FACE VERIFICATION IN UNCONTROLLED LIGHT CONDITIONS OF STREET

Mariusz Leszczyński and Władysław Skarbek
Department of Electronics and Information Technology, Warsaw University of Technology
Nowowiejska 15/19, 00-665 Warsaw, Poland

Keywords: Face verification, Linear Discriminant Analysis, face metrics, Receiver Operating Characteristics.

Abstract: Impact of light conditions on face verification are considered for three linear discriminant feature extraction schemes. Two verification scenarios, the single image query and multi image query, were compared. The extraction algorithms are based on compositions of feature projections on global, intra and inter-class error subspaces: Linear Discriminant Analysis LDA, Dual Linear Discriminant Analysis DLDA, and their combination LDA+DLDA. The metrics for evaluation of the verification error is the Mahalanobis distance between normalized feature vectors. The normalization of feature vectors is justified with the upper bound by Fisher separation index for feature vectors. Experiments conducted on facial databases with complex background show the high performance of DLDA and DLDA+LDA verifiers with Equal Error Rate EER less than one percent. The degradation of results, when controlled light conditions are replaced by uncontrolled ones, is of factor two.

1 INTRODUCTION

Nowadays, due to society demand, face recognition is of significant interest in scientific research. Besides facial image searching and indexing, face identification and face verification are the main tasks implemented in face recognition systems.

Compact representation of extracted facial features is one of the requirements for facial image indexing (cf. contributions in (MPEG-7, 2004)) of which fulfillment is necessary to get real time response for queries in large databases. In case of human id verification systems the size of facial description is not important because the access to features of relevance is direct on the basis of delivered identifier. However, there are several advantages to represent them in computer storage as short as possible within acceptable increase (if any) of verification error (Jain et al., 1999):

- verification can be supported by searching of most similar face images;
- shorter facial descriptions reduce bandwidth requirements in network distributed applications (like intelligent cash machines);
- mass production of biometric passports is easier if their memory requirements are moderate;
- in global security systems archiving billions of biometric passports could be more tractable.

It follows from the experience of MPEG-7 core experiments (MPEG-7, 2004) that scalar uniform quantization from 64 bits of double floating point precision to five bits of fixed point precision for vector components of facial descriptions based on PCA and LDA analysis improves the searching performance. In this research we investigate whether the same conclusion can be drawn in case of verification in the system based on DLDA (Dual Linear Discriminant Analysis).

The algorithms for LDA and DLDA based on two SVDs is described in (Skarbek, W., Kucharski, K. and Bober M., 2004). Recently we have elaborated common conceptual framework for both methods which avoids traditional formal solution through generalized eigenvalue problem with respect to within and between-class scatter matrices by representation of discrimination process as a sequence of projection and scaling operations desribed by Discrimanants Analysis Diagram (DAD) (Skarbek W. and Leszczyński, M., 2007). The above references give a complete mathematical and algorithmic discussion of LDA and DLDA concepts. However, an engineering point of view on linear discriminant modeling of data, given in Section II, can help readers to get right intuitions for using such tools.

In case of cash machine applications not always

Leszczyński M. and Skarbek W. (2007).
FACE VERIFICATION IN UNCONTROLLED LIGHT CONDITIONS OF STREET.
In *Proceedings of the Second International Conference on Signal Processing and Multimedia Applications*, pages 417-421
DOI: 10.5220/0002142004170421

