CATEGORY SPECIFIC FACE RECOGNITION BASED ON GENDER

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ABSTRACT

The idea of category specific face recognition is first to categorize facial images into categories based on visual cues like gender and race and then to perform face recognition using features specific to a category. One main problem in this approach is to find category specific features. We addressed category specific face recognition based on gender and explored which feature descriptor is more suitable for male category and which is more appropriate for female category. We tested four feature extraction techniques: Principle Component Analysis (PCA), Linear Discriminant Analysis (LDA), Local Binary Pattern (LBP) and Weber's Law Descriptor (WLD). To reduce the dimension of the feature space in each case, we used two-stage feature subset selection method. For classification, we used nearest neighbor classifier (NN), and tested the effect of different metrics on classification; spearman distance emerged to be the winner. The results showed that there is a trend that WLD is better feature descriptor for male category and LBP represents the female category in a better way.

Index Terms— *Category specific face recognition, LBP, WLD, PCA, LDA.*

1. INTRODUCTION

Face recognition is an important biometric technology. Face recognition systems that exist now-a-days are not robust or accurate enough. Even though there is a significant progress during the last decade in face recognition research, this problem still needs further investigation. Recognition rate and system time complexity are two main problems. One possible approach to further investigate this problem is to use category specific approach i.e. first to categorize the faces into categories based on different visual cues like gender, race, age etc. and then to recognize the faces based on category. It has been shown that face recognition based on categorization improves the recognition rate and also it reduces the time complexity by reducing the search space [1]. For face recognition based on category, the challenges are categorization i.e. to categorize face images accurately to different categories and category specific feature descriptors i.e. to find which feature type is robust and has enough discriminatory potential specific to a particular a category. In this paper, our focus is on latter challenge i.e. to find category specific feature descriptors for gender based categories (male/female).

To identify the best feature descriptors specific to male and female categories, we explore two holistic (PCA and LDA) and two analytic (LBP and WLD) descriptors. Turk et al. [2] used first time PCA in their Eigenfaces approach for face recognition. Exploiting LDA, Belhumeur et al [3] introduced Fisherfaces for face recognition. Ahonen et al. [4] used LBP descriptor for face recognition; LBP was originally proposed for texture discrimination [5]. WLD was introduced for texture classification [6]; Hussain et al. [7] used multiscale WLD for face recognition.

For classification, we used NN classifier. We explored the best parameter settings for each descriptor, applied it for face recognition after categorizing the faces based on gender in an effort to find the best feature descriptor for each category (male/female). Though LBP and WLD performed better than PCA and LDA, there was no clear indication about which one is the best for male and which performs best for female category. However, there is a trend that WLD is better for male whereas LBP is better for female.

The rest of the paper is organized as follows. Section 2 presents the details of category specific face recognition system. Section 3 is about experimental setup. Results and discussion have been given in Section 4. Section 5 concludes the article.

2. CATEGORY-SPECIFIC FACE ECOGNITION

In this section, we present the system for category specific face recognition based on gender; the system diagram is shown in Figure 1. The first stage is categorization based on gender and the next stage is face recognition based on this categorization. Our focus is on the latter stage and in the following subsections, we give its detail.

2.1. Feature Extraction

We explore four feature descriptors to find out which forms the best representation for males and which represents female in the best way. We consider PCA, LDA, LBP and

WLD, give an overview of each method in the following sections. We assume that the training data $\{(I_i, l_i), |\ 1 \leq i \leq n\}$ of C subjects is given, where I_i and l_i are the facial image and identity of ith subject.

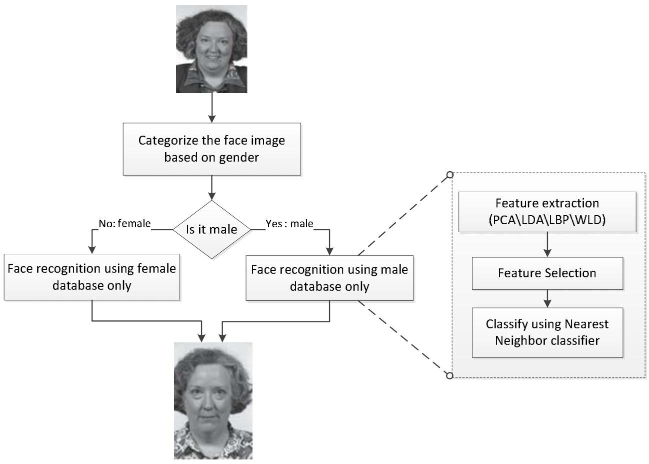

Figure 1. System Diagram for Category specific face recognition based on gender.

