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High Resolution Palmprint Recognition System Using Multiple Features

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Abstract

During the past decade, more efforts have been put to utilize palmprint as a biometric identity. This research work presents novel algorithms to extract multiple palmprint features from high-resolution palmprint. The major contributions in this research include the following: 1) Use of preprocessing techniques such as Binarization, ROI Extraction, Enhancement and Thinning. 2)Extraction of multiple features from ridges such as ridge orientation, its frequency, minutiae points (termination and bifurcation points) and pores which during the matching process produces higher accuracy 3) Use of a novel framework in fusion method for an authentication application which performs better than existing techniques. The results of this research work have been compared with the various existing methods and different databases. The comparison results are illustrated through the time taken for execution, ROC and DET curves.
Keywords: palmprint, biometric authentication system, ROI Extraction, Binarization, Enhancement and Thinning, ridge orientation, ROC and DET curves.

1. Introduction:

A very challenging issue faced by the recognizing systems is the precise personal identification. Authentication is the process of permitting authorized legal users to access resources when required. Traditional identification methods used are token-based or knowledge-based [1] which can be easily compromised. Biometrics, a robust automation technique for identification of an individual,has become very popular nowadays in most of the automated recognizing system. Physiological biometric traits, namely fingerprint, palmprint, face, ear, iris, DNA, knuckleprint, retina, hand geometry, etc., are permanent since they are inherited within the individual naturally at the time of birth and are time invariant whereas the behavioral attributes[2]. Sections 2 and 3 outline the proposed technique, while Section 4 discusses the paper's findings. This paper is structured as follows. Conclusions and recommendations for further research are provided in Section 5.

2. Related works:

Numerous studies have been done on various facets of palmprint recognition up to this point, and many insightful ideas for improving its performance have been put forth [3]. Researchers have put forth numerous conventional techniques for 2D palmprint identification, which can be further broken down into sub-categories such palm line-based, texture-based, orientation coding-based, correlation filter-based, and subspace learning-based[4].To extract principal lines and create a pixel-to-area technique to compare the principal lines of two palmprints, Work [5] introduced the modified finite Radon transform (MFRAT). Author [6] suggested a dynamic matching approach utilising a positive linear dynamical system and employed a morphological top-hat filtering algorithm to extract principal lines. The descriptor of histogram of oriented lines (HOL) was proposed by [7] for palmprint identification, replacing the gradient by the response of Gabor filters in the local descriptor of histogram of oriented gradients (HOG).Later, [8] used the modulation of two orientations to propose the descriptor of local line directional pattern (LLDP). The local discriminant direction binary pattern (LDDBP), the discriminant direction binary palmprint descriptor, and other methods were presented by [9] in order to fully exploit the various direction information of a pixel and investigate the most discriminant direction representation (DDBPD) [10]

3. Proposed Methodology:

In score level fusion, extracted features are matched individually and then computed matching score is fused to make a decision whether individual is genuine or impostor. Score level fusion has a good fault tolerance, more effective, simple, easy to implement, etc. Moreover, match scores provide the richest information obtained from the feature sets. Hence, fusion at score level is the most widely and commonly used fusion approach.

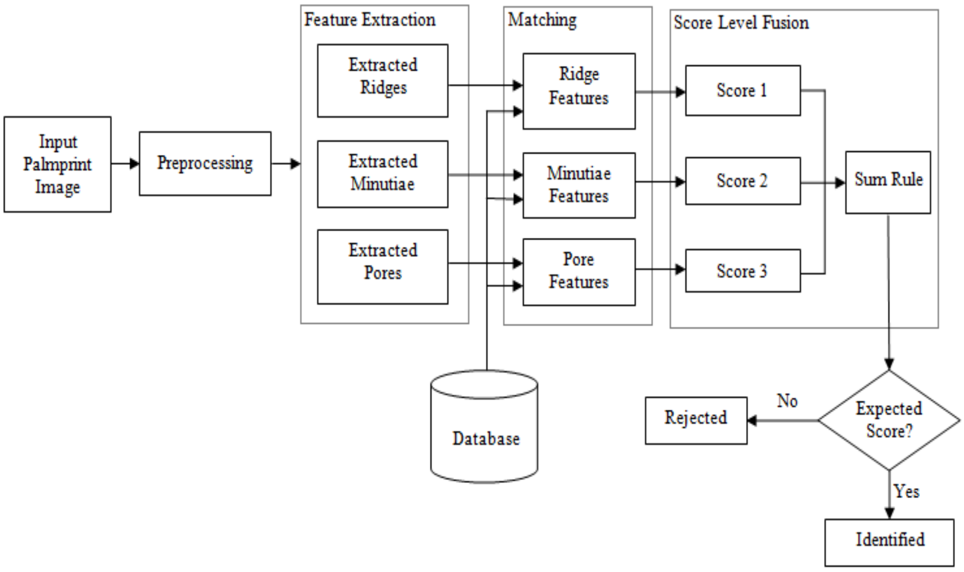

Figure 4: Architecture of Proposed High Resolution Palmprint Recognition method

Architecture of the developed high resolution palmprint recognition system is as shown in the figure 4. Multiple features are extracted and matching is performed on individual features. The match-score is computed for each feature and then fused. Decision is taken based on final computed score i.e., whether the individual is identified or rejected.

