

Feature Level Fusion of Face and Palmprint using Gaussian Mixture Model: Application to Single Sample Analysis

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Abstract: With growing concern about the security, the world over, biometric based person verification is gaining more and more attention. One of the major limitation in Biometric authentication is single sample biometric recognition (unimodal) problem. In this paper, we combine two biometrics namely face and palmprint at feature level using the novel approach based on Log Gabor transform and Gaussian Mixture Model to address this problem. The proposed technique consists of three important steps: First, we vertically fuse the texture features of face and palmprint that are extracted separately using Log-Gabor transform. Second, we model the fused texture data using Gaussian Mixture Model (GMM) to obtain more than one texture transformation matrices. Third, we analyze each of these texture transformation matrices using Principle Component Analysis (PCA) / Independent Component Analysis (ICA) separately. Extensive experiments are carried out on large face and Palmprint databases to prove the efficacy of the proposed method. The experimental results show the superiority of the proposed method compared to some of the existing schemes.

1 Introduction

Traditional methods of establishing a person's identity include knowledge-based (ex. Password) and token based (ex. ID Card) mechanisms, but these representations can be easily manipulated, shared, lost or stolen, thereby undermining the intended security. The need for reliable identification of Legitimate user is obvious. Biometrics offers a natural and reliable solution to many aspects of identity management by the use of fully automated or semi-automated schemes to recognize individuals based on their inherent physical and/or behavioral characteristics [AKJ06]. The most challenging problem in biometric authentication is the single sample biometric recognition. This is a common problem of real world application as it leads to bad recognition results.

Many unimodal biometric (face) algorithms are reported in literature [TCZZ06] [WZ02] to solve the single sample analysis(SSA). But their performance is greatly hindered and few of them like fisherface and its variants completely collapse. Even though improved Linear Discriminate Analysis (LDA) are reported [CLZ02] [YFM06] to solve this problem, but still good performance is not achieved. Recently, the multimodal biometric approaches are used to address this issue [YJW07] [JYY⁺07]. Unlike unimodal biometrics that use only one trait for person Identification/Verification, the multimodal biometric uses more than one biometric trait to make the decision about Accept/Reject. In [YJW07], the mul-

timodal biometric system using face and palmprint is used to address SSA. Each of these modalities are analyzed separately using Gabor transform and PCA then, feature level fusion is carried out by vertically concatenating the features obtained from PCA. Finally, the classification is carried out using Nearest Neighbor Classifier. In [JYY⁺07], multimodal biometrics using face and palmprint is proposed. Here, Gabor transform is carried out independently to analyze face and palmprint images and then they are fused. Finally, Kernel Discriminate Common Vector followed by Radial Basis Function network (KDCV-RBF) is used for classification.

In this paper, we propose a novel approach using Log Gabor transform and Gaussian Mixture Model (GMM) to address the problem of SSA. The main idea of using GMM is to obtain more than one texture transformation matrix and then we analyze each of them separately using popular subspace methods such as PCA/ICA to make the decision about accept/reject. Thus, as opposed to conventional combination of Log Gabor (or even Gabor) transform with PCA, the proposed method will give more than one texture transformation matrix using GMM, whose parameters are learned using Expectation-Maximization (EM) algorithm.

The rest of the paper is organized as follows: Section 2 describes the proposed method, Section 3 describes the experimental results & discussion and Section 4 draws conclusion.

2 Proposed Method

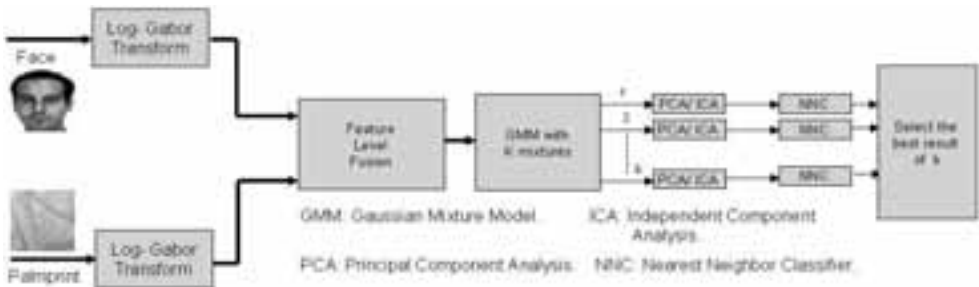


Abbildung 1: Block Diagram of the Proposed Method

Figure 1 shows the block diagram of the proposed method for SSA. The basic idea of the proposed method can be visualized in five different steps: (1) we separately extract the texture features of face and palmprint (2) we do feature level fusion by vertically concatenating the texture features of palmprint and face (3) we model this fused texture features using GMM which in turn gives 'k' (where 'k' denotes the number of mixtures in GMM) different transformed texture matrices (4) we use linear projection techniques such as PCA and ICA (separately) to reduce the dimensionality of 'k' different transformed texture matrices (5) Finally, we do classification using Nearest Neighbor Classifier (NNC).

