Face Verification Based on Gabor Region Covariance Matrices

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Abstract. This paper introduces a novel face verification approach using the Gabor Region Covariance Matrices (GRCM). First, we represent the face images with d dimensional Gabor images. Then, we divide these images into overlapping regions. From each region, we compute a $d \times d$ covariance matrix. Inspired by the GMM-UBM speaker verification framework, we propose a new decision rule based on the Riemannian mean of the Gabor region covariance matrices computed from background faces. Finally, score normalization techniques are incorporated in the proposed framework to enhance the verification performance. Extensive experiments on two benchmark databases, namely Banca and SCface showed very interesting results which compare favorably against many state-of-the-art methods.

1 Introduction

Because of its natural and non-intrusive interaction, identity verification and recognition using facial information is among the most active and challenging areas in computer vision research [13]. Despite the great deal of progress during the recent years, face biometrics is still a major area of research. Wide range of viewpoints, occlusions, aging of subjects and complex outdoor lighting are challenges in face recognition. Face recognition methods can generally be divided into two classes: global matching methods and local or component matching methods. The global methods represent the whole face image with a single feature vector which can be used as an input to a classifier. Among the several classifiers proposed in the literature we can cite: the minimum distance classification applied in the eigenspace [21], the Fisher discriminant analysis [3], the neural network [6], the Support Vector Machine, SVM [4] . In term of performance, the global methods give good results in classifying near frontal faces. However, their robustness degrades against pose changes since the global feature vectors are sensitive to rotation and translation. By dividing the face images into components and allowing certain geometrical flexibility between these components during the classification stage, the local matching methods have shown good performances compared with the global methods [10].

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For both global and local methods, feature extraction and representation is a crucial step. It is widely believed that the features extracted with a spatial-frequency analysis are more robust to pose and illumination changes [26]. As wavelet transformations are localized in both time and frequency domains, it can be a good choice for representing the face images [17]. Among the various wavelet techniques proposed in the literature, the Gabor functions provide the optimal resolution in both spatial and frequency domains [5]. The application of the Gabor wavelet in face recognition was pioneered by Lades et al. in 1993 [12], when they proposed a face recognition system (Dynamic Link Architecture, DLA) based on the Gabor jets extracted from the nodes of a rectangular grid. Later on, Wiskott et al. extended the DLA methods and proposed the Elastic Base Graph Matching method (EBGM) [24], where the rectangular grid was replaced by a number of facial landmarks. Since then, a large number of face recognition systems were proposed based on this Gabor wavelet transformation [20].

In 2006, Tuzel et al. [22] proposed a new object detection and classification method called Region Covariance Matrices (RCMs). This method is based on the analysis of the feature covariance matrices computed inside a region of interest. As the covariance matrices do not encode information regarding the ordering and the number of points, the RCMs method inherits certain robustness against small rotation and scaling. Furthermore, the subtraction of the mean during the covariance computation can reduce the effect of the global illumination changes. In the original RCMs method [22], the covariance matrices were computed from a set of features including pixels coordinates, color values and the norm of the first and second order gradient. Although these features yield in good results in detecting and tracking objects, their application to the face recognition problem [15] did not show promising performance. To enhance this performance, Pang et al. [15] proposed a face recognition system using Gabor Region Covariance Matrices (GRCMs), where the pixel location and the Gabor features were used to construct the region covariance matrices. Their experimental results have demonstrated the effectiveness of GRCM compared to the original RCM method.

In the present work, we adopt the idea behind the use of the Universal Background Model in the GMM-UBM speaker verification system [18], and propose a new face verification approach based on the Gabor Region Covariance Matrices (GRCM) [15]. After constructing symmetric definite positive GRCM from a background set of human faces, we use the Riemannian mean function to compute a Universal Background Gabor Region Covariance Matrices (UBGRCM). These matrices are used later on, in the classification stage to estimate the similarity between the GRCM extracted from the query and the target images. Furthermore, we have studied the effect of the normalization methods on the resulting scores. The experimental results on two challenging databases (Banca and SCface) showed the efficiency of our proposed method compared to many state-of-the-art methods.

The reminder of this paper is organized as follows. In Section 2, we describe the Gabor wavelet transformation. In Section 3 and Section 4, we present the GRCMs and our proposed approach, respectively. Section 5 presents the experimental setup whereas Section 6 discusses the obtained results. Finally, Section **??** concludes this paper.

