ROBUST MULTIMODAL BIOMETRIC SYSTEM USING MARKOV CHAIN BASED RANK LEVEL FUSION

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Abstract: Multimodal biometrics is an emerging area of pattern recognition research that aims at increasing the reliability of biometric systems through utilizing more than one biometric in decision-making process. But an effective fusion scheme is necessary for combining information from various sources. Such information can be integrated at several distinct levels, such as sensor level, feature level, match score level, rank level and decision level. In this research, we develop a multimodal biometric system utilizing face, iris and ear features through rank level fusion method. We apply Fisherimage technique on face and ear image databases for recognition and Hough transform and Hamming distance techniques for iris image recognition. We introduce Markov chain approach for biometric rank aggregation. We investigate various rank fusion techniques and observe that Markov chain approach gives us the best result. Also this approach satisfies the Condorcet criterion which is essential in any fair rank aggregation system. The system can be effectively used by of security and intelligence services for controlling access to prohibited areas and protecting important national or public information.

1 INTRODUCTION

The biometrics based controlled access to the protected resources has emerged shown to offer higher security and convenience to the users. The optimal biometric recognition would be one having the properties of distinctiveness, universality, permanence, acceptability, collectability, and resistance to circumvention (Ross et al., 2006). No existing biometric system simultaneously meets all of these requirements, however the use of more than one biometric can help lead to a system which is closer to these ideals.

The most immediate advantage of multimodal authentication is increased recognition accuracy. Multimodal systems fuse information for more than one source, each of which offers additional evidence about the authenticity of an identity claim. Therefore, one can have more confidence in the result (Dunstone and Yager, 2009).

Multibiometric systems can address the non-universality problem and reduce the FTER (Failure-to-Enroll Rate) and FTCR (Failure-to-Capture Rate). For instance it is estimated that 2% of the population may not be able to provide a fingerprint due to medical/genetic conditions, accidental destruction, or temporary damage (Maio et al., 2004). That group of persons can still be recognized using other biometric traits in a multimodal biometric system.

Multimodal biometric systems are more resistant to spoof attacks because it is difficult for the attacker to simultaneously spoof multiple biometric sources. All multimodal biometric systems need a fusion module that takes two or more data and combines them in order to obtain the authentication result: impostor or genuine user. Figure 1 shows a sample multimodal biometric system.

The fusion strategies are divided into two main categories: *pre-mapping fusion* and *post-mapping fusion* (Revett, 2008). The first strategy deals with the *sensor data fusion level* and *feature vector fusion level.* These techniques are not used because they give many implementation problems (Bubeck, 2003). The second strategy is realized through the *decision level fusion*, based on some algorithms which combine single decisions for each component system, or through the *matching score level fusion,* which combines the matching scores of each component system, or through the *rank level fusion*, which is used when the output of each component system is a subset of possible matches (i.e., identities) sorted in decreasing order of confidence.

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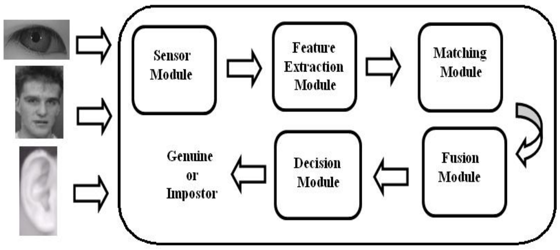

Figure 1: A sample multimodal biometric system.

In this research, we investigate rank level fusion for face, ear and iris biometrics as the other fusion methods have been extensively studied in the literature from the last ten years. Fusion at the rank level is a significantly understudied problem, which has a high potential for efficient consolidation of ranked information obtained from multiple unimodal matchers (Bhatnagar et al., 2007). We introduce Markov chain (Dwork et al., 2001) approach for fusing rank information in this multimodal system.

