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Weighting Estimation for Texture Based Face Recognition via Fisher Discriminant

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Abstract – **Texture based automatic face recognition (AFR) methods proposed in the last few years have been successful in large-scale applications where the database consists of a single frontal view per person. In those methods the global similarity between two faces is generally given by a linear combination of the local similarities computed upon each face region. Little attention has been given so far to the estimation of the weights that express the relative contribution of each face region to global similarity score. This paper addresses this issue and proposes a method to estimate the optimum weighting for texture based AFR. The solution is given by the most discriminative axis within a similarity space using Fisher discriminant analysis. The proposed method is evaluated in experiments conducted on the FERET and on the FEI face databases. For texture coding both Local Binary Patterns (LBP) and Local Phase Quantization (LPQ) are considered. The experiments indicate that the proposed method brings a substantial improvement in terms of recognition performance in comparison to other weightings and weighting methods proposed in the literature.**

Keywords – Biometrics, Face Recognition, Local Binary Pattern, Local Phase Quantization

I. INTRODUCTION

Face Recognition Technology (FRT) has been preferred in relation to other biometric methods in many applications mainly due to its low intrusiveness and good accuracy [1]. In some large-scale applications, such as passport or driver license identification, the database consists of a single frontal view per person. In the recent years texture based approaches are gaining increasing interest in the FRT community for this kind of applications.

Many studies demonstrate the superiority of these methods over alternative face recognition approaches in applications dealing predominantly with frontal views with little variation of facial expression [2] [3] [4] [5] [6] [7]. In these approaches a texture image is generated by replacing each image pixel by a binary code that represents the texture within the pixel's neighborhood. For recognition the texture image is partitioned into non-overlapping blocks and a weight is assigned to each block according to its importance in the recognition process. Following the common psychophysical findings, which indicate that some facial features (such as eyes) are more important in human face recognition than other features, Ahonen and co-authors [2] adopted an empirical procedure to obtain a fixed set of weights based on the recognition rate. They recognize that the values are not optimal, but improve the recognition results when compared to uniform weight values. Since then most texture based automatic face recognition (AFR) [8] methods have been using fixed weight values.

To our knowledge the method reported in [9] is the only approach proposed up to now to adjust the weighting to the kind of perturbation present in a given application. In that approach, the optimum weighting derives from a homogeneous, non linear equation system solved by a least squares technique. Experiments [9] have shown that the least squares based method is able to outperform fixed, application independent weightings proposed to date in the literature. However, it involves a fairly complex equation system and entails a large number of training images per weight being estimated.

This paper proposes a new method for weighting estimation that derives from Fisher linear discriminant [10]. In comparison to the least square based approach, our method demands fewer training samples per weight, and is more efficient computationally. In tests conducted for two texture coding techniques upon two face image databases our method consistently outperformed the alternative strategies proposed in the literature.

The remainder of this paper is organized as follows. The next section briefly describes the texture based AFR strategy. Section III presents the proposed approach for weighting estimation. Experiments for performance assessment are presented in section IV and the main conclusions are summarized in section V.

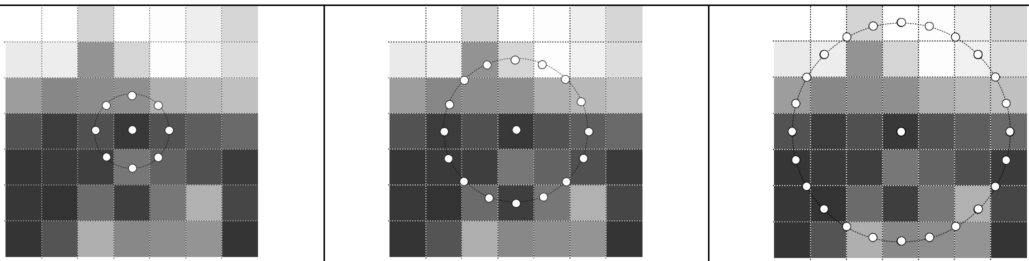
II. TEXTURE BASED FACE RECOGNITION

Texture based AFR involves two main steps: face description followed by face matching. This section describes two widely used texture coding methods and presents the matching procedure that can be applied for both representation approaches.