2 Gabor Based Face Representation

Since the discovery of crystalline organization of the primary visual cortex in mammalian brains by Hubel and Wiesel [11], an enormous amount of research has been concentrated in understanding this area and the proprieties of its cells. As these research works found that the simple cells in human visual cortex are selectively tuned to orientation as well as spatial frequency, Daugman proposed in [5] to approximate the response of these cells by the Gabor function:

$$\varphi_{u,v}(z) = \frac{\|K_{u,v}\|}{\sigma^2} e^{(-\|K_{u,v}\|^2\|z\|^2/2\sigma^2)}[e^{(izk_{u,v})} - e^{-\sigma^2/2}] \quad (1)$$

Where $z = (x, y)$ is the pixel coordinate, $\|.\|$ denotes the norm operator, σ is the standard deviation of a Gaussian envelope and $K_{u,v}$ is a wave vector defined by:

$$K_{u,v} = K_v e^{i\phi_u} \quad (2)$$

Where, $K_v = k_{max}/f_v$ and $\phi_u = \frac{\pi u}{8}$. k_{max} is the maximum frequency and f_v is the spacing factor. v and u represent respectively the scale and the orientation of the wave vector. This Gabor function is similar to enhancing the edge contours as well as the valleys and the ridge contours of an image. In the case of face images, this corresponds to enhancing eyes, mouth and nose which are the main discriminating points in human faces.

Some previous works [14] [25] showed that the use of the Gabor kernels computed in 5 scales ($v \in \{0 \dots 4\}$) and 8 orientations ($u \in \{0 \dots 7\}$) with $k_{max} = \pi/2$, $f_v = \sqrt{2}^v$ and $\sigma = 2\pi$ give a good representation for the face images. The real parts of these kernels are presented in Figure 1.

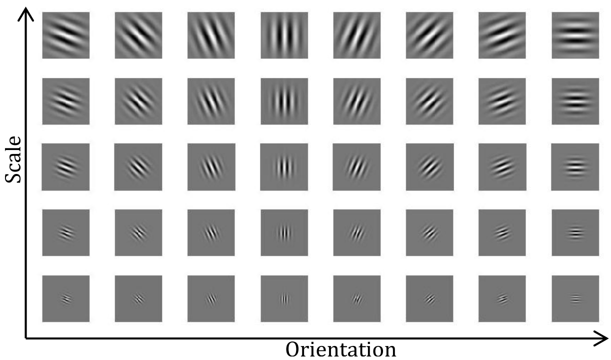

Fig. 1. The real parts of the Gabor Kernels computed in 5 scales and 8 orientations

Finally, The Gabor representation of a face image I can be obtained by convolving this image with the Gabor filters as follows:

$$G_{u,v}(z) = |I(z) * \varphi_{u,v}(z)| \tag{3}$$

Where $z = (x, y)$, $*$ denote the convolution operator and $|.|$ is the magnitude operator.

3 Gabor Region Covariance Matrices

Let I be a face image and let $G_{u,v}\{u = 0...7, v = 0...4\}$ its 2-D Gabor transformation. Each pixel p_i of the original image I will be represented by a row pixel:

$$w_i = [x, y, G_{0,0}(x, y), G_{1,0}(x, y), ..., G_{7,4}(x, y)]$$

Where x and y are the location of the pixel p_i.

The Covariance Matrix of a region R (Figure 2) is a matrix C_R with diagonal entries correspond to the variance of the features and the non-diagonal entries correspond to their correlation.

$$C_R = \frac{1}{n-1} \sum_{i=1}^{n} (w_i - \mu_R)(w_i - \mu_R)^t \tag{4}$$

In equation 4, n represents the number of the row pixels inside the region R and μ_R is their corresponding mean:

$$\mu_R = 1/n \sum_{i=1}^{n} w_i \tag{5}$$

Although the variance of the coordinates x and y is the same for all the regions of the same size, they are still important since their correlations with the other features are used as the non-diagonal entries of the matrix. Therefore, the constructed GRCMs capture both spatial and statistical properties.

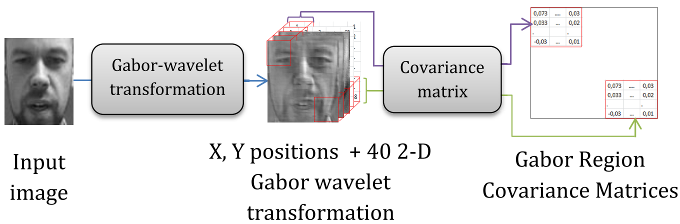

Fig. 2. Computation of the Gabor Region Covariance Matrices (GRCMs)

In [22], the authors used the integral images of each feature and the multiplication of any two features to compute the covariance matrix of any region with only few access memory. For more detail about this technique reader is refered to [22].

