Feature Selection for Hand-Geometry based Person Authentication

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Abstract

Biometrics traits such as fingerprints, hand geometry, face and voice verification provide a reliable alternative for identity verification and are gaining commercial and high user acceptibilty rate. Hand geometry based biometric verification has proven to be the most suitable and acceptable biometric trait for medium and low security application. Geometric measurements of the human hand have been used for identity authentication in a number of commercial systems. However not much research has been done in the area of selection of the optimal discriminating features for hand-gemetry based authentication system. In this paper, We argue that the biometric verification problem can be best posed as the single-class problem. We propose to apply Biased Discriminant Analysis and Nonparametric Discriminant Analysis in order to transform the features into a new space where the samples are well separated.

1 Introduction

Biometric technologies are becoming the foundation of an extensive array of highly secure identification and personal verification solutions. A biometric system is a pattern-recognition system that recognizes a person based on a feature vector derived from a specific physiological or behavioural characteristic that the person possesses. Examples of physiological characteristics that are used in biometric devices include fingerprints, hand-geometry, face features, palmprints and patterns within the iris or retina, or in the layout of the veins. Behavioural characteristics include voice pattern, gait(the manner in which a person walks), and the dynamics of handwriting(signature) or keystrokes. Associating an identity with an individual is called personal identification. The problem of resolving the identiy of a person can be categorized into two fundamentally distinct types of problems with different inherent complexities: (i) verification and (ii) identification. Verification (also called authentication) refers to the problem of confirming or denying a person's claimed identity (Am I who I claim I am?). Identification (Who am I?) refers to the problem of establishing a subjects's identity. The goal of authentication is to protect a system against unauthorised use. This feature also allows for the protection of individuals by denying the possibility for someone else to impersonate authorised users. Authentication procedures are based on the following approaches:

(i) Knowledge - known information regarding the claimed identity that can only be known or produced by an individual with that identity (eg, passport, password, personal identification number (PIN)). There is high probabality that the individual may forget these attributes or share them with others.

(ii) Possession - the user is be authorised by the possession of an object (smartcard, optical card, etc). However, these cards can be stolen or broken and can be shared hence threatening the security of the system.

(iii) Property - the user directly measures certain properties using the unique human characteristics of the individual (eg, biometrics).Biometrics refers to the science and technology of authentication of persons using automatic verification of personal attributes such as fingers, hands, face, eyes and voice using prints, geometry and pattern recognition. A good introduction to biometric systems in general is provided in [1]. They explain working of biometric systems, errors in biometric systems and various biometric techniques. Utilizing biometrics for personal authentication is becoming convenient and considerably more accurate than previous methods. This is because biometrics links the event to a particular individual (a password or card may be used by someone other than the authorized user), is convenient (nothing to carry or remember). Thus, authentication based on biometric techniques obviates the need to remember the password or carry a token or smartcard.

Biometric system works in two phases: (i) enrolment (ii) verification or identification(depending on the application). During enrolment phase, the templates are extracted from the users and stored in the database with the associated identity. During verification, a template with the claimed identity is presented to the system. The system validates a person's identity by comparing the captured biometric characteristic with the individual's biometric template, prestored in the database. In identification mode, the system searches for a match in the whole database for the template presented to it and returns the identity of the person or fails if the person is not enroled in the system database.

1.1 Hand Geometry based Biometrics

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. These features are not as discriminating as other biometric characteristics(such as fingerprints), they can easily be used for verification purpose. The comprehensive survey of biometric methods are available in [1]. The importance of hand geometry and its user acceptibility is discussed in detail. The hand images can be obtained using a simple setup including a low-cost web cam. However, other biometric traits require specialized, 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 palmprint, fingerprint, etc. in multimodal biometric systems.

There has been several hand geometry verification systems published in literature. Jain et al. [2] developed a pegged hand geometry verification system for web security. Later Jain and Duta [3] developed another pegged system which aligns the two images and define a metric, Mean Alignment Error as the average distance between corresponding points measured between the images to be verified.

