

# Palmprint Recognition using Rank Level Fusion

Ajay Kumar<sup>1</sup>, Sumit Shekhar<sup>1,2</sup>

<sup>1</sup>Department of Computing, The Hong Kong Polytechnic University, Hong Kong

<sup>2</sup>Department of Electrical and Computer Engineering, University of Maryland, College Park, USA

Email: ajaykr@ieee.org, taugemini@gmail.com

**Abstract**—This paper investigates a new approach for the personal recognition using rank level combination of multiple palmprint representations. There has been very little effort to study rank level fusion approaches for multi-biometrics combination and in particular for the palmprint identification. In this paper, we propose a new nonlinear rank level fusion approach and present a comparative study of rank level fusion approaches which can be useful in combining multi-biometrics fusion. The comparative experimental results from the real hand biometrics data to evaluate/ascertain the rank level combination using (i) Borda count, (ii) Logistic regression/Weighted Borda count, (iii) highest rank method and (iv) Bucklin Method are presented. Our experimental results presented in this paper suggest that significant performance improvement in the recognition accuracy can be achieved as compared to those from individual palmprint representations. The rigorous experimental results presented in this paper also suggest that the proposed nonlinear rank-level approach outperforms the existing approaches presented in the literature.

## I. INTRODUCTION

THE biometrics recognition has emerged a reliable approach for automated user identification and is attracting significant attention from the researchers in multifaceted disciplines. The hand based biometrics acquisition has high user acceptance and more user friendly with the development of touch-less and peg-free systems. The fingerprint, palmprint, hand geometry, finger geometry, palm vein and knuckle biometrics have been extensively researched and several of these systems are now commercially available for the real deployment. The human recognition process is reconciliation of multiple pieces of behavioral and/or physiological biometric evidences in addition to the contextual information from the environment. Therefore automated biometrics system designed to identify individuals from such pieces of multiple evidences, *i.e.*, multibiometrics, can effectively achieve higher performance.

The region of skin between wrist and fingers is highly rich in texture patterns and is imaged which is commonly referred to as palmprint. The development of palmprint ridge patterns in the foetus highly depends on conserved genes. The usage of palmprint for personal identification is significantly dependent on the uniqueness and stability of palmer friction ridges and palmer flexion creases which forms such random texture patterns. The palmprint identification is of high interest not only for civilian applications but also for forensic applications as about 30% of latent prints lifted from the crime scenes (*i.e.*, steering wheels, knife grips, *etc.*) are from the palmprint [2]. For example, the case involving kidnapping

and killing of Polly Klass was solved by lifting of latent palmprints from Richard Allen Davies from Polly's bed after her murder [13]. In summary, the civilian and forensic applications of palmprints have motivated lot of research interest in palmprint identification using (i) touchless palmprint identification for high user friendliness [3], [8], (ii) hand docking frame or pegs that focuses on higher accuracy [4]-[5], and (iii) latent prints for forensic applications [2].

