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Personal Identification Using Multibiometrics Rank-Level Fusion

Ajay Kumar, *Senior Member, IEEE*, and Sumit Shekhar

***Abstract*—This paper investigates a new approach for the personal recognition using rank-level combination of multiple biometrics representations. There has been very little effort to study rank-level fusion approaches for multibiometrics combination and none using multiple palmprint representations. 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 multibiometrics fusion. The comparative experimental results from the publicly available multibiometrics scores and real hand biometrics data to evaluate/ascertain the rank-level combination using Borda count, logistic regression/weighted Borda count, highest rank method, and 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 rank-level combination approaches presented in this paper.**

***Index Terms*—Biometrics, multibiometrics, palmprint recognition, personal identification, rank-level fusion.**

I. Introduction

THE biometrics recognition has emerged as a reliable approach for automated human identification and is attracting significant attention from the researchers in multifaceted disciplines. The selection of a biometric modality is highly dependent on its application and usage. There have been new efforts in recent months [31]–[38] to further explore various physiological, behavioural, and hybrid characteristics for their potential to support human identification. The hand-based biometrics acquisition has high user acceptance and is more user friendly with the development of touchless 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 a 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.

A. Palmprint

The region of skin between wrist and fingers is highly rich in texture patterns, which is imaged and is commonly referred to as palmprint. The development of palmprint ridge patterns in the fetus highly depends on conserved genes [1]. 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 [3]. For example, the law enforcement officials successfully employed palmprint matching to trace the Polly's killers [39]. In summary, the civilian and forensic applications of palmprints have motivated a lot of research interest in palmprint identification using 1) touchless palmprint identification for high user friendliness [4], 2) hand docking frame or pegs that focuses on higher accuracy [5], [6], and 3) palmprint identification using latent prints for forensic applications [2], [3].

II. Related Work

The palmprint-based personal identification has been extensively studied in the biometrics literature and the range of feature extraction approaches have been investigated. These approaches have been categorized into three categories: 1) texture-based approaches [6], [9]; 2) line-based approaches [5]–[7]; and 3) appearance-based approaches [10]. 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 in [8] and [11], respectively. The online palmprint identification using Gabor phase [6], Gabor orientation [16], Radon orientation [17], and ordinal features [22], [23] has shown competing performance in the literature. However, these promising approaches have been evaluated for their performance on verification, not recognition. It is well known that verification and recognition tasks have different optimization goals [43]. Therefore, these popular palmprint authentication approaches should also be evaluated for recognition tasks. The biometric similarity between the template and the test image can

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also be ascertained by the ranked listing of blockwise matches, and such an approach has shown promising results in [24]. Saranli and Demirekler [25] presented a detailed theoretical investigation into statistical rank fusion using partition observation space theory. While the experimental results on speech data from five speakers are too small to make any reliable conclusion, the details in [25] provide promising insights on learning joint classifier behavior using partition observation space theory. The biometric image quality can be effectively integrated into the ranked identities from multiple matchers and employed for the performance improvement in the rank-level combination, as illustrated in [26]. Brunelli and Falavigna [41] achieved better identification decisions by integrating matching scores with the rank-level information. Tulyakov and Govindaraju [42] have presented a detailed analysis of the score-level dependencies among the component matchers to achieve the performance improvement for the biometric identification. Nandakumar *et al.* [29] have recently proposed a hybrid fusion scheme that can jointly exploit the ranked identities of matchers and their corresponding matching scores to improve the performance for the score-level combination. In the context of palmprint identification, there has not been any attempt to investigate the rank-level combination from multiple palmprint matchers for improving the palmprint *recognition* performance. Although, the combination of palmprint matchers for the performance improvement has been discussed in [8] and [11] and shown to achieve promising performance improvement. However, [8] and [11] have only presented the experiments for the palmprint verification and there are no results/experiments for the recognition tasks.

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 available. The generation of ranked identities, instead of matching scores, can be preferred to secure the proprietary algorithms or the hardware associated with the corresponding biometric system. Therefore, in such situations, the consolidation of confidence in the user identification from such multiple sources of devices/matchers can only be achieved by some reliable rank-level-combination scheme [28]. 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. Such combinations are highly attractive especially in situations arising from the poor generalization of performances that could be due to insufficient and inconsistent training data. Another motivation to pursue rank-level combination could be the incompatibility in the outputs from individual biometric systems or could only be the viable option when only the user identities are supplied by the individual biometric system.

B. Our Study

This paper investigates a new approach for the palmprint identification using rank-level combination. The experimental results presented in this paper [40] suggest that the *rank-level combination* of multiple palmprint representations can achieve significant improvement in the performance as compared to those from individual representations. We present a comparative evaluation of multiple palmprint representations from the various rank-level combinations [28] using Borda count, Logistic regression/weighted Borda count, highest rank method, and the Bucklin majority voting approach. In particular, a new nonlinear rank-level-fusion approach is proposed and comparatively evaluated in combining multiple palmprint representations. The experimental results to ascertain the performance improvement for the false positive and false negative identification using the rank-level combination are also presented on the publicly available biometric databases. In order to ascertain the effectiveness of the proposed nonlinear approach in combining multibiometrics fusion, the experimental results on the publicly available multimodal biometric database from 517 to 6000 subjects are also presented in this paper. These experimental results also consistently suggest the superiority of the proposed nonlinear approach on the large multimodal biometric database.