3.1 Score level fusion

This section presents various proposed score level fusion techniques employed with different combinations of the extracted ridge, minutiae and pore features.

- Type-1 Fusion

Type-1 fusion is based on ridge and minutiae features. Here the weighted score of both ridges and minutiae has been summed using sum rule and finally this fused score value is used to make a decision. The diagrammatic representation of type-1 fusion is as in figure 5.

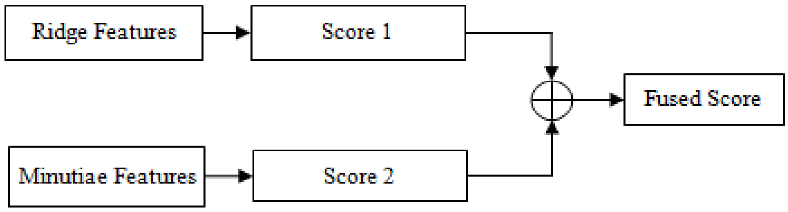

Figure 5: Type-1 Fusion

- Type-2 Fusion

Type-2 fusion is based on ridge and pore features. Here the weighted score of both ridges and pores has been summed using sum rule and finally this fused score value is used to make a decision. The diagrammatic representation of type-2 fusion is as in figure 6.

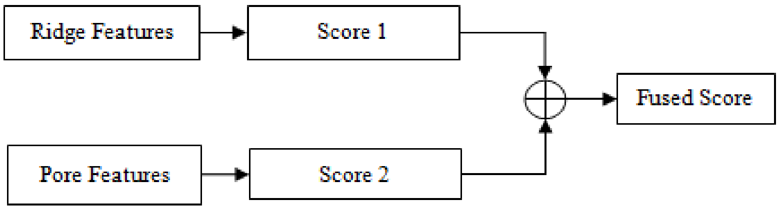

Figure 6: Type-2 Fusion

- Type-3 Fusion

Type-3 fusion is based on minutiae and pore features. Here the weighted score of both minutiae and pores has been summed using sum rule and finally this fused score value is used to make a decision. The diagrammatic representation of type-3 fusion is as shown in figure 7.

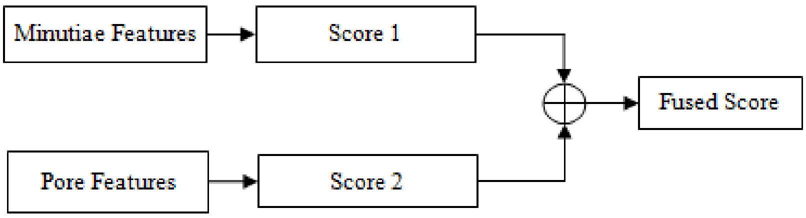

Figure 7: Type-3 Fusion

- Type-4 Fusion

Type-4 fusion is based on all the three extracted features of palmprint i.e. ridge, minutiae and pore features. The weighted score of all these three features have been summed up using the sum rule and finally this fused score value is used to make a decision. The type-4 fusion is as shown in figure 8.

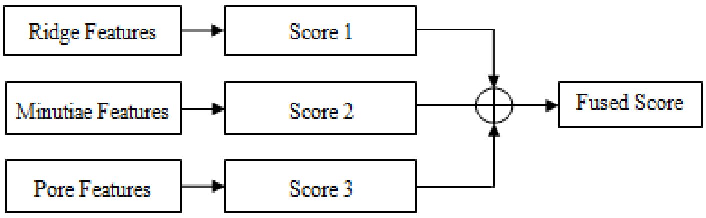

Figure 8: Type-4 Fusion

3.2 Weighted Rule

Weights are assigned to the features according to the accuracy obtained. The table 6.1 shows the assigned score values. For ridges, if the accuracy is greater than 80%, 65%, 50% then the assigned weight is 5, 4, 3 respectively. For minutiae, if the accuracy is greater than 85%, 70% and 55% then the assigned weight is 5, 4 and 3 respectively. For pores, if the accuracy is greater than 90%, 75%, and 60% then the assigned weight is 5, 4 and 3 respectively.