## II. PRIOR WORK

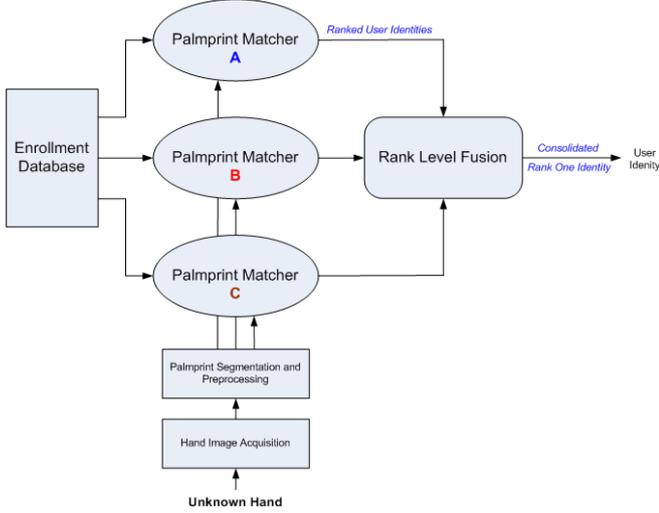
The palmprint based personal identification has been extensively studied in the biometrics literature and range of feature extraction approaches have been investigated. These approaches have been categorized into three categories [1]: (i) texture-based approaches, (ii) line-based approaches, and (iii) appearance-based approaches. The combination of these features can be employed to improve the performance for the palmprint authentication. However, the combination strategies have to be experimentally developed as the degree of correlation among these features varies, since these multiple features are extracted from the same palmprint image. In the context of palmprint literature, the improvement in the palmprint authentication performance using score level and feature level combinations has been investigated with promising results. However, there has not been any attempt to investigate the rank level combination from multiple palmprint matchers that can be employed for improving the palmprint *recognition* performance.

### A. Why Rank Level Fusion?

The output from several commercial biometric devices can be the ranked identities of the users and the information regarding matching scores or features may not be made available. This can often be the case to protect the proprietary biometric algorithms. The rank level combination can also be the option when the matching scores from the matchers are incompatible for combination. Therefore the consolidation of confidence in user identification from such multiple sources of devices/matchers can only be achieved by some reliable rank level combination scheme. In addition, the rank-level combination schemes are also suitable for combining ranked identities from commercial biometric devices that acquire different biometric traits, *i.e.*, for multimodal biometrics.

## III. BLOCK DIAGRAM

The simplified block diagram for the palmprint based recognition system using rank level combination is shown in figure 1. This figure illustrates the usage of three palmprint matchers that generate the ranked identities of the possible subjects/user's identified. Each of these matchers can utilize



**Figure 1:** Block diagram for palmprint recognition using rank level combination of multiple matchers.

different feature extraction algorithm and/or matching schemes. The rank-level fusion is considered for consolidating the ranked identities of users received from these multiple matchers. The rank one identity from this combination is used to recognize the unknown user whose palmprint is presented to the system.

#### IV. RANK LEVEL FUSION

The improvement in the palmprint recognition accuracy can be achieved by selecting appropriate rank-level combination mechanism that can take advantage of strengths of individual matchers while suppressing their weakness. In the following, we briefly summarize various rank level combination approaches investigated in this paper.

**start**

```

get ranks  $R_k(i, j)$  from individual matchers
total_points( $i, j$ ) = 0
for  $i = 1$  to no_of_users step 1
  for  $j = 1$  to test_samples step 1
    temp =  $R_k(i, j) \forall k$ 
    total_points(temp,  $j$ ) = total_points(temp,  $j$ ) +
      (no_of_users -  $i$  + 1)
  end for
end for

```

```

result = sort(total_points, descend)
print result

```

**stop**

##### A. Borda Count

The rank level combination using Borda count approach is based on the generalization of majority vote and the most commonly used method for unsupervised rank level fusion. In this method, each of the rank-one candidate identities, from every palmprint matcher, is given  $M$  votes, the rank-two identities is given  $M-1$  votes and so on. Then for every possible user identity, the votes from all the palmprint matchers are added. The user identity that receives the highest

number of votes is assigned as the winner or the true user identity.

$$C_p = \sum_{j=1}^N r_j(p) \quad (1)$$

for  $\forall p, p = 1, 2, \dots, M$ . The method of consolidating ranks using (1) assumes statistical independence, *i.e.*, ranks assigned to a given user by different matchers are independent. However, this assumption may not be true as the features are extracted from the same palmprint image.

##### B. Weighted Borda Count

The expected performance from the different palmprint is not the same. Therefore the Borda count method can be modified by assigning weights in the ranked output from the individual palmprint matchers. These weights can be computed using logistic regression or using more sophisticated machine learning approaches [10].

