Hand-Geometry based Person Authentication using Incremental Biased Discriminant Analysis

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Abstract

Hand geometry based biometric verification has proved to be the most suitable and acceptable biometric trait for low security applications as it is less invasive and very user friendly. However the hand-geometry features are not unique and hence this technology is limited to the low-security applications. In this paper, we address of the problem of incremental identification of the optimal discriminating features for hand-geometry based authentication system. In this paper, we argue that the biometric verification problem can be best posed as a single-class recognition problem. We apply Biased Discriminant Analysis in order to transform the features into a new space where the samples are well separated. We also propose to update these features incrementally as the new samples are presented to the system in order to improve the performance of the authentication system over time.

1 Introduction

Biometrics is the science of resolving the identity of an individual based on a feature vector derived from a specific physiological (fingerprints, hand-geometry, face features, palm prints and patterns within the iris or retina) or behavioral characteristics (voice pattern, gait (the manner in which a person walks), and the dynamics of handwriting (signature) or keystrokes). Hand geometry refers to the geometric structure of hand, which includes lengths of fingers, widths at various points on the finger, diameter of the palm, thickness of the palm, etc. Using hand geometry as the biometric trait has several advantages over other biometric traits. The hand images can be obtained using a simple setup including a low-cost digital camera. However, other biometric traits require high-cost scanners to acquire the data. User acceptability for hand-geometry based biometrics is very high as it does not extract detail features of the individual. Thus, for applications where the biometric features are needed to be distinctive enough for verification, hand geometry can be used. Further, hand geometry features can be easily combined with other biometric traits, such as palm print, fingerprint, etc. in multimodal biometric systems. The disadvantage of using hand-geometry is that the discriminative power of the features is very less as compared to the discriminative power of other biometric traits. Also, the hand-geometry features in not invariant to the aging factor.

There has been several hand geometry verification systems published in literature. Jain *et al.* [1] developed a pegged hand geometry verification system for web security. Wong and Shi [2] developed system which uses a hierarchical recognition process, with Gaussian mixture model for the one set of features and a distance metric classification for a different set of features. In [3], a feature selection mechanism has been proposed for hand-geometry based identification system. They perform statistical analysis to determine the discriminability of the features using multiple discriminant analysis.

In this paper we address the problem of incrementally improving the discriminative power of hand-geometry features using a discriminant analysis technique called Incremental Discriminant Analysis (IBDA). Incremental Biased Discriminant Analysis is proposed to incrementally select the discriminative features to adapt to the variations in the hand-geometry features of a user over time. Section 2 provides a brief overview of the problem we are addressing and the details of the BDA we use for selection of features for our verification system. Incremental version of BDA (IBDA) used to improve the performance of the authentication system over time is also discussed in Section 2. Section 3 describes entire hand-geometry based verification process, including the setup, proposed algorithm to select the distinctive features for better verification and the algorithm to learn the optimal features incrementally. We conclude with the discussion on experiments conducted and results obtained in Section 4.

2 Incremental Biased Discriminant Analysis for Biometrics

Hand-geometry features have serious drawback of possessing very low discriminative information and being invariant to the changes exhibited as a result of aging, the user growing fat or thin, etc. Thus, a mechanism is needed to select the features of the human hand such that a user can be clearly distinguished from all the other users and adapt these features to the changes coming in the shape of the human hand over time. Increasing the discriminative content of the hand features has obvious advantage of improvement in the accuracy of the verification system and incremental selection of the discriminative features helps the system to learn over time. As the problem is that of finding the distinctive features for a particular individual, discriminant analysis can be used to select the features. Discriminant analysis [4] has been used for various applications, such as face recognition [5, 6], multi-class text categorization [7], content-based image retrieval [8]. In order to adapt to the changes in the features of users, it is required to incrementally update the eigenspace models of the discriminant analysis techniques. Incremental PCA (IPCA) proposed by Hall *et al.* [9] is based on learning by updating the covariance matrix.

It is required to transform the features into a new space such that the discriminative power of the raw features of hand-geometry for each user is enhanced. However, the transformation is required to be such that the feature vectors of the claimed user get well separated from all the other feature vectors in the database. In other words, the discriminant should be biased towards the claimed identity. In transformed space, the features vectors from the claimed identity are required to get clustered closely while those from the other classes are pushed apart from the features of the claimed identity and hence enhance the performance of the verification algorithm.

