Fusion of Support Vector Classifiers for Parallel Gabor Methods Applied to Face Verification

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Abstract. In this paper we present a fusion technique for Support Vector Machine (SVM) scores, obtained after a dimension reduction with Bilateral-projection-based Two-Dimensional Principal Component Analysis (B2DPCA) for Gabor features. We apply this new algorithm to face verification. Several experiments have been performed with the public domain FRAV2D face database (109 subjects). A total of 40 wavelets (5 frequencies and 8 orientations) have been used. Each set of wavelet-convolved images is considered in parallel for the B2DPCA and the SVM classification. A final fusion is performed combining the SVM scores for the 40 wavelets with a raw average. The proposed algorithm outperforms the standard dimension reduction techniques, such as Principal Component Analysis (PCA) and B2DPCA.

Keywords: Biometrics, Face Verification, Gabor Wavelet, Principal Component Analysis, Bilateral 2D Principal Component Analysis, Parallel Gabor Principal Component Analysis, Support Vector Machine.

1 Introduction

Since the last decade, face biometrics applications have been found to be feasible, as well as user-friendly and privacy-respectful methods. One of the working modes of these systems is the so-called face verification, where a user claims an identity, in the same way as a person does when writing his/her PIN number at an automated teller machine. The user's biometric data are compared to his/her corresponding biometric template in order to verify whether or not the person is who he/she claims to be. Therefore face verification is a 1-to-1 problem, much easy to tackle compared to face identification (1-to-*N* problem).

The huge amount of biometric data makes it mandatory to perform a dimension reduction prior to any processing. Turk and Pentland presented the now classical Principal Component Analysis method (PCA), which maximizes the variance over the data, after converting the images into column vectors [1]. There have been several

M. Haindl, J. Kittler, and F. Roli (Eds.): MCS 2007, LNCS 4472, pp. 141–150, 2007.

modifications and improvements of this method. For instance, in [2] the so-called 2DPCA was proposed, which keeps the 2D information in the images, as every pixel is correlated to its neighbours. In fact, this method is equivalent to perform a PCA over the rows of the image [3]. Although 2DPCA outperforms PCA in recognition rates, it usually needs more projection coefficients. A Bilateral-projection-based Two-Dimensional Principal Component Analysis (B2DPCA) was developed as an alternative to 2DPCA [3]. One of the challenges to achieve with B2DPCA was to remove the necessity of more coefficients to represent an image in 2DPCA than in PCA. Furthermore, these authors demonstrated the superiority of this method over the conventional PCA for face recognition.

Gabor wavelets [4] are a useful technique because of their resemblance to the sensibility of visual cortex in mammals. Their good results when applied to face recognition and their robustness to changes of illumination make these wavelets a powerful tool in biometrics systems.

In previous works different strategies have been used to combine Gabor wavelets with dimension reduction methods. For example, in [5] the values of the convolutions were computed only over a set of fiducial points (eyes, nose and mouth) and then fed to a PCA algorithm. Others [6][7][8][9] compute an augmented feature vector via the Gabor feature fusion for all the orientations and scales, and then they perform a downsampling process to reduce the huge dimensionality of the resulting vector. These methods compute all the possible convolutions to build a unique feature vector to be fed into a classifier, such as SVM. Up to now, B2DPCA has not been previously combined with Gabor wavelets.

In this paper we propose a new fusion algorithm for Support Vector Machines (SVM) scores [10] obtained after a dimension reduction with B2DPCA for Gabor features. Recently, we have developed a fusion method based on a dimension reduction with PCA [11]. We would like to evaluate the benefits obtained when different, and more powerful, dimension reduction methods are employed. We compare our methods with B2DPCA and standard PCA.

The remainder of this paper is organized as follows. In Section 2, we present the face database used in this work. In Section 3, we explain the design of our experiments, and we detail the proposed method. In Section 4, we present and discuss our results. Section 5 summarizes the conclusions.

2 FRAV2D Face Database

We have employed a complete facial images database, the public domain FRAV2D Face Database [12]. It contains 109 subjects, mainly 18 to 40 years old. There are 32 images per subject, which is more than the number of images per subject used in other usual databases for face verification. It was collected in a year's time with volunteers (students and lecturers) at the Universidad Rey Juan Carlos in Madrid (Spain). Each image is a 240×340 colour picture obtained with a CCD video-camera. The face of the subject occupies most of the image.

