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RACE RECOGNITION FROM FACE IMAGES USING WEBER LOCAL DESCRIPTOR

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ABSTRACT

This paper proposes a race recognition system from face images based on Weber local descriptors (WLD). In the system, first, WLD histogram is extracted from normalized face images. Then Kruskal-Wallis feature selection technique is used to select the best discriminated bins. City block, Euclidean, and chi-square minimum distance classifiers are used for testing. In the experiments, FERET database is used where there are five major race groups: Asian, African or American Black, Hispanic, Middle-Eastern, and White. Experimental results show that the proposed system with WLD histogram, feature selection, and city block distance classifier achieves accuracies of Asian: 97.74%, Black: 96.89%, Hispanic: 92.06%, Middle: 98.33%, and White: 99.53%. These accuracies are significantly higher than those using principal component analyses.

Index Terms**—** Race recognition, face recognition, Weber local descriptor, FERET

1. INTRODUCTION

There has been a growing interest to extract demographic information from face images due to several applications such as access control, surveillance, identity authentication, etc. It is well known, for example, that people are more accurate at recognizing faces of their own race than faces of other races [1][2]. Therefore, categorizing faces into different race groups should help to reduce the search space as well as to increase the accuracy of person identification. In this paper, we concentrate on race recognition from faces. We often feel that people from other race look similar to each other than the people from our own race. MacLin and Malpass subjectively found that other race faces are encoded categorically and this categorization contributes to human perception [3]. Phillips et al analyze other-race effect on face recognition algorithms based on the result of Face Recognition Vendor Test (FRVT) 2006 [4]. They find that Western algorithms (developed by France, Germany and the United States research groups) recognized Caucasian faces more correctly than East Asian faces and East Asian algorithms (developed by China, Japan, and Korea research groups) recognized East Asian faces more accurately than Caucasian faces. Two class (Asian and non-Asian) ethnicity (race) identification based on face images is proposed in [5]. The authors use multiscale LDA based classifier to classify 132 Asian faces and 131 non-Asian faces. An ensemble is constructed by integrating the classification results using dot product to find the final decision. An overall accuracy of 96.3% is achieved in their experiments. Hosoi et al [6] design ethnicity estimation method using Gabor wavelets transform and retinal sampling as features, and SVM as classifier. Three types of ethnic groups are classified: African, Asian, and European, and an overall approximately 94% accuracy is achieved. Zhiguang and Haizhou use LBP [8] for demographic classification, which includes race, using face images [7]. AdaBoost algorithm is used on chi-square distant metric to form a strong classifier. Experimental results confirm that LBP features are comparable to Haar like features for Asian and non-Asian classification.

It can be stated that race recognition using face images is not fully discovered with the state of the art features, though a significant progress has been made in face recognition. Some attempts are made for only two or three class problems, which is relatively easier than multi class problems. Also no feature selection methods are applied to race recognition problems. Therefore, in this paper, we introduce a new race recognition method that (a) involves state of the art local features, (b) utilizes feature selection technique, and (c) works on five race groups. The proposed method uses Weber local descriptor (WLD) [9] as features, and city block distance measure as classifier.

The rest of the paper is organized as follows. Section 2 presents the proposed race recognition system, Section 3 shows experimental results with discussion, and finally Section 4 draws some conclusion.

2. PROPOSED METHOD

Figure 1 shows a block diagram of the proposed race recognition system using face images. WLD features are extracted from the normalized input face images in blocks.

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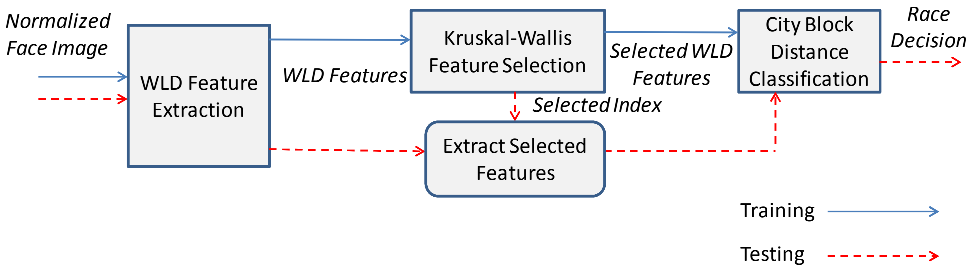

Fig.1. Block diagram of the proposed WLD based race recognition system.