##### C. Maximum Rank Method

In this approach, the highest rank is given to a user amongst all the palmprint matchers and this highest rank is employed for the identification of unknown user. In case of tie, ranks are broken randomly.

##### D. Bucklin Majority Voting

Bucklin method of voting is named after its originator, James Bucklin, from the grand junction Colorado [9]. This is a majority voting system in which if the any candidate user gets the majority vote in the first place, he or she is selected; otherwise the votes of the second preference are added and then again the procedure is repeated. In this paper, this method is slightly modified, and the procedure is repeated until all the candidate users get some rank [6]. The rest of our implementation for the Bucklin Method employed in this paper is same as discussed in [11]-[12].

##### E. Nonlinear Weighted Ranks

Our efforts/experiments to consolidate the ranks from different matchers using above methods (A - D) had limited success. Therefore new approaches for combining ranked identities were investigated. In the proposed method, the ranked list of user identities returned by  $N$  (three in our case) palmprint matchers are nonlinearly weighted and combined. In particular, we investigated three nonlinear combinations:

$$C_p = \sum_{i=1}^N \tanh(w_i r_i(p)) \quad (2)$$

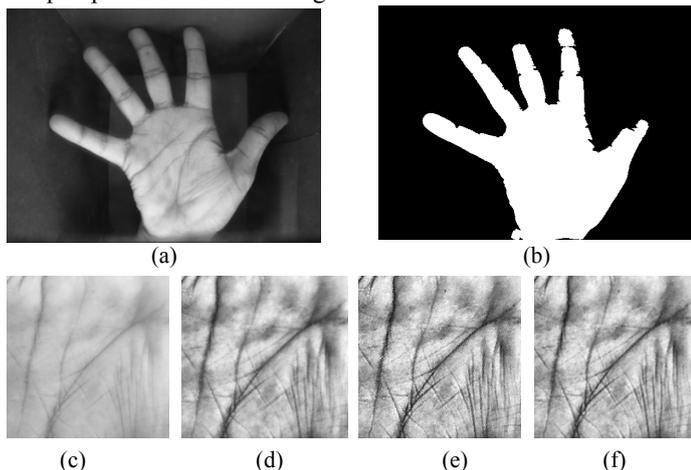
$$C_p = \sum_{i=1}^N \exp(w_i r_i(p)) \quad (3)$$

$$C_p = \sum_{i=1}^N w_i \exp(r_i(p)) \quad (4)$$

where  $r_i(p)$  is the rank assigned to candidate user  $p$  by the  $i^{\text{th}}$  matcher and  $w_i$  represents the weights assigned to the  $i^{\text{th}}$  matcher which, are empirically computed. Our usage of the particular forms of non-linear functions can be theoretically justified from its inherent properties. The hyperbolic tangent function ( $\tanh$ ) maps the input to a constant range (0-1) and is popularly used for scaling images and neural networks. The exponential functions grow faster than polynomial functions and hence can be more effective in gaining from the maximum variations in the output rank;

## V. EXPERIMENTS AND RESULTS

The experimental evaluation to ascertain the effectiveness of proposed approach firstly employed the publicly available touchless palmprint database in [3]. The left hand palmprint images of  $800 \times 600$  pixels are firstly employed to automatically extract the palmprint region of  $150 \times 150$  pixels. The touchless palmprint images have significant pose, scale and translation variations which require systematic pre-processing to extract stable region of interest, *i.e.*, palmprint. The key steps in the automated extraction of pamprints are shown in figure 2.

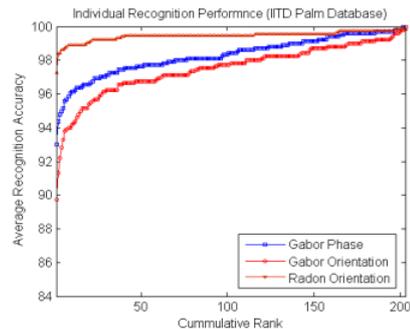


**Figure 2:** (a) Touchless palmprint image, (b) binarized image, (c) segmented region of interest, (d) image after adaptive histogram equalization, (e) sharpened image and (f) final palmprint image after localized image smoothing.