Fig. 1. Examples of images from the FRAV2D Database (from left to right: frontal view with diffuse illumination, gestures, occlusion, and frontal view with zenithal illumination)

The images were obtained in a unique session per person. The subject had to sit down on a stool at a fixed distance to the camera, although he or she was asked to stand up and sit down again between two shots. Only one parameter was changed between two pictures.

The images were taken under several controlled conditions of pose and illumination. The distribution of images is as follows: 12 frontal views with neutral expression (diffuse light from two focuses was used), 4 images with a 15° turn with respect to the camera axis, 4 images with a 30° turn with respect to the camera axis, 4 images performing different face gestures, such as smiles, expression of surprise, etc., 4 images with occluded faces features (the subject is looking at the camera occluding the left part of his/her face with his/her left hand), and 4 images with zenithal instead of diffuse illumination.

In order to apply face normalization in size and orientation, the position of the eyes was found in every image. A window of size 128×128 pixels containing the most meaningful part of the face was selected in every image, with the eyes located in the same position. For the images with occlusions, only the right eye is visible. In this case, the image was cropped so that the right eye is located at the same position as in the other images, but no correction in size and orientation was applied. Finally the images were stored in equalized grey scale and histogram equalization was performed to correct variations in illumination. That is the information to be analyzed (Figure 1).

3 Design of the Experiments

In this section, we describe the experiments that have been considered using the FRAV2D face database. First, the database was divided into a gallery set with 2 frontal images with neutral expression and diffuse illumination per subject and a unique test set, with 2 disjoint frontal images different to the previous ones. A second experiment design was considered with a gallery set with 4 frontal images with neutral expression and diffuse illumination per subject and 4 different test sets, all of them with 4 images per subject: a disjoint set of frontal images with neutral expression diffuse illumination, images with gestures (such as smiles or winks), images with the left part of the face occluded, and a set of frontal images with neutral expression, but with zenithal illumination.

We have performed a dimension reduction process with four different methods: PCA, B2DPCA, Parallel Gabor PCA and Parallel Gabor B2DPCA, the latter being first proposed in this paper. After that, the obtained projection coefficients have been used to train a set of SVM classifiers. Finally, the images in the test sets were projected onto the corresponding reduced frameworks and their projections were fed into the SVMs in order to perform the classification process devoted to face verification.

In the following subsections, let A_i be the i-th image of size $h \times w$ in the face database and let A_i' be the column vector of size $hw \times 1$ computed by the transpose of the concatenation of all the rows in A_i.

3.1 Principal Component Analysis (PCA)

First, we consider a classical dimension reduction method, the standard PCA [1]. The basic idea is to consider only the d highest eigenvalues of the covariance matrix obtained from the images A_i. The corresponding d eigenvectors are concatenated to create the projection matrix P, of size $hw \times d$. The projection coefficients for the image A_i are calculated as follows:

$$C_i = A_i'^{\,T} \; P \, , \tag{1}$$

where T is the transpose operator. C_i is a row vector of size $1 \times d$ that contains the projections of the image A_i onto the framework of the most significant eigenvectors. As this dimensionality d is much lower than the total amount of pixels in the image (hw), there is an important dimension reduction.

After computing the projection matrix for the gallery database, the projection coefficients for each image are calculated. An independent Support Vector Machine (SVM) classifier was trained for each person in the database. For each subject, we considered his/her images as genuine and everybody else's as impostors. Therefore each SVM was prepared to verify the identity of one subject in the database.

All the images in the test set were projected onto the PCA framework and their coefficients were fed to the previously trained SVMs. With the resulting scores, a unique receiver operating characteristic curve (ROC) was computed and the corresponding equal error rate (EER), for which the false acceptance rate equals the false rejection rate, was derived in order to characterize the verification process performance (see Figure 3-a for a summary of the PCA-based classification algorithm).

3.2 Bilateral 2D Principal Component Analysis (B2DPCA)

Kong et al. [3] suggested a generalization of the 2DPCA method, that consists on performing a 2D principal component analysis using two projection matrices, P_L and P_R, which multiply every 2D image from both sides, left and right respectively:

$$C_i = P_L^{\,T} A_i \, P_R \, . \tag{2}$$

The size of P_L is $h \times l$ and the size of P_R is $w \times r$. Therefore the projection coefficients C_i form a matrix of size $l \times r$. Both matrices P_L and P_R are computed with a very fast-convergent iterative process [3], based on the minimization of the approximation error between the original images and their projection in the B2DPCA framework.