Section III briefly describes the block diagram for the rank-level approach in consolidating subject identities from the multiple palmprint matchers. Section IV details the various rank-level-combination schemes considered in this paper. This includes the details on Borda count, Logistic regression/Weighted Borda count, highest rank method, Bucklin majority voting approach, and also the nonlinear approach investigated in this paper. The rigorous experimental results from the publicly available palmprint image databases are detailed in Section V. This section also includes the results from the publicly available biometric database from 517 to 6000 subjects. Finally, Section VI summarizes the discussion on the results and the contributions from this paper.

III. Block Diagram

The rank-level combination for the performance improvement using intramodal and multimodal biometrics data has been investigated in this paper. However, the key experiments in this paper have been performed on the palmprint data, and therefore a generalized model for the consolidation of the palmprint identities is firstly outlined. The simplified block diagram for the palmprint-based recognition system using rank-level combination is shown in Fig. 1. This figure illustrates the usage of three palmprint matchers in this paper that generates the ranked identities for the possible user identification. Each of these matchers can utilize 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-level fusion typically makes the assumption that the information regarding the matching scores, i.e., their nature, distribution, or magnitude, is not available. The rank-one identity from this combination is used to recognize the unknown user.

IV. Rank-Level Fusion

The improvement in the palmprint recognition accuracy can be achieved by selecting rank-level-combination mechanism

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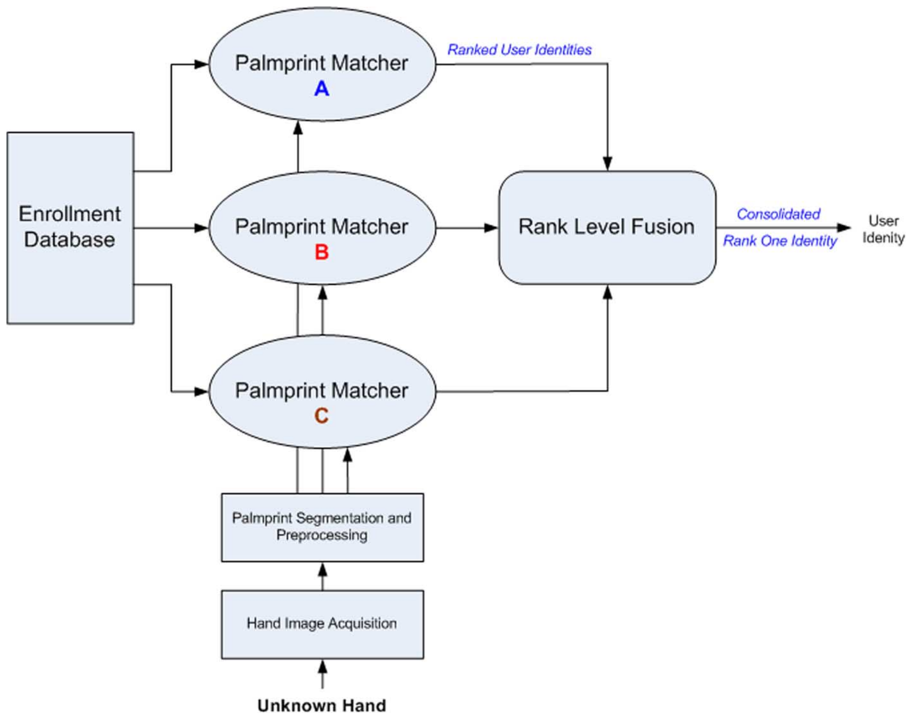

Fig. 1. Block diagram for palmprint-based user identification using rank-level combination of multiple matchers.

that can take advantage of strengths of individual matchers while suppressing their weakness. When the human identification using single palmprint matcher is considered, the final identity of unknown user is the only desired output. While consolidating the combination from multiple palmprint matchers, the usage of only this final user identity could result in the loss of important information, since it has been often observed [18] that when user is misclassified, the true identity of user is often close to top rankings. The challenges associated with score-level combinations resulting from incompatibility, incomparability and scaling of matching scores are of least concern when matching score outputs are utilized in the form of ranked list of possible user identities. In addition, the rank-level combination can also be employed to further improve the score-level performance, as discussed in [29]. In the following, we briefly summarize various rank-level-combination approaches investigated in this paper.

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 are 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

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

for $\forall\ p$, $p = 1, 2, \ldots, M$. 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. The pseudocode in the following details the Borda-count-based fusion.

```
start
        get ranks Rk(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 = Rk(i,j) ∀ 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
```

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 cane be computed using logistic regression or using more sophisticated machine learning approaches.

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 the case of tie, ranks are randomly broken. The maximum rank method does not employ any model to estimate the behaviour of matchers, and therefore it may not be the best approach for combining non-deal palmprint matchers.

D. Bucklin Majority Voting

Bucklin method of voting is named after its originator, James Bucklin, from the Grand Junction Colorado [12], [13]. 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. The pseudocode for our implementation of Bucklin method employed in this paper is as follows.

```
start
    get ranks Rk from individual matchers
    rank(i,j) = 0
    vote(i) = 0
    row_no = 1; ik = 1 ∀ k
    while (j ≦no_test_samples)
        L1: while (size(unranked_users) != 0)
            for k = 1 to no_of_users
                while Rk(ik,j) is ranked
        ik = ik + 1
      end while
                temp = Rk(ik,j)
      vote(temp) = vote(temp) + 1
   end for
      if ∃ user_no s.t. vote(user_no) ≧ 2 then
        rank(user_no,j) = row_no
                vote(user_no) = 0
                mark corresponding entries in Rk as ranked
                row_no = 1
                ik = 1 ∀ k
                goto L1
      else
                row_no = row_no + 1
                goto L1
      end if
    end while
    j = j + 1
end while
print rank
stop
```

