ANALYSIS OF BIPARTITE RANKBOOST APPROACH FOR SCORE LEVEL FUSION OF FACE AND PALMPRINT BIOMETRICS

B. Sateesh Kumar
Assistant Professor of CSE, JNTUH CEJ
JNT University Hyderabad, Telangana State, INDIA

Dr.A.Govardhan
Professor of CSE, School of Information Technology
JNT University Hyderabad, Telangana State, INDIA

ABSTRACT

Biometrics based personal identification is regarded as an effective method for automatically recognizing, with a high confidence a person’s identity. A multimodal biometric systems consolidate the evidence presented by multiple biometric sources and typically better recognition performance compare to system based on a single biometric modality. This paper proposes an authentication method for a multimodal biometric system identification using two biometric types i.e. face and palmprint. The proposed system is designed for application where the training data contains a face and palmprint. Integrating the palmprint and face features increases robustness of the person authentication. The final decision is made by fusion at matching score level architecture in which features vectors are created independently for query measures and are then compared to the enrolment template, which are stored during database preparation. Multimodal biometric system is developed through fusion of face and palmprint recognition. In this paper, Bipartite RankBoost Approach (BRBA) is used for analysis the Score Level Fusion of Face and Palmprint Biometrics

Keywords: Biometrics, Classifiers, BRBA, Palmprint, Face, FRR, FAR, GAR, TER.

1. INTRODUCTION

Uni-modal biometric systems, relying on the evidence of a single source of biometric information for authentication, have been successfully used in many different application contexts, such as airports, passports, access control, etc. However, a single biometric feature sometimes fails to be exact enough for verifying the identity of a person. By combining multiple modalities,
enhanced performance reliability could be achieved. Due to its promising applications as well as the theoretical challenges, multi-modal biometrics has drawn more and more attention in recent years [1].

Face and palm print multimodal biometrics are advantageous due to the use of non-invasive and low-cost image acquisition. We can easily acquire face and palm print images using two touches less sensors simultaneously. Existing studies in this approach [2, 3] employ holistic features for face representation, and results are shown with small data sets (less than 100 subjects) were reported. Note that holistic features are sensitive to global variation, such as illumination and inaccurate alignment. It is believed that the human vision system uses a series of levels of representation, with increasing complexity.

A recent study on local appearance based object recognition [4] shows that features of intermediate complexity are optimal for basic visual task of classification. We consider a class of simple local features, that of ordinal relationship. Ordinal features are defined based on the qualitative relationship between two image regions and are robust against various intra-class variations. Ordinal features have been used for recognition of palm prints [5] and faces [6].

In this paper, we present a face+palmprint multimodal biometric identification method and system to improve the identification performance. Effective classifiers based on BRBA are constructed for faces and palmprints, respectively. Then, the matching scores from the two classifiers are combined using several fusion strategies. Experimental results on a middle-scale data set have demonstrated the effectiveness of the proposed system.

2. UNIMODAL BIOMETRIC SYSTEMS

In this section, the two unimodal biometric systems used in the proposed system will be explored. Each system is briefly explained.

2.1. Face Recognition System

A facial recognition system is a computer application for automatically identifying or verifying a person from a digital image or a video frame from a video source. One of the ways to do this is by comparing selected facial features from the image and a facial database. Every face has different features or landmarks. Approximately every human face has about 80 landmarks such as, the size of the nose, distance between the eyes, depth of the eye sockets, size and shape of the jaw lines and so on.

Normally there are two main techniques (algorithms) for this. First one is the geometric approach which analyzes the distinguish features of the face. The other one is the photometric approach which converts an image to numerical values and compares those values with templates that are created before.

Figure 1: features of face and palmprint
2.2. Palmprint Recognition System

Human beings are interested in the palm lines for fortune telling long time ago. The inner surface of the palm normally contains flexion creases, secondary creases and ridges. The flexion and secondary creases are also called principal lines and wrinkles, respectively. The flexion creases and the main creases are formed between the 3rd and 5th months after conception and superficial lines appear after birth [7].

Palmprint recognition techniques have been grouped into two main categories, first approach is based on low-resolution features and second approach is based on high-resolution features. First approach make use of low-resolution images (such as 75 or 150 ppi), where only principal lines, wrinkles, and texture are extracted. Second approach uses high resolution images (such as 450 or 500 ppi), where in addition to principal lines and wrinkles, more discriminate features like ridges, singular points, and minutiae can be extracted.

3. A FRAMEWORK FOR THE UNIMODAL BIOMETRIC SYSTEMS

Palmprint and facial feature extraction are becoming one of the major issues in finding the identity of a person. Quite a lot of techniques have been available for the extraction of face and palm print. In this paper, we have developed an efficient technique for the extraction of face and palmprint. The framework for proposed system is shown in figure 2. Face and palmprint images are given as inputs from which the input features are extracted and fused using algorithm. By using distance matching the concatenated feature is matched and the distance score will provide recognition identity of a person. By comparing with the templates stored in the database, the matching scores of each classifier are generated. For these two modalities, the classifiers are constructed using the methods proposed in our previous works [8, 9]. Then, the scores output from the two classifiers are combined using several fusion strategies to give a unique matching score. Finally, a decision about whether to accept or reject a user is made.