2 RANK LEVEL FUSION

Rank-level fusion is used only in identification systems and is applicable when the individual matcher's output is a ranking of the "candidates" in the template database. The system is expected to assign a higher rank to a template that is more similar to the query. Very few methods can be found in the literature for consolidation of biometric rank information as it is still an understudied problem. Three methods described by Ho, Hull, and Srihari in (Ho et al., 1994) to find out the final decision in a general multiple classifier system, can be used for rank level fusion in multimodal biometric systems. These methods are highest rank, Borda count and logistic regression methods. Recently Nandakumar and others (Nandakumar et al., 2009) introduced Bayesian approach for rank level fusion. All of these methods for rank level fusion is briefly discussed in the next subsections.

2.1 Highest Rank Method

The highest rank method is good for combining a small number of specialized matchers and hence can be effectively used for a multimodal biometric system where the individual matchers are the best. In this method, the consensus ranking is obtained by sorting the identities according to their highest rank. The advantage of this method is the ability to utilize the strength of each matcher. The disadvantage of this method is that the final ranking may have many ties (Monwar et al., 2009).

2.2 Borda Count Method

The Borda count (Borda, 1781) method is the most widely used rank aggregation method and uses the sum of the ranks assigned by individual matchers to calculate the final rank. This method assumes that the ranks assigned to the users by the individual matchers are statistically independent and the performances of all three matchers are equally well.

The advantage of this method is that it is easy to implement and requires no training stage. These properties made the Borda count method feasible to incorporate in multimodal biometric systems. The disadvantage of this method is that it does not take into account the differences in the individual matcher's capabilities and assumes that all the matchers perform equally.

2.3 Logistic Regression Method

The logistic regression method calculates the weighted sum of the individual ranks. In this method, the final consensus rank is obtained by sorting the identities according to the summation of their rankings obtained from individual matchers multiplied by the assigned weight.

The weight to be assigned to the different matchers is determined by a '*logit*' function using logistic regression (Agresti, 2007). This method is very useful when the different matchers have significant differences in their accuracies but requires a training phase to determine the weights which can be computationally expensive. Also one of the key factors that have direct effect on the performance of a biometric system is the quality of the biometric samples. Hence the single matchers' performance can vary with different sample sets which make the weights allocating process more challenging and inappropriate weight allocation can eventually reduce the recognition performance of this multimodal biometric system (using logistic regression) compared to unimodal matchers.

2.4 Bayesian Approach

Bayesian approach for biometric rank fusion is based on Bayes decision theory. This approach uses the rank distribution (probability that an identity is assigned a rank by an individual matcher is a true identity) which can be estimated provided the marginal genuine and impostor match score densities are known (Nandakumar et al., 2009). The consensus rank is obtained as the product of the posterior probabilities of the individual matchers.

The size of the multimodal biometric database is usually huge and thus only the top few results are usually considered for the final reordered ranking. Hence, a very common scenario of a rank based multimodal biometric system is that some results may rank at top by a few classifiers and the rest of the classifiers do not even output the result. In this situation, the above approaches cannot produce a good recognition performance.

To deal with these shortcomings, in this research, we introduce Markov chain rank aggregation method to find out the consensus rank for person identification. Previously, this approach has successfully been used in web search (Dwork et al., 2001). Due to the ease in implementation and its successful usage in the web ranking, we decide to employ Markov chain approach for multimodal biometric rank fusion.

3 MARKOV CHAIN APPROACH

We consider the biometric rank aggregation as an evaluation of a voting method. In a voting method evaluation, the most important thing is to ensure the fairness of the voting system. Among the fairness criteria, the two most important criteria are Condorcet Winner Criterion and the Condorcet Loser Criterion (Condorcet, 1785).

Condorcet Winner Criterion: If there exists an alternative *a,* which would win in pairwise votes against each other alternative, then *a* should be declared the winner of the election. Note that there is not necessarily such an alternative *a*. This alternative is called the Condorcet winner.

Condorcet Loser Criterion: If there exists an alternative *a,* which would loose in pairwise votes against each other alternative, then *a* should not be declared the winner of the election.

