Multibiometrics User Recognition using Adaptive Cohort Ranking

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Abstract

Personal identification using multibiometrics is desirable in a wide range of high-security and/or forensic application as it can address performance limitations from unimodal biometrics systems. This paper presents a new scheme the multibiometrics fusion to achieve performance improvement for the user identification/recognition. We model the biometric identification solution using an adaptive cohort ranking approach, which can more effectively utilize the cohort information for maximizing the true positive identification rates. In contrast to the tradition cohort-based methods, the proposed cohort ranking approach offers merit of being matcher independence as it does not make any assumption on the nature of score distributions from any of the biometric matcher(s). In addition, our scheme is adaptive and can be incorporated for any biometric matcher/technologies. The proposed approach is evaluated on publicly available unimodal and multimodal biometrics databases, i.e., BSSR1 multimodal matching scores for fingerprint and face matchers and XM2VTS matching scores from synchronize databases of face and voice. In both the unimodal and multimodal databases, our results indicate that the proposed approach can outperform the conventional adaptive identification approaches. The experimental results from both public databases are quite promising and validate the contributions from this work.

1. Introduction

Biometric-based protected access systems are increasingly popular for the personal authentication. The operational mode of unimodal and multimodal biometric authentication systems can be categorized into two categories: verification and identification [1]-[2]. The verification is regarded as 1:1 matching problem where the claimed identity is matched from the presented pattern against the enrolled pattern. In verification, the user is identified by and ID and then verified by the corresponding biometric data. If the user identity is unknown, the authentication can be performed only under the identification mode. The identification problem requires 1:N matching which is computed between the presented pattern against each of the enrolled patterns. As compared to the verification, *identification* * *or recognition* is more challenging, generalized, also less researched problem and is therefore the focus of the problem targeted in this research. It should be noted [29] that the identification and verification are quite distinct problem and requires *different* approaches or fusion strategies to achieve superior results. The N matching scores computed from the N enrolled identities are arranged according to their ranks in the rank list. The minimum (or maximum) match score is widely considered as the best match and referred to as the rank-one score. We propose a new approach to use the N-1 matching scores for improving the *identification* accuracy of the biometric databases. These N-1 matching scores are termed as the cohort scores [3], [14], [21].

1.1. Cohort Ranking in Biometrics Identification

In the conventional biometric identification scheme, the N matching scores computed from 1: N matches of N enrolled user are firstly arranged in decreasing order of their confidences. The best matching score is generally considered as the true identity of user. The ranking of the users is provided based on the arrangement of their matching scores in the ascending order. However, the N-1 matching scores available from N-1 users can be effectively utilized to judiciously modify the ranking of the user and finally helpful in enhancing the true positive identification rate (TPIR) during the biometrics identification.

The earlier studies [3], [7], [14], [21] for the biometric *verification* problems have shown that the cohort information can be well utilized for significantly improving the accuracy in biometric *verification* systems. However, in the best of our knowledge, there has been no attempt to incorporate such information to improve *recognition* or the *identification* accuracy of the biometrics systems. Most of the available works use cohort models either for score normalization [3]-[6] or for extracting discriminative statistical parameters [3] from the input patterns. In the multibiometrics *identification* problem, it is judicious to *also* utilize the matching scores from other biometric matchers to improve ranking capability of a user. In this paper, we investigate a new scheme to utilize cohort information for improving the biometrics identification accuracy. Such ranking of the users, using the cohort

* The term *recognition* and *identification* are interchangeably used in this paper.

information, is referred to as the cohort ranking in this paper. A new method is introduced which can iteratively utilize the cohort ranking corresponding to each enrolled user for improving the *identification* accuracy (TPIR) for the biometrics identification system.

1.2. Related Work

In the literature, there are different studies for using cohort normalization methods for improving the accuracy of biometric systems. Poh *et al*. [3] utilized T-norm for exploiting cohort models to predict the statistical performance parameter of non-matching scores for biometric authentication. Tulyakov *et al*. [13] proposed the integration of the maximum of cohort score or as they referred as "the second-best score" in an identification scenario using a SVM classifier. Aggarwal *et al*. [14] proposed to use the maximum of the cohort scores as the best competent hypothesis in likelihood-ratio based score normalization. One advantage of the approach in [14] over the score-normalization is that, no additional training is required as compared to work in [13]. In the recent decades, few very promising works have been proposed in the literature utilizing the pattern of the sorted cohort scores in order to predict the performance of the biometric identification system [15]-[22]. Reference [15] details the differential features to predict the failure of recognition in an identification system. Authors compute the differential features by subtracting the sorted matching scores which are computed other than the best matching scores from the best score in an identification system. Wang *et al*. [16] proposed a performance metric computing the similarity scores from the enrolled users. Authors generate match scores from all the enrolled samples against all the enrolled reference samples in a closed-set identification system. These scores are sorted by their values and then used to construct a performance prediction system.