We argue that verification problem can be best posed as a single-class classification problem where the user is interested to separate the samples from one individual from those of the uncertain number of individuals. The problem can be approached in various ways. We propose to address this problem using the Biased Discriminant Analysis (BDA) [10] which is a variant of Fisher Discriminant Analysis.

2.1 Biased Discriminant Analysis

Formally, the single-class classification problem or biased classification problem is defined as the learning problem in which there are an unknown number of classes but the user is only interested in one class. The training samples are labeled by the user as only 'positive' or 'negative' as to whether they belong to the desired target class or not. Thus the negative classes can come from an uncertain number of classes.

This section explains Biased Discriminant Aanalysis technique in detail. The Biased Discriminant finds an optimal transformation such that the ratio of 'the negative scatter with respect to the positive centroid' over the 'positive with-in class scatter' is maximized.

The biased criterion function is defined as: Maximize

$$J = \frac{\|W^T S_y W\|}{\|W^T S_x W\|}$$

w.r.t W Let the training set contains N_x positive and N_y negative samples. Then S_x and S_y are defined as,

$$S_x = \sum_{i=1}^{N_x} (x_i - m_x)(x_i - m_x)^T$$

$$S_y = \sum_{i=1}^{N_y} (y_i - m_x)(y_i - m_x)^T$$

where x_i denote the positive samples, y_i denote the negative samples, $m_x = \frac{1}{N_x}\sum_{i=1}^{N_x} x_i$ is the mean vector of the positive samples, and W can be computed from the eigenvectors of $S_x^{-1}S_y$.

Biased Discriminant Analysis works by first minimizing the variance of the positive samples, and then maximizing the distance between the centroid of the positive samples and all the negative samples. In essence, BDA finds the discriminating subspace in which the positive samples are 'pulled' closer to one another while the negative samples are 'pushed' away from the positive ones. Our problem of authentication clearly fits into the single-class framework. In verification problem, all the samples with the same input label are treated as positive while all the other samples are treated as negative. The problem is that of finding a transformation such that the positive cluster is well separated from the negative samples in the transformed feature space.

The scatter of samples in the original feature space is usually high. For verification using techniques such as k-nearest neighbor, the positive samples are needed to be closer to each other so that verification can be performed accurately. Using a single-class discriminant, we can lower the scatter of positive samples and push them apart from the negative samples, thus improving the accuracy of the system.

2.2 Incremental Biased Discriminant Analysis

In this section we present a way to incrementally update the feature vectors of a user in order to improve the performance of the system over time. With BDA, any user can be characterised by the discriminant eigenspace model $\Omega = (S_x, S_y, m_x, m_y, N_x, N_y)$. Let X denote the set of positive samples and Y the set of negative samples. Let x_{new} be the incorrectly verified sample of the user. The problem is that of finding an updated model for all the users using the new sample and the current model. That is, finding $\Omega' = (S_x{}', S_y{}', m_x{}', m_y{}', N_x{}', N_y{}')$ using only $\Omega and x_{new}$. Thus, on every incorrect verification, Ω' is calculated and used for the subsequent verifications. Here we need to consider two cases:

Case(i): The new sample belongs to the positive class, i.e., $x_{new} \in X$ In this case, the set of negative samples remains unchanged. Thus, the number of negative samples and hence the mean of negative samples remain the same. As the new sample belongs to the positive class, number of positive samples increases by 1.

$$N_x{}' = N_x + 1$$

The updated mean of positive samples is

$$m_x{}' = \frac{N_x m_x + x_{new}}{N_x + 1}$$

Updated within class scatter of the positive samples

$$S_x{}' = \sum_{i=1}^{N_x} (x_i - m_x') (x_i - m_x')^T + (x_{new} - m_x')(x_{new} - m_x')^T$$

Using expression for updated mean, $m_x{}'$

$$S_x{}' = \sum_{i=1}^{N_x} \left((x_i - m_x) - \frac{(x_{new} - m_x)}{N_x + 1} \right) \left((x_i - m_x) - \frac{(x_{new} - m_x)}{N_x + 1} \right)^T$$