None of the approaches described in section 2 ensures the election of Condorcet Winner. This motivates us to employ the Markov chain approach for biometric rank fusion in this multimodal biometric system.

In the Markov chain biometric rank aggregation method, it is assumed that there exists a Markov chain on the enrolled identities and the order relations between those identities in the ranking lists (obtained from different biometric matchers) represent the transitions in the Markov chain. The stationary distribution of the Markov chain is then utilized to rank the entities (Dwork et al., 2001). The construction of the consensus ranking list from the Markov chain can be summarized as below:

1) Map the set of ranked lists to a single Markov chain, with one node of the chain represents one identity in the initial ranking lists.

2) Compute the stationary distribution on the Markov chain.

3) Rank the identities based on the stationary distribution. That is, the node with the highest score in the stationary distribution is given the top rank, and so on down to the node with the lowest score in the stationary distribution which is given the last rank.

The proposed Markov chain approach for biometric rank aggregation has several advantages. This method handles the partial ranking list very well and provides a more holistic viewpoint of comparing all candidates against each other. To do so, this method use only the available comparisons (in the partial lists) between the identities to determine the transition probabilities and exploit the connectivity of the chain to infer comparison outcomes between pairs that were not explicitly ranked by any of the matcher. The Markov chain method also handles the uneven comparison, i.e., when the results of the initial ranking lists are very much different. Heuristics for combining rankings are motivated by some underlying principle and the Markov chain model can be viewed as the natural extensions of those heuristics. For example, Borda's method is based on the idea "more wins is better." It is natural to extend this and say "more wins against good players is even better," and so on, and iteratively refine the ordering produced by a heuristic. Some Markov chain models for biometric rank aggregation can be viewed as the natural extensions of Borda's method, sorting by Geometric mean or Copeland's method (sort the candidates by the number of pairwise majority wins minus pairwise majority losses) (Copeland, 1951).

There are four specific Markov chains (Dwork et al., 2001), which can be used for biometric rank aggregation. Among those four methods, the last method satisfies the Copeland method and according the literature, the best performing one. This specific Markov chain can be termed as MC_4 and can be defined as follows:

MC_4: If the current state is *a*, then choose an identity *b* uniformly from the union of all identities ranked by the unimodal matchers. If the rank of *b* is lower than the rank of *a* for majority of the matchers that rank both *a* and *b*, go to *b*, else stay in *a*.

Figure 2 shows a Markov chain with its transition matrix build on MC_4. There are three matchers which outputs three different ranking lists. Based on the ranking list, a Markov chain is constructed

Ranking 1	Ranking 2	Ranking 3
Person 1	Person 3	Person 3
Person 3	Person 2	Person 1
Person 5	Person 1	Person 2
Person 4	Person 4	Person 5
Person 2	Person 5	Person 4

$$MC = \begin{bmatrix} 4/5 & 0 & 1/5 & 0 & 0 \\ 1/5 & 3/5 & 1/5 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 1/5 & 1/5 & 1/5 & 1/5 & 1/5 \\ 1/5 & 1/5 & 1/5 & 0 & 2/5 \end{bmatrix}$$

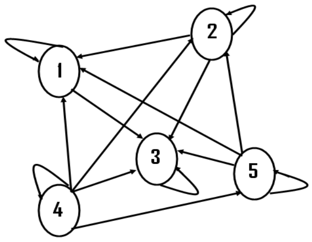

Figure 2: Markov chain and the transition matrix constructed from three ranking lists based on MC_4.

according to MC_4. The final ranking list can be obtained by applying the Copeland method, i.e., by sorting the nodes in the majority graph (Markov chain) by outdegree minus indegrree.

4 THE PROPOSED SYSTEM

The design of a multimodal biometric system is strongly dependent on the application scenario. A number of multimodal biometric systems have been proposed for the last ten years but they differ from one another in terms of their architecture, the number and choice of biometric modalities, the level at which the evidence is accumulated, and the methods used for the integration or fusion of information (Chandran and Rajesh, 2009). The proposed system adopts multiple biometric traits of an individual, to establish the identity.