PCA Features

It is a holistic method that transforms image grayscales into uncorrelated attributes. Using Turk's trick [2], feature extraction with PCA involves the following steps:

Step-1. Convert each I_i into a vector x_i of dimension m, compute the mean vector x and transform x_i to ϕ_i, where $\phi_i = x_i - x$. Form a matrix A where ϕ_i is ith column.

Step-2. Compute $A^T A$, and determine its eigenvalues λ_i and eigenvectors μ_i, $i = 1, 2, \ldots, n$.

Step-3. Select r (< m) eigenvectors corresponding to r greatest eigenvalues.

Step-4. Using the selected eigenvectors, form the matrix M′, and then calculate M = AM′.

Step-5. Using M, project each m-dimensional vector corresponding to training and testing images to r-dimensional vector, which form r dimensional feature space.

Here r is a parameter; its optimal value is found by experiments. All eigenvectors corresponding to the highest eigenvalues may not important; the eigenvectors can be selected adaptively using feature subset selection.

LDA Features

It is also a holistic method that projects facial images onto a low dimensional space in a way that makes the classes well separated. Feature extraction using LDA involves the following steps:

Step-1. Convert each I_i into a vector x_i, and project each x_i to y_i on a lower dimensional space using PCA.

Step-2. Compute within- class and between-class scatter matrices S_w and S_B

Step-3. Compute C-1 eigenvectors of the matrix $S_w^{-1} S_B$

Step-4. Choose r (≤ C-1) eigenvectors, form the matrix M.

Step-5. Using M, project each training and testing image to the feature space

The within-class scatter matrix is usually singular because the number of images in the training set is very small compared to the number of pixels in an image. To solve this problem, PCA is used to reduce the feature space dimensions [3].

LBP Descriptor

This descriptor was proposed by Ojala et al. [5] and is a widely used texture descriptor. It involves three steps:

Step-1. Compute LBP of each pixel p_c of an image I using

$$\mathrm{LBP}_{\mathrm{P,R}}(p_c) = \sum_{i=1}^{P} 2^i S(p_i - p_c),$$

where p_i, i = 1, 2, …, P are the points in the neighborhood of p_c, see Figure 2 and

$$S(p_i - p_c) = \begin{cases} 1 & p_i - p_c \geq 0 \\ 0 & p_i - p_c < 0. \end{cases}$$

Different neighborhood sizes are possible, see Figure 2(b).

Step-2. Compute histogram of LBP codes, which is the LBP descriptor of I.

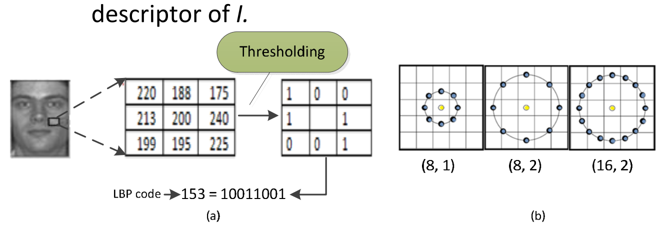

Figure 2. (a) LBP code computation. (b) Some possible neighbourhoods (P, R).

This is a simple LBP descriptor. It also has uniform (u) and rotation invariant (ri) variants denoted by LBP^{u} and LBP^{ri}; LBP^{uri} represents uniform and rotation invariant LBP; detail can be found in [5].

The LBP descriptor computed using the above mentioned approach does not take into account the spatial locality of microstructures; to make it locally enhanced descriptor, we divide each image into non-overlapping blocks, compute LPB histogram from each block and concatenate them. To encode the texture micropatterns at different granularities, we used multiscale LBP, which uses neighborhood of different sizes, see Figure 2(b).

WLD Descriptor

This descriptor is based on Weber's law [6]. Its construction is based on the following three main steps:

Step-1. For each pixel p_c in a facial image I, calculate differential excitation (DE):

$$\zeta(p_c) = \arctan\left[\sum_{i=1}^{P}\left(\frac{p_i - p_c}{x_c}\right)\right]$$

where p_i, i = 1, 2, …, P, are pixels in the neighbourhood of the pixel p_c, as shown in Figure 3(a) for P = 8.

Step-2. For each pixel p_c, calculate the gradient orientation (GO) θ:

$$\theta = \arctan\left(\frac{p_8 - p_4}{p_6 - p_2}\right)$$

and map it to the range [0, 2π]. Then quantize θ values corresponding to all pixels to T dominant gradient orientations Φ_t, t = 1, 2, …, T; a $\theta \in \left[\Phi_t - \frac{\pi}{T}, \Phi_t + \frac{\pi}{T}\right]$ is quantized to Φ_t.

Step-3. Using DE and GO, build WLD histogram for detail consult [6]; this histogram is the descriptor for *I*.

