H-010

IMPROVING THE POSE INVARIANT FACE RECOGNITION PERFORMANCES USING MULTI-STAGE CLASSIFIER

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1. Introduction

The published approaches mostly correlated with the frequency analysis-based face recognitions are global features-based face recognitions combined with PCA and/or LDA as described in Refs. [1-5]. However, most of them have to retrain all face image classes to get optimal projection when the new classes are added into the system. Moreover, our previous research's [3-5], even though they could solve the pose invariant face recognition but they did not reach 100% recognition rate yet because many facial features were overlapping to each other's. The main advantage of those methods is the recognition was performed using compact features, which compressed by about 99.4% of the original data (just using less than 100 of 16384 coefficients).

This paper presents an improvement of our previous research [4,5] that applies multistage classifiers, i.e. APCA as the first stage classifier and the DLDA as the second stage classifier. The function of the first stage classifiers is to determine several class candidates which are closely to the query image and then the second stage classifier determines the best similarity of query image to the class candidates. The APCA is chosen because it is simple and gives better performance than that of CPCA and can solve the retraining problem of CPCA. The DLDA based classifier is chosen because it out of performs compare to the other subspace analyses (CPCA, CLDA, and ICA). However, the DLDA has to retraining problem when new classes are added into the DLDA system.

2. The Proposed Algorithm

The proposed face recognition algorithm can be illustrated briefly in Fig. 1. There are three main processes: features extraction of face image, APCA processing as the first stage of face features classifier, and the DLDA processing as the second stage of classifier which classify just first five the APCA-determined class candidates.

The features extraction is to find the holistic information of any face image which is as much as invariant to pose variations in a single face. This unit consists of colour space transformation, equalization, frequency analysis, and moment analysis. To create face features, the DCT is used as frequency analysis. However, we do not apply the blocked DCT as performed in the JPEG compression. From the DCT decomposition coefficients, the dominant frequency content is created by three steps: firstly, convert the frequency domains coefficients to vector using row ordering technique; secondly, sort the vector descending using quick sort algorithm, finally truncate a small number of vector elements (i.e., less then 100 elements). In order to get robust global features against to face pose variations, the moment information is considered. It is obtained using invariant moment analysis, which is derived from central moment analysis [5]. The invariant moment set is invariant to translation, scale change, and rotation, consequently this concept can be used to get the holistic information of any face pose variations. Those processes are performed on both training and query (probe) face images. However, in the training process, those are performed one time.

Next, the first stage classifier, APCA, performs face image features clustering using the optimum projection matrix, W, which is obtained by eigen analysis of within class scatter (S_w) that satisfy the following criterion.

$$J(W) = \arg\min_{W} \left|W^T S_w W\right| \tag{1}$$

Then, the APCA's optimum projection matrix provides more separable projected data than that of the classical PCA (CPCA). This fact has been proved by experimental data in the Ref [5]. It can be achieved because the APCA has higher power discriminant ($J(W)$) than that of CPCA which satisfy the equation.

$$J_{CPCA}(W) << J_{APCA}(W) \tag{2}$$

In order to define class candidates, the Mahalanobis distance is used to determine the score of similarity between the query and training set and keep first five smallest score as class candidates.

Next, the DLDA is chosen as the second stage classifier because it out of perform over the other subspace methods event the APCA method for large class data. However, it requires retraining problem. In the DLDA, the optimum projection matrix is obtained by eigen analysis of both the within class scatter (S_w) and between class scatter (S_b) that satisfy the following criterion

$$J(W) = \arg\max_{W} \frac{\left|W^T S_b W\right|}{\left|W^T S_w W\right|} \tag{3}$$

By this projection matrix, the DLDA will make the data projection using both the non null space (provided by S_b) and null space (provided by S_b) information. The selected class candidates will be classified by calculating the similarity score using Euclidian distance. In this case, the minimum score is concluded as the best likeness.