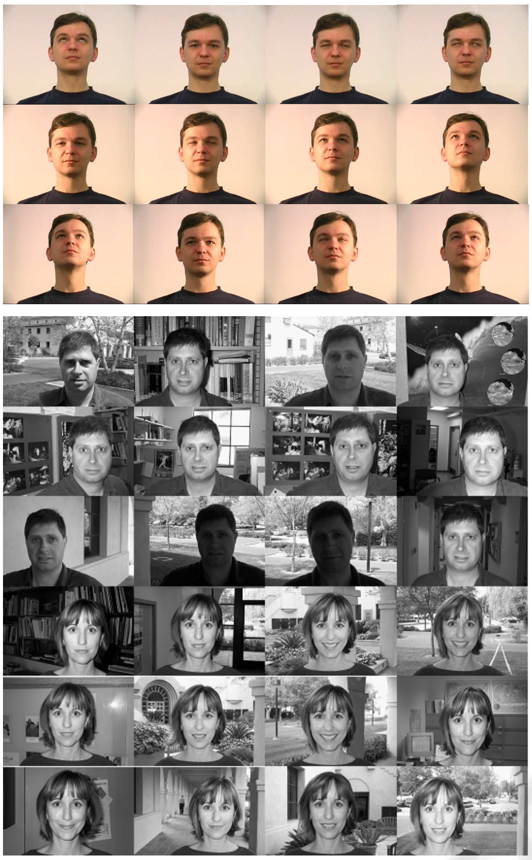

Figure 1: Uniform versus complex background: face images for a person from Altkom database and two persons from Vision database.

light conditions can be controlled. In this research we check experimentally the impact of lighting onto results of verification measured via ROC graphs.

2 DISCRIMINANT FEATURES EXTRACTION

In the presented research the verification is based on thresholding of weighted Euclidean distance of normalized query feature vector to average feature vector of facial images for the person of claimed identity.

The feature vector is obtained from input face image in the following chain of operations:

1. source (spectral) feature extraction: window face detection, face window normalization to fixed eye center positions, transformation of normalized face image into spectral domain 2D DFT, extraction of significant Fourier coefficients, source spectral data centering by grand mean;
2. discriminant feature extraction to get DLDA (LDA) vector: projection onto inter-class (intra) singular subspace, inter-class (intra) componentwise scaling, projection into intra-class (inter) singular subspace;
3. final processing to get target features ready for matching: projection of DLDA (LDA) vector onto the unit sphere, and intra-class (inter) componentwise scaling.

Figure 2: Face images from Yale, MPEG, and WUT databases.

Traditionally LDA model $W = [w_1, \ldots, w_M]$ is obtained from the solutions of the following generalized eigenvalue problem:

$$\begin{aligned} & S_b w_m = \lambda_i S_w w_m \\ & w_m \in \mathbb{R}^N,\ m = 1, \ldots, M,\ M \leq N \end{aligned} \tag{1}$$

by selecting independent eigenvectors of highest eigenvalues (Fukunaga, 1992) of the adjoint classical eigenvalue problem. Here S_b – between-class scatter matrix, S_w – within-class scatter matrix. In order to get the adjoint eigenvalue problem Fukunaga used the Cholesky lower triangular decomposition of $S_w = C_w C_w^t$ which is faster and more accurate than matrix inversion (Golub and Loan, 1989):

$$C_w^{-1} S_b C_w^{-t} (C_w^t w_m) = \lambda_w (C_w^t w_m)$$

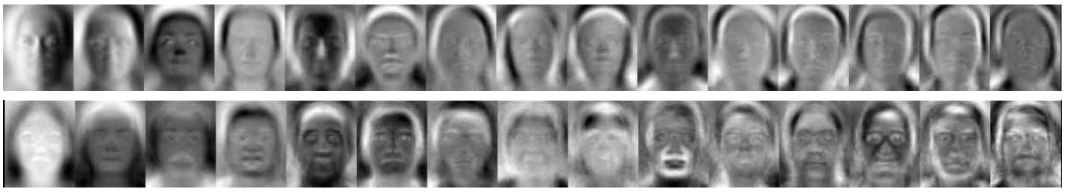

Figure 3: First 15 eigenfaces (fisherfaces) from $U^{(b)}$ in LDA (upper part) and $U^{(w)}$ in DLDA (lower part).

In case of DLDA the model is obtained from the solutions of the following dual generalized eigenvalue problem:

$$\begin{aligned} &S_w w_m = \lambda_i S_b w_m \\ &w_m \in \mathbb{R}^N,\ m = 1,\ldots,M,\ M \leq N \end{aligned} \tag{2}$$

by selecting independent eigenvectors of least positive eigenvalues (Fukunaga, 1992) of the adjoint classical eigenvalue problem obtained also by use of Cholesky matrix decomposition.

Despite its computational advantages the above solution requires full rank property of the matrix S_w in case of LDA and the same property for S_b in case of DLDA.