This descriptor involves three free parameters:

- T, the number of dominant GOs Φ_t: t = 0, 1, 2, …, T-1,
- M, the number of segments $H_{m,t}$ of each sub-histogram H_t corresponding to a dominant GO Φ_t, and
- S, the number of bins in each sub-histogram $H_{m,t}$.

WLD also does not take care of spatial locality of texture micropatterns; to make it spatially enhanced, we use a similar stagey used for LBP descriptor. To define multiscale WLD descriptor, we used neighborhoods of different sizes, see Figure 3.

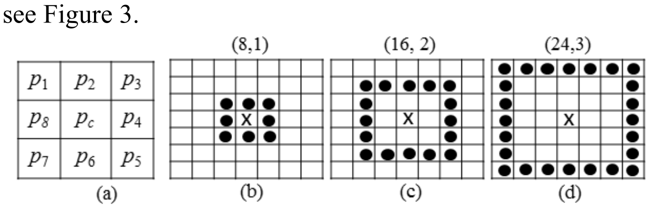

Figure 3. Neighborhoods of a pixel for computing DE

2.2. Feature Subset Selection and Classification

Each of the above descriptors involves large number of redundant features. To select significant features, we use two-stage feature selection approach. First we use Kruskal-Wallis method and then apply Fisher method on the selected features to further reduce the redundant features. Kruskal-Wallis method [8] is a statistical test that tells us if the differences between the classes are so large that they are unlikely to have occurred by chance. Fisher method [9] quantifies the discriminatory power of individual features between equiprobable classes.

For classification, we used nearest neighbor classifier (NN) because the number of samples of each subject is very small. Various metrics exist to measure the nearness of two feature vectors; we tested some well-known metrics to find which gives the best recognition rate.

3. EXPERIMENTAL SETUP

In this section we describe the database used for validation and the parameter tuning for the best recognition rates.

For experiments, we used well-known and challenging FERET database. We employed four sets fa , fb, dup1 and dup2. Table 1 gives the statistics of the database. We used fa as gallery set, and fb, dup1, dup2 as probe sets. For category specific face recognition based on gender, we divided each set into two subsets based on gender.

Table 1. Statistics of FERET database

Set	Total		Male		Female	
	subjs	imgs	subjs	imgs	subjs	imgs
fa	994	994	594	594	400	400
fb	992	992	592	592	400	400
dup1	250	736	171	535	79	201
dup2	75	228	52	168	23	60

The classifier and the feature descriptors involve various parameters, which have significant impact on recognition accuracies. We performed thorough experiments to find the best parameter settings.

For NN classifier, we tested a number of metrics with PCA and LDA features and found that spearman distance gave the best accuracies, see Figure 5.

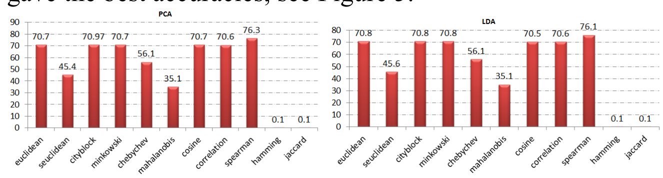

Figure 4. The effect of various metrics on recognition accuracy.

PCA involves one parameter: *r*, the number of features or the number of principal components (PCs) to select; to find which *r* gives the best accuracy, we tried different values, after that we applied two-stage feature selection to further reduce the dimension of the feature space, see Table 2.

Table 2. Selection of features for PCA descriptor, Trainig fa, testing fb

Category	Before FSS		After FSS	
	Acc(%)	#Features	Acc(%)	#Features
Male	80.24	460	80.74	448
Female	79.75	290	80.50	166
Combined	77.72	590	77.82	436

Table 3. Recognition rate by variants of LBP

Category	LBP	LBP^u	LBP^{ri}	LBP^{uri}
	Acc(%)	Acc(%)	Acc(%)	Acc(%)
Male	97.97	**98.82%**	89.70%	93.75%
Female	94.75	**95.75%**	83.00%	88.25%
Combined	96.37	**97.08%**	85.79%	89.72%

For LBP, we tested its four variants: LBP, LBP^u, LBP^{ri}, LBP^{uri}, and found that LBP^u gave the best accuracy, see Table 3. Three types of parameters are involved in the computation of LBP: P (the number of pints in the neighborhood), R (the radius of the neighborhood) , and NB (the number of blocks). We tested P = 8, 12, R = 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5, and NB = 1, 4, 9, 16, 25 with LBP^u. The best configuration is P = 12, R = 3, and NB = 9. We applied fusion with three best configurations P = 12, R = 2.5, 3, 3.5, NB = 9 and two-stage feature selection; it further improved the result.