A. Texture Based Face Description

Face Description with LBP

The LBP image representation [5] is computed by assigning to a pixel at location **x** =(x,y) a code. This code is related to the signs of the differences between the central pixel intensity and the intensity of its m equally spaced neighbors at a distance R, as illustrated in Figure 1. The binary values "0" and "1" are assigned respectively to a negative and to a positive difference. A bilinear interpolation is used whenever the sampling point does not fall in the center of a pixel. The LBP code results from the concatenation of the m 0's and 1's in an arbitrary but fixed order. Figure 2 shows the LBP representation of four image samples, whereby the intensities are related to the LBP code at each pixel location.



m-8, R=1	*m=16, R=2*	*m=24, R=3*

Figure 1. Neighboring pixels for different values of m and R in LBP image coding.

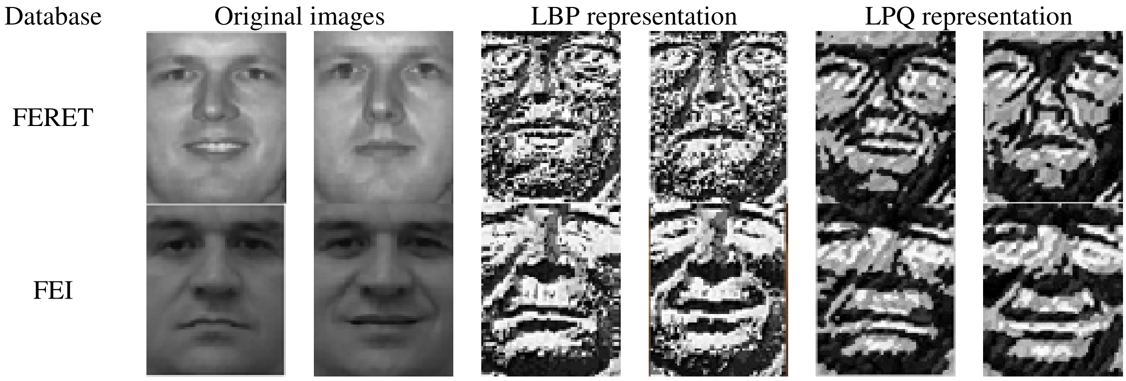


Figure 2. Sample images from FERET and FEI databases and the corresponding LBP and LPQ representations

Face Description with Local Phase Quantisation

LPQ is a method for textures description conceived to outperform LBP in applications where images are affected by blur and uniform illumination changes. Similar to LBP, for each pixel at location **x** =(x,y) a code is computed to represent the texture in the $M\times M$ neighborhood $\mathcal{N}_\mathbf{x}$ centered at **x**.

Phase quantization is performed by looking at the sign of the real and imaginary values of the Fourier transform $\mathbf{F}_\mathbf{x}(\mathbf{u})$, $\mathbf{u}=(u,v)$, of $\mathcal{N}_\mathbf{x}$ at four low frequencies, as indicated in Figure 3b with a white circle. This generates 8 bits, which are “0” or “1” depending on whether each value is negative or non-negative. These bits are concatenated in an arbitrary but fixed order forming an 8 bit integer value that represents the texture in $\mathcal{N}_\mathbf{x}$. This procedure is carried out for all pixels in the image, bringing about the corresponding LPQ image representation.

The method includes a simple procedure that decorrelates the Fourier coefficients before the quantization step. This aims at maximizing the information preserved in the texture code. A detailed description can be found in [6] and [7]. LPQ coded image samples are shown in Figure 2, where intensities are given by the LPQ code at each pixel location.

(a) neighborhood $\mathcal{N}_\mathbf{x}$ (b) magnitude of the Fourier Transform $|\mathbf{F}_\mathbf{x}(\mathbf{u})|$

Figure 3. input neighborhood $\mathcal{N}_\mathbf{x}$ (a) and the modul of the Fourier transformation of the input image in the neigborhood $\mathcal{N}_\mathbf{x}$ (b)

B. Matching Procedure

Let’s assume hereafter that the face database consists exclusively of well-framed images with a constant interocular distance and the eyes are imaged at the same pixel coordinates.