In our experiments, we considered l equal to r, so that the projections C_i are square matrices. We then transformed these projections matrices into 1D vectors via row

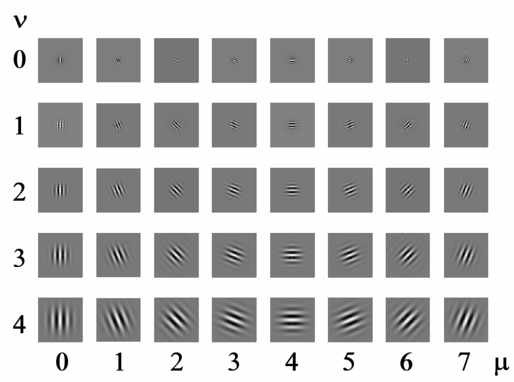


Fig. 2. Real part of the set of 40 Gabor wavelets ordered by frequency (ν) and orientation (μ)

concatenation and transposition in order to train a SVM classifier. An overall ROC curve and the corresponding EER were computed using the resulting SVM scores (see Figure 3-a for a summary of the B2DPCA-based classification algorithm).

3.3 Parallel Gabor Methods

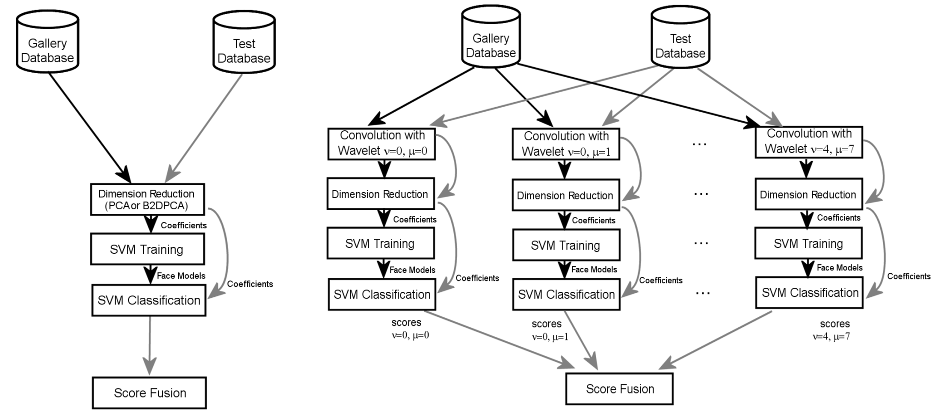
Following notation in [13], Gabor wavelets can be defined as the product of a complex wave and a Gaussian envelope (Figure 2):

$$\psi_{\mu\nu}(\vec{r}) = \frac{k_\nu^2}{\sigma^2}\exp\left(-\frac{k_\nu^2\|\vec{r}\|^2}{2\sigma^2}\right)\left[\exp\left(i\vec{k}_{\mu\nu}\cdot\vec{r}\right)-\exp\left(-\frac{\sigma^2}{2}\right)\right] \quad , \tag{3}$$

where $\vec{r}=(x,y)$, the σ parameter is equal to 2π, the wave vector is defined as $\vec{k}_{\mu\nu}=k_\nu\left(\cos\varphi_\mu,\sin\varphi_\mu\right)$ with a module equal to to $k_\nu=2^{(-(\nu+2)/2)}\pi$ and an orientation $\varphi_\mu=\mu\pi/8$ radians. Usual values of μ and ν are $0 \le \mu \le 7$ (that represents 8 orientations) and $0 \le \nu \le 4$ (5 frequencies), respectively.

The convolution of an image A_i with a wavelet $\varphi_{\mu\nu}$ is a complex matrix of size $h\times w$. It is usual to consider only the magnitude in further computations, instead of the complex value of the convolution. In [11] it was shown that the convolution with a set of Gabor wavelets can be performed in parallel. In this scenario, the face database is convolved with the first wavelet and the results are fed to a dimension reduction algorithm, such as a PCA or a B2DPCA, and then to a classifier, such as SVM. After computing the corresponding classification scores, the whole process is repeated with the following wavelet. Once the 40 Gabor wavelets have been used independently, a final classifier fusion is performed by considering the average of the scores obtained from the SVM for each wavelet. This process can be divided in the following steps (Figure 3-b):

1. The first phase consists on the convolution of the images in the gallery database set with the wavelet of orientation μ and frequency ν. Therefore we generate an alternative gallery database, where each image has been obtained after a convolution with a certain Gabor wavelet.



