Biomimetic Uncorrelated Locality Discriminant Projection for Feature Extraction in Face Recognition

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***Abstract*- We develop a new dimensionality reduction method, named Biomimetic Uncorrelated Locality Discriminate Projection (BULDP), for face recognition. It is based on unsupervised discriminate projection and two human bionic characteristics: principle of homology continuity and principle of heterogeneous similarity. With these two human bionic characteristics, we propose a novel adjacency coefficient representation, which does not only capture the category information between different samples, but also reflects the continuity between similar samples and the similarity between different samples. By applying this new adjacency coefficient into the unsupervised discriminant projection, it can be shown that we can transform the original data space into an uncorrelated discriminant subspace. A detailed solution of the proposed BULDP is given based on singular value decomposition. Moreover, we also develop a nonlinear version of our BULDP using kernel functions for nonlinear dimensionality reduction. The performance of the proposed algorithms is evaluated and compared with the state-of-the-art methods on four public benchmarks for face recognition. Experimental results show that the proposed BULDP method and its nonlinear version achieve much competitive recognition performance.**

I.INTRODUCTION

Face images lie in a very high dimensional space, which makes the task of recognition very difficult. Dimensionality reduction techniques have been widely used to represent the raw data in a compact way without losing too much useful information [6]. These techniques learn a lower dimensional subspace to represent the face such that the image analysis can be performed more efficiently. Principal Component Analysis (PCA) [7] and Linear Discriminant Analysis (LDA) [8] are two famous linear algorithms for unsupervised and supervised dimensionality reduction respectively, which have been widely studied and extensively used in many fields such as computer vision, pattern recognition and other biometrics [8][13]. Wang et al. [14] proposed a robust Compact Fisher Vector (CFV) descriptor for robust face recognition.

They preserve the global structure of the data by using fewer dimensions. However, the world is not always flat, linear dimensionality reduction techniques cannot adequately reflect the nonlinear structure of world [15]. A series of nonlinear dimensionality reduction algorithms have been developed to solve this problem, with two attracting a wide range of attention particularly: manifold based techniques and kernel-based techniques. The basic idea of manifold based techniques is to find the intrinsic low-dimensional nonlinear data structures hidden in the high dimensional space. Isometric feature mapping (ISOMAP) [16], Laplacian Eigenmaps (LE) [17], Local Linear Embedding (LLE) [18] and Local Tangent Space Alignment (LTSA) [19] are the most well-known manifold-based algorithms. Some experiments have validated their excellent performance by discovering the low dimensional embeddings hidden in high dimensional manifold.

This YALE database [56] contains 165 images of 15 individuals, each individual has 11 images, each image is obtained from different perspectives, with large variance in illumination and expression. In our experiments, each image in YALE database was manually cropped and resized to 32×32.

Fig:1 Samples Of YALE Face Database

II. EXISTING SYSTEM

In recent years, sparse representation-based methods have shown strong performance in face recognition and image classification . Gao et al. [35] proposed a new dimensionality reduction approach based on sparse representation, namely SRC-FDC, considers both the local reconstruction relationship and spatial Euclidean distribution, which encode both the local intrinsic geometric and global structure. In order to overcome the drawbacks of the method of changing the representation of the data in sparse representation. Xu et al. [36] proposed a novel transfer subspace learning method which integrates the method of classifier design and changing data representation. In [37], Tan et al., further explored group sparsity, data locality and the kernel trick, and a joint sparse representation method, named kernelized locality-sensitive group sparsity representation (KLS-GSRC) is proposed. Zheng et al. [38] proposed a iterative re-constrained group sparse representation classification (IRGSC) approach to further enhance the robustness of face recognition for complex occlusion and severe corruption, in which weighted features and groups are collaboratively adopted to encode more structure information and discriminative information than other regression based methods.

III. PROBLEM DEFINITION

Face images lie in a very high dimensional space, which makes the task of recognition very difficult. Therefore, Dimensionality reduction technique has been used to represent the raw data in a compact way without losing too much useful information. These techniques learn a lower dimensional subspace to represent the face such that the image analysis can be performed more efficiently. Moreover, we also develop a nonlinear version of our BULDP using kernel functions for nonlinear dimensionality reduction.

IV. PROPOSED SYSTEM

To address above issue, combing with the characteristics of human cognition, we proposed a Biomimetic Uncorrelated Locality Discriminant Projection (BULDP) approach. BULDP is based on UDP, but with a new way of adjacency coefficient construction which is proposed according to the characteristics of imagery thinking. The proposed adjacency coefficient does not only make use of the category information between samples, but also reflect the law between the same samples and the similarity between the different samples. Besides, BULDP introduces the concept of uncorrelated spaces, which makes the last of the vector has no correlation and reduces the redundancy of the extracted vectors. In addition, an extended version of Kernel Biomimetic Uncorrelated Locality Discriminant Projection (KBULDP) is given, which can be considered as a generalization of BULDP in kernel space. To demonstrate its effectiveness, we apply our proposed BULDP methods for face recognition and the experimental results are encouraging.