We denote with S_{ir} the *r-th* image of the *i-th* subject in a database. In the recognition step the texture image is divided in equal-sized non-overlapping blocks numbered from 1 to B. The histogram ${}^{b}H_{ir}$ of the texture codes inside the *b-th* block is computed for $b=1,2,\ldots,B$.

The dissimilarity between histograms ${}^{b}H_{ir}$ and ${}^{b}H_{jt}$ of the *b-th* block respectively of images S_{ir} and S_{jt} is computed by a proper distance function ${}^{b}d_{irjt}({}^{b}H_{ir},{}^{b}H_{jt})$, for simplicity denoted henceforth ${}^{b}d_{irjt}$.

To decide whether two faces are from the same subject or not, a global dissimilarity measure given by a linear combination of the computed histogram distances is used, formally

$$D_{irjt} = \sum_{b=1}^{B} w_b \, {}^{b}d_{irjt} \; . \tag{1}$$

where the coefficients w_b are weights that represent the relative relevance for recognition of the region corresponding to the *b-th* block.

III. Proposed Method for Optimal Weighting Estimation

The solution proposed in this work to estimate the w_b coefficients derives from a simple reinterpretation of the Eq (1). Let’s group the histogram distances between faces S_{ir} and S_{jt} of all B blocks in a vector $\mathbf{d}_{irjt}$ = [${}^{1}d_{irjt}$, ${}^{2}d_{irjt}$, …,${}^{B}d_{irjt}$] of a B-dimensional similarity space. Let’s further group the set of coefficients w_i‘s in the vector $\mathbf{w}=[w_1, w_2,\ldots, w_B]$. Eq. (1) may take the following form

$$D_{irjt} = \mathbf{d}_{irjt}\, \mathbf{w}^T \; . \tag{2}$$

Therefore, the global dissimilarity measure is the projection of the distance vector $\mathbf{d}_{irjt}$ over a direction in the similarity space defined by the coefficient vector $\mathbf{w}$. We assume that the optimum weighting corresponds to the direction in the similarity space along which pairs of image of the same subject achieve maximum separation from pairs of images of different subjects.

If it can be plausibly assumed that the covariance matrices of both classes of image pairs are equal, the problem of finding the optimum weighting boils down to a direct application of Fisher discriminant method, whose solution is given by

$$\mathbf{w} = \left(\overline{\mathbf{d}}_{other} - \overline{\mathbf{d}}_{same}\right)\mathbf{\Sigma}_{pooled}^{-1} \tag{3}$$

where $\overline{\mathbf{d}}_{same}$ and $\overline{\mathbf{d}}_{other}$ are the mean distance vectors for pairs of images respectively from the same and different subjects and $\mathbf{\Sigma}_{pooled}$ is the pooled covariance matrix. Most books on Multivariate Statistical Analysis (e.g. [10]) report that Fischer's approach usually works fine even when the equal covariance assumption does not hold exactly.

It is important to point out right away that the weights delivered by Eq. (3) generally do not follow the expected left-to-right face symmetry. Nevertheless, it is generally interesting to enforce weight symmetry to reduce the problem complexity by halving the number of coefficients to estimate. Assuming that blocks b and $b+B/2$, for B even, correspond to symmetric face regions, weight symmetry may be imposed by making ${}^{b}w = {}^{b+B/2}w$. In consequence Eq (1) may be rewritten as

$$D_{irjt} = \sum_{b=1}^{B/2} w_b \left({}^{b}d_{irjt} + {}^{b+B/2}d_{irjt}\right). \tag{4}$$

IV. Experiments

A. Experiment Setup

Two databases were used for performance assessment. The first one consists of 1640 frontal images of 820 subjects, 2 images per subjects from the *fa* and *fb* sets of the FERET database [11], containing slight variation in facial expression. The second database is build up from the FEI [12] database and consists of 2 frontal faces of 50 subjects in neutral and in smiling expression.

In all cases the images were framed to 80×64 pixel resolution [9] with the right and left eyes located at pixels coordinates (20,14) and (20,51) respectively. Figure 2 shows image samples of both databases used in our experiments.