Since $\sum_{i=1}^{N_x} (x_i - m_x) = 0$,

$$S_x{}' = \sum_{i=1}^{N_x} (x_i - m_x)(x_i - m_x)^T + \frac{(x_{new} - m_x)(x_{new} - m_x)^T}{(N_x + 1)^2}$$

Using the definition of S_x and simplifying the above equation,

$$S_x{}' = S_x + \frac{(x_{new} - m_x)(x_{new} - m_x)^T}{N_x + 1}$$

Updated scatter of negative samples w.r.t the positive mean

$$S_y{}' = \sum_{i=1}^{N_y} (y_i - m_x{}')(y_i - m_x{}')^T$$

Using expression for updated mean, $m_x{}'$

$$S_y{}' = \sum_{i=1}^{N_y} \left((y_i - m_x) - \frac{(x_{new} - m_x)}{N_x + 1} \right) \left((y_i - m_x) - \frac{(x_{new} - m_x)}{N_x + 1} \right)^T$$

$$S_y{}' = \sum_{i=1}^{N_y} (y_i - m_x)(y_i - m_x)^T - \sum_{i=1} N_y \frac{(y_i - m_x)(x_{new} - m_x)^T}{N_x + 1}$$

$$- \sum_{i=1}^{N_y} \frac{(x_{new} - m_x)(y_i - m_x)^T}{N_x + 1} + \frac{(x_{new} - m_x)(x_{new} - m_x)^T}{(N_x + 1)^2}$$

Simplifying the above equation,

$$= S_y - \frac{N_y}{N_x + 1} (m_y - m_x)(x_{new} - m_x)^T - \frac{N_y}{N_x + 1} (x_{new} - m_x)(m_y - m_x)^T$$

$$+ \frac{N_y}{(N_x + 1)^2} (x_{new} - m_x)(x_{new} - m_x)^T$$

Finally, rewriting the above equation in terms of S_y and simplifying, we get the expression for updated S_y

$$S_y{}' = S_y - \frac{N_y}{N_x + 1} [(m_y - m_x)(x_{new} - m_x)^T + (x_{new} - m_x)(m_y - m_x)^T]$$

$$+ \frac{N_y}{(N_x + 1)^2} (x_{new} - m_x)(x_{new} - m_x)^T$$

Case(ii): The new sample belongs to the negative class, i.e. $x_{new} \in Y$ Number of positive samples, mean of positive samples and hence the within class scatter of the positive samples remain unchanged. Hence, Number of negative samples increases by 1.

$$N_y{}' = N_y + 1$$

Updated mean of negative samples

$$m_y{}' = \frac{N_y m_y + x_{new}}{N_y + 1}$$

Updated scatter of negative samples with respect to the positive mean:

$$S_y{}' = \sum_{i=1}^{N_y} (y_i - m_x)(y_i - m_x)^T + (x_{new} - m_x)(x_{new} - m_x)^T$$

Rewriting in terms of S_y,

$$S_y{}' = S_y + (x_{new} - m_x)(x_{new} - m_x)^T$$

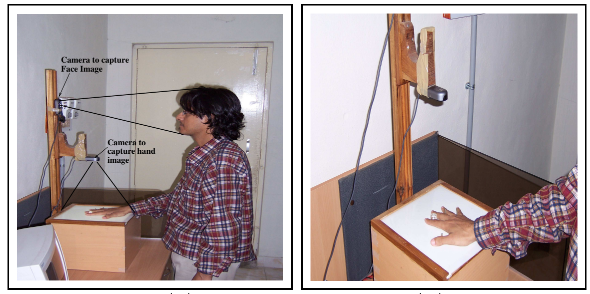
2.3 Online Adaptation using IBDA

Incremental Biased Discriminant Analysis can be applied to the biometric verification problem to select the optimal features for each user to distinguish him from the rest of the users and learn the new model for each of the users if any error occurs during the verification phase. The incorrectly verified sample is used as positive sample for the genuine user and negative sample for all the other users. The discriminant eigenspace models for each of the users is then updated using the formulae derived above. The updated models are used for the subsequent verification phases, updating the models whenever any sample is incorrectly verified. Using IBDA, the system learns using the new incorrectly verified samples and hence improving the performance over time. The features are adapted to the changes in the geometric features of the hand and hence are invariant of the aging factor.