![Figure 2: A Framework for the Unimodal Biometric Systems](image)

4. PROPOSED SYSTEM

Palmprint and Face acquisition: There are various ways to capture palmprint and face image. Researchers utilize specialized scanners, digital scanners, video camera and tripod to collect palmprint and face images. Specialized scanner captures high resolution images and aligns palms accurately because it has pegs for guiding the placement of hand. Digital scanners produces low quality image and requires large time for scanning, therefore it cannot be used for real time
applications. Digital and video cameras can also capture palm images but can cause recognition problems. In this paper, we used specialized scanners for capturing the palm images and high definition cameras for capturing the face images.

**Preprocessing:** Preprocessing is used to correct distortions, align different images and to crop the region of interest for feature extraction. Research on preprocessing commonly focuses on five steps 1) Binarizing the palm images 2) Boundary tracking 3) Identification of key points 4) Establishing a coordination system and 5) Extracting the central part. The key points for the coordination system are calculated as the midpoint of the two tangent points.

![Flowchart of Palmprint and Face Recognition system](image)

**ROI extraction:** The central part of the palm and face image is segmented after the preprocessing. Different algorithms segment circular, half elliptical or square regions for feature extraction. The square region is the easiest and widely used. The cropped image is then passed through a low pass filter (LPF), which blurs the image. In this blurred image, the minor lines get suppressed. The major lines are also affected, but they are prominent. These are then used for feature extraction.

**Feature extraction and matching:** The aim of this section is to recognize a correct person to authenticate and to prevent multiple people from using the same identity. In identification, the system recognizes an individual by searching the templates of all users in the database for matching.

**Fusion:** Fusion of multiple traits of an individual can improve the matching accuracy of a biometric system. Some of the limitations such as noisy data, intra-class variations, spoof attacks and unacceptable error rates of a unibiometric system can be addressed by designing a system that consolidates multiple sources of biometric information. Multimodal biometric systems are those which utilize, or are capable of utilizing, more than one physiological or behavioral characteristic for enrollment, verification, or identification. The multimodal biometrics has drawn more and more attention in recent years due to its promising applications and theoretical challenges.

**Other Approaches:** Some approaches are difficult to classify because they combine several image processing methods to extract palmprint and face features such as neural network to make final decision, two dimensional dual-tree complexes transform on preprocessed palmprint/face to decompose the images, phase only correlations etc.
5. EXPERIMENT AND RESULTS

Generally, the performance of any biometric recognition system is measured by False Acceptance Rate (FAR) and False Rejection Rate (FRR) or Genuine Acceptance Rate (GAR). The system should have a high GAR with a corresponding low FAR, FRR and Total Error Rate (TER) [28].

FRR, FAR, GAR and TER are determined as follow:

\[ FAR(\%) = \frac{\text{false acceptance numbers}}{\text{No of imposter test}} \times 100\% \]

\[ FRR(\%) = \frac{\text{false rejection numbers}}{\text{No of client test}} \times 100\% \]

\[ GAR(\%) = 100 - FRR(\%) \]

\[ TER(\%) = FRR(\%) + FAR(\%) \]

For palmprint images, PolyU palmprint database is used [10], contains 7752 grayscale images corresponding to 386 different palms (10 samples for each hand). 200 persons have been selected, for each person we have 6 palmprint images for training and 4 for testing.

For face images, database images introduced in [11] is used, collected from 600 volunteers (12 samples for each user). 200 persons have been selected, for each person 6 finger-knuckle images for training and 4 for testing. Table I shows the results of palmprint and Face recognition systems. It could be noticed that the TER is too much to be suitable for high security applications.

**Feature Level Fusion Experimental Results:** The goal of this experiment is to evaluate the system performance when using a unimodal biometric system versus a multimodal biometric system using feature fusion by the aid of Bipartite RankBoost Approach (BRBA) as an optimizer. As mentioned earlier, the first set of experiments (scheme 1) is based on applying BRBA after fusing the features of the palmprint and face. Whereas, the second feature fusion experiments (scheme 2) is based on applying BRBA on each biometric separately, then fused the feature vectors together.

<table>
<thead>
<tr>
<th>Biometric Type</th>
<th>No. of Features</th>
<th>GAR%</th>
<th>FAR%</th>
<th>FRR%</th>
<th>TER%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Palm print</td>
<td>4096</td>
<td>96.76</td>
<td>0.00</td>
<td>3.24</td>
<td>3.24</td>
</tr>
<tr>
<td>Face</td>
<td>4096</td>
<td>85.50</td>
<td>0.00</td>
<td>14.50</td>
<td>14.50</td>
</tr>
</tbody>
</table>

Table 2 shows the results of the classification rate including FAR, FRR, TER and GAR for the proposed multimodal biometric fusion approach by the aid of BRBA as an optimizer (scheme 1). And the number of features before and after using BRBA. It is clear that the performance of the proposed multimodal biometric system outperforms the unimodal systems and strongly reduces the TER, and the number of features to the half. The proposed system achieves significant results with best GAR 98.83% and TER 1.16%.
Table 2: Results of the classification rate including FAR, FRR, TER and GAR (scheme 1)