We considered three feature extraction approaches which have shown to offer promising results in the literature (but on constrained imaging using hand-pegs). Firstly, the extraction of palmprint features using a pair of Gabor filters was employed to extract the phase information, *i.e.*, using *PalmCode* encoding as also in [8]. Secondly, six even Gabor filters were employed to ascertain the orientation of palm lines and creases and the direction of dominant (magnitude) filter is encoded as the feature (referred to as *CompCode* in [4]). The parameters of Gabor filters were same as detailed in [8]. Thirdly, the direction of palm lines and creases using localized Radon transform (maximum magnitude of direction sum) was employed. This approach is detailed in [5] and we employed  $3 \times 3$  pixel regions, with length of 27, to extract  $50 \times 50$  templates (dominant orientation images) from each of the palmprint images. In this work, we employed four images for the training and one image to ascertain the recognition

**Table 2:** Average Palmprint Recognition Rate from the Various Rank Level Combination Schemes

	Borda Count	Weighted Borda Count	Max	Product	Bucklin	Proposed Nonlinear Method		
						$\sum \tanh(w_i R_i)$	$\sum e^{w_i R_i}$	$\sum w_i e^{R_i}$
Rank 1	94.0	94.8	92.5	93.9	93.25	96.75	97.86	98.75
Rank 2	94.6	95.6	99.2	94.7	96.5	97.25	98.45	99.83
Rank 3	95.1	96.4	99.7	95.2	98.7	97.48	98.5	99.83

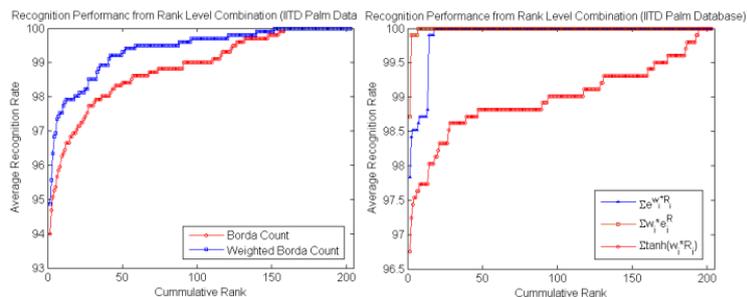


**Figure 3:** Individual recognition performance using CMC.

performance. The average of the recognition results, when each of the five images are used for testing (5-fold cross validation), are reported. The matching scores from the first 30 subjects were employed for the training phase, *i.e.*, to ascertain the weights for weighted Borda and nonlinear method, and the scores from rest of the 204 subjects were employed as independent test data to ascertain the performance improvement from the rank level combination approaches. The average recognition performance from 204 subjects is illustrated in figure 3 and table 1.

**Table 1:** Average Recognition Rate from IITD Touchless Palmprint Database

	Rank 1	Rank 2	Rank 3
Gabor Phase	89.75	91.33	92.22
Gabor Orientation	93	94.38	94.78
Radon Orientation	97.25	98.37	98.47



**Figure 4:** Combined recognition performance using CMC.

The experimental results from the combined performance are summarized in table 2 and figure 4. The weights for nonlinearities in equation (2)-(4) were also computed during training phase and were as follows:  $w_1 = 0.0250$ ,  $w_2 = 0.4750$ , and  $w_3 = 0.500$  for *exp(1)*, *i.e.* using nonlinearly weighted ranks as in equation (3);  $w_1 = 0.0250$ ,  $w_2 = 0.4750$ , and  $w_3 = 0.500$  for *exp(2)*. It can be observed from figure 4 and table 2 that the proposed nonlinear method achieves the best