Reference [17] details a method to recover discriminative information from the cohort models. Authors have shown that if cohort model is sorted with respect to their closeness to the target model they can produce discriminative score pattern for matching and non-matching queries. In a similar work, Reference [18]-[19] details the cohort ordered selection method using polynomial regression for score normalization. Another framework for cohort-based score level fusion appears in [20] where the video-based score level fusion scheme is proposed, and it relies on a set of distribution descriptors for producing matching scores for each valid frame of the biometric video. A promising effort to incorporate the cohort information for reliable palmprint verification is presented in [21] and offers significant performance improvement.

Most of the methods in the literature use the cohort information by modeling the score-normalization [3]-[6], [15]-[21] in biometric verification problem. However, there has been very little, or negligible work devoted for utilizing the cohort information in improving the ranking of the biometric identification. Our research detailed in this paper indicates that the cohort information can be effectively utilizing to provide a new ranking for the biometric *matchers* in order to improve the *identification* accuracy.

1.3. Our Work and Contribution

This paper develops a novel adaptive cohort based ranking approach for the performance improvement in biometrics *identification* systems. Our method uses cohort information for ranking the biometric matchers in the identification system. We demonstrated that the cohort ranking approach can significantly improve *identification* accuracy, *both* for the unimodal biometrics identification and multibiometrics user identification.

The block diagram for cohort ranking in multimodal biometric identification system is shown in Fig. 1. For the unknown identity, a matching score list is computed from N enrolled users. The N matching scores are sorted in the decreasing order of confidence. The sorted matching score list is then divided into three groups, namely: G1, G2, and G3. The G1 contains the highest-ranked score in the sorted

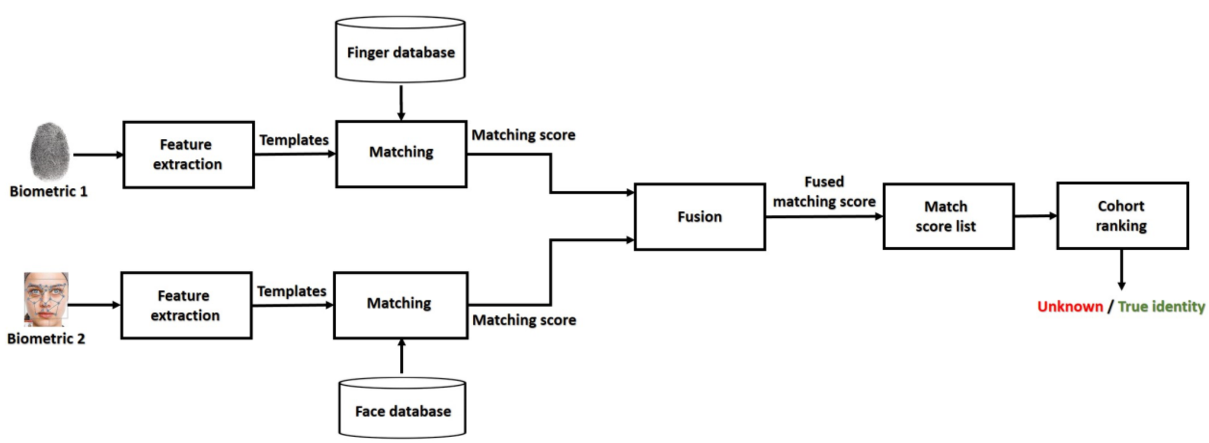

Figure 1: Block diagram for the cohort ranking based multimodal biometrics identification system.

array, which can be assumed to be the rank-one identity. The G2 and the G3 are the N-1 matching scores (cohort information) divided as per their ranking by the biometrics matcher. The matching scores in G2 are the medium-ranked scores, which scores lower than the rank-one. The matching scores in G3 are the lowest ranked matching scores with the matching scores lower than the matching scores in G2. The matching scores are then updated according to their groups in order to maximize the separation between the rank-one identity (G1) and the N-1 cohort matching scores (G2 and G3). The iterative updating of these groups can not only improve the rank-1 accuracy but also achieve better recognition rate with higher ranks.

The idea of partitioning the N matching scores in three groups is to update the matching scores according to their rank assigned by a biometric matcher. It may be noted that, in the conventional biometric identification system, all the N matching scores are updated with equal weightage during their ranking. The proposed method is evaluated on two publicly available biometrics (match score) databases. The experimental results detailed in section 3 are highly promising and validate the effectiveness of the approach presented in this paper.

2. The Framework for Cohort Ranking

The biometric identification problem requires us to generate a list of K-highest scored users from the N enrolled users [11]. These users can be referred to as the top K-ranked users where K = 1, …, N and identification of such top-K matchers has wide range of applications in surveillance and forensics. The case when K = 1 is referred to as rank-one identification where the true identities are expected to be identified from the topmost matches. Most of the available approaches in the literature operate on rank-one consideration for the identification as it has wide applications in the automated user identification. However, better identification has been achieved with increase in rank-one to rank-K where K=1 to N [23]. The plot depicting the identification rates corresponding to each of the ranks is referred to as *cumulative match curve* (CMC) and is a conventional way to illustrate the performance in biometrics *identification* problem.