To extract texture features of face and palmprint, we use Log Gabor transform as it is suitable for analyzing gradually changing data such as face, iris and palmprint [YJW07] and also it is described in [Dav87] that Log Gabor transform can reflect the frequency response of image more realistically. On the linear frequency scale, the transfer function of Log Gabor function has the form [ZCMQ02]:

$$G(\omega) = exp \left\{ \frac{-\log(\omega/\omega_o)^2}{2 \times \log(k/\omega_o)^2} \right\} \quad (1)$$

Where, ω_o is the filter center frequency. To obtain constant shape filter, the ratio k/ω_o must also be held constant for varying ω_o .

The Log Gabor filter used in our experiments has 4 different scale and 8 orientations. Thus, each facial image is analyzed using 32 different Log Gabor filters that results in 32 different filtered images. So, each sample (face/palmprint) image is represented using 32 different images.

After representing each face and palmprint images using Log Gabor filter; we implement the feature level fusion as follows: Let X_{face} and Y_{palm} represents the face and palmprint image sample sets and let x_{face} represents a sample of X_{face} with size 60×60 . Performing the Log Gabor filtering on x_{face} , we get 32 (4×8) different images and then we combine them to get a Log Gabor image sample $x_{LogGaborFace}$ which is of size 240×480 . To reduce the computation cost, transformed image is downsampled by a ratio equal to 4. Thus, the final size of $x_{LogGaborFace}$ is reduced to 60×120 . Similar procedure is also applied on palmprint Y_{palm} to obtain Log Gabor transformed feature set $y_{LogGaborPalm}$. Then, combine $x_{LogGaborFace}$ and its corresponding $y_{LogGaborPalm}$ vertically to get a fused image sample x_{fuse} that is of size 120×120 and repeat this for all the samples of face and palmprint to obtain complete fused set X_{fuse} . Figure 2 shows a sample fused image which combines Log-Gabor transform features (expressed by magnitude values) of face and palmprint vertically. As the imaging conditions of face and palmprint are different feature vector normalization is carried out as follows:

$$x_{fusenorm} = \frac{x_{fuse} - \mu_{face}}{\sigma_{face}} \quad (2)$$

Where μ_{face} and σ_{face} indicates the mean and variance value of X_{fuse} . We then obtain the normalized sample set $X_{fusenorm}$.

In the next step, GMM is used to model the fused texture data $X_{fusenorm}$. Given a N-dimensional data set $X_{fusenorm} = [x_{fusenorm1}, x_{fusenorm2}, \dots, x_{fusenormN}] \in \mathcal{R}^N$ is partitioned into k different clusters and each of these clusters are represented by a linear combination of component density as[MP00]:

$$f(x) = \sum_{i=1}^k p_i G(X_{fusenorm} / \mu_i \Sigma_i) \quad (3)$$

where P_i represents the mixing coefficients or weights for i th term and $G(X_{fusenorm} / \mu_i \Sigma_i)$ represents the multinormal or Gaussian density function. Thus, $G(X_{fusenorm} / \mu_i \Sigma_i)$ can be written

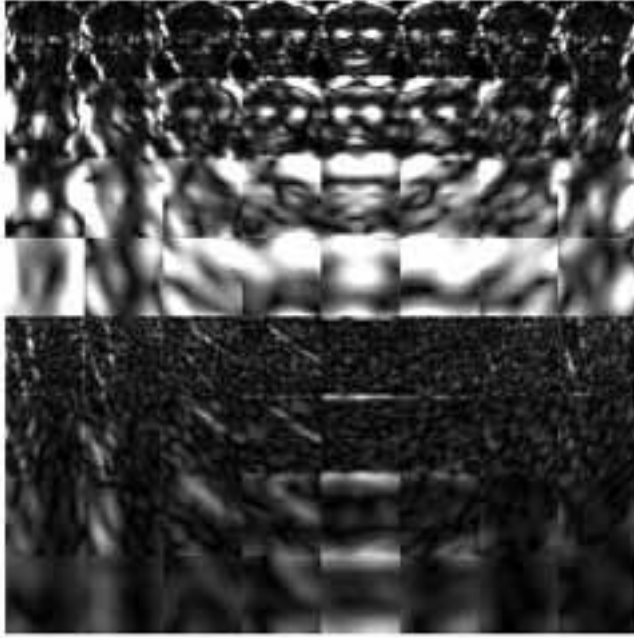


Abbildung 2: Fused Sample Image

as:

$$G(X_{fusenorm}/\mu_i \Sigma_i) = \frac{1}{(2\pi)^{\frac{n}{2}} |\Sigma_i|^{\frac{1}{2}}} \exp \left\{ -\frac{1}{2} (X_{fusenorm} - \mu_i)^T \Sigma_i^{-1} (X_{fusenorm} - \mu_i) \right\} \quad (4)$$

where $X_{fusenorm}$ is the N -dimensional vector, μ_i is the N -dimensional vector of means and Σ_i is a $N \times N$ covariance matrix of i th mixture. In employing the GMM, we first learn the different Gaussian mixtures as done classically in the literature [MP00]: in practice after determining the right number of mixtures, we use the EM algorithm in order to learn the GMM parameters using learning (training) database. In majority of analysis, the GMM is used to obtain the likelihood ratio, but, in our proposed method, we use square symmetric (covariance) matrices (Σ_i) given by GMM for further analysis. Thus, a GMM with k mixtures will give k different square symmetric matrices. For each square symmetric matrix, we then determine the associated PCA/ICA transformation separately. Thus, we have two different approaches: First, the approach based on Log-Gabor, GMM and PCA (LG-GMM-PCA) in which PCA is used to reduce the dimension of texture transformation data. More details of PCA can be found in [MA91]. Second, the approach based on Log-Gabor, GMM and ICA (LG-GMM-ICA). According to literature [BMS02], there are two ways in which ICA architecture can be implemented in image recognition task. In Architecture I (ICA I) input images in $X_{fusenorm}$ are considered as a linear mixture of image of a statistically independent basis S combined with an unknown mixing matrix

M. The ICA I algorithm learns the weight matrix w that corresponds to the coefficients of the linear mixture [BMS02]. Architecture II (ICA II) finds the statistically independent coefficients for input data. In practice, ICA II separates the data taking into account higher statistics while ICA I addresses the variation up to second order statistics. Here, we have two methods such as LG-GMM-ICA I and LG-GMM-ICA II. After projecting the k transformation matrices using PCA/ ICA (ICA I & ICA II separately), the classification is carried out using Nearest Neighbor Classifier (NNC). That is, for each test and training images, we calculate k distances (k is the number of mixtures) using NNC and, at the end, we select the transformation matrix that gives the minimal distance.

2.1 Model Order

Before using the Mixture model, one has to determine the number of mixture components i.e. number of mixtures. Choosing few components may not accurately model the distinguishing features present in our fused data. Also, choosing too many components may over fit the data and reduce the performance and also result in excessive computational complexity both in training and classification. In our experiments, we find the model order by cross validation. Given a training dataset, we evaluate the performance over different numbers of mixture components. We then select the number of mixture components which give the best performance.

3 Experimental Results and Discussion

This section describes the results obtained using proposed algorithm on feature level fusion of Face and Palmprint. Here, we first introduce face and palmprint databases and then provide the feature level fusion results. We use the public face database, the AR database [ard]. The AR database contains over 4000 images corresponding to 126 users under conditions where there is a variation over time, in lighting variation, in facial expression and in occlusion conditions. The pictures of most persons are taken in two sessions separated by two weeks. Each session contains 13 images and 119 individual (65 men and 54 women) were participated in both session. The images of these 119 users are selected and used in our experiments. All image samples are with resize to the resolution of 60×60 pixels. We use PoluU palmprint database (version 2) provided by Hong Kong Polytechnic university[pol]. This database consists of 7752 images captured from 386 different palms. The samples of each palm are collected in two sessions where average between first and second session is about two months and each palmprint has 20 images. For our experiments, we extract the Region of Interest (ROI) as mentioned in [HJZ08] with a fixed size of 60×60 .