3. Experiment and Result

The experiments are carried out using several databases, such as ITS-Lab. Kumamoto University database[3-5], India database[7], and FERET database[6]. The ITS-Lab database consists of 48 people and each person has 11 pose orientations that were taken under varying lighting condition. The INDIA database consists 61 people (22 women and 39 men), each person has eleven pose orientations. From FERET database, we

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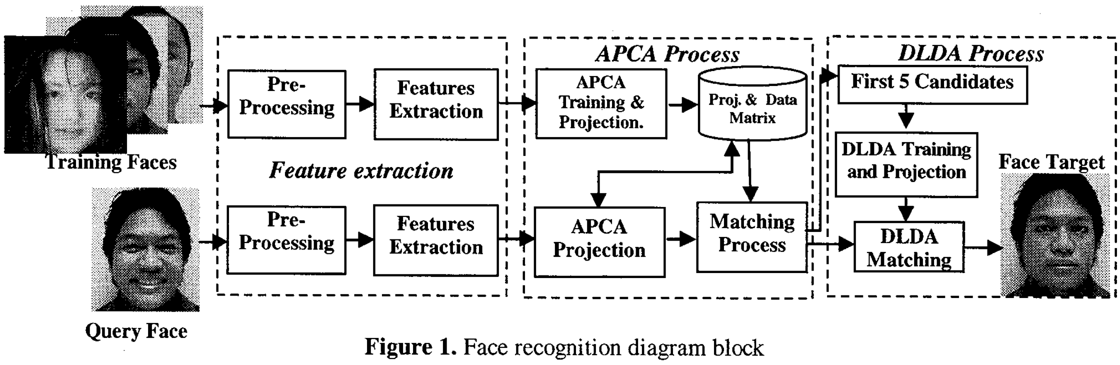

Figure 1. Face recognition diagram block

selected about 508 people and each person has 4 images (*fa, fb, ql, qr*). From each class half of class member are selected as training data and the remaining as query.

The results, shown on Table 1, show that the APCA+DLDA gives higher recognition rate than the DLDA+DLDA for small size database (i.e. ITS and INDIA), because the APCA classifier had out performs over the DLDA for small size database, as proved in Ref. [5]. In other side, the DLDA performance is better for large size database than APCA, because it uses not only within class discriminant information (obtained from S_w) but also the between class information (obtained from S_b). Generally, The APCA+DLDA and DLDA+APCA could improve our previous method performances [4-5], because the second stage recognizes strongly the face likeness by seeking it in just around first five class candidates. However, the multistage requires longer time processing than single stage methods.

Regarding to the ROC analysis the DLDA+APCA has lower EER than APCA+DLDA as shown in Fig. 2, it means that the DLDA+APCA is good for face image classification when the size of data samples are large. The main disadvantage is it requires longer time processing than because the DLDA has to calculate S_b and retraining problem while the APCA has not at all.

Table 1. The average recognition rate comparison.

No	Methods	Rec. Rate (%)		
		ITS	INDIA	FERET
1	APCA	97.50	96.23	94.00
2	DLDA	97.29	95.48	96.91
3	APCA+DLDA	**98.54**	**97.74**	95.62
4	DLDA+APCA	98.13	96.987	**97.69**

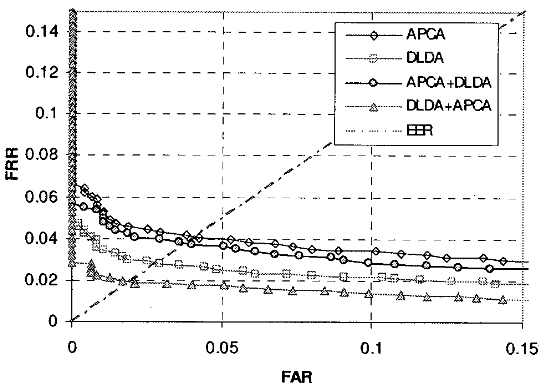

Figure 2 The ROC of the proposed method compare to others on FERET databases.

Regarding to time consumption, the proposed method requires the same training time processing (80.49 second) when the data training size is 508 face classes or 1750 face images. However, the querying time is longer than the single stage (increasing about 0.03 second of single stage's querying time).

4. Conclusion

The proposed method is an alternative pose invariant face recognition which gives better performances than our previous methods when it performs in the holistic and moment features of face image. By implementing this feature to the multi stage classifier (APCA+DLDA), the recognition rate can be increased by about 1.04%, 1.51%, 1.62% of APCA recognition rate of ITS, INDIA, and FERET database respectively. In other combination (DLDA+APCA), in can increased the base line recognition rate (DLDA) by about 0.84%, 1.51%, and 0.78% However, this method still has retraining problem.

5. References

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