLASSIFIER

Classification has been done by KNN classifier. The k-Nearest Neighbors algorithm (or k-NN for short) is a non-parametric method used for classification and regression. The input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification. k-NN is a type of instance-based learning, or lazy learning, where the function is only approximated locally and all computation is deferred until classification. It can be useful to weight the contributions

of the neighbors, so that the nearer neighbors contribute more to the average than the more distant ones.The purpose of the KNN algorithm is to use a database in which the data points are separated into several separate classes to predict the classification of a new sample point. The following steps are performed by KNN classifier to classify test samples: 1. A positive integer K is specified. 2. The K entries in database are selected which are closest to the test sample based on Euclidean distance. This distance between train sample x and test sample y with 6 features is calculated as:

$$D_E(x, y) = \sqrt{\sum_{k=1}^{n} (X_k - Y_k)}$$

The labels (class) of K-nearest neighbors in train samples are extracted. The test sample y is assigned to the class that have maximum samples among K-nearest samples. It can be seen that performance of the KNN classifier depends on value K. Therefore, in this paper, we obtain the performance of the proposed algorithm for different values of K and the highest performance is chosen as performance of the proposed identification algorithm.

1. Performance Analysis:

- The accuracy, sensitivity and specificity of the classifier is measured.
- The accuracy represents the efficiency of the process.
- The sensitivity shows how the algorithm gives correct classification.
- The specificity shows how the algorithm rejects the wrongly classification results.
- The performance of the process is measured based on the calculation of Accuracy, Area under curve of the process.

$$ACC = \frac{(TP + TN)}{(FT + TN) + (TP + FN)}$$

- The performance of the process is measured in terms of performance metrics like Precision, Recall, F-measure and false positives. The

Recall = TP / TP + FN

Precision = TP / TP + FP

F = (2) Recall. Precision / Recall + Precision

Where;

- TP is the total number of correctly classified foreground (true positives).
- FN is the total number of false negatives, which accounts for the incorrect number of disease type pixels classified as dataset (false negatives).
- FP is the total number of false positives, which means the pixels are incorrectly classified as images (false positives).
- True negative = correctly rejected

V. SIMULATION RESULT

The performance of the proposed algorithm is evaluated using the palmprint database . The database is divided into two sets which consist of training data and testing data. From the PolyU palmprint database, 5 samples are taken at random. Each sample consists of 20 images taken in two different instances.

During training 7 images are considered whereas for testing 4 images are taken. For classification of features, multiclass SVM algorithm is implemented with two approaches: (i) One-Against-All (ii) One-Against-One. The experimental results are performed with Intel Core 2 Duo processor having Matlab version 8.0 with image processing toolbox and 2 GB RAM.

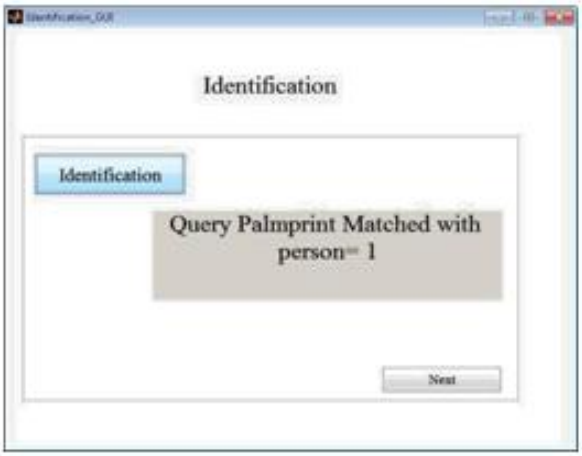


Fig 4. Identification Palmprint.

Fig 5. Performance of Matching Palmprint.

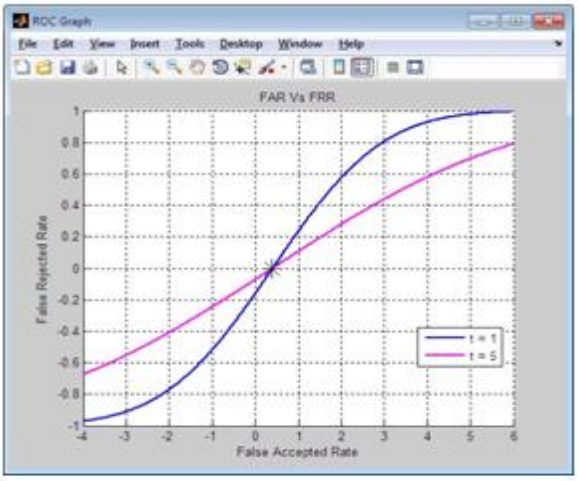


Fig 6. FAR vs FRR Graph.