Kruskal-Wallis feature selection method is then applied to WLD features to select highly discriminative components. This optimized WLD is the input to the classifier. In the classifier, city block distance is calculated using training face images and test face image. The minimum distance is used to get the final decision.

2.1. WLD

WLD is a recently developed robust and very powerful local descriptor [9]. It consists of two components: differential excitation and gradient orientation. It has been inspired by psychological law called Weber's Law.

Differential excitation: Differential excitation is calculated by taking the ratio between the sum of intensities differences of the center pixel against its neighbor's pixels and the intensity of the center pixel. It can be translated into a mathematical formula as Eq. (1).

$$\xi(x_c) = \arctan\left[\sum_{i=0}^{P-1}\left(\frac{x_i - x_c}{x_c}\right)\right] \qquad (1)$$

Where x_c is the center/current pixel, $\xi(x_c)$ is the differential excitation of the center pixel, p is the number of neighbors (P=8), and x_i corresponds to the ith neighbor of x_c.

Gradient orientation: This component is calculated as the basis of Eq. (2):

$$\theta = \arctan\left(\frac{v_{10}}{v_{11}}\right) \qquad (2)$$

where $v_{10} = x_5 - x_1$ and $v_{11} = x_7 - x_3$. x_5, x_1, x_7, and x_3 are the neighbors of x_c in 3×3 neighborhood as shown in Fig. 2.

Gradient orientation (GO) is then quantized into T number of dominant orientations. Final WLD histogram is calculated as follows: For each dominant orientation, find the deferential excitation that will produce T sub-histograms, then divide these sub-histograms which are in the range of

x_0	x_1	x_2
x_7	x_c	x_3
x_6	x_5	x_4

Fig. 2. 3×3 neighborhood of pixel x_c.

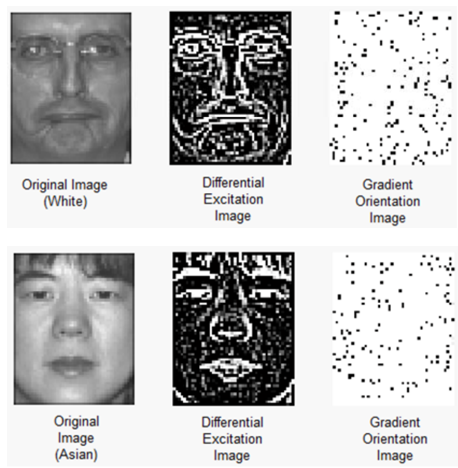

Fig. 3. Sample faces and their differential excitation and gradient orientation for White and Asian races.

$\left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$ of deferential excitation values, into M segments l_m, and for each interval l_m, (m = 0,1,2,…,M-1) compute the segment with S bins.

Figure 3 shows differential excitation images and gradient orientation images of sample White and Asian faces. From these images we see that both DE and GO capture different information for different race faces.

As mentioned in [9], this method has several advantages, such as: perfectly extracting the edges of image even if there is heavy noise, robust against changing in illumination and powerful representation ability. It is also reported that WLD outperforms LBP for highly texture images. However, WLD is not explored in face recognition applications yet. In WLD, there are three parameters that affect on optimizing the results: the number of dominant orientations (T), the number of differential excitation segments (M), and the number of bins in sub histogram segments (S). In the experiments in this paper, the values of the parameters are varied as the following (T = 6 or 8; M = 4 or 6; S = 10 or 15).

2.2. Kruskal-Wallis feature selection

The number of bins in WLD histogram is very large, especially when they are calculated in blocks. Many of these bins may not contain sufficient discriminative information, and as a consequence may contribute to low performance of the recognition system. Also dealing with too many features slows down the classification process. In the proposed system, we use Kruskal-Wallis (KW) feature selection method, which is very simple to implement and involves less computation. KW method is a non-parametric one-way ANOVA (analysis of variance) test that can be applied to two or more classes. It tests the null hypothesis that the samples from two or more groups have equal medians, and returns p value (this p value is different than that in Eq. (1)). If the p value is close to zero for a certain feature, we select that feature for its discriminative power. On the other hand, if the p value is far from zero for a certain feature, we discard the feature.