The system employs three unimodal matchers for face, ear an iris biometric traits. The main goal of this research is to evaluate the performance of the multimodal biometric system based on rank level fusion over the unimodal biometric system. So, we decide to use face, ear and iris biometric traits for this system. Although ear is not a frequently used biometric trait, but we choose this trait because w want to use biometrics from the similar region of the human body keeping in mind that, it will help us to create the multimodal database in future.

All the biometric traits that will be used in this project are images. For face and ear images, we use Fisherface (Belhumeur et al., 1997), as this method has significant advantages over the popular eigenface method (Turk and Pentland, 1991) in case of images of the same subject with certain illumination change. Fisherimage is a combination of principle component analysis (PCA) and linear discriminant analysis (LDA). The prime difference between LDA and PCA is that PCA does more of feature classification and LDA does data classification. Researchers have demonstrated that the LDA based algorithms outperform the PCA algorithm for many different tasks (Zhao et al., 1998).

For iris recognition, hamming distance method is used for recognition after the iris image pre-processing and encoding. At first, the iris part of the eye image (from inside the limbus (outer boundary) and outside the pupil (inner boundary)) are localized. For iris localization, Hough transform (Wildes, 1997) is used. After localizing the region of interest, the Rubber Sheet Model (Daugman, 2004) is used for un-wrapping the iris image. Then a Gabor filter encodes the iris data. After encoding, the binary data is available which is compared by Hamming distance method.

A detailed diagram of the proposed system is shown in figure 3. In the enrolment phase, face, ear and iris images will be acquired first and then will be processed according to the training algorithms and saved as face, ear and iris templates.

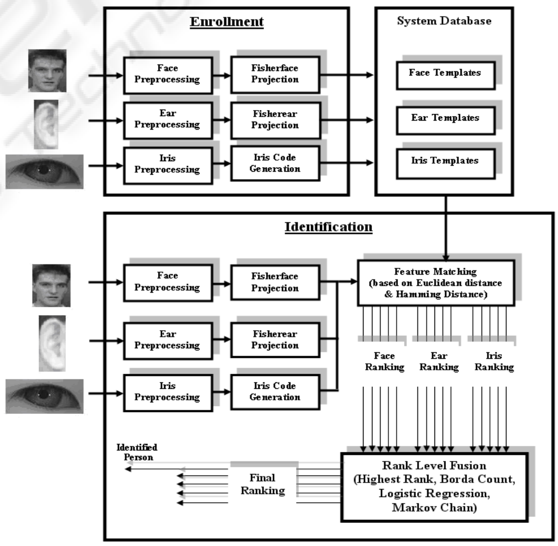

Figure 3: Proposed system architecture.

In the Identification phase, face and ear images will be recognized measuring the Euclidian distance between the test image and the images in the fisherfaces and fisherears. For iris, the Hamming distance will be calculated between the codes generated from the test iris with the iris codes in the database. In each of the three cases, five identities will be obtained as output that will be ranked according to their distances. The identities of these three ranking list then be integrated using the rank level fusion approach to find out a consensus rank of the identities and the identity at the top of the consensus ranking list will be identified as the desired identity. For rank level fusion, highest rank, Borda count, logistic regression and Markov chain approaches are used to find out the consensus ranking from the three ranking lists.

5 EXPERIMENTS AND RESULTS

Due to the inherent cost and effort associated with constructing a multimodal database, the database used in this system is not the "original" multimodal database (different biometric traits are collected from the same person), but rather we use a "virtual" database which contains records created by consistently pairing a user from one unimodal database (e.g., face) with a user from another database (e.g., iris) (Ross et al., 2006). The creation of virtual users is based on the assumption that different biometric traits of the same person are independent.

For iris, we use the CASIA Iris Image Database (ver 1.0) from the Chinese Academy of Science (CASIA, 2004). CASIA database (ver 1.0) includes 756 black and white iris images from 108 eyes. For each eye, 7 images are captured in two sessions.