The so called uniform LBP variant with 8 sampling points ($m=8$), over a circle of radius equal to 2 pixels ($R=2$) has been selected. Following [6] and [7] the Fourier transform for LPQ was computed over each 7×7 pixel neighborhood (M=7) and the phase quantization was performed at the frequencies corresponding to a=1/7. In both databases histograms were computed over 10×8 non-overlapping blocks of size 8×8 pixel.

In all experiments the individuals in the databases were randomly separated, half for training and half for test. The rates were measured by picking up one test image, whose matching face should be identified from all other images of the test set. After repeating this procedure for all test images the average rate was computed. The results reported in the next sections for each configuration of database and texture coding are averages over 5 runs, each run with a different random distribution of the individuals in the training and test sets.

B. Performance Results

The first experiment sequence aimed at comparing our method with other approaches in terms of recognition performance. The plots in Figure 4 refer to rank recognition rates measured on FERET and FEI databases using LBP and LPQ texture coding. Each plot contains four curves relative to four different weightings: uniform, computed by our method, proposed by Ahonen and coauthors [4] and computed according to the Least Squares method [9].

The weight matrix proposed by Ahonen was resampled so as to fit the 10×8 grid. With the Least Square method we imposed as in [9] that certain groups of blocks have equal weights. This was mandatory because the method did not generalize well for more weights with the available training faces. In Firsher's method we assumed face symmetry, so that only 40 coefficients were estimated and then mirrored to form a 10×8 weighting matrix.

Figure 4 shows that our method consistently delivered the highest performance, for both databases and coding techniques. The weightings computed by the Least Squares method was the second best performing method. In relation to the uniform and Ahonen's weightings, our method was clearly superior.

Notice that the recognition rates for the Least Squares shown in Figure 4 start close to 100%. Any possible improvement is restricted to what is missing to achieve 100%. Under this perspective the gain of our method over the Least Squares approach was substantial in most cases shown in Figure 4.

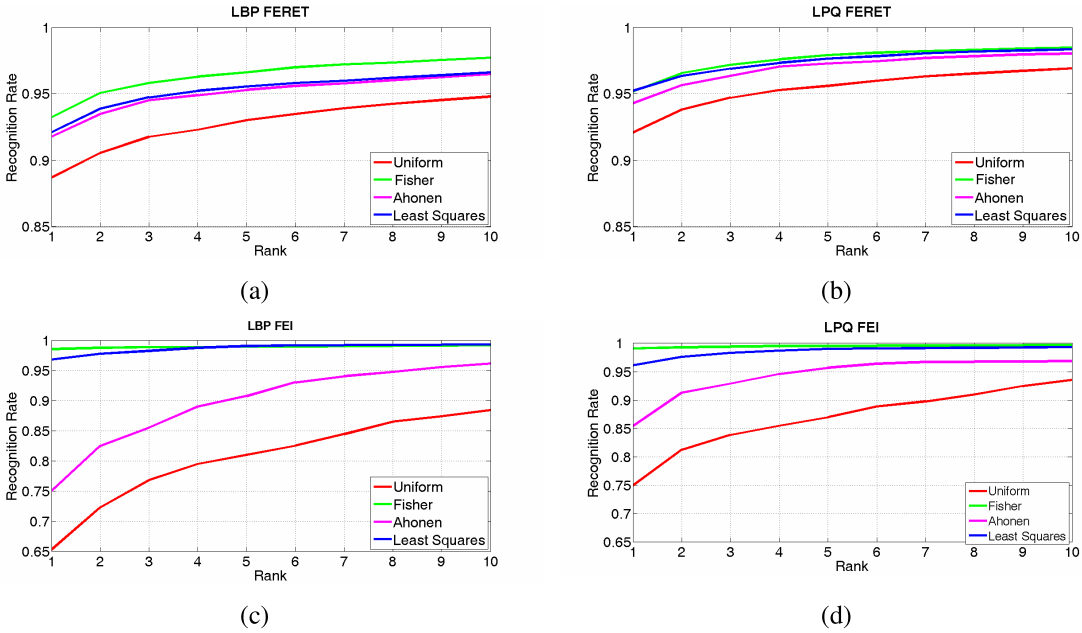


Figure 4: Cumulative rank rates for different weightings measure on (a) FERET database working with LBP (b) FERET database working with LPQ, (c) FEI database working with LBP and (d) FEI database working with LPQ.