In the proposed method, during training, KW method is applied to WLD features. The features that have p value less than a threshold are selected, and their indices are stored for testing. During testing, the features with those indices are selected for classification.

3. EXPERIMENTS

3.1. Database

In the experiments, FERET database [10] of gray face images is used. There are eight race groups in the database. The race groups are: Asian, Black-or-African-American (Black), Hispanic, Asian-Middle-Eastern (Middle), White, Pacific-Islander, Native-American, and other. The number of subjects in each group of Pacific-Islander, Native-American, and other is less than 10. Therefore, we study the other five major race groups, each of which contains more than 50 subjects. In our experiments, we focus on two sets of gray image database: *fa* and *fb*. *fa* set includes 1,204 frontal images with regular expression. This set of images are called gallery images and used for training. *fb* set includes 1,195 images of the same subjects in *fa* set but with alternative facial expression. The major five race group consists of 1180 images. The *fb* set is termed as probe set and used for testing. All the face images are normalized and cropped to 60×48 pixel sizes.

3.2. Experimental results and discussion

Three types of minimum distance classifiers: city block (L1), Euclidean (L2), and chi-square (CS), are used in the experiments. As a baseline experiment, principal component analysis (PCA) is applied as features. Different numbers (200 – 800) of principal components are evaluated. The optimum result is obtained with 200 principal components

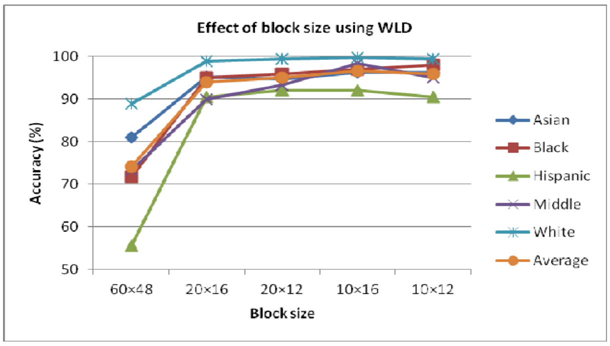

Fig. 4. Effect of block size on the performance using WLD.

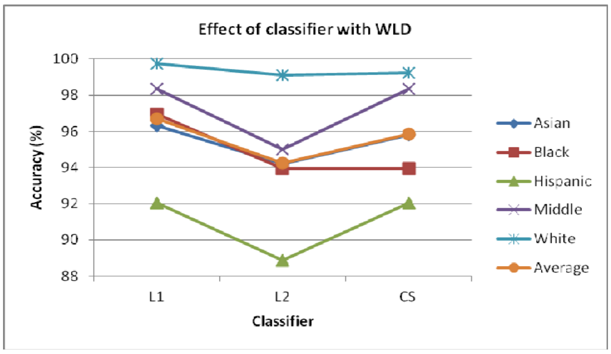

Fig. 5. Effect of classifiers on the performance using WLD.

and L1 classifier. The accuracies in this case are Asian: 86.84%, Black: 66.67%, Hispanic: 65.08%, Middle: 81.67%.

In the experiments, block size of the face images is varied as: (20×16), (20×12), (10×16), (10×12), and the whole image size (60×48). Figure 4 shows the effect of block size on race recognition using WLD. The results shown are with L1 classifier and WLD with T=8, M=4, S=5. Using the whole image size (60×48), the performance is the lowest in all the race groups. The average accuracy is 74.09%, which is worse than that using PCA (79.17%). This finding suggests that local descriptors do not perform well if they are applied globally. If WLD is applied in blocks, the performance increases. The best performance in terms of average accuracy is 96.68%, achieved in our experiments using 10×16 block size. However, the performance decreases if the block size is too small; for example, the average accuracy is down to 95.85%, if the block size is 10×12. This indicates that very small block size cannot capture global information, and there must be some balance between global and local information to achieve high performance.

The parameters T, M, and S do not exhibit any clear trend of decreasing or increasing accuracy, hence we do not provide detail results using these parameters.

