FACE RECOGNITION SYSTEM BASED ON STATISTICAL LOCAL FEATURES, MARKOV CLASSIFIER AND DYNAMIC RANKING

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Abstract

This paper presents theoretical analyses of face recognition system based on increased kernel representation, Markov classifier and dynamic ranking. The main aim of this work is to minimize the error rate and complexity of recognition techniques in Face Recognition. To achieve this, robust classification techniques can be formulated and evaluated in this research so that to facilitate the recognition of faces in an effective way.This work acts as platform to study the improvement in accuracy and time complexity, when optimization techniques and neural networks are used in Face Recognition. Theoretical analysis of face recognition system with robust kernel representation, Markov network based classifier and dynamic ranking are implemented. Numerical values for recognition accuracy, error rate, system complexity and efficiency are found.

Keywords
Face recognition system, Statistical local feature, Markov classifier, Multi partition Max pooling, dynamic ranking,

1. INTRODUCTION

Face recognition system has been gained momentum in both the research community and industry for its emerging applications and it can be achieved using probabilistic decision based neural network[1]. The approach behind the objective of face recognition is identification / verification of a specific facial image from a large database of face datasets. Having the complexity of the system as an aim, an initiative has been taken to articulate and apply a new optimization algorithm for recognizing facial data thereby improving the performance and efficiency of searching. Practitioners have put their effort to attain the accuracy in various methods of classification and machine learning techniques to maximize recognition rate and minimize error rate and complexity.

2. FACE RECOGNITION USING STATISTICAL LOCAL FEATURES

The main challenges in robust face recognition are misalignment and pose invariation. In case of traditional face recognition system, discriminant eigen features for image retrieval is used[2]. In robust face recognition, statistical features are successfully taken for feature extraction. An efficient method in which the invariance of statistical local features are improved by Multi Partition Max Pooling (MPMP) and the discrimination information fixed in the statistical local features is used by the kernel representation model[3]. The root cause of facial misalignment can be assumed as transformations such as scaling, rotation and translation. To minimize lot of troubles caused by these transformations, it is essential to strengthen the robustness of feature extraction step. Multi Partition Max

Pooling (MPMP) is one such technique meant for effective pooling. In general, pooling techniques are used in object classification to extract invariant features. The implementation of the method involved two procedures: feature extraction using multi partition max pooling and robust kernel representation. The illustration of multi partition max pooling is shown in the Figure 1. The process of pooling is worked on the sequence of statistical local features created in each partitioned block. After multi partition max pooling based statistical local feature extraction, kernel representation is formulated.

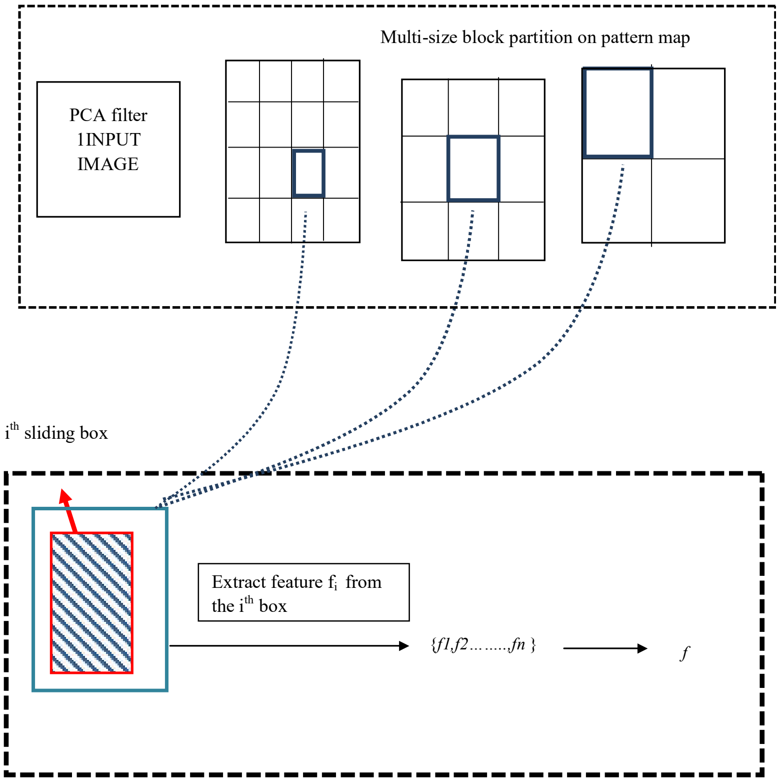

Figure 1 Illustration of Multi partition Max Pooling (MPMP) method

The performance of the MPMP method is experimented on JAFFE and ORL databases. The results were analysed and it was noticed that the method exhibited a recognition rate of about 93.5%.