If $\text{rank}(S_w) < N$ then data regularization is performed by PCA (Principal Component Analysis). Actually the change of coordinates in global error space is performed, followed by rejection of least variance components till the resulting principal subspace has trivial intersection $\{0_N\}$ with kernel space of S_w. Since there is unknown direct formula for the number of rejected PCA component a trial-error process is applied and its result strongly depends on the actual training data set $X := [x_1,\ldots,x_L]$. Mathematically the result depends on mutual relationship between the kernel of total (global error) scatter matrix $S_t = S_w + S_b$ and the kernel of S_w.

Introducing in (Skarbek W., Kucharski K. and Bober M., 2006) our LDA and DLDA approach based on orthogonal projections onto two singular subspaces we intended to replace the relative analysis of those kernels by the single kernel analysis for S_w in case of LDA and kernel analysis for S_b in case of DLDA.

In order to give intuitive interpretation for our discriminant modelers (LDA and DLDA) we use the following concepts:

1. change of Cartesian coordinate system in selected error space by rotation and scaling of axis vectors;
2. projection onto subspace of maximum energy of inter-class error (LDA case);
3. projection onto subspace of minimum energy intra-class error (DLDA case).

In terms of the above operations the DLDA extraction process can be described as follows:

1. Compute global error x_1 by source data x_0 centering:
$$x_1 := x_0 - \bar{x};$$
2. Get major PCA inter representation, i.e. represent the global error in major PCA base $U^{(b)}$ found at training time for inter-class errors:
$$x_2 := (U^{(b)})^t x_1$$
3. Scale PCA inter representation using diagonal matrix $\Sigma^{(b)}$ which normalized training PCA inter coefficient to unit values:
$$x_3 := \Sigma^{(b)} x_2$$
Note: For training data the variance of x_3 variable equals to the dimensionality of x_3.
4. Get minor PCA intra representation, i.e. represent scaled PCA inter feature vector in minor PCA base $U^{(w)}$ found at training time for intra-class errors:
$$x_4 := (U^{(w)})^t x_3$$

Hence the aggregated DLDA matrix W has the following effect:

$$y = W^t(x_0 - \bar{x}) = (U^{(w)})\Sigma^{(b)}(U^{(b)})^t(x - \bar{x}) \tag{3}$$

It is interesting that in matching stage the best results are achieved by Mahalanobis distance for unit length feature vectors:

$$\delta(y_A, y_B) := \left(\frac{y_A}{\|y_A\|} - \frac{y_B}{\|y_B\|}\right)^t \Lambda \left(\frac{y_A}{\|y_A\|} - \frac{y_B}{\|y_B\|}\right) \tag{4}$$

where $\Lambda := (\Sigma^{(b)})^2$ in case of LDA and $\Lambda := (\Sigma^{(w)})^2$ in case of DLDA.

The normalization of feature vectors is closely related to the Fisher separation index between LDA or DLDA feature vectors y_A and y_B of face images A and B:

$$\frac{1}{2}\left\|\frac{y_A}{\|y_A\|} - \frac{y_B}{\|y_B\|}\right\| = 1 - \frac{2y_A^t y_B}{2\|y_A\|\|y_B\|} \leq$$

$$\leq 1 - \frac{2y_A^t y_B}{\|y_A\|^2 + \|y_B\|^2} = \frac{\|y_A - y_B\|^2}{\|y_A\|^2 + \|y_B\|^2}$$

Since discriminant analysis indirectly reduces the Fisher separation index then it also reduces the normalized intra-class error.