Table 4: Average Palmprint Recognition Rate from Various Rank Level Combination Schemes

	Borda Count	Weighted Borda Count	Max	Product	Bucklin	Proposed Nonlinear Method		
						$\sum \tanh(w_i R_i)$	$\sum e^{w_i R_i}$	$\sum w_i e^{R_i}$
Rank 1	87.8	95	75.2	87.4	89.8	94.6	97.6	97.4
Rank 2	90	96.8	93.4	89.8	96.6	96.4	98.6	98.4
Rank 3	91.8	97	98.4	91.4	97.8	96.6	98.8	98.8

performance (average rank one recognition rate of 98.75%) among all the rank level combination methods investigated in this paper.

In the second set of experiments to ascertain the performance improvement using rank level combination, we employed 3 representative palmprint matchers. These palmprint matchers extract the (i) texture features using Gabor filters, (ii) line features using line detector masks, and (iii) appearance-based features using eigenpalms. The palmprint dataset from 100 users which consists of 1000 images, 10 images per user, acquired from digital camera using unconstrained peg-free setup in indoor environment, was employed. This dataset is same as employed in [1] and used with same feature extraction method/parameters. While reference [1] has presented experimental results for the palmprint authentication, there are no experiments to ascertain the *recognition* performance using the same training /test data. The cumulative match characteristics (CMC) using three palmprint matchers is shown in figure 5. The average rank one recognition rates from these three matchers can be ascertained from table 3 and figure 5. The experimental results from the combined rank level performance are shown in figure 5 and table 4. The weights employed were (0.14, 0.77, 0.09), (0.34, 0.32, 0.34), (0.49, 0.02, 0.49) corresponding to  $(w_1, w_2, w_3)$  for equations (2), (3), (4) respectively. The experimental results achieve significant recognition performance improvement using the proposed approach over the other rank level combination approaches.

Table 3: Recognition Accuracy from Palmprint Matchers

	Rank 1	Rank 2	Rank3
Line Features	90.4	92.8	94.2
EigenPalm Features	89.2	92	93.8
Gabor Features	92.6	95	95.8

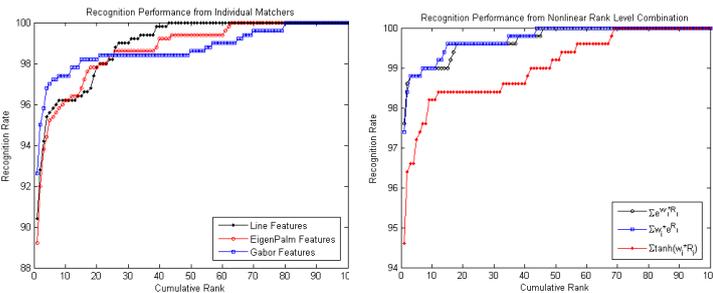


Figure 5: Individual and combined performance using CMCs

## VI. CONCLUSIONS

This paper has investigated rank level combination of multiple palmprint matchers to achieve the performance improvement. In particular, we have investigated the rank level combination for palmprint matchers using four different approaches, *i.e.*, Borda count, weighted Borda count, highest and product of ranks, Bucklin majority voting, and also proposed a new nonlinear approach for combining the ranks. The experimental results are presented on two palmprint databases, from 234 and 100 subjects palmprint image database, consistently suggests that rank level combination can be effectively employed to achieve the performance improvement from the combination of matchers. Secondly, our proposed nonlinear rank level fusion approach consistently outperforms the existing popular rank level fusion approaches as illustrated from the experimental results presented in this paper. We have also investigated our approach on NIST BSSR1 dataset [7] (both on 517 subject and 6000 subject sets) and confirmed that the proposed approach also achieves the superior performance among other methods (results not presented in this paper due to limited space). *The usage of nonlinearities in conjunction with the weights computed from the training stage has been highly effective in achieving the performance improvement.*

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