3. FACE RECOGNITION USING MARKOV CLASSIFIER

The face recognition system is implemented by designing a unique framework using Markov classifier. In this method, a direct LDA algorithm is used to extract features for high dimensional data [4] and an incremental linear discriminant analysis also used for feature extraction [5]. A new model of system which worked under Markov premise to study the correlation of different classifiers by the association of hidden nodes is in the form of similarity matrix [6]. In this method, the query image is partitioned into several blocks and labelled them under Markov assumption. Since the resultant network consists of multiple classifiers, the framework exhibited complexity.

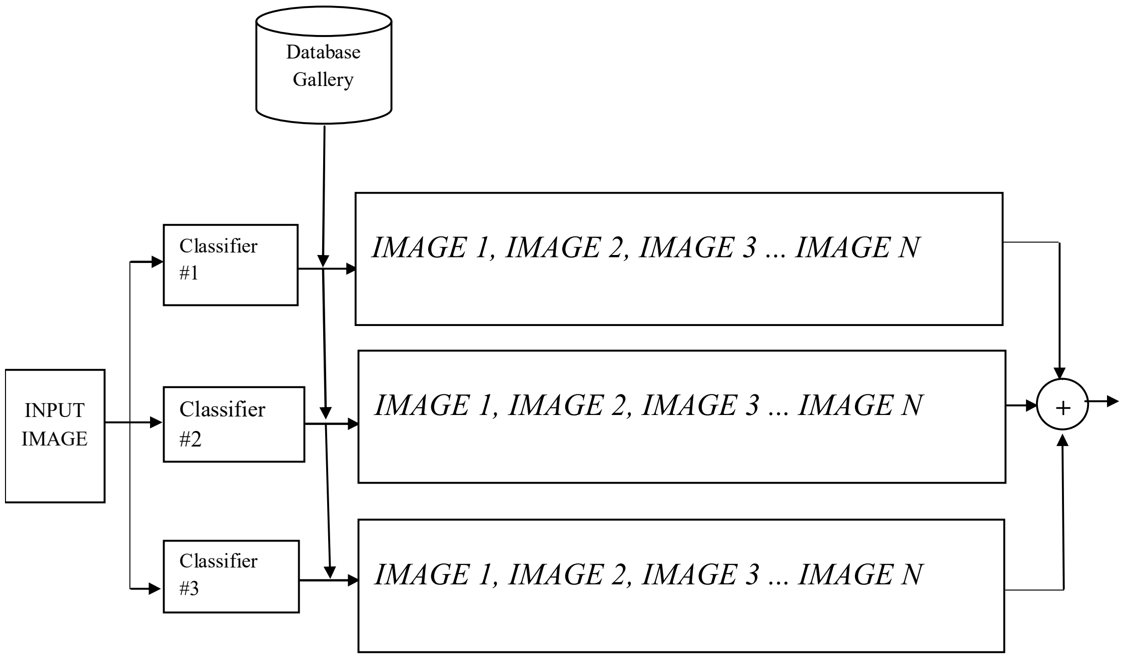

Figure 2 Representation of multiple classifiers under Markov assumption

The representation of multiple classifiers under Markov's assumption is depicted in the Figure 2. Each classifier is regulated by the two adjacent classifiers and it worked with the combination of *N* observation and hidden node pairs. Unlike conventional methods of face recognition, the hidden nodes are linked by set of connections. When examining a hidden node, it has its own collection of *n* gallery images since they regain the appropriate features from the image database. The Markov network probabilistically modelled the relationships between a query image and gallery images, as well as among neighbouring gallery images. With each observation-hidden node pair, gallery images retrieved were most similar to the query image from the database using a query image face model. The statistical dependency between the hidden nodes was calculated using similarities among the retrieved gallery images. Hence, the resulting inference mechanism can be viewed as a type of clustering-based face recognition method. This method improves face recognition performance using Random sampled Gabor (RSG) classifiers and Extended Curvature Gabor (ECG) classifiers. Since the multiple classifiers are interdependent, the *n* gallery images in each node are not indistinguishable. Therefore it is mandatory to understand the correlation between classifiers so that to revise the comparison attainments and from this value, the sequence of the gallery images is refined iteratively.