2.1 Cohort Ranking

In the proposed framework, N match scores from N enrolled users are updated iteratively to form a new ranking which is referred here as the cohort ranking. The block diagram for the proposed cohort raking approach is shown in Fig. 2. The cohort ranking is used to compute identification rate referred to as true identification rate (TPIR). Let S1, S2,....,SN are the N matching scores computed from the user template and N enrolled users. These N matching scores are sorted in the decreasing order of their confidence to provide the rankings. These matching scores are divided into three groups as per their ranking. The rank-one matching score is considered as best matching score hence assigned in the first group referred as G1. The N-1 matching scores are referred as cohort matching scores, and these are further divided into two groups: G2, and G3. The matching scores in G2 are the lower ranked users taken as 50% of the N-1 matching scores while G3 is the lowest ranked users with the least priority. Let m1 and m2 be the total number of matching scores in G2 and G3 respectively. The description of these groups is as in the following.

The First Group: G1

This group belongs to the highest matching score when N matching scores are arranged in the decreasing order of confidence. The score of G1 is therefore the rank-one identity and has the highest confidence among other identities. The member of this group will *not* participate in the update process during ranking and remain unchanged in the iteration.

The Second Group: G2

This group belongs to the lower rank identities with low matching scores in comparison to the rank-one identity. The members of this group are defined to be 50% of the N-1 matching scores (cohort matching scores) arranged in the decreasing order of confidence. The members of this group need to be updated according to the rank-one matching score and mean of the matching scores belong to the G2. Let M_i^{G2} be the i^{th} member of the G2, M_i^{G1} is the i^{th} member of G1, and r is the random number in the range [0 1]. Then, the update equation for G2 can be written as follows:

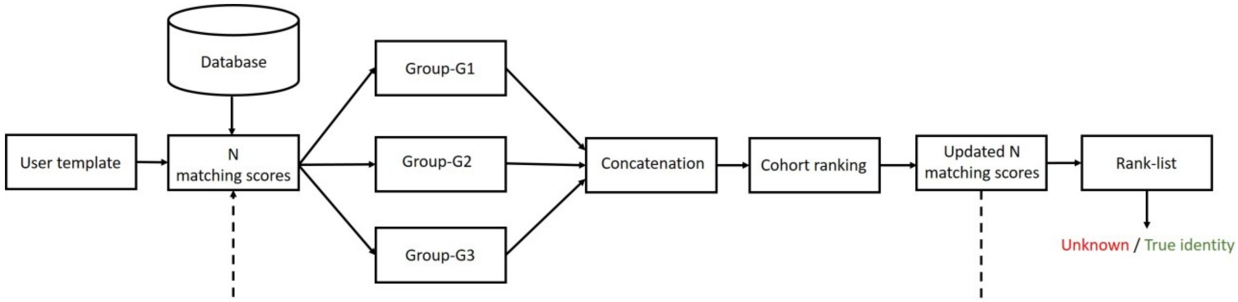

Figure 2: Block diagram for proposed cohort ranking in biometric identification problem.

$$M_i^{G2}=r\times(M_i^{G1})+(1\text{-}r)\times mean(G2) \quad (1)$$

here, i = 1, 2, 3… $m1$. Since, G1 has only one member, its value is same for all i in the update formulae.

The members of group G2 are updated with a weighted sum of the best match score and central tendency of the group. This equation updates the position of the scores toward the central tendency of this group and the random number generated in the range of [0-1] acts as a normalization factor which provides the range of the normalized scores.

```
The Cohort Ranking Algorithm
Function Cohort Ranking (Score Matrix Mat)
{
Function Sort (Mat): Smat, Rmat
Function Cohort Rank (Smat)
  { for iteration=1 to iter
     Function Create Group (Smat)
      {G1, G2, G3}
     Function Update G2(G1, G2)
      {for Group Member = 1 to m1
         R = rand( 0,1)
          UG2 = R×G1 + (1 - R) × mean (G2)
      end for}
      return UG2 }
     Function Update G3(G1, G2, G3)
      {for Group Member= 1 to m2
         R1 = rand( 0,1)
         R2 = rand( 0,1)
         UG3 = R1×(G3-G1) + R2× [G3- mean(G2)]
      end for
      return UG3 }
     Function Update Score Matrix (G1,UG2,U G3)
     {U Smat = Concatenate [G1 UG2 UG3] }
     Function TPIR (U Smat)
  end for
}
```