Table 1: Features with Weights Assigned

Features	**Weights assigned**		
	5	**4**	**3**
Ridge	> 80	> 65	> 50
Minutiae	> 85	> 70	> 55
Pore	> 90	> 75	> 60

3.3 Sum Rule

The sum rule offers the most straightforward method of fusion that sums the separate scores of several biometric units.Weighted sum rule adds the weighted scores obtained during matching different features. The weighted match scores generated for various palm features are summed up to obtain a final score using the equation 1.

$$F = s(RW) + s(MW) + s(PW) \quad (1)$$

where F is the final score, RW, MW and PW denotes the weights of ridge, minutiae and pore features respectively. F is obtained by adding the weighted scores of ridge, minutiae and pore. Based on this final match score F, decision is made during recognition process.

4. Results and Discussion

This section presents time taken by entire proposed system for both the databases, comparison of various fusion types in terms of accuracy using ROC curve and the error rates using DET curve

4.1 Proposed System – Timing Accuracy

Average time taken by proposed technique to perform various operations for the configuration of the system used is calculated and summarized in table 2. From the table, it is observed that average time taken by proposed method for THU-HRPD is lesser than LPIDB v1.0.

Table 2: Average Time Taken by the Proposed System

Processing Steps	**Average Time (s)**	
	THU-HRPD	*LPIDB v1.0*
Preprocessing	3.72	3.72
Minutiae Extraction	2.61	2.94
Ridge Extraction	0.75	0.90
Pore Extraction	3.24	4.06
Minutiae Matching	0.42	0.38
Pore Matching	0.68	0.59
Ridge Matching	0.94	0.43
Decision Making	0.52	0.52
Total Time	12.88	13.54

Figure 9 proves that the proposed combination of ridge + minutiae + pore features using THU-HRPD database provides very less error rate than the error rates of minutiae + pore, ridge + pore and ridge + minutiae. The error rates for ridge + minutiae, ridge + pore, minutiae+pore and ridge + minutiae + pore are 5.98%, 5.05%, 4.75% and 4.05% respectively.

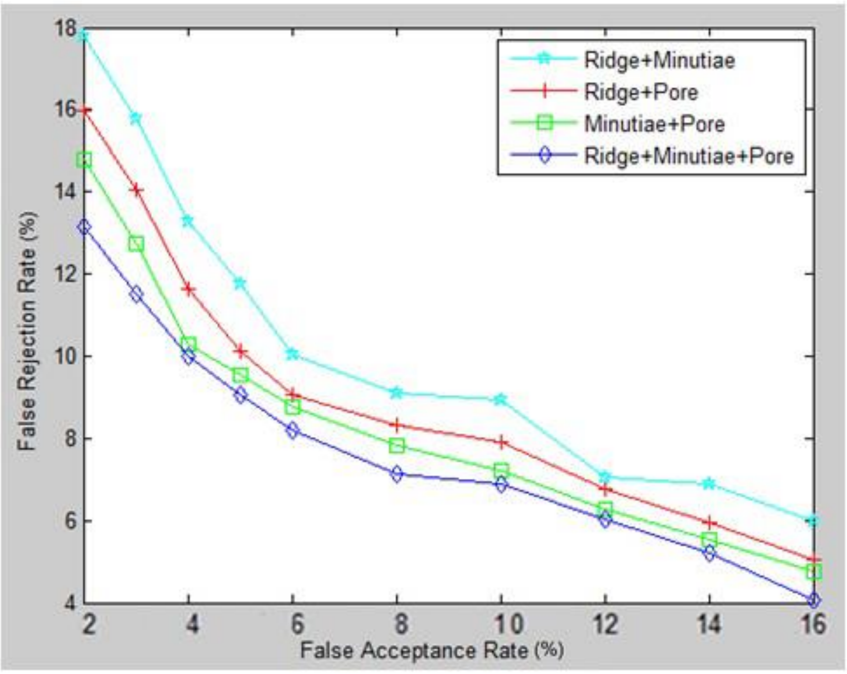

Figure 9: DET curve illustrating the error rates of type-4 fusionusing THU-HRPD database

Figure 10 proves that the proposed combination of ridge + minutiae + pore features using LPIDB v1.0 database provides very less error rate than the error rates of minutiae + pore, ridge + pore and ridge + minutiae. The error rates for ridge + minutiae, ridge + pore, minutiae + pore and ridge + minutiae + pore are 6.86%, 6.48%, 6.28% and5.13% respectively.