Wong and Shi [4] developed system which uses a hierarchical recognition process, with gaussian mixture model used for the one set of features and a distance metric classification for a different set of features.

Although considerable amount of work has been done in order to improve the accuracy of the biometric verification system in the recognition or classification front, not much work has been reported in the area of feature selection for biometric based verification systems. In [5] 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 propose to perform feature selection in order to improve the performance of k-nearest neighbor algorithm for hand-geometry based verification system. We propose to select features for each user such that his features can be clearly distinguished from those of other users. We propose to use discriminant analysis(BDA) to verify identity of a user against all the other users enroled into the system. Section 2 provides a brief overview of the problem we are addressing and the details of the techniques (BDA and NDA) we propose to select features for our verification system. Section 3 describes entire hand-geometry based verification sytem, including the data-collection, feature- extraction and the proposed algorithm to select the disctinctive features of each user for verification. We conclude with the discussion on experiments conducted and results obtained.

2 Feature Selection for Biometrics

Traditionally, biometric verification is done using the distance calculated between the feature vector presented to the system during verification and the feature vectors stored in the database corresponding to the claimed identity. The decision is usually made based on hard-coded thresholds. However, the raw feature vectors usually do not possess much discriminating information. As a result, the samples from one user may get confused with those in some other user, hence lowering the accuracy of the verification system. We propose to address the verification problem as the single-class or (1+x)-class problem and select the features for each individual such that his feature vector is clearly distinguishable from the feature vectors of all the other users. 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 [6] has been used for various applications, such as face recognition [7, 8], multi-class text categorization [9], content-based image retreival [10].

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 tranformed 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 k-nearest neighbor algorithm for verification.

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 variants of Fisher Discriminant Analysis, namely, Biased Discriminant Analysis(BDA) [11] and Non-parametric Discriminant Analysis(NDA) [10].

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.

Our problem of authentication clearly fits into the single-class framework. In verification problem, as opposed to the identification problem the system is presented with a labeled feature vector and it is required to respond back stating whether the feature vector belongs to the claimed user. Hence, all the samples with the input label are labeled positive while all the other samples are labeled negative. The problem is that of finding a transformation such that the positive cluster is well separeted 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 discriminate, we can lower the scatter of positive samples and push them apart from the negative samples, thus improving the accuracy of the system.

As the single-class discriminant analysis brings the positive samples closer and pushes the negative samples from the positive mean, non-linearity in data does not pose problem in case of verification. However non-linearity has serious impact on the performance of the identification problem. Thus, these techniques are best suited to the biometric systems working in verification mode.

Traditionally, the single-class classification problem is addressed simply as a two-class classification problem with symmetric treatment on positive and negative samples, such as FDA. However the intuition is "all positive samples are alike in one way, each negative sample is negative in its own way". Hence, we need a variant of FDA, with biased treatment towards positive samples.

2.1 Single Class Discriminant Analysis

This section explains the existing single class discriminant analysis techniques, namely BDA and NDA in detail. The Biased Discriminant finds an optimal transformtaion 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.

BDA assumes all positive samples form a single Gaussian distribution. This means all positive samples should be similar with similar view angle, similar illumination, etc. However, during data collection, these conditions may not always be similar. To avoid the single Gaussian distribution assumption, a discriminant analysis with non-parametric approach is used.

The optimization function used in NDA is given by:

Maximize

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

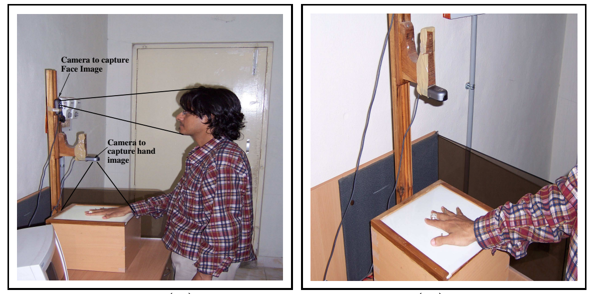
w.r.t W

$\widehat{S_x}$ and $\widehat{S_y}$ are defined as,

$$\widehat{S_x} = \sum_{i=1}^{N_x} (x_i - {m_{xi}}^{kx})(x_i - {m_{xi}}^{kx})^T$$