E. Nonlinear Weighted Ranks

Our efforts/experiments to consolidate the ranks from different matchers using the aforementioned 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 (four in our case) palmprint matchers are nonlinearly weighted and combined. In particular, three nonlinear combinations were investigated and the consolidated ranks were generated as follows:

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

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

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

where $r_i(p)$ is the rank assigned to candidate user p by the ith matcher, and w_i represents the weights assigned to the ith matcher. The weight w_i are assigned to reflect the significance of each matcher and are empirically computed. The usage of the particular forms of nonlinear functions can be theoretically justified from its inherent properties. The usage of matcher-specific variable parameter w_i helps to controls the shape and slope of the nonlinear function. 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 key objective from this nonlinearity is to utilize the varying slope on the nonlinear function so that some ranges, which have slope greater than one can achieve magnification of ranks, while and other ranges, which have slope less than one can have demagnification effect. The exponential functions grow faster than polynomial functions and hence can be more effective in gaining from the maximum variations in the output rank. In summary, the nonlinear functions shown in (2) and (3) are with different properties and add to variation in the evaluation of proposed approach.

V. Experiments and Results

The key objective of our experiments was two fold; first, we performed experiments on the publicly available multimodal biometrics database to ascertain the robustness of the proposed nonlinear rank-level combination for the performance improvement. Second, we focused on the main experiments to ascertain and comparatively evaluate the possible performance improvement for the palmprint identification using various rank-level-combination schemes discussed in Section IV. We first present the experimental results from the National Institute of Standards and Technology (NIST) Biometric Set Release-1 (BSSR1) dataset in the following section. This is followed by the experimental results to ascertain the performance improvement for the palmprint identification in Section IV-B.

A. Results From NIST BBSR Database

The NIST BSSR1 is the multimodal biometrics database from the NIST [20]. The NIST BSSR1 dataset is a truly multimodal biometric dataset from fingerprint and face matchers. It has largest number of subjects (6000) among all the known publicly available multimodal biometric dataset. This dataset consists of three partitions, and we first employed two partitions to evaluate the comparative performance. The first partition of NIST BSSR1 dataset consists of the fingerprint and face matching scores from 517 subjects. The fingerprint score dataset are generated from the left index finger and right index finger of an individual. In addition, the frontal face images from the same subjects were acquired at the same time to generate matching scores from the two different face matchers, which are referred to as

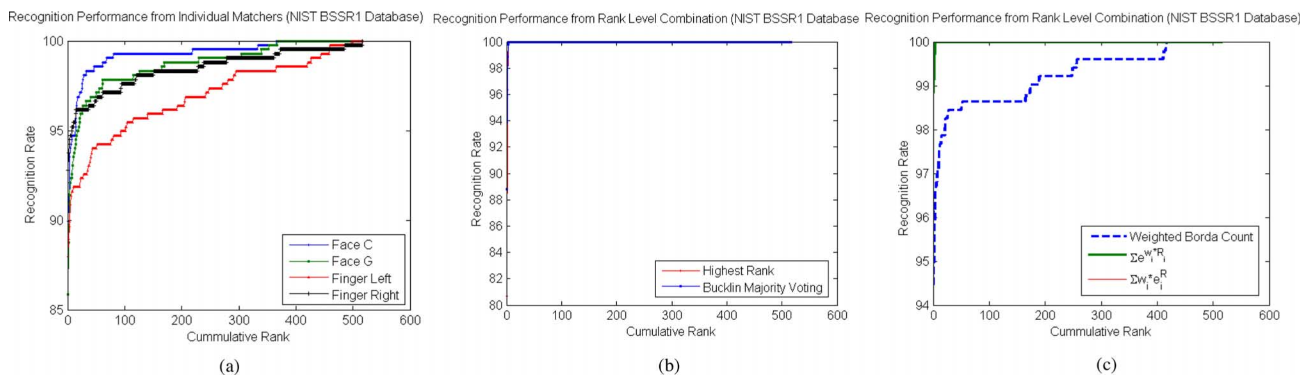

Fig. 2. Performance from individual matchers using CMC from four matchers in (a); the CMC for the combined performance using highest rank and Bucklin majority voting in (b), and CMC for the combined performance using weighted Borda and nonlinear methods in (c).

C and G. The matching scores from the first 100 subjects were employed for the training phase, i.e., to ascertain the weights for the weighted Borda and nonlinear methods, and the scores from rest of the 417 subjects were employed as independent test data to ascertain the performance from the rank-level-combination approaches discussed in this paper.

The cumulative match characteristics (CMCs) from the individual four matchers corresponding to the independent test data (417 subjects) is shown in Fig. 2(a). The estimated weights employed in this set of experiments were as follows: $w_1 = 0.1$, $w_2 = 0.1$, $w_3 = 0.1$, and $w_4 = 0.7$ for weighted Borda count; $w_1 = 0.3$, $w_2 = 0.1$, $w_3 = 0.1$, and $w_4 = 0.3$ for exp(1), i.e., using nonlinearly weighted ranks, as in (3); $w_1 = 0.3$, $w_2 = 0.1$, $w_3 = 0.3$, and $w_4 = 0.3$ for exp(2), i.e., using nonlinearly weighted ranks as in (4); where the w_1 represents weight for Face C matcher, w_2 for Face G matcher, w_3 for left fingerprint matcher, and the w_4 represents the weight for right fingerprint matcher. The CMC from the rank-level combination using different combination schemes are shown in Fig. 2(b) and Fig. 2(c). Table I presents the summary of experimental results, i.e., percentage recognition rate for first three ranks using different rank-level-combination schemes considered in this paper. The experimental results summarized in Table I illustrate significant improvement (achieves 99.28% rank-one recognition rate) in performance using the proposed approach as compared to any other rank-level combination approach considered in this paper.