Real applications may have to deal with much larger databases consisting of poor quality images. We have conducted experiments on images from a non public database provided by a Brazilian security agency that contains millions of samples. Such tests indicated that in more realistic conditions the recognition rates tend to be much lower than in Figure 4 and the absolute gain of the proposed method over the alternative ones is expected to become even more expressive.

C. Weights Estimates

In this section we analyze the variability of the weightings produced by our method in distinct configurations. Table 1 presents the results for four different combinations of database and coding techniques. To improve visualization the values were scaled, so that all weighting vectors have the same magnitude, and then rounded to the closest integer.

At this point, it is worth mentioning that the vector defining the discriminant axis has often negative components, which may be counterintuitive for those used to regard the weights as denoting the relative importance of face regions in the recognition process. In our method, however, vector $\mathbf{w}$ is a projection direction. In this case, the negative values in vector $\mathbf{w}$ indicate that differences among the histogram distances of some face regions are relevant for the recognition process.

Notwithstanding the evident differences, a certain common structure among the four weightings of Table 1 is perceptible. To measure the level of agreement among these results, we computed the correlation between each pair of weightings of Table 1. The results are shown in Table 2. For clarity we shadowed the cells containing redundant (the table is symmetric) or unimportant values (the diagonal is all 1).

As expected, the weightings are indeed highly correlated, but the difference brought by changing the database, the texture coding or both is not negligible. In the next section we investigate how meaningful are those differences in terms of recognition performance.

Table 2 shows that the correlation is high when it comes to the same database, independently of the texture coding method. It may lead one to assess that the weights may be more or less the same for different texture coding methods. On the other hand, it is clear that one mask cannot be generally used for any database, and should be computed for each specific database.

D. Impact of weighting variation over the recognition performance

A final experiment was carried out for assessing the impact of the weighting variation observed in the previous section over the recognition rates.

For each weighting estimated in the first experiment, we computed the rank recognition rates on the test images for all possible combinations of database and coding technique. Results are shown in Figure 5.

Each plot title specifies the configuration of coding technique and data base upon which the rates have been measured. The curves in each plot correspond to the training sets used for weighting estimation.

Table 1: Weightings obtained by Fisher discriminant for FERET and FEI databases using LBP and LPQ coding.

Data base	**texture coding**															
	LBP								**LPQ**							
FERET	19	0	31	16	16	31	0	19	18	-10	15	-6	-6	15	-10	18
	32	14	48	40	40	48	14	32	16	53	13	70	70	13	53	16
	5	25	-7	39	39	-7	25	5	-5	18	-12	14	14	-12	18	-5
	9	18	32	48	48	32	18	9	6	5	31	55	55	31	5	6
	-17	-19	-12	13	13	-12	-19	-17	-11	-9	-31	22	22	-31	-9	-11
	-19	-11	39	42	42	39	-11	-19	-17	-7	30	26	26	30	-7	-17
	6	16	7	-7	-7	7	16	6	-9	7	2	-3	-3	2	7	-9
	19	3	22	23	23	22	3	19	36	0	23	12	12	23	0	36
	14	12	11	14	14	11	12	14	7	-2	2	19	19	2	-2	7
	-11	14	2	4	4	2	14	-11	-11	14	-6	5	5	-6	14	-11
FEI	30	36	2	12	12	2	36	30	12	45	-5	-3	-3	-5	45	12
	26	19	35	39	39	35	19	26	12	26	44	44	44	44	26	12
	7	-4	6	13	13	6	-4	7	20	-15	-20	0	0	-20	-15	20
	-6	1	-7	63	63	-7	1	-6	-20	-15	3	37	37	3	-15	-20
	1	4	-13	55	55	-13	4	1	7	-10	-24	68	68	-24	-10	7
	-12	2	-8	37	37	-8	2	-12	-22	20	-29	23	23	-29	20	-22
	-2	6	-20	-15	-15	-20	6	-2	17	-6	11	-18	-18	11	-6	17
	41	-3	-22	19	19	-22	-3	41	10	-6	-3	14	14	-3	-6	10
	1	9	13	16	16	13	9	1	11	-1	15	10	10	15	-1	11
	25	19	5	3	3	5	19	25	18	24	2	0	0	2	24	18

Table 2: Correlation between weightings estimated for different databases and coding techniques.