$$\widehat{S_y} = \sum_{i=1}^{N_y} (y_i - m_{xi}{}^{ky})(y_i - m_{xi}{}^{ky})^T + \sum_{i=1}^{N_x} (x_i - m_{yi}{}^{kx})(y_i - m_{yi}{}^{kx})^T$$

where X_i are positive samples, Y_i are negative samples, $m_{xi}{}^{kx} = \frac{1}{k}\sum_{l=1}^{k} x_l$ is the mean vector of k-positive neighbors of the i^{th} positive sample x_i, $m_{yi}{}^{kx} = \frac{1}{k}\sum_{l=1}^{k} y_l$ is the mean vector of k-negative neighbors of the i^{th} positive sample x_i, $m_{xi}{}^{ky} = \frac{1}{k}\sum_{l=1}^{k} y_l$ is the mean vector of k-positive neighbors of the i^{th} negative sample y_i. The optimal weight vector W can be computed from the eigenvectors of $\widehat{S_x}^{-1}\widehat{S_y}$. In essence, NDA finds the optimal feature set to maximize the margin between all positive samples and all negative samples in the nput feature space.



(a) (b)

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

3 Feature Selection for Hand Geometry

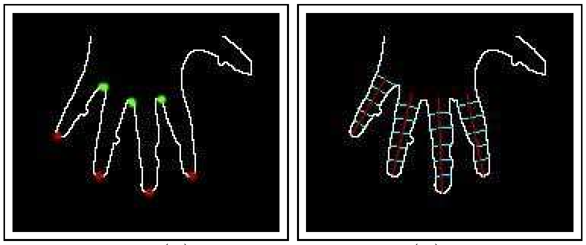
3.1 System and Feature Extraction

The hand images were acquired using a setup with two webcams(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). Both the images(face and hand) are taken simultaneously using the two cameras shown in the figure. In this paper, we address 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(a). As we are not using complex image-processing routines to extract features from the image of the hand, we assume that the user places his hand over the flat surface such that the fingers are well separted. The five rigid pegs shown in the figure serve that purpose. The 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 was clearly separated from the background, simple thresholding was used to binarize the image. From this binary image, we obtained 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 used very simple and primitive raw features for our system and were extracted using very simple image-processing algorithms. We used 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 did not include the length and widths on 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. The fingertip points are called peaks and the points joining adjacent fingers are termed valleys. The peaks and valleys of each finger were extracted by traveling along the hand boundary (Figure 3(a)). These landmarks are then used to extract raw 24-component feature vector (Figure 3(b)). As stated above, these components include lengths of four fingers and widths at five equidistant points on each finger.

(a) (b)

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

During data collection phase, we collected data of 40 students from the same batch whose ages differ by 4-5 years. For each student, features vectors of 10 images were extracted and stored in the database. All the images were captured under similar illumination condition. The similar illumination condition was achieved due to the light source provided beneath the translucent flat surface.



(a) (b)

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

3.2 Training and Verification

The feature vectors from each of the users is obtained and stored in database which are used during training phase. During training phase, samples from each of the user is fed as input to the training algorithm (BDA) and optimal weight matrix is stored. The BDA algorithm for training is presented below:

1. Data Set : $\mathbf{S = s_i, i = 1..N}$,
   where

   N is the number of samples

   $\mathbf{s_i}$ is a $24x1$ vector.

2. for each $k = 1..c, c$ is number of users

3. label all samples in $\mathbf{S}$ from user k as positive and rest as negative:

   - $X = x_i, i = 1..N_x, N_x$ is the number of positive samples.
   - $Y = y_i, i = 1..N_y, N_y$ is the number of negative samples.