The main advantages of using the covariance matrices to represent the face images are 1) The covariance matrices provide a natural way to fuse multiple features without the need of any normalization methods. 2) They are basically invariant to scaling and rotation of the images, as the order and the number of the points are not represented by the covariance matrices. 3) They are robust to global illumination changes, since the mean is subtracted during the covariance computation.

4 Proposed Approach

In this work, we assume that the region covariance matrices representing the face images contain two types of information: discriminating information specific to each user and common information shared between the human faces. Thus, to enhance the discrimination of the GRCMs method it is worth to reduce the effect of the common information. Inspired by the use of the Universal Background Model (UBM) in Gaussian Mixtures Model-Universal Background Model (GMM-UBM) speaker verification framework [18], we propose to model the common information by a Universal Background Gabor Region Covariance Matrices (UBGRCMs), and use these matrices in the scoring stage to estimate the similarity between the test and the enrollment GRCMs. The UBGRCMs are the mean of the GRCMs extracted from a background set of human faces (Figure 3). As the covariance matrices are symmetric definite positive and lie in the Riemannian manifold, the Riemannian mean is used instead of the Euclidean mean.

4.1 Riemannian Mean

Let $\{C_1, C_2, ..., C_P\}$ a set of P covariance matrices. The Riemannian mean [16] of these matrices is the matrix C which minimizes the sum of the squared distances.

$$C = \underset{C}{\operatorname{argmin}} \sum_{i=1}^{P} \rho^2(C_i, C) \tag{6}$$

Where $\rho(C_i, C)$ is the distance between the two covariance matrices C and C_i (see Section 4.2). As C is defined through a minimization procedure, we approximate it by the intrinsic Newton gradient descent method. In the following (Algorithm 1), we describe the algorithm computing the mean Riemannian of a P covariance matrices.

In this algorithm, $ln(M)$ and $exp(M)$ were computed as:

$$ln(M) = U ln(D) U^t$$
$$exp(M) = U exp(D) U^t$$

Algorithm 1. Computation of the mean Riemannian covariance matrix

Data: Covariance Matrices $\{C_1, C_2, ..., C_P\}$
Result: Mean Covariance Matrix C
$C = C_t \ (t \in \{1..P\})$;
nb_iterations=5;
it=1;
while *it<=nb_iterations* **do**
  M=zeros(size(C));
  for *i=1:P* **do**
    $M = M + C^{1/2} ln(C^{-1/2} C_i C^{-1/2}) C^{1/2}$
  M=M/P;
  $C = C^{1/2} exp(C^{-1/2} M C^{-1/2}) C^{1/2}$;
  it=it+1;

Where U is an orthogonal matrix and D is the diagonal matrix of the eigenvalues ($M = UDU^t$).

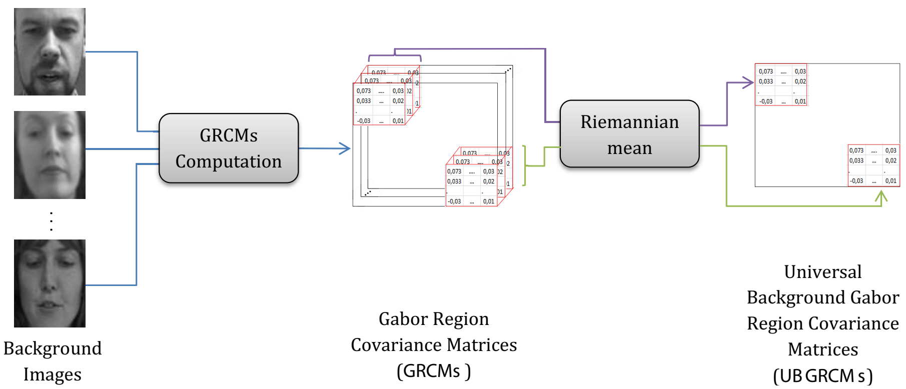

Fig. 3. Computation of the Universal Background Gabor Region Covariance Matrices (UBGRCMs)

4.2 Distance Measure

To compare two covariance matrices (C_1 and C_2), the eigenvalue based distance [7] is adopted. This distance is calculated as follows:

$$\rho(C_1, C_2) = \sqrt{\sum_{i=1}^{n} ln^2 \lambda_i (C_1, C_2)} \quad (8)$$

Where $\{\lambda_i(C_1, C_2)\}_{i=1...n}$ are the generalized eigenvalues of the two covariance matrices C_1 and C_2.

