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Biometric Uncorrelated Face Recognition Using Unsupervised Learning

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Abstract:- In this paper we developed 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..

Keywords: Biomimetic Uncorrelated Locality Discriminate Projection (BULDP).Face recognization, Unsupervised Learning

1. Introduction

Face recognition is the primary concept in the field of pattern recognition in the recent year. For face recognition researchers have to implement the different methods. By using this kind of techniques from the viewpoint of reducing original feature dimensions, map the original high-dimensional data to a low dimensional feature space with better characterization of data distribution, to remove the noise, and hence improve the learning performance.

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 [1]. 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) [2] and Linear Discriminant Analysis (LDA) [3] are two famous linear algorithms for unsupervised and supervised dimensionality reduction respectively, which have been widely studied and extensively used in many fields such ascomputer vision, pattern recognition and other biometrics [8][13]. The author by [4] 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 [5]. 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

2. Literature Review

Face recognition is the primary concept in the field of pattern recognition in the recent year. For face recognition researchers have to implement the different methods. By using this kind of techniques from the viewpoint of reducing original feature dimensions, map the original high-dimensional data to a low dimensional feature space with better characterization of data distribution, to remove the noise, and hence improve the learning performance.

Face image is lie in very high dimensional space, which makes the task of recognition very difficult. Recently we are going to use the Dimensionality recognition techniques have been widely used to describe the raw data compactly without losing too much useful information. These techniques learn a lower dimensional subspace to represent the face such that image analysis can be performed more efficiently. Along with this technique also using same techniques Principal component analysis (PCA) and linear discriminate analysis (LDA) are the two famous linear algorithms for unsupervised and supervised dimensionality reduction, respectively, which have been widely studying and extensively used in many like computer vision, pattern recognition, other biometrics and robust Compact Fisher Vector (CFV) descriptor for robust face recognition. They preserve the global structure of the data by using fewer dimensions. Linear dimensionality reduction techniques cannot adequately reflect the nonlinear structure of the world. A series of nonlinear dimensionality reduction algorithms have been developed to solve this problem, with two attracting a wide range of attention, mainly: manifold based techniques and kernel-based techniques. The representative algorithms are Kernel Principal Component Analysis (KPCA) and Kernel Linear Discriminant Analysis (KLDA) that have been demonstrated to be highly efficient in many practical applications.

However, one important challenge in the above mentioned manifold-based techniques is that an explicit mapping function is not easy to find. Many researchers have done a lot of work to resolve this challenge. Locality Preserving Projection (LPP) [19], [20] is proposed to preserve the local structure of data in order to capture the non-linearity of the manifold. As this algorithm considers the manifold structure of samples, it achieves very good recognition performance in pattern recognition and draws wide attention in machine learning. In contrast to most other manifold based algorithms, LPP apparently has the advantage that it can generate an explicit map easily. However, the objective function of LPP only emphasizes the local structure and ignores the global structure. Many extensions of LPP [13]–[14], have also been proposed in literature and are widely used in face and expression recognition problems. In order to settle the shortcomings of LPP, Cai et al. proposed an Orthogonal Locality Preserving Projection (OLPP) [14] algorithm and Zhao et al. proposed Uncorrelated Locality Preserving Projection (ULPP) [16] algorithm. Wang et al. proposed an Fast and Orthogonal Locality Preserving Projections (FOLPP) [15] for dimensionality reduction, which simultaneously minimizes the locality and maximizes the globality under the orthogonal constraint. Motivated by the idea of classification-oriented multi-manifolds learning, an Unsupervised Discriminant Projection (UDP) [27] algorithm was proposed, which characterizes the local scatter and the non-local scatter. The objective function of this method is similar to Fisher Linear Discriminant Analysis; this property contributes to make UDP more powerful and more intuitive than most other LPP-based methods.

To increase the nonlinear ability of LPP, a Kernel Locality Preserving Projection (KLPP) [8] was proposed in which the kernel trick was used for computation and solution of an eigenvalue problem. Moreover, a Supervised Kernel Locality Preserving Projections (SKLPP) [9] was proposed for face recognition, in which geometric relations are preserved according to prior class-label information and complex nonlinear variations of real face images are represented by nonlinear kernel mapping.

However, all above improved methods do not consider the problem from the perspective of classification. Yu et al. [3] proposed a Discriminant Locality Preserving Projections (DLPP) method to improve the classification performance of LPP. Yang et al. [11] presented a Null space Discriminant Locality Preserving Projections (NDLPP) algorithm. Wong et al. [12] proposed a Supervised Optimal Locality Preserving Projection (SOLPP) which uses both local information and class information to model the similarity of the data.

The objective function of LPP only considers the local scatter of the projected data. In some cases, this criterion cannot be guaranteed to get a good projection for classification purposes [7]. UDP, KLPP and SKLPP did not explicitly take classification into account, but only adopt a supervised weight matrix [2]. DLPP and NDLPP utilize the classification information, but their feature space does not have the property of uncorrelated, a great quantity of redundant information exists between the extracted feature vectors. In addition, they did not take into account the continuity characteristics between samples with different labels. So with face image expression, posture change obviously, the recognition performance of these algorithms will be significantly reduced.