		FERET		FEI	
		LBP	LPQ	LBP	LPQ
FERET	LBP	1	0.80	0.59	0.42
	LPQ	0.80	1	0.60	0.49
FEI	LBP	0.59	0.60	1	0.80
	LPQ	0.42	0.49	0.80	1

In all cases the highest performance was achieved when training and test were performed on the same database and for the same texture coding. The change from LBP to LPQ or vice-versa brought slight performance changes as long as both training and test were conducted upon the same database. In contrast, the plots reveal a substantial performance loss when the weighting was estimated upon one database and tested upon the other. This result is consistent with the correlation analysis of weights presented on the previous section.

The results of Figure 5 demonstrate that significant performance gains may be attained by tuning the weighting to the kind of image variation present in the target application, as we claimed in the introduction.

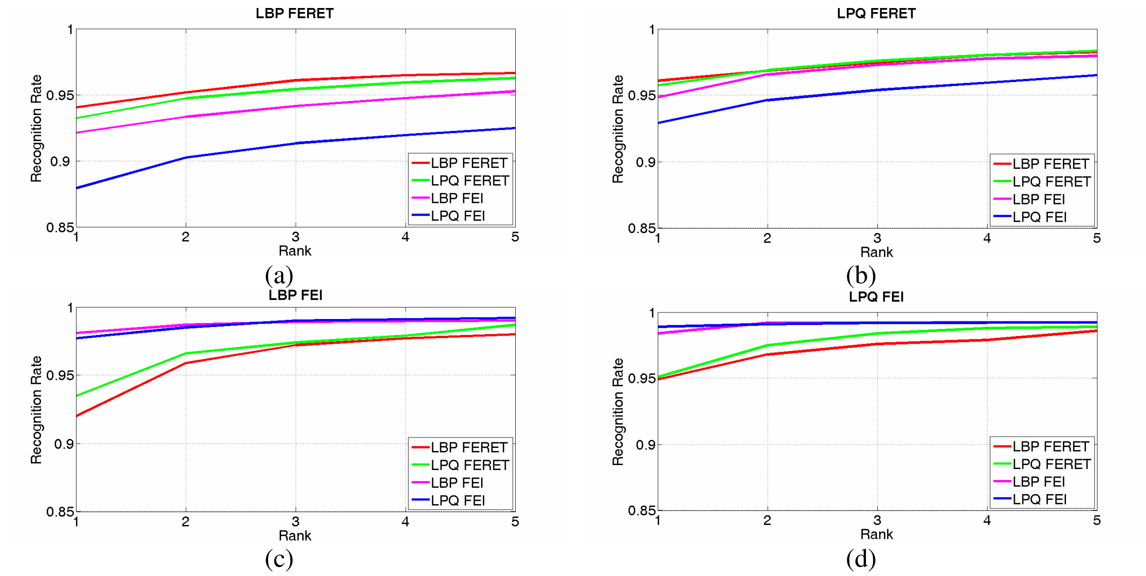


Figure 5: Rank recognition rates for different configurations of database and coding: the plot title indicates the configuration used for rates measurement, while the legend indicates the configuration for weighting estimation.

V. CONCLUDING REMARKS

In this work we presented a novel method to estimate optimal facial region weights for texture based face recognition. More than a standard general weighting, the present work introduces a method to determine the set of weights that best fits the image characteristics within a particular application.

Experiments based on two public databases using two distinct texture coding techniques have shown substantial improvements in recognition performance brought by our method in comparison to other weightings and weighting methods proposed in the literature. It was assumed in all our experiments that the weights were symmetric following the left-to-right face symmetry. This assumption simplifies the problem by halving the number of coefficients to estimate. The results let presume that the method is able to capture systematic asymmetries that may appear in face images within a given application, for instance due to a non symmetric illumination pattern.

Although the paper focused on texture based approaches, we further believe that the proposed technique may be successful in other approaches that measure the global similarity between two faces as a linear combination of the similarity computed upon each face region.

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