Figure 5 shows the effect of the classifiers on race recognition. In most of the races, the performances of L1 and CS are comparable, while that of L2 is the least. The

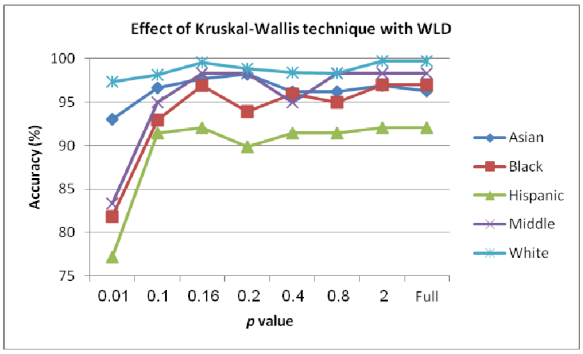

Fig. 6. The effect of Kruskal-Wallis technique with WLD.

average accuracies using L1, L2, and CS are 96.68%, 94.23%, and 95.87%, respectively, for WLD. KW technique is applied on the best combination: 10×16 block size, L1 metric, and [T,M,S] = [8,4,5], where the total number of features is 2880. The value of p (significance) is varied to define a threshold above which all the bins are discarded. Figure 6 shows recognition accuracies (%) of the five races after applying the method and Table 1 gives the number of WLD features for different values of p. Almost similar accuracies compared to those using full length WLD (without feature selection) are found at half number of features when $p = 0.16$. The confusion matrix in this case is given in Table 2. Some misrecognition race faces are given in Fig. 7.

Table 1. Number of WLD features at different p values.

P value →	0.01	0.1	0.16	0.2	0.4	0.8	2	Full
# of WLD features	752	1433	1632	1793	2206	2685	2801	2880

Table 2. Confusion matrix of the proposed method.

		Output				
		Asian	Black	Hispanic	Middle	White
Input	Asian	97.74%	-	-	1.05%	1.21%
	Black	-	96.89%	1.01%	-	2.10%
	Hispanic	1.59%	-	92.06%	-	6.35%
	Middle	1.67%	-	-	98.33%	-
	White	0.13%	-	0.34%	-	99.53%

Fig. 7. Some misrecognized race faces by the proposed method.

4. CONCLUSION

WLD based race recognition using face images is proposed. Kruskal-Wallis feature selection is applied to select the optimum bins from WLD histogram. The proposed method is evaluated against PCA based holistic method. From the experimental results, we can conclude the followings: (i) WLD outperforms PCA in all the race groups, (ii) medium size block performs better than full size or very small block size, (iii) Kruskal-Wallis feature selection reduces the size of the feature vector by half without affecting the recognition performance. In a future work, other local descriptors will be evaluated in race recognition applications.

5. REFERENCES

[1] Brigham, J., "The influence of race on face recognition", Aspects of face processing (H. Ellis, M. Jeeves, and F. Newcombe, eds), pp. 170-177, 1986.

[2] O'Toole, A. et al., "Another-race effect for classifying faces by sex", Perception, vol. 25, pp. 669-676, 1996.

[3] MacLin, O.H. and Malpass, R.S., "Racial categorization of faces: The ambiguous race face effect", Psychology, Public Policy, and Law, vol. 7, no. 1, pp. 98-118, 2001.

[4] Phillips, P. J., et al., "An Other-Race Effect for Face Recognition Algorithms", ACM Transactions on Applied Perception (TAP), vol. 8, Issue 2, January 2011.

[5] Lu, X. and Jain, A.K., "Ethnicity Identification from Face Images", Proc. of SPIE International Symposium on Defense and Security, pp. 114-123, 2004.

[6] Hosoi, S., et al., "Ethnicity Estimation with Facial Images," Proc. 6th IEEE Int. Conf, on Automatic Face and Gesture Recognition (AFGR), pp. 195-200, 2004.

[7] Zhiguang Y., and Haizhou A., "Demographic Classification with Local Binary Patterns", Proc. International Conf. on Biometrics (ICB), pp.464-473, 2007.

[8] Ahonen, T., et al., "Face description with local binary patterns: Application to face recognition," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 28, pp. 2037—2041, 2006.

[9] Chen, J., et al., "WLD: A Robust Local Image Descriptor," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 32, no. 9, pp. 1705-1720, Sep. 2010.

[10] Phillips, P.J., et al., "The FERET evaluation methodology for face-recognition algorithms," IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 22, no. 10, pp. 1090- 1104, Oct. 2000.