The Third Group: G3

This group belongs to the lowest rank identities with lowest matching scores in comparison to the matching scores of G2. The members of this group are defined to be the remaining 50% of the N-1 matching scores (cohort matching scores) arranged in the decreasing order of confidence. The members in this group are also required to be updated according to the rank-one matching score, the difference of the matching scores belong to the G3 and G1 and mean of the members of G3. Let M_i^{G3} be the i^{th} member of the G3, M_i^{G1} is the i^{th} member of G1, and r_1 and r_2 are the random numbers in the range [0 1]. The update formulation for G3 is shown in (2) below. Here, i = 1, 2, 3… $m2$.

$$M_i^{G3} = r_1\times(M_i^{G3} - M_i^{G1}) + r_2\times\left\{M_i^{G3} - mean(G2)\right\} \quad (2)$$

The updated groups G2 and G3 are concatenated with G1 to generate an updated rank list. The updated rank list is then used to compute the TPIR in the biometric system. In our cohort ranking approach, the updated ranked list is iteratively updated to maximize the TPIR. Our empirical evaluation indicated that 20 iterations were adequate to achieve stable results. The objective function of the presented cohort ranking is to maximize the TPIR. The process of optimization is repeated for a number of iterations to maximize the TPIR from rank-one identity. When the numbers of iterations are exhausted, the new rank list is utilized for computing the final CMC curve. The final optimized rank list is used to compute the TPIR associated with the rank-one identity. The complete algorithm for cohort ranking has been summarized as in the *cohort ranking algorithm* shown on this page.

In order to ensure fair comparison with other *adaptive* fusion approach in [23], [24], we considered four score-level fusion rules for the combination of matching scores from multiple biometric matchers. We use two linear score-level fusion rules as; *sum* rule and *product* rule, and two non-linear fusion rules as; *exp* and *tanh* and other details are same as detailed in our earlier work in [23].

3. Experiments and Results

In this section, we detail the experimental setup, employed databases, and results obtained from the proposed method.

3.1 Databases

In order to evaluate the performance from the proposed method, we considered two different publicly available datasets.

***NIST BSSR1 dataset*:** The first set of experiments are performed using NIST BSSR1 public database of face and fingerprint [6]. This database contains match *scores* from two face matchers (C and G) and two fingerprint matcher's (Li and Ri) from *same* individuals. The BSSR1 multimodal database contains match scores from 517 users. There are 517 genuine scores and 266,772 (516×517) imposter scores for each user.

XM2VTS dataset: Second set of experiments are reported from XM2VTS face and speech database [27]. It contains the synchronized databases of frontal face and speech 295 users. Four set of matching scores from face and speech matchers are used in this work. These matching scores are coded in combination of (features, classifier) as follows: (DCTb, GMM), (DCTs, GMM), (FH, MLP), and (LFCC, GMM) [25]. We utilized fusion development set of genuine and imposter scores, which contains 600 genuine and 40,000 imposter scores.

3.2 Results for Unimodal Biometrics Identification

The comparative performance between the conventional ranking (baseline) and the cohort ranking for the BSSR1 database corresponding to the matching scores C, G, Li, and Ri is shown in Fig. 3 (a), 3 (b), 3 (c), 3 (d) respectively. It can be observed from the results in these figures that the cohort ranking scheme achieved better identification accuracy compared to the baseline method on matching scores of BSSR1 datasets. In particular, the proposed method improved the rank-1 accuracy from 89.3% to 95.3% for dataset C, 84.3% to 100% for dataset G, 86.4% to 93.9% for dataset Li, and 92.6% to 94.3% for dataset Ri. Moreover, the comparison of the TPIR for first three ranks for all the four matching scores C, G, Li, and Ri is summarized in Table 1. It is important to note that the proposed cohort ranking method cannot be directly compared to the other cohort-based methods in the literature because almost all of them either require us to consider nature of (genuine) score distribution or tailored for the *verification* problems.

The comparative performance between the baseline and cohort ranking for the XM2VTS database corresponding to DCTb, DCTs, FH, and LFCC is shown in Fig. 4 (a), 4 (b), 4 (c), 4 (d) respectively. On all the four datasets, the proposed method illustrates consistent improvement over the baseline performance (from respective/provided datasets). In particular, the proposed method improved the rank-1 accuracy from 94.0% to 98.0% for dataset DCTb, 76.5% to 92.5% for dataset DCTs, 91.0% to 96.0% for dataset FH, and 90.0% to 97.5% for dataset LFCC. Moreover, the comparison of the TPIR for first three ranks for all the four matching scores DCTb, DCTs, FH, and LFCC has been summarized in Table 2.