3.1 Calculation of similarity measures

The similarity between two feature vectors is estimated by the normalized values among the vectors and there are *n* gallery images regained at each and every classifier. There exists an compatibility function between hidden nodes *i* and *j* which can be given by,

$$\psi_{i,j}(x_i, x_j) = \exp(-\frac{|s_{ij}(x_i, x_j) - 1|^2}{2\sigma^2}) \quad (1)$$

where σ is noise parameter and s_{ij} is the similarity measure between hidden node *i* and *j*.

The performance of the method is tested on JAFFE and ORL databases. The results were examined and it was observed that the concatenated classifiers under Markov's theory showed the evidence of higher recognition rate of about 94%. It is observed that the fusion of simple RSG classifiers outperformed a set of sophisticated ECG based classifiers combined with a traditional fusion method, thereby showing that the proposed Markov network-based classifier fusion can significantly boost retrieval performance.

It was also monitored that the sequential arrangement of multiple classifiers with Markov's assumption increased the complexity of the system.

4. FACE RECOGNITION USING DYNAMIC RANK REPRESENTATION

Dynamic rank representation is implemented to increase the efficiency of face recognition system in which the dynamic rank is used as an optimal subspace. A low rank representation is proposed which involved the extraction of dynamic subspaces of images attained substantial recognition rate in terms of accuracy and efficiency [7]. The low rank representation of feature extraction is estimated first and it is optimised to achieve dynamic rank representation. As Low Rank Representation (LRR) has good retrieving performance, the erroneous data can be made clear. But this choice does not work in case of some specific errors caused due to uncontrolled environment and sensor failures. Therefore there is a need for subarea to reconstruct the discriminative information of corrupted data. The objective of the method is to select a subspace from various classes which can be optimal enough and as far as possible to store the discriminative information. In general, principal component analysis or linear discriminant analysis is selected based on the characteristics of given images [8].

5.1 Architecture of dynamic rank representation

In this method, k-nearest neighbour algorithm is employed for classifying the samples in the feature space. The distance matrix is generated by estimating the Euclidean distance between testing and training image. The aggregate of distance matrix is calculated and arranged in an increasing form in order to choose the first *n* samples. Then the predominance of class value is identified for categorizing the samples in an accurate way. The architecture of dynamic rank representation is shown in the Figure 3. In this system, singular value decomposition method is used for dimensionality reduction and in turn is used to extract features in a reduced format.

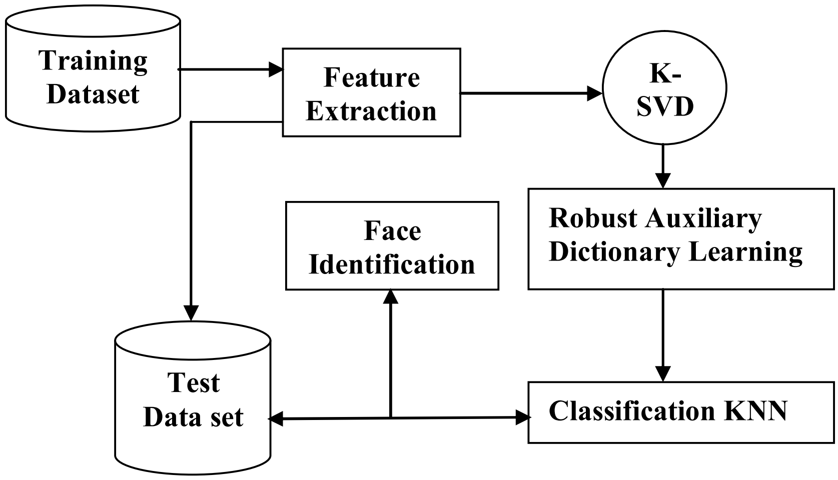

Figure 3 Architecture of Dynamic Rank Representation

Face recognition system can also effectively be done by using Bayesian features [9]. Singular value decomposition technique in extracting features thereby afforded lower dimensional data which in turn paved the way for lesser computational cost and a simple model [10]. Since the approach dealt with smaller number of vectors, singular value decomposition algorithm is also used to reconstruct the images. Experimentation is conducted on publicly available face databases such as ORL and JAFFE. This method achieved recognition rate of about 95.2%.

5.2 Step by step procedure of dynamic ranking algorithm

Input: Training data X, Testing data Y and its size $S_1 x S_2$. A matrix of normalized training samples $= [D_1, D_2, \dots D_k] \epsilon R^{mxn}$, for K classes, a test sample $y \epsilon R^m$.

Step 1: Estimation of dynamic rank for the above inputs.

Step 2: For each and every subject in the training samples, perform singular value decomposition.