<table>
<thead>
<tr>
<th>Biometric Type</th>
<th>No. of Features before BRBA</th>
<th>No. of Features After BRBA</th>
<th>GAR%</th>
<th>FAR%</th>
<th>FRR%</th>
<th>TER%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Palm print - Face</td>
<td>8192</td>
<td>3991</td>
<td>98.83</td>
<td>0.00</td>
<td>1.16</td>
<td>1.16</td>
</tr>
</tbody>
</table>

Table 3 shows the result of the classification rate including FAR, FRR, TER and GAR for the proposed multimodal biometric fusion approach by the aid of BRBA as an optimizer (scheme 2), and the number of features before and after using BRBA. It is clear that the performance of the proposed multimodal biometric system outperforms the unimodal systems and strongly reduces the TER, and the number of features to the half. The proposed system achieves significant results with best GAR 98.58% and TER 1.41%.

Table 3: Result of the classification rate including FAR, FRR, TER and GAR (scheme 2)

<table>
<thead>
<tr>
<th>Biometric Type</th>
<th>No. of Features before BRBA</th>
<th>No. of Features After BRBA</th>
<th>GAR%</th>
<th>FAR%</th>
<th>FRR%</th>
<th>TER%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Palm print - Face</td>
<td>8192</td>
<td>4047</td>
<td>98.58</td>
<td>0.00</td>
<td>1.41</td>
<td>1.41</td>
</tr>
</tbody>
</table>

From tables 2 and 3, it’s clear that the results of scheme 1 outperform that of scheme 2 in terms of recognition rates and total equal error rates. But scheme 2 achieves better results in only one case (palmprint). This is because here the recognition rate and error basically depends on the rates of each biometric separately.

Table 4: time consuming in classification without and with using BRBA optimization

<table>
<thead>
<tr>
<th>Fusion without using BRBA</th>
<th>Fusion using BRBA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Palm print - Face</td>
<td>Palm print - Face</td>
</tr>
<tr>
<td>0.10054</td>
<td>0.0490</td>
</tr>
</tbody>
</table>

Table 4 show the time consuming in classification without and with using BRBA optimization. It’s clear that the time consumed decreases to half as the features reduced by 50%. The multimodal system has been designed at multiclassifier & multimodal level. At multi-classifier level, multiple algorithms are combined better results. At first experimental the individual systems were developed and tested for FAR, FRR & accuracy. Table 5 shows FAR, FRR & Accuracy of the systems.

Table 5: Shows FAR, FRR & Accuracy of the systems.

<table>
<thead>
<tr>
<th>Biometric type</th>
<th>Algorithm</th>
<th>FAR%</th>
<th>FRR%</th>
<th>Accuracy%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Face</td>
<td>BRBA</td>
<td>4.5</td>
<td>8.7</td>
<td>97</td>
</tr>
<tr>
<td>palmprint</td>
<td></td>
<td>1.5</td>
<td>2.0</td>
<td>96</td>
</tr>
<tr>
<td>Palmprint-Face</td>
<td></td>
<td>2.4</td>
<td>0.8</td>
<td>98</td>
</tr>
</tbody>
</table>

In the last experiment both the biometric types are combined at matching score level using sum of score technique. The results are found to be very encouraging and promoting for the research in this field. The overall accuracy of the system is more than 98%, FAR & FRR of 2.4% & 0.8% respectively.
Table 6: Performance of BRBA with Other Classifiers

<table>
<thead>
<tr>
<th>Classification Techniques</th>
<th>FAR%</th>
<th>FRR%</th>
</tr>
</thead>
<tbody>
<tr>
<td>PNN</td>
<td>0.005</td>
<td>4.542</td>
</tr>
<tr>
<td>SVM</td>
<td>0.002</td>
<td>5.827</td>
</tr>
<tr>
<td>DT</td>
<td>0.004</td>
<td>6.025</td>
</tr>
<tr>
<td>BRBA</td>
<td>0.005</td>
<td>3.027</td>
</tr>
</tbody>
</table>

6. CONCLUSION

In this paper, we applied Bipartite RankBoost in multimodal biometrics score level fusion with understanding its ability in AUC optimization. We reformulated weak learner used in Bipartite RankBoost for applications in which scores are meaningful. Biometric systems are widely used to overcome the traditional methods of authentication. But the unimodal biometric system fails in case of biometric data for particular biometric types. Thus the individual score of two biometric (face & palmprint) are combined at classifier level and biometric types level to develop a multimodal biometric system. The performance table shows that multimodal system performs better as compared to unimodal biometrics with accuracy of more than 98%. The multimodal system has been designed at multiclassifier & multimodal level. At multi-classifier level, multiple algorithms are combined better results. we conclude that Classifier approach outperforms compared to transformation based score fusion and density based score fusion and AdaBoost achieves the same level of performance compared to Bipartite RankBoost.

7. REFERENCES


7