This book chapter appears in *Encyclopedia of Biometrics*, pp.607-611
Stan Z. Li (*Eds*), Springer, August 2009

# Rank Level-Fusion

Ajay Kumar
Indian Institute of Technology Delhi
Hauz Khas, New Delhi 110016, India

## Definition

Rank level fusion is the method of consolidating more than two identification results to enhance the reliability in personal identification. In multimodal biometric system, rank level fusion can be used to combine the biometrics matching scores from the different biometric modalities (for example face, fingerprint, palmprint and iris). It can also be used for performance improvement in unimodal biometric system by combining multiple classifier output that use different classifiers (*K* nearest neighbor, neural network, support vector machine, decision tree, *etc*.), different training set, different architectures (different number of layers or transfer function in neural network) or different parameter values (different kernels in support vector machine or different *K* in *K* nearest neighbor).

## Main Body Text

### Introduction

The majority of biometric system deployed use feature extraction from a single biometric modality and a particular classification procedure to determine the identity on an individual. The perfect solutions for user identification are often difficult to achieve, mainly due to the large number of user classes and the imperfection in the feature extraction process. Therefore the improvement in the user identification results using the simultaneous extraction of features and classifiers of different types has been investigated. The combination of potentially conflicting decisions in multimodal or unimodal biometric system employing different classifiers can be achieved in several ways: at feature, score and decision level. In general, the improvement in identification accuracy is achieved by selecting combination mechanism that can take advantage of strengths of individual classifiers while suppressing their weakness.

Any biometric recognition system is capable of generating matching scores for the input user with those of the enrolled possible identities. The set of all the possible user identities can be ranked by sorting the matching scores in the descending order.

Thus a biometric system can identify an unknown user by generating ranks, *i.e.*, integer numbers for each of the possible user identity. The rank level fusion refers to the mechanism of combining such output ranks from the various biometrics **matchers** (subsystems), to consolidate the combined output ranks in order to establish the identity of an individual with higher confidence. The matching score contains more information than ranks and therefore matching score level fusion schemes are believed to be more flexible. However, the rank level fusion schemes do not require **transformation** of ranks from various biometrics matchers into a common domain and are simpler to implement. Several decision level fusion schemes only use **top choice** (rank) from each of the biometric classifiers which is likely to be sufficient for biometric systems with small number of users. However, with the increase in number of enrolled identities or users, the correct rate for top choices drops, the **secondary choices** often contain near misses that should not be overlooked and are made use of in the rank level fusion.

**Methods for Combining Ranks**

The voting techniques proposed by different researchers [1]-[3] for consolidating rank output from the different biometric matchers will now be introduced. Given the ranked list of user identities returned by $M$ different biometric matchers, let $r_i(k)$ be the rank assigned to the user $k$ by the $i^{\text{th}}$ matcher. The user identity for $k^{\text{th}}$ user is assigned by computing the fused rank score $m_k$ from all the $M$ matchers.

(i) The Highest Rank Method: In highest rank method, the user identity is ascertained from the highest ranks returned by the individual matchers. Each of the possible user identity receives $M$ ranks, each from the $M$ matchers. The fused rank score $m_k$ for every possible user identity $k$ is computed from the minimum (highest) of these $M$ ranks. The user identities are then sorted in the order of fused rank scores to obtain the combined or new ranking from all $M$ matchers. Any ties in the fused rank scores ($m_k$) are randomly broken to obtain linearly ordered combined ranking. These ties are due to a number of user identities sharing the same combined ranks and depend on the number of employed matchers. The chances of the occurrences of such ties will be smaller if the number of enrolled user identities are large and the number of matchers employed in the fusion are small. The advantage of this method lies in the utilization of strength of each of the biometric matchers. However, large number of matchers can result in more ties in the combined ranking which is the major problem with this method. Therefore this method is considered useful in biometric systems combining small number of matchers with large number of enrolled users.

(ii) Borda† Count Method: The Borda count is the generalization of majority vote and the most commonly used method for **unsupervised** rank level fusion. It is the voting method in which each matcher gives priority to all possible user identities. Each matcher ranks the fixed set of possible user identities in the order of its preference. For every matcher, the top ranked user identity is given $N$ votes, the second ranked candidate identity is given $N$-1 votes and so on. Then for every possible user identity, the votes from all the matchers are added. The user identity that receives the highest number of votes is assigned as the winner or the true user identity.

$$m_k = \sum_{i=1}^{M} r_i(k) \qquad \forall\, k, k = \{1, 2, \ldots N\} \tag{1}$$

The Borda count score $m_k$ represents strength of agreement among different biometric matchers. The Borda count method assumes statstical independence, *i.e.*, ranks assigned to a given user by different matchers are independent. This assumption is often made in practice but it may not be true. The Borda count method is particularly considered suitable for combining the biometrics matchers with large number of user identities that often generate the correct user identities *near* the top of list (ranks) but not *at* the top. This method is efficient, simple and does not require any training. However, it assumes that all matchers are equally correct. This may not be the case when some matchers are more likely to be correct than others. Therefore weighted Borda count method has been suggested to utilize the strength of individual matchers.