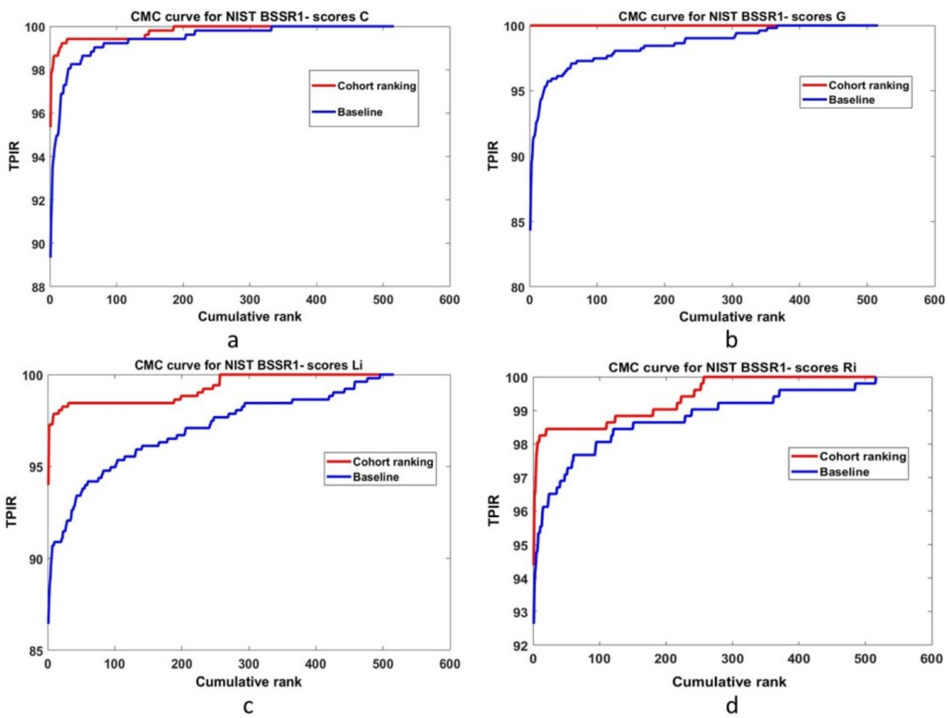

Figure 3: The CMC curves using NIST BSSR1 dataset for, comparison between the performance from the Cohort ranking and baseline, (a) Face C, (b) Face G, (c) Fingerprint Li, and (d) Fingerprint Ri.

Table 1: Comparative TPIR results from NIST BSSR1 database for first three ranks.

Dataset	Ranking schema	Accuracy (TPIR in %)		
NIST BSSR1		Rank-1	Rank-2	Rank-3
Face C	cohort ranking	**95.3**	97.8	97.8
	Baseline	89.3	91.0	92.0
Face G	cohort ranking	**100**	100	100
	Baseline	84.3	87.4	89.5
Finger Li	cohort ranking	**93.9**	97.0	97.2
	Baseline	86.4	87.7	88.5
Finger Ri	cohort ranking	**94.3**	96.5	96.5
	Baseline	92.6	93.7	94.1

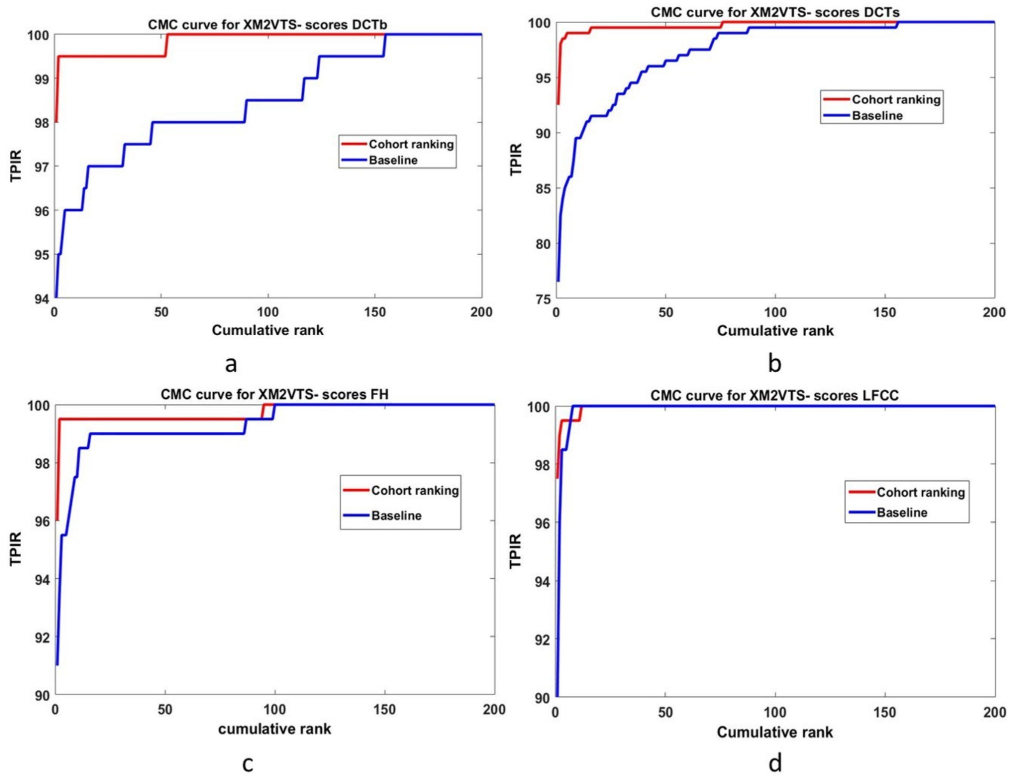

Figure 4: The CMC curves using XM2VTS dataset for, comparison between the performance from the Cohort ranking and baseline, (a) DCTb, (b) DCTs, (c) FH, and (d) LFCC.