In recent years, sparse representation-based methods have shown strong performance in face recognition and image classification. Gao et al. [6] 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. [7] proposed a novel transfer subspace learning method which integrates the method of classifier design and changing data representation. In [38], 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. [9] 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. Considering that most sparse representation algorithms do not suitable for characterizing the low rank structural information of image matrix, Xie et al. [4] proposed a novel robust matrix regression model (RMR) by building the robust nuclear norm for measuring the error matrix. For the problem of face recognition, methods based on sparse representation can achieve high recognition rate, and excellent robustness, for some pixel error, noise and occlusion. However, these methods require high standard face database and require strict face alignment. Besides, a large number of complex sparse decompositions are required to identify each target.

3. System Study

3.1 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.

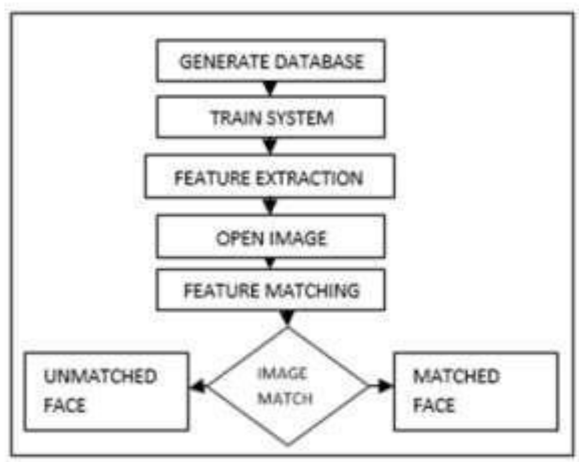

Fig 1. Flow model

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.

3.2 Challenges

- Linear dimensionality reduction techniques cannot adequately reflect the nonlinear structure of world.
- uncorrelated space is not using in this methods
- Sparse representation can achieve high recognition rate, and excellent robustness, for some pixel error, noise and occlusion.

3.3 Proposed Method

To address above issue, combing with the characteristics of human cognition, we proposed a Biometric Uncorrelated Face Recognition Using Unsupervised Learning (BUFRUL) approach. BUFRUL 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, BUFRUL 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 Biometric Uncorrelated Face Recognition using Unsupervised Learning(KBUFRUL) is given, which can be considered as a generalization of BUFRUL in kernel space. To demonstrate its effectiveness, we apply our proposed BUFRUL methods for face recognition and the experimental results are encouraging.

4.Methodology

The biomimetic method in the field of information science has been successfully applied in many fields such as pattern recognition and other technologies . 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 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. 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).

5. Implementation

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.

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.

Expression Recognition: Facial expression recognition is performed by using a Support Vector Machine (SVM) to evaluate the performance of the proposed method.

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.

6. Result Analysis

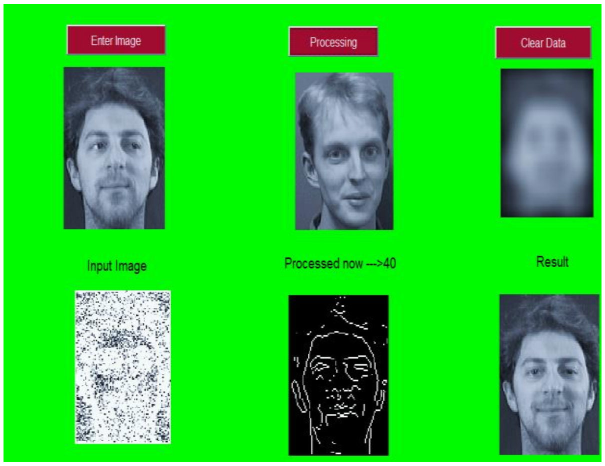

Figure 2. Output Results to compare the face recognition

From the above result it demonstrate that initially system takes input image which will compare with training model and validate with the trained model. For the experiment we have trained 40 images [face images] and test with few sample images to recognize the face if it matches then the original image will be retired and validated

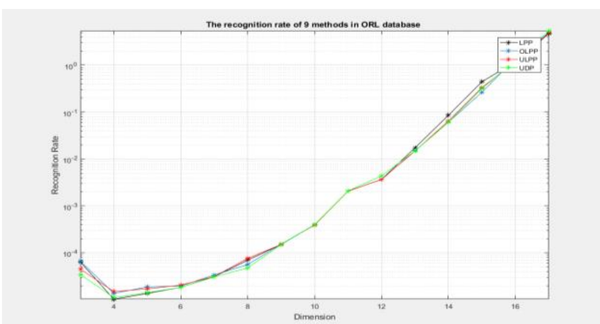

Figure 3. The Recognization rate of proposed methods

7. Conclussion

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 vectorshave 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 perform significantly better than the state-of-art methods.

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