(iii) Weighted Borda Count Method: The performance of different biometric matchers is not uniform, for example a biometric matcher using iris images is expected to perform better than those matchers using hand geometry or face images. Therefore modification of Borda count method by assigning corresponding weights to the ranks produced by individual matchers has been suggested. The fused rank scores in weighted Borda count method are computed as follows:

$$m_k = \sum_{i=1}^{M} w_i r_i(k) \tag{2}$$

where the $w_i$ represents the weights assigned to the $i^{th}$ matcher. The weight $w_i$ are assigned to reflect the significant of each matcher and can be computed from the overall assessment of the performance. The weights are computed during the training phase using logistic regression (as detailed in [3]) or using

†Named for the French scientist *Jean-Charles de Borda* (1733-1799) who formulated this preferential voting system.

more sophisticated machine learning techniques.

(iv) Bayes Fuse: The Bayes fuse is the **supervised** rank level fusion method based on Bayesian inference. Each of the possible user identity is ranked according to the fused rank scores computed as follows:

$$m_k = \sum_{i=1}^{M} \log \frac{\Pr[m_k(i) \mid gennuine]}{\Pr[m_k(i) \mid imposter]} \quad (3)$$

where $P_r[m_k(i)|\ imposter]$ is the probability that an imposter user would be ranked to $m_k(i)$ by the $i^{\text{th}}$ matcher and $P_r[m_k(i)|\ gennuine]$ is the probability that a gennuine user would be ranked to $m_k(i)$ by the $i^{\text{th}}$ matcher. These two likelihood probabilities are computed from the training data during training phase. The above equation is easily derived [2] from the estimation of two posterior probabilities, each for the gennuine and imposter class, using Bayes rule. The combined ranks generated using (3) makes a common naïve Bayes assumption, *i.e.*, individual ranks assigned to the user identities by $M$ matchers are independent. The training phase in Bayes fuse method required the collection of simple statistics about the distribution of ranks among various user identities. The rank level fusion using Bayes fuse was originally introduced for information retrieval but is equally useful in biometrics fusion.

**Example**

The four different rank level fusion methods discussed above can be better clarified with a simple example in multimodal biometric fusion. This example illustrates the combination of three different biometric matchers (figure 1), using iris, fingerprint and face image, to generate matching scores. These matching scores are internally sorted to produce different ranking among the possible user identities. There are only five different users (user A, user B, user C, user D, user E) and 1, 2, …5 represents the ranks for the possible input user identity with 1 being the highest rank/possibility. Let the weights of different matchers computed from the training data using linear regression be 0.5, 0.15, 0.35 for the matcher 1, matcher 2, and matcher 3 respectively. Let the probability that a genuine user be ranked at ranks (1, 2, 3, 4, 5) be (0.8, 0.1, 0.06, 0.02, 0.02), (0.5, 0.42, 0.06, 0.01, 0.01) and (0.6, 0.2, 0.08, 0.07, 0.05) for matcher 1, matcher 2 and matcher 3 respectively. Similarly the prior probabilities for an imposter user be ranked at ranks (1, 2, 3, 4, 5) have been obtained from the training data and are listed as (0.2, 0.9, 0.94, 0.98, 0.98), (0.5, 0.58, 0.94, 0.99, 0.99) and (0.4, 0.8, 0.92, 0.93, 0.95) respectively for matcher 1, matcher, and matcher 3.

Let us now compute the fused rank scores ($m_{\text{A}}$, $m_{\text{B}}$, $m_{\text{C}}$, $m_{\text{D}}$, $m_{\text{E}}$) and the new rankings