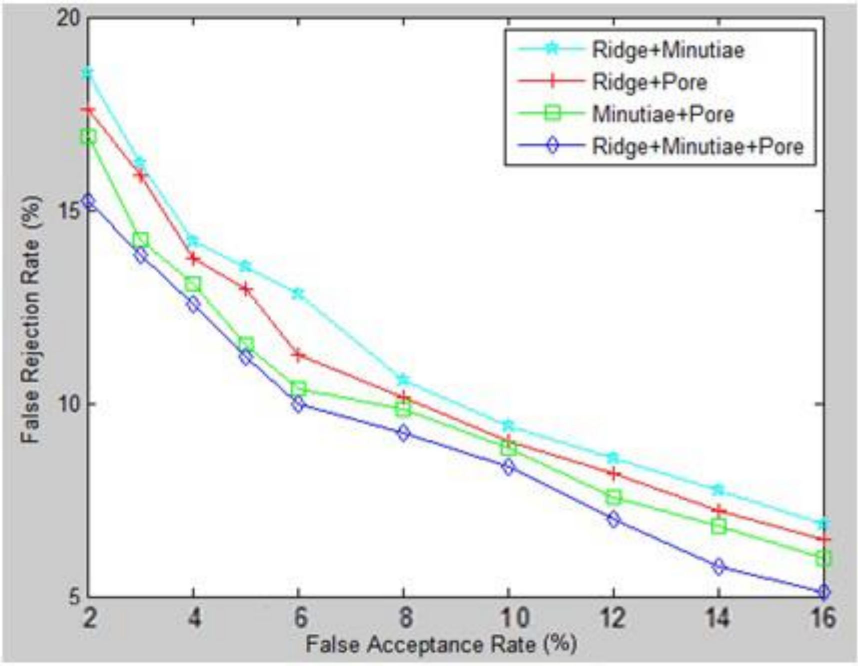

Figure 10: DET curve illustrating the error rates of type-4 fusion using LPIDB v1.0 database

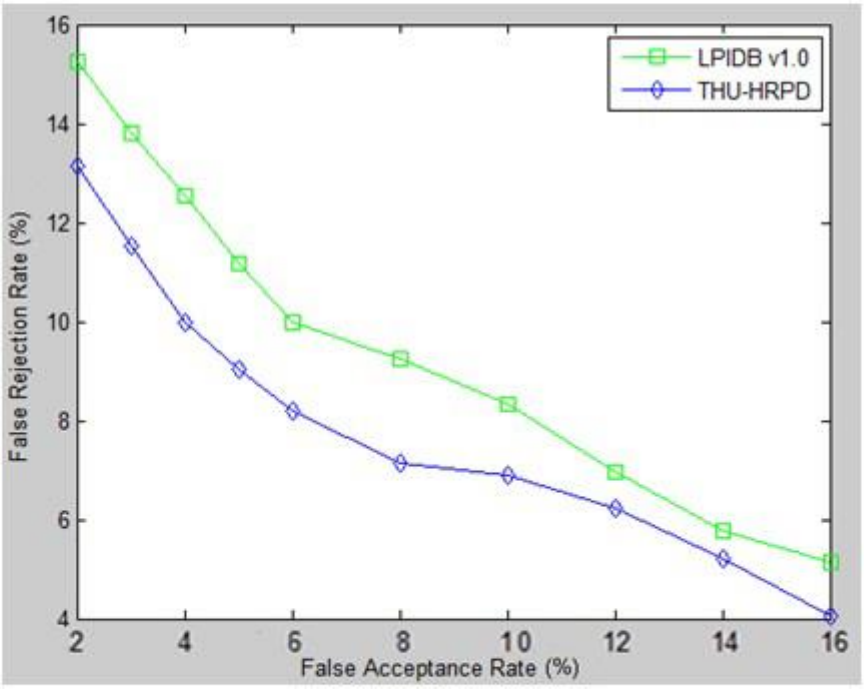

Figure 11: DET curve illustrating the comparison of error rates for type-4 fusion using THU-HRPD and LPIDB v1.0 databases

Figure 11 shows that the proposed combination of all the features provides less error rate for THU-HRPD than the LPIDB v1.0 database whose error rates are 4.05% and 5.13% respectively.

From all the above DET curves, it is observed and proved that the proposed type-4 fusion technique which combines all the features extracted from palmprint provides less error rate than the other types of fusion such as type-3, type-2 and type-1 techniques. Further, it is also observed that all the types of fusion provides less error rate for THU-HRPD database than LPIDB v1.0 database.

5 Conclusion:

In this paper, the proposed score level fusion with weighted sum rule improved the accuracy of the overall palmprint recognition system compared with the existing systems. Hence fusing ridge with minutiae, minutiae with pore and ridge with pore was employed and examined that the identification rate was higher. Hence, there arouse a feasibility to combine different kinds of palmprint features so as to boost the performance of high-resolution palmprint system in terms of accuracy. So, for achieving the state-of-art performance, all the extracted features namely level-1, level-2 and level-3 were integrated and score level fusion technique with weighted sum rule was used which proved that the system provided better accuracy than the other methods used. Further it has been studied that the images from the hypothenar region provided higher accuracy by reducing the time complexity than the other two regions namely thenar and Interdigital regions.

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