To a build a chimeric multimodal biometric database for our SSA, we take sample set of same size from these two databases. We use all 119 face classes with each class containing the first 20 sample and use first 119 palmprint classes with each other containing all 20

samples. In our experiments, we set number of training sample per class to be 1 and remainder are used as testing samples. Thus, we have 119 training samples and 2261 testing samples and we repeat this training and testing partition for 20 times. In our experiments, We select the dominant PCs corresponding to 90% of variance (Extensive experiments are carried out for different variances and finally, we fix the value to 90% as it gives the best result). Figure 3 shows the recognition results for all compared methods when the selected single sample is varied form 1 to 20. For the clarity of figure, we have shown the comparison of three proposed method with individual biometrics and also with fusion of face and palmprint using Log Gabor transform alone. It is observed from Figure 3 that the proposed LGMM based on ICA II outperforms all remaining methods.

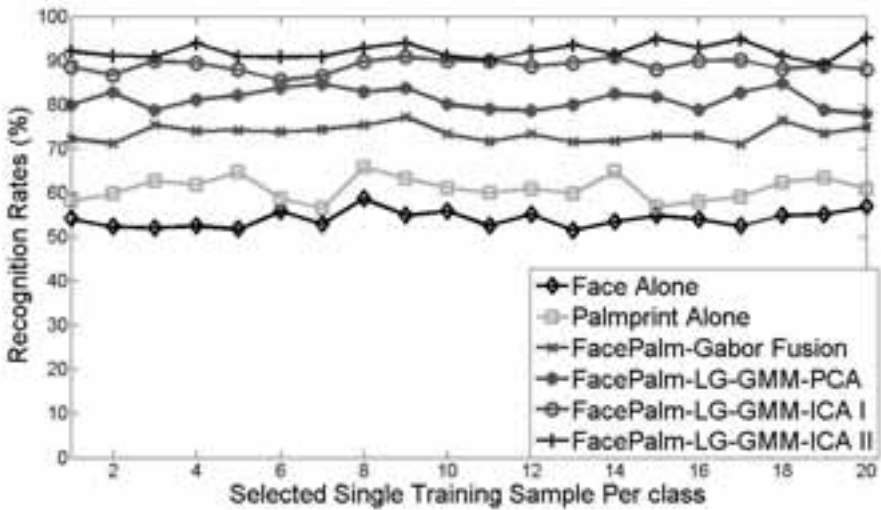


Abbildung 3: Recognition results of the Proposed Methods

Table 1 shows the average recognition results of three proposed method with the performance of individual biometrics, fusion and fusion followed with PCA, ICA I and ICA II. The best performance is noted for our proposed LGMM based on ICA II with average recognition rate of 92.16%. It is also observed from Table 1 that the performance of proposed mixture models is better than non mixture models approaches. In order to explain why ICA II is performing better with GMM while it is the worst method in the non Mixture Model case, we suggest the following interpretation. We think that the GMM will effectively model the higher order statistics while ICA II is able to properly address these higher order statistics presented by GMM. For this reason, the proposed ICA II MM shows the best performance over the other methods. Thus, the combination of Log Gabor Transform with GMM followed with ICA II appears gently as the best method.

Tabelle 1: Average Recognition Results of Proposed Methods

Methods	Recognition Rates (%) Mean Value and Variance	Standard Error
Face-Log Gabor Alone	54.07 ± 3.56	0.42
Palm-Log Gabor Alone	60.95 ± 7.13	0.60
FacePalm-Log Gabor-Fusion	73.54 ± 2.99	0.38
FacePalm-Log Gabor-Fusion-PCA	76.62 ± 6.95	0.58
FacePalm-Log Gabor-Fusion-ICA I	80.75 ± 5.14	0.50
FacePalm-Log Gabor-Fusion-ICA II	74.04 ± 6.13	0.55
FacePalm-LG-GMM-PCA	81.21 ± 4.91	0.49
FacePalm-LG-GMM-ICA I	88.86 ± 2.97	0.38
FacePalm-LG-GMM-ICA II	92.16 ± 2.08	0.32

4 Conclusion

In this paper, we propose a possible solution for single sample biometric recognition using Log Gabor transform and GMM. The main advantage of proposed method is that, it gives more than one set of texture transformation matrices. Based on the extensive experiments carried out on large database of face and palmprint following can be concluded:

1. In general Mixture Models and Multimodal features perform better than non Mixture model and Unimodal biometric based authentication systems.
2. Specifically the proposed GMM based approaches such as LG-GMM based on PCA, ICA I and ICA II outperforms non mixture model approaches such as PCA, ICA I and ICA II.
3. Proposed LG-GMM based on ICA II shows the best result with recognition rate of 92.16% with lowest standard error of 0.32%.

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