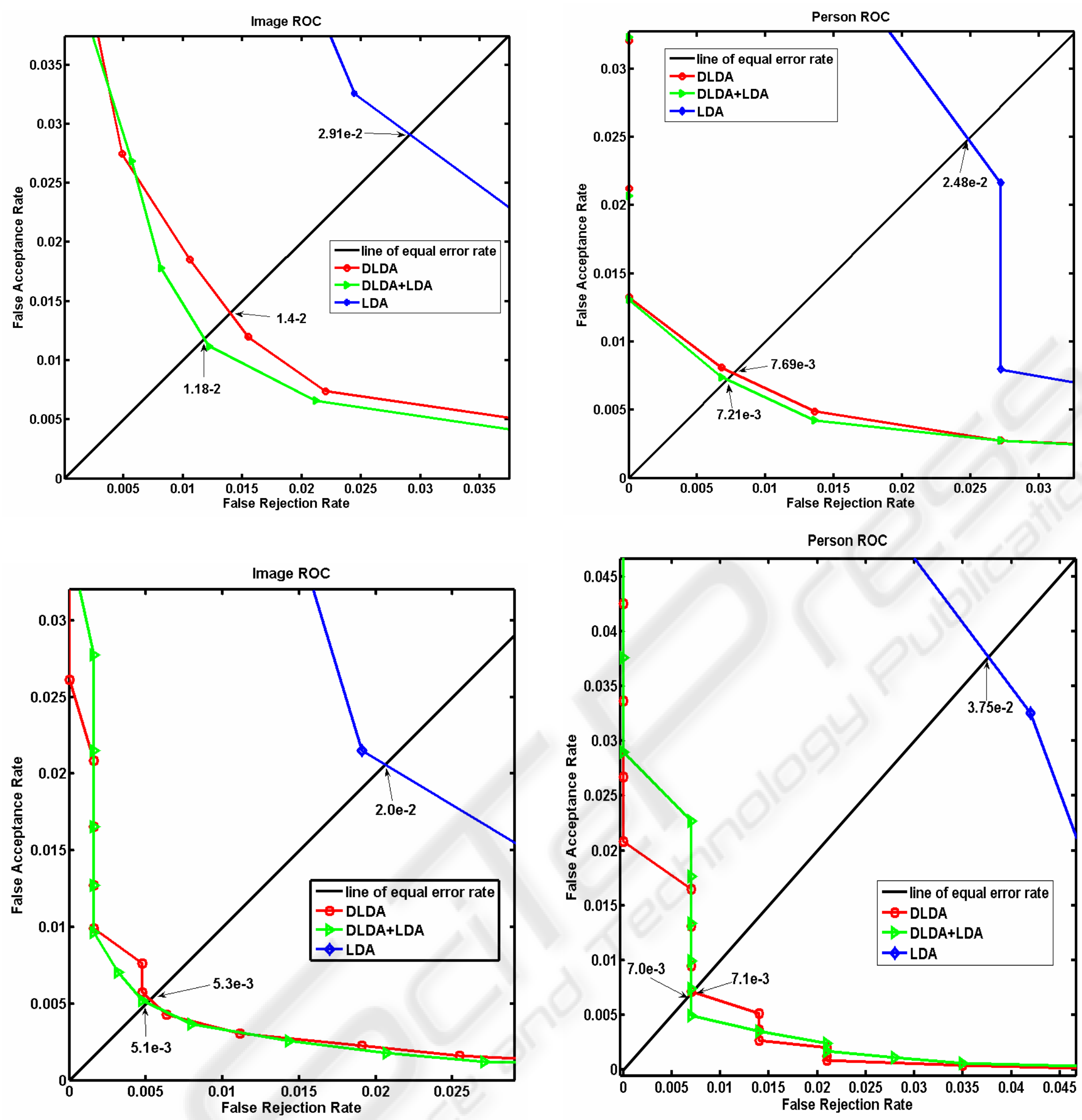

Figure 4: ROC results for face verifiers in uncontrolled (upper row) and neutral (lower row) lighting conditions. Face images from Altkom, Vision, Yale, MPEG, and WUT databases.

3 EXPERIMENTAL RESULTS

We selected the normalized luminance facial images (46×56 resolution with the same position of eyes) from the following databases (cf. Fig. 1,2): Altkom (80 persons with 15 images each), Vision (26 persons with varying number of images per person), Yale (15 persons with 11 images each), MPEG (110 persons with 5 images each), WUT (54 persons with 3 images each).

From the previous works described in (Skarbek, W., Kucharski, K. and Bober M., 2004) it is already known that in case of face verification the optimization of inverse Fisher ratio (DLDA) leads to better results than the optimization of Fisher ratio (LDA). Figure 3 gives more insight for this phenomenon. Namely, DLDA eigenfaces (fisherfaces) are more contrasted and more focused on particular facial parts.