VI. COMPARATIVE RESULT

Sr.No	Author	Method	Precision
1	Merlin Linda Georgeet al [1]	Ant Colony Optimization to palm ROI	98
2	Proposed method	Knn Classifier applied to palm ROI	99

VII. CONCLUSION

In this process, we have investigated the relationship between two orientations of a palmprint to identify the more discriminative orientation and then used a group of neighboring direction indicators to represent the relation of these orientations.

The neighboring direction indicator can not only essentially represent the most dominant orientation feature of the palmprint, but can also better denote the multiple orientations of some special points having double dominant orientations. In addition, a simple and effective smoothing convolution has been introduced to improve the precision of the orientation feature of the palmprint.

Experimental results show that the proposed method can achieve higher accuracy in palmprint recognition than the state-of-the-art orientation-based methods. Moreover, the proposed method gives the most competitive performance in multispectral palmprint verification

REFERENCES

[1] Shalini Agarwal, Mohd Aamir, "An Optimized Palm Print Recognition Approach using Gabor filter," IEEE Trans. 8th ICCCNT 2017 July 3-5, 2017, IIT Delhi.
[2] Yassir Aberni, Larbi Boubchir, "Multispectral Palmprint Recognition: A State-of-the-Art.
[3] Amit Chauhan, " Latent Palm Prints- an Appraisal of Concealed individualize Evidence and Its Aspect in Forensic Investigation," J Forensic Sci & Criminal Inves Volume-6 Issue 5 - December 2017.
[4] Komal Kashyap, Ekta Tamrakar, "Accurate Personal Identification Using Left and Right Palmprint Images Based on ANFIS Approach," International Journal of Mineral Processing andExtractive Metallurgy 2017; 2(2): 13-20.
[5] Srushti Kureel1, Praveen Kumar, " Shape and Texture based Palm Print Recognition System for Biometric identification" International Journal of Engineering Trends and Technology (IJETT) – Volume 50 Number 1 August 2017.
[6] Urvashi Agrawal, Rucha Nimbhorkar, " Palmprint Recognition Using HOL", International Journal of Recent Scientific Research Research Vol. 9, Issue, 1(C), pp. 23070-23074, 2017.
[7] Ali Younesi and Mehdi Chehel Amirani, "Gabor Filter and Texture based Features for Palmprint Recognition", International Conference on Computational Science, ICCS 2017, 12-14 June 2017, Zurich, Switzerland.
[8] Shruthi .N, "Combining Left and Right Palm Print Images for more Accurate Personal Identification", International Journal of Advance Research, Ideas and Innovations in Technology. Impact factor: 4.295 (Volume3, Issue3).
[9] Vivek kr. Sharma, Nisha Vasudeva, "A Review on Palm Print Recognition Techniques", 2017, IJARCSSE.
[10] R. Raghavendra* and Christoph Busch, "Texture based features for robust palmprint recognition: a comparative study", Raghavendra and Busch EURASIP Journal on Information Security (2015) .
[11] H. K. Kalluri, M. Prasad, and A. Agarwal, "Palmprint identification and verification based on wide principal lines through dynamic ROI," Int. J. Biometrics, vol. 7, no. 1, pp. 1–30, 2015.
[12] R. Raghavendra and C. Busch, "Novel image fusion scheme based on dependency measure for robust multispectral palmprint recognition," Pattern Recognit., vol. 47, pp. 2205–2221, 2014.
[13] F. Yue, B. Li, and M. Yu, "Hashing based fast palmprint identification for large-scale databases," IEEE Trans. Inf. Forensics Security, vol. 8, no. 5, pp. 769–778, May 2013.
[14] G.S. Badrinath and P.Gupta, "Palmprint based recognition system using phase-difference information," Future Gener. Comput. Syst., 2012, pp. 287–305.
[15] W. Li, L. Zhang, D. Zhang, G. Lu, and J. Yan, "Efficient joint 2D and 3D palmprint matching with alignment refinement," in Proc. IEEE Conf. Comput. Vision Pattern Recognit., 2010, pp. 795–801.
[16] G. S. Badrinath and P. Gupta, "Palmprint based recognition system using phase-difference

information," Future Gener. Comput. Syst., 2012, pp. 287–305.

[17] W. Li, L. Zhang, D. Zhang, G. Lu, and J. Yan, "Efficient joint 2D and 3D palmprint matching with alignment refinement," in Proc. IEEE Conf. Comput. Vision Pattern Recognit.,2010, pp. 795–801.

[18] D. Zhang, Z. Guo, G. Lu, L. Zhang, and W. Zuo, "An online system of multi-spectral palmprint verification," IEEE Trans. Instrum. Meas., vol. 59, no. 2, pp. 480–490, Feb. 2010.

[19] A. Kong, D. Zhang, and M. Kamel, "A survey of palmprint recognition," Pattern Recognit., vol. 42, no. 7, pp. 1408–1418, 2009.

[20] D. Zhang, Advanced Pattern Recognition Technologies with Applications to Biometrics. Hershey, PA, USA: Med. Inf. Sci. Ref., 2009.