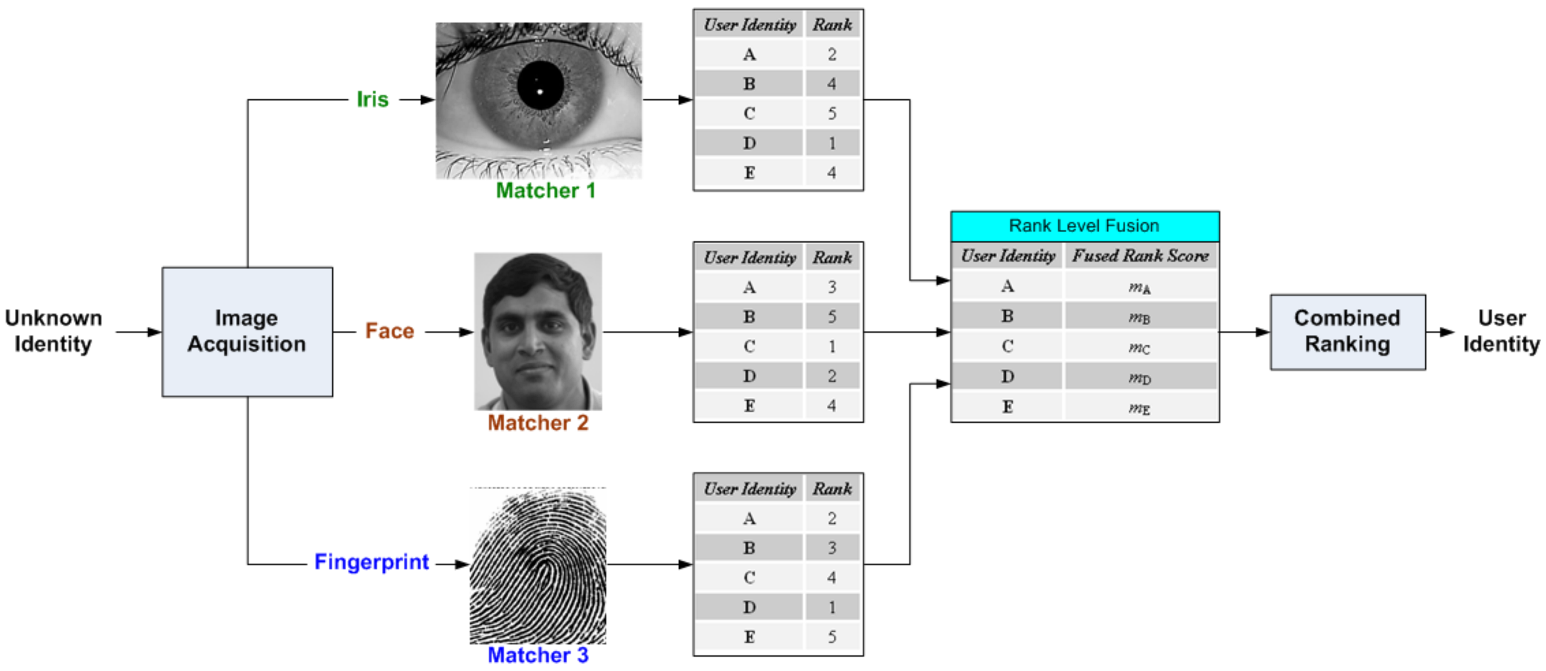


**Figure 1**: An example of multimodal biometric system employing rank level fusion.

for each of the four methods discussed in previous section.

(1) Highest Rank: The fused rank scores using highest rank level method are shown in table 2. The fused rank score for user A ($m_A$) will be 2 (highest rank or minimum of 2, 3, 2). The ties for $m_C$ and $m_D$ are randomly broken and the combined ranking is also shown in table 1. The highest rank method achieves highest ranking for C and therefore the unknown input identity is user C.

(2) Borda Count: The fused rank scores using Borda count are computed as follows: $m_A = (2 + 3 + 2) = 7$, $m_B = (4 + 5 + 3) = 12$, $m_C = (5 + 1 + 4) = 10$, $m_D = (1 + 2 + 1) = 4$, $m_E = (4 + 4 + 5) = 13$. Thus $m_D$ is lowest and user D achieves highest combined ranking (table 1).

**Table 1** : Example for consolidating ranks using unsupervised rank level fusion methods

| | Highest Rank Method | | | Borda Count Method | | |
|---|---|---|---|---|---|---|
| User Identity | Fused Rank Score | | Combined Ranking | Fused Rank Score | | Combined Ranking |
| A | $m_A$ | 2 | 3 | $m_A$ | 7 | 2 |
| B | $m_B$ | 3 | 4 | $m_B$ | 12 | 4 |
| C | $m_C$ | 1 | 1 | $m_C$ | 10 | 3 |
| D | $m_D$ | 1 | 2 | $m_D$ | 4 | 1 |
| E | $m_E$ | 4 | 5 | $m_E$ | 13 | 5 |

(3) Weighted Borda Count: The fused rank scores $m_A = (2 \times 0.5 + 3 \times 0.15 + 2 \times 0.35) = 2.15$. Similarly rank fused scores for rest of the users can be computed and are

shown in table 2.

(4) Bayes Fuse: The prior probabilities that each of the ranks are true (untrue), *i.e.* belongs to the genuine (imposter) class, can be obtained from the training data and are provided in the problem. The fused rank score for user A can be computed using (3) as follows: $m_A$ = log (0.1/0.9) + log (0.06/0.94) + log (0.2/0.8) = -6.34. The rest of the fused rank scores and the combined rankings are displayed in table 2.