The second set of experiments was performed on the second partition of NIST BSSR1 database, which comprises matching scores generated from the fingerprint images of the 6000 subjects. The matching scores from the first 1000 subjects were employed to ascertain weights, for the training phase, and rest of the scores from the 5000 subjects were employed as independent test data to ascertain the comparative performance.

The CMC from the two individual matchers corresponding to the independent test data (5000 subjects) is shown in Fig. 3(a). The CMC corresponding to the suggested nonlinear rank-level-combination schemes in Fig. 3(b). Table II presents the summary of experimental results, i.e., percentage recognition rate for first three ranks using different rank-level-combination schemes considered in this paper. The experimental results summarized in Table III again confirm the significant improvement (achieves 89.56% rank-one recognition rate) in performance using the proposed approach as compared to other rank-level-combination approaches considered in this paper. It may also be noted that, except for very little (minor) improvement from weighted Borda, other three approaches have not been successful in achieving the performance improvement using rank-level combination on the 6000 subject NIST BSSR1 database.

B. *Results for Palmprint Identification Using Rank-Level Combination*

One of the key objectives of this paper is to investigate the performance improvement for the palmprint identification. We first investigated the performance improvement for the touchless palmprint identification using rank-level combination. The performance improvement is ascertained on the publicly available IITD touchless palmprint database [14]. In this set of experiments, we employed right-hand images from 233 subjects. These images have high pose, translation, and scale variations resulting from unconstrained and touchless imaging (see Fig. 4). The hand images are firstly normalized to automatically segment 150×150 pixels palmprint images (see Fig. 4). We considered three feature extraction approaches, which have shown to offer promising results in the literature (but on images acquired with pegs). First, the extraction of palmprint features using a pair of Gabor filters was employed to extract the phase information, i.e., PalmCode [6] similar to IrisCode in [15]. The Gabor filters of size 65×65, centered at frequency $2\sqrt{2}$, were employed to extract Gabor phase information, and the Hamming distance was employed to generate matching scores. Second, 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 [16]). Third, the direction of palm lines and creases using localized Radon transform (maximum magnitude of direction sum) was employed. This approach is detailed in [17] and we employed 3×3 pixel regions, with length of 27, to extract 50×50 templates (dominant orientation images) from each of the palmprint images.

In this paper, we employed four images for training and one image to ascertain recognition performance. The average of the

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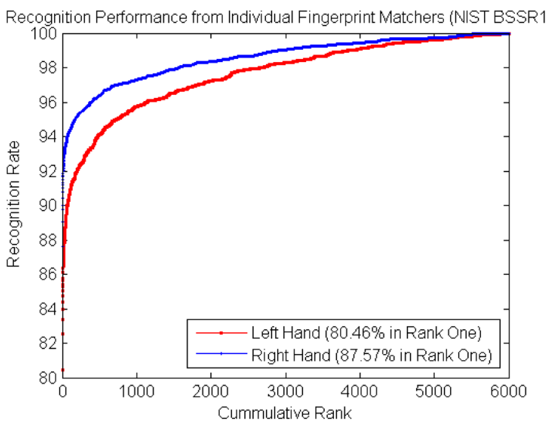
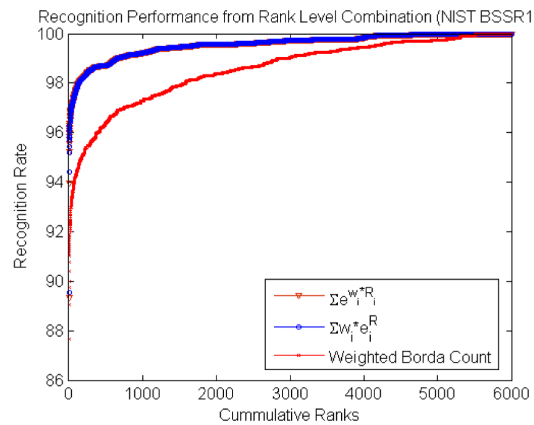
TABLE I
PERFORMANCE FROM NIST BBSR1 FINGERPRINT AND FACE DATABASE (517 SUBJECTS)

	Weighted Borda	Exp(1)	Exp(2)	Borda	Bucklin	Highest Rank
1st Rank	94.39	98.84	99.28	91.68	88.78	80.66
2nd Rank	95.55	99.42	99.76	93.81	98.84	96.32
3rd Rank	96.32	100	100	94.97	99.81	100



(a)



(b)

Fig. 3. Performance from the two fingerprint matchers using CMC from 5000 test subjects in (a); the CMC for the rank-level combination using nonlinear approach (b).

TABLE II
PERFORMANCE FROM NIST BBSR1 FINGERPRINT DATABASE (6000 SUBJECTS)

	Weighted Borda	Exp(1)	Exp(2)	Borda	Bucklin	Highest Rank
1st Rank	87.74	89.34	89.56	85.65	74.58	82.57
2nd Rank	89.04	93.98	94.42	86.68	88.23	94.43
3rd Rank	89.74	95.22	95.2	87.33	93.75	94.8

TABLE III
AVERAGE RECOGNITION RATE FROM IITD TOUCHLESS PALMPRINT DATABASE

	Rank1	Rank2	Rank3
Gabor Phase	87.55	89.8	90.59
Gabor Orientation	92.84	94.51	95.0
Radon Orientation	97.55	98.43	98.63

recognition results, when each of the five images are used for testing (five-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 methods, and the scores from rest of the 203 subjects were employed as independent test data to ascertain the performance improvement from the rank-level-combination approaches. The average recognition performance from 203 subjects is illustrated in Fig. 5 and Table III. The experimental results from the rank-level combination using highest rank and product of ranks are illustrated in Fig. 6. The performance from the highest rank is significantly better than those from the product of ranks. The combined performance from the highest rank significantly improves for the lower ranks (ranks ≥ 2), however its rank-one performance has not improved. The experimental results from the Borda and weighted Borda count approaches are shown in Fig. 6(d).