The verification using the IBDA-transformed features does not add to the computational complexity of the system as the training and learning is done offline. During verification phase only multiplication of the samples with the weight matrix adds to the complexity. All the samples incorrectly verified are stored and the updated discriminant eigenspace models for all the users are calculated during learning phase.

3 The System and Feature Extraction

The hand images are acquired using a setup with two digital cameras (one to capture image of hand and the other to capture face image) and a flat platform with five rigid pegs. The setup is designed for multimodal biometric system in which we are trying to fuse the results of hand-geometry and face-based recognition to obtain better accuracy. The setup is shown in Figure 1(a). In this paper, we address incremental feature selection mechanism for hand-geometry based biometric (unimodal) authentication. The top view of flat surface used to capture hand images is shown in Figure 1(b). The five rigid pegs are used to help the user place his hand properly such that the acquired images are well-aligned. The flat surface is translucent white colored and is illuminated by a light source beneath it to ensure that the background is well separated from the foreground (hand image). This helps to binarize the image and use simple image-processing routines to extract the boundary and hence the features from image of the hand. The image capture for both the unimodal (hand geometry) and multimodal systems is shown in Figure 1. As the hand-image is clearly separated from the background, simple thresholding is used to binarize the image. From this binary image, we obtain the longest contour by using the chain code contour extraction method. The acquired and contour-extracted images are shown in Figure 2. The boundary of the hand is defined by the largest contour. We extract lengths of four fingers and widths at five equidistant points on each finger as raw features. As these measurements for thumb show high variability for the same person, we do not include the length and widths of thumb in the feature vector for our system. Hence we obtain the feature vector of size 24 for each person. The raw features are extracted with the help of landmarks defined as the peaks and valleys (Figure 3(a)). The finger tip points are called peaks and the points joining adjacent fingers are termed valleys. These landmarks are then used to extract raw 24-component feature vector (Figure 3(b)).

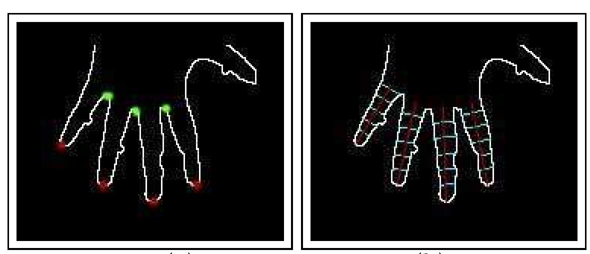


(a) (b)

Figure 1: (a) Face and Hand image acquisition (b) Hand image acquisition

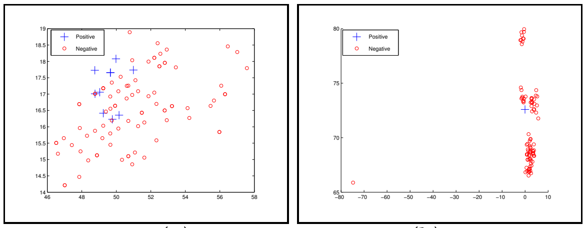
(a) (b)

Figure 2: (a) The acquired image (b) Boundary extracted using contour



(a) (b)

Figure 3: (a) The landmarks (peaks and valleys) extracted (b) The raw features for hand geometry



(a) (b)

Figure 4: (a)Raw training samples (b)The BDA transformed training samples. Positive samples are shown with '+' and negative samples with 'o'

3.1 Training, Verification and Learning

The feature vectors from each of the users is obtained and stored in database. During training phase, samples from each of the users is fed as input to the training algorithm (BDA) and optimal weight matrix and the discriminant eigenspace model Ω for each user is computed and stored.

During the verification phase, the system is presented a new feature vector with the claimed identity. The discriminant eigenspace model for the claimed user is left unchanged if the user is verified correctly. Otherwise the sample is marked as incorrectly verified and it is stored and later used during the next learning phase for updation of the discriminant eigenspace model and optimal weight matrix for the claimed user.