3.3 Results for Multibiometrics User Identification

The final set of experiments were performed on multimodal database from NIST BSSR1 and XM2VTS databases. The four score-level fusion rules were utilized for simulating adaptive multibiometrics system [22]-[23] and these rules were; sum rule, product rule, exponential rule, and tan-hyperbolic rule. Two multimodal systems were employed in this work: Li and Ri from matching scores of NIST BSSR1 databases and (DCTb, GMM) and (FH, MLP) from matching scores of XM2VTS databases.

The achieved results from the implemented cohort ranking method with best performing fusion rule on simulated multimodal datasets, with comparison to the unimodal systems, are shown in Fig. 5(a) and 5(b). Moreover, the comparative TPIR for the first three ranks from the two simulated multimodal datasets, NIST BSSR1 and XM2VTS, with best performing fusion rules is summarized in Table 3. It can be observed from the results in Fig.4 that the cohort ranking method can consistently offer significantly improved rank-1 accuracy for the *multimodal* biometrics identification. In particular, the fusion approach based on the product rule achieves the best accuracy as compared to other fusion approaches on simulated NIST BSSR1 multimodal dataset with 99.8% rank-1 accuracy, whereas, the fusion approach based on the exponential rule achieves the best accuracy as compared to other fusion approaches on simulated XM2VTS multimodal dataset with 98% rank-1 accuracy.

Table 2: Comparative TPIR results from ts of XM2VTS database for first three ranks.

Dataset	Ranking schema	Accuracy (TPIR in %)		
NIST BSSR1		Rank-1	Rank-2	Rank-3
DCTb	cohort ranking	**98.0**	99.5	99.5
	baseline	94.0	95.0	95.0
DCTs	cohort ranking	**92.5**	98.0	98.5
	baseline	76.5	82.5	84.0
FH	cohort ranking	**96.0**	99.5	99.5
	baseline	91.0	93.5	95.5
LFCC	cohort ranking	**97.5**	99.0	99.5
	baseline	90.0	96.0	98.5

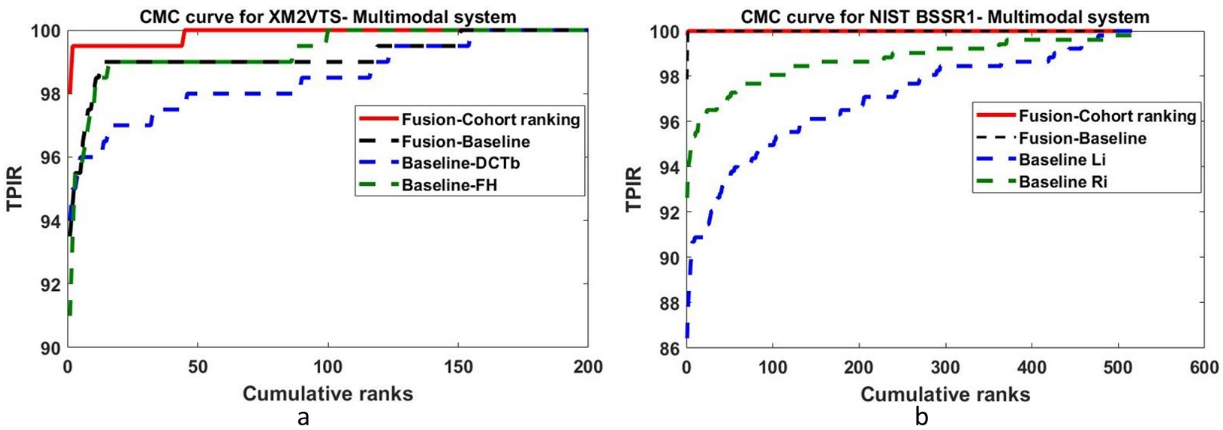

Figure 5: Comparative CMC curve for multimodal biometrics identification from (a) XM2VTS dataset using DCTb and FH, (b) NIST BSSR1 datasets Li and Ri.

3. Conclusions and Further Work

This paper has investigated the development of a cohort ranking based approach which can optimize the ranking of biometrics matcher(s) for the unimodal and multimodal biometrics *identification* applications. We proposed a novel adaptive cohort ranking approach to improve the *identification* accuracy for the biometrics system operating for the identification problem. The matching scores from N-1 users, or the cohort matching scores, were divided into three groups and the cohort ranking approach iteratively updated these groups to compute true identity of the user.