The estimated weights for the weighted Borda count experiments were 0.2, 0.125, and 0.675, respectively, for the Gabor phase, Gabor orientation, and Radon orientation features. The experimental results in Fig. 6(a) and Table IV suggests that the Borda count approach does not improve the results for lower ranks, while weighted Borda count does improve the average recognition performance. The experimental results from the rank-level combination using Bucklin majority voting are shown in Fig. 6(c). The rank-one recognition rate from Bucklin voting is poor, while significant performance improvement can be observed for other ranks (ranks ≥ 2). The experimental results from the nonlinear rank-level fusion combination (see Section IV-E) are illustrated in Fig. 6(d). The estimated weights

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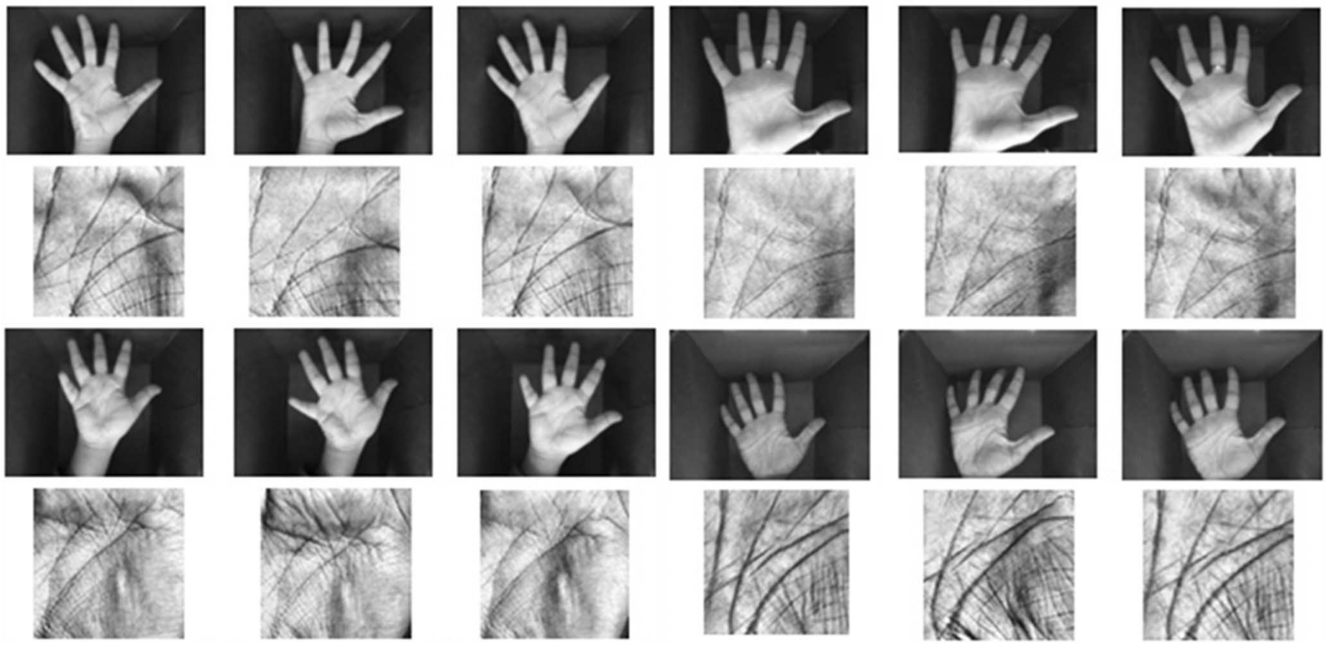

Fig. 4. Image samples from four subjects in IITD touchless palmprint database and their corresponding segmented images.

(from the first 30 subject) employed for nonlinear combinations were as follows: $w_1 = 0.1000$, $w_2 = 0.8750$, and $w_3 = 0.0250$ for tanh, i.e., using nonlinearly weighted ranks as in (2); $w_1 = 0.3730$, $w_2 = 0.2250$, and $w_3 = 0.400$ for exp(1), i.e., using nonlinearly weighted ranks as in (3); $w_1 = 0.2750$, $w_2 = 0.3250$, and $w_3 = 0.400$ for exp(2), i.e., using nonlinearly weighted ranks as in (4); where the w_1 represents weight for the matcher that uses Gabor phase, w_2 for Gabor orientation, and w_3 represents the weight for the matcher that uses Radon orientation features. It can be observed from this figure and Table IV that the proposed nonlinear method achieves the best performance (average rank-one recognition rate of 99%) among all the rank-level combination methods investigated in this paper. The exponential nonlinearity with weights [(using ([4])] achieved the best results among the three combinations considered in this paper.