(a) PCA/B2DPCA. (b) Parallel Gabor.

Fig. 3. A schematic view of the PCA/B2DPCA (a), and Parallel Gabor (b) methods. In both cases, the black arrows correspond to the training phase, where the gallery database is used to train the SVMs and to generate the face model for each subject. The grey arrows correspond to the test phase, where the test database is used to perform the SVM classification and the fusion of the scores.

2. Then, a dimension reduction process is applied. We propose to use a B2DPCA or a standard PCA.
3. With the projection coefficients computed in the previous step, a set of SVM classifiers are trained, one per each subject in the database. For a certain person, the coefficients of his/her images are considered as genuine values, while those of the remainder subjects are used as fake values. Each SVM yields a face model for every subject in the database.
4. Next, the images in the test database set, which are different to those in the gallery database, are convolved with the wavelet of orientation μ and frequency ν. These convolutions are then projected onto the eigenvector framework (PCA or B2DPCA) and the resulting coefficients are evaluated into the set of the previously trained SVMs.
5. Every classifier produces a set of numerical scores: the more positive, the more confident is the acceptance, and the more negative, the more confident is the rejection. For intermediate values, the classifier is not able to verify the identity of the subject. We compute the scores obtained for all subjects in the test set considering each SVM face model. The resulting scores for all the SVMs are then concatenated to a unique score vector, to be used in the final score fusion.
6. After repeating the steps 1–5 for each Gabor wavelet (considering every orientation μ and every frequency ν), we obtain 40 score vectors. Then we perform the fusion of scores by averaging them element-wise. Finally, a unique ROC curve and the corresponding EER can be computed.

4 Results and Discussion

4.1 Influence of the Strategy for the Fusion of Scores for Parallel Gabor Methods

First of all, we consider the 2-image training and 2-image test experiment (only frontal views with neutral expression and diffuse illumination). We compared the Parallel Gabor PCA method with the Parallel Gabor B2DPCA. For every Gabor wavelet, there is a set of scores obtained from the SVM classification of the test database (step 5 in the Section 3.3).

We have considered three different strategies for the fusion of the scores of these 40 sets: an element-wise average of the scores (from now on called “raw average”), a previous normalization of the scores into the range 0–1, followed by an element-wise average as before (“normalized average”) and a previous standardization of the scores, transforming them into zero mean and unit variance and then an element-wise average as before (“standardized average”).

The results obtained for the test database are presented in Table 1. The raw average strategy yields the best results in both Parallel Gabor methods compared to the normalized average and the standardized average. Parallel Gabor B2DPCA improves Parallel Gabor PCA (EER equal to 0.14% vs. 0.15%), but it needs a bigger dimensionality for the projection coefficients (22×22 vs. 185).

Table 1. Best equal error rate and corresponding dimensionality for the Parallel Gabor Methods for the 2-image training and 2-image test experiment, considering three types of fusion of scores

	Parallel Gabor PCA			Parallel Gabor B2DPCA		
	Raw average	Normalized average	Standardized average	Raw average	Normalized average	Standardized average
EER (%)	0.15	0.18	0.19	0.14	0.16	0.18
Dimension	185	205	205	22×22	20×20	18×18

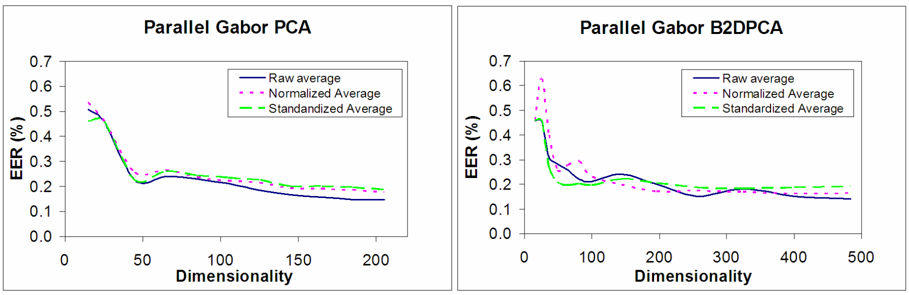


Fig. 4. Evolution of the EER for Parallel Gabor PCA and Parallel Gabor B2DPCA, with a raw average of the scores (continuous line), a normalization of scores to the range 0–1 plus an average (dashed line) and a standardization of scores to zero mean and unit variance plus an average (long dashed line)