WLD descriptor involves four parameters: NB, the number of blocks, T, M and S. We tested NB = 1, 4, 9, 16, 25, T = 4, 6, 8, 10, 12, 16, M = 4, 6 and S = 4, 6, 8, 10, 12, 16, 20, and found that NB = 25, T = 16, M = 6 and S = 8 gave the best recognition rate.

4. EXPERIMENTS AND DISSCUSION

In this section, we present the results for each feature descriptor got using the optimal parameter combinations as discussed in the previous section. Table 4-6 give the recognition results for three testing sets: fa, dup1, dup2. The results shown in the tables indicate that overall there is improvement in the recognition accuracy after categorization. Regarding the question that which descriptor is better for male and which is better for female, there is no clear indication; WLD performs better for male in case of fb and dup2, but not in case of dup1; similarly LBP results in better recognition rate for female in case of fb and dup1, but not in case dup2. However there is a trend that WLD forms better descriptor for male and LBP gives a better representation for female.

Table 4. Recognition rates by four descriptors, training fa testing fb

Category	PCA	LDA	LBP	WLD
	Acc (%)	Acc(%)	Acc(%)	Acc(%)
Male	80.74	80.57	99.16	99.32
Female	80. 50	81.25	98.50	98.25
Combined	77.82	77.92	98.49	98.19

Table 5. Recognition rates by four descriptors, training fa testing dup1

Category	PCA	LDA	LBP	WLD
	Acc (%)	Acc(%)	Acc(%)	Acc(%)
Male	41.12	41.31	57.57	53.46
Female	47.26	48.26	71.14	69.15
Combined	42.12	42.12	57.07	54.35

Table 6. Recognition rates by four descriptors, training fa testing dup2

Category	PCA	LDA	LBP	WLD
	Acc (%)	Acc(%)	Acc(%)	Acc(%)
Male	30.95	32.14	57.14	58.93
Female	38.33	42.00	73.30	80.00
Combined	34.21	33.77	56.58	56.14

5. CONCLUSION

We addressed the problem of category specific face recognition based on gender. Here the main issue is to find feature descriptors specific to each gender category: male and female. For this purpose, we investigated four feature descriptors: PCA, LDA, LBP and WLD. We explored the parameter space for each descriptor to come up with the best parameter values. LBP and WLD perform better than PCA and LDA. Categorization improves the recognition rate. The experimental results do not give a clear indication about which descriptor (LBP, WLD) is better for which gender (male/female), however there is a trend that WLD better represents male category whereas LBP is better descriptor for female category. For classification we employed NN classifier and examined the effect of different metrics on classification rate; we found that spearman distance resulted in the best accuracy. There is the need to explore for better descriptors specific to each gender category; we will explore further multiscale features like Gabor features. We will also use other databases for validation.

Acknowledgement

This work is supported by the National Plan for Science and Technology, King Saud University, Riyadh, Saudi Arabia under project number 10-INF1044-02.

6. REFERENCES

[1] K. Veropoulos, G. Bebis, and M. Webster, "Investigating the impact of face categorization on recognition performance," presented at the Proceedings of the First international conference on Advances in Visual Computing, Lake Tahoe, NV, 2005.

[2] M. Turk and A. Pentland, "Eigenfaces for Recognition," Journal of Cognitive Neuroscience, vol. 3, no. 1, pp. 71-86, 1991.

[3] P. N. Belhumeur, J. P. Hespanha, and D. J. Kriegman, "Eigenfaces vs. Fisherfaces: recognition using class specific linear projection," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 19, pp. 711-720, 1997.

[4] T. Ahonen, A. Hadid, M. Pietikäinen, "Face description with local binary patterns: Application to face recognition," IEEE TPAMI, vol. 28, pp. 2037—2041, 2006.

[5] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 24, pp. 971-987, 2002.

[6] Jie Chen, Shiguang Shan, Chu He, Guoying Zhao, Matti Pietikainen, Xilin Chen, and Wen Gao, "WLD: A Robust Local Image Descriptor," IEEE TPAMI, vol. 32(9) 2010.

[7] M. Hussain, G. Muhammad, G. Bebis, "Face Recognition using Multiscale and Spatially Enhanced Weber Law Descriptor," Proc. IEEE SITIS 2012, pp. 85-89 Nov. 25-29, 2012, Naples, Italy.

[8] L. J. Wei, "Asymptotic Conservativeness and Efficiency of Kruskal-Wallis Test for K Dependent Samples," Journal of the American Statistical Association, vol. 76, pp. 1006-1009, 1981.

[9] P. E. H. R. O. Duda and D. G. Stork. Pattern Classification. Wiley-Interscience Publication, 2001.