The correlation among the palmprint matchers itself can significantly influence the performance from the rank-level-combination strategies. The palmprint matcher using Radon orientation and Gabor orientation are expected to be more correlated as both of these matchers typically encode the orientation information from the palmprint features. However, the Gabor-phase-based palmprint matcher is expected to least correlate with other two employed palmprint features as this feature attempts to encode the phase information from the complex Gabor filter response. As outlined in [44], the analysis and selection of fusion strategy simply based on the correlation among the matchers may not be useful. In addition, it may be noted that for a typical rank-level-fusion strategy, the information regarding matching scores or matchers may not be available and is therefore not considered (e.g., as in Borda count, weighted Borda, Bucklin, etc.). In our paper, the relative importance of matchers is automatically ascertained in the training phase when the parameters for the nonlinear combinations [(2)–(4)] are ascertained. These parameters typically ensure that higher importance is given to the matchers that yield more discriminatory information.

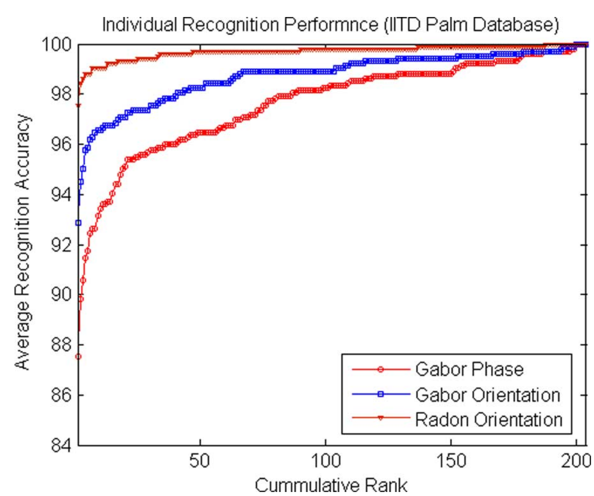

Fig. 5. Performance from the individual palmprint matchers.

VI. Discussion

The experimental results presented on the palmprint databases consistently suggests that the rank-level combination can be effectively employed to achieve the performance improvement from the combination of matchers. The touchless palmprint database from 234 subjects presents high pose, rotation, and translation variations, and was therefore employed to ascertain the performance improvement from the rank-level combination. Our experimental results in Section V have also consistently

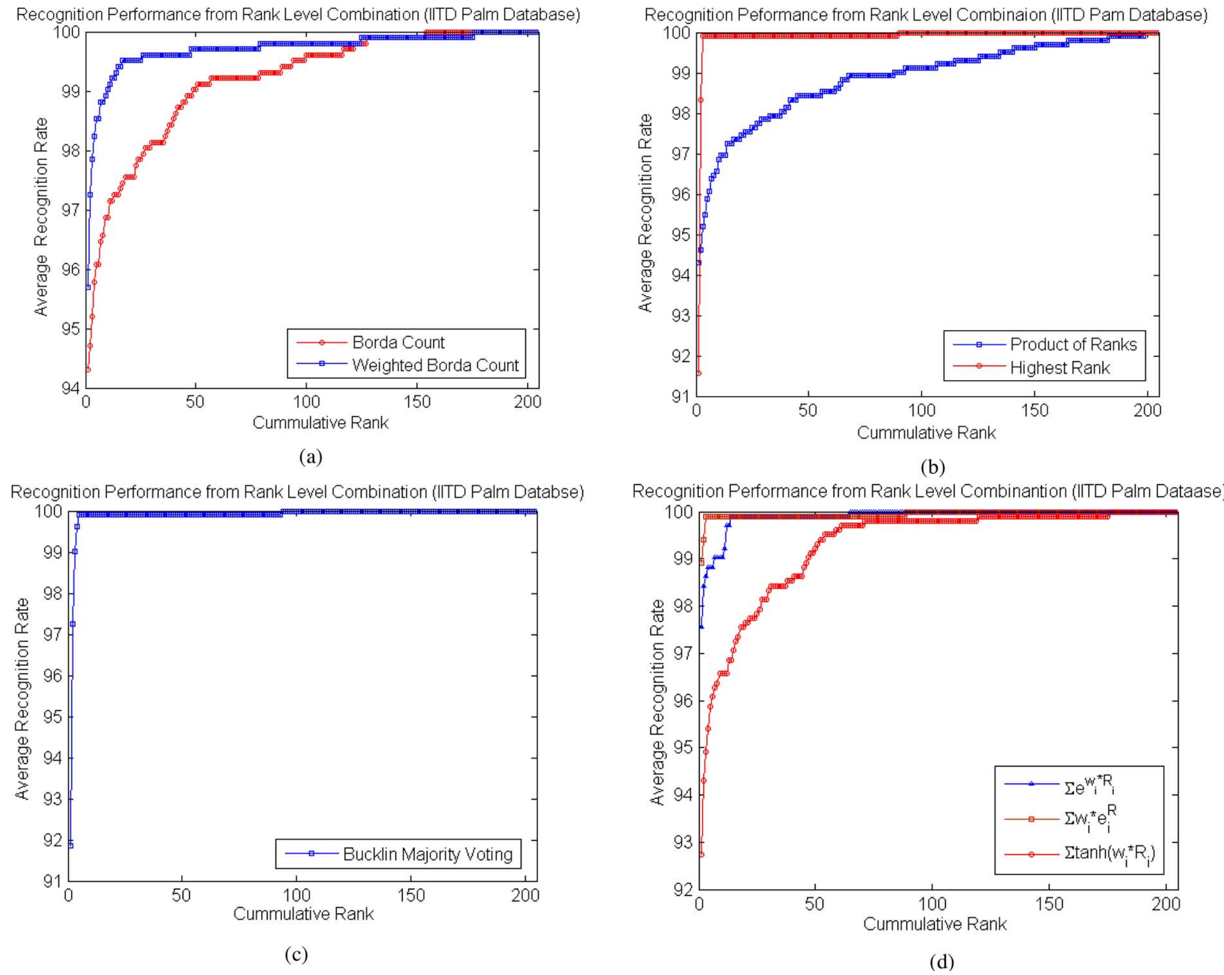

Fig. 6. CMC from the combined performance using three palmprint matchers; the CMC from Borda count and weighted Borda count in (a); using highest rank and product of ranks in (b); Bucklin majority voting in (c), and using nonlinear methods in (d).