The proposed algorithm has incorporated the update mechanism for the cohort matching scores divided into three groups: G1, G2, and G3. All these groups can be iteratively updated, to maximize the TPIR for the rank-one accuracy. The advantage of the proposed method over, other cohort-based methods in the literature, lies in the fact that the proposed cohort ranking approach has a provision of being matcher-independent as it does not make any assumptions on the nature of the score distributions from the biometric matchers. Moreover, this approach is adaptive and can be incorporated with any biometric technologies.

It is important to note that the members of group G2 in our scheme are updated according to the rank-one matching score and first-order moment of the matching scores belong to the G2. This is motivated by the fact that, the members of the group G2 should change their position with regard to the *best* match score and the central tendency of the group. The update rules in the proposed algorithm is not absolutely random and seems reasonable to update new positions of the cohort scores in order to maximize the inter-class variations of the matching scores, and hence improve the identification accuracy of the system. We investigated several statistical parameters and found that the first order moments give the best position update rule in our algorithm. It may be noted that every optimization algorithm requires updating the position and velocity of the particles using a fixed rule in each iteration. This update of parameter can be done by using a formula along with some random values (e.g. random numbers in velocity and position updates for PSO).

This formula updates the position of the scores toward the central tendency of this group and the random number generated in the range of [0-1] acts as a normalization factor which provides the range of the normalized scores. After each update, the algorithm tests the fitness function which is the maximization of TPIR. The algorithm performs a certain number of iterations for updating the groups G2 and G3. Finally, the TPIR is computed on the final updated scores to report the identification accuracy of the system.

The proposed method has been evaluated on two publicly available biometric datasets NIST BSSR1 and XM2VTS. The achieved results consistently indicate that the proposed cohort ranking approach can operate on significantly higher TPIR for rank-one and higher ranks (CMC) in comparison

Table 3: Comparative TPIR results from NIST BSSR1 database, using four different fusion rules, for first three ranks.

Database	Fused Modalities	Cohort ranking scheme with best performing fusion rule	Accuracy (TPIR in %)		
			Rank 1	Rank 2	Rank 3
XM2VTS	DCTb and FH	Fusion-Cohort ranking	**98.0**	99.5	99.5
		Adaptive Fusion - Baseline	93.5	94.5	95.5
NIST BSSR1	Li and Ri	Fusion-Cohort ranking	**99.8**	100	100
		Adaptive Fusion- Baseline	97.8	100	100

the proposed method on two multimodal datasets: Li and Ri from NIST BSSR1 matching scores and (DCTb, GMM) and (FH, MLP) from XM2VTS. The achieved results consistently underline that the cohort ranking based approach can also improve the *identification* accuracy for *multimodal* biometric identification using the popular score-level fusion. The cohort ranking approach introduced in this work requires performance evaluation on large scale databases. Detailed study, using this approach, on the influence from age/gender/ethnicity group on groupings is also required and is part of further work in this area.

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References

[1] P. Verlinde, G. Chollet, and M. Acheroy, "Multi-modal identity verification using expert fusion," *Information Fusion*, vol. 1, pp. 17-33, 2000

[2] A. K. Jain, A. Kumar, "Biometric recognition: An overview," *Second Generation Biometrics: The Ethical, Legal and Social Context*. Springer, Dordrecht. 2012.

[3] N. Poh, A. Merati, and J. Kitter, "Making better biometric decisions with quality and cohort information: A case study in fingerprint verification," *Proc. 17th European Signal Processing Conf.*, Eusipco, Glasgow, 2009.

[4] J. Bigun, J. Fierrez-Aguilar, J. Ortega-Garcia, and J. Gonzalez-Rodriguez, "Multimodal biometric authentication using quality signals in mobile communications," *Proc. 12th Intl. Conf. Image Anal. & Processing*, Mantova, Italy, 2003.

[5] N. Poh, T. Bourlai, and J. Kittler, *A BioSecure DS2 Report on the Technological Evaluation of Score-level Quality-dependent and Cost-sensitive Multimodal Biometric Performance*. 2007.

[6] N. Poh and J. Kittler, " On the Use of Log-likelihood Ratio Based Model-specific Score Normalisation in Biometric Authentication,", *Proc. IEEE/IAPR Int'l Conf. Biometrics*, ICB 2007, LNCS 4542, pp. 614–624, Seoul, 2007

[7] D. E. Sturim and D. A. Reynolds, "Speaker adaptive cohort selection for tnorm in text-independent speaker verification," *Proc. IEEE Intl. Conf. Acoustics, Speech, and Signal Processing*, ICASSP 2005, pp. 741–744, 18-23, 2005.