Step 3: Repeat step 2 as an iterative process in order to get clean data M_{i1}

Step 4: Calculate the ranking using optimal subspace and obtain the value of L_i^*.

Step 5: Compute discriminative information of the samples by solving$L_i * M_{i1}$.

Step 6: Determine the residual associated with i^{th} class using the formula

$$e_i = \|L_i * y - L_i * M_{i1}\|_2^2 \quad (4.2)$$

Step 7: The required output: $identify(y) = arg_i \min\{e_i\}$ (4.3)

5. RESULTS AND DISCUSSION

Experiments are verified using ORL and JAFFE data sets and the simple description of the data sets and performance comparison graphs are given below:

ORL: The database contains images of 40 individuals and each subject had its own 10 variations of pose, time, expression and illumination conditions.

JAFFE: The Japanese Female Facial Expression database contains images of 10 distinct persons, under same illumination and different face expressions.

5.1 Performance of Multi Partition Max Pooling Method

Recognition Rate: While experimentation of recognition rate for the above datasets, the number of training samples tend to vary from 50 to 250 images. In this system, multi partition max pooling method is used for extracting features. The performance of MPMP method is compared with traditional PCA based feature extraction and the results are given in the Figure 4. From the Figure, it is evident that the recognition rate of face recognition system using MPMP method attained a maximum of 93.5% when measured with PCA based method.

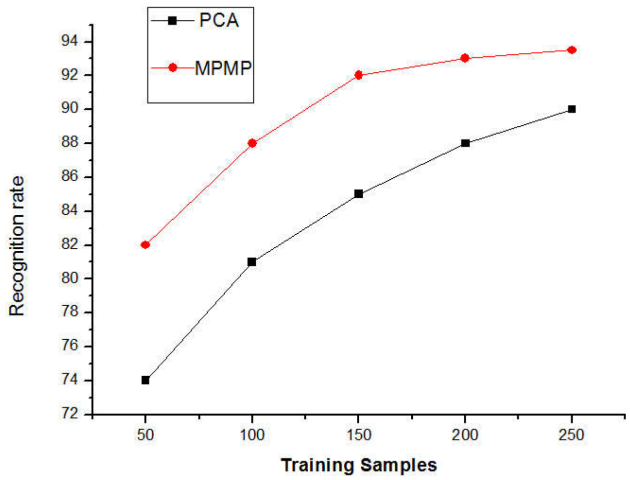

Figure 4 Recognition rate of Multi-Partition Max Pooling (MPMP)

Time Complexity: It is essential to estimate the time required to execute the above method. The comparison of execution time taken for MPMP and PCA method is shown in the Figure 5. The Figure represented the existence of execution progress of MPMP method in an agreeable manner. From the graph, it is easier to understand that the time taken to complete the execution process is 75ms and this value seems to be maximum.

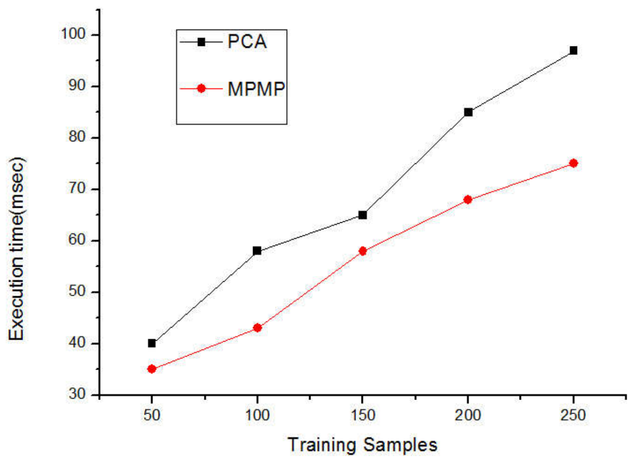

Figure 5 Execution time of Multi-Partition Max Pooling (MPMP)

5.2 Performance of Multiple Classifiers under Markov's Assumption

While examining the face databases for the estimation of recognition rate using multiple classifiers under Markov's theory, the number of classifiers has been made to vary from 1 to 10 numbers. Comparison of recognition rates of multiple classifiers in traditional framework and Markov's assumption is carried out. The resultant graph is presented in the Figure 6. From the graph, it is understood that the recognition rate of the system using Markov's theory achieved 94% when assessed with classifiers under traditional framework.