TABLE IV
AVERAGE RECOGNITION RATE FROM VARIOUS RANK-LEVEL-COMBINATION SCHEMES

	Borda Count	Weighted Borda Count	Max	Product	Bucklin	Proposed Nonlinear Method		
						$\sum\tanh(w_iR_i)$	$\sum e^{w_iR_i}$	$\sum w_ie^{R_i}$
Rank1	94.3	95.6	91.53	94.3	91.85	92.7	97.56	**98.92**
Rank2	94.7	97.2	98.25	94.6	97.25	94.3	98.45	**99.41**
Rank3	95.3	97.8	99.89	95.2	99.1	94.8	98.62	**99.9**

suggested that the proposed nonlinear rank-level-combination approach achieves the best performance among all the considered approaches for the palmprint combination. *The usage of nonlinearities in conjunction with the weights computed from the training stage has been highly effective in achieving the performance improvement*. In summary, following observations are made from the experiments.

1) The nonlinear fusion approach using exponential nonlinearity give the best results for the first-rank recognition rates. The weighted Borda and nonlinear fusion using hyperbolic function also achieves some performance improvement. This can possibly be explained from the fact that exponential function maps the linear rank vector such that the first rank is given much higher value than the last rank. Hence, the range of variation in the values of the ranks assigned is also quite high, for example, with 203 subjects, the range will be exp(203)–exp(1). Hence, the correct user, who is likely to be ranked higher by the input features, will have more chances of being correctly recognized.
2) The hyperbolic nonlinearity maps the rank function into the range (0,1). Therefore, even though the performance

improves, it is not as high as from the rank-level fusion using exponential nonlinearity.

3) The Bucklin and highest rank methods, though do not show improvement at the first-rank recognition, they does achieve performance improvement for further ranks.

There are two other possibilities which can also be explored for rank-level combination from multiple matchers: Nansons's approach and Coomb's approach [30]. The Nanson's approach is a modification of the Borda count method and eliminates k lowest ranks or users with scores less than certain threshold. This method results in incomplete rank list and for optimum performance and the threshold (k or score) needs to be explored. The Coombs' method goes on eliminating the user with the most votes for last position until a particular user has majority votes. Hence, it is not likely to improve the first-rank recognition rate over the approaches investigated in this paper. The objective in this paper has been to achieve the improvement in the rank-one recognition, which is highly unlikely from such an approach, and was therefore not considered in this paper. The experimental results presented in Section V-A on the publicly available NIST BSSR1 database, from 517 and 6000 subjects, provide another convincing evidence on the superiority of nonlinear rank-level-combination approach suggested in this paper. Some commercially available biometric matchers may not release matching scores, but instead provide ranked list of possible identities from the matcher. It may be noted that the provision of only the ranked list, instead of the matching scores, is highly useful in protecting the algorithms employed in the matcher for commercial reasons. Therefore, effective rank-level combination from such multiple sources of evidences can be employed for the performance improvement.

The combination of multibiometrics matchers can achieved at various levels, i.e., sensor, feature, score, and rank level. Each of these combinations has distinct scope and domain of applications. Therefore, a straightforward comparison among various combination strategies is difficult (or could be misleading). As discussed in [19], it is generally believed that the combination strategy applied as early in the integration stage can deliver better performance than the integration at later stage. The feature-level representation contains more information about the unknown biometric patterns and their corresponding matching score representation (similarly, the matching score combination is expected to provide better performance than the rank-level combination). In real biometrics systems, this however may not be always true mainly due to the noise resulting from the inaccurate pattern segmentation, poor feature representation, and matching algorithms. We however attempted to ascertain the score-level combination performance using likelihood ratio-based fusion [27] on NIST BSSR1 database (517 subjects). As in our rank-level experiments, we employed matching scores from the first 100 subjects for the training and rest 517 subjects for the test. The performance of the score-level combination (rank-one recognition rate of 99.76% but the nonlinear rank-level combination performed slightly better for higher ranks, i.e., ranks > 2) was found to be at par with those from the nonlinear rank-level combination.

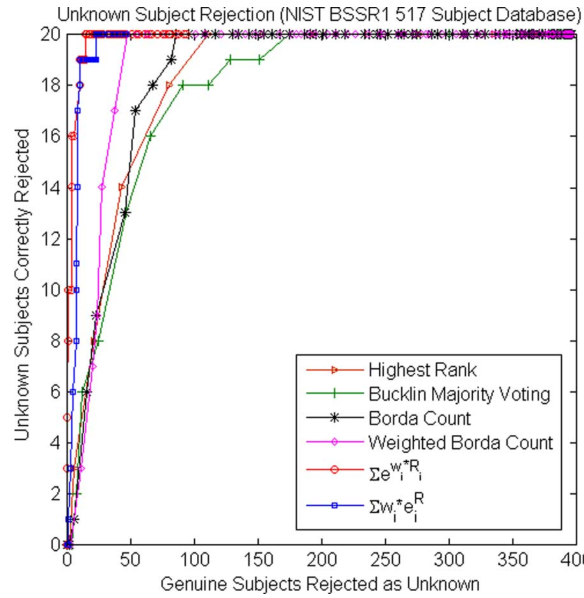

Fig. 7. Comparative performance for the unknown subject rejection using rank-level combination.