[8] S. Lawrence, C. L. Giles, A.C. Tsoi, and A.D. Back, "Face recognition: A convolutional neural network approach", *IEEE Trans. Neural Networks*, vol. 8, pp. 98–113, 1997.

[9] M. J. Er, S. Wu, J. Lu, and H. L. Toh, "Face recognition with radial basis function (RBF) neural networks", *IEEE Trans. Neural Networks*, vol. 13, no. 3, pp. 697–710, May 2002.

[10] Y. Sheng, V. Phoha and S. M. Rovnyak, "A Parallel Decision Tree-Based Method for User Authentication Based on Keystroke Patterns", *IEEE Trans. Sys. Man and Cybern. — part B: Cybernetics*, vol. 35, no. 4, Aug. 2005.

[11] J. Kittler, M. Hatef, R. P. W. Duin, and J. Matas, "On combining classifiers," *IEEE Trans. Patt. Anal. Machine Intell.*, vol. 20, pp. 226-239, Mar. 1998.

[12] R. W. Frischholz and U. Deickmann, "BioID: A multimodal biometric identification system," *Computer*, vol. 33, no. 2, pp. 64–68, Feb. 2000.

[13] S. Tulyakov, Z. Zhang, and V. Govindaraju, "Comparison of combination methods utilizing T-normalization and second-best score model," *IEEE Conf. on Computer Vision and Pattern Recognition*, CVPR'W 2008, 2008.

[14] G. Aggarwal, N. Ratha, R. M Bolle, and R. Chellappa, "Multibiometric cohort analysis for biometric fusion," *Proc. ICASSP 2008*.

[15] W. Li, X. Gao, and T. E. Boult, "Predicting biometric system failure," *Proc. IEEE Int;. Conf. Computational Intelligence for Homeland Security and Personal Safety*, CIHSPS 2005. pp. 57–64, 2005.

[16] P. Wang, Q. Ji, and J. L. Wayman, "Modeling and predicting face recognition system performance based on analysis of similarity scores," *IEEE Trans. Pattern Analysis and Machine Intelligence,* vol. 29, no. 4, pp. 665–670, 2007.

[17] N. Poh, A. Merati, and J. Kitter, "Making better biometric decisions with quality and cohort information: A case study in fingerprint verification," *Proc. 17th European Signal Processing Conf.*, EURIPCO, Glasgow, 2009.

[18] A. Merati, N. Poh, and J. Kittler. "User-Specific Cohort Selection and Score Normalization for Biometric Systems." *IEEE Trans. Info. Forensics and Security*, vol. 7, no. 4, pp. 1270-1277, 2012.

[19] N. Poh, and M. Tistarelli. "Customizing biometric authentication systems via discriminative score calibration." *Proc. IEEE Conf. on Computer Vision and Pattern Recognition*, CVPR 2012, pp. 2681-2686, 2012.

[20] N. Poh, J. Kittler, and F. Alkoot. "A discriminative parametric approach to video-based score-level fusion for biometric authentication." *Proc. IEEE 21st Intl. Conf. on Pattern Recognition*, pp. 2335-2338, 2012.

[21] A. Kumar, "Incorporating cohort information for reliable palmprint authentication,: *Proc. CVGIP 2008*, pp. 583-590, 2008.

[22] K. Veeramachaneni, L. A. Osadciw, and P. K. Varshney, "An Adaptive Multimodal Biometric Management Algorithm", *IEEE Trans. On Systems, Man, and Cybernetics—Part C: Applications and Reviews*, 2005.

[23] A. Kumar, V. Kanhangad, and D. Zhang, "A New Framework for Adaptive Multimodal Biometrics Management", *IEEE Trans. Info. Forensics and Security*, Vol. 5, no. 1, pp. 92-102, 2010

[24] A. Kumar, M. Hanmandlu, and H. M. Gupta, "Decision level biometric fusion using Ant Colony Optimization", *Proc. 17th IEEE Intl. Conf. Image Processing*, ICIP, pp. 3105-3108, 2010.

[25] K. Nandakumar, "Integration of Multiple Cues in Biometric Systems", PhD Thesis, Michigan State University, 2005.

[26] CASIA IRIS Database, /http://www.cbsr.ia.ac.cn/english/IrisDatabase.aspS, 2008.

[27] XM2VTS Database, avilable at http://info.ee.surrey.ac.uk/Personal/Norman.Poh/web/fusion/main.php?bodyfile=entry_page.html

[28] N. Poh and S. Bengio, "Database, Protocol and Tools for Evaluating Score-Level Fusion Algorithms in Biometric Authentication," *Pattern Recognition*, vol. 39, issue 2, pp. 223-233, Feb. 2006.

[29] R. Bolle, J. Conell, S. Pankanti, N, Ratha, "The relationship between the ROC-Curve and the CMC," *Proc. AutoID 2005*, pp. 15-20, Buffalo, USA, 2005.