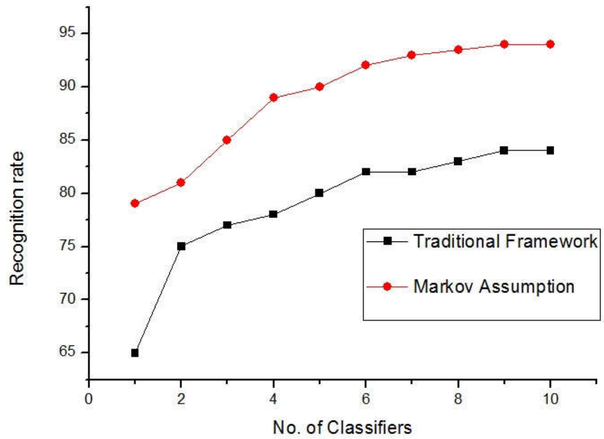

Figure 6 Recognition rate of multiple classifiers under Markov's assumption

5.3 Performance of Dynamic Rank Representation

In this system, dynamic rank representation method is used for efficient reconstruction of information from contaminated images. The existing method used for the retrieval is low rank representation. To measure the performance of dynamic ranking, the method is needed to compare with existing low rank representation method and it is depicted in the Figure 7.

. From the Figure, it is clear that the recognition rate of face recognition system using dynamic ranking method accomplished 95.2% when measured with low rank representation method.

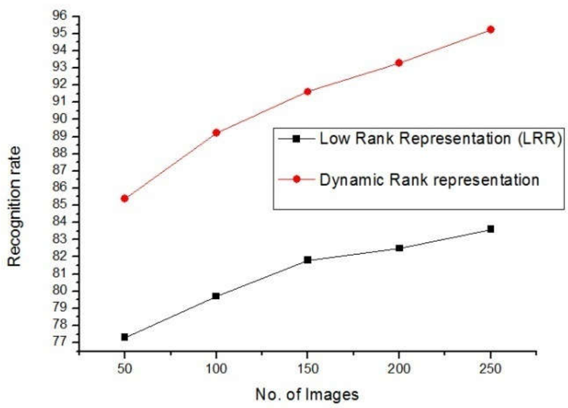

Figure 7 Comparison between low-rank and dynamic rank representation

Therefore constructive face recognition algorithms using multi partition max pooling, multiple classifiers under Markov's framework and dynamic rank representations are implemented and the results are encouraging. It is also noticed that the three procedures exhibited a pitfall in the recognition accuracy and time complexity.

This chapter described face recognition system through multi partition max pooling, multiple classifiers under Markov's framework and dynamic rank representations. In this work, the recognition accuracy cannot be met by all the three algorithms and it created the requirement of using optimization techniques and neural networks. The further chapters discuss the algorithms based on optimization which is a prerequisite to arrive at an optimized solution.

REFERENCES

[1] Shang-Hung, L, Sun-Yuan, K & Long-Ji, L 1997, 'Face recognition/detection by probabilistic decision-based neural network', IEEE Transactions on Neural Networks, vol. 8, no. 1, pp. 114-132.

[2] Swets, DL &Weng, JJ 1996, 'Using discriminant eigen features for image retrieval', IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 18, no. 8, pp. 831-836.

[3] Yang, M, Zhang, L, Shiu, SCK & Zhang, D 2013, 'Robust kernel representation with statistical local features for face recognition', IEEE Transactions on Neural Networks and Learning Systems, vol. 24, no. 6, pp. 900-912.

[4] Yu, H & Yang, H 2001, 'A direct LDA algorithm for high-dimensional data - with application to face recognition', Pattern Recognition, vol. 34, no. 10, pp. 2067-2070.

[5] Zhao, H & Yuen, PC 2008, 'Incremental Linear Discriminant Analysis for Face Recognition', IEEE Transactions on Systems, Man & Cybernetics: Part B, vol. 38, no. 1, pp. 210-221.

[6] Hwang, W & Kim, J 2015, 'Markov Network-Based Unified Classifier for Face Recognition', IEEE Transactions on Image Processing, vol. 24, no. 11, pp. 4263-4275.

[7] Li, H &Suen, CY 2016, 'Robust face recognition based on dynamic rank representation', Pattern Recognition, vol. 60, pp. 13-24.

[8] Martínez, AM &Kak, AC 2001, 'PCA versus LDA', IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 23, no. 2, pp. 228-233.

[9] Moghaddam, B, Jebara, T &Pentland, A 2000, 'Bayesian face recognition', Pattern Recognition, vol. 33, no. 11, pp. 1771-1782.

[10] Modarresi, K 2015, 'Unsupervised feature extraction using singular value decomposition', Procedia Computer Science, vol. 51, no. 1, pp. 2417-2425.