The ear images are from the USTB, China database (USTB, 2002). The database contains ear images with illumination and orientation variation. The images are 300 x 400 pixels in size.

For face, Facial Recognition Technology (FERET) database (Phillips et al., 1998) is used. There are 14,051 images (256 x 384) of 1199 person. There are various face images with expression, pose and illumination variation.

To build the virtual multimodal database for the proposed system, we consider 600 iris images from 300 subjects of CASIA database. In addition, 600 ear images and 600 face images are also be considered from USTB and FERET database respectively. Then each sample of these 600 iris images will randomly be combined with one sample of 600 ear images and one sample of 600 face images. Half of these 600 combined samples are used for training purposes and the remaining half are used for testing. Thus we have a virtual multimodal database containing 300 training and 300 testing multimodal samples. Fig 4 shows a portion of our sample multimodal database.

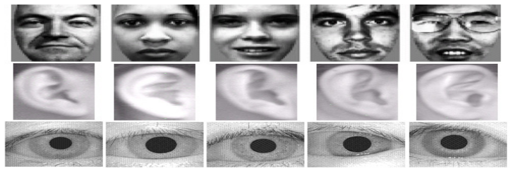

Figure 4: A small portion of our virtual database.

After experiment, we observe the result by plotting the recognition value on a Cumulative Match Characteristic (CMC) curve. CMC curve is used to summarize the identification rate at different rank values. As rank level fusion method can only be applied in identification (not in verification) systems, so, we insist on the identification rate which is the proportion of times the identity determined by the system is the true identity of the user providing the query biometric sample. If the biometric system outputs the identities of the top x matches, the rank-x identification rate, is defined as the proportion of times the true identity of the user is contained in the top m matching identities.

Figure 5 shows the CMC curves of the individual face, ear and iris matchers and for Markov chain and logistic regression rank fusion approaches. We investigate highest rank, Borda count, logistic regression and Markov chain approaches on this virtual multimodal database and obtained the best identification rates through Markov chain approach (98.2%). Among the other three, logistic regression approach is better (97%).

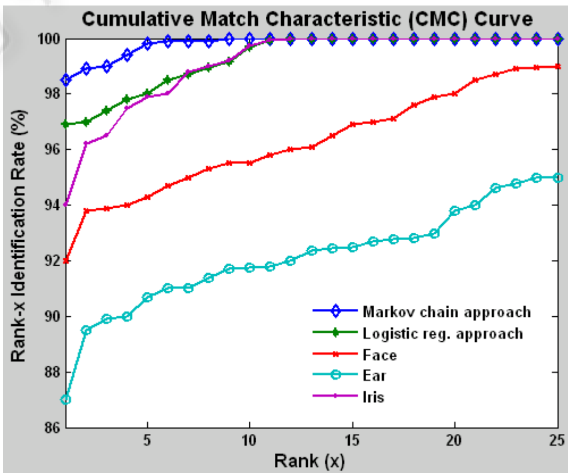

Figure 5: CMC curve of Markov chain and logistic regression rank fusion approaches along with face, iris and ear unimodal systems.

As the performances of our individual matchers are not equal, hence we report only the identification rates of Markov chain and logistic regression approaches. Also we report the identification rates of the face, iris and ear matchers on the CMC curves to show the differences.

6 CONCLUSIONS

The design of a multimodal biometric system is a challenging task due to heterogeneity of the biometric sources in terms of the type of information, the magnitude of information content, correlation among the different sources and conflicting performance requirements of the practical applications. Extensive research has been done to identify better methods to combine the information obtained from multiple sources. In this research, we combine face, ear and iris biometric information using rank level fusion method. We introduce Markov chain approach for biometric rank fusion and obtain better identification rate over other rank fusion approaches. Thus, Markov chain method can be a reliable solution of integrating biometric ranking lists to obtain a consensus rank list and can be effectively used in various security systems.

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