V. SYSTEM DESIGN

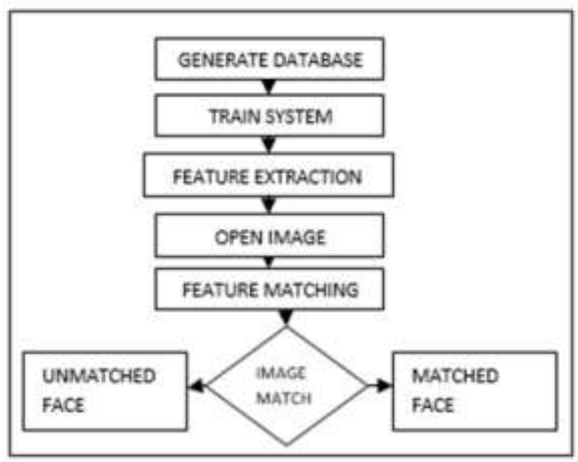

Fig :2 Workflow Of System

System Design is the next development stage where the overall architecture of the desired system is decided. The system is organized as a set of sub systems interacting with each other. While designing the system as a set of interacting subsystems, the analyst takes care of specifications as observed in system analysis as well as what is required out of the new system by the end user.

As the basic philosophy of Object-Oriented method of system analysis is to perceive the system as a set of interacting objects, a bigger system may also be seen as a set of interacting smaller subsystems that in turn are composed of a set of interacting objects. While designing the system, the stress lies on the objects comprising the system and not on the processes being carried out in the system as in the case of traditional Waterfall Model where the processes form the important part of the system.

VI. IMPLEMENTATION

1 Face recognition: The first step of our system is to Design the system, such that first the image dataset folder should be indexed by the user. After index is made, it shows the number of images in the folder which we indexed. Next the query image is selected by the user. The corresponding face of the feature vector with the lowest measured value indicates the match found.
2 Histogram generation: The histogram is generated based on the query image selected from the image dataset. The horizontal axis of the graph represents the tonal variations, while the vertical axis represents the number of pixels in that particular tone.
3 Expression Recognition: Facial expression recognition is performed by using a Support Vector Machine (SVM) to evaluate the performance of the proposed method.
4 Face Retrieval: Then retrieve the similar images based on the expression recognized on the previous module. The efficiency of the descriptor depends on its representation and the ease of extracting it from the face. These descriptors are used in several areas, such as, facial expression and face recognition.

VII. METHODOLOGY

The biomimetic method in the field of information science has been successfully applied in many fields such as pattern recognition and other technologies [41][43]. It has been shown that it is an effective way to solve imagery problems of image processing, speech recognition, image thinking, etc. These approaches are mainly based on the following characteristics of human cognition effective way to solve imagery problems of image processing, speech recognition, image thinking, etc.: 1) Principle of Homology Continuity: The concept of homology was originally applied in anatomy and morphology. Futuyma's [44] description of homology as the possession by two or more species of a trait derived, with or without modification, from their common ancestors and that homologies form the basis of phylogenetic reconstruction probably represents the most widely accepted definition of this fundamental biological concept. Cognitive scientists consider that one thing will form a low dimensional continuous manifold with the changing of space, time and other factors. The strong cognitive ability of human is the visual memory for this stable manifold [45]. In the real world, if two intra-species are not exactly the same, the difference between them must be gradually changed. There is a certain relationship between two intra-species, and there must be a continuous path from a sample point to another, the process of which is gradual, the samples passed in this transition process or path belong to the same class, the law about homology continuity between samples is called the Principle of Homology Continuity (Principle of Homology Continuity, PHC) [46].

VIII. CONCLUSION

The advantages and disadvantages of UDP and other extensions of LPP are discussed in this paper. On the basis of these methods, a Biomimetic Uncorrelated Locality Discriminant Projection (BULDP) approach is proposed. First of all, a new construction method of adjacency coefficient is proposed according to the characteristics of human perception. Secondly, the concept of uncorrelated space is introduced, whose purpose is to make sure the final discriminant vectors have no correlation. And then, We give a concrete solution of BULDP. Finally, an extended version of kernel biomimetic uncorrelated locality discriminant projection, namely KBULDP, is proposed. Experimental results on LFW, YALE, ORL, FERET and CMU PIE indicate that BULDP and KBULDP performs significantly better than the state-of-art methods.

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