During the learning phase, the incorrectly verified samples are used to update the corresponding models and the updated models are stored for further testing and subsequent learning phases.

4 Results and Discussions

For initial training, we collected data from 20 users with 5 samples from each user. The optimal weight matrix for each user and the corresponding discriminant eigenspace model was obtained and stored using the training algorithm presented above. The scatter of the training samples and the BDA-transformed samples in the first two principal components are shown in the Figure 4.

As can be observed from the figures, the positive samples are scattered more in the original feature space while those in the transformed feature space are less scattered. Hence, the performance of verification algorithm improves as the positive samples come closer to each other.

The performance of the biometric system is measured in terms of False Acceptance Rate (FAR) and False Rejection Rate (FRR). FAR is the rate at which the system accepts a non-authenticated user. FRR is the rate of rejection of a genuine user by the system. 120 images (different from those used for training) were presented during the testing phase. The FAR using the raw features was observed to be 3.3% which reduced to 0.8% as a result of application of BDA-transformed features to the verification algorithm. The system showed FRR of 15% with raw features while with the BDA-transformed features, the FRR of the verification system declined to 8.3%. These results are shown in Table-1. These results were obtained by selecting the number of dimensions of the new feature space as 15.

The improvement in performance (in terms of percentage of number of correctly verified samples) of the verification process over time was observed using Incremental BDA. This experiment was conducted by observing the performance of the verification system for 15 days, taking one sample from each of the enrolled users every day. Figure 5 shows the improvement in performance of the verification system against the number of verification phases. As can be seen from the plot, the performance improves drastically initially due to the model updations performed on the classes corresponding to the incorrectly classified samples. However, the performance declines as a sample which was incorrectly verified was recieved. Required updations were performed on the the corresponding class and the performance was observed to improve again.

	Raw Features	BDA-transformed Features
FRR	3.3%	0.8%
FAR	15%	8.3%

Table 1: Comparison of performance of verification using raw features and BDA-transformed features

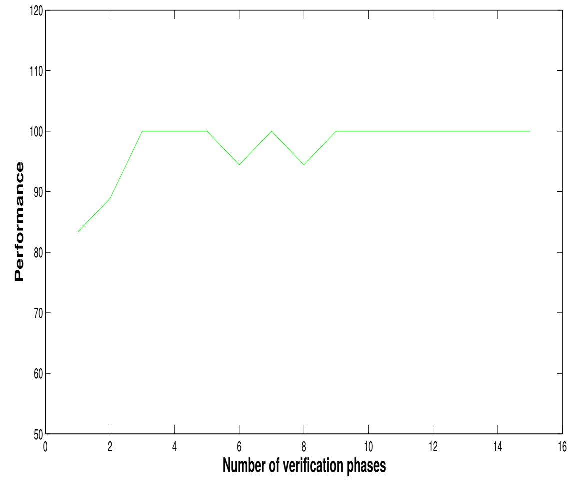


Figure 5: Improvement in Performance using IBDA features

Day	1	2	3	4	5
BDA	83.3	88.8	94.4	88.8	88.8
IBDA	83.3	88.8	100	100	100

Day	6	7	8	9	10
BDA	88.8	94.43	83.3	88.8	94.4
IBDA	94.4	100	94.4	100	100

Day	11	12	13	14	15
BDA	83.3	88.8	94.4	88.8	88.8
IBDA	100	100	100	100	100

Table 2: Comparison of performance of verification using raw features and BDA-transformed features

A comparison of the performance of the verification system over 15 days with BDA features and IBDA features is shown in the Table-2. As can be observed from the table, the performance of the system does not improve when we use BDA features for verification. However, the performance of the system is observed to improve over time with the IBDA features.

5 Conclusion

We proposed to use BDA as a feature selection technique to enhance the performance of hand-geometry based authentication system. With the transformed features, we obtained FRR and FAR of the system as 8.3% and 0.8% respectively over a test set of 120 samples. The performance of the system with transformed features is compared with the raw features and it was experimentally shown that the performance of the authentication greatly improved. We proposed to use IBDA to improve the performance of the system over time. We also compared the performance of the system using BDA and IBDA over time. The performance was observed to improve considerably when IBDA was used as the feature selection mechanism.

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