An automated biometrics system should be able to effectively recognize unknown subjects, i.e., able to reject those subjects not enrolled in the database. The proposed nonlinear rank-level combination scheme can more effectively reject such subjects not enrolled in the database. In order to explicitly demonstrate such capability, we selected the last 20 subjects from the NIST BBSR1 dataset (517 subjects) as unknown subjects, apart from the 100 subjects already excluded as training set. These unknown subjects are then identified from each of the rank-level-fusion strategy to ascertain the comparative performance. Fig. 7 shows the plot of number of unknown subjects identified as unknown versus known subject rejected as unknown. These experimental results also suggest that the proposed scheme outperforms other rank-level-combination approaches in the literature. The superiority of performance for the nonlinear rank-level combination for improving false positive identification rate (FPIR) and false negative identification rate (FNIR) was also observed on IITD palmprint database. We selected the last 20 subjects as unknown subjects from the test data, and rest of the subjects, excluding the training data from the first 30 subjects, were used as test data (subjects 31–203) for the performance evaluation (from left palmprint). A ranked list of the subjects was then generated with the addition of unknown users as a separate class. The unknown was given the first rank or the last rank, depending upon the user being classified as unknown or known. The rank-level-combination methods were then applied to this new ranked list. The performance improvement can be ascertained from the resulting FPIR and FNIR characteristics shown in Fig. 8. This figure also explicitly illustrates FPIR versus FNIR characteristics from the NIST BBSR1 database (517 subjects). In summary, the rank-level-combination strategies are also expected to improve FPIR and FNIR for their usage in biometric identification, and our nonlinear rank-level-combination strategy has shown to consistently outperform other popular rank-

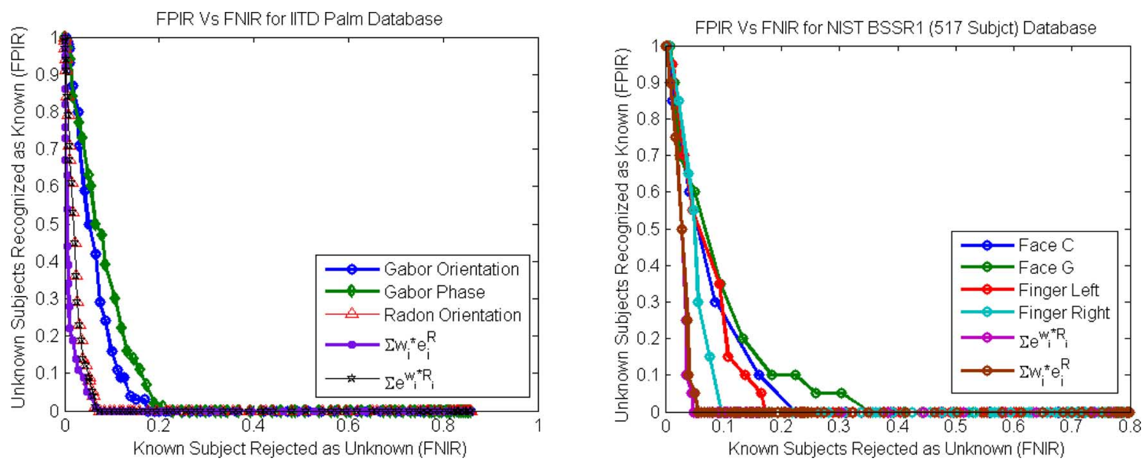

Fig. 8. FPIR versus FNIR characteristics from the (a) IITD palmprint database and (b) NIST BBSR1 (517 subjects) database.

level-combination approaches. The performance improvement from the rank-level combination using NIST BBSR1 database (illustrated in Section V-A results) is higher than those obtained from palmprint recognition (illustrated in Section V-B results). The plausible explanation for this lies in the increased correlation from the matcher outputs as, unlike for NIST BBSR1 matchers, the palmprint matchers employed in this paper have same input images (i.e., palmprint image) for the three palmprint matchers.

VII. Conclusion

This paper has investigated rank-level-combination approach to combine multiple palmprint representations 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, and Bucklin majority voting, and also proposed a new nonlinear approach for combining the ranks. The experimental results suggested in this paper suggest that the significant performance improvement in the recognition accuracy can be achieved from rank-level combinations as compared to those from individual palmprint representations. The rigorous experimental results presented in this paper, also on the NIST BSSR1 database from 517 and 6000 subjects, suggest that the proposed nonlinear rank-level approach outperforms the rank-level-combination approaches considered in this paper. The experimental results in this paper also suggest that the proposed nonlinear approach can also be employed to simultaneously improve the FPIR versus FNIR performance.

In summary, there has been very little attention in the multibiometrics literature [18], [19] paid to ascertain the performance improvement from the rank-level combination approaches.

The rank-level combination is, however, the only effective mechanism to consolidate the output from those commercial or proprietary biometric devices, which can only generate/provide ranked identities for the unknown subjects. In this paper, the performance improvement using the rank-level combination of the palmprint matchers was investigated. Further efforts to ascertain the performance improvement for other biometric modalities, on some commercially available devices that employ different sensors (for same or different biometric modalities), will be highly useful (for example, in combining the touchless biometric systems such as face, iris, hands, etc., that often independently operate) and suggested for the extension of this paper.

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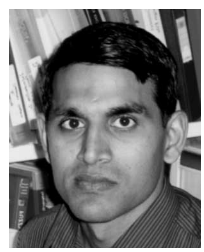

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