Now, let $X = \{C_x^1, C_x^2, ...C_x^N\}, Y = \{C_y^1, C_y^2, ...C_y^N\}, U = \{C_u^1, C_u^2, ...C_u^N\}$ be three sets of GRCMs corresponding respectively to the reference image r, the test image t and the UBGRCMs of a background set images u.

In the first step, the similarity (D_1) between the test and the reference Gabor region covariance matrices is computed as follows:

$$D_1(Y, X) = \sum_{i=1}^{N} \rho(C_y^i, C_x^i) \tag{9}$$

In the second step and in order to reduce the effect of the common information, the similarity between the test and the reference GRCM (D_2) is computed using the Log-Likelihood Ratio test.

$$D_2(Y, X, U) = \log(p(Y|X)) - \log(p(Y|U)) \tag{10}$$

As the similarity between two sets of GRCM (X_1 and X_2) is given by the Eigen-value based distance (equation 9), we use the following approximation to transform this distance into probability:

$$p(X_1|X_2) = \exp(-\alpha D_1(X_1, X_2)) \tag{11}$$

Where α is a positive constant. By substituting (11) into (10) we obtain:

$$\begin{aligned} D_2(Y, X, U) &= \log(\exp(-\alpha D_1(Y, X))) - \log(\exp(-\alpha D_1(Y, U))) \\ &= -\alpha(D_1(Y, X) - D_1(Y, U)) \end{aligned} \tag{12}$$

Because α is a positive constant, we consider only the difference between the two distances $D_1(Y, X)$ and $D_1(Y, U)$ as a final score. Figure 4 illustrates the computation of the two similarity measures D_1 and D_2.

5 Experimental Data and Setup

We tested our approach on two benchmark databases: Banca [2] and SCface [8]. Following, we describe these databases and their corresponding parameters.

SCface database: The Surveillance Cameras face database (SCface) [8] is a very challenging database. It was acquired in a real-life scenario using commercially surveillance equipments. In the DayTime authentication protocol used in this study, the clients of the database were divided according to their ID numbers into three subsets. The clients with ID numbers between 1-43 were used to construct the training subset, used to learn the background parameters such as the background models and the subspace matrices. In our work, we use the high quality migshot images of this subset to compute the UBGRCMs. The development and the test subsets are constructed respectively by the clients

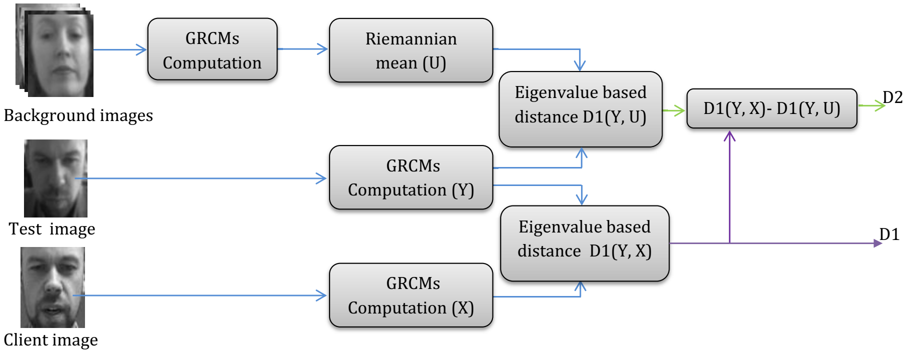

Fig. 4. Computation of the two distances D_1 and D_2

with ID numbers between 44-87 and 88-130. In both these subsets, the mugshot images were used to construct the clients models, while the test images were taken from 5 surveillance cameras at 3 different distances: close (1 m), medium (2.60 m) and far (4.20 m). Because of the low quality of the SCface images, the face images were cropped with dimension of 112×96 and histogram equalization is applied to each cropped image. Finally, the GRCMs were computed from 16×16 pixels regions with 8 pixels step.

BANCA database: The multi-modal BANCA database [2] contains video recordings of 52 subjects (26 male and 26 female). These recordings were captured over 12 different sessions spanning on three months. Sessions 1-4 contain recordings under controlled scenario, while sessions 5-8 and 9-12 contain degraded and adverse scenarios, respectively. Five pre-selected still face images were taken from each video. The 52 subjects were divided into 2 equal groups: G1 and G2 (13 male and 13 female each) which represent respectively the development and the evaluation sets.

From the 7 authentication protocols proposed for BANCA database, our experiments were done only on the pooled (P) protocol as it is the most challenging protocol. In this protocol, the client models of the two groups were created using only 5 images from the controlled scenario, while the test images were taken from the three scenarios (controlled, degraded and adverse). The GRCMs are computed from 8×8 pixel regions with 4 pixels step. Before computing the GRCM, the Banca face images were cropped and resized to 88×68 and Tan & Triggs pre-processing was applied on each image. The GRCMs extracted from the background set images are used to compute the UBGRCM.