Figure 4 shows the evolution of the EER for both Parallel Gabor methods, with the three strategies of fusion of scores. For Parallel Gabor PCA, the raw average always produces the lowest error. However, for Parallel Gabor B2DPCA, the raw average and the normalized average alternate to yield the lowest error, depending on the dimensionality considered. As a comparison, the best EER for PCA in this experiment was 2.98% (dimensionality 150), for B2DPCA it was 2.01% (dimensionality 18×18).

4.2 Comparison of the Parallel Gabor Methods

The previous experiment showed that the best EER for both Parallel Gabor methods was obtained with the raw average of the scores. Therefore, this will be the fusing strategy considered in the 4-image training and 4-image test experiment. In this case, four different test sets were considered: frontal image with diffuse illumination, gestures, occlusions and frontal image with zenithal illumination.

Table 2. EER (%) obtained when the test set contains (a) frontal images with diffuse illumination, (b) images with gestures, (c) images with occlusions and (d) frontal images with zenithal illumination

	Dimension	PCA	Parallel Gabor PCA	Dimension	B2DPCA	Parallel Gabor B2DPCA
(a)	20	1.80	0.23	4×4	2.74	0.23
	50	0.69	0.0064	7×7	0.67	0.030
	100	0.46	***0.0021***	10×10	0.46	***0.0021***
	150	0.46	***0.0021***	12×12	0.46	***0.0021***
(b)	20	12.98	7.80	4×4	15.83	8.90
	50	9.40	5.73	7×7	10.76	5.68
	100	8.03	5.15	10×10	8.38	5.28
	150	7.34	***4.94***	12×12	8.72	5.06
(c)	20	41.51	30.73	4×4	47.25	31.48
	50	37.39	24.06	7×7	39.91	25.26
	100	33.79	23.41	10×10	36.38	23.40
	150	32.34	23.10	12×12	36.99	***22.71***
(d)	20	5.28	1.83	4×4	9.19	2.98
	50	3.07	0.46	7×7	2.73	0.69
	100	2.06	***0.23***	10×10	2.30	0.34
	150	1.84	***0.23***	12×12	1.83	***0.23***

Table 2 shows the evolution of the EER for selected dimensions for the four test sets and the four methods considered here. For images with gestures, the best results are obtained for Parallel Gabor PCA. For images with occlusions, Parallel Gabor B2DPCA is the method that produces the lowest error. For the remainder test sets (frontal images with diffuse illumination and zenithal illumination, respectively), both algorithms draw with the same EER. As a summary, the results obtained for Parallel Gabor B2DPCA were similar to those for Parallel Gabor PCA. Therefore, these methods seem to be robust regarding the dimension reduction technique.

5 Conclusions

In this paper, we presented a new method for the fusion of SVM classifiers obtained from Parallel Gabor B2DPCA for face verification applications. Up to now, B2DPCA had not been previously combined with Gabor wavelets. We developed two experiments with the public domain FRAV2D face database.

In the first one (2-image-per-person training and 2-image-per-person test), the best results were obtained when an element-wise average of the SVM scores was applied. In this case, the Parallel Gabor B2DPCA obtained a better error than the Parallel Gabor PCA (0.14 % vs. 0.15 %).

In the second experiment (4-image-per-person training and 4-image-per-person tests), the Parallel Gabor Methods obtained similar results, outperforming the standard dimension reduction techniques (PCA and B2DPCA). Although further experiments are needed to draw definitive conclusions, the Parallel Gabor Methods proposed here seem to be robust regarding the dimension reduction technique.

As future work, we will enlarge the battery of tests to take into account other dimension reduction methods. Other combination of information techniques for SVM will be used [14]. We will also consider the analysis of other public face databases to evaluate our methods.

Acknowledgments. A part of this work has been carried out at the University of Nottingham (United Kingdom), with financial support of the Universidad Rey Juan Carlos of Madrid (Spain). Special thanks have to be given to Ian Dryden, from the School of Mathematics of the University of Nottingham, for his interesting discussions.

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