**Table 2** : Example for consolidating ranks using supervised rank level fusion methods

| | Weighted Borda Count Method | | | Bayes Fuse Method | | |
|---|---|---|---|---|---|---|
| User Identity | Fused Rank Score | | Combined Ranking | Fused Rank Score | | Combined Ranking |
| A | $m_A$ | 2.15 | 2 | $m_A$ | -6.34 | 2 |
| B | $m_B$ | 3.8 | 3 | $m_B$ | -10.93 | 4 |
| C | $m_C$ | 4.05 | 4 | $m_C$ | -6.48 | 3 |
| D | $m_D$ | 1.15 | 1 | $m_D$ | 1.47 | 1 |
| E | $m_E$ | 4.35 | 5 | $m_E$ | -11.43 | 5 |

**Summary**

In the biometrics literature, one can find several examples [1], [3]-[4], [6] of above rank level fusion methods to consolidate the outputs from different matchers. Reference [4] employs a variation of Borda count method that uses partitioning of templates to consolidate the combined ranks. Highest rank method is employed in reference [6] is referred as lowest rank method since it chooses the minimum rank from the list of dissimilarity score instead of conventional maximum rank methods that employ highest ranks from the list of similarity scores. Several other variations of Borda count method have also been developed in the literature [7]; *Nenson's method* that uses successive elimination from Borda count that are below average Borda count or *Quota Borda method* that includes the quota element in counting ranks. However, they have not yet been investigated for their utility in the biometrics literature.

A survey of biometrics on various fusion techniques [5] suggests that the rank level fusion method is less preferred method of fusion while score level fusion continues to be the most popular method. The rank level fusion can be more useful in combining decisions from a large number of biometric matchers and such large systems has not yet been evaluated in the biometrics literature.

**References**

[1] Y. Lee, K. Lee, H. Jee, Y. Gil, W. Choi, D. Ahn, and S. Pan, "Fusion for

multimodal biometric identification," *Proc. ABVPA 2005*, LNCS 3546, pp. 1071-1079, 2005.

[2] J. A. Aslam and M. Montague, "Models for metasearch," *Proc. 24th ACM SIGIR Conf. on Research and Development in Information Retrieval*, pp. 379-381, Sep. 2001.

[3] T. K. Ho, J. J. Hull, and N. Srihari, "Decision combination in multiple classifier systems," *IEEE Trans. Pattern Anal. Machine Intell.*, pp. 66-75, vol. 16, Jan. 1994.

[4] J. Bhatnagar, A. Kumar, N. Saggar, "A novel approach to improve biometric recognition using rank level fusion," *Proc. CVPR 2007*, Minneapolis, Minnesota, pp. 1-6, Jun. 2007.

[5] A. Ross, K. Nandakumar and A.K. Jain, *Handbook of Multibiometrics*, Springer Verlag, 2006.

[6] M. Rautiainen and T. Seppanen, "Comparison of visual features and fusion techniques in automatic detection of concepts from news video," *Proc IEEE Intl Conf. Multimedia and Expo.*, ICME 2005, Amsterdam, pp. 932-935, Jul. 2005.

[7] M.A.E. Dummett, *Principles of Electoral Reform*, Oxford University, New York, 1997.

**Definitional Entries**

**Matcher**

A biometric identification system compares the templates stored during user enrollment with those extracted from the presented biometric sample and generates a matching score. The module that generates this matching score is referred as matcher.

**Transformation**

The transformation refers to the process of normalizing the output (score) for a matcher to a desired range. The range of output matching scores generated from the different biometric matchers can vary significantly. This variation can be attributed to the different distance criteria used to generate matching scores or the different biometric features employed by different matchers.

**Unsupervised**

The rank level fusion methods can be generally categorised under the headings of supervised and unsupervised. The rank level fusion method that does not require any training data to achieve the fusion of ranks can be categorized as unsupervised methods. Thus using unsupervised rank level fusion methods, one can combine the ranks from different matchers without any 'teacher' or training data. The Highest rank method and Borda count methods are the examples of unsupervised rank level fusion methods.

**Supervised**

The rank level fusion methods that require some training phase to compute the parameters of the fusion model can be categorised under supervised methods. The weighted Borda count method and Bayes fuse are two such examples of the supervised rank level fusion methods. The training phase is necessary, from the training data, to compute the weights for the different matchers in weighted Borda count method and to compute the distribution of user identities above different ranks in the Bayes fuse method.

**Top and secondary choices**

Every biometric matcher employed for user recognition compares the presented biometric with the stored templates and generates the matching scores corresponding to each of the possible user identities. The top choice refers to the user identity corresponding to user template generating the highest matching score. The secondary choices refer to the remaining choices of the possible user identities corresponding to the templates that do not generate the highest matching score. If the difference between the highest matching score and the second highest matching score is large, there is high probability that the top choice represents the correct user identity. However, if this difference is small, the top choice may not represent the correct user identity and secondary choices become important in generating the decisions.