4. Calculate mean vector of all the positive samples :m_x.

5. Calculate the scatter matrices: S_x, S_y as defined in Section 3.

6. Calculate W_k as a $(dxd^{'})$ matrix whose columns are the eigen vectors of ${S_x}^{-1}S_y$, where $d^{'}$ is the number of non-zero eigen values. Store W_k.

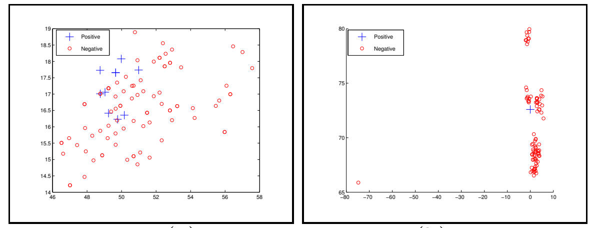
During the verification phase, the system is presented a new feature vector $\mathbf{v}$ with the claimed identity, l.

1. Retrieve W_l corresponding to the user l.

2. Apply the tranformation to all the samples in the data set and to $\mathbf{v}$

   - ${s_i}^{'} = {W_l}^T\mathbf{s_i}, \mathbf{i = 1..N}$
   - $v^{'} = {W_l}^T\mathbf{v}$

3. Apply k-nearest neighbor algorithm to verify the claimed identity, l



(a) (b)

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

4 Experiments and Results

As all the images were extracted under similar illumination condition and the setup was fixed, we used BDA for our experiments. We collected data from 40 users with 10 samples from each user. The optimal weight vector for each user was obtained and stored using the training algorithm presented above. The raw training samples and the 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 k-nearest neighbor algorithm improves as the positive samples come closer to each other.

The performance of the biometric system is measured in terms of False Accept Rate(FAR) and False Reject 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 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 k-nearest neighbor algorithm to the BDA-transformed features. 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.

We observed the effect of changing the dimensionality of the transformed feature space on FRR and FAR of the system. We tested the FRR and FAR of the system with 1, 5 , 8, 10, 15, 20, 22, 24 dimensions. The FRR and FAR of the system was very high with 1 and 5 dimensions. This

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

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

Table 2: Effect of dimensionality on performance of the verification system

Dimensions	1	5	8	10
FRR	23.33%	9.17%	8.33%	8.33%
FRR	5%	0.83%	0.83%	0.83%
Dimensions	15	20	22	24
FRR	8.33%	8.33%	9.17%	9.17%
FRR	0.83%	0.87%	0.92%	0.92%

is because only one dimension was not appropriate to discriminate between the features. However, after that, the FRR and FAR of the system was observed to decline with increasing dimension. This is because the discriminating information is present in the first few dimensions corresponding to the larger eigen values. Thus, as we increase the dimensions, the lower-discriminating components also contribute to the distance between the test sample and the training samples and hence the error rate increases. The results are summarised in the Table-2.

We also observed the effect of number of users enroled into to system on performance of the verification process. The effect of number of users on the performance of the system using Fisher Discriminant Analysis is also presented in the table. Fisher Discriminant Analysis was applied assuming positive and negative to be from two different classes. The performance of verification system using FDA was observed to decline rapidly with increasing number of classes as compared to raw features and BDA-transformed features. This is because the negative samples came from different users and hence did not cluster in the discriminating space. The FRR of the verification system declined when we used BDA-tranformed features. The experiment conducted on 120 samples is summarised in Table-3.

Table 3: Effect of number of users on performance of verification system

No. of Users	10	20	30	40
Accuracy using Raw features	88.33%	88.33%	86.67%	86.67%
Accuracy using FDA features	91.67%	87.50%	80.00%	78.33%
Accuracy using BDA features	92.50%	92.50%	91.67%	91.67%

5 Conclusion

We have proposed a feature selection technique to enhance the performance of hand-geometry based authentication system. With the tranformed features, the FRR and FAR of the system are reported to be 8.3% and 0.8% respectively over a test set of 120 samples. We also discussed the effect of dimensionality and number of users enroled in the system on performance of the system. The performance of the system with tranformed features was compared with the raw features and it was experimentally shown that the performance of the authentication greatly improved.

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