It is interesting that aggregation of DLDA and LDA verifiers by the maximum, the arithmetic mean, and the harmonic mean of distances give intermediate results (in ROC sense) between the best DLDA results and and significantly worse LDA results. However, the geometric mean of both distances leads to slight improvements of EER and ROC over DLDA.

In Fig. 4 we compare this results in two query scenarios: single image (*Image ROC*) and multi-image (*Person ROC*) and two lighting scenarios: unconstrained (upper part ROCs) and neutral (lower part ROCs).

In case of Image ROC, we observe the improvement of Equal Error Rate EER for the neutral lighting for about two times. The insignificant improvement in case of Person ROC is justified by small number of neutral photos for most of persons engaged in training and testing.

4 DISCUSSION AND CONCLUSIONS

Impact of light conditions on face verification are considered for three linear discriminant feature extraction schemes. Two verification scenarios, the single image query and multi image query, were compared. The extraction algorithms are based on compositions of feature projections on global, intra and inter-class error subspaces: Linear Discriminant Analysis LDA, Dual Linear Discriminant Analysis DLDA, and their combination LDA+DLDA.

The metrics for evaluation of the verification error is the Mahalanobis distance between normalized feature vectors. The normalization of feature vectors is justified with the upper bound by Fisher separation index for feature vectors.

Experiments conducted on facial databases with complex background show the high performance of DLDA and DLDA+LDA verifiers with Equal Error Rate EER less than one percent. The degradation of results when controlled light conditions are replaced by uncontrolled ones is of factor two.

In cash machine application the input of verification system is given as temporal sequence of images. On the basis of the previous works we recommend the design of face verifier for this application by the following six steps:

1. Detect frontal pose of face by Discrete Gabor Jet DGJ algorithm w.r.t. inner eye and nose corners (Skarbek W. and Naruniec J., 2007).
2. Compensate lighting by Quotient Illumination Relighting algorithm (QIR) (Cao B., Shan S., Gao W. and D. Zhao, 2003).
3. Compensate pose by inner eye and mouth corners to find the homographic mapping.
4. Align the compensated image by alignment of the line segment joining outer eye corners.
5. Design the feature extraction scheme by optimizing DAD diagram.
6. If the verifier of 5 is not satisfactory then optimize DLDA cascade.

ACKNOWLEDGEMENTS

The work presented was developed within VISNET 2, a European Network of Excellence (http://www.visnet-noe.org), funded under the European Commission IST FP6 Programme.

REFERENCES

Fukunaga, K. (1992). *Introduction to Statistical Pattern Recognition*. Academic Press.

Golub, G. and Loan, C. (1989). *Matrix Computations*. The Johns Hopkins University Press.

Jain, A. K., Bolle, R., and Pankanti, S., editors (1999). *Biometrics: Personal Identification in Networked Society*. Kluwer Academic Publishers.

Cao B., Shan S., Gao W. and D. Zhao, (2003). *Illumination normalization for robust face recognition against varying lighting conditions in* . IEEE ICCV-2003, 157:164, 2003

MPEG-7, editor (2004). *Multimedia content description interface. Visual Descriptor Extensions.*, volume 15938-3:2002/Amd.1:2004. ISO/IEC.

Skarbek W., Kucharski K. and M. Bober, (2004). *Dual LDA for Face Recognition in* . Fundamenta Informaticae 303:334:2004

Skarbek W., Kucharski K. and Bober M. , (2006). *Cascade of dual LDA operators for face recognition in* . Geometric properties from incomplete data, Kluwer Academic Publishers 199:219, 2006

Leszczyński M. and Skarbek W., (2007). *Biometric Verification by Projections in Error Subspaces in* . Rough Set and Knowledge Technology, Springer LNAI 4481, 166:174, 2007

Naruniec J. and Skarbek W., (2007). *Face Detection by Discrete Gabor Jets and Reference Graph of Fiducial Points in* . Rough Set and Knowledge Technology, Springer LNAI 4481, 187:195, 2007