In both Banca and SCface databases, the scores generated on the development set were used to compute the Equal Error Rate (EER) which represent the point where the False Acceptance Rate (FAR) and the False Rejection Rate (FRR) are equal. The threshold θ corresponding to this point was then applied to the evaluation scores to obtain the Half Total Error Rate (HTER), which is the mean of the FAR and FRR at that threshold.

Table 1. The performance of the GRCM method on BANCA and SCface databases

	BANCA		SCface	
Method	EER%	HTER%	EER%	HTER%
GRCM $+D_1$	18.8	19.8	31.3	34.7
GRCM $+D_2$	9.1	10.7	16.9	19.8
GRCM $+D_2+$ Z-NORM	9.8	8.9	15.0	16.2
GRCM $+D_2+$ T-NORM	6.2	9.3	16.5	24.6
GRCM $+D_2+$ ZT-NORM	**6.2**	**6.0**	**13.6**	**15.7**

Table 2. Comparison of the proposed approach with state-of-the-art methods on Banca and SCface databases

	BANCA		SCface	
Method	EER%	HTER%	EER%	HTER%
MRH [19]	14.3	13.8	42.6	42.5
GMM [23]	11.9	12.8	30.3	29.8
LBP	15.2	15.4	41.1	42.8
LGBPHS [9]	13.2	16.1	-	-
Gabor Graphs [9]	11.7	12.4	-	-
GRCM $+D_2$	**9.1**	**10.7**	**16.9**	**19.8**
MRH+ZT-Norm [19]	9.3	8.4	28.3	30.3
GMM+ZT-Norm [23]	8.3	7.0	23.3	22.7
LBP+ZT-Norm	6.7	**5.0**	17.4	19.0
GRCM $+D_2$+ZT-Norm	**6.2**	6.0	**13.6**	**15.7**

In this work, we have also studied the effect of the score normalization techniques on the performance of our system. Three normalization methods [1] have been tested: Zero-Normalization (Z-Norm), Test-Normalization (T-Norm) and ZT-Norm which is a combination of the two previous methods. The Z-Norm method aims to characterize the response of each client model to a variety of (impostor) test images, while the T-Norm is used to compensate the variations of the testing image. As in both Banca and SCface databases the development and the evaluation sets are independent, the normalization statistics of the development set were estimated using the evaluation set data and vice versa.

6 Results and Discussion

In this section, we report the performance of the proposed approach on the aforementioned databases. First, a comparison between the performance of the two decision rules (D_1 and D_2) is presented. From Table 1, we can clearly see that the D_2 method provides performance improvement for both databases compared to the D_1 method. Specifically, the HTER is reduced with 42.93% and 45.95 % on Banca and SCface databases, respectively.

To further improve these performances, we applied normalization on the obtained scores. Although these methods were proposed for speaker recognition, their application to the face modality showed significant performance improvements [23]. The results also show that the ZT-Norm method improves the performance with 20,70% and 43,92%, on SCface and Banca databases, respectively.

Tables 2 compares the performance of the proposed method against some state-of-the-art face verification methods. From this table, we can observe that without the ZT-Norm normalization our proposed approach outperforms the Local Binary Pattern (LBP), the Multi-Region probabilistic Histograms (MRH) and the Gaussian Mixture models (GMM) methods on both Banca and SCface databases. Our method gives better results than the Local Gabor Binary Pattern Histogram Sequence (LGBPHS) and the Gabor graph methods on Banca database. With the ZT-Norm normalization, our approach still gives the best performance compared to LBP, GMM and MRH methods, except on the development set of Banca database where the LBP method outperforms our approach.

7 Conclusion

In this work, we investigated the use of the Gabor Region Covariance Matrices (GRCMs) in the face verification problem. First, we represented the face images with $W \times H \times d$ dimensional feature matrices which are divided into many overlapping regions. For each region, we computed a $d \times d$ covariance matrix. The direct use of the eigenvalue-based distance between the covariance matrices extracted from the test and the enrollment images did not yield in reliable performances. To overcome these limitations, we proposed a new decision rule using UBGRCMs computed from a background set of human faces. The UBGRCMs theoretically represent the common information of different human faces which should be ignored when comparing two faces. The conducted experiments showed that the proposed decision rule improved the performance of our system on two challenging databases: Banca and SCface. In addition, we have further improved the obtained results by applying different scores normalization methods. Finally, a comparison with some state-of-the-art methods showed the efficiency of our proposed method.

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